FIRM DEFAULT AND AGGREGATE FLUCTUATIONS

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Abstract

This paper studies the relationship between macroeconomic fluctuations and corporate defaults while conditioning on industry affiliation and an extensive set of firm-specific factors. By using a panel data set for virtually all incorporated Swedish businesses over 1990–2009, a period which includes a full-scale banking crisis, we find strong evidence for a substantial and stable impact from aggregate fluctuations on business defaults. A standard logit model with financial ratios augmented with macroeconomic factors can account surprisingly well for the outburst in business defaults during the banking crisis, as well as the subsequent fluctuations in default frequencies. Moreover, the effects of macroeconomic variables differ across industries in an economically intuitive way. Out-of-sample evaluations show that our approach is superior to models that exclude macro information and standard well-fitting time-series models. Our analysis shows that firm-specific factors are useful in ranking firms' relative riskiness, but that macroeconomic factors are necessary to understand fluctuations in the absolute risk level. (JEL: C35, C52, E44, G33)

The editor in charge of this paper was Fabio Canova.

Acknowledgments: We would like to thank Rikard Kindell, who co-authored the working paper version of this paper on a shorter data sample for outstanding contributions to this project. Discussions with and suggestions from Franklin Allen, Ed Altman, Mitch Berlin, Mark Carey, Ines Drumond, Xavier Freixas, Bob Hunt, Wenli Li, Leonard Nakamura, Dragon Tang, Cees Ullersma, and Kostas Tsatsaronis have been very helpful in improving upon earlier drafts. We are also grateful for comments from seminar participants at the Bank of Austria, the Bank of Hungary, the Einaudi Institute for Economics and Finance, the Bank of England, the Bank of Finland, the Federal Reserve Bank of Philadelphia, the Federal Reserve Bank of New York, Uppsala University, EARIE, the C.R.E.D.I.T. 2008 conference, the EEA-ESEM meetings in Budapest (2008) and Barcelona (2009), the 2009 BIS Research task force workshop, the 2008 ASSA meetings, the DNB conference on Financial Stability and Financial Crises, and the BIS. Erica Reisman, Erik von Schedvin and Ingvar Strid provided outstanding research assistance. The views expressed in this paper are solely the responsibility of the authors and should not be interpreted as reflecting the views of the Executive Board of Sveriges Riksbank, the Board of Governors of the Federal Reserve System or of any other person associated with the Federal Reserve System.

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1. Introduction

Business failure is an event of fundamental importance in economic life. Despite extensive study devoted to the subject, our understanding of the determinants of business defaults is far from complete, particularly with respect to the influences of broader economic conditions. Recent economic events—namely, a global financial crisis shifting into a recession of exceptional depth—highlight the importance of understanding and predicting this crucial aspect of the economy for the express purpose of suggesting timely and appropriate policy measures.

The aim of this paper is to shed light on the dynamics of business defaults. In particular, we seek to understand the interactions between macroeconomic fluctuations and firms’ individual likelihoods of defaulting and the relationship between macro variables and the aggregate rate of default. Toward this end we have compiled a new panel data set with detailed firm-level information on all incorporated Swedish businesses over the period 1990Q1–2009Q2. The panel comprises more than 16 million firm-date observations, with an average of more than 200,000 firms per moment in time. The length and width of this panel enable several extensions of previous research; among other things, we can carefully evaluate industry-specific effects of macroeconomic fluctuations. Because the data set includes virtually all incorporated Swedish firms, our findings provide insight into the significance of aggregate fluctuations for both listed and privately held firms; the latter group is typically responsible for over half of gross domestic product (GDP) in developed economies. This inclusiveness is important because Merton-like models of default, which are based on equity price information, are thus limited to listed firms in practice.


Over time, the average default frequency and individual default probabilities display comovement with macroeconomic and financial variables in a way that suggests aggregate shocks might be an important driver of default. The seminal work of Bernanke, Gertler, and Gilchrist (1999) provides a theoretical framework in which firm-specific factors as well as macro shocks affect the default outcome of individual firms. In this framework, firm default is affected by firm-specific productivity shocks and aggregate shocks (e.g., an aggregate productivity shock). It follows that an empirical model of default should feature variables that proxy for the underlying firm-specific productivity, as well as variables that proxy for unobserved aggregate shocks. Hackbarth, Miao, and Morellec (2006) suggest an additional mechanism through which macroeconomic conditions affect default risk. These authors argue that, when cash flows depend on economic conditions, firms’ optimal default thresholds will
be affected by aggregate shocks. Hence, aggregate shocks can trigger simultaneous defaults.

These theoretical insights have recently been explored in the empirical literature on default modeling, and there is a small but growing number of papers investigating the importance of macroeconomic fluctuations on business defaults. The work of Pesaran, Schuermann, Treutler, and Weiner (2006) and Duffie, Saita and Wang (2007) and more recently of Bonfim (2009), Lando and Nielsen (2010), and Tang and Yan (2010) provide empirical evidence that firm-specific factors alone do not fully explain the variation in corporate default rates and credit spreads. Using structural and reduced-form approaches on aggregate times series and data on publicly listed industrial firms, these authors find that macrofinancial covariates have significant explanatory power for credit losses, spreads, and corporate default rates.

In this paper, we adopt a standard econometric specification and estimate multiperiod logistic regressions on firm-level default data. Shumway (2001) shows that, under some mild restrictions, this model is equivalent to a discrete-time hazard model, and is therefore not prone to the bias and inconsistency of the static model previously used in bankruptcy modeling. In addition to an extensive set of financial statement variables and payment remarks reflecting a firm’s financial track record, we include four standard macroeconomic variables. The default risk models are estimated both at an economywide level and for 10 industries on a subsample covering 1990Q1–1999Q4.

Our large panel data set enables us to make several contributions to the aforementioned literature. First, we show that a simple logit model with constant parameters can account for the outburst in default rates during the Swedish banking crisis and also for the historically low rates occurring in subsequent recovery periods. The included macroeconomic variables are of key importance for explaining the time-varying likelihood of default. Firm-specific variables prove insufficient for explaining variation in the level of default risk over time, but are very useful for ranking firms according to their relative riskiness. Second, with access to a very rich set of firm-specific controls we can credibly reject the possibility that the empirical significance of macroeconomic variables is merely (or partially) an artifact of a shortage of firm-specific controls. Third, the length of our panel enables extensive out-of-sample performance testing for the period 2000Q1–2009Q2. The results suggest that our default risk models—with both macroeconomic and firm-specific variables included—perform remarkably well out-of-sample; this holds in both the cross-sectional and the time-series dimension. Fourth, the width of our panel permits us to investigate the relationship between aggregate fluctuations and business defaults across industries. By isolating and comparing industry-specific effects from macroeconomic variables we get an additional measure of the robustness of their impact on business defaults. Our obtained results are economically intuitive and suggest that the effects are stronger in such sectors as construction and real estate, which a priori can be deemed to be more cyclical because they involve production of more durable goods. Fifth, the combined width and length of our panel allow us to assess the stability over time of cross-sectionally estimated parameters. We show that models estimated on cross-sectional
data are likely to suffer from substantial parameter instability over time, and therefore will be unable to account for variations in the average default frequency strykes: over time. Finally, our analysis also suggests that considering only macroeconomic variables, while ignoring relevant firm-specific information, leads to a substantial loss of out-of-sample prediction accuracy.

According to our analysis, the two key macroeconomic factors affecting business defaults are the nominal interest rate and the output gap. Under current conditions, where economic activity and the output gap in many countries have dropped at the fastest pace since the Great Depression, our results suggest that central banks can reduce the likelihood of an outburst in default rates—and the associated spike in credit losses for banks—by aggressively cutting nominal interest rates. Hence, the unprecedented cuts in policy rates by leading central banks during the crisis have presumably mitigated sharp upturns in default rates, by reducing financing costs for firms and indirectly by stimulating aggregate demand.

The remaining of this paper is structured as follows. Section 2 presents the micro and macro data sets. The regression results are presented in Section 3 along with an assessment of the in-sample fit. In Section 4, we undertake a thorough out-of-sample investigation of the estimated models along several dimensions. Section 5 concludes.

2. Data

The firm data set is a panel consisting of 16,928,521 quarterly observations on the population of Swedish aktiebolag, or firms, between 1 January 1990 and 30 June 2009. Aktiebolag are roughly the Swedish equivalent of US corporations and UK limited liability businesses. Swedish law requires every aktiebolag to have at least 100,000 SEK (Swedish krona; about 13,000 US dollars) of equity to be eligible for registration at Bolagsverket, the Swedish Companies Registration Office (SCRO). Swedish corporations are also required to submit an annual report to the SCRO.

The firm data were obtained from Upplysningscentralen AB (UC), the leading credit bureau in Sweden, which is independently operated but jointly owned by the Swedish commercial banks. The UC data come from two general sources. First, annual balance sheet and income statement data come from firms’ compulsory annual reports submitted to the SCRO. These data cover the period 1 January 1989 through 30 June 2009, and their format follows European Union standards. We use linear interpolation to convert the annual report data into quarterly observations; that is, we assume that the variables remain constant over the quarters in a given reporting period.

The second information source is atypical in the existing literature on default and is somewhat unique for Sweden. The credit bureau systematically collects information about events related to firms’ payment behavior from all relevant sources, including the Swedish retail banks, the Swedish tax authorities, and institutions dealing with the legal formalities of firms’ bankruptcy processes. The credit bureau thus has a register of more than 60 different “payment remarks” concerning primarily credit and tax-related events, as well as records of various steps in the legal procedures leading up to
formal bankruptcy. The information in the register includes a “flag” for the occurrence of an event in the form of a date and the amount of due payment (if applicable). Some examples of registered events are delays in tax payments, repossession of delivered goods, seizure of property, restructuring of loans, and actual bankruptcy. It turns out that payment remarks are powerful predictors of default and are essentially available in real-time. These payment remarks are generally not available outside Sweden, so one could argue for excluding them to enhance comparability with other studies. However, we prefer to include the payment remarks in our analysis because doing so yields a more comprehensive set of firm-specific control variables. We thus seek to eliminate the possibility of macroeconomic variables spuriously proxying for omitted firm-specific controls. In Appendix B (available online) we show that neither the role of accounting variables nor that of the macroeconomic factors is much affected by inclusion of the remark variables.

The population of existing firms in quarter $t$ is defined as including those firms that (i) have issued a financial statement covering that quarter and (ii) are classified as “active”; that is, the firm has reported total sales and total assets in excess of 1,000 SEK (about 130 US dollars). However, since there are firms that neglect to fulfill their reporting obligation—a behavior typically associated with distress—we would miss an important segment of firms by considering only those that submit annual reports regularly. Hence we will add firms that, according to the data set that includes payment remarks, are classified as defaulted in quarter $t$. Many firms that default choose not to submit their compulsory annual reports in that year or even for a number of years prior to default, so the payment remark registers are often the only records of their existence. A firm is defined to have default status if any of the following events has occurred: the firm is declared legally bankrupt, has suspended payments, has negotiated a debt composition settlement, is undergoing a reconstruction, or has lost assets via distraint. More details on the construction of the default variable are provided in Appendix A (available online).

Selecting which financial ratios to use in the default risk models, we evaluated a large number of frequently used ratios in the literature on bankruptcy risk and on the balance sheet channel.¹ Many papers employ measures of liquidity, profitability and efficiency, and solvency or leverage; others also make use of a size variable. For this paper we selected the following six financial ratios: the earnings ratio or earnings before interest, depreciation, taxes and amortization (EBITDA) over total assets (TA); the interest coverage ratio or interest payments (IP) over the sum of interest payments and earnings before interest, depreciation, taxes and amortization; the leverage ratio or total liabilities (TL) over total assets; the debt ratio or the log of total liabilities over total sales (TS); the quick ratio or liquid assets (LA) in relation to total liabilities; and the inventory turnover ratio or inventories (I) over total sales. Details on selection of financial ratios (along with a graphical exposition of the data)

¹ Table A.1 in Appendix A.3 provides an account of the variables considered in Altman (1968), Altman, Frydman, and Kao (1985), Shumway (2001), Pesaran et al. (2006), Duffie et al. (2007), Bharath and Shumway (2008), and Bonfim (2009).
are provided in Appendix A.2. It is important to note that the nonlinear feature of some financial ratios does not imply that these variables are uninformative about default risk when entered linearly into the logit model. The reason for this is the substantial covariation between the financial ratios in the cross section, which means that each variable contributes substantially to predicting default events in the joint linear empirical model. The accounting data also provide information on whether or not a firm has paid out dividends to shareholders, which we enter as a dummy variable (PAYDIV) in the models.

As mentioned previously, some firms (whether classified as active or defaulted) fail to submit a financial report in every period; this leads to the problem of missing observations. For the purpose of using an aggregate default series that closely corresponds to the official default frequency series as computed in the official statistics for Sweden—and to ensure unbiased macro coefficients in the econometric model—we decided to retain firms with missing variables in the sample and replaced missing values by imputation. In order to capture the relationship between failing to submit a financial statement and subsequent default, we include the dummy variable TTLFS (short for time to last financial statement). In line with actual reporting lags, this dummy equals unity at time \( t \) if a firm has not issued a financial statement in the 18 months prior to the current quarter \( t \) (and equals zero otherwise). This indicator variable attempts to capture the signal that many firms (deliberately) choose not to file a financial report when in financial distress, and thus are more likely to default. In Appendix B.2 we document that our results are robust—with respect to how we deal with missing observations—by reporting results that include only the firms for which data on all the financial ratios are available (i.e., we only include firms for which TTLFS equals zero).

To capture the information in payment remark variables we also use dummy variables, setting them to unity if certain remarks existed for the firm during the year prior to quarter \( t \) (and to zero otherwise). A reasonable starting point was to find remark events that (i) lead default in time as much as possible and (ii) are highly correlated with default. We ultimately find that the correlation between payment remarks and default behavior is either contemporaneous or insignificant. For our final model, we constructed the PAYREMARK variable as a composite dummy of four events: “a bankruptcy petition”; “the issuance of a court order—because of absence during the court hearing—to pay a debt”; “the seizure of property” and “having a nonperforming loan”. The TAXARREARS variable reflects whether the firm is in various tax arrears. We emphasize that these two remark variables do not entail a subsequent default incident. The share of defaulted firms that have received payment remarks (resp. are in tax arrears), is about 0.15 (resp. 0.41); the corresponding shares for nondefaulted firms

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2. The imputation consists of a sequential procedure whereby, for the variable in question, we first perform a backward search for the last available observation for that particular firm and then perform a forward search for the next available future observation; if these measures fail, we make a randomized draw from the data (conditional on industry and default status).

3. See Appendix A.2 for more details about TTLFS.
are 0.00 and 0.03. Therefore, using these variables to predict default events involves no tautology. Table A.2 in Appendix A.3 provides descriptive statistics for all firm-specific variables that are used in the subsequent analyses.

We make use of four aggregate variables: the output gap (i.e., the deviation of GDP from its trend value); the yearly inflation rate (measured as the fourth difference of the GDP deflator); the repo interest rate (a short-term nominal interest rate that is set by the Riksbank), and the real exchange rate. The output gap series is computed via Hodrick-Prescott (HP) filtering GDP, where the smoothing coefficient $\lambda$ is set to the standard value of 1600. The real exchange rate is measured as the trade-weighted nominal exchange rate multiplied by the trade-weighted foreign price level (CPI deflators) over the domestic CPI deflator. During the sample period, the real exchange rate is characterized by an upward (depreciating) trend; we therefore detrended it using the HP-filter to achieve stationarity. Figure A.2 in Appendix A plots the macro data and Appendix B.3 verifies that the results reported here are robust with respect to our procedure for detrending the real exchange rate.

3. Models of Default Risk: Estimation and In-Sample Fit

In this section, we examine whether or not default risk at the firm level is affected by aggregate fluctuations beyond the set of firm-specific variables at our disposal.

We study the in-sample gains of estimating separate models for each industry and assess the role of aggregate fluctuations for improving the models’ fit. The in-sample period is chosen to be 1990Q1–1999Q4. For this period there are 8,106,176 observations, of which 105,605 are defaults. The out-of-sample period, 2000Q1–2009Q2, is saved to allow for extensive model evaluation exercises; it comprises 8,822,345 observations, of which 55,945 are defaults. Thus, in our data set the average default frequency per quarter is about 1% for the full sample period. This is somewhat higher than the 0.75% per quarter US business failure rate (see, e.g., Bernanke et al. 1999), but if we exclude the banking crisis (and consider instead the period 1995Q1–2009Q2) then our average unconditional default frequency essentially equals the value reported by Bernanke et al. Analyses of industry effects will be conducted at the 1-digit SIC level to ensure sufficiently many default observations in each industry along both the cross-sectional and the time series dimensions. In addition, we estimate the model for all firms jointly and refer to this as the economywide model.

3.1. The Default-Risk Models

The reduced-form statistical model that we employ for estimating probabilities of default for all Swedish incorporated firms is similar to the multiperiod logit approach used in Shumway (2001) and in Campbell, Hilscher, and Szilagyi (2008). Using a reduced-form model avoids the problem with the Merton’s (1974) model—namely, that it cannot be implemented for privately held companies without strong assumptions. The reduced-form model enables us to use a unified approach for all
businesses, both privately and publicly held. As discussed in the Introduction, there is also a recent theoretical literature (see, e.g., Bernanke et al. 1999; Hackbarth et al. 2006; Tang and Yan 2010) in which it is argued that both firm-specific and aggregate shocks can trigger simultaneous defaults. Thus we propose to estimate the following model:

$$y_{i,t} = x_{i,t} \beta + z_t \gamma + \varepsilon_{i,t},$$

where

$$y_{i,t} = \begin{cases} 1 & \text{if } x_{i,t} \beta + z_t \gamma + \varepsilon_{i,t} \geq 0 \text{ (firm defaults)}, \\ 0 & \text{if } x_{i,t} \beta + z_t \gamma + \varepsilon_{i,t} < 0 \text{ (firm stays in business)}, \end{cases}$$

under the assumption that the vector of firm-specific regressors (i.e., $x_{i,t}$) and the macroeconomic variables under consideration (collected in the vector $z_t$) are stochastically independent with respect to the error term $\varepsilon_{i,t}$. This approach also allows us to control for the competing risks of exiting firms for reasons other than default (Allison 1995). We make the additional assumptions that, conditional on the extensive sets of firm-specific and macroeconomic covariates that we consider, the errors are independent between firms as well as over time; that is, $f(\varepsilon_{i,t}, \varepsilon_{j,t}) = f(\varepsilon_{i,t}) f(\varepsilon_{j,t})$ for $i \neq j$ and $f(\varepsilon_{i,t}, \varepsilon_{i,t+p}) = f(\varepsilon_{i,t}) f(\varepsilon_{i,t+p})$ for $p \neq 0$. These assumptions are rejected by Das, Duffie, Kapadia, and Saita’s (2007) study of US data. However, Lando and Nielsen (2010) revisit the relation between contagion through covariates and conditional dependence addressed in Das et al. and find that the assumption of conditional independence can no longer be rejected when the set of firm-specific and macroeconomic controls is slightly altered and expanded. Hence, conditional on an appropriate set of covariates, Lando and Nielsen find no evidence that the default of a firm causes default intensities of other firms to increase—supporting our assumptions on the error term. Moreover, for a similar model estimated on a subset of the data used in this paper, Carling, Roszbach, and Rönnegård (2004) find that the estimated parameters are robust once the correlation between residuals is taken into account. These results, along with the excellent out-of-sample performance of the model with respect to time and cross-section documented in Section 4, provide additional support for our assumptions on the error term.

Our theoretical basis for selecting the set of macroeconomic variables is that they should span shocks to both aggregate “demand” and “supply” that hit the economy. The output gap is intended as an indicator of demand conditions; in other words, increased demand in the economy is expected to reduce default risk. We also include the nominal interest rate in $z_t$ because credit conditions facing firms, especially firms in distress, are likely to be tightly linked to the interest rate. Since one could plausibly argue that the real interest rate (rather than the nominal one) is what should affect the default frequency, we also include the inflation rate in $z_t$. Moreover, apart from capturing the effects of supply shocks, higher inflation obviously implies higher nominal income for firms, which should further tend to reduce default risk. However, it is also conceivable that higher inflation rates are associated with less certainty about correct relative prices
and therefore may lead to increased default risks. For these reasons, the sign of the inflation coefficient is unclear and will depend on the relative strength of the underlying sources of macroeconomic fluctuation. Furthermore, given that the export-to-GDP ratio in Sweden was about 0.40 during the sample period, the real exchange rate is a potentially important variable because a depreciation enhances competitiveness of Swedish export firms.\(^4\)

### 3.2. Estimation Results

To document how aggregate variables contribute to the default risk models, we present estimation results for two specifications: one with and one without macroeconomic variables.

**Table 1 about here**

Table 1 contains estimation results for a model with firm-specific determinants of default risk only (i.e., the six financial ratios augmented with the dummy variables PAYDIV, TTLFS, PAYREMARK, and TAXARREARS), while Table 2 shows results with the macroeconomic variables added. The regressors were not re-scaled to have the same mean, so we cannot directly judge the importance of a particular variable from the size of its coefficient. However, suitably transforming each variable allows us to calculate its marginal impact, and we verify in Appendix B that such calculations yield similar rankings of importance as do standard \(t\)-statistics (see Appendix B.4). We therefore approximate the importance of each variable below by the size of its \(t\)-statistic.

Because the firms’ annual financial reports are typically submitted with a significant time lag, it cannot in general be assumed that accounting data for year \(\tau\) are available in (or even at the end of) year \(\tau\) and enable forecasted default risks for year \(\tau + 1\). To account for this phenomenon, all accounting data is lagged by four quarters in the estimations. For most firms, which report balance sheet and income statement data over calendar years, this means that data for year \(\tau\) are assumed to have been available in the first quarter of year \(\tau + 1\). It should be emphasized that this assumption—which makes the model “operational” in real time—has only minor implications for the coefficients. When we re-estimated the model using contemporaneous accounting data, the results were strongly similar to those reported in Tables 1 and 2.

The results in Table 1 show that the firm-specific information we consider is indeed important for explaining default behavior in both the industry-specific models and in the economywide model. In particular, both the indicator variable TTLFS (which takes a value of 1 if a firm has not filed a timely annual report, and 0 otherwise) and the variables for remarks on firms’ payment records are very powerful predictors of

\(^4\) In addition to these four variables, we have also experimented with a few others: real housing prices (taken as deviations from a linear/HP trend) and a measure of the spread between the interest rate charged to nonfinancial firms and the policy rate set by the central bank. For our sample period, these variables are largely redundant in light of the variables already included in the benchmark specification.
default. Among the financial ratios we find the earnings ratio EBITDA/TA, the leverage ratio TL/TA, and the debt ratio TL/TS to be useful default predictors. However, the roles played by financial ratios in the various industry models differ substantially; whereas accounting data are less important in the financial services (bank, finance, and insurance) sector, they are more important in the manufacturing industry. The coefficients for the payment remarks and the indicator variable TTLFS are quite similar across industries. So to the extent that these variables are the more important ones for explaining firm default behavior, there is no clear gain at the firm-specific level from conditioning on industry.\(^5\)

**Table 2 about here**

Turning now to the results in Table 2, we find that the coefficients for the firm-specific variables in Table 1 do not change much when the model is augmented with the macroeconomic variables. Moreover, and despite the robustness of the firm-specific coefficients, we find that all coefficients for the macroeconomic variables are significant in the economywide model and have the expected signs. One possible exception is inflation, but for reasons discussed in Section 3.1, it is hard to have a strong view a priori on the sign of the inflation coefficient. The importance of conditioning on macroeconomic variables in default risk modeling is further supported by the industry-specific model results. Table 2 shows that the impact of the macroeconomic factors is estimated to be more important in industries that are arguably more cyclical. For instance, the output gap is more important in the construction and in the real estate sectors in comparison with other industries and, as expected, the nominal interest rate is very important for the financial services and the real estate sectors. The remaining macroeconomic variables—inflation and the real exchange rate—appear to be less important overall. However, it is reassuring to find that a depreciating real exchange rate (i.e., increasing values) is associated with a significantly lower default risk in the manufacturing sector, which is the most export-oriented industry. The coefficient for the real exchange rate is also large for the financial services industry, possibly reflecting that Swedish credit conditions, which were very tight in the resolution of the banking crises, subsequently eased when the krona was allowed to depreciate in November 1992. The relative insignificance of inflation allows us to reject (with the possible exception of the financial services industry) the view that it is only the real interest rate that matters for default risk at the firm level.\(^6\)

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5. Notice that by defining a default event at the quarterly frequency and by transforming yearly statements to quarterly ones, we might underestimate the effects of accounting variables. Therefore, as a robustness check we estimated the default-risk models using annual data and found that the coefficients for the accounting variables are quite similar to those reported in Table 1 (see results in Appendix B.3).

6. As a robustness check, we examined a model allowing for nonlinear relationships between default and the financial ratios and found that the macroeconomic variables are still highly significant and quantitatively important. We used the cumulated distributions depicted in Figure A.1 in Appendix A to categorize the variables (three categories for each variable). For instance, we classified EBITDA/TA into the decile-based categories 0 – 10, 10 – 90, 90 – 100 whereas TL/TA was classified into the categories 0 – 75, 75 – 90, 90 – 100. This categorization resulted in an increase in pseudo-$R^2$ from 0.34 to 0.42 in the economywide Table
Finally, we would like to emphasize the substantial gain of using firm-specific data for default-risk modeling. OLS estimation of a model of the average quarterly default rate on average financial ratios and the four macroeconomic variables yields:

\[
    df_t = -9.45 \begin{pmatrix} \text{EBITDA/TA} \end{pmatrix}_t + 0.17 \begin{pmatrix} \text{TL/TA} \end{pmatrix}_t - 0.003 \begin{pmatrix} \text{LA/TL} \end{pmatrix}_t - 0.40 \begin{pmatrix} \text{1/TS} \end{pmatrix}_t - 0.02 \begin{pmatrix} \text{TL/TS} \end{pmatrix}_t + 0.16 \begin{pmatrix} \text{IP/IP+EBITDA} \end{pmatrix}_t - 0.12 \gamma_{d,t} - 0.007 \pi_{d,t} - 0.005 R_{d,t} - 0.02 q_{t} + \hat{u}_{df,t}, \tag{1}
\]

\[R^2 = 0.88, \quad DW = 1.98, \quad \text{Sample: } 1990Q1 - 1999Q4, \quad (T = 40).
\]

If we compare the point estimates for the financial ratios in (1) with the economywide model in Table 2, we see that they differ substantially and that the ratios I/TS and TL/TS here appear with counterintuitive signs. The coefficients for the macroeconomic variables are more robust except for the nominal interest rate, which has a counterintuitive sign. Since the average financial ratios are quite smooth over time, it is not surprising that we obtain spurious results when the firm-specific information is aggregated. Moreover, we notice that some explanatory power is lost by aggregating data; the model in (1) yields an $R^2$ of 0.88, which can be directly compared with the aggregated fit ($R^2 = 0.95$) of the corresponding model in Table 2. This reduction in fit is driven primarily by the inability of regressions at the aggregate level to incorporate the dummy variables for payment remarks, dividends, and failure to submit a financial statement. Finally, we note that TSLS estimation of the average quarterly default rate using lagged variables as instruments yields similar results to OLS estimation.

### 3.3. Assessing the Models’ In-Sample Fit

The last several rows in Tables 1 and 2 report on the number of observations, the mean log-likelihood, and the pseudo-$R^2$. The latter measures the ability of the estimated models to explain default at the firm level and is computed using the method of McFadden (1974). Another important and interesting feature of the models is their aggregate performance over time—that is, how well they account for the average default frequency. Hence, these tables also report what we label as “industry” or “aggregate” $R^2$ values. These are calculated by aggregating all the fitted firm default probabilities in a particular industry model for each quarter 1990Q1 – 1999Q4 and then using the resulting 40 time-series observations to compute the implied aggregate $R^2$. To assess the gain in estimating separate industry-specific models, we also report the pseudo- and industry $R^2$ values conditional on the economywide model coefficients instead of the industry model coefficients.
Comparing Tables 1 and 2, we see that the pseudo-$R^2$ is not much affected by conditioning on macroeconomic factors in any of the industries, the difference is merely 1–2 percentage points. Tang and Yan (2010) find a somewhat larger role for macro factors: about 6 percentage points. However, the industry $R^2$ is doubled and sometimes even more than doubled by the introduction of macroeconomic variables. Thus, the firm-specific variables account for the cross-section of the default distribution, while the macroeconomic variables in the model play the role of shifting the mean of the default distribution in each period. This also implies that the model with firm-specific information cannot capture the upturns and downturns in the average default rate over time. We illustrate this finding in Figure 1, where the average default rate over time is plotted against the fitted values from the economywide models with (Table 2) and without (Table 1) macroeconomic variables. The plot on the right-hand side of the vertical line pertains to out-of-sample results and will be discussed in Section 4.1.

According to Figure 1, the model that includes both microeconomic and macroeconomic variables indeed appears able to replicate not only the extreme default rates of the deep recession/banking crisis during the early 1990s but also the downturn to moderate default rates toward the end of the in-sample period. This finding is of considerable interest because it suggests that the extreme default rates recorded during
the banking crisis in the early 1990s were not exceptional events that are uninformative in a model context; instead they appear to be consequences of unusually bad economic outcomes. Another interesting feature of Tables 1 and 2 is that the fall in pseudo-
$R^2$ values associated with conditioning on the economywide model coefficients is distinct but limited, whereas the corresponding reduction in industry $R^2$ is often quite substantial. In three cases—the agricultural sector, the bank, finance, and insurance sector, and the “non-classified” sector—the industry $R^2$ values are negative conditional on the economywide model coefficients. At first sight this may seem strange, given that the industry-specific coefficients in Table 2 are not much different from the economywide model coefficients. However, these seemingly inconsistent results are driven by the unreported intercept, which is larger in the economywide model than in the sector models and therefore induces a systematic overprediction of default risk in those three sectors.

A conceivable objection to our claim for the importance of conditioning on macroeconomic factors in default risk models is that the significance of these variables simply reflects the changing impact of firm-specific variables over time. Accordingly, if one were to re-estimate continuously the coefficients of the models in Table 1 using the most recent quarterly information only, then the aggregate $R^2$ values of the resulting models would increase dramatically and suggest that the macroeconomic variables are redundant. Figure 2 displays the estimated coefficients for the financial ratios in the economywide model for such a set of separate cross-sectional models. These results are computed for the economywide model only, because there are not enough defaults available in each quarter to estimate industry-specific models. Figure 2 shows that the coefficients for most ratios are highly unstable and some even switch sign over time. Accordingly, any out-of-sample forecasts beyond a very short horizon generated by any of these 40 models would be deficient. To be convincing, a model of firm-level defaults with time-varying coefficients for firm-specific variables would require an understanding of how the time variation in its coefficients arises. The irregular and economically implausible patterns in Figure 2 render such a model highly improbable.

To understand further the role of macroeconomic variables for default risk, we now approach the issue from a different angle and study the importance of firm-specific variables in the models. An intuitive way to demonstrate the information loss from omitting the micro data is to regress the average default frequency on the macroeconomic variables only. This yields the following result:

$$df_t = 0.40 - 0.20 y_{d,t} + 0.007 \pi_{d,t} + 0.10 R_{d,t} - 0.03 q_t + \hat{u}_{df,t},$$

$$R^2 = 0.81, \; DW = 1.43, \; Sample: 1990Q1 - 1999Q4, \; (T = 40). \quad (2)$$

7. We have also conducted these cross-sectional regressions while imposing the restriction that the constant equals the estimated intercept in the economywide model in Table 1 and subtracting the panel mean from each regressor. So instead of running the regressions underlying Figure 2, namely $y_{i,t} = \alpha_t + x'_{i,t} \beta_t + e_{i,t}$ for each quarter, we estimated $y_{i,t} = \tilde{\alpha} + (x'_{i,t} - \bar{x}') \beta_t + e_{i,t}$. This alternative estimation procedure yielded very similar results to those reported in Figure 2.
Time-varying coefficients for the accounting ratios in the economywide model. Coefficients were calculated by estimating a separate economywide model without macroeconomic variables for each quarter. Intercepts are allowed to vary by quarter. Solid lines are coefficient estimates and dashed lines provide 95% confidence bands. The solid horizontal lines correspond to the estimated coefficients for the economywide model in Table 1.
Comparing this regression with the economywide model in Table 2, we see that excluding the financial statement variables is associated with a loss of nearly 15 percentage points of explanatory power. Moreover, omitting the firm-specific information introduces misspecification problems in (2), as indicated by the Durbin–Watson (DW) statistic—in contrast with the results in (1), which has a DW statistic of about 2 and hence displays no signs of autocorrelation. A simple $F$-test reveals that the loss of fit in (2) relative to (1) is significant at the 5% level using asymptotic critical values. Autocorrelation turns out to induce further problems with out-of-sample stability for the model in (2), as documented in Section 4 (see Table 3). Our interpretation is that omitting firm-specific variables when modeling in-sample default risk attributes too much of the variation in default risk to macroeconomic factors. Hence model (2) does not perform as well out-of-sample.

4. Out-of-Sample Performance of the Estimated Models

In this section we investigate the robustness of our results in Section 3 by examining the out-of-sample performance of the models of Tables 1 and 2 for the period 2000Q1–2009Q2. We evaluate the models along two dimensions. First, we study each model’s performance at the industry and aggregate level; in other words, we assess their ability to predict future average default rates. The predictions we consider are static one-step-ahead forecasts because we do not have a complete dynamic model for all the regressors. There are no major fluctuations in the aggregate default rate during the out-of-sample period (see Figure 1), yet this period is very informative about our models’ out-of-sample performance because there is still substantial variation in the macroeconomic variables (see Figure A.2 in Appendix A). Second, we evaluate the models’ properties for predicting future default events at the firm level. Toward this end, there is a substantial amount of information (55,945 default observations) that can be used to assess the stability of the models.

4.1. Evaluating the Models at the Aggregate and Industry levels

In Figure 1, the results to the right of the vertical bar show the one-step-ahead, out-of-sample performance for the economywide model at the aggregate level. Overall, the out-of-sample fit is remarkably good, although there is a tendency for the model to under predict during the years 2006 and 2007. It is noteworthy that the model captures the emerging spike in the default frequency during the recent recession through the steep decline in the output gap from 4 to -4 percent.

Table 3 about here

In Table 3, we report the root-mean-squared, one-step-ahead prediction errors (RMSEs) for the estimated models of Tables 1 and 2. For reference we also show results for three time series models: a random walk, a four-quarter moving-average model, and the model estimated on only macroeconomic data (equation (2), denoted
“Industry OLS macroregression”). The results in Table 3 pertain to default risk models that have been re-estimated using macroeconomic variables that are lagged one quarter. This ensures that all models in Table 3 have been estimated on the same information set, thereby allowing for a fair comparison between the logit and the time-series models. In the “Industry OLS macroregression” models an additional dummy for the third quarter is included.

In order to assess the extent to which the forecasting errors are quantitatively different from a statistical point of view, we perform the Diebold–Mariano (DM) test on the forecast errors underlying the computed RMSE differentials in the lower panel of Table 3. In table, RMSE ratios that are set in bold (resp., italic) indicate that the forecasting performance is significantly better (resp., worse) than the corresponding models in Table 2. Finally, it is imperative to observe that the RMSEs are shown in percent; that is, the actual and fitted default frequencies have been multiplied by a factor of 100 before we calculate the prediction errors.

In Table 3, the lower panel’s first row confirms the substantial effect on forecasting performance of conditioning on both macro and firm-specific information. The largest gain is found for the economywide model, where forecast precision increases by a factor of 3.6 when we include macroeconomic variables. Disregarding the residual “not classified” sector (for which the model with macro variables is associated with a significant loss of out-of-sample accuracy), the corresponding factors for the industry-specific models range between 1.2 and 3.6 and constitute a significant improvement in eight out of nine cases. Moreover, the second row in the lower panel shows that the industry-specific models often generate significantly lower RMSEs compared with the industry models conditional on coefficients from the economywide model in Table 2—except for the manufacturing, retail, and hotel and restaurant sectors, where these errors are slightly (but not significantly) higher.

Summing up, our findings constitute solid evidence that the industry-specific models are not overparameterized with respect to the macroeconomic variables. Hence it will be worthwhile to work with an industry-specific model if the research focus is on understanding default behavior in a particular industry; however, for modeling aggregate default behavior only it appears that the economywide default risk model suffices. This tentative conclusion can be drawn from the two rightmost columns in the second row of Table 3. In the next-to-last column, the forecasts computed with the industry-specific models have been weighted by industry size to yield a forecast for the aggregate default frequency. This results in a slightly lower RMSE (0.0716) than that (0.0802) for the economywide model. In absolute terms this difference in RMSE is moderate in comparison with the other models, but it is still significant in favor of the industry models according to the DM test.

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8. Our application of the test suggested by Diebold and Mariano (1995) examines the null hypothesis: $E \left[ L \left( \epsilon_t^i \right) \right] = E \left[ L \left( \epsilon_t^j \right) \right]$, where $L$ is the squared loss function of the one-step-ahead forecast errors $\epsilon_{t+1|t}$ for models $i$ and $j$. Diebold and Mariano show that a test statistic based on the loss differential $d_t^i$ (and suitably normalized by the asymptotic variance of $d_t^i$) is asymptotically standard normal.
Comparing the industry models in Table 3 with the time-series models, we see that—even though the random walk model performs significantly better in 3 of 10 sectors and the 4-quarter moving-average specification is better 6 of 10 times at the industry level—both these alternatives are significantly inferior at the aggregated industry level. This implies that they are also inferior in terms of RMSE fit to the economywide model specification in Table 2 (which conditions on aggregate fluctuations). The OLS regression models of average industry default frequencies on macroeconomic variables only are often associated with a significant increase in RMSE (7 of 10 industries) in comparison with the Table 2 models.

In sum, we have found strong evidence that the favorable in-sample fit of the estimated industry and aggregate models, conditional on macroeconomic variables, is preserved out-of-sample at the industry and aggregate level. This is reassuring for the hypothesis that aggregate variables matter because, taken together, the in-sample and out-of-sample periods cover several upturns and downturns in the Swedish economy. Finally, we have also documented that there are relatively small gains, in terms of forecasting accuracy, to be made by using industry-specific models rather than simply an economywide model—provided an appropriate set of macroeconomic variables is included.

4.2. Evaluating the Models at the Firm and Industry levels

We turn now to evaluating the ability of each model to (i) rank firms according to their relative riskiness and (ii) determine firms’ absolute risk level for the out-of-sample period. In addition, we report the industry-specific pseudo-$R^2$ conditional on the industry-specific model coefficients of Table 2 as well as the pseudo-$R^2$ calculated conditional on the economywide model coefficients. The results are displayed in Table 4.

Table 4 about here

First, starting with the pseudo-$R^2$ for the models with industry-specific coefficients and comparing the in-sample and out-of-sample results reported (respectively) in Tables 2 and 4 we see that the explanatory power out-of-sample is actually no less or even greater than in-sample in 8 of 10 industries.

Next we address the pseudo-$R^2$ values for predictions based on the economywide model coefficients. The lower panel of Table 4 shows that the average explanatory power has increased substantially, from 0.34 in-sample to 0.38 out-of-sample. We also see, relative to Table 2, that the explanatory power has increased in all sectors except for agriculture, real estate, and construction. Moreover, by comparing the pseudo-$R^2$ values generated when using industry-specific coefficients with those obtained using economywide model coefficients (i.e., the values reported in the upper and lower panels of Table 4), we find that they differ in four industries but are similar in others. This implies that pseudo-$R^2$ at the aggregate level is about the same (0.38) for the economywide model as an aggregation of pseudo-$R^2$ values over the industry-specific models (denoted “Industry Aggregate” in Table 4). These results provide support for two important conclusions. First, the industry models are not overparameterized. Second,
the reduced-form coefficients appear to be stable over time and the regressions thus reflect relationships that hold out-of-sample.

Moving on to measures of relative risk, we follow Shumway (2001) and evaluate the models’ ability to rank firms according to their riskiness in terms of ex post default frequencies. We see from Table 4 that the estimated models classify roughly 75–80% of the subsequently defaulting firms in the riskiest decile. These numbers are about the same as those reported in-sample by Shumway for a data set that was substantially smaller and included only listed firms. Our models cover the entire population of Swedish incorporated businesses, of which only a very small subset is publicly listed on the stock exchange (slightly less than 500 of 260,000 firms). We therefore conclude that our models are quite successful in ranking firms according to their level of default risk, which supports our conclusion that the estimated effects of macroeconomic variables in our models of default risk are not instead driven by the omission of key microeconomic variables.

Table 4 also reveals that the quality of the risk rankings does not depend on whether we condition on industry-specific coefficients or coefficients from the economywide model. At first glance, this is in contrast with our findings in Section 4.1, where conditioning on industry-specific parameters improved the models’ empirical performance at the industry level. The reason for these seemingly inconsistent results is that the most important difference between the economywide and industry-specific models is due to the varying impact of aggregate factors. Such factors have little impact on the firms’ relative risk ranking, so naturally the inclusion (or omission) of them has little impact on the models’ ability to rank firms by risk.

Finally, we assess the out-of-sample properties of the models at the microeconomic level in an absolute sense, in contrast to the relative appraisal documented in Table 4. We do this by sorting all estimated default probabilities according to size and then calculating the average probability of default in each percentile. Finally, we compare the average probabilities of default with the actual default experience of the firms for each of these percentiles. The results are plotted in Figure 3, where we have used both the industry-specific and the economywide model coefficients in Tables 1 and 2 to compute the estimated default probabilities for each firm. The x-axis marks the estimated default frequency in a given percentile while the y-axis marks the actual default frequency; in the scatter plots each dot represents a percentile. In order to make the results easier to interpret, a logarithmic scale is used for both the estimated and the actual series. If the estimated models could perfectly predict the absolute riskiness of the firms within each percentile, then all dots would line up along the 45-degree line drawn in each panel and corresponding to a slope coefficient of unity and an intercept of zero. As can be seen in Figure 3, this is not the case for either model, but the dots are generally close to the line, indicating that the absolute riskiness predictions are very accurate. In particular, the results show that both the industry-specific models and the economywide model with macroeconomic variables included pass our test in the cross-sectional dimension, since they are not systematically below or above the 45-degree line. In contrast, the models without macroeconomic variables tend to overestimate default risk. These findings provide further support for the main theme of this paper:
Figure 3. Sorted estimated default percentiles versus actual default frequencies for both economywide and industry-specific parameters. Left, only firm-specific variables included (Table 1 models); right, macrovariables also included (Table 2 models).
macroeconomic variables are crucial for establishing the absolute risk level but are not important for ranking firms according to their relative riskiness in a given period.

5. Conclusions

In this paper, we study the interaction between macroeconomic fluctuations and default risk at the firm level using reduced-form methods and present five main findings. First, we provide insight into the significance of aggregate fluctuations for defaults among both listed and privately held firms. This is important because privately held businesses typically account for over half of GDP in developed economies. Second, a nearly exhaustive set of firm-specific background variables permits us to investigate both the importance of and the interaction between firm-specific variables and macroeconomic information—an area that so far has received little attention. Third, we document that a standard logit approach to modeling default at the firm level using both firm-specific and macroeconomic variables can explain the extreme default frequencies observed during the Swedish banking crisis of the early 1990s as well as the considerably lower default frequencies in the late 1990s. Fourth, the estimated models are shown to be very robust and successful out-of-sample, suggesting that aggregate fluctuations play an important role in understanding the absolute level of firm default risk. Fifth, the width of our panel permits us to investigate the relationship between aggregate fluctuations and firm defaults across industries. This shows that macroeconomic variables have a robust impact on business defaults.

We stress that our results do not imply that aggregate fluctuations are the most important source of default risk at the firm level. Rather, the results suggest that macroeconomic factors shift the mean of the default risk distribution over time and thus are the most important determinants of fluctuations in the average level of default.

In view of these results, we conclude by providing some suggestions as to why aggregate fluctuations have an important impact on firm default behavior beyond the effects of firm-specific variables, which themselves move in response to macroeconomic fluctuations. In this paper we have relied on (among others) the work of Bernanke et al. (1999) and Hackbarth et al. (2006) to motivate why firm default should be affected by aggregate shocks. In addition, one could imagine several other channels through which aggregate variables could harbor predictive information on firm default risk over and above firm-specific information. One such explanation is related to the costliness of monitoring. If monitoring borrowers is costly for banks, then banks may use aggregate information to assess the probability of getting outstanding loans repayed. That is, banks may base their credit-granting policies on macroeconomic forecasts and decide against extending new lines of credit to firms with a given set of performance indicators in one particular phase of the business cycle—even though they might readily extend credit given those same indicators in another phase. The tightening and loosening of banks’ credit standards over various phases
of the business cycle reflects such behavior. Yet another argument follows a similar line of reasoning. Suppose entrepreneurs have imperfect information about their own future business prospects; then they might resort to using aggregate conditions as a basis for their decision to either invest more effort in a firm or declare bankruptcy. A final possibility is that firms may be inclined to adjust their yearly accounts (e.g., to smooth profit over time) in order to please banks’ monitoring efforts, thereby reducing the predictive power of firm-level information. We believe that further work on the theory of how macroeconomic variables affect firm defaults—and on assessing the empirical relevance of the arguments presented here—are important avenues for future research.

References


