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 loan 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 return on the banks' risk–free investment alternative, which is also likely to affect the supply of loans, we derive a credit crunch indicator, which measures that part of the shift in the loan supply that is neither explained by firm–specific factors nor by the opportunity costs of providing risky loans.

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 –3.4 percent in December 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 typically encountered with aggregate data by applying a micro data approach that uses information about the loan supply behavior of banks, which is 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' loan supply conditions. From a theoretical perspective, the survey responses are exclusively used as indicators for the location of the loan supply curve, which allows us to avoid controlling for the demand side of the loan market.

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 an article by Bernanke and Lown (1991) in which they 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 banks’ opportunity costs of providing risky loans or changes in the creditworthiness of borrowers.

The purpose of the paper is to derive a credit crunch indicator that represents shifts in the supply of loans, which cannot be explained by ‘normal’ determinants of the loan supply curve. 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 discrete 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 loan supply decision of the bank. In a second step we separate the variation of lending policies, which is captured by the time dummy coefficients, from changes in the banks’ opportunity costs of providing risky loans. This is achieved by regressing the estimated time dummy coefficients on the evolution of the safe real interest rate over time using a simple linear regression model. The variation of the time dummy coefficients, which cannot be explained by changes in the safe real interest rate, i.e. the residuals of the linear regression, are finally interpreted as bank industry–specific determinants of loan supply. The more positive the contribution of the bank industry–specific determinants of loan supply to the firms’ perception of a restrictive willingness to lend (holding constant both the safe real interest rate and the quality of potential borrowers), the higher the probability that the economy is affected by an adverse loan supply shock and, hence, a credit crunch.

Our results show that the probability of a credit crunch in the German economy was highest during the years 2003/04, following the economic downturn after the burst of the New Economy Bubble. In the subsequent boom of the years 2006 to 2008 the loan supply of banks was much laxer. Even after controlling for the on average good quality of the firms and the low safe real interest rate, 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 much weaker than in the years 2003 to 2004. Only large firms that mainly negotiate credits with state–owned landes banks and private commercial 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 the banks' opportunity costs of providing risky loans.

To our knowledge this paper is the first to identify credit crunches by using direct (qualitative) information about loan 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 1997/98 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 loan volumes. However, since their dependent variable was loan volume, the identification problem still remained and loan supply shifts had to be identified by including some proxies for loan demand into the regression. Our approach solves this identification problem *a priori* by using a proxy for loan supply as dependent variable in the regressions.

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. The main advantage of our approach is that it results in an indicator for the existence of a credit crunch (or, to put it more general, of loan supply shocks) over time.

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 variable y_{it}, representing qualitative information about the loan supply conditions,

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

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 distribution function of either the logistic distribution (logit model) or the standard normal distribution (probit model). Since y_{it} may vary across firms for reasons we cannot control for, the model is estimated with unobserved firm–specific effects α_i.[1] A random effects (_re) model treats the α_i as an unobserved random variable with a specified distribution, typically the normal distribution. However, the random effects model hinges on the unlikely assumption, that the α_i

[1] Good descriptions of discrete response models for panel data can be found in Greene (2008) or Hsiao (2003).

are independent from all x_i. 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}. Thus, in contrast to the random effects model, the fixed effects model makes inference based only on the intra–firm variation of the variables, implying that unobserved time–invariant differences across firms have no effects. A major problem of the fixed effects model is that 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. While this problem cannot be solved for the probit model, it is possible to consistently estimate a logit model with the conditional maximum likelihood estimator. This estimator 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, which leads to the loss of those observations where $y_{it} = 0$ or $y_{it} = 1$ for all t.

2.1 Data

In all regressions the dependent variable y_{it} is *creditsupply*, 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' loan supply policy as "restrictive", and 0 if the firms indicate "normal" or "accommodating".[2] 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 included in the regular monthly survey from November 2008 on. The November 2010 survey is the latest survey that is included in the sample. On average we have 2100 responses to the credit question in each survey.

The regressors x_{it} consist of two groups of variables. The first group com-

[2] In Section 2.3.3 we will also present regressions which take into account the ordinal character of the variable.

prises 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 bad (more unfavorable business expectations, poor 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 good (more favorable business expectations, good 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.[3] 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 man-

[3]For example, Bougheas, Mizen, and Yalcin (2006) use ratios such as tangible assets to total assets or the return to capital as firm–specific determinants of loan supply.

ufacturing 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 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. In the chemical sector (DG), for example, which accounts for about 6 percent of the observations, firms report on average much more favorable business situations and expectations than in the textile sector (DB with about 5 percent of the observations).

Table 1: Sector–specific Economic Activity

climatesector	mean	std.dev.	N
DA (food products, beverages and tobacco)	-4.49	7.27	4517
DB (textiles and textile products)	-17.43	16.52	3625
DC (leather and leather products)	-14.03	20.86	956
DD (wood and wood products)	-6.40	20.71	3188
DE (pulp, paper and paper products; publishing and printing)	-10.81	16.61	11556
DF (coke, refined petroleum products and nuclear fuel)	2.92	31.90	258
DG (chemicals, chemical products and man–made fibres)	9.65	23.04	5038
DH (rubber and plastic products)	-3.73	25.64	5024
DI (other non–metallic mineral products)	-12.90	18.50	4464
DJ (basic metals and fabricated metal products)	-12.83	24.19	11373
DK (machinery and equipment n.e.c.)	-6.49	26.08	13192
DL (electrical and optical equipment)	-4.67	27.16	9414
DM (transport equipment)	-17.28	31.73	2607
DN (not elsewhere classified)	-14.50	18.05	3858
Total	-8.16	23.46	79070

Some descriptive statistics for the variables are shown in Table 2. The sample comprises 79070 responses to the credit question over the period 2003 to 2010. In 38 percent of the observations the firms assessed the banks' loan supply policy as "restrictive". On average, those firms are characterized by a poorer state of the business (i.e. a lower value of *statebus*), more unfavorable business expectations (i.e. a lower value of *comexp*) and a lower business activity in the sector they are operating in (i.e. a lower *climatesector*). The low values of the standard errors indicate that the differences between the two sub–groups are statistically significant at conventional levels.[4]

Table 2: Descriptive Statistics

creditsupply	variable	mean	std.dev.	std.err.	min	max	N
1 (restrictive)	*statebus*	1.65	0.66	0.0038	1	3	29761
	comexp	1.9	0.68	0.0039	1	3	29761
	climatesector	-12.82	22.02	0.1276	-71.2	53.6	29761
0 (else)	*statebus*	1.99	0.69	0.0031	1	3	49309
	comexp	2.01	0.63	0.0028	1	3	49309
	climatesector	-5.36	23.85	0.1074	-71.2	53.6	49309
Total	*statebus*	1.87	0.7	0.0025	1	3	79070
	comexp	1.97	0.65	0.0023	1	3	79070
	climatesector	-8.16	23.46	0.0834	-71.2	53.6	79070

Notes: *creditsupply* = 1, if the firms assess the banks' loan supply policy as "restrictive", *creditsupply* = 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 firms' quality. We include a set of $T-1$ time dummies, where $T = 37$ is the number of surveys between June 2003 and November 2010 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 loan supply decision of the bank.

2.2 Regression Results

The results of the logit and probit regressions are shown in Table 3.[5] The coefficients on the quality measures are significant and have the correct negative sign. If the state of the business is "good" or business expectations are "more favorable", the probability that a firm perceives the loan supply policy of banks as restrictive decreases. If the economic activity in the sector that a firm belongs to increases, the probability of a restrictive loan supply policy decreases.

[4]The standard error of the mean is estimated by the sample estimate of the population standard deviation divided by the square root of the sample size N (assuming statistical independence of the values in the sample).

[5]All estimates reported in this paper are done with Stata 11.

These results are robust across the assumption made with respect to α_i and the distribution function F (column (1) shows the results of the random effects logit model, column (2) those of the fixed effects logit model, and column (3) those of the random effects probit model).

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 (with the exception of the year 2004 and December 2009) 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 December 2009 to values below those estimated for the year 2003. The year 2010 was again characterized by continuous decline of the estimated time dummy coefficients. This 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 2003/04 or 2009/10 (see Figure 1). Moreover, during the latest crisis period loan supply to firms of equal quality was on average less restrictive than in 2003/04. Interestingly, the timely pattern of the coefficients on the time dummies are unaffected by the assumption about the cumulative distribution function and the way how the firm–specific effects are modeled.

2.3 Robustness

2.3.1 Linear Probability Model

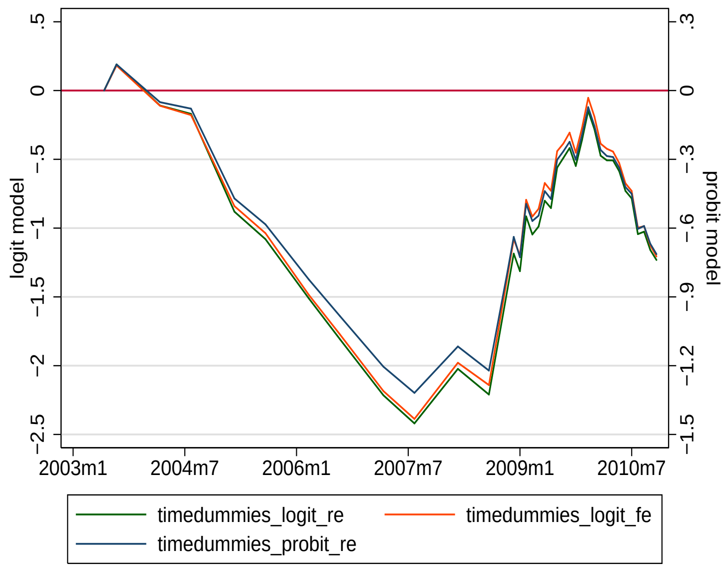
Since the parameters β (which include the coefficients on the time dummies) are estimated from a non–linear binary regression model, they only provide information about the sign and the statistical significance of the relationship between the independent variables and the outcome and cannot be interpreted as marginal effects. Nevertheless, also in a binary response model it holds that for a given positive value of the independent variable the probability of an outcome is larger at a given point in time, the greater the estimated coefficient on the independent variable is. Thus, larger coefficients on the time dummies imply a higher probability of a restrictive loan supply for a given quality of a firm. A quantitatively more meaningful interpretation of the estimated coefficients can

Table 3: Regression Results

	(1) logit_re	(2) logit_fe	(3) probit_re
statebus	-0.557***	-0.475***	-0.312***
	(-26.90)	(-22.40)	(-26.81)
comexp	-0.116***	-0.104***	-0.065***
	(-5.90)	(-5.21)	(-5.78)
climatesector	-0.011***	-0.010***	-0.006***
	(-9.09)	(-7.98)	(-8.93)
t_0308	0.190*	0.182*	0.114**
	(2.37)	(2.24)	(2.59)
t_0403	-0.109	-0.110	-0.051
	(-1.36)	(-1.35)	(-1.14)
t_0408	-0.170*	-0.178*	-0.079
	(-2.02)	(-2.10)	(-1.71)
t_0503	-0.881***	-0.840***	-0.471***
	(-10.76)	(-10.16)	(-10.38)
t_0508	-1.081***	-1.037***	-0.584***
	(-12.79)	(-12.16)	(-12.48)
t_0603	-1.512***	-1.486***	-0.825***
	(-15.99)	(-15.47)	(-15.73)
t_0608	-1.808***	-1.773***	-0.984***
	(-18.39)	(-17.78)	(-18.10)
t_0703	-2.215***	-2.184***	-1.204***
	(-20.89)	(-20.26)	(-20.71)
t_0708	-2.420***	-2.387***	-1.319***
	(-22.16)	(-21.46)	(-22.10)
t_0803	-2.023***	-1.979***	-1.116***
	(-20.22)	(-19.55)	(-20.19)
t_0808	-2.210***	-2.141***	-1.221***
	(-24.07)	(-23.09)	(-24.10)
t_0811	-1.442***	-1.349***	-0.789***
	(-16.61)	(-15.36)	(-16.41)
t_0812	-1.185***	-1.082***	-0.638***
	(-12.81)	(-11.54)	(-12.39)
t_0901	-1.313***	-1.197***	-0.727***
	(-14.95)	(-13.45)	(-14.80)
t_0902	-0.915***	-0.794***	-0.494***
	(-10.33)	(-8.83)	(-9.98)
t_0903	-1.046***	-0.916***	-0.569***
	(-11.91)	(-10.25)	(-11.58)
t_0904	-0.989***	-0.860***	-0.546***
	(-11.31)	(-9.68)	(-11.13)
t_0905	-0.801***	-0.672***	-0.439***
	(-9.22)	(-7.61)	(-8.99)
t_0906	-0.854***	-0.729***	-0.473***
	(-10.05)	(-8.43)	(-9.90)
t_0907	-0.560***	-0.441***	-0.302***
	(-6.68)	(-5.17)	(-6.38)
t_0908	-0.490***	-0.385***	-0.265***
	(-5.84)	(-4.52)	(-5.58)
t_0909	-0.418***	-0.306***	-0.224***
	(-4.68)	(-3.37)	(-4.42)
t_0910	-0.548***	-0.452***	-0.302***
	(-6.62)	(-5.36)	(-6.43)
t_0911	-0.361***	-0.272**	-0.194***
	(-4.29)	(-3.18)	(-4.09)
t_0912	-0.148	-0.053	-0.072
	(-1.68)	(-0.59)	(-1.45)
t_1001	-0.281**	-0.189*	-0.154**
	(-3.15)	(-2.07)	(-3.03)
t_1002	-0.474***	-0.386***	-0.259***
	(-5.21)	(-4.17)	(-5.02)
t_1003	-0.507***	-0.423***	-0.286***
	(-5.51)	(-4.52)	(-5.46)
t_1004	-0.508***	-0.444***	-0.290***
	(-5.34)	(-4.59)	(-5.37)
t_1005	-0.587***	-0.528***	-0.337***
	(-6.07)	(-5.37)	(-6.13)
t_1006	-0.729***	-0.674***	-0.421***
	(-7.57)	(-6.88)	(-7.67)
t_1007	-0.784***	-0.730***	-0.450***
	(-7.85)	(-7.16)	(-7.93)
t_1008	-1.043***	-0.997***	-0.603***
	(-10.29)	(-9.66)	(-10.48)
t_1009	-1.026***	-0.986***	-0.591***
	(-9.38)	(-8.84)	(-9.49)
t_1010	-1.159***	-1.124***	-0.668***
	(-11.04)	(-10.51)	(-11.24)
t_1011	-1.232***	-1.206***	-0.714***
	(-11.50)	(-11.03)	(-11.78)
_cons	1.178***		0.653***
	(13.21)		(13.17)
lnsig2u			
_cons	1.812***		0.655***
	(55.61)		(20.73)
N	79070	62615	79070
AIC	68056.34	45714.10	68245.75
LogL	-3.4e+04	-2.3e+04	-3.4e+04

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

Figure 1: Coefficients on Time Dummies



be given in the context of a linear probability model:

$$Pr(y_{it} = 1|x_{it}, \beta, \alpha_i) = \beta' x_{it} + \alpha_i. \tag{2}$$

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.[6] In Table 9 in Appendix A columns (1) and (2) show that for a given quality of the firm the probability of a restrictive loan supply was, depending on the assumption made with respect to α_i, between 25 and 28 percentage points lower in August 2008 than in June 2003 (when the time dummy coefficients are set to zero).

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

2.3.2 Instrumental Variable Regressions

A linear probability model is also useful for running instrumental variable (IV) regressions in order to account for the potential endogeneity of the regressors. If a firm faces a restrictive loan supply, profitable investments cannot be financed. Thus, it is possible that the firm's assessment about the banks' loan supply policy (*creditsupply*) 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 loan supply conditions. If the firm–specific regressors were endogenous, our estimators would be biased 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 the fixed effects linear probability model with IV methods (see column (3) in Table 9 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 and probit regressions are not subject to endogeneity problems. Finally, all the conclusions drawn henceforth based on the logit and probit models are almost identical to the results of the linear IV model.

2.3.3 Nonlinear Probability Model for Ordered Outcomes

Since the dependent variable y_{it} has three potential outcomes, "accommodating", "normal" and "restrictive", and since these outcomes are inherently ordered, we check the robustness of our baseline results using an ordered logit random effects model and an ordered probit random effects model.[7] As in our baseline regressions the coefficients on the firms' quality measures are significant

[7] The ordered nonlinear probability models were estimated using the `gllamm` programs for Stata (see `http://www.gllamm.org/`).

and have the correct negative sign (see columns (4) and (5) in Table 9 in Appendix A). Moreover, the coefficients on the time dummies show time patterns that are similar to those of the baseline regressions.

2.3.4 Data Frequency

The inclusion of the credit question in the regular monthly survey from November 2008 on implies a break in the frequency of the data. In the first five years between June 2003 and August 2008 the question was asked two times a year, implying 12 surveys with 28295 observations in total. Between November 2008 and November 2010 the question was asked monthly, i.e. 25 times with 50775 observations in total. Due to the change of frequency of the survey the period of the world financial crisis has an over–proportionally large weight in the regression, which may induce some bias in our estimates. For this reason we re–ran our baseline regressions using only data from March and August of each year in the sample. The results are shown in Table 10 in Appendix A. As in our baseline regressions the coefficients on the firms' quality measures are significant and have the correct negative sign. Moreover, the coefficients on the time dummies show time patterns that are similar to those of the baseline regressions.[8]

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 loan 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 loan supply of banks can also be explained by changes in the return of the banks' risk–free investment alternative, which can be interpreted as the opportunity costs of providing risky loans. These opportunity costs are measured by the real interest rate on safe government bonds. If the

[8]Additionally, we ran regressions with observations only from November 2008 on. Again, the results, which are available from the authors upon request, are very close to those of the baseline regressions.

safe real interest rate increase, banks invest more of their funds in risk–free assets and will consequently reduce their loan supply, everything else being equal (Bernanke and Blinder, 1988).

Those shifts in loan supply that are not caused by normal determinants of the loan supply curve and that therefore reflect a credit crunch are isolated by regressing the estimated time dummy coefficients on the evolution of the safe real interest rate over time using a simple linear regression model:

$$\widehat{td_t} = c + \delta i_t + \varepsilon_t. \tag{3}$$

$\widehat{td_t}$ corresponds to the estimated coefficients on the time dummies t_yymm shown in Table 3, c is an intercept, and i_t is the real interest rate on safe 10–year government bonds. The real interest rate is calculated by the European Central Bank from AAA–rated euro area central government bonds (European Central Bank, 2008, provides some further information). Thus, we assume that the banks' investment alternative to risky loans to German firms is a government bond issued by euro area central governments with the lowest credit risk. The variation of the time dummy coefficients, which cannot be explained by changes in the safe real interest rate, i.e. the residuals ε_t of the linear regression, are finally interpreted as loan supply shocks. The more positive the contribution of loan supply shocks to the firms' perception of a restrictive willingness to lend (holding constant both the banks' opportunity costs and the quality of potential borrowers), the higher the probability that the economy is affected by a credit crunch.

Table 4: Results of the Second–Stage Regression

	(1) logit_re	(2) logit_fe	(3) probit_re
δ	0.246*	0.275**	0.138*
	(2.61)	(2.98)	(2.68)
c	-1.533***	-1.538***	-0.852***
	(-5.95)	(-6.09)	(-6.02)
N	37	37	37
R^2	0.163	0.202	0.170
$LogL$	-32.139	-31.412	-9.943

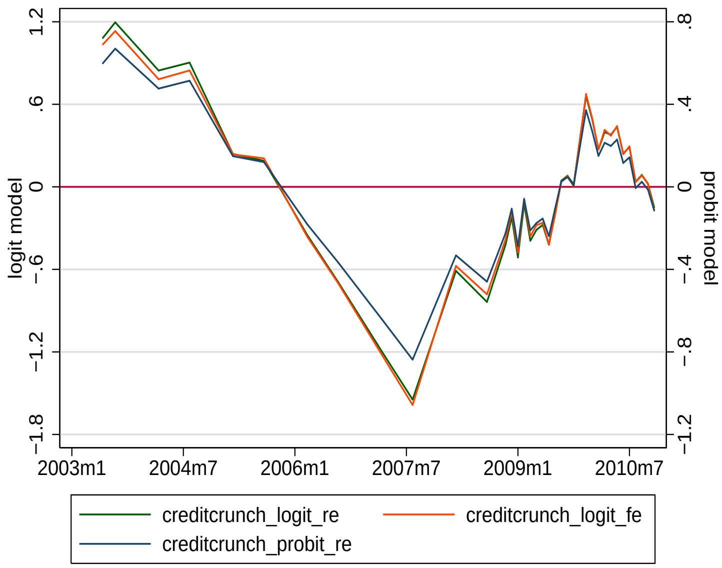
t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The estimated coefficients on the real interest rate δ are positive and significant, implying that higher opportunity costs may contribute to a leftward shift of the loan supply curve (see Table 4). 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 highest during the years 2003/04, following the economic downturn after the burst of the New Economy Bubble. In the subsequent boom of the years 2006 to 2008 the loan supply of banks was laxer. Even after controlling for the on average good quality of the firms and the low safe real interest rate, 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 much weaker.[9]

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 3, which shows the average shares of the negative responses to the survey questions across firms over time and the safe real interest rate. 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 unfavorable business expectations for the next six months. Moreover, the real interest rate is on average higher than during the cyclical upturn in the period from 2005 to 2008. Despite these similarities a closer look at the years 2003 and 2009 shows some remarkable differences. Firstly, the leftward shift of the loan supply curve seems to be more pronounced in the former period, as the share of firms indicating a restrictive loan supply was about 11 percentage points

[9]This result holds for all robustness exercises presented in Section 2.3. The credit crunch indicators resulting from the linear probability models (with or without instruments), the ordered probability models and the binary choice models with only two observations per year are almost identical to the credit crunch indicators of the baseline model (see Figures 8, 9 and 10 in Appendix C). In the case of the linear models we can give a quantitative interpretation of our results. For a given quality of firms and a given safe real interest rate the probability of a restrictive loan supply was about 7 percentage points higher in mid–2003 than by the end of the year 2009. When our sample is reduced to two observations per year (March and August), the last three observations are ignored (September until November 2010). Since the negative values of the credit crunch indicator in the baseline regression only occurred in November 2010, this modification of the sample explains why in this case the credit crunch indicator ends with larger values.

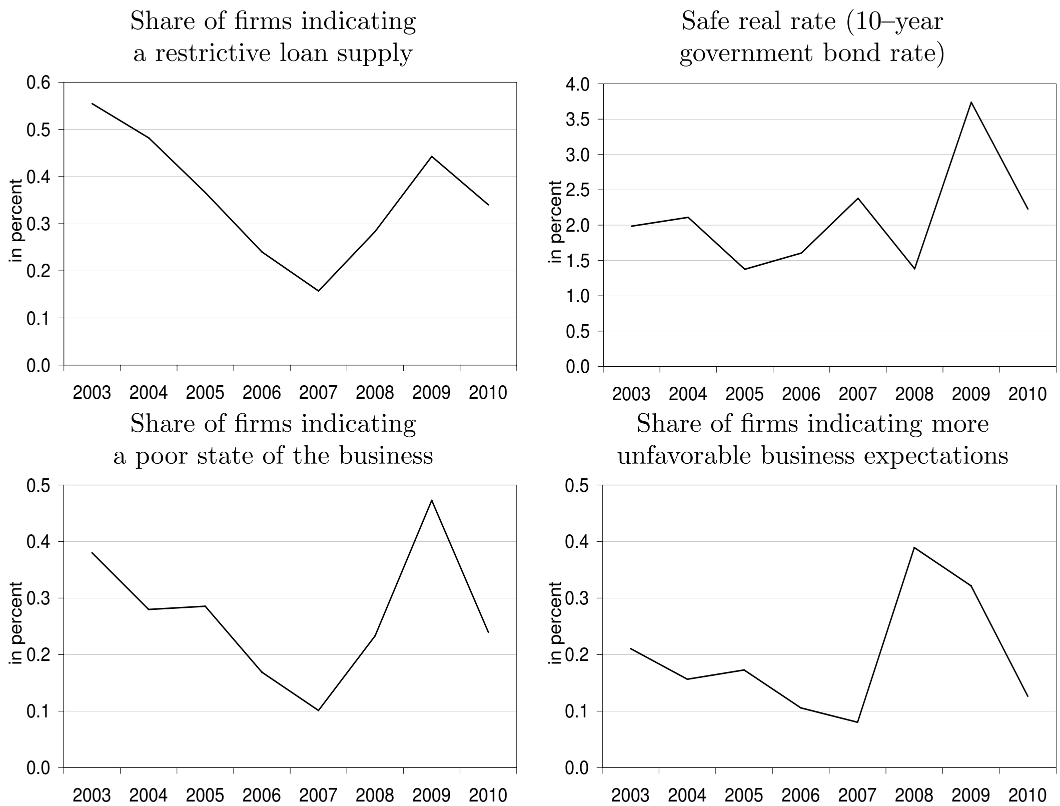
Figure 2: Credit Crunch Indicator



higher in 2003 than in 2009. Secondly, at the same time the average quality of firms was better and the opportunity costs of providing risky loans were lower in 2003 than in 2009, both of which indicates that the part of the leftward shift due to the normal determinants of the loan supply curve was smaller in 2003 than in 2009. In sum, the unexplained residual of the time–variation in loan supply, which is reflected by the credit crunch indicator, is much larger in the former than in the latter period.

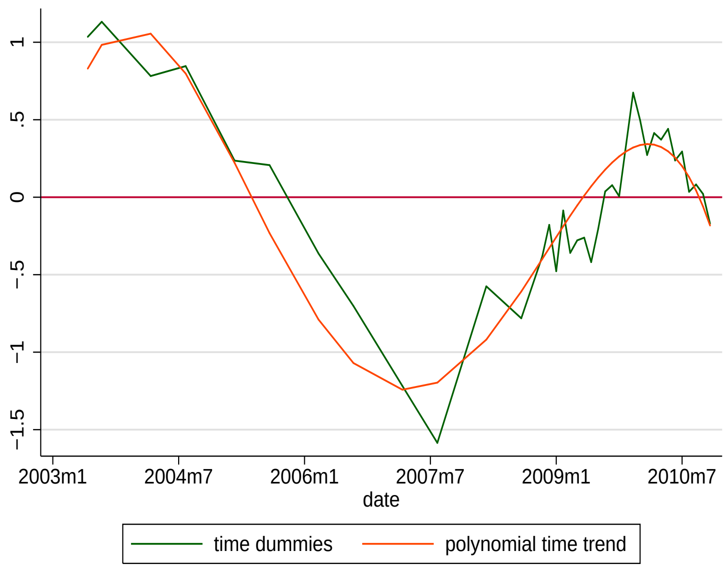
The two–step procedure for calculating the credit crunch indicator is required since the safe real interest rate i_t and the time dummies t_{yymm} cannot be simultaneously used as regressors in the first–stage regression due to collinearities. The reason for this is simply that the T observations for the safe real interest rate 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 (1) 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 busi-

Figure 3: Determinants of the Credit Crunch Indicator (Annual Averages)



ness cycle over and above the quality assessment of the bank, 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 safe real interest rate, as non–firm–specific regressors in our non–linear panel model (1) and derived the credit crunch indicator directly from the estimated coefficients of the polynomial (see Table 11 in Appendix A for the regression results). Figure 4 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 from the two–step approach (see Figure 11 in Appendix C for the credit crunch indicators resulting under different model assumptions). Most importantly, it confirms our previous result that the probability of a credit crunch was lower during the latest financial crisis than in the aftermath of the burst of the New

Figure 4: Credit Crunch Indicator (Fixed Effects Logit Model)



Economy Bubble

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 5 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 5: Descriptive Statistics

	mean(*creditsupply*)	N
Firm size		
< 250 employees	0.40	40397
≥ 250 employees	0.44	22218
Bank relationship		
savings banks	0.41	13741
landes banks	0.49	2125
credit cooperatives	0.39	5804
private commercial banks	0.41	14126
other banks	0.43	4225

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 loan 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); co-operative 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 (Hüfner, 2010).

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[10] 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 5 shows that the information about the bank relationship is available for about 64% of the observations in our sample.

The results of both regressions with interaction terms are shown in Table 6. Since the estimation with interactions terms is time–consuming, we only applied the fixed effects logit model in this Section, which is based on the more realistic assumption that the unobserved firm–specific effects and the regressors are correlated. 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. 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. 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 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. In the model with bank interaction the group–specific intercept dropped out of the regression because of no within–firm variance.[11] We performed joint Wald

[10]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).

[11]The fact that the group–specific intercept was estimated in the model with firm–size

Table 6: Results with Interactions

	Interaction with firm size		Interaction with bank relationship				
	< 250 ee	> 250 ee	savings	landes	credit	private	other
statebus	-0.436***				-0.521***		
	(-20.22)				(-19.10)		
comexp	-0.112***				-0.098***		
	(-5.52)				(-3.81)		
climatesector	-0.005***				-0.006***		
	(-3.92)				(-3.47)		
dummy_group		-0.813***					
		(-5.49)					
t_0308	0.132	0.028	0.223	1.474*	-0.072	0.034	-0.118
	(1.30)	(0.17)	(1.09)	(2.36)	(-0.18)	(0.12)	(-0.27)
t_0403	-0.151	-0.184	-0.086	0.162	-0.661	-0.248	0.458
	(-1.49)	(-1.11)	(-0.43)	(0.27)	(-1.69)	(-0.88)	(1.07)
t_0408	-0.169	-0.344*	-0.208	0.717	-0.307	-0.345	0.273
	(-1.60)	(-2.00)	(-1.01)	(1.22)	(-0.76)	(-1.19)	(0.62)
t_0503	-0.793***	-0.410*	-0.818***	0.471	-0.363	-0.412	0.086
	(-7.74)	(-2.38)	(-4.08)	(0.80)	(-0.93)	(-1.45)	(0.20)
t_0508	-1.063***	-0.285	-1.270***	0.985	-0.281	-0.021	0.550
	(-10.15)	(-1.60)	(-6.24)	(1.72)	(-0.71)	(-0.07)	(1.25)
t_0603	-1.607***	-0.392*	-1.895***	0.821	0.032	-0.106	0.983*
	(-14.08)	(-2.10)	(-8.87)	(1.38)	(0.08)	(-0.36)	(2.28)
t_0608	-1.918***	-0.377	-2.197***	0.541	-0.432	0.160	0.748
	(-16.22)	(-1.86)	(-9.98)	(0.87)	(-1.04)	(0.52)	(1.62)
t_0703	-2.368***	-0.443*	-2.636***	0.612	-0.311	0.291	0.845
	(-18.76)	(-2.03)	(-11.55)	(0.97)	(-0.74)	(0.93)	(1.82)
t_0708	-2.712***	0.153	-3.297***	0.596	0.304	0.880**	1.520**
	(-20.51)	(0.69)	(-13.35)	(0.81)	(0.70)	(2.65)	(3.14)
t_0803	-2.390***	0.530**	-3.130***	1.894**	0.332	1.113***	1.655***
	(-19.36)	(2.71)	(-13.54)	(3.18)	(0.80)	(3.61)	(3.73)
t_0808	-2.438***	0.516**	-2.719***	0.714	-0.475	0.451	1.281**
	(-21.13)	(2.66)	(-12.95)	(1.17)	(-1.16)	(1.52)	(2.97)
t_0811	-1.953***	1.761***	-2.257***	2.045***	-0.320	1.120***	2.141***
	(-17.66)	(9.70)	(-11.21)	(3.68)	(-0.82)	(4.01)	(5.26)
t_0812	-1.643***	1.774***	-1.807***	2.238***	-0.851*	1.067***	1.572***
	(-14.05)	(9.43)	(-8.67)	(3.92)	(-2.14)	(3.74)	(3.76)
t_0901	-1.705***	1.644***	-1.946***	2.383***	-1.030**	0.974***	1.501***
	(-15.40)	(9.19)	(-9.77)	(4.27)	(-2.63)	(3.54)	(3.72)
t_0902	-1.356***	1.902***	-1.560***	2.146***	-0.711	1.085***	1.878***
	(-12.26)	(10.53)	(-7.85)	(3.87)	(-1.86)	(3.95)	(4.64)
t_0903	-1.450***	1.863***	-1.582***	2.041***	-0.829*	0.899***	2.008***
	(-13.26)	(10.41)	(-8.05)	(3.72)	(-2.18)	(3.32)	(4.95)
t_0904	-1.397***	1.826***	-1.622***	1.644**	-0.598	0.908***	2.038***
	(-12.80)	(10.08)	(-8.30)	(2.98)	(-1.58)	(3.36)	(5.07)
t_0905	-1.261***	1.995***	-1.349***	1.539**	-0.745*	0.902***	1.734***
	(-11.62)	(10.99)	(-6.96)	(2.78)	(-1.98)	(3.36)	(4.33)
t_0906	-1.327***	1.989***	-1.321***	1.711**	-0.836*	0.927***	1.497***
	(-12.45)	(11.04)	(-7.05)	(3.16)	(-2.27)	(3.52)	(3.82)
t_0907	-1.024***	1.859***	-1.112***	1.570**	-0.531	0.961***	1.654***
	(-9.71)	(10.27)	(-5.84)	(2.84)	(-1.43)	(3.58)	(4.09)
t_0908	-0.982***	1.778***	-1.022***	2.119***	-0.689	0.829**	1.594***
	(-9.28)	(9.72)	(-5.32)	(3.76)	(-1.83)	(3.06)	(3.97)
t_0909	-1.020***	2.075***	-0.870***	1.570**	-1.152**	0.715*	1.613***
	(-9.00)	(10.60)	(-4.35)	(2.76)	(-2.95)	(2.53)	(3.88)
t_0910	-1.117***	1.876***	-1.099***	1.823**	-0.733	0.859**	1.368***
	(-10.61)	(10.36)	(-5.74)	(3.28)	(-1.95)	(3.19)	(3.39)
t_0911	-0.954***	1.866***	-1.118***	1.779**	-0.410	1.003***	1.713***
	(-8.96)	(10.16)	(-5.71)	(3.21)	(-1.09)	(3.66)	(4.19)
t_0912	-0.693***	1.667***	-0.781***	2.083***	-0.569	0.894**	1.515***
	(-6.21)	(8.70)	(-3.92)	(3.66)	(-1.48)	(3.19)	(3.68)
t_1001	-0.870***	1.699***	-0.858***	1.990***	-0.530	0.858**	1.196**
	(-7.59)	(8.87)	(-4.24)	(3.40)	(-1.37)	(2.98)	(2.81)
t_1002	-1.067***	1.671***	-1.034***	2.170***	-0.496	0.588*	1.015*
	(-9.15)	(8.65)	(-5.10)	(3.68)	(-1.27)	(2.04)	(2.35)
t_1003	-1.125***	1.644***	-1.141***	2.520***	-0.487	0.754**	1.144**
	(-9.55)	(8.54)	(-5.57)	(4.30)	(-1.23)	(2.60)	(2.66)
t_1004	-1.215***	1.691***	-1.252***	2.516***	-0.712	0.840**	1.653***
	(-10.04)	(8.78)	(-5.91)	(4.26)	(-1.78)	(2.86)	(3.82)
t_1005	-1.298***	1.653***	-1.322***	2.696***	-0.703	1.003***	1.492***
	(-10.58)	(8.50)	(-6.22)	(4.52)	(-1.76)	(3.42)	(3.37)
t_1006	-1.434***	1.595***	-1.511***	2.599***	-0.511	0.950**	1.378**
	(-11.64)	(8.28)	(-7.11)	(4.41)	(-1.27)	(3.24)	(3.17)
t_1007	-1.574***	1.700***	-1.747***	2.338***	-0.352	1.191***	1.735***
	(-12.43)	(8.79)	(-7.98)	(3.97)	(-0.88)	(4.01)	(3.97)
t_1008	-1.804***	1.562***	-1.875***	2.119***	-0.429	0.871**	1.551***
	(-13.96)	(8.03)	(-8.53)	(3.62)	(-1.06)	(2.92)	(3.51)
t_1009	-1.734***	1.397***	-1.805***	2.730***	-0.634	0.668*	1.526***
	(-12.58)	(6.55)	(-7.73)	(4.54)	(-1.49)	(2.11)	(3.34)
t_1010	-1.868***	1.347***	-2.031***	2.231***	-0.580	1.054***	1.475***
	(-14.18)	(6.77)	(-9.01)	(3.83)	(-1.41)	(3.49)	(3.33)
t_1011	-1.938***	1.273***	-2.050***	2.243***	-0.498	0.896**	1.188**
	(-14.40)	(6.33)	(-9.03)	(3.72)	(-1.20)	(2.94)	(2.65)
N	62615				40021		
AIC	44595.30				29240.35		
LogL	-2.2e+04				-1.4e+04		

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

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 safe real interest rate to be the same across all subgroups. As in the case without interactions the estimated coefficients on the safe real interest rate are positive and significant, implying that higher opportunity costs may contribute to a leftward shift of the loan supply curve (see Table 7). Concerning the credit crunch indicators 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 5). Thus, large firms were more 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 the banks' opportunity costs of providing risky loans.

Table 7: Results of the Second–Stage Regression with Interactions

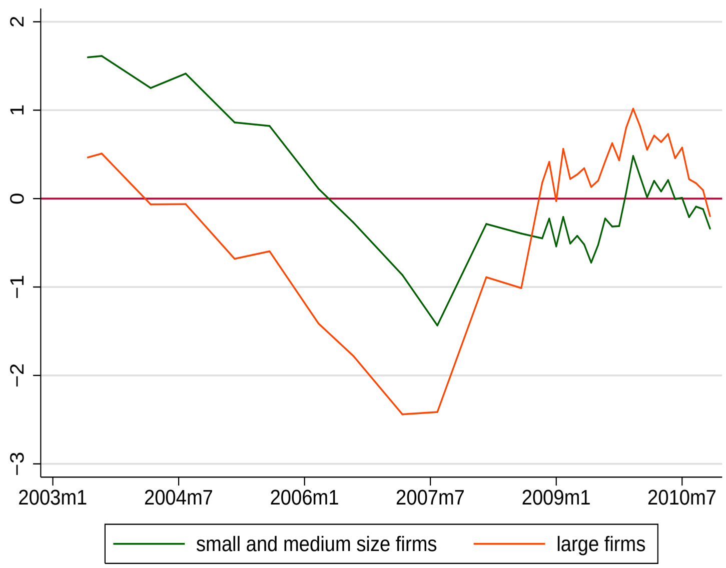
	(1) firm size	(2) bank relationship
δ	0.377***	0.393***
	(3.96)	(5.52)
c_1	-2.288***	-2.460***
	(-8.58)	(-11.25)
c_2	-1.969***	-0.789***
	(-7.12)	(-3.32)
c_3		-2.951***
		(-13.14)
c_4		-1.794***
		(-8.73)
c_5		-1.177***
		(-5.85)
N	37	37
AIC	168.86	166.78
$LogL$	-81.429	-77.391

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

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 8 reveals that large firms typically demand credit from private commercial banks and landes banks, and hence from those banks that

interaction implies that some firms switched from large to small firms or *vice versa* over the sample period.

Figure 5: Credit Crunch Indicator (Firm Size)



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 6). Before 2008 customers of private commercial banks and landes banks reported a less restrictive loan supply than customers of credit cooperatives and savings banks, given an identical quality of the firms and the same safe real interest rate across banks. The situation changed with the financial crisis. Our results indicate that in 2010 mainly customers of landes banks and, to some extent, private commercial banks were affected by adverse credit conditions, while small firms that are getting loans from credit cooperatives and savings banks reported a much better credit market situation.

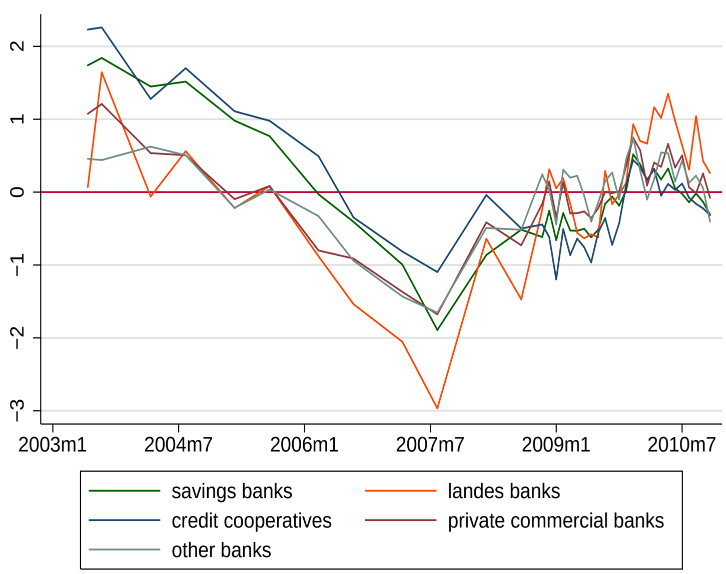
An explanation for the result that the situation during the financial crisis was so different from the situation in 2003/2004 can be given by the evolution of the banks' capital ratio. An important factor which may lead to a contraction in loan supply is related to the difficulties that banks encounter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

Table 8: Bank Relationship and Firm Size

Bank relationship	share of large firms
savings banks	22%
landes banks	45%
credit cooperatives	11%
private commercial banks	49%
other banks	52%

Notes: In the special question of the Ifo Business Survey in June 2009 about the firms' bank relationships 64% 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.

Figure 6: Credit Crunch Indicator (Bank Relationship)



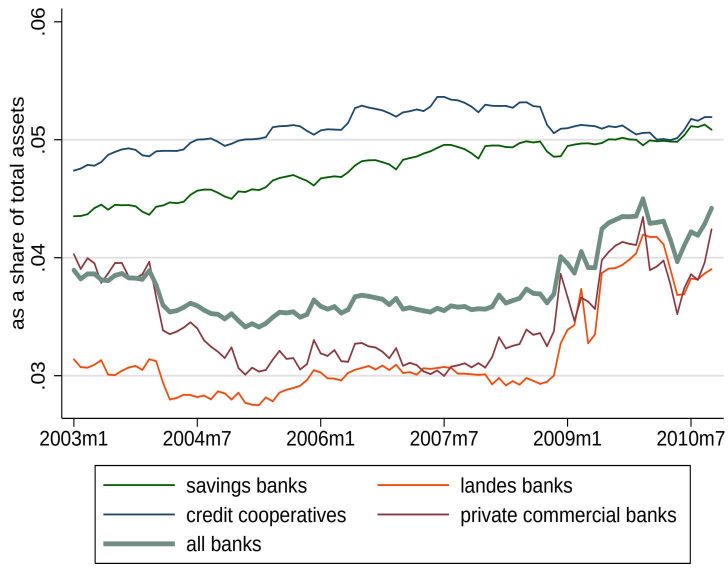
side of their balance sheet and, in particular, in maintaining an adequate level of capital, be it connected with prudential regulation or market discipline (see Mora and Logan, 2012, for some recent evidence on the impact of bank capital on bank lending). This is the reason why the label capital crunch is often used synonymously with a credit crunch (Bernanke and Lown, 1991). Figure 7 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 3.6% 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–sector enterprizes, which amounted to 29 billions of euros until November 2010, and hence to approximately 0.7% of average total assets of private commercial banks and landes banks in 2010.

Another explanation could be the European Central Bank's quick and vigorous response to the crisis. According to a recent study by Dovern, Meier, and Vilsmeier (2010), above all monetary policy shocks turn out to have an important impact on the stress in a banking system. In order to ensure the functioning of financial markets, the ECB cut interest rates to very low levels and took a number of non–standard liquidity measures to support the smooth functioning of the euro area financial markets. Since these measures have exceeded all expectations, they can indeed be seen as an expansionary monetary policy shock that has positively contributed to the stability of the German banking sector.

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' assess-

Figure 7: Banks' Capital



ment of the current willingness of banks to extend credit we estimate the probability of a restrictive loan 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' opportunity costs of providing risky loans, which are measured by the safe real interest rate and 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 loan supply that is neither explained by firm-specific factors nor by the safe real interest rate.

Our results show that the probability of a credit crunch in the German economy was relatively high in the years 2003/04, following the economic downturn after the burst of the New Economy Bubble. In the subsequent boom of the years 2006 to 2008 the loan supply of banks was laxer. Even after controlling for the on average good quality of the firms and the low safe real interest rate, 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 much weaker. 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 credit-worthiness of these firms, nor by the large increase of the banks' opportunity costs of providing risky loans.

A nice feature of our approach is that it uses data that is published with a very short time lag. That makes it more suitable for use in policy institutions than other approaches that rely on macroeconomic data or information in the banking sector.

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Appendices

A Regression Results (Robustness)

Table 9: Results of the Linear and the Ordered Nonlinear Model

	(1) linear_re	(2) linear_fe	(3) linear_iv_fe	(4) ologit_re	(5) oprobit_re
statebus	-0.069***	-0.060***	-0.053***	-0.547***	-0.299***
	(-27.46)	(-14.48)	(-3.46)	(-31.67)	(-32.01)
comexp	-0.014***	-0.012***	0.003	-0.143***	-0.077***
	(-5.67)	(-3.62)	(-0.16)	(-8.69)	(-8.46)
climatesector	-0.002***	-0.001***	-0.002***	-0.009***	-0.005***
	(-10.15)	(-5.00)	(-7.44)	(-9.42)	(-8.93)
t_0308	0.025*	0.024*	0.022	0.178*	0.087*
	(-2.07)	(-2.49)	(-1.62)	(-2.48)	(-2.22)
t_0403	-0.016	-0.015	-0.013	-0.066	-0.034
	(-1.35)	(-1.34)	(-0.92)	(-0.92)	(-0.88)
t_0408	-0.026*	-0.026*	-0.032*	-0.178*	-0.115**
	(-2.07)	(-2.12)	(-2.22)	(-2.39)	(-2.84)
t_0503	-0.119***	-0.115***	-0.124***	-0.799***	-0.435***
	(-9.95)	(-9.36)	(-8.87)	(-11.07)	(-11.08)
t_0508	-0.143***	-0.140***	-0.148***	-1.063***	-0.583***
	(-11.84)	(-11.05)	(-10.61)	(-14.32)	(-14.58)
t_0603	-0.192***	-0.191***	-0.189***	-1.409***	-0.763***
	(-15.40)	(-12.15)	(-12.70)	(-17.71)	(-17.76)
t_0608	-0.221***	-0.220***	-0.220***	-1.653***	-0.902***
	(-17.74)	(-14.18)	(-15.15)	(-20.41)	(-20.68)
t_0703	-0.251***	-0.251***	-0.241***	-1.951***	-1.056***
	(-19.86)	(-15.00)	(-15.86)	(-23.40)	(-23.41)
t_0708	-0.267***	-0.266***	-0.265***	-2.062***	-1.123***
	(-21.48)	(-16.58)	(-17.62)	(-24.72)	(-24.86)
t_0803	-0.238***	-0.236***	-0.225***	-1.819***	-0.985***
	(-19.51)	(-15.37)	(-15.31)	(-22.63)	(-22.64)
t_0808	-0.265***	-0.261***	-0.251***	-1.908***	-1.024***
	(-23.03)	(-20.15)	(-16.60)	(-25.58)	(-25.36)
t_0811	-0.188***	-0.179***	-0.167***	-1.211***	-0.652***
	(-15.45)	(-12.67)	(-9.72)	(-16.13)	(-15.99)
t_0812	-0.156***	-0.146***	-0.128***	-1.043***	-0.549***
	(-12.08)	(-9.49)	(-7.13)	(-12.99)	(-12.49)
t_0901	-0.173***	-0.162***	-0.149***	-1.126***	-0.593***
	(-14.27)	(-10.80)	(-9.52)	(-14.77)	(-14.18)
t_0902	-0.122***	-0.110***	-0.104***	-0.826***	-0.430***
	(-9.84)	(-7.06)	(-6.85)	(-10.70)	(-10.09)
t_0903	-0.140***	-0.127***	-0.125***	-0.912***	-0.468***
	(-11.48)	(-8.38)	(-8.38)	(-11.96)	(-11.12)
t_0904	-0.134***	-0.121***	-0.117***	-0.930***	-0.494***
	(-11.11)	(-8.06)	(-8.13)	(-12.23)	(-11.80)
t_0905	-0.110***	-0.097***	-0.087***	-0.808***	-0.426***
	(-9.14)	(-6.51)	(-6.25)	(-10.66)	(-10.19)
t_0906	-0.116***	-0.104***	-0.099***	-0.794***	-0.407***
	(-9.89)	(-7.13)	(-7.25)	(-10.70)	(-9.92)
t_0907	-0.078***	-0.067***	-0.066***	-0.560***	-0.280***
	(-6.82)	(-4.79)	(-4.93)	(-7.63)	(-6.86)
t_0908	-0.070***	-0.059***	-0.056***	-0.500***	-0.260***
	(-6.11)	(-4.27)	(-4.17)	(-6.80)	(-6.35)
t_0909	-0.061***	-0.050***	-0.052***	-0.450***	-0.227***
	(-5.09)	(-3.47)	(-3.69)	(-5.79)	(-5.24)
t_0910	-0.077***	-0.067***	-0.062***	-0.542***	-0.279***
	(-6.82)	(-4.80)	(-4.67)	(-7.47)	(-6.92)
t_0911	-0.053***	-0.044**	-0.036**	-0.398***	-0.205***
	(-4.61)	(-3.06)	(-2.62)	(-5.40)	(-5.02)
t_0912	-0.028*	-0.019	-0.017	-0.237**	-0.110*
	(-2.42)	(-1.30)	(-1.20)	(-3.09)	(-2.57)
t_1001	-0.045***	-0.036*	-0.028*	-0.335***	-0.172***
	(-3.86)	(-2.46)	(-2.02)	(-4.33)	(-3.97)
t_1002	-0.068***	-0.058***	-0.040**	-0.466***	-0.249***
	(-5.70)	(-3.96)	(-2.82)	(-5.92)	(-5.70)
t_1003	-0.072***	-0.063***	-0.050***	-0.492***	-0.263***
	(-6.06)	(-4.11)	(-3.47)	(-6.20)	(-5.97)
t_1004	-0.071***	-0.063***	-0.053***	-0.526***	-0.289***
	(-5.88)	(-3.89)	(-3.67)	(-6.47)	(-6.44)
t_1005	-0.081***	-0.073***	-0.061***	-0.606***	-0.332***
	(-6.59)	(-4.42)	(-4.20)	(-7.36)	(-7.31)
t_1006	-0.097***	-0.090***	-0.077***	-0.641***	-0.348***
	(-7.96)	(-5.49)	(-5.39)	(-7.83)	(-7.67)
t_1007	-0.103***	-0.096***	-0.080***	-0.714***	-0.390***
	(-8.19)	(-5.48)	(-5.40)	(-8.45)	(-8.39)
t_1008	-0.131***	-0.124***	-0.113***	-0.894***	-0.492***
	(-10.43)	(-7.03)	(-7.59)	(-10.55)	(-10.58)
t_1009	-0.127***	-0.121***	-0.113***	-0.892***	-0.482***
	(-9.65)	(-6.66)	(-7.37)	(-9.86)	(-9.70)
t_1010	-0.142***	-0.136***	-0.125***	-0.982***	-0.530***
	(-11.03)	(-7.47)	(-8.21)	(-11.32)	(-11.16)
t_1011	-0.147***	-0.143***	-0.134***	-1.051***	-0.582***
	(-11.34)	(-7.75)	(-8.68)	(-11.93)	(-12.11)
_cons	0.654***	0.610***		1.857***	1.019***
	(-53.53)	(-39.42)		(-92.27)	(-95.59)
_cut1				-6.142***	-3.335***
				(-79.45)	(-80.70)
_cut2				-1.054***	-0.568***
				(-14.81)	(-14.53)
N	79070	79070	59991	79070	79070
AIC	.	53616.34	39066.27	97665.50	98896.34
LogL	.	-2.70E+04	-1.90E+04	-4.90E+04	-4.90E+04

t statistics, which are shown in parentheses, are robust to heteroskedasticity.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: Results of the Baseline Model with only Two Observations per Year

	(1) logit_re	(2) logit_fe	(3) probit_re
statebus	-0.601***	-0.437***	-0.342***
	(-20.70)	(-14.18)	(-20.69)
comexp	-0.104***	-0.086**	-0.057***
	(-3.60)	(-2.85)	(-3.48)
climatesector	-0.014***	-0.011***	-0.008***
	(-7.77)	(-5.44)	(-7.59)
t_0308	0.200**	0.164*	0.118**
	(2.59)	(2.05)	(2.67)
t_0403	-0.039	-0.090	-0.022
	(-0.48)	(-1.08)	(-0.48)
t_0408	-0.073	-0.140	-0.037
	(-0.86)	(-1.61)	(-0.77)
t_0503	-0.758***	-0.767***	-0.431***
	(-9.32)	(-9.15)	(-9.20)
t_0508	-0.960***	-0.971***	-0.546***
	(-11.41)	(-11.21)	(-11.29)
t_0603	-1.269***	-1.364***	-0.729***
	(-12.27)	(-12.43)	(-12.34)
t_0608	-1.541***	-1.631***	-0.879***
	(-14.58)	(-14.62)	(-14.59)
t_0703	-1.910***	-2.043***	-1.080***
	(-16.23)	(-16.29)	(-16.25)
t_0708	-2.122***	-2.230***	-1.204***
	(-18.01)	(-17.82)	(-18.09)
t_0803	-1.752***	-1.821***	-0.996***
	(-16.39)	(-16.20)	(-16.42)
t_0808	-1.995***	-1.983***	-1.132***
	(-21.92)	(-21.15)	(-21.96)
t_0903	-1.117***	-0.927***	-0.622***
	(-12.29)	(-9.69)	(-12.02)
t_0908	-0.557***	-0.447***	-0.307***
	(-6.92)	(-5.37)	(-6.66)
t_1003	-0.443***	-0.376***	-0.251***
	(-4.90)	(-3.98)	(-4.84)
t_1008	-0.805***	-0.837***	-0.460***
	(-7.44)	(-7.28)	(-7.46)
_cons	1.236***		0.694***
	(11.94)		(11.78)
lnsig2u			
_cons	1.477***		0.351***
	(37.37)		(9.16)
N	36635	26250	36635
AIC	34956.99	18180.78	34997.18
LogL	-1.7e+04	-9.1e+03	-1.7e+04

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

Table 11: Regression with Time Trend

	(1) logit_re	(2) logit_fe	(3) probit_re	(4) linear_re	(5) linear_fe
statebus	-0.575***	-0.494***	-0.323***	-0.072***	-0.063***
	(-28.00)	(-23.52)	(-27.99)	(-28.62)	(-15.16)
comexp	-0.099***	-0.087***	-0.055***	-0.012***	-0.010**
	(-5.13)	(-4.45)	(-4.99)	(-4.86)	(-3.03)
climatesector	-0.010***	-0.010***	-0.006***	-0.001***	-0.001***
	(-12.52)	(-11.93)	(-12.38)	(-12.09)	(-7.71)
trend	0.110***	0.113***	0.061***	0.010***	0.011***
	(12.02)	(12.31)	(12.14)	(8.27)	(8.01)
trend2	-0.010***	-0.010***	-0.005***	-0.001***	-0.001***
	(-20.95)	(-21.01)	(-20.80)	(-17.49)	(-15.66)
trend3	0.000***	0.000***	0.000***	0.000***	0.000***
	(22.50)	(22.55)	(22.21)	(19.98)	(17.22)
trend4	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(-21.98)	(-22.06)	(-21.63)	(-20.13)	(-16.98)
safe_real_rate	0.122***	0.129***	0.070***	0.017***	0.017***
	(7.58)	(8.05)	(7.72)	(9.34)	(8.17)
_cons	0.781***		0.430***	0.612***	0.565***
	(8.97)		(8.84)	(52.62)	(36.41)
lnsig2u					
_cons	1.804***		0.646***		
	(55.32)		(20.44)		
N	79070	62615	79070	79070	79070
AIC	68256.79	45918.90	68448.61	.	53797.82
LogL	-3.4e+04	-2.3e+04	-3.4e+04	.	-2.7e+04

t statistics, which are shown in parentheses, are robust to heteroskedasticity in the case of the linear models.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

B Instrumental Variable Regression

In order to account for the potential endogeneity of the regressors *statebus* and *comexp*, we estimate the fixed effects linear probability model with IV methods (see the last column (3) in Table 9 in Appendix A).[12] The fixed effects model is chosen to reduce the possibility of biased IV estimates due to unobserved variables. As instrument we use 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".

We assume that *proexp* is exogenous for the following reasons. Since it cannot be ruled out that the current availability of credit may have an impact on the firms' production plans in the near future, we only use lagged values of *proexp* as instruments. In order to ensure the consistency of the IV estimator and to be able to test the validity of the overidentifying restrictions, we need at least two instruments. By using five lags of the monthly available production expectations for the next three months, the expectation horizon for two instruments (the fifth and the fourth lag) ends in months $t-2$ and $t-1$. Moreover, an analysis of the accuracy of the production expectations with respect to the realization, which is also queried by the Ifo Business Survey on a monthly basis, shows that the fraction of firms committing an expectations error is lowest one month after production expectations have been asked and that this fraction increases when realizations two or three months later are used as reference for the expectation error.[13] From this we conclude that the expectation horizon of at least two of our instruments ends in months, which lie prior to the date when the credit question is asked. Most importantly, as was shown by Madsen (1993), variables other than past production and expectations only influence the formation of current production expectations weakly. Finally, unobserved and time–invariant firm heterogeneity should not violate the assumption of exogenous instruments, as the IV model is estimated with firm–specific fixed effects

[12] The IV regression was performed using the Stata command xtivreg2, written by Schaffer (2005) and Baum, Schaffer, and Stillman (2010).

[13] The expectation error has been computed as in Bachmann, Elstner, and Sims (2010).

α_i.

Since the dependent variable *creditsupply* is binary, the error term is heteroscedastic and we calculate heteroscedasticity–robust standard errors. The results of the first–stage regression is availbale from the authors upon request. To test the validity of our overidentifying restrictions we calculate Hansen's J–statistic, which is 1.60. With 3 degrees of freedom this results in a p–value of 0.659, 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 model is 2.49 with 2 degrees of freedom resulting in a p–value of 0.287. 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 of tests on parameters in finite samples 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 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 8: Credit Crunch Indicator (Linear Model)

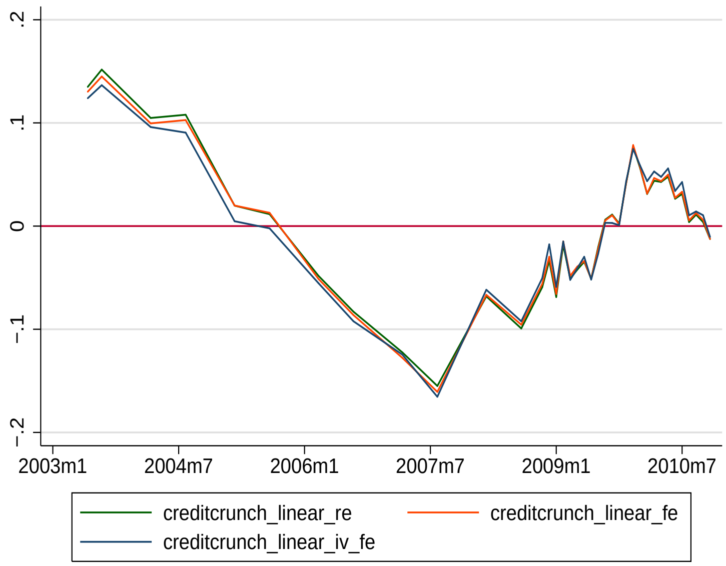

Figure 9: Credit Crunch Indicator (Ordered Nonlinear Model)

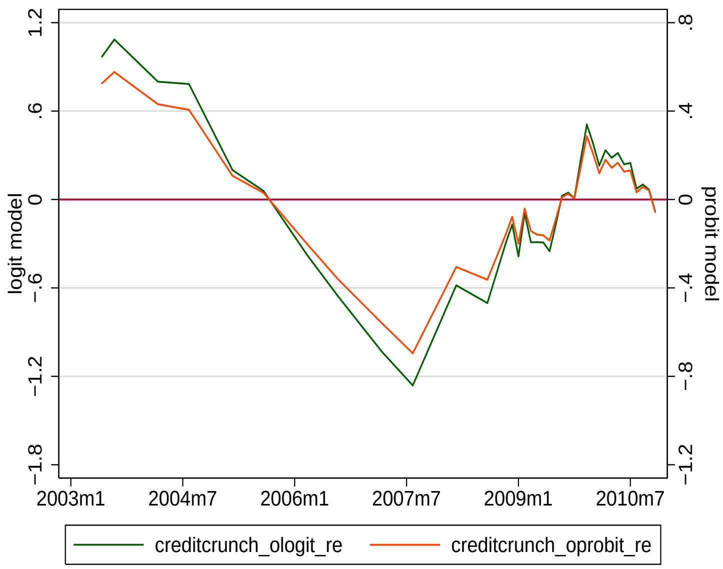

Figure 10: Credit Crunch Indicator (only Two Observations per Year)

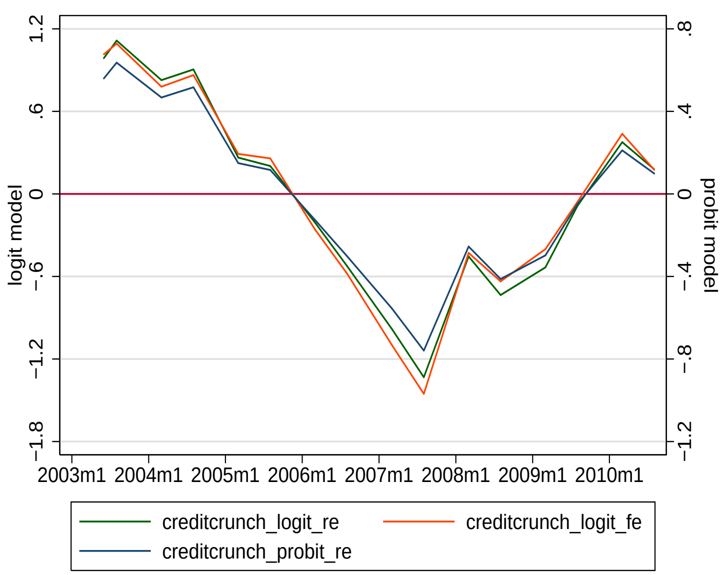

Figure 11: Credit Crunch Indicator with Time Trend