Determinants of default: Evidence from a sector-level panel of Irish SME loans.

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Abstract

This paper uses unique SME loan-level data complete with quarterly loan ratings assigned by the lending institution over the period 2008-2010. This allows us to examine the evolution of loan performance throughout the period of economic and financial crisis. We document the shift in the distribution of loans across ratings as economic conditions deteriorated, but also show that this effect was heterogeneous across sectors. In panel data estimations, changes in employment across sectors are shown to be a leading indicator of loan performance, demonstrating the importance of the link between real economy demand and loan impairment. Levels of outstanding credit in a sector cannot explain current loan performance. However, in keeping with a growing literature on the dangers of post-boom debt overhang, we calculate a measure of excess credit using deviations from a long-run trend that is strongly associated with higher levels of current impairment. This provides new evidence on the effect of relaxed credit standards during a boom on crisis-era loan delinquency.

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1 Introduction

While a vast literature exists on credit risk modeling for large publicly-listed corporates, for whom relevant information is readily available to the researcher, literature on the credit risk of Small and Medium Enterprises (SMEs) has been relatively limited. This owes mainly to the fact that these smaller, unlisted firms do not publicly release accounts, nor do they have stock prices, making modeling of the probability of default impossible unless access to data from sources such as credit registers can be accessed. The issue of SME credit risk is of particular interest to policy makers, given both their importance on banks' balance sheets and their contribution to real economic activity. Newly available data on Irish SMEs' loan performance allows sector-level modeling of SME credit risk in this paper. We provide a proxy for real economic activity that is shown to predict loan impairment as expected. We further contribute by identifying that excess credit accumulation is positively associated with credit risk during the downturn, thus exposing the dangers of credit expansions such as that experienced in Ireland up to 2008.

Ireland from 2008 to the present day is a particularly interesting laboratory for such a study. The Irish economy has undergone dramatic change since the financial crisis first began to unfold. Between the first quarter of 2008 and the fourth quarter of 2010, real GDP and real GNP fell by 10.3 and 10.9 per cent respectively, GNP at current market prices fell by 17.5 per cent, while unemployment rose from 4.8 to 14.8 per cent over the same time period. Outstanding credit to private sector Irish resident firms has contracted sharply, falling by 18% in two years (March 2009 to March 2011). This followed a spectacular boom, which saw credit grow by 194% beween 2003 and the peak in March 2009. The level of debt accummulation during the boom period, coupled with the fall in domestic demand, has placed significant pressure on Irish firms. Furthermore, SMEs in Ireland are of keen policy interest, accounting for 69 per cent of employment[1] (CSO, 2012) and relying on domestic demand more than larger firms (Lawless et al. 2012).

This paper takes a large sample of loan level data provided to the Central Bank of Ireland as part of the 2011 stress-testing of Irish banks (more formally known as the Financial Measures Programme or FMP) and analyses the evolution of loan performance over a three-year period. Previous studies have already utilized data sets that form part of this loan level data. Lawless and McCann (2012a) present a snapshot of a fuller version of the data on the SME lending of Irish banks as of December 2010, but they cannot track the evolution of loan performance over time. McCann and McIndoe-Calder (2012) also make use of a detailed cross-section of loan performance data at the borrower-level, but again they cannot analyse changes in loan performance over time. The data used in this paper are particularly

[1] We follow the European Commission definitions of a small firm as one employing fewer than 50 employees and a medium firm as having between 50 and 250 employees (European Commission, 2009).

useful for credit risk modeling as they contain records of quarterly internal ratings assigned by the lending institution to each loan for the twelve quarters of 2008-2010. The downside to the data lies in the fact that it cannot be matched with any borrower-level balance sheet or profit and loss information. For this reason, our panel data modeling of SME credit risk must be carried out at the sector level.[2]

We begin by showing that there has been a huge deterioration in the performance of SME loans between 2008 and 2010. At the most extreme, the construction sector moved from an impairment rate of 2.8 per cent in Q1 2008 to 15.3 per cent in Q4 2010. Importantly, there is a large heterogeneity across sectors, with e.g. only 1.8 per cent of loans in agriculture and fishing in our sample being impaired in Q4 2010.

Empirical results show that changes in the employment level in a sector can be a reliable leading indicator for predicting changes in delinquency rates among loans to that sector, thus providing a simple method of modelling SME losses which requires relatively little data. A decrease in employment of 10,000 leads to a 1 per cent decrease in the share of performing loans. We also provide the first evidence of which we are aware on the effect of debt overhang on loan performance: sectors where lending deviated most from a linear long-run trend are shown to be the sectors with the largest shares of impaired or watch-listed loans. The damaging effect of credit booms, of which our finding on loan impairment is one component, has been identified previously by authors such as Reinhart and Rogoff (2009).

There is relatively limited literature on the credit risk associated specifically with SME loans and the determinants of loan performance for these firms. This is in spite of the finding that in times of recession or crisis, SMEs are particularly vulnerable as their limited diversification and dependence on short-term credit give them much less of a buffer against demand falls than are available to larger firms (OECD, 2009). Unfortunately, however, data on the financial structure of SMEs tends to be much less readily available than that of larger quoted companies. Altman and Sabato (2007) find that credit risk models designed for large firms perform poorly in predicting SME default but that a small number of financial ratios tailored to SME specificities functions considerably better. Papers such as Fidrmuc and Hainz (2010), Behr, Guttler and Plattner (2004), Dyrberg-Rommer (2005b) and McCann and McIndoe-Calder (2012) are among a small group of papers to model SME credit risk. These papers use financial variables similar in spirit to those used in Altman's (1968) seminal Z-score for corporate defaults and generally find that indebtedness, liquidity, profitability and sector-specific effects are important borrower-level determinants of SME default. We are unaware of studies that have modelled loan impairment for SMEs at the sector level, or focused on the role of debt overhang in explaining difficulties in the SME lending market. Nor are we aware of studies that have highlighted

[2]Cross-sectional firm balance sheet data is available for a subset of these loans and is used to analyse credit risk by McCann and McIndoe-Calder (2012).

the differential impact of the business cycle on the impairment of types of loan facility.

The relationships identified in this study give rise to a potential contribution of this analysis to stress-testing, where the frequent absence of up-to-date balance sheet information is an obstacle for estimating the riskiness of SME loans. In our strategy, a very reduced form use of employment forecasts across sectors would be enough to generate predictions about movement into default.

The remainder of the paper is organised as follows. The data are described in Section 2, along with summary statistics of the changes in loan performance over time. We then aggregate the loans to sector level in Section 3 and estimate the effects of employment changes and debt overhang on the probability of loan defaults. Section 4 concludes.

2 Loan Performance

This paper uses a large sample of individual loan-level data collected from Irish banks in order to carry out the Central Bank of Ireland's stress tests and estimates of recapitalisation requirements in 2011, which resulted in the Financial Measures Programme report (Central Bank of Ireland, 2011). Although commercial sensitivity means that the number of observations and other precise details of the data cannot be released, there is a substantial amount of information on the distribution and evolution that can be used to get a fuller picture of the condition of outstanding SME loans in Ireland.[3]

The dataset used here is a subset of the cross-section of loans described by Lawless and McCann (2012a). Crucially, the data we look at in this paper contain historic information on the internal ratings of the loans. These ratings are available on a quarterly basis from the first quarter of 2008 to the fourth quarter of 2010, and provide us with the first picture of the changes in loan performance over time at a disaggregated level. While it would be preferable to have loan data for time periods of both economic growth and distress, this data coverage nonetheless represents a step forward in understanding the determinants of SME loan delinquency. For convenience, we group the more detailed set of internal ratings into three broad categories - performing loans, watchlist or at risk loans and impaired. It is important to emphasise that the rating procedure was carried out by the banks themselves and the consistency with which the different categories are applied may therefore vary somewhat, both across bank loan portfolios and over time.

[3]One caveat to comparing these data with aggregate SME data is that, as this was the first time data was provided to the Central Bank at this level of disaggregation, banks classification of SMEs in these data does not match the traditional definitions used by statistical agencies. In some cases, the majority of business banking, which may include firms with more than 250 employees, is included in the SME loan books. A consistent definition is being developed so that future datasets contain information on the exact same type of firms across banks.

To give an overview of the variation of the loan types across sectors, Table 1 provides average loan size and levels of arrears for each of the four separate lending facilities distinguished in the data (revolving credit, term loans, hire purchase (HP) and leasing agreements). The average facility amount is considerably smaller for revolving credit facilities compared to term loans, most likely due to term loans being more commonly used to fund an investment project while revolving credits are generally used for working capital or day-to-day operations. This may explain to some extent why the revolving credit performance is somewhat better. Leasing and hire purchase arrangements are also both of a smaller average size than term loans. The variation in average loan size across sectors is largest for term loans, which is consistent with using this type of facility for capital projects - the relevance of which would be expected to be different across sectors. Unfortunately we cannot distinguish between loans used for property and loans for other types of investment.

Comparing average loans with the loan performance results, it is worth noting that the average loan size for all facility types tends to be lower for Agriculture than for other sectors. Hotels and Restaurants, which had a particularly low percentage of performing loans, have the highest average loan size for term loan facilities. On the other hand, the Education and Health and Social Work sectors also have large average loan sizes with good performance levels (these are two of the smallest sectors in terms of number of loans).

Table 1 also presents the average level of arrears for each sector as of the end of December 2010. Construction and the Hotels and Restaurants sectors stand out with particularly high levels of arrears, both in absolute terms and as a percentage of average loan size.

Figures 1 and 2 show the gradual increase in watch and impaired loan balances at quarterly intervals from Q1 2008 to Q4 2010, for revolving credit facilities and loan accounts within each sector. Across all sectors, we see that the deterioration in loan performance emerged gradually over the three-year period. We also see that the percentage of loans that are impaired remains low in all sectors, apart from Construction and Hotels and Restaurants, whereas the increase in Watch loans is more broadly based.

For revolving credit facilities there was a slight increase in the number of facilities between Q1 2008 and Q4 2010 but the pattern across sectors was essentially unchanged. At the beginning of the sample period, over 80 percent of loans were classified as performing in all sectors with the exception of Hotels and Restaurants, which was already showing signs of difficulty with close to 20 percent of loans in the category of loans labeled “Watch”. These loans are not in default but have been characterised as at risk by the banking institutions. Impaired loans made up a very small percentage of the number of outstanding accounts, with the highest incidence of 2.8 percent being found in the Construction sector.

The deterioration in the performance of these revolving credit facilities over the sample period is striking. The percentage of “watch” or “at risk” loans increases considerably in all sectors, with a corresponding reduction in performing loans. The best performing sectors are Agriculture, Education and Health and Social Work, all of which still had over 80 percent of loans categorised as performing in Q4 2010, and under 2 percent categorised as impaired. Construction loans have experienced the largest fall in performance, with impaired loans increasing from 2.8 percent at the start of the period to 15.3 percent at the end of the sample period. The Hotels and Restaurants and Transport and Communications sectors have in excess of 10 percent of outstanding facilities in the impaired category.

Figure 2 presents a similar breakdown applied to loan facilities, which we aggregate to include term loans, leasing finance and hire purchase facilities. The initial distribution of the percentage of performing loans across sectors is broadly similar to that of revolving credit. However, these loans show a greater likelihood of becoming impaired, with just three sectors having less than 5 percent of loans categorised as impaired in Q4 2010 (the same sectors as those with the best performance in revolving credit). The percentage of impaired loans reaches as high as a quarter in the Construction sector, which has a further 31.8 percent of loans on watch.

In Table 2 the frequency of each $(t, t+1)$ status pair for each facility type is outlined, where each t is a quarter. The rows reflect the initial status, and the columns reflect the status the following period. Each row sums to 100, and the individual values show the distribution across categories in period $t+1$ separately for each of the starting categories. The dominant probability in each type of loan is for a facility to remain in the same category from one quarter to the next. Looking first at performing loans, we see that between 92.7 and 95 percent of them will remain performing one period later, with the lowest probability of staying performing being for leases and the highest for revolving credit.

Performing loans almost never move directly to being impaired (no more than 0.35 percent) but have between a 5 and 7 percent chance of moving to the watch category. Loans on watch are more likely to return to being performing loans than they are to move into being impaired, indicating that it need not be assumed that loans in this category will inevitably develop into crystallized losses. This is particularly the case for revolving credit, where close to 22 percent of watch loans return to performance. This is less likely for the other types of credit, perhaps because the other facility types are more likely to be related to longer term investments where quick recovery from a negative shock is less likely.

3 Econometric analysis

Having described the performance of the SME loans in the preceding sections, we now look at some of the determinants of the share of performing and impaired loans in each sector. The analysis must be aggregated to the sector level at this point, as at the micro level, the data set provides no behavioural information which could be used to predict changes in loan performance. We focus on two factors that are likely to be related to each sector's ability to service its debts. We proxy for conditions in the real economy using data on employment at the sector-quarter level.[4] The second factor analysed is a measure of outstanding credit to the sector, which may proxy for post-boom debt overhang, as well as reflecting current lending trends.

3.1 Data

In order to link our loan-level data with developments in the macroeconomy, we aggregate the data at the sector level. In all regression analysis, the data presented up to now are condensed into 120 observations: 10 sectors[5] over the twelve quarters of 2008-2010. Loan performance data are given by the share of the number of loans and the share of loan volume that are performing or impaired in a given sector-quarter, calculated from the micro data presented earlier in the paper.

We examine the effect on sector loan performance of two key variables, controlling in all specifications for sector and time effects. The main indicator of how the sector has been affected by the economic crisis and falls in domestic demand is its employment level. Employment data at the sector-quarter level come from the *Quarterly National Household Survey* which is carried out by the Central Statistics Office. This is a quarterly employment survey of roughly 40,000 households in Ireland and can allow a reliable estimate of the amount of people working in a sector in each quarter.

We use the outstanding stock of credit to examine the extent to which debt overhang is now impacting sector performance and, hence, bank balance sheets. Data on credit outstanding to a sector come from the Central Bank of Ireland's *Money and Banking Statistics* and are again collected quarterly, giving a balanced panel of 120 observations on loan performance, conditions in the real economy, and lending to each sector. Table 3 provides summary statistics for the dependent and explanatory variables used.

3.2 Results

In examining the impact of employment and outstanding credit on loan performance, we present results here on the share of the number of loans in the different performance categories.[6] We separately estimate the percentage of performing loans and the percentage impairment. As there is the possibility of endogeneity in the relationship between loan performance at the sector level and the sector's

[4] Further covariates such as measures of GDP per sector would have added to the paper but were unavailable at a satisfactory level of disaggregation.

[5] Employment data from the QNHS was not available separately for the Electricity, Gas and Water sector.

[6] The working paper version, Lawless and McCann (2012b) also applies the same specification to shares of outstanding loan amounts with similar results.

employment and credit overhang, we use an instrumental variables GMM specification, using lagged values of the independent variables as instruments.

Beginning with the effects of employment and credit stocks in each sector on loan performance, Table 4 reports results from the following regression model:

$$Y_{it} = Emp_{it} + Credit_{it} + \delta_i + \delta_t \tag{1}$$

in which the dependent variable Y_{it} is the share of loans that are performing or impaired in sector i in quarter t, where each one unit is a percentage. The results show that, controlling for both sector and time fixed effects, the amount of employment in a sector is an important determinant of the performance of loans in that sector. The level of credit in the sector has a marginally statistically significant effect for the level of performing loans but this becomes insignificant when employment is also controlled for. Employment in a sector has a positive association with the percentage of performing loans and is negatively related to the percentage of impaired loans. This is the case when employment is entered as a regressor on its own (as in Columns 1 and 2) or when credit is also controlled for (as in Columns 5 and 6). This suggests that, intuitively, the real economy performance of a sector of activity feeds through to loan performance.

The interpretation of the coefficient in Column (5) is as follows: conditional on the general economic environment in a quarter, a positive deviation from a sector's own mean of 1,000 more employees would result in that sector having one tenth of a percent more performing loans in that quarter. A one standard deviation decrease in employment is therefore estimated to lead to a decrease of three quarters of one standard deviation in the share of performing loans. Similarly, a one standard deviation decrease in employment is estimated from Column (6) to lead to a 1.02 standard deviation increase in the share of impaired loans.

In Table 4, the coefficients on the sector fixed effects are presented relative to the agricultural sector. Column (5) reports that, controlling for employment and credit stock changes, all sectors have on average lower shares of performing loans than the agricultural sector, with the manufacturing, construction and the wholesale and retail sectors performing particularly poorly with performing loan shares 25 to 28 per cent lower than agriculture. Column (6) reports that the mirror image, the share of impaired loans, follows a similar pattern, where a larger positive coefficient implies weaker loan performance.

3.3 Estimates of bubble lending

So far, we have seen a strong effect of employment on loan performance, but almost no impact of the outstanding amount of credit. However, the stock of credit outstanding to a sector at a given point in time may not conceptually be an appropriate explanatory variable for the performance of loans. In particular, different levels of capital intensity across sectors would result in differing levels of outstanding debt, as certain sectors may require more external financing to fund investment (an idea first formalised by Rajan and Zingales (1998)). On the other hand, the effects of the credit bubble that occurred in Ireland up to the end of 2008 appear worth exploring. Increases in credit allocated to a sector that outstrip the amount predicted by a long-run linear trend are likely to be highly correlated with decreases in credit standards in lending to that sector. As an alternative measure to the stock of outstanding credit in a sector-quarter, the over-supply of credit in a given sector relative to a long-run trend is estimated using a sector-specific equation of the form:

$$Credit_t = Trend_t, t \in (1970Q1, 2011Q3) \tag{2}$$

To estimate this deviation of credit during the boom from its longer-run trend, we use quarterly lending data for eight of the sectors in our sample from 1970 to 2011.[7] The residuals $\hat{u}$ give the outstanding stock of credit in a given sector-quarter over and above that predicted by a long-run linear trend over 41 years. This $\hat{u}$ in any given observation in the regression time period, 2008-2010, can be thought of as a measure of how inflated the credit bubble had become in that sector. The expectation is that $\hat{u}$ will have a negative sign on performing loans and a positive sign on impaired loans, as those sectors that experienced the largest bubbles should experience larger corrections and hence deteriorations in loan quality once the bubble bursts.

Table 5 reports results of regression models of the form

$$D.Y_{it} = D.Employment_{it} + \hat{u}_{it} + \delta t \tag{3}$$

It is necessary to refrain from estimating this sector-level model using sector fixed effects as the estimation of the $\hat{u}_{it}$ variable in Equation 2 has already stripped away sector-level information relative to a long-run sector mean. As a result, using sector fixed effects in estimating equation 3 is unlikely to lead to informative results. For this reason, differences in employment are taken to complement the levels in $\hat{u}_{it}$, as levels of employment do not contain the information necessary to proxy developments in the real economy that drive loan performance. Equation 3 is estimated using a instrumental variables GMM approach, again using lags of the independent variables as instruments. The dependent variables are the first-differenced shares of performing loans and loan volumes, and impaired loans and loan volumes.

The coefficient on the difference in employment levels is always significant and similar to that estimated in previous models. The "Surplus Credit" variable, $\hat{u}$ enters each model with the predicted sign. This suggests that this method of proxying a sector-specific credit bubble gives more predictive power than simply using levels of credit outstanding in a sector. Interpreting Column (1), a one

[7] Changing the start date for the trend has no appreciable effect on the results.

standard deviation increase in Surplus Credit leads to a one-fifth of a standard deviation decrease in the share of performing loans. These findings provide direct evidence of decreasing credit standards during a boom leading to increased loan delinquency during a crisis.

The results presented in Table 5 contribute to a growing policy and academic literature on the dangers of post-2008 debt overhang in the developed world by directly illustrating the detrimental impact on banks' losses, and by extension on national financial stability, of the quasi-exponential growth rates in credit that existed in the run-up to the crisis.

For robustness, the analysis was also conducted separately for each of the facility types, details of which can be found in the working paper version (Lawless and McCann, 2012b). As discussed in the data description, term loans were observed to be more likely to have become impaired than revolving credit, possibly due to their larger size and because in general they more likely to be used for more risky activity such as investment, while revolving credit is generally used for cash flow purposes. For this reason, one prior in separating the regression model by facility type is that term loans should have a greater reaction to changes in employment than revolving credits. This is found to be the case, with employment's effect on term loan impairment having a coefficient twice as large as for revolving credit. In looking at the effect of over-supply of lending, the results suggest that the size of the credit bubble in a sector impacts on all types of loan facilities, with little by way of a consistent pattern across the different types.

4 Conclusion

This paper documents the evolution of SME loan performance over a three-year period using data on internal bank ratings attached to the loans. Aggregating up to the sector level, the impact of real economy developments and excess credit taken on during the boom are used to explain the shares of performing and impaired loans. The economic crisis has resulted in a broad-based decline in the quality of outstanding SME loans, but a considerable degree of heterogeneity is found to exist across sectors.

The econometric analysis shows that changes in employment across sectors are a reliable leading indicator of loan performance. The presence of excess or bubble credit accumulated during the pre-2008 boom is also an important factor associated with higher levels of current impairment. This highlights the extent to which debt overhang can be a drag on the banking system even if economic conditions more generally improve. This also has consequences for the banks' ability to extend new credit to the SME sector, as well as the borrowers' ability to invest and grow.

The strength of the relationships between the two chosen sector variables and loan performance give rise to a potential contribution of this analysis to stress-testing and prediction of default probabilities. This is frequently difficult for the SME sector due to the scarcity of up-to-date balance sheet information. A sectoral approach as used here, with a small number of timely variables could go some distance toward filling this gap.

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Figure 1: Change in revolving credit performance over time, 1 = q1 2008; 12 = q4 2010.

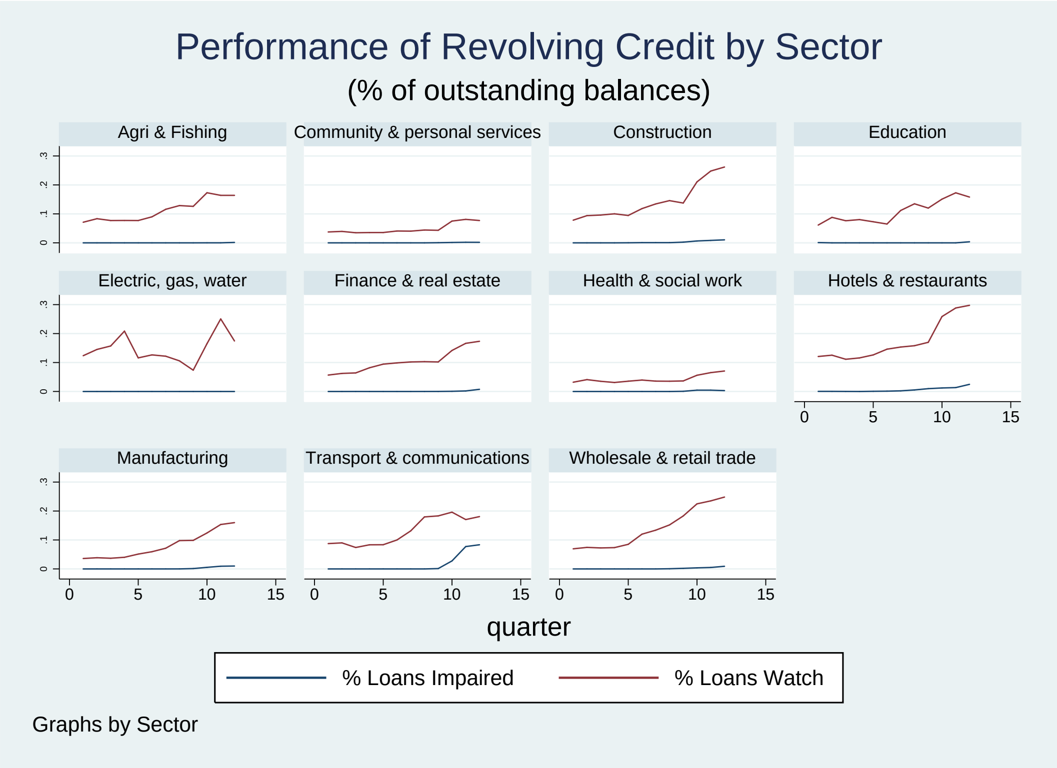

Figure 2: Change in loan performance over time, terms loans, hire purchase, leasing agreements. 1 = q1 2008; 12 = q4 2010.

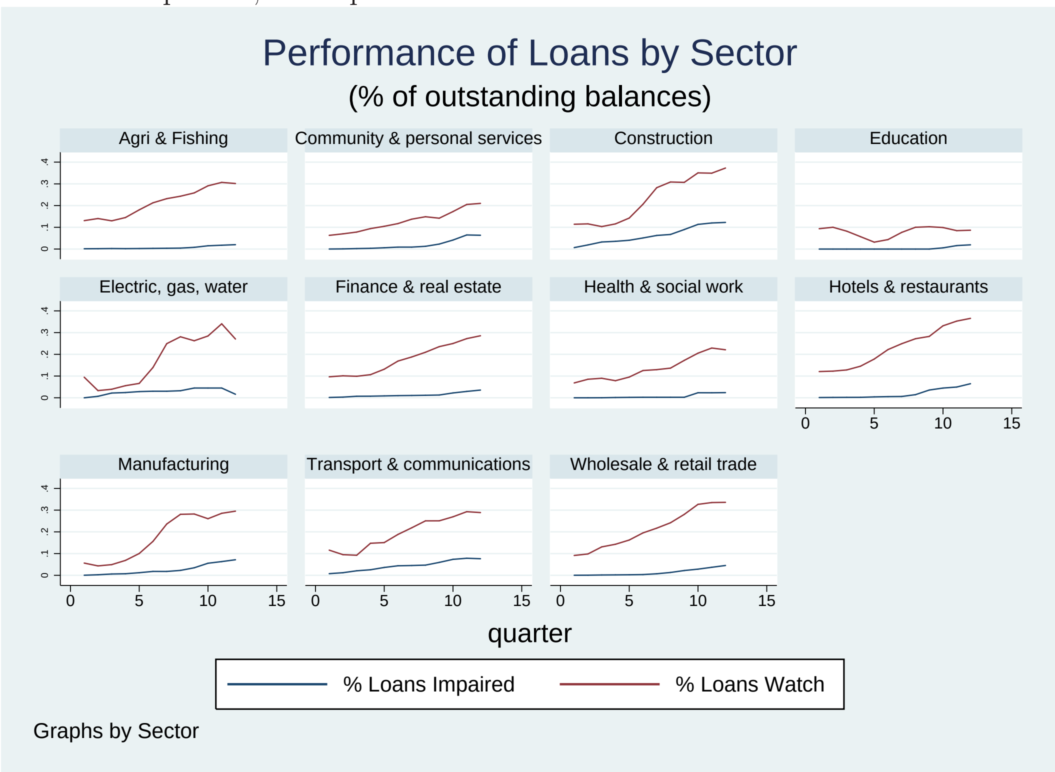

Table 1: Average Loan Size and Arrears

	Revolving		Term Loan		HP		Lease	
	Av. Loan	Av. Arrears	Av. Loan	Av. Arrears	Av. Loan	Av. Arrears	Av. Loan	Av. Arrears
Agriculture & Fishing	21826	843	79662	16309	12706	1113	13644	2827
Community & Personal Services	36383	1790	132527	23288	18545	4010	17498	3072
Construction	19854	6409	48974	39719	13113	5446	18127	5793
Education	23455	498	358594	11419	18048	53	7496	836
Electric, Gas, Water	19556	929	35521	1511	8414	1897	8763	1972
Finance & Real Estate	37631	4147	152988	37792	12079	3968	9798	3585
Health & Social Work	40466	849	289338	35162	16972	4055	21444	514
Hotels & Restaurants	24098	8565	301232	100820	11009	1450	13808	4121
Manufacturing	48598	3903	176755	21540	35141	5217	26815	4488
Transport & Communications	24591	3191	67647	18746	26712	3345	21260	2984
Wholesale & Retail Trade	43319	4707	244866	52016	14151	1746	17270	2425

Table 2: Rating Changes by Facility Type

		Performing (t)	Watch (t)	Impaired (t)
Revolving Credit				
	Performing	94.56	5.40	0.04
t-1	Watch	21.95	74.91	3.15
	Impaired	0.01	0.22	99.77
Term Loan				
	Performing	93.29	6.63	0.08
t-1	Watch	14.49	80.48	5.04
	Impaired	0.01	0.17	99.82
Hire Purchase				
	Performing	93.55	6.25	0.20
t-1	Watch	9.28	84.32	6.40
	Impaired	0.01	0.85	99.13
Lease				
	Performing	92.71	6.95	0.35
t-1	Watch	7.76	83.56	8.69
	Impaired	0.05	0.37	99.58

Table 3: Summary statistics for variables involved in econometric analysis.

Variable	Obs	Mean	Std. Dev.	Min	Max
Share of Performing Loans	120	77.0807	9.881147	50.6334	91.728
Share of Impaired Loans	120	6.019113	4.595713	0.3855591	20.4512
Share of Performing Loan Volume	120	83.36278	9.205012	58.26865	95.94294
Share of Impaired Loan Volume	120	1.453624	1.878532	0	7.824576
Employment (1,000)	120	161.2775	70.37975	82.3	314.3
Credit Outstanding (€billion)	120	22.84888	51.46756	0.661	187.906
Surplus Credit (€billion)	96	18.31031	-20.28401	0.3683271	62.94356

Table 4: Determinants of the share of loans that are performing or impaired, IV estimation

	(1) Perform	(2) Impair	(3) Perform	(4) Impair	(5) Perform	(6) Impair
Employment (1,000)	0.109***	-0.0679***			0.108***	-0.0687***
	(8.42)	(-10.81)			(8.34)	(-10.78)
Credit (Million Euro)			0.205*	-0.0877	0.0102	0.0357
			(1.85)	(-1.44)	(0.21)	(0.79)
Manufacturing	-29.65***	16.78***	-12.40***	5.955***	-29.63***	16.86***
	(-12.78)	(14.21)	(-8.61)	(9.82)	(-12.76)	(14.22)
Construction	-27.26***	15.77***	-20.26***	11.37***	-27.25***	15.79***
	(-23.42)	(21.17)	(-16.70)	(11.65)	(-23.50)	(21.04)
Wholesale Retail	-27.80***	16.41***	-9.358***	4.618***	-27.83***	16.31***
	(-11.16)	(12.93)	(-8.66)	(6.69)	(-11.16)	(12.47)
Transport, Comms	-14.60***	7.033***	-14.32***	6.989***	-14.57***	7.147***
	(-11.01)	(8.89)	(-12.88)	(10.66)	(-10.87)	(8.88)
Hotels and Restaurants	-19.10***	7.719***	-17.45***	6.493***	-19.14***	7.565***
	(-16.66)	(10.93)	(-16.39)	(9.78)	(-16.28)	(9.93)
Financial, Real Estate, Business	-10.18***	6.093***	-44.44**	20.58*	-11.93	-0.00308
	(-11.83)	(9.69)	(-2.32)	(1.95)	(-1.42)	(-0.00)
Government, Community	-7.077***	4.168***	-5.435***	3.273***	-7.042***	4.290***
	(-7.98)	(6.82)	(-6.99)	(6.21)	(-8.01)	(6.96)
Education	-4.530***	2.974***	2.072	-0.944	-4.466***	3.195***
	(-2.93)	(3.85)	(1.27)	(-1.17)	(-2.77)	(3.93)
Health, Social Work	-10.19***	8.139***	4.924***	-1.164	-10.13***	8.362***
	(-5.16)	(7.84)	(4.40)	(-1.56)	(-5.08)	(7.90)
Constant	65.94***	11.34***	74.69***	5.744***	65.93***	11.29***
	(44.98)	(12.77)	(61.79)	(7.29)	(45.64)	(12.63)
N	110	110	110	110	110	110
r2	0.946	0.940	0.923	0.900	0.946	0.939

Instrumental variables GMM regressions using lagged values of dependent variables as instruments.
Time dummies included in all specifications
t statistics in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$

Table 5: Determinants of the changes in share of loans or loan volumes that are performing or impaired. Dependent variable in first differences

	(1) Performing Loans	(2) Impaired Loans	(3) Performing Volume	(4) Impaired Volume
D.Employment (1,000)	0.105***	-0.0675***	0.144***	-0.0222**
	(2.85)	(-4.21)	(2.63)	(-2.14)
Surplus Credit (Eur Bn)	-0.0205***	0.0122***	-0.0261***	0.00776***
	(-3.02)	(4.29)	(-3.31)	(3.57)
Constant	0.548**	-0.182	-0.940**	0.483***
	(2.05)	(-1.07)	(-2.55)	(3.20)
N	80	80	80	80
r2	0.725	0.455	0.399	0.437

Instrumental variables GMM regressions using lagged values of dependent variables as instruments.

Time dummies included in all specifications

t statistics in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$