Exploring relationships between Firms' Balance Sheets and the Macro Economy*

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Abstract

In this paper, we study the interaction between the real activity and the financial stance empirically. Using aggregate data, we find strong evidence of substantial spillover effects from our preferred measure of the financial stance of the economy on aggregate activity. Given this result, we use a large micro data-set for corporate firms to develop a macro-micro model of the interaction between the financial and real economy. This approach implies that the impulse responses of a given shock will be time dependent of the portfolio structure at any given point in time.

Keywords: Default-risk models; Business Cycles; Financial Stability; Price stability; Financial and real economy interaction

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1 Introduction

In this paper we propose to empirically study the relationships between Swedish firms' balance sheets and the evolution of the Swedish economy. Most economists would consider it trivially true that macroeconomic conditions determine the state of the firms' balance sheets (good times result in prosperous firms with strong balance sheets, likewise a slowdown in the economy will be reflected by weak balance sheets) and ultimately the evolution of the macroeconomy will be determined by its firms' relative successes. Nevertheless, quantifying such relationships is not trivial. The underlying idea for this project is very simple: we use aggregate credit risk, approximated by firms' bankruptcy frequency over time, as a link between the micro and the macro perspective.

Among policymakers, there appears to exist a broad consensus that market imperfections and instability in the financial sector can have significant and long-lasting effects on the real economy, cf. Lowe (2001). For academics, however, the role of the financial sector and credit in the macroeconomy has been a source of frequent debate, with some economists, see e.g. Poole (1993) arguing that credit only plays a role of its own in periods of financial crises while others, see e.g. Bernanke (1993) and Calomiris and Hubbard (1989), hold that credit markets *generally* affect the macroeconomy through the so called credit channel.

Bernanke and Gertler (1995) describe the credit channel as "set of factors that amplify and propagate conventional interest rate effects" of monetary policy through endogenous changes in the external finance premium. Adherents of this "credit view" have identified two main linkages between central banks' actions and credit markets (the external finance premium): a (borrowers') balance sheet channel and a bank lending channel.[1] The first link stresses the importance of borrowers' balance sheets and income statements, acknowledging that changes in monetary policy will have an impact on variables such as borrowers' net worth, cash flow and liquid assets. The second transmission mechanism focuses more closely on the potential effect of monetary policy on the supply of loans by financial institutions. A common premise is, however, that frictions interfere with the smooth functioning of financial markets, creating a wedge between between the cost of externally raised funds and the the opportunity cost of internal funds.

A large number of studies has explained and tested the mechanisms by which shocks to the

[1] The balance sheet channel has sometimes also been called broad credit channel. See for example Repullo and Suarez (2000).

financial sector are propagated into the real sector of the economy and found evidence in support of the existence of a balance sheet channel. As far as the bank lending channel is concerned, the evidence in favor and against is still very much under debate. One of the studies that revived the debate on the balance sheet channel is Bernanke (1983). In his study of non-monetary effects of the financial crisis during the Great Depression, he contends that the financial crisis of the 1930's "affected the macroeconomy by reducing the quality of certain financial services, primarily credit intermediation", which in its turn disrupted the normal flow of bank credit. He also brings forward evidence of how the increase in defaults and bankruptcies and the progressive erosion of borrowers' collateral relative to their debt burdens during this period increased the cost of credit intermediation. Banks then reacted to these changes by stopping to make loans to lower-quality investors, to which they had lent before.[2] The events in the financial sector ultimately affected the bearing of the macroeconomy because the resulting higher effective cost of credit reduced businesses demand for current-period goods and services. An analysis of the determinants of output by Bernanke shows that two proxies for the financial crisis - changes in the deposits of failing banks and changes in the liabilities of failing businesses have substantial additional explanatory power for the growth rate of industrial production. In related work Coe (2002), using a Markov switching model to estimate conditional probabilities of a financial crisis occurring, finds that these probabilities have additional explanatory power in an model of real output, evidence that supports Bernanke's findings. Bernanke and Gertler (1989) develop a small model in which they use the inverse relationship between borrower net worth and the agency costs of investment to explain why changes in the condition of borrowers' balance sheets can be a source of business cycle fluctuations - without any financial crisis preceding the shocks.[3] In the companion paper, Bernanke and Gertler (1990) also argue that financial factors can have quantitatively significant real effects by demonstrating how changes in the creditworthiness of borrowers affect investment spending, expected returns and the overall economy.

More recently research efforts have attempted to meet the criticism that earlier studies of the credit channel failed to isolate supply shocks from demand shocks and persuasively establish the existence of real effects. To avoid identification issues, this later work has tested the cross-section implications of the credit view. For example, Gertler and Gilchrist (1993, 1994) find that larger firms have better access to credit and typically respond to unexpected adverse

[2] An important indicator of this phenomenon is the bond spread between Baa corporate bonds and Treasury bonds, that increased from 2.5 percent in 1929-30 to nearly 8 percent in mid 1932. See Bernanke (1983) p.266.

[3] Bernanke and Gertler (1990) define financial instability ("fragility") as a situation in which potential borrowers have low wealth relative to the sizes of their projects.

conditions by increasing short-term borrowing, while smaller firms instead respond by squeezing inventories and cutting production. Bernanke, Gertler and Gilchrist (1996) obtain similar findings when they split up firms according to their degree of bank dependency rather than based on size. Samolyk (1994) examines the relationship between banking conditions and economic performance at the U.S. states level and finds that local bank balance-sheet conditions help to predict the performance of regional economies in a way that is consistent with the existence of credit market imperfections. Ludvigson (1998) uses automobile credit data from bank and non-bank sources and finds evidence for the presence of a bank lending channel. Peek and Rosengren (2000) study the effects of the Japanese banking crisis on construction activity in the U.S. Their work makes clear that the retrenchment of Japanese lending had a substantial impact on U.S. real estate activity, indicating that at least some borrowers were not able to obtain alternative financing and that credit markets thus were suffering from imperfections. Repullo and Suarez (2000) develop a theoretical model that can compare the macro implications of both the balance sheet channel and the bank lending channel and conclude that the presence of a balance sheet channel is most likely.

This paper is closely related to the above work as we study the interaction between real activity and firms' balance sheets. Unlike the earlier studies, however, that exploited either time-series or panel data, we combine a microeconometric model of firms' financial default behavior and a macroeconometric model to study how macro aggregates and the aggregate effects of changes in individual firms' balance sheets and income statements interact with each other. Our focus is not so much on the existence of a "credit channel" but rather on the interaction between the economy's financial stance at the firm level and the economy's aggregate behavior. Although the way in which we link micro conditions to the macro model is not derived from any micro foundations, we believe that this eclectic approach offers a number of advantages. For one thing, we will be able to investigate if macroeconomic policy will affect businesses equally both cross-sectionally and through time. We will also be able to look into the relative importance of firm specific and aggregate disturbances.[4]

We model the macroeconomy by a set of macroeconomic time-series, including the aggregated, quarterly bankruptcy frequency, in a vector autoregressive model. Furthermore, the impact of firms' balance sheet variables on bankruptcy risk can be modelled in a dynamic panel data model, where it is also possible to condition on macroeconomic variables. To this end we

[4] Although we are aware of the importance of job and business creation, our focus here is on interaction between the macroeconomy and business default (destruction).

have collected an extensive and quite unique data set containing balance sheet information on the entire population of Swedish firms limited by shares (some quarter of a million firms) for 40 consecutive quarters, $1990Q1 - 1999Q2$ (in total, close to 8 million firm-observations). This sample period cover the "banking crisis" period in Sweden $(1991 - 1993)$, but also a period with high growth in the late 1990s

The empirical model is a system made up of three blocks. The first one is a Vector Auto Regressive (VAR) model for the macroeconomic variables we consider. Based on work by Lindé (2002), we choose to include the following variables in the VAR; output, inflation, nominal interest rate (the REPO rate), and the real exchange rate. As an "exogenous" variable in the VAR we include our chosen main financial variable, the default frequency of firms limited by shares. This variable is chosen because the possibility to acquire firm level data for this variable. It should however be noted that in the aggregate, this variable is highly positively correlated with the banking sector credit losses during the 1990s. Thus, a first step in the analysis is to use a multivariate Granger-causality test, or block-exogeneity test to examine if the financial indicator variable is a helpful predictor of the macro economy.

In the second block we have a logit model for the default risk at the firm level where the macroeconomic variables enter as regressors, as well as various balance sheet variables. The logit model will carefully follow the methods that have been applied in earlier studies on company default, such as Altman and Saunders (1997), Shumway (2001) and Carling, Jacobson, Lindé and Roszbach (2001). Let X_t denote the set of macroeconomic variables included in the VAR model in period t, $D_{i,t}$ denote default status of firm i, and $X_{i,t}$ a set of relevant balance sheet variables, then the model can be written $D_{i,t} = c + \beta Y_{i,t} + \gamma X_t + u_{i,t}$. By computing $\left(\sum_i D_{i,t}\right)/N_t$ for each t where N_t is the number of firms each time period we retrieve a series of the aggregate default frequency that can be inserted in the VAR model. So, once equipped with a VAR model and the estimated logit model, we can simulate the effects of various disturbances in the economy. For instance, we can study the dynamic effects of a shock to monetary policy on inflation and the default frequency in a joint framework.

A third block in the empirical approach is an attempt to estimate how the balance sheet variables that are included in the logit model depend on the macroeconomic variables X_t. Due to the panel-data nature of our firm level dataset, we estimate for each balance sheet variable that is included in the logit model the follow equation $Y_{i,t} = \Theta_Y Y_{i,t-1} + \Theta_X X_{t-1} + \varepsilon_{i,t}$. We can then study how quantitatively important the real macroeconomic impact on the balance sheet variables are.

The results are as follows. [**Remains to be written.**]

The paper is structured as follows. In the next section, we present our micro and macro data set. The dependency of the real side of the economy on the financial variable we study is examined in Section 3. In Section 4, we develop the empirical model that are used to examine the interaction between the real and financial side of the economy. The empirical micro-macro model are then used in Section 5 to shed light on some interesting policy issues. Finally, Section 6 concludes.

2 Data

2.1 Micro data

In this subsection, we will make a detailed description of our data set at the firm level.

The final data set is a panel consisting of $7,652,609$ quarterly observations on firms limited by shares, covering ten years of quarterly data for all Swedish *aktiebolag* companies that have issued a financial statement between January 1, 1990, and June 30, 1999. *Aktiebolag* are by approximation the Swedish equivalent of US corporations and UK limited businesses. Swedish law requires every *aktiebolag* to have at least SEK 100,000 (approximately US$ 10,000) of equity to be eligible for registration at the Swedish Patent and Registration Office (PRV). Firms are also required to submit an annual report to PRV. Although we have annual report data on small firms such as general partnerships, limited partnerships and sole proprietors, these will be disregarded because we do not dispose of the relevant credit histories. However, as reported by Jacobson and Lindé (2000), it is the firms limited by shares that account for the largest fraction of loans and display the most cyclical variation in default risk.

The data on the firms come from Upplysningscentralen AB (UC), a major credit bureau in Sweden. Upplysningscentralen has provided us with two sources of information about the firms limited by shares. First of all, UC have provided us with balance sheet and income statement data from the annual report which they collect from the PRV annual report data for the period January 1, 1989 to December 31, 1999. Second, UC has provided us with historical data on events related to payment remarks and payment behavior for the company and for its principals. These data were available at different frequencies, varying from daily for payment remarks to (most often) annually for accounting data. We will discuss the specifics of the data in greater detail below.

The accounting data contains information on most standard balance sheet and income statement variables. Appendix A, which is available upon request, contains a complete list of all annual report variables. In addition to the annual report data, we have information on the firms' track records regarding payment behavior as recorded by remarks for 61 different credit and tax related events. Two types of remarks exist. The first type is non-payment remarks, the storage and usage of which are regulated by the Credit Information Act, the Personal Data Act and overseen by the Swedish Data Inspection Board. Examples of events that are registered are: delays in tax payments, the repossession of delivered goods, the seizure of property, the resettlement of loans and actual bankruptcy. In practice, with a record of non-payment remarks individuals will not be granted any new loans and businesses will find it very difficult to open new lines of credit. The second type is bank remarks, which give an image of a firm's payment behavior at banks. All Swedish banks participate in this scheme and report any abuse of a bank account or a credit card and slow loans (of which repayment is considered questionable) to the credit bureau that maintains these records. Their storage and usage is only regulated by the Personal Data Act. Appendix B, which is available upon request, contains the complete list of non-payment and bank remarks.

We define the population of existing firms in quarter t as the firms which have issued a financial statement covering that quarter and are classified as "active". For a firm to be classified as active, we require that is has total sales and total assets over 1000 SEK (roughly 100$). In addition to these firms, we add the firms which according to the data set on remarks are classified as defaulted firms.[5] The adopted definition of default is the definition employed by the leading credit bureau (UC) in Sweden.[6]

In Table 1, we report all descriptive statistics for the employed accounting ratios and other variables, such as non-payment remarks and average delayed time to the last issued financial report for the defaulted and non-defaulted firms. Because of varying availability of data, the statistics in Table 1 were calculated based on different numbers of observations. For defaulted firms for which accounting data are not available, we replace missing values by the panel mean

[5] The reason why we need to add firms that have defaulted to the population of firms that are defined by the accounting data is that many firms that default choose not to report balance sheet and income statements data prior to default.

[6] According to the definition, a firm has default status if the following condition is true: A firm has any of the following type of remarks ?? while at the same time the PRV has not given the firm the following status codes ??. We differ somewhat from the credit bureau's definition though, in that we have a one quarter horizon, whereas they currently employ a one-year horizon.

for the defaulted firms.[7] As is visualized in the part A of Table 1, which shows non-truncated data, there are some accounting data observations which are severe outliers. These observations would severely distort the estimation results if they were included in the credit risk model. Therefore, we have truncated the top and bottom 1 percent observations for the accounting variables.[8] Given the large number of observations, this approach is more or less equivalent to simply delete 1 percent of the observations that have accounting data that fall outside a certain region. Part B of Table 1 shows the descriptive statistics for the truncated micro data set.[9]

As financial reports issued by firms typically become available with a significant time lag, it cannot in general be assumed that accounting data for year τ are available during or even at the end of year τ to forecast default risk in year $\tau + 1$. To account for this, we have lagged all accounting data by 4 quarters in the estimations. For most companies, who report balance sheet and income data over calendar years, this means that data for year τ is assumed to have been available in the first quarter of year $\tau + 1$. For a number of firms some transformation had to be applied to the accounting variables to adjust for reporting periods that did not coincide with the calendar year, to assure that each variable is measured in identical units for all companies. Some companies, for example, report accounting information referring to three-month or four-month periods for one or several years. In such cases, annual balance sheet figures were calculated as weighted averages of the multiple period values. In other cases companies did report numbers for a 12-month period, but the period did not coincide with the calendar year. The 1995 figures, for example, could refer to the period 1995-04-01 until 1996-03-31. In these cases, such "deviations" were accounted for by adjusting the "four quarter lag" (and thus the date at which the information is assumed to have been available) correspondingly.

Before we decided to restrict our attention to the set of financial ratios that are shown in Table 1, we studied a number of commonly used accounting ratios that were employed in frequently cited articles studying bankruptcy risk and the balance sheet channel, but the ones reported

[7] Imputing the mean for missing values may lead to underestimation of standard errors. Little and Rubin (1987) propose use of multiple imputations to overcome this problem in a situation where values are missing in a non-systematic manner. Since statistical significance is hardly a matter of concern with well over seven million observations, we have chosen not to apply their technique in the analysis.

[8] This approach is quite common in the literature, and e.g. Shumway (2001) truncate 1 percent of the top and bottom observations. It should be emphazied that the results are not at all sensitive when varying the truncation rate between 0.5 and 2 percent.

[9] From Table 1, comparison of the descriptive statistics for the untruncated data makes it clear that defaulted firms are unproportionally more affected when truncating all the observations simultaneously. Since the REMARK1, REMARK2, PAYDIV and TTLFS variables are dummy variables that are never affected by our truncation procedure, our truncation procedure may lead to underestimation of the importance of the accounting data variables in the default risk model relative to these variables. To check the robustness of our chosen approach, we used an alternative approach where we truncated 1 percent of top and bottom observations of the healthy and defaulted firms separately. As expected, the estimation results of the default-risk model with this truncation suggested a somewhat larger role for the accounting ratios, but the general picture is still the same.

showed the most strong correlation with default risk.[10] In our empirical model, we employ six accounting ratios: earnings before interest, depreciation, taxes and amortization over total assets (earnings ratio); interest payments over the sum of interest payments and earnings before interest, depreciation, taxes and amortization (interest coverage ratio); total liabilities over total assets and total liabilities over total sates (debt ratios); cash in relation to total liabilities (cash ratio); and inventories over total sales (turnover ratio).[11] These six ratios were selected following a two-step procedure. First, the univariate relationship between the ratio and default risk was investigated. By visual inspection, ratios that lacked any correlation with default risk were deleted from the set of candidate explanatory variables. Figure 1 illustrates this for the six selected ratios by comparing default rates (solid line) and the cumulative distributions of the variables (dotted line). Default rates are calculated as averages over an interval of +/- 5000 observations. Given the density of the observations, there is a positive relationship between default risk and the leverage, interest coverage and turnover ratios, while the figure suggests a negative relationship with both the debt and the liquidity ratios. The diagrams in Figure 1 suggest that the relationship between default-risk and the earnings ratio, total liability over total sales ratio and interest costs over the sum of interest costs and earnings are not linear. For instance, for the interest coverage variable, this relationship is perhaps what one would have expected; low (negative earnings) can turn this ratio highly negative if interest costs are high but earnings are slightly more negative, and this event is naturally associated with an increasing default risk. On the other hand, high interest payments and low earnings will make this ratio large as well, and is also associated with an increasing default risk. Similar reasoning can be be applied to the other ratios as well. What is important to note is that this feature for some of the financial ratios do not imply that these variables are uninformative for default risk in the empirical model. The reason for this being that the correlations between these financial ratios in the cross section are substantial, which makes each of these variables contribute to default risk in the joint empirical model.[12] Taking these insights into account, Figure 1 confirms the picture in Table 1 which shows that there is a clear difference between healthy and defaulted firms for these variables.

[10] See Altman (1969, 1971, 1973, 1984), Carling et al. (2001), Frydman, Altman and Kao (1985), and Shumway (2001).

[11] It should be noted that the level of debt, in addition to the leverage ratio ($\mathrm{TL}_{i,t}/\mathrm{TA}_{i,t}$) for firm i in period t, appear to contain predictive power for default risk. We therefore decided to include $\mathrm{TL}_{i,t}$ as separate variable, but scaled it with average total sales in period t to obtain a stationary accounting ratio. So the debt to sales ratio is actually defined as $\mathrm{TL}_{i,t}/\mathrm{TS}_t$ where TS_t denotes average total sales in period t.

[12] For instance, taking the square of the interest coverage ratio, which seems appropriate from Figure 1 in single variable analysis, reduces the explanatory power of this transformed variable in the multivariate model.

Table 1: Descriptive statistics for the micro data.

Part A: Non-truncated data

Firm Type	N	μ	σ	Statistic min	1%	50%	99%	max
Non-defaulted	7549041							
EBITDA/TA	7471212	-0.12	220.40	-256885	-1.03	0.11	0.85	66424
TL / TA	7474248	3.56	1351.21	-408	0.03	0.73	2.42	1703742
LA / TL	7451325	1.09	109.37	-71203	0	0.13	7.94	54655
I/TS	7355762	4.84	6254.23	-26845	0	0.01	2.18	16500000
TL/TS	7474248	2.32	120.73	-32.25	0	0.08	17.02	48536
IP/(IP+EBITDA)	7457030	-1.7e10	2.8e13	0	-3.59	0.10	3.95	2.2e16
Defaulted	103568							
EBITDA/TA	67093	-6.04	1201.38	-215719	-5.40	0.03	1.23	164895
TL / TA	67110	208.17	25784.42	-23304	0.01	0.94	18.97	5407312
LA / TL	66729	0.57	24.20	-436	0	0.02	4.87	3258
I/TS	63138	27.05	6319	-0.19	0	0.03	5.21	1587085
TL/TS	67110	0.80	8.46	-0.08	0	0.12	9.53	787
IP/(IP+EBITDA)	66670	0.35	28.53	-1216	-6.09	0.23	6.90	5794

Part B: Truncated data

Firm type	N	μ	σ	Statistic min	1%	50%	99%	max
Non-defaulted	7549041							
EBITDA/TA	7471212	0.11	0.25	-1.05	-1.03	0.11	0.84	0.84
TL/TA	7474248	0.71	0.35	0.03	0.03	0.73	2.42	2.46
LA/TL	7451325	0.53	1.12	0	0	0.13	7.81	7.81
I/TS	7355762	0.12	0.29	0	0	0.01	2.13	2.13
TL/TS	7474248	0.58	2.08	0	0	0.08	14.74	18.61
IP/(IP+EBITDA)	7457030	0.15	0.76	-3.55	-3.55	0.10	3.91	3.91
PAYDIV (%)	7549041	13.15	33.80	0				1
REMARK1 (%)	7549041	0.33	5.77	0				1
REMARK2 (%)	7549041	3.06	17.21	0				1
TTLFS (%)	7549041	1.54	12.30	0				1
Defaulted	103568							
EBITDA/TA	67093	-0.03	0.35	-1.05	-1.05	0.03	0.84	0.84
TL/TA	67110	1.00	0.50	0.03	0.03	0.94	2.46	2.46
LA/TL	66729	0.21	0.82	0	0	0.02	4.87	7.81
I/TS	63138	0.18	0.38	0	0	0.03	2.13	2.13
TL/TS	67110	0.57	1.75	0	0	0.12	9.52	18.61
IP/(IP+EBITDA)	66670	0.24	0.99	-3.55	-3.55	0.23	3.91	3.91
PAYDIV (%)	103568	0.70	8.31	0				1
REMARK1 (%)	103568	14.90	35.61	0				1
REMARK2 (%)		40.60	49.11	0				1
TTLFS (%)	103568	33.42	47.17	0				1

Notes: The definition of variables are: EBITDA = earnings before taxes, interest payments and depreciations; TA = total assets; TL = total liabilities; LA = liquid assets; I = inventories; TS = total sales; IP = sum of net interest payments on debt and extra-ordinary net income; PAYDIV = a dummy variable equal 1 if the firm has paid out dividends during the accounting period and 0 otherwise; REMARK1 = a dummy variable taking the value of 1 if the firm has a payment remark due to one or more of the following events in the preceding four quarters; (i) a "non-performing loan" at a bank, or (ii) a bankruptcy petition, or (iii) issuance of a court order to pay a debt, or (iv) seizure of property; REMARK2 = a dummy variable taking the value of 1 if ??; TTLFS = a dummy variable equal to 1 if the firm have not filed a income and balance sheet data the previous year and 0 otherwise.

For the remark variables, we employ the same approach as in Carling et al. (2001) and used a simple dummy variable approach by setting it to 1 if certain remarks existed for the firm during the year prior to the quarter, and 0 otherwise.[13] An intuitively reasonable starting point was to find remark events that (i) lead default as much as possible and (ii) are highly correlated with default. As it turned out, many remark variables are either contemporaneously correlated with default or lack a significant correlation with default behavior. For our final model, we constructed the remark 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 non-performing loan". In the accounting data, we also have information whether a firm has paid out dividends or not. We therefore included this information as a dummy variable (PAYDIV) in the model, taking the value of 1 if the firm has paid out dividends and 0 otherwise.

Also, we decided to include a dummy variable, denoted TTLFS, which equals unity if the firm has not issued a financial statement one and a half year prior to default, and zero otherwise.[14] The reason for including this variable in the default-risk model is the notion that firms who are about to default are less willing to report information about their financial status. By comparing defaulting and healthy firms in Table 1 we see that this mechanism is at work in the panel.

2.2 Macro data

The importance of macroeconomic effects for default frequency at the firm level has not been extensively studied in the empirical literature on credit-risk models, in all likelihood due to a lack of suitable historical data. We hope to contribute to this area using the micro data described above. The idea is that the micro data identifies the default risk in the cross-section at a given point in time, whereas the macro variables moves the whole distribution over time.

The macro data used in this paper is adopted from Lindé (2002) and covers the period $1986Q3 - 2002Q4$. We restrict the sample size is to this period because Swedish financial

[13] See notes to Table 1 for what type of remarks are included.

[14] There are three things worth noting in connection with the definition of TTLFS. First, this information is assumed to be available with a 1.5 year time lag since financial statement for year τ are typically available during the third quarter in year $\tau + 1$., and by allowing this dummy variable to equal unity with a 1.5 year time lag only we take the real-world time delay into account. Second, given the way we define the population of existing firms, firms that are newly registered and enter into the panel after $1990Q1$ would automatically be assigned TTLFS = 1 in the third quarter 1990 since they have not issued any financial statement prior to entering. For these new firms, TTLFS has been set to 0 and the accounting data variables have been taken from their first-year balance sheet and income statements. Third, for defaulting firms that are in the panel but have never reported any accounting data prior to default, we also set TTLFS equal to 0. This is the case for 38,352 out of 103,568 defaulting firms in the panel. So although TTLFS turns out to be very important in the default-risk model, the construction of this variable is rather down-playing its importance that overstating it.

markets were heavily regulated prior to 1986. The domestic variables are y_t^d - the output-gap (i.e. deviation of GDP around trend value), π_t^d- the annual inflation rate (measured as the fourth difference of the GDP-deflator), R_t^d - the REPO nominal interest rate (a short-term interest rate, controlled by the Riksbank), and q_t - the real exchange rate.[15] Because there is a strong trend for the real exchange rate during the sample period, this variable is detrended as well.[16] Since Sweden is an open economy, it is important to condition on foreign variables in the Vector autoregressive (VAR-) model. Consequently, we include y_t^f - the foreign output gap (computed by Lindé, 2002), π_t^f - foreign inflation rate, and R_t^f - the 3-month nominal interest rate in the VAR as well. To acquire data on the aggregate default frequency, denoted df_t for the sample outside the panel period $1990Q1 - 1999Q2$, we linked the panel series depicted in Figure 2 for $1986Q3 - 1989Q4$ with the aggregate default frequency data for all business firms (made available by Statistics Sweden), and for the period $1999Q3 - 2002Q4$ with the aggregate default frequency for firms limited by shares (again, source Statistics Sweden).

3 The dependency of real variables on financial variables

In this section, we will use aggregate data to examine if there is a feedback from the financial side to the real side of the economy. Throughout the analysis, we will work with the VAR model estimated by Lindé (2002) as the tool to study this issue. The VAR(p)-model with p lags is specified as

$$X_t = C_d + \delta_1 D_{923} + \delta_2 D_{931013} + \tau_d T_t + \sum_{i=0}^{p} F_i Z_{t-i} + \sum_{i=1}^{p} B_{d,i} X_{t-i} + u_{d,t} \qquad (1)$$

where D_{923} is a dummy variable equal to 1 $1992Q3$ and 0 otherwise, D_{931013} is a dummy variable equal to 1 $1993Q1$ and thereafter, T_t is a linear timetrend, and Z_t is a vector with exogenous variables. The dummy variable for the third quarter in 1992 is included to capture the exceptionally high interest rate increase (up to 500 percent) implemented by the Riksbank in order to defend the fixed Swedish exchange rate. Despite the efforts to defend the Swedish krona, Sweden entered into a floating exchange rate regime in late November 1992, and the

[15] The real exchange rate is measured as the nominal TCW-weighted (TCW= trade competitive weights) exchange rate times the TCW-weighted foreign price level (CPI deflators) divided by the domestic CPI deflator.

[16] Lindé (2002) estimates a VAR with 2 lags for the period $1986Q3 - 2002Q4$ and generates a trend for the variables by doing a dynamic simulation of the estimated VAR by performing a dynamic simulation under the assumption of no shocks hitting the equations. The detrended variables are then computed as actual values minus the trend values. It should be noted however, that using HP-filtered data for output and the real exchange rate produces very similar results to those reported.

dummy variable D_{931013} is included in order to capture possible effects of the new exchange rate regime.

The variables in X_t and Z_t are

$$X_t = \begin{bmatrix} y_{d,t} & \pi_{d,t} & R_{d,t} & q_t \end{bmatrix}' \tag{2}$$

and

$$Z_t = \begin{bmatrix} y_{f,t} & \pi_{f,t} & R_{f,t} \end{bmatrix}'.$$

Lindé (2002) shows that two lags is sufficient (i.e. we set $p = 2$), and that the foreign variables are block exogenous with respect to the domestic variables, i.e. the variables in Z_t are not affected by variables in X_t.

One natural way to test if there is a feedback from the financial sector into the real side of the economy is to augment the specification in (1) with lags of the financial variable, i.e. df_{t-1} and df_{t-2} and examine if they contain useful information for predicting the endogenous variables in the model. This has the flavor of a multivariate Granger-causality test. Essentially, one tests if the coefficients for the lags are significantly different from zero or not simultaneously. By using the block-exogeneity test described in detail by Hamilton (1994), cf. pages 309-312, we find that the p-value for that these coefficients are around 0.02, indicating that the macroeconomic variables in X_t are not exogenous with respect to the aggregate default frequency.

An alternative way to examine this is to include df_t ordered last in the X_t-vector and estimate the five variable VAR-model. If the impulse response functions in the estimated VAR model for a shock to df_t identified via a so called Cholesky decomposition are very close to zero, the quantitative feedback from the default frequency to the real economy is small. In Figure 3, we show the impulse response functions a positive shock to the df_t variable. We see that the results for the statistical test is confirmed, the financial shock has significant effects on the real economy. Output and inflation falls, while the nominal interest rate increase (although not significantly), and the real exchange rate appreciates. According to the VAR, exogenous variations in the default rate account for roughly 20 percent of the variation of the other variables.

We have also investigated whether the average balance sheets ratios (depicted in Figure 4) explain the variation in the macrovariables over and above the explanatory power of the default rate variable and the other macrovariables included in the VAR. Since we only have data on the balance sheets ratios for the period $1990Q1 - 1999Q2$, we regressed the VAR-residuals for this period on the balance sheet ratios equation by equation with OLS. A simple F-test revealed that the balance ratios conveyed no information w.r.t. the VAR residuals, the average p-value being around 0.60 and the lowest p-value 0.25 (real exchange rate residuals). Consequently, we will adopt the approximation in the rest of the paper that the macrovariables included in the VAR above are not directly affected w.r.t. to the balance sheet ratios that we consider. We will, however, allow for indirect effects via the average default rate.

To complete the analysis, we have also applied the block-exogeneity tests for other commonly used measures of the financial stance of the economy such as the term-structure, the change in the stock of loans by banks to firms and households, the change in stock prices and the change in housing prices. We obtained the following p-values; term structure - 0.39, annual change in stock of outstanding loans - 0.25, quarterly change in stock prices - 0.90, and quarterly change in housing prices - 0.01 Notice that for the variables in changes, we used both the quarterly and annual change in respective indicator, but here we only report the results with the lowest p-values. These findings suggest that only housing prices contain significant predictive power for the real economy during this sample period. Since stock markets are supposedly forward-looking, it is perhaps surprising that stock prices appear to contain little predictive power. The reason is simply that there is too excessive volatility in stock prices, which are not transmitted to the real economy. Although we find evidence that housing prices are important, the default rate is slightly more important in the sense that if we redo the block exogeneity test for the VAR for housing prices when the default rate is included, we find that the p-value being 0.13. The converse experiment, i.e. testing for the predictive power of the average default frequency given that the first difference of the housing prices are included in the VAR, we obtain a p-value of 0.09. Based on the evidence above, and since we are in disposal of very interesting micro data on firms default behavior, we will work with this variable as the link between the financial and real side of the economy, but future research should further address the link between the housing prices and the real economy.

Despite our encouraging statistical evidence in favor of our choice of using the average default frequency for firms limited by shares as a link between the real and financial side of the economy, we still need to motivate from an economic perspective why the aggregate default rate is an appropriate measure of the financial stance of the economy. There are several arguments why we think this is the case. First, as shown in Figure 5, we see that the average (aggregate) default frequency follows a very similar pattern as credit-losses over the stock of loans to non-financial firms, the correlation coefficient being 0.90.[17] In particular, the comovement between the variables are large at the lower frequencies, but there are some differences at the higher frequencies, e.g. the upturn of credit losses during the Asian and Russian crisis. In our view, the lower frequency component of these variables are most interesting, since they are arguably more related to the systematic risks in the banking sector. Second, neither credit-losses nor default are leading or lagging the other variable. Third, Figure 5 suggests that our choice of restricting our analysis to default risk and not studying implied credit-losses (e.g using total liabilities) due to lack of accounting data for many defaulted firms, does not seem to be a serious restrictive approximation. Third, from an financial stability perspective, we also think that this variable should be of high relevance given that it is forecastable, whereas e.g. operational risks are much harder to forecast. For instance, it would have been extremely difficult for a central bank to foresee the Barings bank affair. Fourth and finally, we think that our variable ought to capture well the leverage/systematic risk in the banking system in the sense that when a bank experience high default-/credit-risk, it is most likely that other banks will too if there are common factors that drive default risk (e.g. if macroeconomic factors are important for the absolute level of default-risk, which we find). Thus we conclude that our variable ought to be a good operational predictor of the systematic risk in the banking sector and the financial stance of the economy.

The conclusions from the analysis above are that, (i), there seems to be an important link from the financial side of the economy to the real side of the economy that it is not only statistically, but also quantitatively important, and (ii), that the aggregate default rate is a good measure of the financial stance of the economy.

4 The dependency of financial variables on aggregate activity

In this section, we are going to examine if the default risk at the firm level are affected by aggregate shocks over and above firm-specific information. Moreover, we will present some brief evidence of the balance channel by investigating to what extent standard balance sheet ratios are affected by aggregate shocks.

[17] Credit losses are here defined as the credit losses to non-financial firms by the four big banks in Sweden (SEB, Nordea, SwedeBank and SHB) in relation to their stock of loans to non-financial firms.

4.1 The default-risk model

In this subsection we present a reduced form statistical model for estimation of probability of default for all Swedish firms limited by shares. The general idea is to enter factors that determine the probability of default and quantify how these contribute towards predicting default realizations. With such estimated probabilities we may proceed to calculate the expected aggregate default frequency over time.

So far relatively few studies contain a rigorous analysis of the effects from macroeconomic conditions on default behavior and credit risks at the firm level, see e.g Carling et al. (2001) for a discussion. The logit model of the default probability that we present in this subsection includes both idiosyncratic and macroeconomic explanatory variables.[18] The reason why there is a need to include aggregate variables in the model is clear from by inspection of Figures 4 and 5. In Figure 4, we plot the mean values of the idiosyncratic financial variables that are used in the model $1990Q1 - 1999Q2$. It is obvious that there are no dramatic changes in the variables during the deep recession 1992-1993. Therefore, a model with only idiosyncratic variables included cannot probably fully account for the higher default frequency outcome at the aggregate level depicted in Figure 2. Therefore, we conjecture that it is important to use aggregate variables in the model.

The macroeconomic variables that we use in the model are the ones included in the domestic VAR model given by (1), i.e. the output gap, the domestic annual inflation rate, the REPO rate, and the real exchange rate. A priori, we think that these should have a measurable impact on the default risk of any given firm. Starting with the output gap, it may supposedly work as an indicator of demand conditions, i.e. increased demand in the economy reducing default risk. Figure 5 seems, at large, consistent with this view, although there are some spikes in the default rate that presumable have to be attributed to other variables. Also, it is clear from Figure 2 that there has been some variation the output gap around 1996-1998 which has not been met with an increased default rate. Therefore, there must be some other aggregate variables that ought to be important as well. Here, we decided to include the nominal interest rate (i.e. the REPO rate) because we know that the nominal interest rate was very high during the recession in the beginning of the 1990s, but has came down substantially after the introduction

[18] For simplicity, we estimate a logit-model rather than a duration model as is done by Carling et al. (2001). However, since Carling et al. and Shumway (2001) found find weak evidence of a duration dependence, this approximation may not be of decisive importance. But an interesting extension of this work is to test for duration dependence in the model.

of the inflation target in Sweden. Given the fact that the export to GDP ratio being around 0.40, the real exchange rate is also a potentially important variable, a deprecation leading to improved competitiveness of Swedish firms. Finally, the inflation rate may also be important for firm pricing decision; higher inflation rates are potentially associated with less certainty about correct relative prices, and thus potentially higher default risk. Of course, it also convenient to work with variables that can be generated from the VAR model in the previous section. This is the reason why we did not experimented neither the term structure variable nor measures of household expectations as is done in Carling et al. (2001). Finally, as can be seen from Figure 3, there is a large spike in the REPO rate in the third quarter 1992 due to the fact that the Riksbank raised the REPO rate to 500 percent in order to defended the fixed exchange rate. By not adjusting the REPO rate for this exceptional event, the estimation procedure leads to underestimation of the importance of financing costs for default behavior. We therefore decided to adjust the REPO rate series that we use when estimating the model in the third quarter 1992 with the estimated value of the dummy variable in the third quarter 1992 in the VAR model (1).[19]

In order to highlight how various variables contribute to default risk, we present three different models in Table 2. One model with accounting ratios only, one with the dummy variables added (PAYDIV, REMARK and TTLFS variables), and finally one with the macroeconomic variables added.[20]

[19] Since the estimated dummy coefficient in the VAR for D_{923} equals 28.2, the adjusted REPO rate value for this quarter equals 9.8 percent instead of 38 percent.

[20] Since no data on the payment records of firms (i.e. the dummy variables REMARK1 and REMARK2) exist prior to $1992Q3$ for legal storage reasons, the estimation results of Model II and Model III reported in Table 2 also includes one additional variable (not reported) which is constructed to be a good guess about the average value of the sum of the payment record variables REMARK1 and REMARK2 would be during the quarters $1990Q1$-$1992Q2$. This variable was constructed by estimating a logit model for the event of either of the dummy variables REMARK1 and REMARK2 taking on the value 0 or 1 for the period $1992Q3$-$1999Q2$, using all the variables in Model III (except REMARK1 and REMARK2 as explanatory variables, of course). The imputed average value of this variable for the period $1990Q1$-$1992Q2$ (after $1992Q2$, it is set to nil) was then constructed as the average estimated probability for each firm and period, i.e. $\mathrm{RD}_t = \frac{1}{N_t}\sum_i \hat{p}_{i,t}$ where $\hat{p}_{i,t}$ denotes the estimated probability for firm i in period t to have either REMARK1 or REMARK2 and N_t denotes the number of firms in period t. The largest gain with including this variable is that the macrovariables are more accurately estimated, for the idiosyncratic variables this variable is of little importance.

Table 2: Logit estimation results of the default-risk model.[a]

Type of regressor	Model I Coefficient	Model I Std error	Model II Coefficient	Model II Std error	Model III Coefficient	Model III Std error
Constant	−4.76	0.018	−5.22	0.025	−5.88	0.053
Idiosyncratic variables[b]						
EBITDA/TA	−1.07	0.022	−1.10	0.028	−1.09	0.041
TL/TA	1.07	0.015	0.54	0.020	0.52	0.029
LA/TL	−0.10	0.014	−0.15	0.017	−0.16	0.025
I/TS	0.27	0.016	0.20	0.021	0.21	0.031
TL/TS	0.19	0.004	0.23	0.005	0.22	0.007
IP/(IP+EBITDA)	0.09	0.007	0.07	0.009	0.08	0.013
PAYDIV			−1.91	0.080	−1.85	0.123
REMARK1			1.73	0.032	1.89	0.046
REMARK2			2.66	0.020	2.74	0.030
TTLFS			3.32	0.019	3.27	0.028
Aggregate variables[c]						
Output gap - $y_{d,t}$					−0.110	0.007
Inflation rate - $\pi_{d,t}$					−0.005	0.008
Nominal interest rate - $R_{d,t}$					0.072	0.005
Real exchange rate - q_t					−0.006	0.002
Summary statistics[d]						
Mean log-likelihood	−0.0669		−0.0491		−0.0484	
Pseudo R^2	0.16		0.37		0.39	
Aggregate R^2	0.26		0.36		0.94	
Number of observations	2,066,206		1,607,049		1,836,625	

Notes: [a] Since we have as many as 7,652,609 quarterly observations, the computer program used to do the Maximum Likelihood estimation of the logit model (GAUSS version 3.5) cannot handle all observations simultaneously. For Model I and II presented below, we therefore made a random selection of 27 and 21 percent of the observations such that the aggregate default frequency over time is identical to the one computed using all observations, and used this sample to estimate the model. To check that we have convergence in parameter values, we decreased the sample selection to 26 and 20 percent of the observations and reestimated the models. Fortunately, we found convergence in parameter at the three digit level and the estimation results in Table 2 are thus based on the 27/21 percent samples, respectively. For Model III below this approach was not feasible because we could not find convergence at the three digit level given the increased number of regressors. For this model, we therefore draw 50 samples of size 15 percent of the population, and for each parameter we report the mean estimate and standard deviation of the resulting distribution of 50 estimates. [b] See Subsection 2.1 for exact definition of these variables. [c] See Subsection 2.2 for definition and sources. The variables are not scaled so the importance of a variable cannot be read directly off the size of the parameter estimate. [d] We use Laitila (1993) measure of pseudo R^2. The aggregate R^2 is computed using all 7,652,609 quarterly observations.

The results in Table 2 show that both idiosyncratic and aggregate information is important for explaining default behavior. Note that the standard errors are typically larger for the aggregate variables than for the idiosyncratic ones. That is because the time dimension identifies the macro variables, while the cross-section identifies the idiosyncratic variables. Among the idiosyncratic variables, the variables for omitted (not-reported) financial report and remarks on firms payment record are the strongest determinants of default in the model. A nice feature of the estimations is that the coefficients for each variable does not change substantially when the model is augmented with more variables. In particular, the accounting ratios in Model I have roughly the same coefficients as in the complete Model III. The predictive power of the accounting data is somewhat more modest, although the liability-to-assets ratios (TL/TA and TL/TS) and earnings ratios are quite useful.[21] The turnover ratio for inventories, liquid asset over total liabilities and the interest coverage ratio appear to be less important. Turning to the macro variables, we find that they are significant with the exception of inflation and have the correct signs. Note that a higher value of the real exchange rate implies an depreciation, and therefore the negative estimate for this variable suggest that a depreciation reduces the default risk at a given point in time on average.

The advantage of using firm-specific data when estimating the default-risk model cannot be overstated. If we estimate Model III without the dummy variables (REMARK1, REMARK2, PAYDIV, and TTLFS are left out because they do not enter significantly, which makes sense at the aggregate level) on aggregate/average data with OLS (TSLS give very similar results), we obtain

$$
\begin{aligned}
df_t \quad = \quad & \underset{(0.06)}{-0.23} \; \underset{(0.13)}{-0.23}\left(\frac{\text{EBITDA}}{\text{TA}}\right)_t + \underset{(0.06)}{0.30}\left(\frac{\text{TL}}{\text{TA}}\right)_t + \underset{(0.03)}{0.09}\left(\frac{\text{LA}}{\text{TL}}\right)_t \cdots \\
& \underset{(0.21)}{-0.94}\left(\frac{\text{I}}{\text{TS}}\right)_t + \underset{(0.08)}{0.19}\left(\frac{\text{TL}}{\text{TS}}\right)_t - \underset{(0.12)}{0.02}\left(\frac{\text{IP}}{\text{IP+EBITDA}}\right)_t \cdots \\
& -\underset{(0.03)}{0.05}\, y_{d,t} - \underset{(0.03)}{0.05}\, \pi_{d,t} + \underset{(0.03)}{0.12}\, R_{d,t} + \underset{(0.009)}{0.002}\, q_t + \hat{u}_{df,t}, \qquad (3) \\
& R^2 = 0.93, \; \text{DW} = 2.10, \; \text{Sample: } 1990Q1 - 1999Q2 \; (T = 38)
\end{aligned}
$$

If we compare the point estimates in Table 2 with those in (3), we see that they differ substantially. In particular, the balance sheet variables I/TS and LA/TL account for a lot of the variation in the aggregate default rate, but with the wrong sign. Because the accounting ratios are relatively smooth in the aggregate, which is clear from Figure 4, it is not surprising that we obtain spurious results when estimating the model on aggregate data rather than at the firm level.

[21] Regarding the importance of the accounting data in the model, we would like to emphasize the following features. First, because firms typically issue annual financial statements, which we transform into quarterly observations by assuming that they remain the same throughout the reporting period. Given that we define the default incident at the quarterly frequency, this assumption could presumably lead to underestimation of the importance of the balance sheet variables in the default risk model. Therefore, we examined this by estimating the credit risk model at the annual frequency instead, and the coefficients for the balance sheets variables was found to be very similar. In fact, only the coefficients for EBITDA/TA and TL/TS were found to be slightly higher (−1.2945/0.2652 instead of −1.0635/0.1768, respectively), whereas the other coefficients were actually found to be lowered. Moreover, the decision to lag the accounting data 4 quarters in the estimation in order to make the model “operationable” in real-time could presumably also affects the estimated coefficients. Therefore, we reestimated the model using contemporaneous data instead, but again, the estimation results were to found to be very similar.

In Figures 6 and 7, we plot the aggregate default rate together with the average predicted default rate from the model for Model I (Figure 6) and Model III (Figure 7) for the whole sample of firms, i.e. using the $7,652,609$ observations. Very interestingly and as conjectured previously in the paper, we note in Figure 6 that the model with firm specific information only cannot capture the up- and downturn in average default rates over time, whereas the model with both micro and macro variables included is indeed able to replicate the high default rate during the banking crisis, as well as the downturn to very moderate default rates during the latter part of the sample. The explained fraction of variation (r-square) in the model with macro variables included is 94 percent at the aggregate level whereas it is as low as 26 percent in the model with balance sheet ratios only. This finding is very interesting for several reasons. First, because it suggests that the high default rates recorded during the banking crisis were not unusual events that we cannot learn anything useful from, rather the results suggest that they were an outcome of unusually bad economic outcomes, both domestically and internationally since Lindé (2002) shows that a significant portion of the variation in the domestic variables are of foreign origin. Second, when the aggregate default rate is included in the VAR model (1) as an endogenous variable, the share of the explained variation in the default rate is about 88 percent and the sum of the two lags for the average default rate is as high as 0.74. Without the lags, the share of the explained variation in the average default rate shrinks considerably down to about 82 percent.[22] One possible interpretation of these results is that the estimated high weight on the lags in the aggregate default rate equation are proxies for missing information at the firm level, because Model III estimated at the microeconomic level gives a better fit at the aggregate level without any intrinsic dynamics in the model.

4.2 The dependcy of balance sheet ratios on aggregate shocks

An interesting question is to what extent the balance sheet ratios that are included in the default-risk model are driven by macroeconomic factors and to what extent they are living their own life, i.e. driven by ideosyncratic shocks. The are good reasons to believe that some of the balance sheet ratios may be more independent of the aggregate state of the economy than others. Consider for example the variable earnings over total assets (EBITDA/TA). In a favorable macroeconomic situation, earnings should improve, but also total assets. Therefore,

[22] Note that the numbers for the aggregate default rate are taken from the VAR estimated on a slightly different data sample, $1986Q3 - 2002Q4$. However, when restricting the sample to the same sample as the default-risk model above, the results are actually even more in favor of the micro model.

the net effect on EBITDA/TA is not obvious. However, the coverage ratio, is likely to be more heavily affected by aggregate shocks, since $\frac{\text{IP}}{\text{IP+EBITDA}}$ after an increase in the nominal interest rate, both interest payments on debt (IP) should increase while earnings (EBITDA) fall.

Let $Y_{i,t} = \begin{bmatrix} \text{EBITDA/TA}_{i,t} & \text{TL/TA}_{i,t} & \text{LA/TL}_{i,t} & \text{I/TS}_{i,t} & \text{TL/TS}_{i,t} & \frac{\text{IP}}{\text{IP+EBITDA}}_{i,t} \end{bmatrix}'$ denote a 6×1 vector with the financial ratios for firm i, and let $Y_t = \begin{bmatrix} Y_{1,t} & . & . & . & Y_{N_t,t} \end{bmatrix}'$ denote a $6 \times N_t$ matrix where N_t is the number of firms in the panel in quarter t. Then the process for the financial ratios can be written

$$Y_t = \Theta_Y Y_{t-1} + \Theta_X X_t + u_t, \ \text{var}(u_{Y,t}) = \Sigma_u \tag{4}$$

where X_t is defined by (2). Because we want to estimate the model on quarterly data in order to better identify the aggregate shocks, but typically have new information about the financial ratios annually, we use annual moving averages when estimating (4). Each equation in (4) is estimated with the Arrellano and Bond (1991) estimator using $1,701,878$ observations that are constructed from the original dataset consisting of all the $7,652,609$ observations.[23] The estimation results of (4) are

$$\Theta_Y = \begin{bmatrix} 0.807 & 0.025 & -0.0002 & -0.029 & -0.0003 & -0.006 \\ -0.016 & 0.968 & -0.002 & 0.005 & -0.001 & 0.007 \\ 0.007 & -0.062 & 0.938 & -0.011 & -0.0091 & -0.021 \\ -0.004 & -0.001 & -0.0005 & 0.940 & 0.0001 & 0.002 \\ -0.0007 & -0.033 & 0.005 & -0.005 & 0.990 & 0.008 \\ -0.031 & 0.069 & -0.005 & 0.034 & 0.006 & 0.573 \end{bmatrix},$$

$$\Theta_X = 100 * \begin{bmatrix} -0.039 & 0.060 & -0.010 & 0.031 \\ -0.026 & 0.016 & 0.053 & 0.004 \\ 0.187 & 0.180 & -0.089 & -0.048 \\ 0.033 & 0.007 & 0.039 & -0.008 \\ -0.524 & -0.092 & 0.154 & 0.088 \\ -0.167 & -0.007 & 0.148 & -0.021 \end{bmatrix},$$

[23] Suppose the true model is given by (4). If we define the variables $\bar{Y}_t = \frac{1}{4}(Y_t + Y_{t-1} + Y_{t-2} + Y_{t-3})$ and $\bar{X}_t = \frac{1}{4}(X_t + X_{t-1} + X_{t-2} + X_{t-3})$, we can write (using 4),

$$\bar{Y}_t = \Theta_Y \bar{Y}_{t-1} + \Theta_X \bar{X}_t + \bar{u}_t \tag{5}$$

where $\bar{u}_t \equiv \frac{1}{4}(u_t + u_{t-1} + u_{t-2} + u_{t-3})$. This implies that after estimating (5), we can retrieve the parameters of interest Θ_Y, Θ_X and $\Sigma_u = 4\Sigma_{\bar{u}}$. As valid instruments (i.e. instruments uncorrelated with the shocks $\bar{u}_t$) when estimating (5), we use $\bar{Y}_{t-5}$ and $\bar{X}_{t-4}$, thus allowing for one period serially correlated measurement erros in Y_t. This procedure implies that in order for a firm to be included in the estimation, it must have reported a financial statement for 9 consequtive quarters (3 years). This is why the sample used to estimate (5) is considerably smaller than the total number of observations.

$$\Sigma_Y = \begin{bmatrix} 0.15390 & 0.02288 & -0.22309 & 0.04976 & 0.23547 & 0.37508 \\ 0.02288 & 0.03079 & -0.10535 & 0.01890 & 0.12979 & 0.14406 \\ -0.22309 & -0.10535 & 1.35270 & -0.18691 & -1.04964 & -1.45223 \\ 0.04976 & 0.01890 & -0.18691 & 0.07183 & 0.20798 & 0.31972 \\ 0.23547 & 0.12979 & -1.04964 & 0.20798 & 1.24893 & 1.60151 \\ 0.37508 & 0.14406 & -1.45223 & 0.31972 & 1.60151 & 2.78039 \end{bmatrix}.$$

We see that there is considerable persistence in the variables, which is presumably due to the fact that we do not allow for firm or industry specific effects when estimating the model. The macro parameters are seemingly small, but the p-values for joint Wald-test of all the macro variables are essentially zero in all the equations. However, given that large number of observations, this might not come as a big surprise. Arguably more interesting is to examine to what extent aggregate shocks account for variation in the financial ratios according to the estimates. We found that the macro variables account for maximum 0.1 percent of the fluctuations in the financial ratios included in Y_t , which implies that the accounting ratios are essentially are living their life on their own.[24] By looking at Figure 4, these results are not that surprising given that the balance sheet ratios do not display a strong degree of cyclical behavior, with possible exception of EBITDA/TA and IP/(IP+EBITDA).

Because the effects of the aggregate shocks were found to be surprisingly low, we also conducted the following experiment. For each balance sheet ratio, we ran simple OLS regressions

$$Y_{i,t} = \sum_{s=0}^{p} b_s X_{t-p} + \varepsilon_{i,t},$$

using both quarterly (setting $p = 4$) and annual data (using $p = 0$). From the OLS results, the share of explained variation in $Y_{i,t}$ be aggregate shocks can be directly read off the R^2 for this regression. In none of the estimated equations, we obtained an R^2 larger than 0.03, again suggesting a very low role of aggregate shocks for explaining the fluctuations in firms balance sheet ratios.

However, before drawing too strong conclusions upon these estimation results. The following aspects should be considered. First, the adopted estimation procedure does not allow for firm

[24] Assuming that the unconditional variance in X_t are unaffected by the variables in Y_t in the long-run, which is as a reasonable approximation for reasons discussed in Section 3, we can compute the contribution of the macro variables to fluctuations in Y_t as follows. Noting that (4) implies that $\Sigma_Y = \Theta_Y \Sigma_Y \Theta_Y' + \Theta_X \Sigma_X \Theta_X' + \Sigma_u$ where Σ_Y, Σ_X and Σ_u are the unconditional covariance matrices for Y_t, X_t and u_t, respectively. Since the VAR is stable, Σ_X and Σ_u known (Σ_X is computed as the covariance matrix for the domestic macro variables $1986Q3 - 2002Q4$ and an estimate of Σ_u is computed through the residuals in 4), we can compute Σ_Y by iterating on this equation, starting with an arbitrary positive definite matrix as an initial guess. Let Σ_Y^{tot} denote the resulting covariance matrix. The amount of variation due to the idiosyncratic shocks can be found by iterating on $\Sigma_Y = \Theta_Y \Sigma_Y \Theta_Y' + \Sigma_u$, and we let Σ_Y^{mic} denote the resulting covariance matrix. Similarly, the amount of variation in Y_t due to aggregate shocks are found by iterating on $\Sigma_Y = \Theta_Y \Sigma_Y \Theta_Y' + \Theta_X \Sigma_X \Theta_X'$, and we let Σ_Y^{mac} denote the resulting covariance matrix. We can then compute the share of fluctuations in the balance sheet ratios due to aggregate shocks as $\text{diag}(\Sigma_Y^{mac}./\Sigma_Y^{tot})$. Notice that $\Sigma_Y^{mac} + \Sigma_Y^{mic} = \Sigma_Y^{tot}$.

specific effects, i.e. there is a common intercept in (4) for all firms. However, when we redid the estimation results allowing for firm-specific effects by allowing for a firm-specific constant, we found the importance of the aggregate shocks at most to be 1.9 percent (EBITDA/TA), i.e. very similar to the previous results. But surely, the way one models the firm-specific effects can be of importance for the results. Second, the model is linear, and of course non-linear effects can be of important. Third, and perhaps most important, is that we do not allow for different propagation of aggregate shocks in different industries, because we do not have access to a consistent industry classification over time for all the firms (industry classification was changed in 1992). But it seems unlikely that that the basic message conveyed, namely that idiosyncratic risk is more important than aggregate shocks, could be overturned.

5 Putting all things together: A simple empirical model of the interaction between the real and financial economy

In this section, we will briefly describe a simple, but complete model that can be used to study the interaction between the real and financial side of the economy. The model consists of three blocks.

First, we have the VAR models for the domestic and foreign variables that are estimated on aggregate data. The domestic VAR model is given by (1) with the terms $\sum_{s=1}^{2} \Lambda_s df_{t-s}$ added. In order to be able to study the dependency of the foreign variables, we follow Lindé (2002) and estimate the following VAR(2)-model for the foreign variables

$$Z_t = C_f + \tau_f T_t + \sum_{i=1}^{2} B_{f,i} Z_{t-i} + u_{f,t}. \tag{6}$$

The second block of the model is the default risk model (Model III). This model is used to compute the average default frequency that enters into the estimated VAR model for the domestic variables, i.e. $df_t = \frac{1}{N_t} \sum_{i=1}^{N_t} \hat{p}_{i,t}$ where $\hat{p}_{i,t}$ is the estimated default probability for firm i in period t and N_t is the number of firms in the panel in period t. The third block of the empirical model is the VAR model (4) for the financial ratios which enter into the default-risk model. The default-risk model is the crucial link between the "financial" and "real" side of the economy in the empirical model.

6 Policy experiments with the empirical model

In this section, we will discuss how the empirical model can be used to shed light on various policy issues. We will show why we think it is useful for policy makers to use micro information rather than just aggregate data on default risk. That is, we will examine why we think it is better to include the estimated default-risk model in the empirical model rather than making aggregate default frequency an endogenous variable in the VAR model given by (1). We will also study how the trade-off regarding stabilizing inflation and the aggregate default rate with monetary policy have changed over time in the estimated empirical model. Finally, we will show how one can use the estimated model to compute model consistent joint forecasts for default-frequency and inflation along with uncertainty bands.

6.1 Computing default frequency distribution percentiles with the model $1991Q1$ and $1998Q1$

In this section, we report the results of computing default frequency distribution percentiles with the estimated empirical model, consisting of the estimated credit-risk model (see Section 4.2), the domestic VAR model (1) with two lags of the aggregate default rate as an additional exogenous variable, the VAR model for the foreign variables (6), and the process for the financial ratios (4). As initial conditions, we use how the portfolio look like in $1991Q1$ and $1998Q1$, along with the macroeconomic stance. Note that the default frequency distribution is the same thing as computing the Value-at-Risk (VaR) distribution under the assumption that all loans are of the same size. Computing the default frequency distribution is done in the following way. First we compute a "trend path" by simulating the economy when no shocks are hitting the economy, i.e. u_t^d, u_t^f and $u_{i,t}^y$ are all zero and we use actual values on the macro variables $\{1990Q4, 1991Q1\}$ and $\{1997Q4, 1998Q1\}$ are used as starting values (two lags are used in the VARs). Let d_{t+h}^{trend} denote the computed trend default rate at horizon $h = 1, 2, ..., 8$. Second, we make an additional simulation using exactly the same initial conditions but this time we allow for shocks hitting the economy (i.e. u_t^d, u_t^f and $u_{i,t}^y$ are non-zero). Let d_{t+h}^{shock} denote the outcome when the shocks are included in the model. Third, we compute $d_{t+h}^{Dfd} = d_{t+h}^{shock} - d_{t+h}^{trend}$. Fourth, we generate 1000 realizations of d_{t+h}^{Dfd} and choose the largest XX'th percentile for each horizon h of the simulated distribution as our measure of the VaR at the XX'th level. We also report the XX'th percentile of the distribution for d_{t+h}^{shock}, to ensure that the model is consistent with the facts that the default risk was higher in the beginning of the 1990s than during the boom in late 1990s.[25]

In Table 3, we show the resulting figures for the 1991Q1 portfolio and 1998Q1 portfolio of firms. In the table, the absolute default frequency distribution percentile refer to XX'th percentile for the d_{t+h}^{shock}-distribution at horizon h, while the relative default frequency distribution percentile refer to the XX'th percentile for the d_{t+h}^{Dfd}-distribution at horizon h. It is important to note that using an aggregate approach, i.e. including the aggregate default frequency as an endogenous variable in the VAR-model, would give rise to exactly the outcome for the XX'th percentile for the d_{t+h}^{Dfd}-distribution at horizon h (since the VAR-model is linear), so if these number are different, that is evidence in favor that non-linearities induced by the default-risk model at the firm level differ from a pure macro approach. It is harder to say with certainty whether the differences we observe are due to the different portfolios of firms or the difference in the initial macroeconomic conditions.

Table 3: Absolute and relative default frequency distribution percentiles at different horizons h into the future using the empirical model 1991Q1 and 1998Q1.

Absolute default frequency percentiles at horizon h (quarters ahead)								
	Time period 1991Q1				Time period 1998Q1			
Percentile	$h=1$	$h=4$	$h=6$	$h=8$	$h=1$	$h=4$	$h=6$	$h=8$
95-percent	2.02	2.73	2.97	2.78	0.99	0.99	0.99	1.01
99-percent	2.17	3.08	3.48	3.46	1.04	1.09	1.06	1.06

Relative default frequency percentiles at horizon h (quarters ahead)								
	Time period 1991Q1				Time period 1998Q1			
Percentile	$h=1$	$h=4$	$h=6$	$h=8$	$h=1$	$h=4$	$h=6$	$h=8$
95-percent	0.30	0.67	0.85	0.82	0.13	0.18	0.19	0.20
99-percent	0.45	1.02	1.36	1.50	0.18	0.28	0.26	0.26

Notes: The absolute default frequency distribution percentiles have been computed out of a distribution of 1000 outcomes h periods ahead of simulating the empirical model with shocks added in the domestic and foreign VARs, and to the model of the financial ratios. The relative default frequency percentiles have been computed from a distribution where a "trend-path" for the default frequency level (given by a simulation of the empirical model where no shocks are added to the economy using same initial conditions) have been subtracted from the absolute default frequency level.

We learn two things from the results in Table 3. First, the empirical model correctly identifies that the absolute default risk was substantially higher in 1991 than in 1998. The chosen percentiles cover the actual default frequency during $1991-1992$ and $1998-1999$, although the variables REMARK and TTLFS that are included in the model and kept at their initial values

[25] Note that we keep REMARK and TTLFS equal to their intial distributions 1991Q1 and 1998Q1 in the simulations because we have no model for the dynamics of these variables.

throughout the simulations which, at least in the first period, will tend to give a downward bias in the percentiles. Second, and most importantly, we note that the relative default frequency distribution percentiles at least two times larger for the 1991 portfolio of firms that the 1998 portfolio of firms. This is a clear indication that the micro-data approach using the non-linear default-risk model differ substantially from a pure macro approach, because - as mentioned earlier - a pure macro approach would imply that these numbers come out the same. And since the default risk model is estimated using both cross-section and the time dimension through the inclusion of the macro variables which should result in more reliable parameter estimates, we conclude that the micro-macro approach ought to add a lot of information in comparison to a pure macro approach.

This latter result is quite pronounced, although we have not taken into account in the estimated default-risk model that different branches might display different degree of sensitivity to the macroeconomic stance. And if this is true, and the composition of shares of firms in different branches have changed over time, the results reported in Table 3 would be even more pronounced, and the evidence in favor of the micro-macro based approach even more pronounced.

6.2 Is there a trade-off between real and financial stability?

In this subsection, we compute the impulse response functions to an identified monetary policy shock, and examine if there is a trade-off between stabilizing inflation and output and the default frequency. As in Lindé (2002), the monetary policy shock is identified using the so-called recursiveness assumption adopted by Christiano, Eichenbaum, and Evans (1999, 2001). The assumption being that goods market clear before and financial markets after the central bank set the interest rate. In our empirical model, this implies that output and inflation do not react contemporaneously to a policy shock, whereas the real exchange rate and the default rate do react contemporaneously.

In Figure 8, we show the impulse response functions to a shock to monetary policy in the estimated VAR where the default rate is included as an endogenous variable. There are several features worth noting from this graph. According the VAR, output and inflation fall after an increase in the interest rate, whereas the real exchange appreciates.[26] As in most other studies, the maximum effects are quite delayed in time with peak effects after $1-2$ years. At the same time, there is a significant and persistent rise in the average default rate. Consequently, the

[26] Note that the real exchange rate q_t is defined as $s_t + p_t^f - p_t$, implying that a smaller value being an appreciation.

results in Figure 8 suggest that there is a sizable trade-off between stabilizing the inflation rate and the default rate for monetary policy. If the Riksbank at a given point in time would like to fight inflation more than the rule they normally follow prescribe, thereby injecting a positive policy shock (i.e. an unanticipated increase in the REPO rate), this would lead to increasing default frequencies according to the VAR.

However, if we do the same experiment in our empirical micro-macro model outlined in Section 4, the picture changes dramatically. According to our micro-macro model, the potential trade-off between stabilizing the real economy (i.e. output and inflation) and financial stability (approximated by the default rate) is highly time dependent. In Figures 9 and 10, we plot the impulse response functions for the portfolio of firms 1991Q1 and 1998Q1 to an identical policy shock as in Figure 8 along with the impulse response functions in the estimated VAR model where the default rate is endogenous.[27] As can be seen from Figures 9 and 10, the effects on output, inflation and the default rate is very different in the micro-macro model compared to the aggregate VAR approach. For 1991Q1, the impulse response functions are roughly the same as in the aggregate VAR model, although the persistence in the default rate is somewhat lower due to the fact that there is a lot intrinsic persistence for that variable in the VAR, but none in the estimated logit model. Turning to 1998Q1, however, we see that the picture changes dramatically. In this case, the effects of the same sized policy shock is very different in the micro-macro model than in the aggregate VAR model. In this case, there is no longer evident that there is a clear trade-off between real and financial stability, in any case it is much less pronounced that in the aggregate VAR. Moreover, the different response of the default rate implies that the impulse response functions for output and inflation are very different. The effects on inflation is less than half as big for the 1998Q1 period than in the estimated VAR.

If our estimated micro-macro model is correct, the effects of monetary policy on the economy is very state-dependent. An interesting question, of course, is whether most of these effects comes from the difference in macroeconomic stance rather than the changes in the balance sheet variables of the firms in the portfolio. Unfortunately, we cannot provide clear-cut satisfactory

[27] The impulse response functions in the micro-macro model have been computed as follows. As initial conditions, we use how the portfolio look like in 1991Q4 and 1998Q1, along with the macroeconomic stance. We then compute a "trend path" by doing a dynamic simulation of the model when no shocks are hitting the economy, i.e. u_t^d, u_t^f and $u_{i,t}^y$ are all zero and we use actual values on the macro variables $\{1990Q3, 1990Q4\}$ and $\{1997Q3, 1997Q4\}$ are used as starting values (two lags are used in the VARs). Let X_{t+h}^{trend} denote the computed trend default rate at horizon $h = 1, 2, ..., 20$. Second, we make an additional simulation using exactly the same initial conditions but this time we allow for the policy shock hitting the economy (i.e. u_t^d is non-zero). Let X_{t+h}^{shock} denote the computed default rate at horizon $h = 1, 2, ..., 20$ in this case. The impulse responses are then computed as $X_{t+h}^{shock} - X_{t+h}^{trend}$ for each variable in X.

answer to this question. The reason being that the population of existing firms in a given period is most likely to be dependent on the stance of the macroeconomy and although we cannot find any evidence in favor of aggregate shocks affecting the existing firms balance sheet ratios, we cannot preclude that the population of existing firms itself is dependent on the macroeconomic stance because banks credit policies may hinder new firms to enter. But the estimation results for the default risk model I and III, are suggestive that the different macroeconomic stance might play a larger role than the firms balance sheets.

6.3 Joint forecasts of default-frequency and inflation

In this last subsection, we use the empirical model to produce joint forecasts of the default-frequency and inflation rate. We use the same initial conditions as in the previous sections. We do this for two quarters, $1991Q1$ and $1998Q1$, i.e. the beginning of a recession and the beginning of boom in the economy. To produce these forecasts and associated uncertaintly bands, we perform $1,000$ simulations with the estimated model 8 quarters into the future. This produces $1,000$ projections in period $t+1,...,t+8$ for the default frequency and inflation. The resulting forecasts and uncertainty bands are shown in Figure 11. The dashed line is the median forecast, the and the dotted lines represent the 2.5 and 97.5 percentiles in the simulated distributions. The solid line shows the actual outcome for $1991Q2-1993Q1$ (left panel) and $1998Q2-2000Q1$ (right panel). There are a couple of interesting features worth noting. First, the model forecasts the actual inflation and default frequency quite well. In the forecast starting $1998Q1$, the actual default frequency below the 95 percent confidence interval in one quarter. It should be noted that since the default risk model is only estimated on data up to $1999Q2$, this forecast is to some extent out-of-sample. Second, confirming the results reported in Table 3, we see that the uncertainty is much lower in the $1998Q1$ forecast. The width of the 95 percent confidence intervals are around 2 and 11 percent for the default frequency and the inflation rate in the $1991Q1$ forecast, while they are only 0.4 and 6 percent for the $1998Q1$ forecast. [**It would be very interesting to compare the RMSE and MAPE for our model with those in the aggregate VAR where the aggregate default frequency is included as an endogenous variable.**]

7 Conclusions

Literature on how real economy affects financial system: businesses balance sheets, VAR's

Credit risk literature

Trade-off between effects of interest rate changes on real economy and financial stability?

Describe that BRANCH analysis should be done in future.

Third, we cannot draw to strong conclusions regarding the existence of the so-called credit-channel based on the weak effects of aggregate shocks on balance sheet ratios, because a lot of new loans may not have been granted.

What's the gain in using micro data for the financial sector? Can explain idiosyncratic part of the movement in credit losses / mean default rate

Correlation credit losses and mean default rate = approx. .98

Talk about how the results relate to the existence of a quantitatively important bank-/credit-channel of monetary policy.

[**Remains to be written.**]

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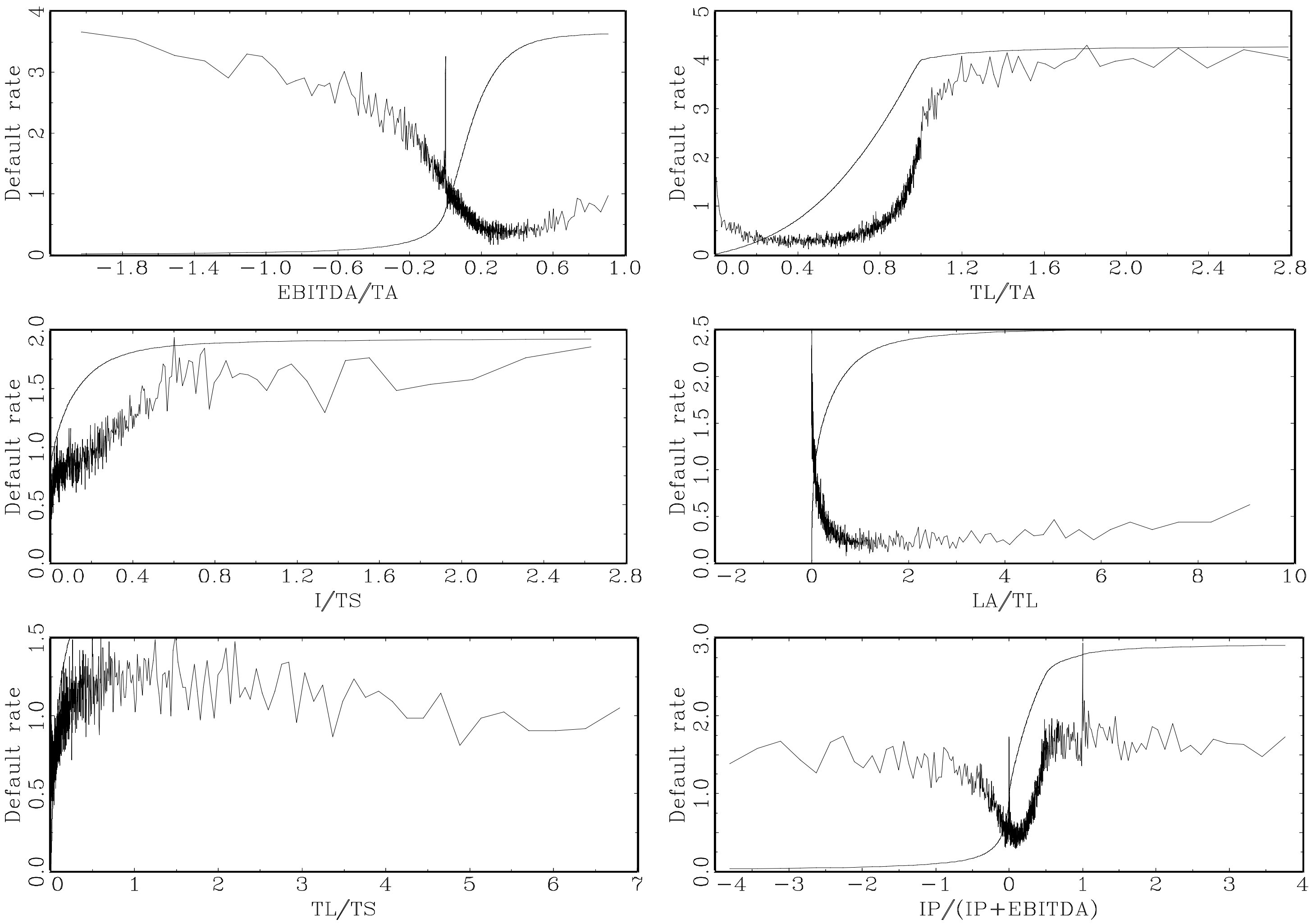

Figure 1: Default rates and the cumulative distribution functions for the accounting data.

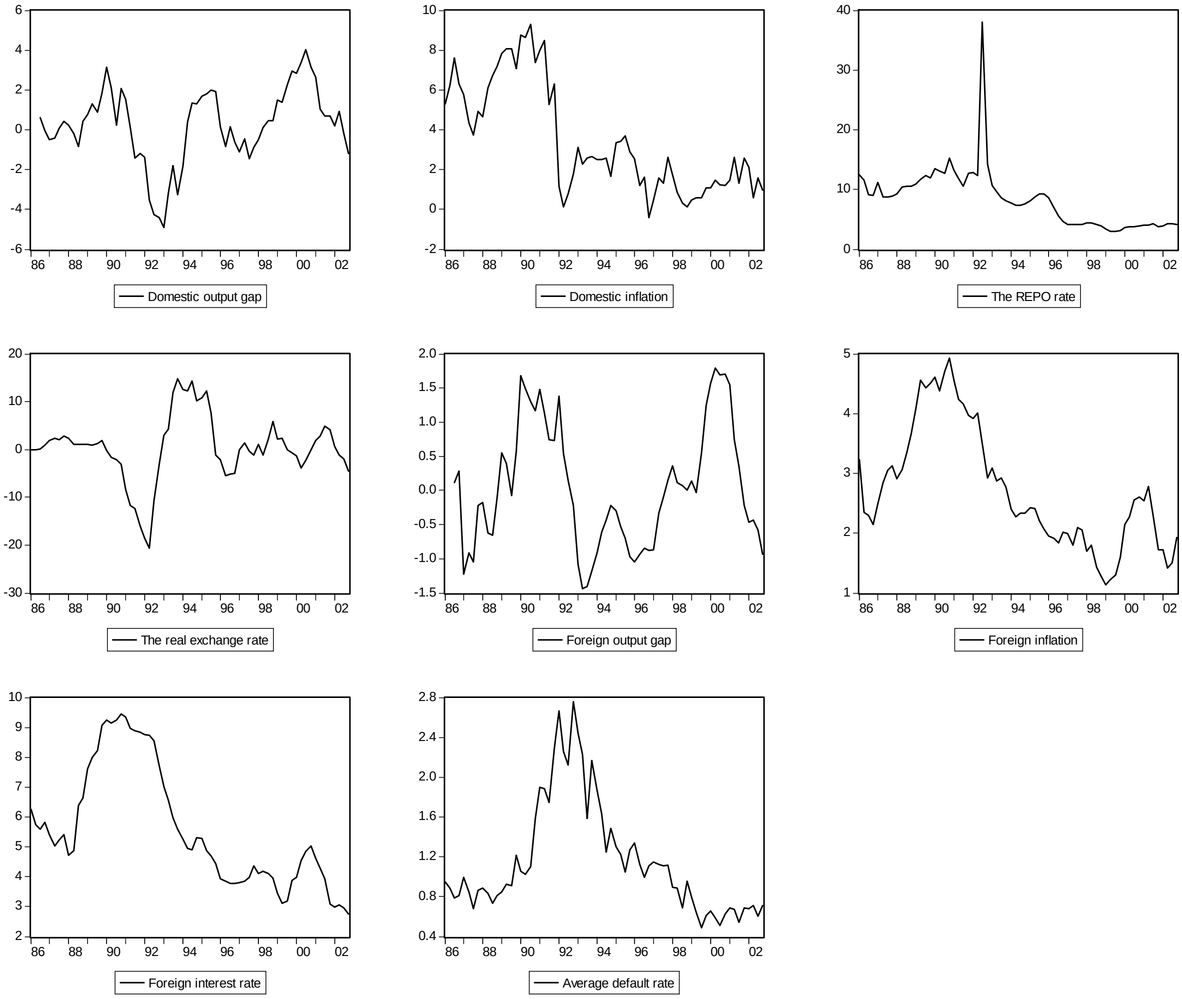

Figure 2: Macro data used in the estimated VAR models.

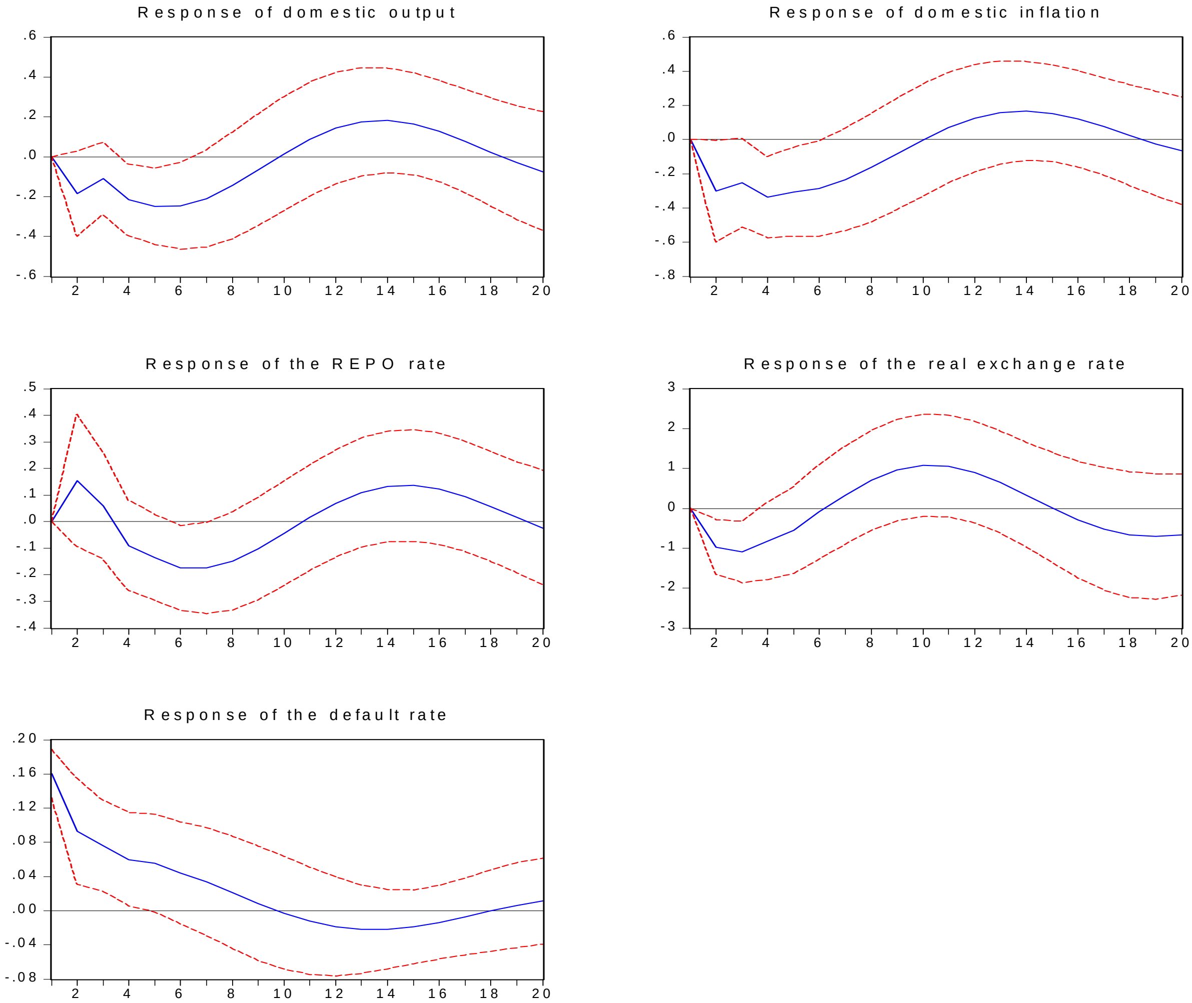

Figure 3: Impulse response functions to a aggregate default frequency shock in the estimated VAR where default frequency is included in X_t.

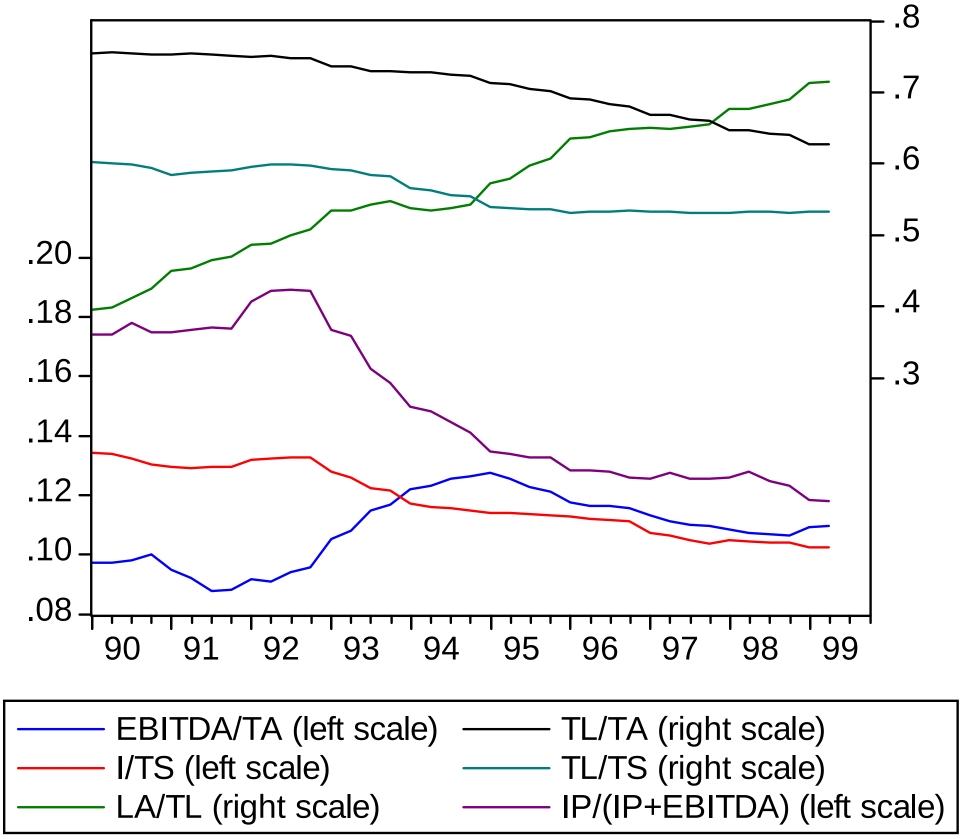

Figure 4: Averaging accounting data over time $1990Q1 - 1999Q2$ in the panel.

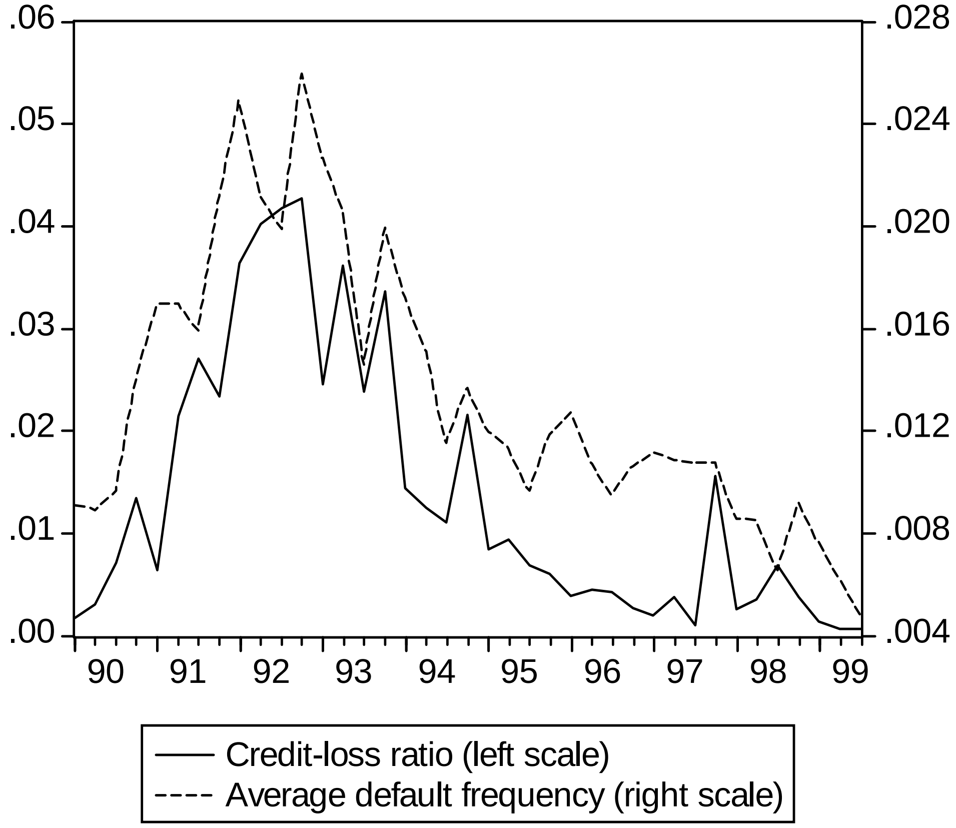

Figure 5: Average default frequency over time in the panel and credit losses by non-financial firms relative to loan stock.

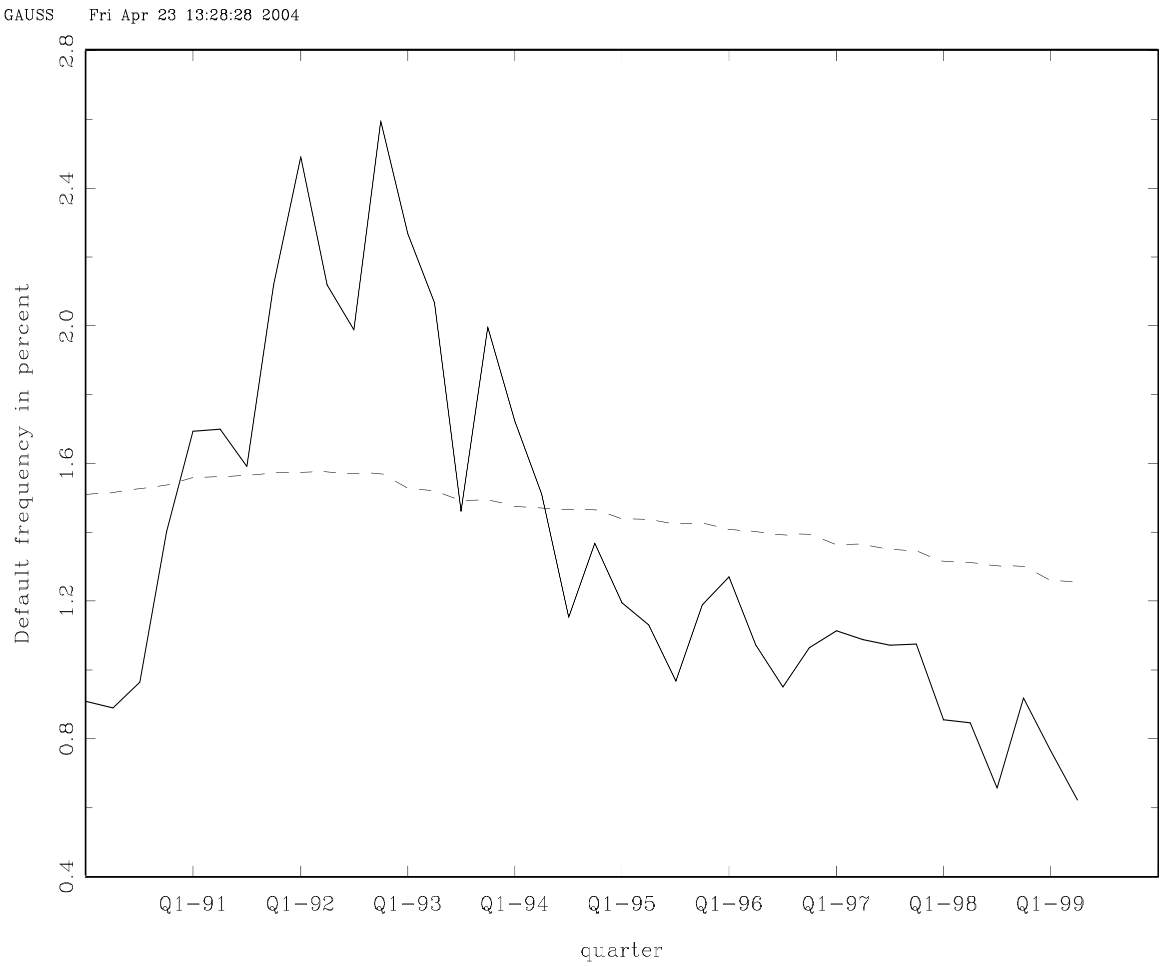

Figure 6: Actual and projected default rates at the aggregate level in the estimated default-risk model with only balance sheet variables included (Model I).

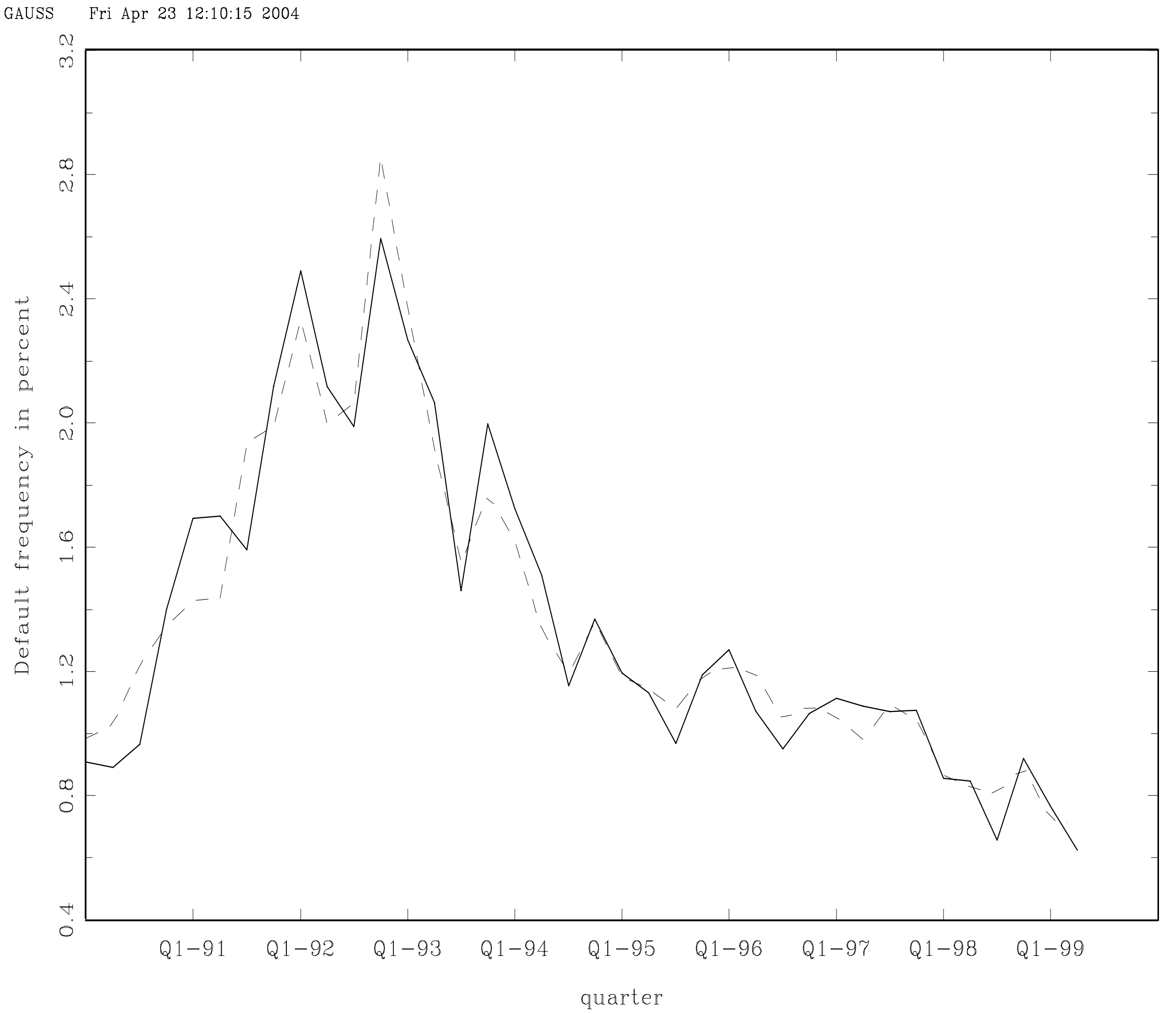

Figure 7: Actual and projected default rates at the aggregate level in the estimated default-risk model with macro variables (Model III).

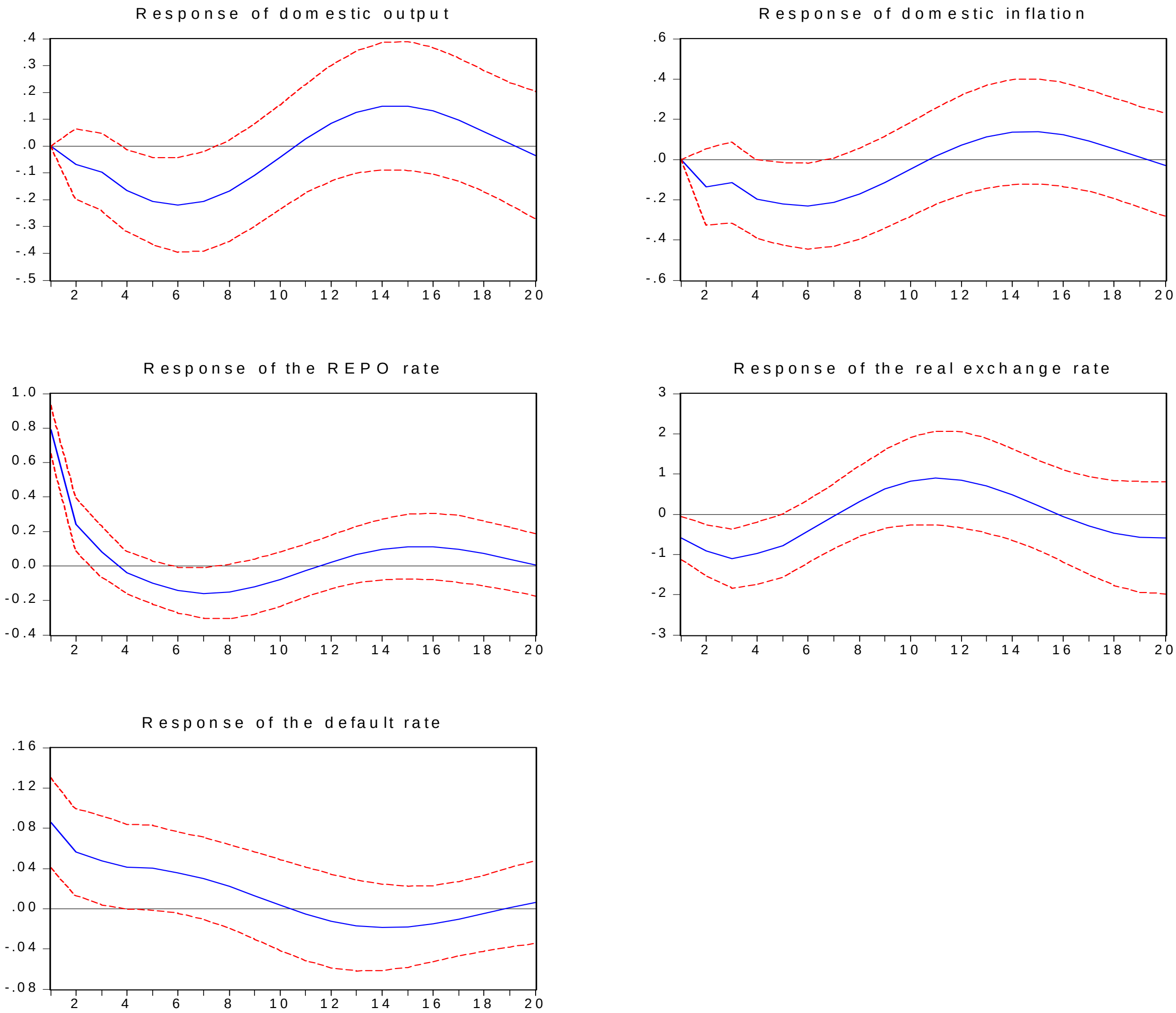

Figure 8: Impulse response functions to an identified shock to monetary policy in the VAR model where the default rate is endogenous. Solid line shows point estimates and dashed lines 95 percent confidence interval.

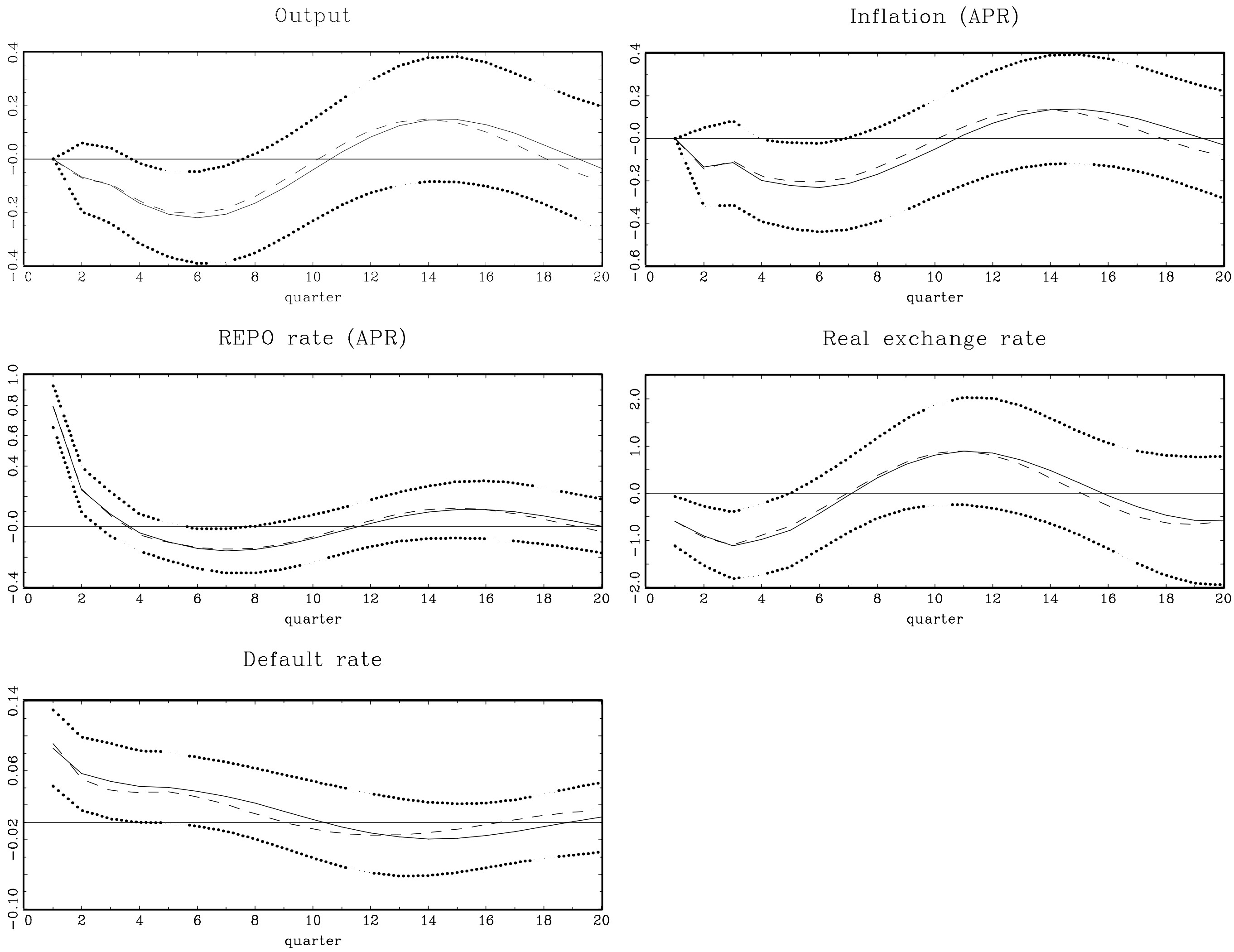

Figure 9: Impulse response functions in the estimated VAR model with the default rate endogenous (point estimates - solid line, dotted lines shows 95 percent confidence interval) and in the empirical micro-macro model (dashed line) for $1991Q1$.

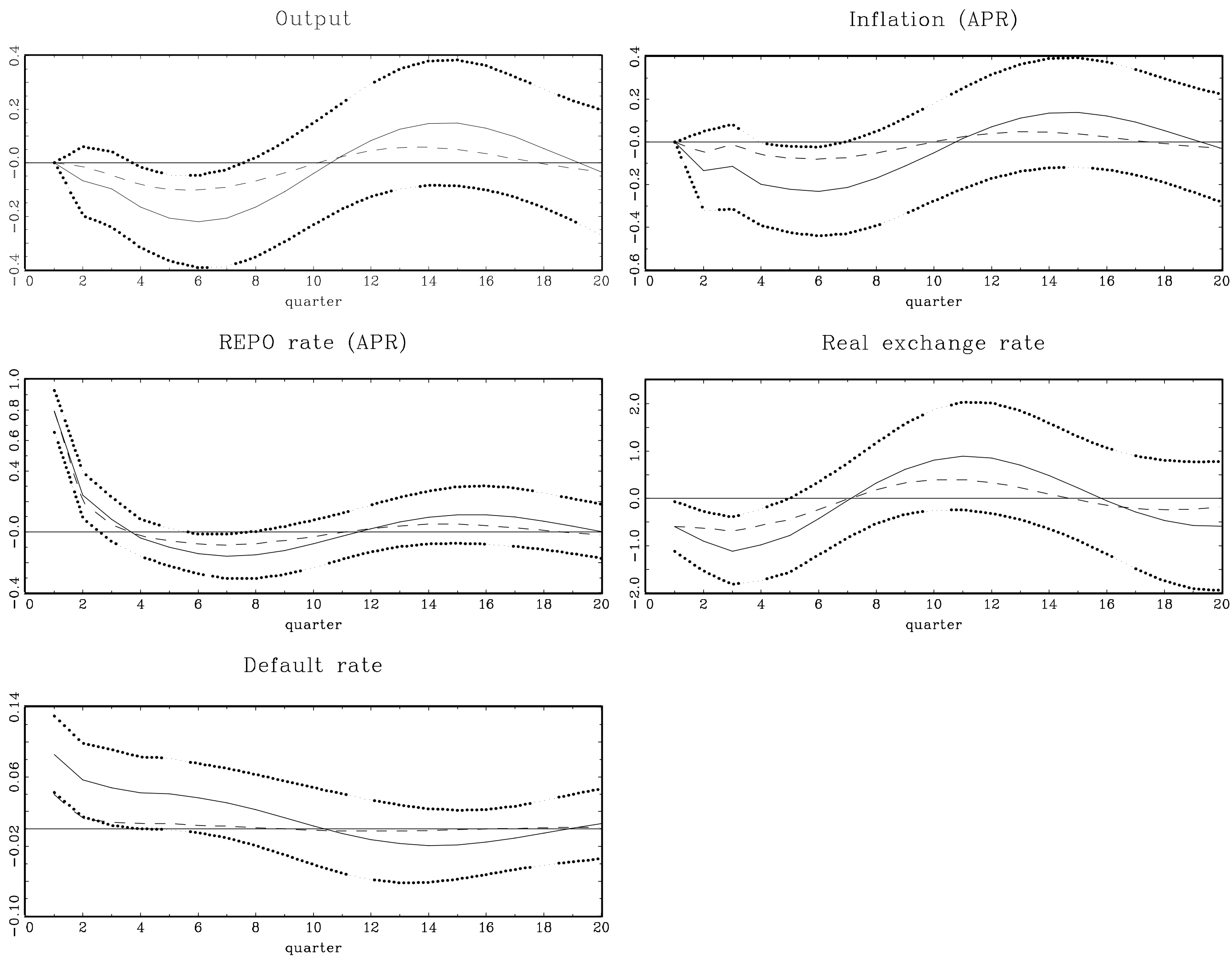

Figure 10: Impulse response functions in the estimated VAR model with the default rate endogenous (point estimates - solid line, dotted lines shows 95 percent confidence interval) and in the empirical micro-macro model (dashed line) for 1998Q1.

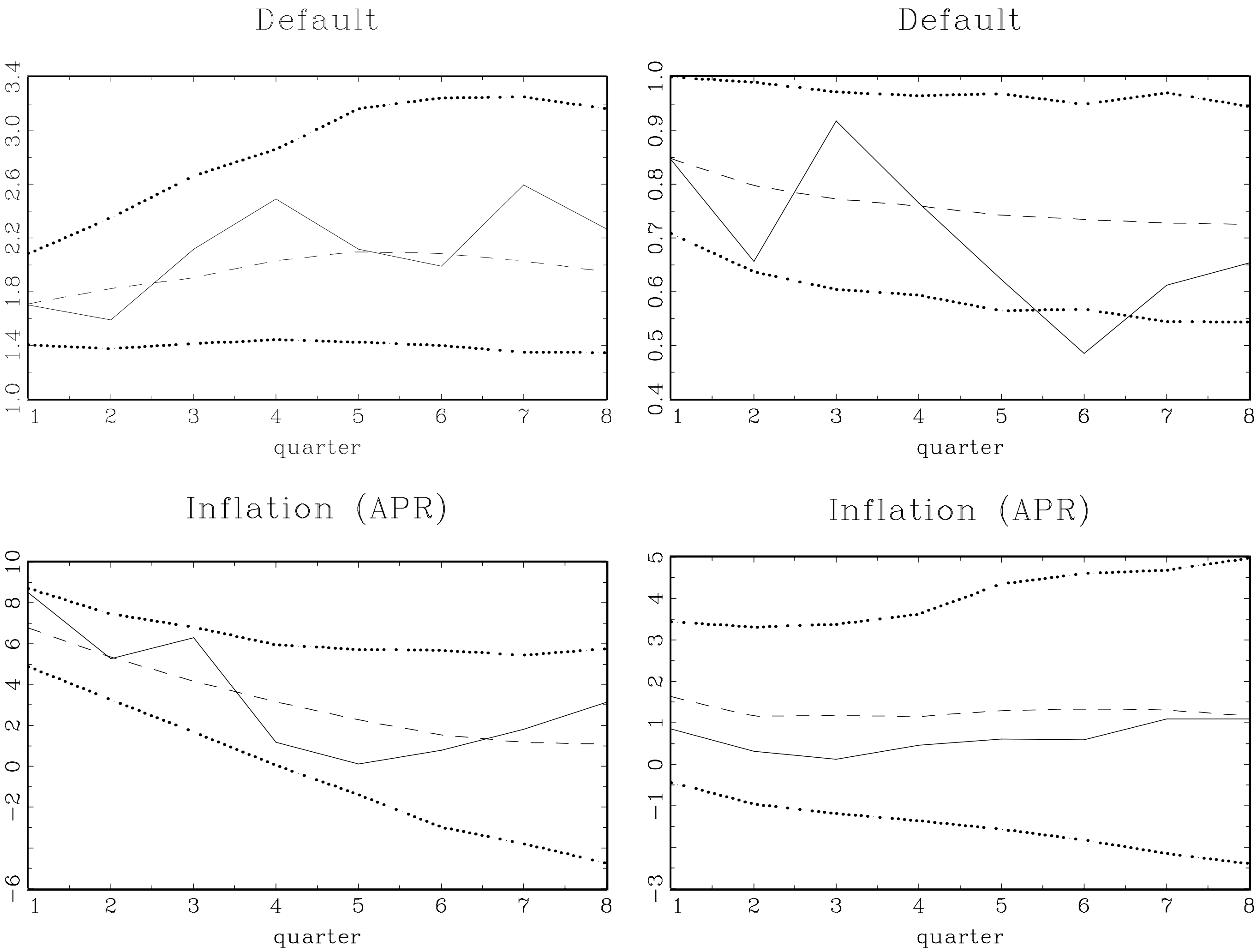

Figure 11: Joint forecasts of the default frequency 8 quarters ahead starting 1991Q1 (left panel) and 1998Q1 (right panel). Dashed line is the median forecast, and the dotted lines indicate the 95 percent cofidence interval. The solid line shows the actual outcome.