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A long-run survival analysis of corporate liquidations in Ireland

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Abstract

This paper examines the role of credit and the macroeconomy in SME distress during a prolonged economic downturn. Specifically, we estimate the determinants of SME distress in Ireland during the severe financial and economic crisis which began in 2007/2008. We use a measure of distress, insolvencies, which captures both bank and non-bank forms of credit. We conduct a survival analysis of insolvent liquidations and find that, controlling for firm location and economic activity, both variables capturing a build-up of stress in the macroeconomy and those capturing bank credit standards and availability throughout the cycle are determinants of firm survival.

JEL classification: C25, D20, L0
Keywords: Ireland, corporate liquidations, firm default, survival analysis.

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Non-technical summary

The Irish economy has undergone a significant change since the onset of the financial crisis in 2008. By its nature, a systemic crisis impacts not just the financial sector, but also the broader real economy. The financial crisis in Ireland has impacted the corporate sector severely, resulting in an unprecedented increase in insolvencies. Understanding the drivers of such an increase in SME insolvencies ensures a better assessment of the risk of financial distress throughout the economic and financial cycle.

The role that credit access and indebtedness play in determining the condition of SMEs is well known in the academic literature. While credit can take many forms, small firms are generally reliant on banks for external financing. However, SME access to bank credit is procyclical with alternative sources of financing becoming increasingly important during stressed periods. We therefore use a measure of corporate sector distress - insolvent liquidations - which captures both bank and non-bank forms of credit. We disaggregate insolvent liquidations by sector of activity and geographical location, to determine the relative impact of the crisis compared to historical norms.

To determine what drives the probability of SME failure during a protracted period of stress we conduct a survival analysis. We find that, after taking account of firm location and economic sector, both macroeconomic conditions and bank credit conditions are determinants of firm survival. In terms of macroeconomic factors, we find that macroeconomic variables which capture the build-up in distress, such as the unemployment rate, explain the behaviour of insolvent liquidations better than variables which only capture short-term fluctuations in economic activity. We also find that insolvencies are affected by the procyclicality of bank credit standards and availability throughout the cycle. First, we find that firms that are "born" during boom periods when credit standards are loose, are more likely to become insolvent than those "born" when credit standards are tighter. Second, a reduction in bank credit availability at any point in time also decreases the probability of firm survival.

1 Introduction

This paper examines the role of credit and the macroeconomy in SME distress during a prolonged economic downturn. Specifically, we estimate the determinants of SME insolvent liquidations in Ireland. The Irish economy underwent a severe financial crisis in 2007/2008 followed by a prolonged macroeconomic collapse. The corporate sector, predominantly comprising small and medium enterprises (SMEs), was particularly affected by this crisis; the insolvency rate almost quadrupled from 0.20 per cent in 2007 to 0.77 per cent in 2011. These rates were unprecedented in Ireland, and eclipsed previous maximum rate of 0.66 per cent. Understanding the drivers of such an increase in SME insolvencies ensures a better assessment of the risk of financial distress throughout the economic and financial cycle.

The role that credit access and indebtedness play in determining the condition of small and medium enterprises (SMEs) is well known (Campello, et al. (2009)). While credit can take many forms, small firms are generally reliant on banks for external financing, and many measures of SME distress capture only bank-related distress (credit register data, bank balance sheet information on bad loans). However, SME access to bank credit is procyclical with alternative sources of financing becoming increasingly important during stressed periods (McCann et al (2013)). This reflects both the ability of banks to make loans and the companies' financial position. In particular, banks' balance sheets may become impaired in a crisis inhibiting their ability to make loans. Furthermore, as the corporate failure rate rises, it becomes increasingly difficult for banks to distinguish between potential borrowers that are creditworthy and those that are not. This pushes firms towards non-bank sources of financing. However, the number of less-creditworthy firms is also increasing. This is evidenced by the fact that SMEs that use non-bank forms of financing are often at higher risk of financial distress (Croce et al (2014)). In assessing SME distress, it is therefore necessary to use a measure which captures not just bank loan distress but all forms of creditor financing.

We conduct a survival analysis of insolvent liquidations in Ireland, to determine the causes of firm failure during a protracted period of stress. We find that, controlling for firm location and economic sector, both macroeconomic conditions and financing ability are determinants of firm survival. In terms of macroeconomic factors, we find that stock variables which capture the build-up in distress, such as the unemployment rate, explain the behaviour of insolvent liquidations better than flow variables, such as GDP changes, which only capture short-term fluctuations in economic activity. We also find that insolvent liquidations are affected by the procyclicality of bank credit standards and availability throughout the cycle. First, we find that firms that are 'born' during boom periods when credit standards are loose, are more likely to become insolvent than those 'born' when credit standards are tighter. Second, a reduction in bank credit availability at any point in time also decreases the probability of firm survival.

The remainder of the paper is structured as follows. In Section 2 we review the literature on the determinants of corporate liquidations. While there are a number of studies of the determinants of corporate distress, we believe our sample period, covering a prolonged downturn with unprecedented increases in insolvent liquidations is novel. Section 3 describes the company level dataset, incorporating registered company "births" and "deaths", utilised in this paper and outlines summary statistics. In Section 4, we present our survival model including both micro and macro variables. We estimate the model in a complimentary log-log framework using a panel setting where the dependent variable takes a value of one when a firm becomes insolvent. Our model fits well and in-sample forecasts appear reasonable. Section 5 concludes.

2 Previous Literature

Macroeconomic determinants of corporate liquidations are linked to the business cycle and include the overall indebtedness of the corporate sector, interest rates, oil prices, exchange rates and equity prices, GDP and the output gap. For example, Vlieghe (2001) investigates the determinants of corporate failures in the UK using aggregate time series data. He finds that the debt-to-GDP ratio, the real interest rate, deviations of GDP from trend and real wages are long-run determinants of the liquidation rate, while the birth rate of new companies, an index of property prices and nominal interest rates have significant short-term effects. In an examination of corporate liquidations in Austria, Boss (2002) finds that variables such as industrial production, inflation, the stock index, the nominal short-term interest rate, and the oil price are the most important determinants of corporate default rates. Other studies using similar variables include Virolainen (2004), Castren, Dees and Zaher (2008) Åsberg and Shahnazarian (2008).

The role of credit in firm decisions is well documented. For instance, Campello et al (2009) find that financially constrained firms give up attractive investment opportunities and undertake deeper cuts in a recession. Similarly, Mach and Wolken (2011) show that credit constraints are a key predictor of small firm market exit. Other studies emphasise the role of non-bank forms of financing. Carbo-Valverde et al. (2012) analyse a panel of over 40,000 Spanish SMEs from 1994 to 2008. They find that credit constrained SMEs depend on trade credit rather than bank loans to finance capital expenditures, particularly when financing constraints are tighter. Casey and O'Toole (2013) use a survey of European SME's access to finance (SAFE survey) and find evidence that credit constraints raise the likelihood that companies apply for either trade credit or other sources of non-bank financing by between 18 per cent and 25 per cent.

The existing literature uses a number of different definitions of corporate liquidations or defaults, including: actual bank loan defaults or write-offs (Jimenez and Saurina (2005), Hoggarth, Sorensen and Zicchino (2005)), expected default frequencies (EDFs) as calculated by statistical models such as Moody's KMV (Åsberg and Shahnazarian (2008), Castren, Dees and Zaher (2008)) and the overall level or rate of corporate liquidations (Vlieghe (2001), Virolainen (2004), Hamerle, Liebig and Scheule (2004)). Different types of companies will be captured depending on the definition used. For instance, the overall liquidations rate and bank loan defaults will include small and medium enterprises, which will not be captured by Moodys KMV and similar proprietary models to the same extent. At the same time, the overall liquidations rate, depending on how it is defined, could include companies for which no bank losses are incurred, unlike the other two measures which are based on financial default. Similarly, different types of credit are captured by these different measures. Moody's KMV is based on credit risk associated with corporate bonds, bank-originated data captures bank loans only, while an insolvent liquidations rate will capture non-bank

SME finance.

A number of different methodological approaches are taken in the literature. Bunn and Redwood (2003), in finding profitability, interest cover, liquidity and the debt-to-asset ratio as determinants of corporate liquidations, estimate a probit model using firm-level data on public and private companies over the period 1991 to 2001. Tudela and Young (2003), find that a hybrid model which incorporates a Merton-based default probability into a probit framework outperforms a purely probit model, finding that both firm level characteristics and GDP impact on firm default. Lawless and McCann (2013) use SME bank loan-level data to examine the evolution of loan performance through the period 2008 to 2010 in Ireland in a panel data setting. They show that the shift in the distribution of loans across ratings as economic conditions deteriorated was heterogeneous across sectors and that changes in employment and a measure of excess credit are found to be determinants of bank loan impairment.

Many papers use a vector autoregression or error correction approach. Among these, Alves (2005) and Åsberg and Shahnazarian (2008) find cointegrating relationships between the macroeconomic and EDF variables, and find that short-term interest rates, GDP and inflation are important determinants of EDFs. Vlieghe (2001) also adopts a VECM framework, and finds that micro balance sheet factors seem to drive rising insolvencies during the early 1990s but that macroeconomic factors were important in the decline in insolvencies during the subsequent economic pick-up. Orzechowska-Fischer and Taplin (2010) conduct a similar study for Australian liquidations, and find that GDP, unemployment and business profits are important determinants of liquidations. Jacobson, Linde and Roszbach (2005) use a VAR approach to examine how Swedish companies' balance sheets interact with the wider economy and find that macroeconomic variables help explain time-varying default frequency. Finally, Castren, Dees and Zaher (2008) use a Global-VAR model and construct a linking satellite equation for EDFs to show that GDP, exchange rates, oil and equity prices are key determinants of EDFs in the euro area.

A strand of the literature uses survival analysis to analyse aspects of the corporate sector. However, the focus here tends to be more on comparisons across the industrial sectors or types of firm within the broader corporate sector, rather than the estimation of absolute probabilities of default. For instance, Agarwal and Aaudretsch (2001) test whether the size of a firm upon entering an industry impacts the likelihood of its survival. They find that the likelihood of survival for smaller entrants is generally lower, but that this relationship does not hold for mature stages of the product life cycle, or in technologically intensive products. Boyer and Blazy (2014) investigate the role of innovation in firm survival, and find that innovative enterprises tend to fail sooner than non-innovative ones. Chava and Jarrow (2004) test the forecasting accuracy of bankruptcy hazard rate models for U.S. companies from 1962 to 1999. They show that sector information significantly affects both the intercept and slope coefficients in the forecasting equations and that accounting variables add little predictive power when market variables are already included in the bankruptcy model.

3 Data Description

We build on the data presented by Kearns (2003). That paper introduced an aggregate series of corporate liquidations in Ireland, and developed a definition of insolvent liquidations[1]. There are two categories of liquidations in Ireland: those where there are no outstanding bad debts because the proceeds of the liquidation are sufficient to repay any outstanding debts and those where this may not be the case. We use the latter category of liquidations below. However our dataset is richer than that of previous studies incorporating all registered company "births" and "deaths" since 1980. A further improvement to the data is it includes both sectoral and geographical information for each observation. The data are provided by the Irish Department of Jobs, Enterprise and Innovation (DJEI) which collects figures directly from the Irish Companies Registration Office (CRO). The dataset is cleaned to exclude duplicate records and observations missing information such as location and sector of operation. Liquidated companies for which a registration date is not available (i.e. companies registered prior to 1980) are excluded from the dataset. The resulting dataset contains approximately 450,000 companies which were registered between 1980 and 2012.

For each company in the dataset the available information includes:

- Company number -allowing for the identification of individual companies
- Company name
- Company registered address - allowing for analysis by location[2]
- Date of registration - used to identify company births
- Date of liquidation (where relevant) - used to identify company deaths
- NACE principle object code (where available) - which allow for the categorisation of companies by the sector in which they operate.

3.1 Company Status

Of the total 450,000 observations, almost 40 per cent remain "alive" (referred to as active companies) as of the end of the sample, 2012Q4, while the remaining 60 per cent were dissolved during the sample period. Companies can be dissolved, and therefore removed from the companies register, either where a company is subject to a wind-up (liquidation) or where they are subject to strike-off. Company wind-up can occur in one of a number of ways:

- Members' voluntary wind-up - where directors must make a statutory declaration that the company will be able to pay its debts in full.

[1] The vast majority of Irish companies are SMEs; the Central Statistics Office of Ireland's Business in Ireland Survey 2009 reports that 99.8 per cent of enterprises were SMEs.

[2] It is possible that the registered address is that of the firms solicitor rather than the company itself. Where this is obviously the case, the company is removed from the sample.

- Creditors' voluntary wind-up - where creditors must receive notice of the intention to wind-up the company and are allowed to supervise the conduct of the liquidation.
- Court wind-up - where the company is wound up by a court order at the instigation of a member or creditor.

Company strike-off can occur in one of two ways:

- Voluntary strike-off - where a company that ceases to trade and has no outstanding creditors requests the Registrar to strike off the company.
- Involuntary strike-off - where the Registrar institutes a strike-off procedure. This can occur for instance where a company has failed to deliver an annual return to the CRO.

Since strike-offs and Members Voluntary liquidations are not the result of credit distress, we exclude them from our sample, and instead include only "creditors voluntary" and "court winding-up" liquidations. Although some of these liquidations do not result in actual losses to creditors, liquidations of these types generally result from credit distress (since they are mostly instigated by creditors) and are indicative of the firm being in arrears on loan repayments. We therefore refer to these as "insolvent liquidations" below.

3.2 Summary Statistics

Before looking in more detail at these insolvent liquidations, summary information on the overall dataset is presented. Figure 1 shows the number of company births and deaths over the sample. The top panel shows the evolution of the sample of active companies - this grows with the registration of new companies which then fall out of the sample if and when they are dissolved. In later years the sample of active companies should be relatively close to the overall population of registered companies, as the proportion of active companies that were registered prior to 1980 diminishes. The second panel of figure 1 shows company registrations over the sample period with the remaining three panels showing company wind-ups by type. The most common form of company death is strike-off. However, as you can see the number of strike-offs has been quite erratic over the sample, with a number of quarters around the year 2000 where more than 10,000 companies were struck-off. This to a certain extent can be enforcement related as strike-off can be initiated by the CRO on foot of non-compliance by companies. Members' voluntary liquidations (labelled "Voluntary" in figure 1), while significantly less frequent than strike-off, show a general upward trend for much of the sample period. By the end of the sample they were in the region of 1,000 voluntary liquidations a year. It is insolvent liquidations (labelled "Insolvent" in figure 1) which are of most interest from a financial stability point of view. As mentioned, these are the company deaths most likely to result in losses for creditors. However, the trend in insolvent liquidations is also interesting as it seems to follow the pattern of the business cycle most closely - suggesting liquidations of this sort may be most closely related to macroeconomic conditions. Figure 1 shows a significant increase in the number of insolvent liquidations occurred during the recent economic downturn.

Such a pattern becomes more obvious if one looks at the insolvent liquidations rate plotted against the annual rate of GDP growth (Figure 2). Now it can be seen that for instance, following a period of weak economic activity in the late-1970s and early-1980s, the liquidations rate increased throughout much of the 1980s. Brief downturns in economic growth in the early 1990s and 2000s coincided with somewhat smaller increases in the level of the liquidations rate. Conversely, strong economic growth through much of the 1990s and 2000s coincided with an extended decline in the rate to a historical low of 0.20 per cent in 2007. Finally, the most dramatic movement coincided with the recent financial crisis, during which the insolvent liquidations rate increased to its highest level on record at 0.77 per cent.

3.3 Insolvent Liquidations

We now look in a little more detail at the cohort of companies which were subject to insolvent liquidation. The distribution of insolvently liquidated companies, along with distribution of active companies, by sector and location is shown in Table 1. The sectoral breakdown is based on the NACE principle object codes which have been assigned to companies on their establishment since they were first introduced in the 1970s. For the purposes of our analysis companies have been grouped into eight broad sectors[3]. The other business activities sector, which incorporates computer, legal and accounting services amongst others, is the largest accounting for about 40 per cent of companies followed by the construction and real estate and retail and wholesale sectors. In general the distribution of liquidated companies is similar to the distribution of active companies; however the manufacturing sector does show a discrepancy where the sector accounts for a much larger portion of liquidated companies than it does active companies. Turning to location, the regional breakdown is based on companies' registered address - which may not necessarily be where the business activity was carried out - with companies assigned to one of the eight NUTS 3 level regions[4]. The analysis shows that the majority of companies have a registered address in Dublin, with 60 per cent of liquidated companies in the sample having had an address in Dublin. While a small region, accounting for about 6 per cent of active companies, the Midwest is interesting as it is the only region, except for Dublin, where the share of liquidated companies is larger than its' share of active companies.

4 Empirical Analysis

The level of economic activity within a jurisdiction is a key driver affecting firm survival. Specifically, a broad-based acceleration of economic activity and increases in the national and regional output levels is likely to reduce the level of firm failures, and similarly a slow-down in economic activity would have the opposite effect. Changes in GDP and GNP are the commonly used measures of economic activity but these measures can be volatile quarter on quarter. Additionally, it is unlikely there will be large scale firm failure in the first

[3]The eight sectors used are agriculture (including forestry, fishing and mining), retail & wholesale, manufacturing, transport & communications, construction & real estate, financials, hotels & restaurants and other business activities which incorporates utilities.

[4]The NUTS 3 regions for Ireland are Dublin, Southeast, Southwest, West, Mideast, Border, Midlands, Midwest. In the NUTS 3 division Tipperary is split between the Midwest and Southeast. In our analysis we include Tipperary in the Southeast.

quarter of an economic slowdown. Instead, it is a prolonged period of poor economic performance which will undermine a firm's survival. To capture this effect, any measure should be cumulative in nature. Unemployment provides a good proxy for economic performance and reflects preceding periods of poor economic performance. In addition, unemployment rates are available on a regional basis allowing for local differences in economic conditions[5].

An important consideration when investigating the impact of economic conditions on the probability of company failure is the effect of survival bias, i.e., the longer a firm survives in a recessionary period the less likely the company will become insolvent. This is consistent with the idea of high risk companies failing when economic conditions begin to worsen but well established companies with a stock of capital will have greater resiliency. The net effect is a non-linear relationship between unemployment and company survival captured in the model by taking the natural log of unemployment.

Lawless & McCann (2012) show the important role played by excess credit in the probability of loan default for a Irish SME. Building on this finding, the role of excess credit is considered here in the wider context of overall company survival. There are two channels through which credit relates to company survival. The first is point in time credit availability, when there is increased risk of company failure in a period of sudden credit reduction. This can be captured in the model as the quarterly change in credit at the sector level. The second relates to credit standards. Excess credit growth requires a lowering of credit standards; therefore companies born in periods of credit expansion are on average a risker proposition. To capture this effect a measure of excess credit at birth (ECaB) is required. Excess credit is defined as the deviation from the trend level, τ of credit in a given sector based on a Hodrick-Prescott(HP) filter, given by,

$$\text{Excess Credit}_t = TC_t - \tau_t, \quad \text{where } \tau_t \text{ is solved to minimise,}$$
$$\sum_1^T (TC_t - \tau_t)^2 + \lambda \sum_2^T -[(\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1})]^2$$

The trend and deviations are estimated on a quarterly time series spanning 1970 to 2012 at the broad sector level. The optimal lambda value for modelling the financial cycle has received a lot of attention in light of the Basel III counter-cyclical capital buffer implementation. Borio (2012) investigates the empirical features of the financial cycle and finds the optimal lambda value to be 400,000. Excess credit is calculated as the per cent deviation from trend credit levels. This accounts for the difference in credit levels across sectors independent of any surpluses. Figure 3 shows the sector excess credit measure from 1995 to 2012.

Before formal modelling of the survival rates, Figure 4 shows the dependence between the quarterly failure rates by location and the two macro determinants discussed above[6].

[5] Unemployment rates are available from the Central Statistics Office (www.cso.ie) at the NUTS 3 regional classification.

[6] This is a modified correlation measure using a Bayesian approach allowing for the relaxation of the bivariate normality assumption of the Pearson measure and the use of priors to inform the means standard deviation and heaviness of the tails. Barnard et al. (2000) outline in detail but the net effect is correlation estimates robust to outliers.

The correlation of failure rates with both unemployment and the credit gap is significant and positive. The top of each plot shows the posterior distribution for the correlation coefficient (median of 0.63 and 0.30 for unemployment and the credit gap respectively). Below is a scatter plot of the data with superimposed posterior predictive distributions, i.e. the distribution one expects new data points to follow[7].

While the above correlation estimates show a strong relationship between macroeconomic conditions and company failure, a more sophisticated methodology is required to estimate the survival probability of a company. Due to the quarterly recording of economic data, a discrete time survival model is employed to estimate the probability of company failure, which takes the form of a complementary log log classification model.

Data organisation in the estimation of discrete time hazard models is important to yielding consistent and unbiased estimates of failure. The data set must be re-organised so that, for each company, there are as many data rows as there are time intervals at risk of the event occurring for each company. A company will enter the panel in the quarter of birth and will be repeated in each subsequent quarter until the end of the sample (2012Q4) or company exit. As discussed above, there are three possible reasons for company exit; voluntary liquidation, strikeoff and insolvent liquidation. If the exit occurs due to the first two; the company is no longer repeated in the sample. If the reason for exist is insolvent liquidation, the company also exists the panel but a value of one is recorded in a company failure variable for that quarter only. At all other times and reasons for exit, the company failure variable takes on a value of zero. In effect, an unbalanced panel is created with a failure variable recorded as one in the quarter a company exists due to insolvent liquidation.

When modelling survival probabilities, an important consideration is the functional form of the baseline hazard function. This dictates the probability of company failure due to time independent of the macro environment. There are several possible alternative specifications, with Figure 5 displaying a range of functional forms and the calculated errors associated with each. The combination of time and time squared is found to minimise error. Therefore, the first two covariates in the model are defined as the number and square of the number of quarters since the birth of the company. The model provides a good fit with the observed empirical rate remaining within the 95 per cent confidence interval.

While the baseline hazard governs the time dimension of the model, discrimination power and sensitivity to economic and banking conditions to determine which companies are more likely to fail requires additional covariates. In addition to the two macro variables outlined above; regional unemployment and the ECaB, sectoral and locational controls are also included, yielding a survival model of the form,

$$Insolvent_{i,t} = \alpha + \beta_1 t + \beta_2 t^2 + \gamma_i Loc_i + \kappa_i Sector_i + \zeta \Delta Credit_t + \zeta ECaB_i + \eta ln(Un_{t-4}) + e_{i,t} \tag{1}$$

where $Insolvent_{i,t}$ is binary variable of company failure due to insolvency. t, and t^2 are time and time squared since the birth of the company. The effects of credit are captured by ΔCredit and ECaB, the quarterly change in credit and the excess credit at birth respectively. The sample includes companies' registered post 1980. Figure 2 shows a sharp growth in the

[7] The darker and lighter blue areas show the 50 and 95 per cent density regions respectively. Half of all new data points are predicted to fall within the darker blue area.

sample during the 1980's and early 1990's. To avoid potential bias from outliers in periods with potentially small numbers, the model is estimated on quarterly data between 1995q1 and 2012q4.

Table 2 presents the estimates of equation (1). Model 1 constrains the estimation to sectors, while location controls and macro variables are introduced in models 2 and 3 respectively. Both macro variables, some locations such as Dublin, Mideast and the Midwest, along with certain sectors including hotels & restaurants, retail & wholesale, manufacturing and transport have a significant positive impact on the probability of company failure. Taking the odds ratio of the coefficients provides the hazard rate associated with each coefficient. The hazard rate gives the increased risk of company failure for a one unit increase in the associated covariate. A company operating in the retail & wholesale sector has a 72 per cent greater risk of failure compared to one in the agriculture sector. In terms of location, a company operating in Dublin has an almost 2 times greater risk of failure compared to the Southwest. The current state of the economy has a significant impact on survival. The effect of unemployment is non-linear. For example, the effect of unemployment is three times greater when unemployment increases from 4 to 5 per cent compared to 14 to 15 per cent. Credit also has a significant impact, with a 1 per cent fall in credit levels causing a 58 per cent increase in the risk of company failure. There is also a significant positive coefficient on the measure of credit standards, with a 1 per cent deviation above trend credit levels at time of company birth yielding a 77 per cent increase in the risk of company failure. These findings are consistent with Lawless and McCann (2013) showing surplus credit, usually a result of decreasing credit standards during a boom leads to an increase in company failures during the crisis.

A key advantage of modelling the macro drivers of company failure is to accurately provide predictions of changes to economic conditions. For example, if credit supply were to remain constrained in the medium term but the domestic economy experiences a recovery, the lower unemployment rates would result in a significant improvement in the failure rates. Figure 6 presents the insample model fit, showing an accurate estimate of the failure trend from 1995 through 2011 with only a small level of error, always remaining within the 95 per cent confidence bands.

5 Conclusions

This paper examined the role of credit and the macroeconomy in SME distress during a prolonged economic downturn. The prolonged financial crisis in Ireland has impacted the SME sector severely, resulting in an unprecedented increase in insolvencies. While credit can take many forms, small firms are generally reliant on banks for external financing. However, SME access to bank credit is procyclical with alternative sources of financing becoming increasingly important during stressed periods. We therefore use a measure which captures not just bank loan distress but all forms of creditor financing. Our measure of SME distress - insolvencies - can be disaggregated by both sector of activity and geographical location, to determine the relative impact of the crisis compared to historical norms.

To understand the drivers of the probability of SME distress through a prolonged and aggravated downturn, we conducted a survival analysis in a complementary log log framework.

Controlling for location and economic sector, we find that variables capturing a build-up of stress in the macroeconomy and those capturing bank credit standards and availability throughout the cycle are determinants of firm survival. Our model fits well and in-sample forecasts appear reasonable.

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7 Tables & Figures

Table 1: Summary Statistics by Sector and Location

		Active		Liquidated	
		%	Num	%	Num
		100.00	171212	100.00	14099
Sector	Other Bus. inc Utilities	45.42	77770	43.68	6159
	Retail/Wholesale	11.74	20094	12.71	1792
	Manufacturing	6.59	11287	12.40	1748
	Agri etc	2.20	3770	1.16	163
	Transport/Communications	3.57	6114	4.03	568
	Construction/Real Estate	20.76	35539	17.80	2510
	Financials	5.20	8903	1.40	198
	Hotels/Restaurants	4.52	7735	6.82	961
Location	Southwest	13.24	22673	8.96	1263
	Dublin	41.40	70878	59.56	8398
	Southeast	9.11	15600	4.55	642
	West	7.50	12844	5.32	750
	Mideast	9.75	16690	6.48	913
	Border	8.74	14969	5.09	717
	Midlands	4.14	7083	3.04	429
	Midwest	6.12	10475	7.00	987

Notes: Active is defined as all companies operating as of 2012Q4. Liquidated is defined as all companies subject to insolvent liquidation between 1980Q1 and 2012Q4.

Table 2: Coefficient Estimates and Hazard Rates from Discrete Time Survival Model

	Model 1		Model 2		Model 3		
							Hazard Rate
	Estimate	z-Value	Estimate	z-Value	Estimate	z-Value	
(Intercept)	-7.79	-29.20***	-8.14	-27.83***	-9.91	-30.60***	0.00
Time	0.03	6.99***	0.03	7.12***	0.03	6.88***	1.03
Time Squared	-0.00	-5.02***	-0.00	-5.03***	-0.00	-5.30***	1.00
Construction/Real Estate	0.57	2.16*	0.41	1.55	0.22	0.80	1.24
Hotels/Restaurants	1.14	4.13***	0.96	3.47***	0.78	2.78**	2.18
Manufacturing	0.85	3.15**	0.63	2.34*	0.64	2.37*	1.90
Other Bus. inc Utilities	-0.01	-0.03	-0.31	-1.17	-0.39	-1.48	0.68
Retail/Wholesale	0.85	3.16**	0.68	2.53*	0.54	2.00*	1.72
Transport/Communications	0.92	3.20**	0.71	2.47*	0.69	2.41*	2.00
Dublin			0.88	6.55***	1.09	8.10***	2.98
Mideast			0.44	2.74**	0.66	4.06***	1.94
Midlands			0.26	1.23	0.18	0.81	1.19
Midwest			0.67	3.95***	0.73	4.31***	2.07
Southeast			-0.03	-0.16	-0.13	-0.70	0.88
Southwest			0.05	0.29	0.20	1.22	1.22
West			0.18	0.98	0.23	1.27	1.26
ln(Unemployment)					0.83	13.40***	2.30
$Delta$ Credit					-0.86	-2.34*	0.42
ECaB					0.57	3.60***	1.77

Notes: Estimates from a complementary log log model with the dependent variable defined as a one in the quarter a company exits due to insolvency. The sample is an unbalanced panel of active companies registered between 1980q1 and 2012q4.***, ** and * denotes significance at the 99.9%, 99% and 95% levels respectively. The deviation at birth is proxy for credit standards measure as the deviation of credit from trend at the sector level at the time of company birth; where trend credit is measured using a Hodrick-Prescott filter with a lambda value of 400,000.

Figure 1: Evolution of Company Births and Deaths(by type) 1980-2012

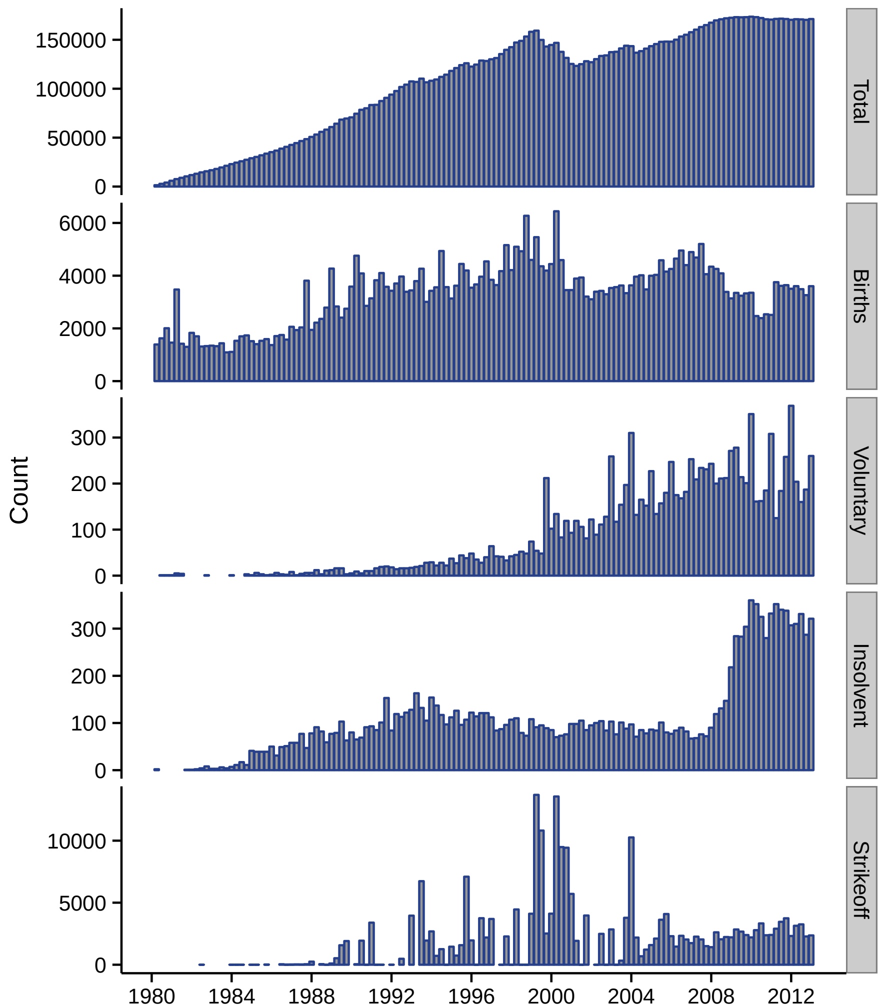


Figure 2: Time Series of Real GDP Changes and Company Failure Rates(Insolvencies) 1982-2012

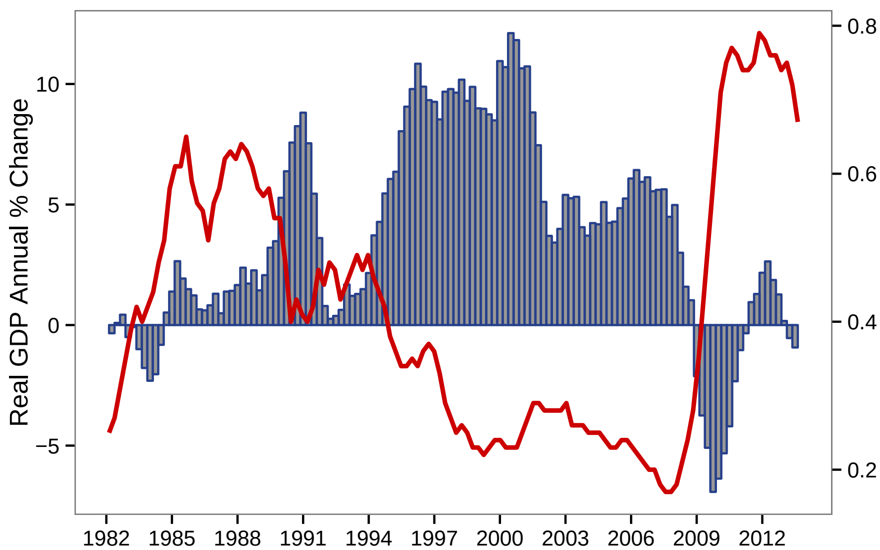


Figure 3: Credit Gap by Sector; 1995-2012

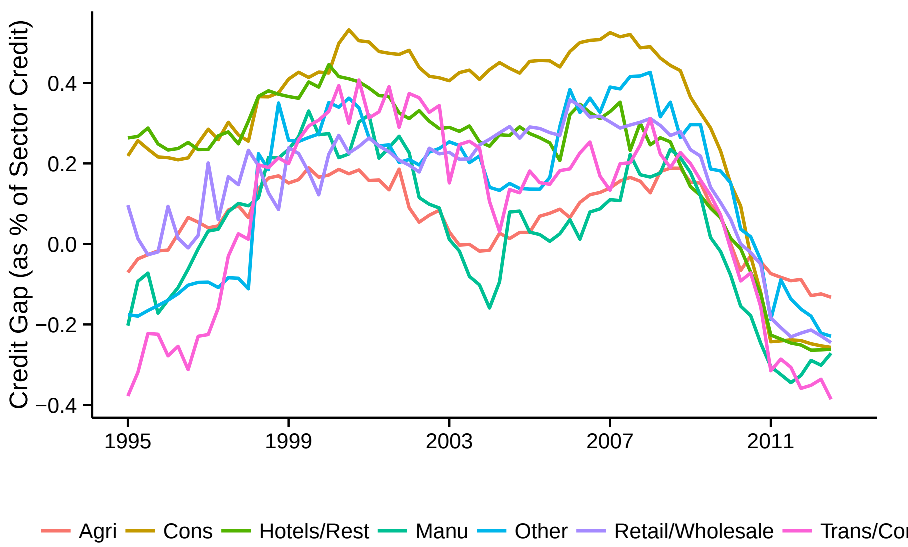
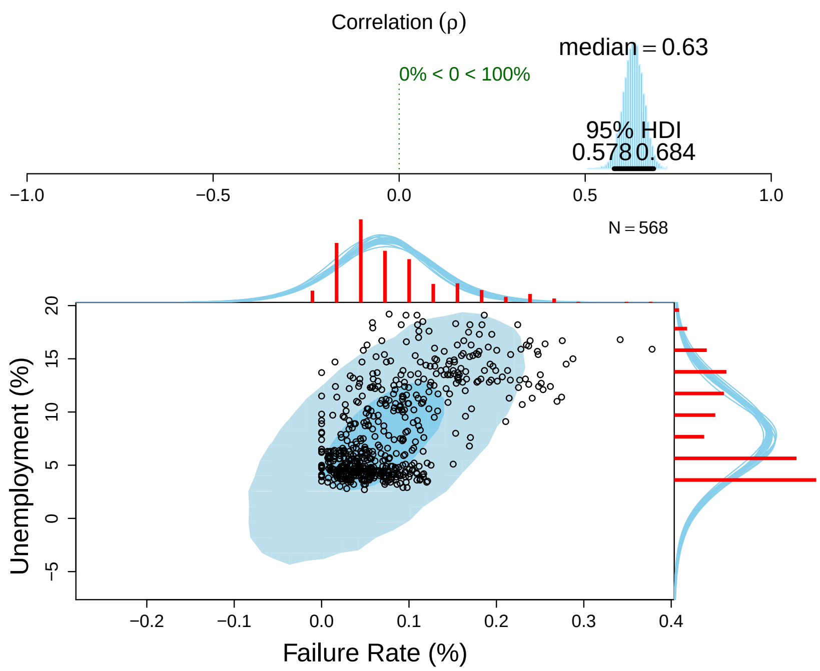


Figure 4: Correlation between Failure Rate and Macro Factors

Unemployment



Credit Gap

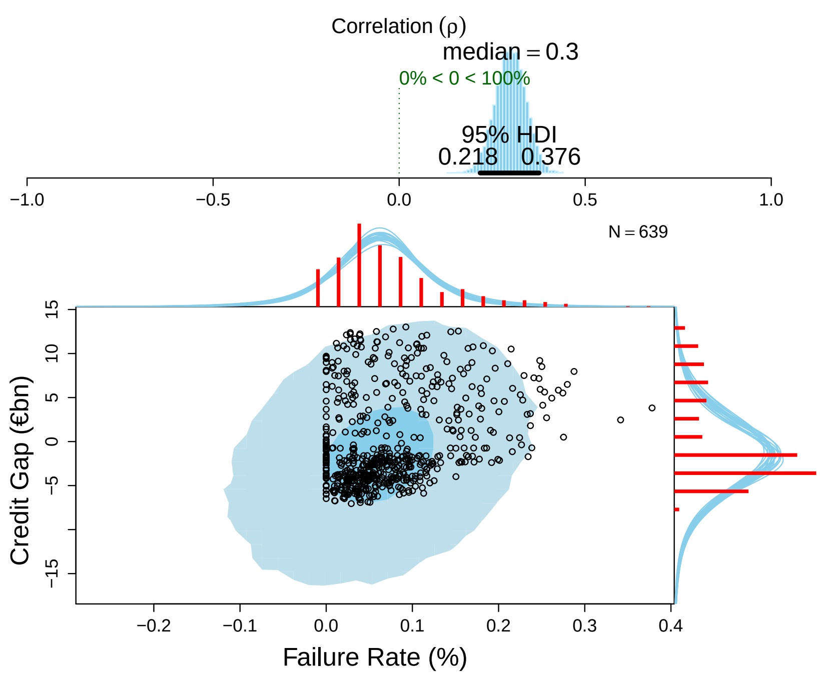


Figure 5: Comparison of Model Specification for the Baseline Hazard Function

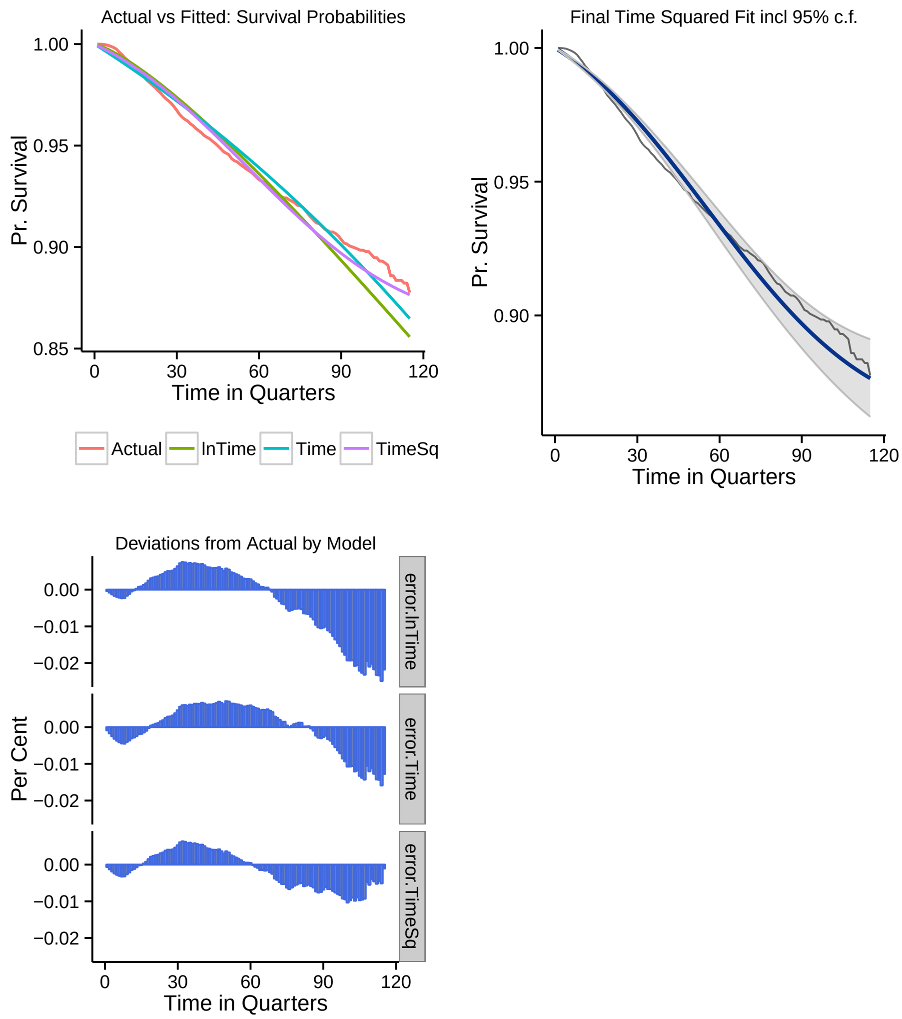


Figure 6: In Sample Time Series Fit of Failure Rates