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 financial variable on the real economy. 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 the impulse responses of a given shock will be time dependent of the portfolio structure in any given point in time.

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

JEL: C41, G21, G33, G38, ??

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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 macro-economic 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, $1990Q1 - 1999Q4$ (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 definition of default is adopted from 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 for the defaulted firms.[7] As is visualized in the part A of Table 1, which shows non-truncated

[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 ??.

[7] Imputing the mean for missing values may lead to underestimation of standard errors. Little and Rubin

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 0.5 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] [**Should do robustness check with this fraction.**]

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, but the ones reported showed the most strong correlation

(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.

[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 REMARK 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. To check the robustness of our chosen approach, we used an alternative approach where we truncated 0.5 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.

with default risk.[10] In our empirical model, we employ four accounting ratios: earnings before interest, depreciation, taxes and amortization over total assets (earnings ratio); total liabilities over total assets (debt ratio); cash in relation to total liabilities (cash ratio); and inventories over total sales (turnover ratio). These four 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 displayed a clearly non-monotonic relation or lacked any correlation with default risk were deleted from the set of candidate explanatory variables. Figure 1 illustrates this for the four 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. There is a positive relationship between default risk and the leverage and turnover ratios, while the figure suggests a negative relationship with both the earnings and the liquidity ratios. Thus, Figure 1 confirms the picture in Table 1 which shows that there is a clear difference between healthy and defaulted firms for these variables

The above process led to the selection of six candidate variables: the four described above and two other (total sales and total assets). In a second step, their multivariate properties were studied by estimating a couple of permutations of the empirical model. Neither of two additional variables turned out to make any significant contribution in the empirical model and were therefore disregarded.

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

Table 1: Descriptive statistics for the micro data.

Part A: Non-truncated data

		Statistic						
Firm Type	N	μ	σ	min	1%	50%	99%	max
Non-defaulted	7549041							
EBITDA/TA	7471212	-0.11	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
REMARK (%)	7549041	0.33	5.77	0				1
TTLFS (%)	7549041	1.54	12.30	0				1
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
REMARK (%)	103567	14.90	35.61	0				1
TTLFS (%)	103567	33.42	47.17	0				1

Part B: Truncated data

		Statistic						
Firm type	N	μ	σ	min	1%	50%	99%	max
Non-defaulted	7549041							
EBITDA/TA	7471212	0.11	0.28	-1.84	-1.03	0.11	0.85	1.18
TL/TA	7474248	0.72	0.43	0.01	0.03	0.73	2.42	4.28
LA/TL	7451325	0.56	1.39	0	0	0.13	7.66	12.99
I/TS	7355762	0.14	0.45	0	0	0.01	2.18	4.87
REMARK (%)	7549041	0.33	5.76	0				1
TTLFS (%)	7549041	1.54	12.30	0				1
Defaulted	103567							
EBITDA/TA	67093	-0.05	0.45	-1.84	-1.84	0.03	1.18	1.18
TL/TA	67110	1.06	0.74	0.01	0.01	0.94	4.28	4.28
LA/TL	66729	0.24	1.13	0	0	0.02	4.87	13.84
I/TS	63138	0.22	0.63	0	0	0.03	4.87	4.87
REMARK (%)	103567	14.90	35.61	0				1
TTLFS (%)	103567	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; REMARK = 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; 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 variable, we employ the same approach as in Carling et al. (2001) and used a simple dummy variable approach by setting it to1 if certain remarks existed for the firm during the year prior to the quarter, and 0 otherwise.[11] An intuitively reasonable starting point was

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

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".

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.[12] 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.

Finally, it should be emphasized that our choice of using the average default frequency for firms limited by shares as measure of the financial stance of the economy may not be the ideal variable. However, there is some evidence in favor of our choice. First, as shown in Figure 2, 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.[13] 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 (**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 2 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. Fourth, there are many alternative measures of the financial stance of the economy, e.g. stock prices or housing prices, but we think that our variable are more direct and broadly linked to the banking industry.

[12] 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, 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 credit-risk model, the construction of this variable is rather down-playing its importance that overstating it.

[13] 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.

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 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.[14] Because there is a strong trend for the real exchange rate during the sample period, this variable is detrended as well.[15] 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 interaction between the real and financial economy

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

[14] 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.

[15] 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.

specified as

$$X_t = C + \delta_1 D_{923} + \delta_2 D_{931013} + \tau T_t + \sum_{i=0}^{p} \Upsilon_i Z_{t-i} + \sum_{i=1}^{p} \Gamma_i X_{t-i} + u_t^d \tag{1}$$

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 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

$$\begin{aligned} X_t &= \begin{bmatrix} y_t^d & \pi_t^d & R_t^d & q_t \end{bmatrix}' \\ &\text{and} \\ Z_t &= \begin{bmatrix} y_t^f & \pi_t^f & R_t^f \end{bmatrix}'. \end{aligned} \tag{2}$$

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.

As motivated in the previous section, we conjecture that the real economy is important for the financial variable that we study here, the aggregate default rate of firms limited by shares. We will examine this conjecture more thoroughly in the next section, when we estimate the credit-risk model and the process for the financial ratios. Therefore, what we want to do in this section is to test if there is a feedback from the financial sector into the real side of the economy.

One natural way to do this 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 4, 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 5) 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. 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. Moreover, this is an additional argument for using the default rate as the link between the real and the financial side of the economy.

The conclusion from these results is that 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.

4 A simple empirical micro-macro model of the interaction between the real and financial economy

In this section, we will develop a simple, but complete model that can be used to study the interaction between the real and financial side of the economy. The model is estimated using both firm specific and aggregate data. As already mentioned in the introduction, the model consists of three blocks; (i) VAR models for the domestic and foreign variables that are estimated on aggregate data, (ii) a credit-risk model for the default risk estimated at the firm level, and

(iii) a model of the financial ratios that enters into the credit-risk model. We will describe each of these models here and present estimation results.

4.1 The VAR models

To describe the dependence of the domestic real side of the economy on the financial side and foreign variables, we estimate the VAR model in (1) augmented with the average default frequency as an exogenous variable. 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

$$Z_t = C_f + \tau_f T_t + \sum_{i=1}^{2} B_i Z_{t-i} + u_t^f \tag{3}$$

Thus, the VAR model given by (1) with the terms $\sum_{i=1}^{2} \Lambda_i df_{t-i}$ added and the VAR model above for the foreign variables describe the evolution of the macro variables in the empirical model.

4.2 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 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.[16] The reason why there is a need to include aggregate variables in the model is clear from by inspection of Figures 5 and 2. In Figure 5, we plot the mean values of the idiosyncratic financial variables that are used in the model $1990Q1 - 1999Q2$. It is obvious that there is 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

[16] 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.

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 are included. 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 2 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 3 that there has been some variation the output gap 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 a lot with the introduction of the inflation targeting regime 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, a higher inflation 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).[17]

Because we have as many as $7,652,609$ quarterly observations, the computer program that we used to do the Maximum Likelihood estimation of the logit model (GAUSS version 3.5) could

[17] 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.

not handle all observations simultaneously. We therefore made a random selection of 23-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 increased the sample selection to 24 percent of the observations and reestimated the model. Fortunately, we found convergence in parameter at the three digit level and the estimation results in Table 2 are thus based on the 24 percent sample. 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 REMARK and TTLFS added, and finally one with the macroeconomic variables added.

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

	Model I		Model II		Model III	
Type of regressor	Coefficient	Std error	Coefficient	Std error	Coefficient	Std error
Constant	−4.6491	0.0126	−5.0292	0.0145	−5.8392	0.0270
Idiosyncratic variables[a]						
EBITDA/TA	−0.6197	0.0160	−0.5564	0.0174	−0.5501	0.0176
TL/TA	0.5668	0.0092	0.4813	0.0103	0.4956	0.0105
LA/TL	−0.3421	0.0141	−0.5029	0.0170	−0.4710	0.0168
I/TS	0.1804	0.0094	0.1517	0.0109	0.1464	0.0110
REMARK (%)			3.3313	0.0267	3.5891	0.0275
TTLFS (%)			3.4259	0.0164	3.3921	0.0166
Aggregate variables[b]						
Output gap					−0.0856	0.0042
Inflation rate					0.0075	0.0042
Nominal interest rate					0.0798	0.0033
The real exchange rate					−0.0057	0.0008
Mean log-likelihood	−0.0686		−0.0558		−0.0550	
Number of observations	1,836,625		1,836,625		1,836,625	

Notes: [a] See Subsection 2.1 for exact definition of these variables. [b] 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. The estimations was conducted in GAUSS version 3.5. The results are based on a random sample of 24 percent of the total sample such that the aggregate default rate over time coincides with the default rate for the total panel. Convergence of the parameters at the 3-digit level were checked by estimating the model on sample consisting of 23-percent of the panel.

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 ag-

gregate 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 completely Model III. Of the accounting data variables, the turnover ratio inventories over total sales are least important. Given that the diagram for this variable in Figure 1 shows the least strongest sign of correlation with default, this outcome is not surprising and strengthens the selection approach of variables adopted in the paper. If a firm obtains a REMARK or TTTFS, the estimated risk of default increases by XX and YY times, respectively. The predictive power of the accounting data is somewhat more modest, although the liability-to-assets ratio (TL/TA) is quite useful, confirming the evidence reported by Carling et al. (2001).

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.

In Figures 6 and 7, we plot the aggregate default rate together with the average predicted default rate from the model for Model II (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 micro 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 91 percent at the aggregate level whereas it is as low as 11 percent in the model without macro variables. 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.[18] 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 disaggregate level, because the model at the microeconomic level gives a better fit at the aggregate level without any intrinsic dynamics in the model.

4.3 The model for the financial ratios

To close the model and set it up for useful simulations, we need to specify a process for the financial ratios EBITDA/TA, TL/TA, and LA/TL that are included in the credit-risk model. An interesting question is to what extent they are driven by macroeconomic factors and to what extent they are living their own life. The are good reasons to believe that some of the financial 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, the net effect on EBITDA/TA is not obvious.

Let $Y_{i,t} = [\text{EBITDA/TA}_{i,t}\ \text{TL/TA}_{i,t}\ \text{I/TS}_{i,t}\ \text{LA/TL}_{i,t}]'$ denote a 4×1 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 $4 \times N_t$ 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

$$Y_t = \Theta_Y Y_{t-1} + \Theta_X X_{t-1} + u_t^y,\ \text{var}\,(u_t^y) = \Sigma_Y \tag{4}$$

where X_t is defined by (2). In this draft of the paper, each equation in (4) is estimated with OLS using $3,341,928$ observations that are constructed from the original dataset consisting of all the $7,652,609$ observations.[19] The OLS estimation results of (4) are

$$\Theta_Y = \begin{bmatrix} 0.879 & 0.015 & -0.006 & 0.001 \\ -0.013 & 0.964 & 0.003 & 0.000 \\ -0.006 & -0.001 & 0.920 & -0.000 \\ 0.009 & -0.066 & -0.005 & 0.916 \end{bmatrix},\ \Theta_X = 100 * \begin{bmatrix} 0.030 & -0.016 & -0.003 & 0.024 \\ -0.022 & 0.005 & 0.009 & 0.007 \\ -0.028 & -0.001 & 0.052 & -0.003 \\ -0.056 & -0.123 & -0.143 & -0.014 \end{bmatrix},$$

[18] 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.

[19] Note that the number of observations that can be used to estimate (4) is lower than the total number of observations in the panel for two reasons. First, because only firms covering two subsequent quarters can be included, and second, due to computer limitations (we used a 2.5 Ghz computer with 2 GB internal memory).

$$\Sigma_Y = \begin{bmatrix} 0.018 & -0.006 & -0.001 & 0.002 \\ -0.006 & 0.016 & 0.001 & -0.015 \\ -0.001 & 0.001 & 0.032 & -0.003 \\ 0.002 & -0.015 & -0.003 & 0.303 \end{bmatrix}.$$

We see that there is considerable persistence in the variables, partly as a consequence of how they are constructed (mapping typically annual reports to quarterly data). The macro parameters are seemingly small, the macro variables account for 5, 30, 15, and 3 percent, respectively of the fluctuations in the financial ratios included in Y_t according to these estimates, so in this version of the paper the accounting ratios are mostly living their life on their own.[20] [**These estimations should be redone with the Arellano and Bond (**1991**) estimation procedure.**]

5 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 when computing default frequency distributions with the model. That is, we will examine why we think it is better to include the estimated credit-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.

5.1 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 (3), and the process for the financial ratios (4). As initial conditions, we use how the portfolio look like in $1991Q4$ and $1998Q1$, along

[20] Assuming that the unconditional variance in X_t are unaffected by the variables in Y_t, which seems as a reasonable approximation for reasons discussed in Section 3, the contribution of the macro variables to fluctuations in Y_t can read off the diagonal elements in the matrix $\frac{(I-\Theta_Y)^{-1}\Theta_X\Sigma_X}{(I-\Theta_Y)^{-1}\Theta_X\Sigma_X+(I-\Theta_Y)^{-1}\Sigma_Y}$.where Σ_X is the covariance matrix of X_t. By the way these number have been computed, they will overstate the importance of the macro variables since the balance sheet ratios indirectly contribute to fluctuations in the macro variables via the aggregate default rate.

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 $\{1990Q3, 1990Q4\}$ and $\{1997Q3, 1997Q4\}$ 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.[21]

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 the micro data approach differ from a pure macro approach.

[21] 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.

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	1.76	2.28	2.43	2.32	1.03	1.05	1.07	1.11
99-percent	1.85	2.49	2.76	2.58	1.10	1.13	1.17	1.20
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	0.25	0.63	0.84	0.86	0.12	0.24	0.29	0.34
99-percent	0.34	0.84	1.17	1.12	0.19	0.33	0.39	0.44

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 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 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.

5.2 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.[22] 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 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 rates 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.[23] As can be seen from Figures 9 and 10, the effects on

[22] 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.

[23] 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

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 aggregate VAR model since the firms balance sheets are in a much better condition. 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 effect 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. The results provide clear evidence in favor of the existence of a quantitatively important bank-/credit-channel of monetary policy.[**We should analyze if most of these effect comes from the difference in macroeconomic stance rather than the changes in balance sheet variables of the firms in the portfolio.**]

Thus, we conclude that a micro-macro approach ought to be a lot more informative when forecasting the macroeconomy and assessing the financial stance of the economy than the standard aggregate approach.

6 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

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

$\{1997Q3, 1997Q4\}$ 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.

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

[**Remains to be written.**]

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A Exact definition of firm specifc variables

SAOMSTIL = Current Assets

SAKORTSK = Current Liabilities

SATILLG = Total Assets

LIKVID = Cash

VARULAG = Inventories

SALONGSK = Long Liabilities

LEVSKULD = Accounts Payable

SAANLTIL = Fixed Assets

SAEGETKA = Total Equity

OMSAETT = Total Sales

RESFOEAV = Earnings bef. Interest, Depreciation and Amortizations

ANTANS = No. employees

LOENER = Wages

AVSKRIVN = Depreciation

FININT = Financial income

FINKOST = Financial costs

EXTORDIN = Extraordinary costs

EXTORDKO = Extraordinary income

SKATT = Taxes

KUNDFORD = Accounts receivable

OVOMSTIL = Other liquid assets

SPAERRKO = Blocked accounts (e.g escrows)

GOODWILL = Goodwill

INVENT = Machinery etc

OBESRES = Untaxed reserves

AKTIEKAP = Nominal equity

OVREGBUN = Other Equity

SASKOEGE = Sum of taxes and equity (equals total assets)

SCBSNIKO = Statistics Sweden industry code

SCBSTKL = Statistics Sweden company size code

ORGNR = Company's 10 figure identification number

PANTER = Total of property pledges for non-mortgage loans)

ANSVAR = Total guaranties assumed for third party loans

SAFTGINT = Total of property pledges for mortgages in public register

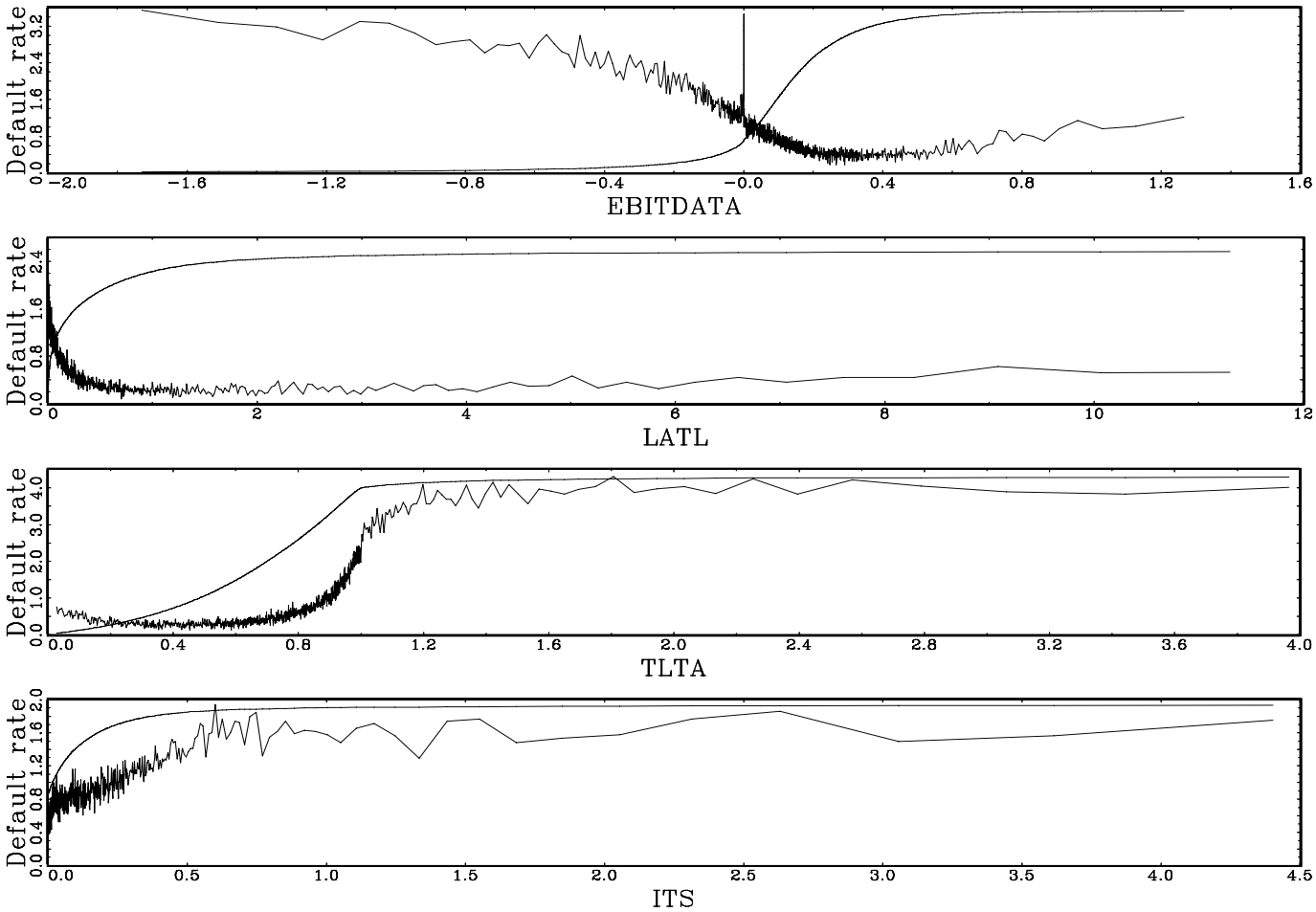

Figure 1: Default rates and the cumulative distribution functions for the accounting data.

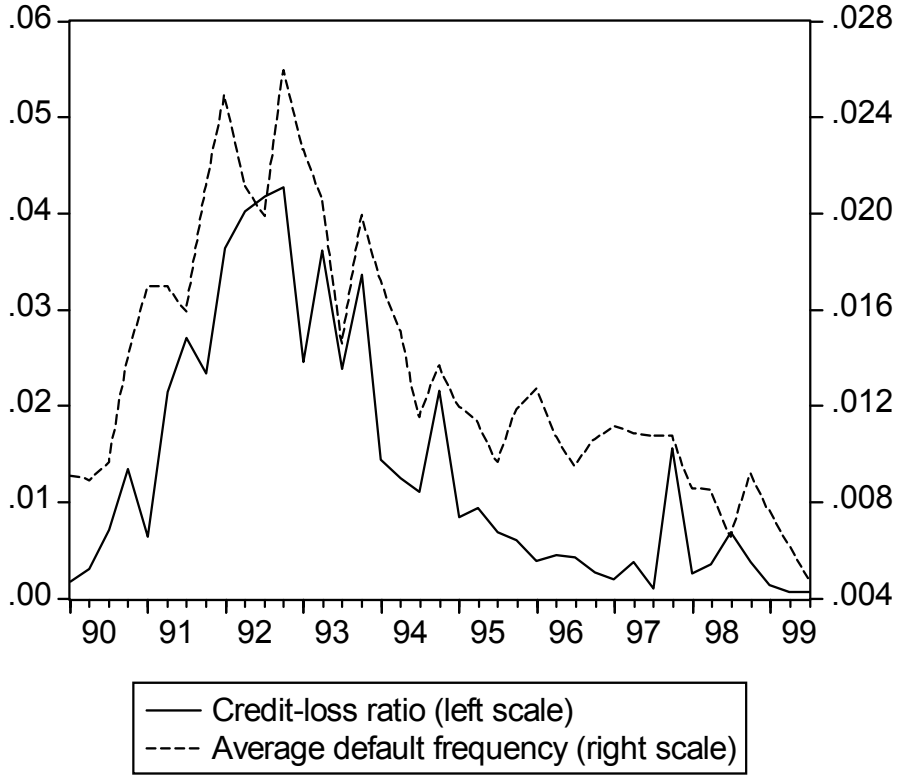

Figure 2: Average default frequency over time in the panel and credit losses by non-financial firms relative to loan stock.

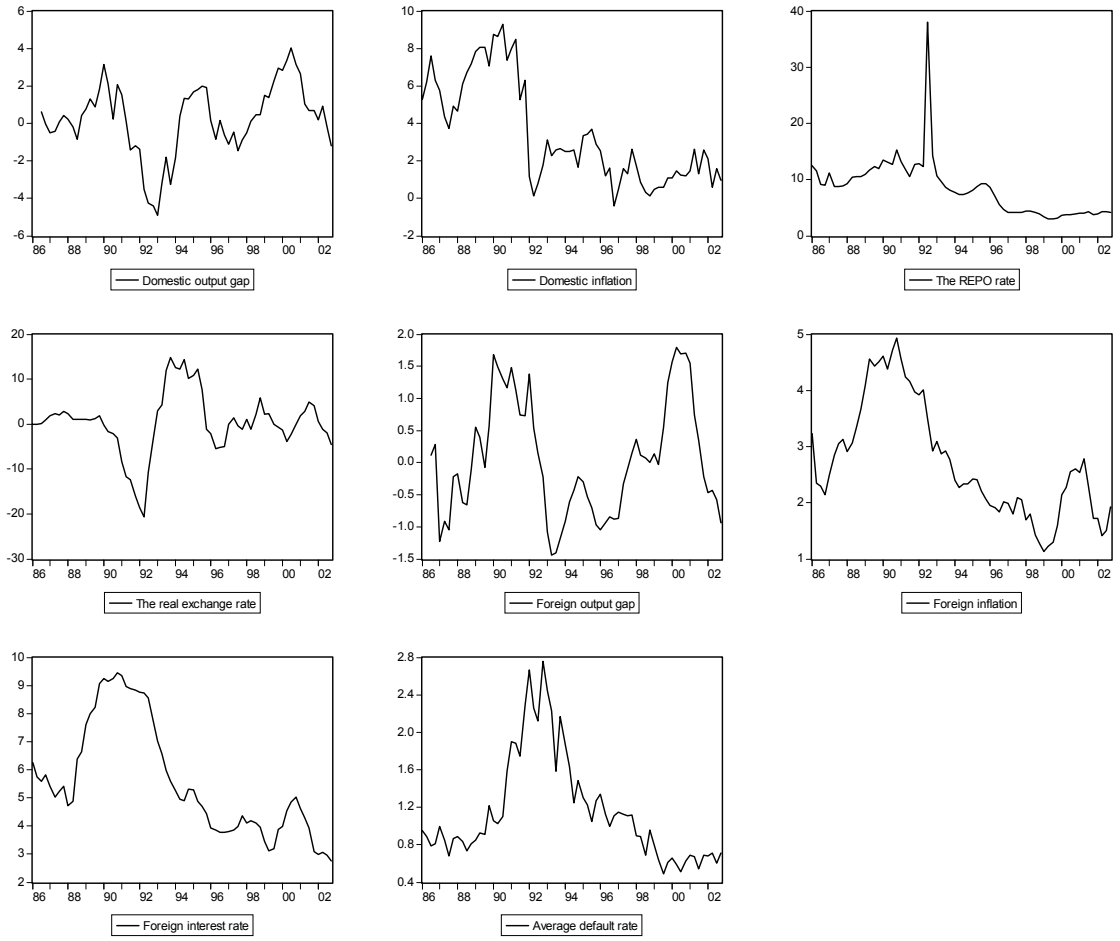

Figure 3: Macro data used in the estimated VAR models.

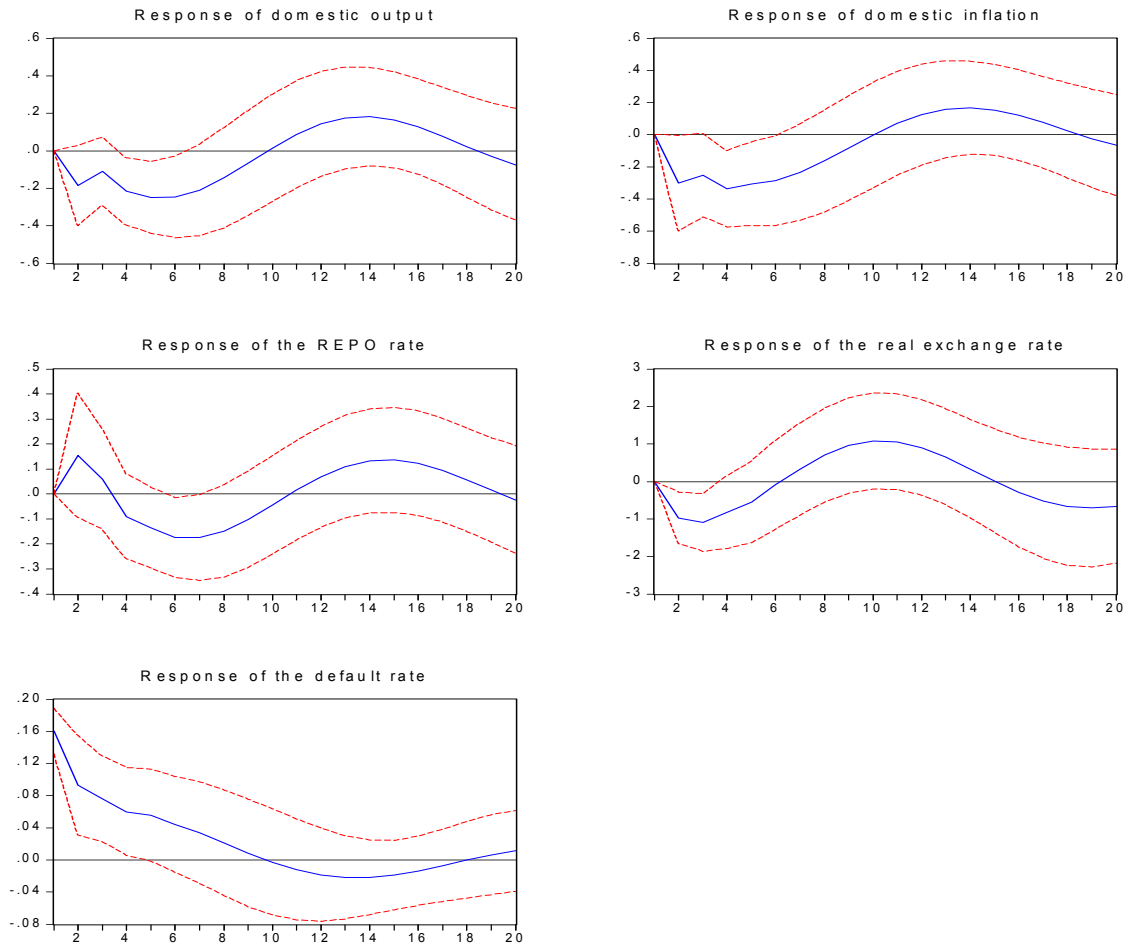

Figure 4: Impulse response functions to a aggregate default frequency shock in the estimated VAR where default frequency is included in X_t.

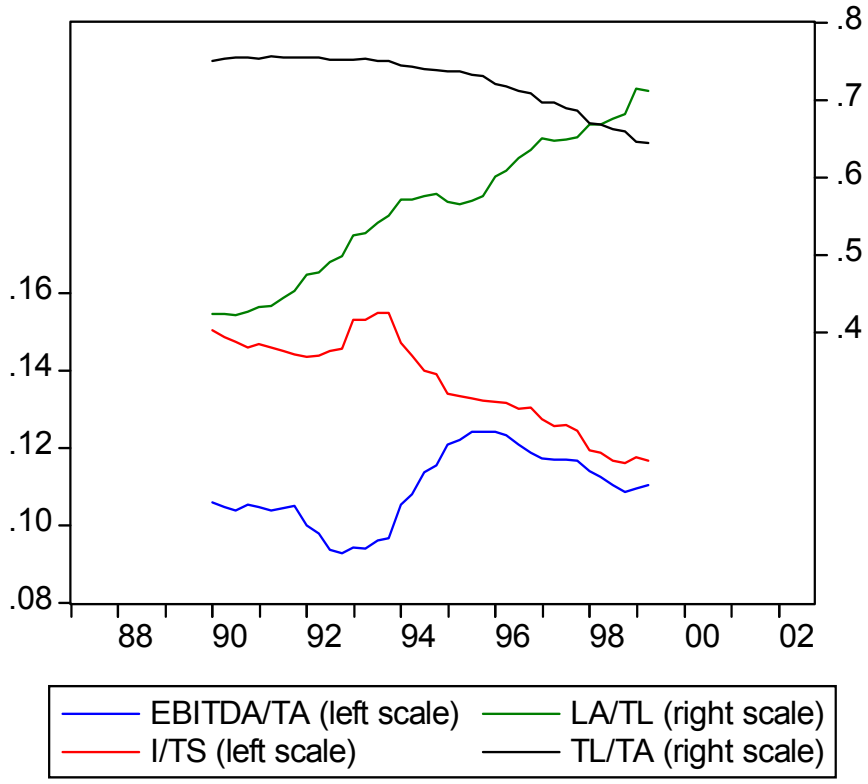

Figure 5: Averaging accounting data over time $1990Q1 - 1999Q2$ in the panel.

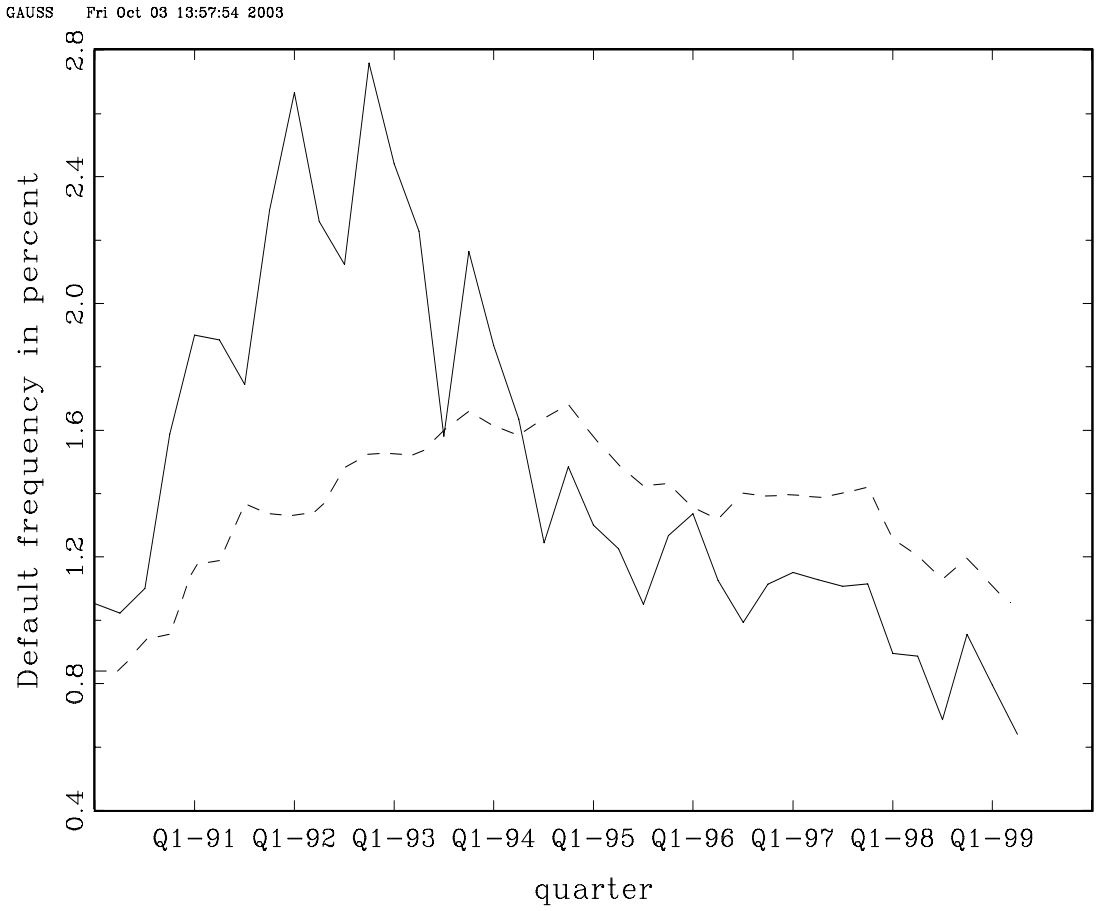

Figure 6: Actual and projected default rates at the aggregate level in the estimated default-risk model with only firm specific variables included (Model II).

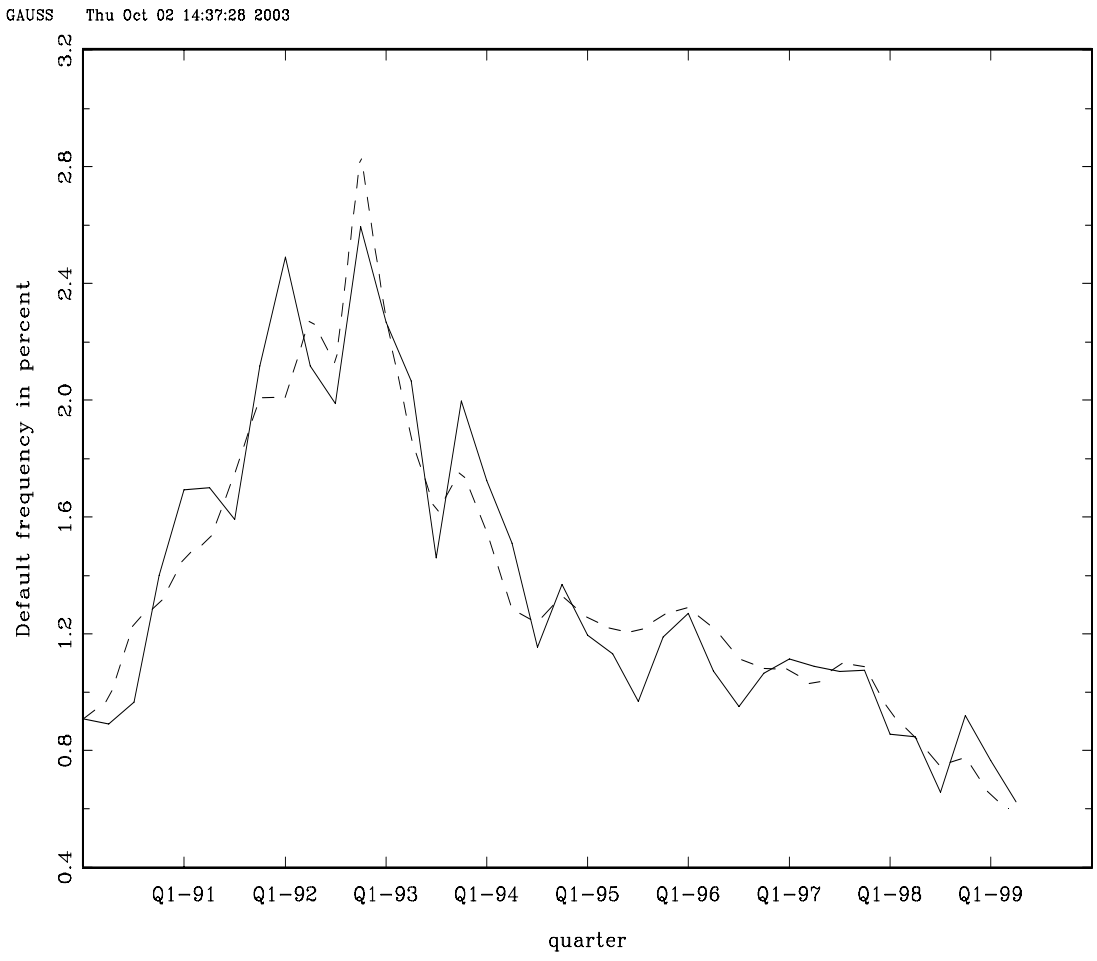

Figure 7: Actual and projected default rates at the aggregate level in the estimated default-risk model with macro variables (Model III).

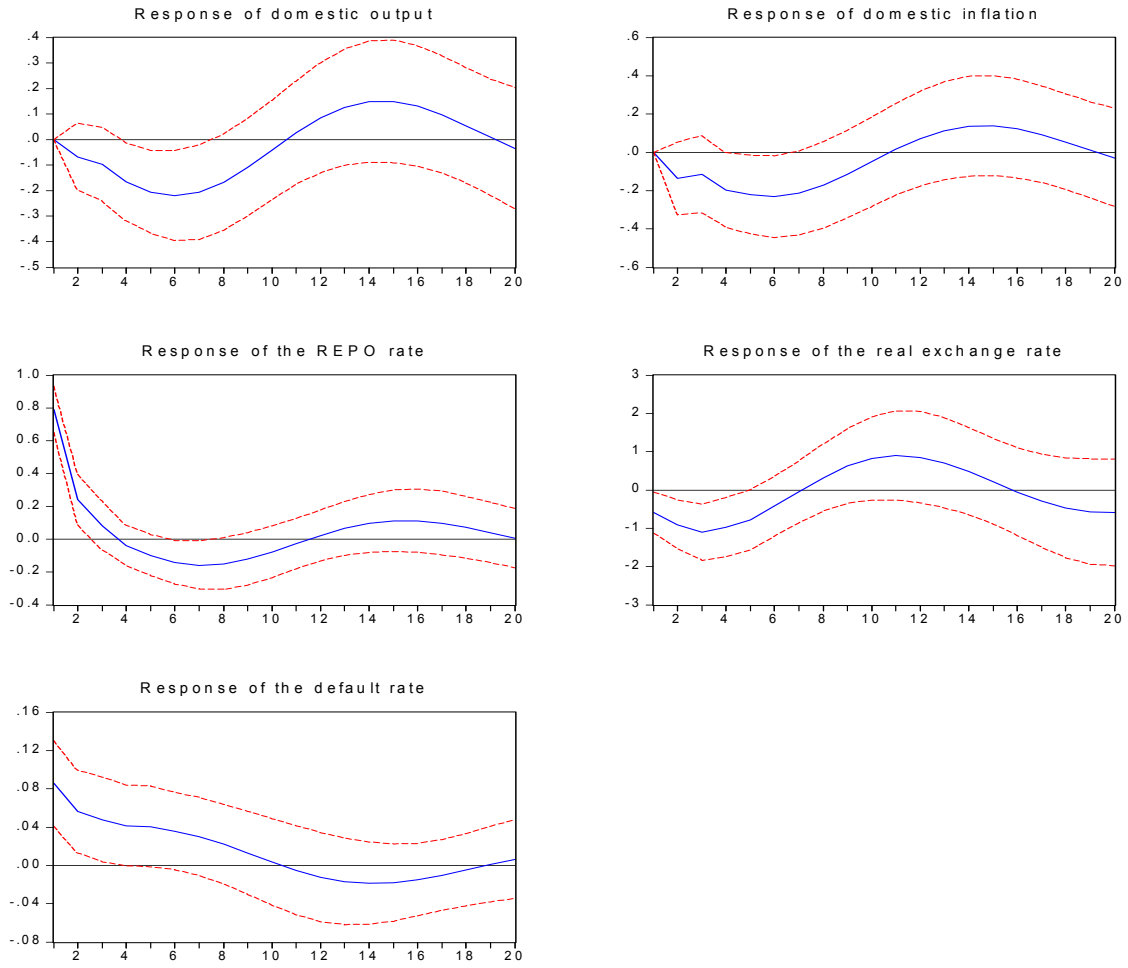

Figure 8: Impulse response functions to an identified shock to monetary policy in the VAR model where the default rate is endogenous. Solid line shows point estimates and dashed lines 95 percent confidence interval.

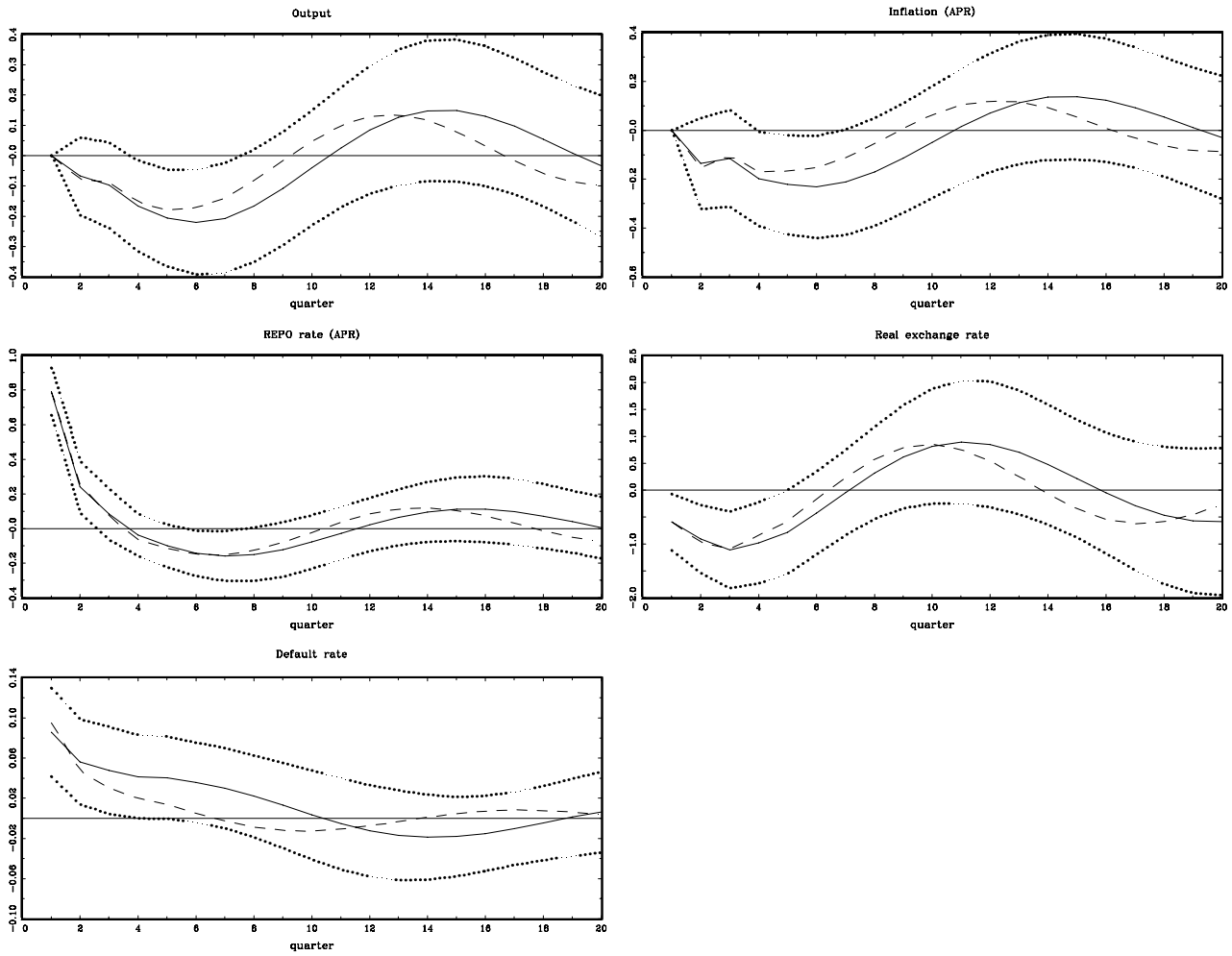

Figure 9: Impulse response functions in the estimated VAR model with the default rate endogenous (point estimates - solid line, dotted lines shows 95 percent confidence interval) and in the empirical micro-macro model (dashed line) for 1991Q1.

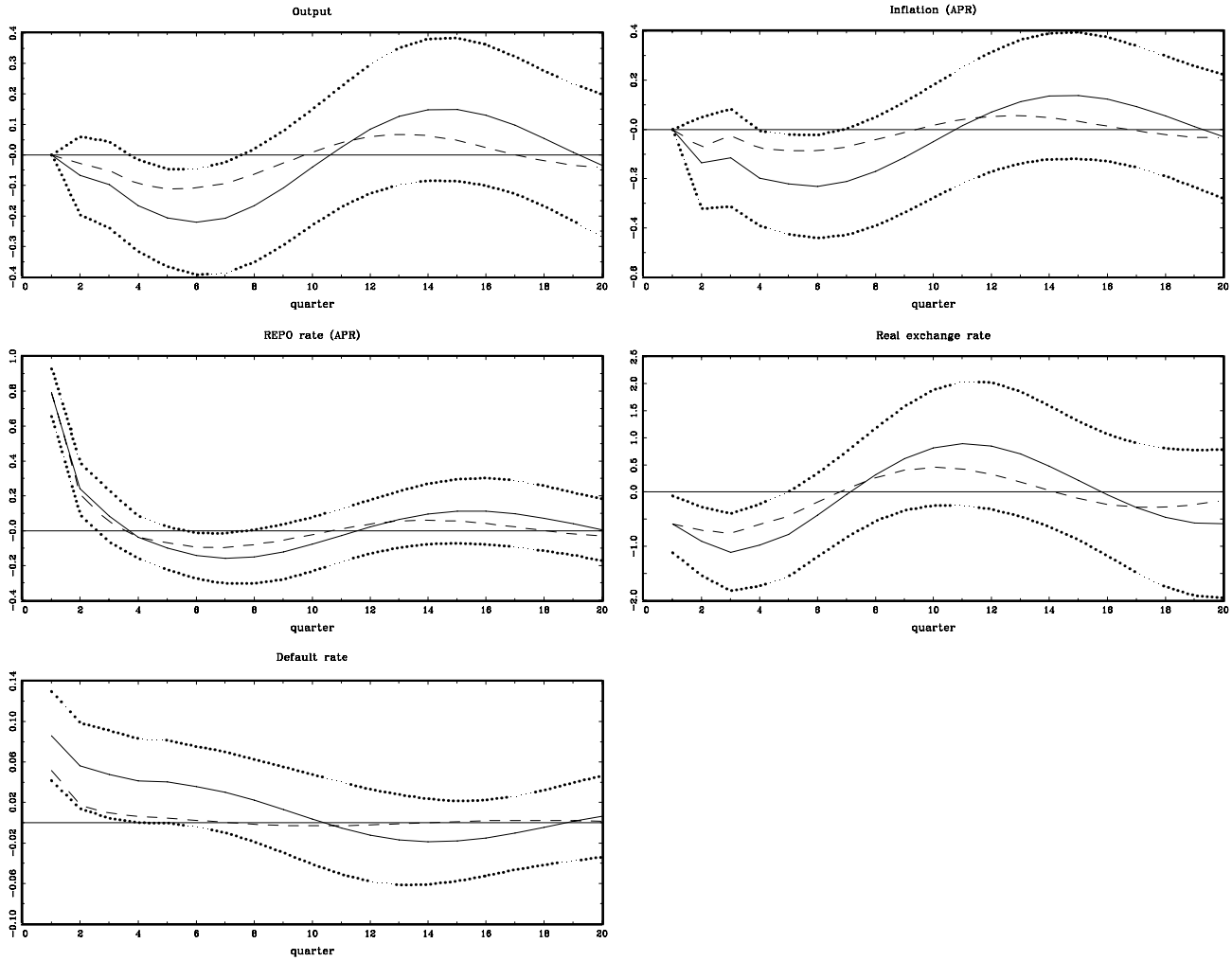

Figure 10: Impulse response functions in the estimated VAR model with the default rate endogenous (point estimates - solid line, dotted lines shows 95 percent confidence interval) and in the empirical micro-macro model (dashed line) for 1998Q1.