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The Bank Lending Channel: a FAVAR Analysis

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Abstract

We examine the role of commercial banks in monetary transmission in a factor-augmented vector autoregression (FAVAR). A FAVAR exploits a large number of macroeconomic indicators to identify monetary policy shocks, and we add commonly used lending aggregates and lending data at the bank level. While our results suggest that the bank lending channel (BLC) is stronger than previously thought, this feature is not robust. In addition, our results indicate a diffuse response to monetary innovations when individual banks are grouped according to asset sizes and loan components. This suggests that other bank characteristics could improve the identification of the BLC.

Keywords: Bank Lending Channel; FAVAR; Monetary Policy

JEL: E51, E52, C32

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1. Introduction

Since Bernanke and Blinder's (1992) observation that significant movements in aggregate bank lending volume follow changes in the stance of monetary policy, the bank lending channel (henceforth, BLC) has been a prominent mechanism in the literature on monetary transmission. The BLC focuses on the balance sheets of commercial banks and assumes that insured, reservable deposits and other forms of external loan finance (e.g. time deposits, CDs, etc.) are not perfect substitutes due to the higher costs of acquiring the latter. A monetary contraction resulting in less reservable deposits should therefore result in a decrease in the contemporaneous supply of loans.

Building upon the initial intuition for the BLC, the literature has since stressed cross-sectional differences among commercial banks' balance-sheets as well as loan components. Kashyap and Stein (1995, 2000) considered bank assets and liquidity positions as aggregating criteria and find that increases in the Federal funds rate are followed by significant declines in lending volume for the smallest (in terms of assets) and least liquid banks.[1] Den Haan et al. (2007) consider loan components aggregated across banks and find that real estate and consumer loans sharply decline in response to a monetary contraction while commercial and industrial (C&I) loans increase.[2] While Perez (1998), Ashcraft (2006), and others have suggested the irrelevance of the BLC in monetary transmission, Kashyap and Stein (1995, 2000) and Den Haan et al. (2007) provide evidence for its existence.

This evidence is not without its limitations. For example, the common use of the Federal funds rate as the monetary policy instrument may not result in an appropriate identification of monetary policy innovations. In addition, aggregating bank lending across either asset categories or loan components may be contaminating the true responses of individual banks who are responding to both bank-specific and aggregate sources of fluctuations. It should

[1]Kishan and Opiela (2000) further find that banks with the weakest capital positions are the most responsive to monetary policy.

[2]The authors suggest that the perverse response of C&I loans could still be consistent with the BLC due to a bank's preference for the relative safety and term of a C&I loan rather than a longer-term asset (**such as** a real estate loan).

be noted that most contributions to the literature which either supports or refutes the BLC are in some way subjected to these limitations. The goal of this paper is to empirically put these limitations to the test.

We examine the lending response of commercial banks in a factor-augmented vector autoregression (FAVAR). A FAVAR, which combines standard structural VAR methods with factor analysis, exploits a large number of time series and summarizes the information into a relatively small set of estimated indexes (i.e. factors). It also has many desirable properties for an analysis of the BLC. First, utilizing a large data set of macroeconomic variables like those used by central banks is important when properly identifying monetary policy innovations. Bernanke et al. (2005) argue that the measurement of policy innovations is likely to be contaminated by limiting the analysis to a small number of comprehensive macroeconomic variables.[3] Second, one does not need to take a stand on specific observables (such as industrial production or real GDP) which need to correspond to theoretical concepts (such as *economic activity*) because a FAVAR summarizes these concepts using large amounts of economic information. Finally, a FAVAR provides impulse responses for every variable in the conditioning set, as well as a decomposition of their individual fluctuations into those due to aggregate factors and specific innovations.

Our FAVAR framework considers the large set of macroeconomic indicators used by Bernanke et al. in their identification of monetary policy shocks, and extends this data by appending a variety of commercial-bank lending variables. First, total loan growth and growth in loan components are aggregated up to the total banking system (as in Bernanke and Blinder, 1992 and Den Haan et al., 2007) as well as up to groups according to asset size (as in Kashyap and Stein, 1995 and 2000).[4] While these variables deliver an indication of how aggregate bank lending responds to an improved identification of monetary policy shocks,

[3] Imperfectly controlling for the information central bankers may have is exactly Sim's (1992) critical interpretation of an increase in aggregate prices in response to a monetary contraction (i.e. the *Price Puzzle*) observed in traditional VAR analyses.

[4] Following Kashyap and Stein (1995, 2000), we consider the asset groups to be banks with assets within the 95th percentile or less (small), banks with assets within the 95th and 99th percentile (medium), and banks with assets within the 99th percentile or more (large).

we also consider a large amount of lending data at the individual-bank level. This allows us to disentangle the fluctuations in bank-level lending data which are due to aggregate macroeconomic factors (such as a change in monetary policy) from those that are due to bank-specific conditions. To our knowledge, our analysis is the first to consider purely disaggregated lending data within the same framework as their commonly used aggregates and provides a comparison between the responses of individual and aggregate lending in response to monetary policy.

Our findings suggest a stronger BLC than previously thought when examining data aggregated up to the banking sector and asset groups. In particular, we find that total, C&I, and individual consumer loan growth all significantly decline after a monetary policy contraction for the entire banking sector as well as bank groups according to asset size. While this suggests that the BLC effects more than just the smallest banks, this result weakens when employing post-1984 data.

Our results also suggest that the individual, bank-level responses to a monetary policy innovation are quite diffuse. There are almost as many banks who increase lending as those who decrease, and this result remains if we control for bank groups and loan components. A main reason for these varied responses is that macroeconomic fluctuation explain on average between 8 and 22 percent of the variation in individual bank lending for the banks within our sample. Therefore, most of the variation in individual bank-lending reflect bank-specific shocks to which the banks immediately respond. Nonetheless, when considering lending aggregates comprised of only those banks we observe individually, there are significant declines for all bank groups in one or more loan components, and these declines remain when employing post-1984 data.

Our analysis indicates that while particular measures of the BLC are strengthened by our FAVAR framework, the large degree of heterogeneity observed in the individual-bank responses cast doubt on the notion that the BLC is stronger for banks based on asset size or loan components. This does not imply that other banking characteristics might prove more suitable to differentiate banks which have a different BLC effect. For example, Cetorelli and Goldberg (2009) show that the degree of globalization of a commercial bank could matter for the BLC because globalized banks can activate foreign capital markets to insulate themselves from domestic liquidity conditions. Evidence of this type will prove useful to target the important features of intermediation in monetary transmission and provide theorists with a set of crucial features of banking to incorporate into their environments.

The rest of the paper is organized as follows. Section 2 outlines the formulation and estimation of the FAVAR. Section 3 discusses the data sets used. Section 4 presents our empirical results by first detailing the impulse responses of loan aggregates to a monetary policy shock, and then examining the characteristics of disaggregated loan data. Section 5 concludes.

2. The FAVAR

Our implementation of the FAVAR follows Bernanke et al. (2005). A general description of the framework is as follows. Assume the economy is affected by a vector C_t of common components which affect all variables in the data set. For example, we assume that a measure of the stance of monetary policy is considered to be a common component, and we follow the literature and assume that this stance is measured by the Federal funds rate (R_t). The remaining shared dynamics of each data series are captured by a $K \times 1$ vector of unobserved factors F_t, where K is relatively small. These unobserved factors capture fluctuations in general economic concepts such as *economic activity*, *aggregate prices*, *credit conditions*, etc., that cannot be easily represented by a few time series but rather are reflected in a wide range of economic variables.

We assume that the joint dynamics of F_t and R_t are given by

$$C_t = \Phi(L) C_{t-1} + v_t \tag{1}$$

where $C_t' = [F_t' \ R_t]$ and $\Phi(L)$ is a conformable lag polynomial of infinite order which may contain a priori restrictions as in the structural VAR literature. The error term v_t is i.i.d. with zero mean and covariance matrix Q.

While (1) is a VAR in C_t, it cannot be directly estimated because the factors comprising F_t are unobserved. However, since these factors are interpreted as representing forces affecting many economic variables, one can potentially use a large set of observed "informational" series to infer something about them. Let X_t denote the $N \times 1$ vector of these informational variables, where N is relatively large. It is assumed that the X_t is related to all common components according to

$$X_t = \Lambda C_t + e_t \tag{2}$$

where Λ is an $N \times (K+1)$ matrix of factor loadings. The $N \times 1$ vector e_t contains the zero-mean, series-specific components that are uncorrelated with C_t, but allowed to be serially correlated and weakly correlated across indicators. Equation (2) reflects that C_t represents pervasive forces which drive the common dynamics of X_t. Conditional on R_t, the X_t are thus noisy measures of the underlying unobserved factors F_t. Bernanke et al. note that the implication of X_t depending only on current factors is not restrictive in practice, as F_t can be interpreted as including arbitrary lags of the fundamental factors.

Estimation of the above model involves a two-step principal component approach. In the first step, principal components are extracted from X_t to obtain consistent estimates of the common factors. In the second step, the Federal funds rate is added to the estimated common factors and the data set is used to estimate (1). In particular, estimation of our model follows Boivin et al. (2009), who slightly differ from the estimation described by Bernanke et al. insofar that it is assumed that R_t is one of the factors in the first-step. This guarantees that the latent factors recover common dynamics not captured by the Federal funds rate.[5]

[5] See Boivin et al. (2009) for details.

3. The Data

Our data set is a balanced panel of 1512 quarterly series from 1976:1 to 2005:3. The first 111 series are macroeconomic indicators originally considered in the initial FAVAR analysis of Bernanke et al., and also used by Boivin et al. (see appendix for details).[6] Included in these series are several measures of industrial production, price indices, interest rates, employment as well as other key macroeconomic and financial variables, which have been found to contain information useful to capture the state of the economy and identify monetary policy.

The remainder of our data set includes several variables constructed using loan information for individual commercial banks taken from the Consolidated Report of Condition and Income (Call Reports) that all insured banks submit to the Federal Reserve. For each commercial bank, data on total loans, total C&I, total real estate loans, and individual loans were collected following the detailed instructions on forming consistent time series attributable to Kashyap and Stein (2000). For each quarter, we used total asset holdings of the commercial banks to assign each bank into one of three possible size categories: banks with total assets below the 95^{th} percentile (small banks), banks with total assets between the 95^{th} and 99^{th} percentile (medium banks), and banks with total assets above the 99^{th} percentile (large banks). To retain comparability with previous studies of the BLC, we use these asset categories to construct a disaggregation of the commercial banking data. In particular, we use the lending data to construct loan growths for all bank components aggregated up to the entire sector as well as the three asset groups. However, since the FAVAR framework can handle large amounts of data, we also keep individual banks separate and use the asset size categories to determine if there are any common movements in banks that differ across this characteristic.

In order to arrive at a manageable data set for our FAVAR analysis, we had to apply several filters on the individual bank-level data. In particular, our balanced panel of commercial banks initially consisted of 4743 individual banks. Of these, 219 banks were removed because

[6] We are grateful to Marc Giannoni for providing us with this data.

their bank size was not consistent throughout the sample. The resulting data set consisted of 18 large banks, 24 medium banks, and 4482 small banks. Since the small banks are still too numerous, the data set we settled on to estimate the FAVAR consists of a random selection of 10 percent of the small bank population.[7] We then used these banks to construct time series for their loan growths in the exact same way as in the loan aggregates. In addition, in order to directly compare the individual bank responses with some aggregate measure of their response, we also constructed loan aggregates similar to those above for all banks but only using the banks we observe in our bank-level data set.

4. Estimation Results

We estimate the above system (1) and (2) for four different FAVARs which differ in the type of bank lending (total, C&I, real estate, and individual). For each FAVAR, the data set X_t consisted of the macroeconomic indicators as well as the aggregate and bank-level lending data for each particular loan category. We chose the size of factors F_t for each FAVAR after some experimentation to ensure that our conclusions are not affected by additional latent factors.[8] All models use 4 quarterly lags in estimating (1).

The first subsection focuses on the response of aggregated lending data to a monetary policy shock, while the second subsection focuses on the characteristics and behavior of the disaggregated lending data.

4.1. Aggregated Lending

Following Bernanke et al. and Boivin et al., we assume that the Federal funds rate may respond to contemporaneous fluctuations in estimated factors, but that none of the latent common components can contemporaneously respond to monetary policy shocks. This is

[7] The estimation was conducted for several different samples of small banks to ensure robustness of the results.

[8] Our FAVARs for Total and Real Estate loans required 5 latent factors, while C&I and Industrial loans required 4.

the FAVAR extension of the standard recursive identification of monetary policy shocks in conventional VARs, which has been used for instance by Den Haan (2007). Note that in contrast to VARs, the macroeconomic indicators (X_t) are allowed to contemporaneously respond to monetary shocks. We can therefore disentangle monetary policy shocks from the other macroeconomic shocks.

The responses of our lending aggregates to an unexpected (25 basis point) increase of the Federal Funds rate are illustrated in Figure 1. Each panel illustrates the response of a particular loan component for loans aggregated across all banks as well as the three asset groups. A diamond indicates that the impulse response at that particular time horizon is significantly different than zero at the 90 percent level. As the figure indicates, there are significant and persistent declines in Total, C&I, and Individual loans in response to a monetary policy shock for all bank groups (including the total). This result suggests that the BLC is actually stronger than previously reported under this identification of monetary policy. Previous analyses only find a significant BLC in either the smallest (asset-wise) or least liquid banks. Only aggregate real estate lending illustrates a BLC for the smallest banks exclusively.

Our result of a stronger BLC, however, is not a consistent feature of the data. Due to the evidence of widespread instability in many macroeconomic series, a change in monetary policy, and a decline in overall macroeconomic volatility around 1984, we re-estimated our FAVARs using post-1984 data. Figure 2 illustrates a large reduction in the significance of the impulse responses. In fact, some loan components actually increase (albeit, insignificantly) after a monetary contraction. The only loan component which retains a significant BLC is Individual loans, which accords with the results of Den Haan (2007) who find the largest BLC effect in aggregate consumer loans.[9]

[9] It should be noted that our results for real estate loans also mimic the results of Den Haan (2007), but fail to be significant.

4.2. Disaggregated Lending

This section turns to an analysis of the bank-specific lending data which was used along with the loan aggregates for estimating the system (1) and (2). For all loan growth series considered, (2) implies

$$x_{it} = \lambda_i' C_t + e_{it}, \tag{3}$$

where x_{it} is the quarterly change in loan growth for bank i. The fluctuations for all banks due to the macroeconomic factors are represented by the the common components C_t which have a diffuse effect on the individual banks due to differences in λ_i, while the bank-specific fluctuations are captured by e_{it}.

We detail some summary statistics on the average volatility of loan components and their corresponding aggregates in Table 1. It should be noted that the corresponding aggregates are not the aggregates discussed in the previous section, but the aggregation of banks that appear in our bank-level data set. This comparison serves to illustrate potential aggregation effects among the individual banks.

The first column of Table 1 suggests a large amount of average volatility in our bank-level lending data. This volatility is decomposed into volatility stemming from common macroeconomic and specific factors, and the R^2 statistic measures the fraction of the variance in aggregate lending explained by the common components. The results suggest that loan fluctuations stemming from aggregate or common shocks make up a very small amount of the average volatility in our lending data. For example, when considering banks with assets less than the 95th percentile, bank-specific shocks account on average for 76 percent of their fluctuations in total lending and as much as 92 percent of their fluctuations in lending components. When comparing these volatilities with their corresponding aggregates, one finds a large reduction in volatility due to a large reduction in the bank-specific component. The R^2 statistics now state that 75 percent or more of the fluctuations in these variables are attributable to fluctuations in macroeconomic components. While this comparison is the most stark for the smallest bank group, similar comparisons for all bank groups and all loan components report a reduction in volatility due to aggregating the bank-level data as well as an increased R^2. Quite naturally, these results suggests that disturbances arising at the individual bank level tend to cancel each other out when aggregating.

Returning focus to the bank-level data, Figure 3 illustrates a strongly positive correlation between the macroeconomic and bank-specific components of lending volatility. While the figure considers all banks, this positive relationship between the volatility of the idiosyncratic shocks ($Sd\,(e_i)$) and the volatility of the common component ($Sd\,(\lambda_i' C_t)$) would remain if we considered banks groups separately. Among the loan components, the tightest relationships are among C&I and Real Estate loans, with a weaker relationship among Individual loans and the total. All slope coefficients are statistically different from zero at the 95 percent level, and are corrected for possible heteroscedasticity.[10] From this perspective, banks with the highest idiosyncratic volatility also respond the strongest to macroeconomic shocks. Therefore, whatever characteristics which help banks smooth over individual shocks will also help smooth over macroeconomic shocks.

Our final analysis of the bank-level data is to document how loan growth responds to bank-specific and macroeconomic disturbances. These impulse responses are illustrated in Figures 4 through 6 for large, medium, and small banks, respectively. The left panels of the figures report the response of each of the individual banks to an adverse (one standard deviation) shock to its bank-specific component. The solid lines represent an unweighted average response. Across all bank groups and loan components, lending responds sharply and promptly to bank-specific disturbances. There is very little persistence in the response of all banks, and they quickly reach a new equilibrium.

While bank-specific shocks rapidly shift the loan growth of individual banks to a new level, the macroeconomic shocks are quite different. The middle panels of the figures illustrate the response of each bank group and loan component to an innovation (of minus one

[10] The respective t statistics for the slope coefficients are 10.5, 22.9, 26.7, and 12.4.

standard deviation) to its common component $\lambda_i' C_t$. These figures suggest a large amount of sluggishness in the response to macroeconomic disturbances, and this persistence is shared by all bank groups and all loan components. In particular, the figures illustrate that all banks behave quite similarly to a common macroeconomic shock. While this exercise fails to identify a specific structural macroeconomic shock and instead illustrates the response to a combination of macroeconomic shocks, the response to these shocks strongly contrast with the responses to bank-specific shocks.

We finally turn to the effects of monetary policy on our bank lending panel. The identification of monetary policy shocks is accomplished in the same way as the previous section focusing on the aggregated lending data, and the results are illustrated in the third columns of Figures 4 through 6 for our three bank groups. The thick solid lines again represent an unweighted average response, while the thick dashed lines illustrate the response of the corresponding aggregated data mentioned in the discussion of Table 1. A circle indicates that the impulse response at that particular time horizon for the aggregated data is significantly different than zero at the 90 percent level. Similar to the responses illustrated in Figures 1 and 2, there is a fair amount of significance in the aggregated data for all bank groups. The most significant declines appear to be coming from C&I and Real Estate loan components, with only a few significant periods of decline for Individual loans exclusively from the small bank group. It should be kept in mind that these aggregates are not over the entire banking sector, but for the banks that made it into our bank-level panel. These banks have their own individual response to the same monetary policy shock, and are illustrated in the figures by the thin dotted lines. A striking feature of these bank-specific responses is that there is a large amount of heterogeneity among banks of similar asset size, with almost as many banks increasing their lending in response to a surprise monetary contraction as there are banks decreasing their lending. This is a robust feature of the data across bank size and loan components, and suggests a rather stark discrepancy between an individual bank response and the aggregate of which it is a member.

4.3. Robustness Results

4.3.1. Disaggregated Lending, Post-1984

Similar to the aggregate lending results, the disaggregated bank-level data was also re-estimated using post-1984 data. In contrast to the loan aggregates, the disaggregated-loan results tell a similar story to the results under the full sample. As illustrated in Table 2, we find much less volatility in the aggregated time series relative to the average volatility of the bank-level panel, as well as a much larger percentage of the aggregate fluctuations being attributable to fluctuations in macroeconomic components. More importantly, our impulse response analysis under post-1984 data retains much of the significance of the BLC illustrated under the full sample. These are illustrated in Figures 7-9. Again, it should be noted that these aggregates are constructed using only the individual banks in our panel and therefore is not a complete picture of aggregate lending.

4.3.2. Alternative Factor Estimations

In order to verify that the number of factors in our FAVARs were reasonable, we performed robustness checks as in Bernanke et al. by re-estimating the FAVARs with an increased number of factors. The impulse responses for bank specific, common component and monetary policy shocks did not qualitatively change from the main results discussed above for total, C&I, or Real Estate loans. The only minor change in impulse responses was for individual loans, which displayed a slightly positive response to a contractionary monetary shock for aggregated large banks. In terms of the disaggregated data, increasing the number of factors did not qualitatively change the results reported in Table 1, in particular, the R^2 calculations measuring the amount of fluctuation in individual bank lending attributable to macroeconomic shocks.

5. Conclusion

This paper examined the role of commercial banks in monetary transmission in a factor-augmented vector autoregression (FAVAR). The ability of a FAVAR to exploit a large conditioning set of macroeconomic indicators when identifying monetary policy shocks, coupled with the ability to calculate impulse responses for every variable in this set, allows us to assess the bank lending channel of monetary policy using commonly considered lending aggregates and a panel of individual lending data.

Our analysis delivers two results. First, our results suggest that the BLC is stronger than previously thought for loan aggregates and particular loan components. In particular, we find a significant BLC for more bank groups than the smallest banks (asset-wise) as well as for Total, C&I, and Individual loans. While this result suggests that an improved identification of monetary policy shocks uncovers a profound BLC, it is not robust when employing post-1984 data. Second, the bank-level data show a diffuse response to monetary innovations. We find that almost as many commercial banks increase their lending in response to a monetary contraction as there are banks that decrease. This result is unchanged when considering different loan components as well as banks grouped according to asset size. However, the responses of loan aggregates using only the banks in our balanced panel still show a stronger BLC than previously thought, and this result is robust to employing post-1984 data.

We believe that these results deliver two conclusions. First, the improved identification of monetary policy shocks stemming from a FAVAR analysis is a useful tool for uncovering the BLC and potentially many more monetary matters. Second, the large degree of heterogeneity among commercial banks of similar asset size as well as loan components suggests that these might not be the best characteristics for differentiating whether or not a bank is susceptible to the BLC. Some alternative characteristics (such as the level of global operations, geographic characteristics, etc.) are presently being proposed in the literature, and it would be interesting to see if the individual lending responses from our FAVAR would behave similarly when banks share these similar characteristics. Uncovering these important characteristics of banking can uncover their role in monetary transmission, and provide theorists with a set of crucial features of banking to incorporate into their environments.

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Appendices

6. Data Appendix

Our data set consists of 111 macroeconomic indicators, a series of loan aggregates, and a series of lending at the individual bank level. The macroeconomic indicators are the same as those used by Bernanke et al. and Boivin et al., and we refer to the data appendix of Bernanke et al. (2005) pages 416-420.

Our lending data was constructed following Notes on Forming Consistent Time Series written by Anil Kashyap and Jeremy Stein and is available at the Federal Reserve Bank of Chicago website.[11]

7. Tables and Figures

[11] http://www.chicagofed.org/economic_research_and_data/commercial_bank_data.cfm

Table 1: Volatility and Persistence of Bank Lending

		Disaggregates				Aggregates			
		x_{it}	Common	Specific	R^2	x_{it}	Common	Specific	R^2
Total Loans	All	5.82	2.54	5.23	0.22	5.47	2.51	4.86	0.21
	Large	9.04	2.64	8.63	0.10	6.03	2.69	5.39	0.20
	Medium	6.01	2.09	5.58	0.16	2.10	1.42	1.55	0.46
	Small	5.67	2.56	4.95	0.24	1.30	1.23	0.43	0.89
C&I Loans	All	18.38	4.69	17.68	0.08	6.97	3.20	6.19	0.21
	Large	10.30	3.19	9.71	0.12	7.38	3.34	6.58	0.20
	Medium	9.90	3.18	9.28	0.14	2.99	2.02	2.21	0.46
	Small	19.20	4.84	18.50	0.08	2.13	1.84	1.07	0.75
Real Estate	All	9.06	2.82	8.54	0.13	3.78	2.33	2.97	0.38
	Large	10.66	3.14	10.14	0.10	4.24	2.59	3.35	0.37
	Medium	7.56	2.44	7.13	0.12	1.99	1.16	1.61	0.34
	Small	9.07	2.82	8.55	0.13	1.23	1.09	0.58	0.78
Individual	All	11.79	3.73	11.02	0.13	4.30	1.31	4.09	0.09
	Large	14.80	3.32	14.33	0.08	4.88	1.35	4.69	0.08
	Medium	9.04	2.91	8.48	0.15	2.91	2.00	2.11	0.47
	Small	11.82	3.78	11.03	0.13	1.94	1.86	0.55	0.92

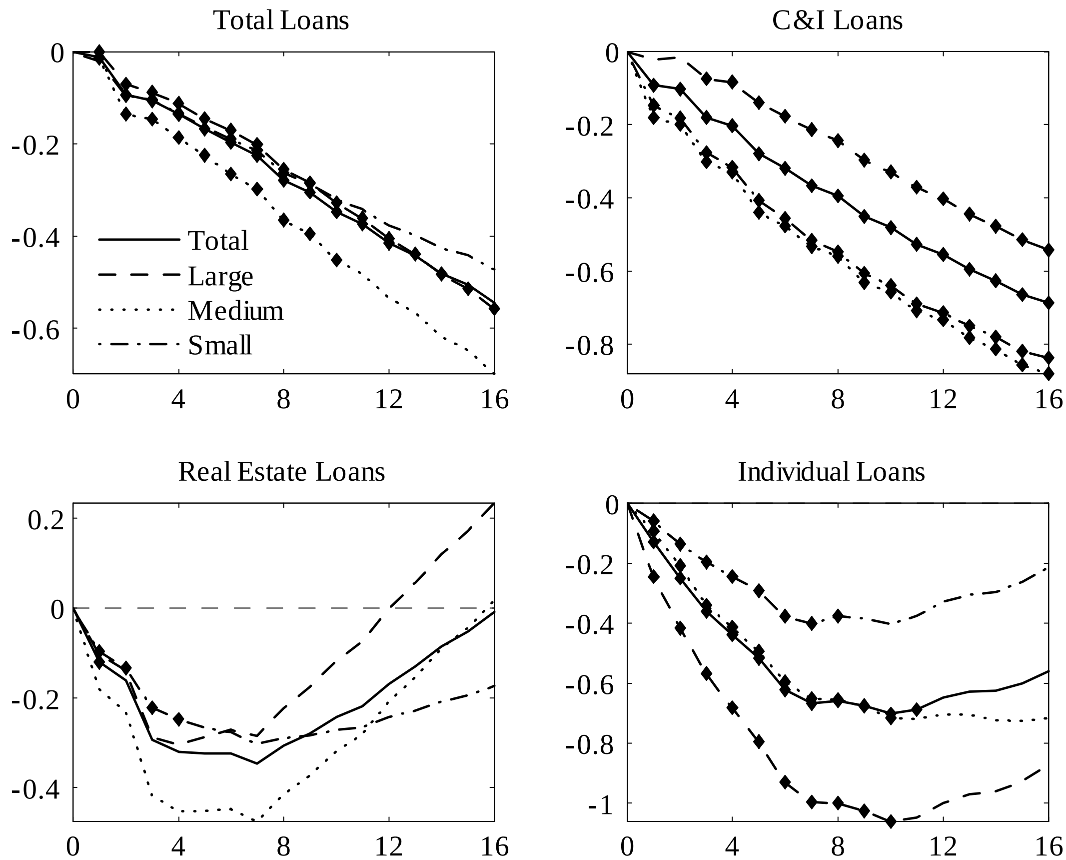

Figure 1: Impulse responses of lending aggregates (in %) to an identified monetary policy shock. The monetary shock is a surprise of 25 basis points in the Federal funds rate. The label Total stands for each loan component aggregated across all banks, while sizes stand for aggregates according to asset size. A diamond indicates a significant distance from zero at the 90 percent confidence level.

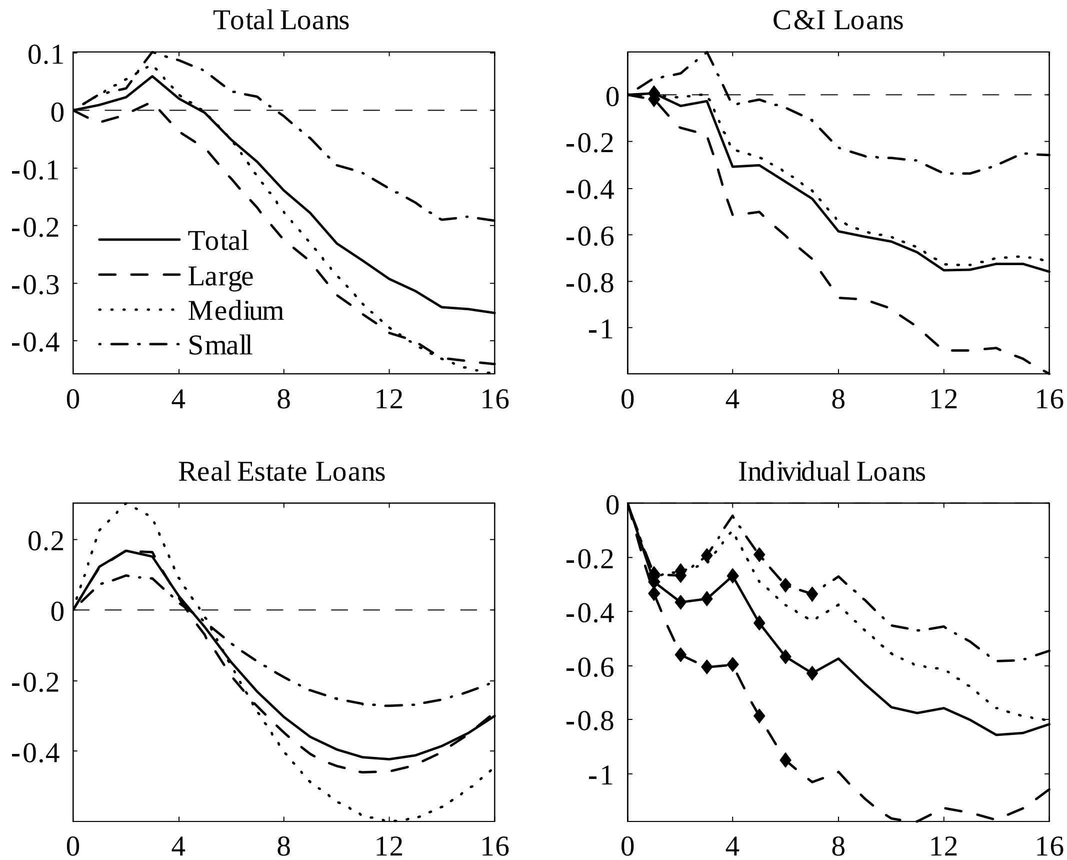

Figure 2: Post-1984: Impulse responses of lending aggregates (in %) to an identified monetary policy shock. The monetary shock is a surprise of 25 basis points in the Federal funds rate. The label Total stands for each loan component aggregated across all banks, while sizes stand for aggregates according to asset size. A diamond indicates a significant distance from zero at the 90 percent confidence level.

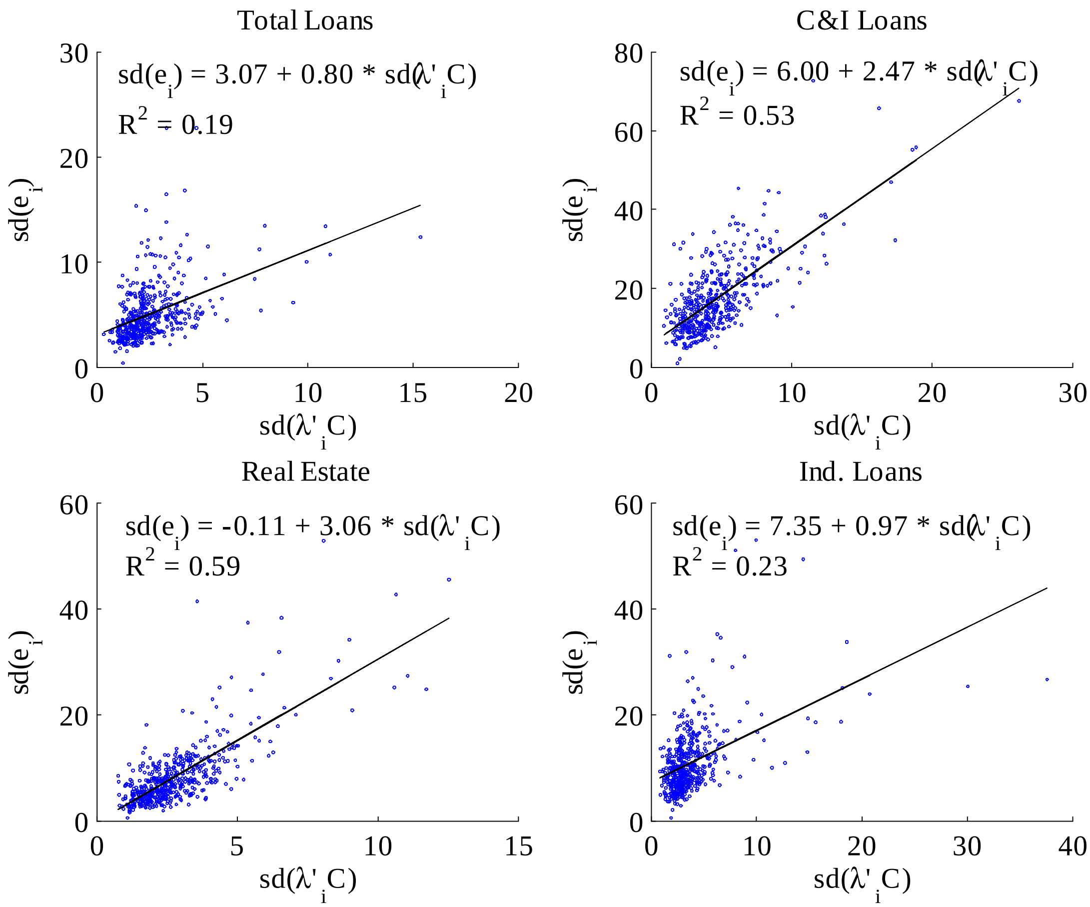

Figure 3: Standard deviation (in %) of bank-specific and macroeconomic (common) components of bank lending. The solid line denotes the cross-section regression line.

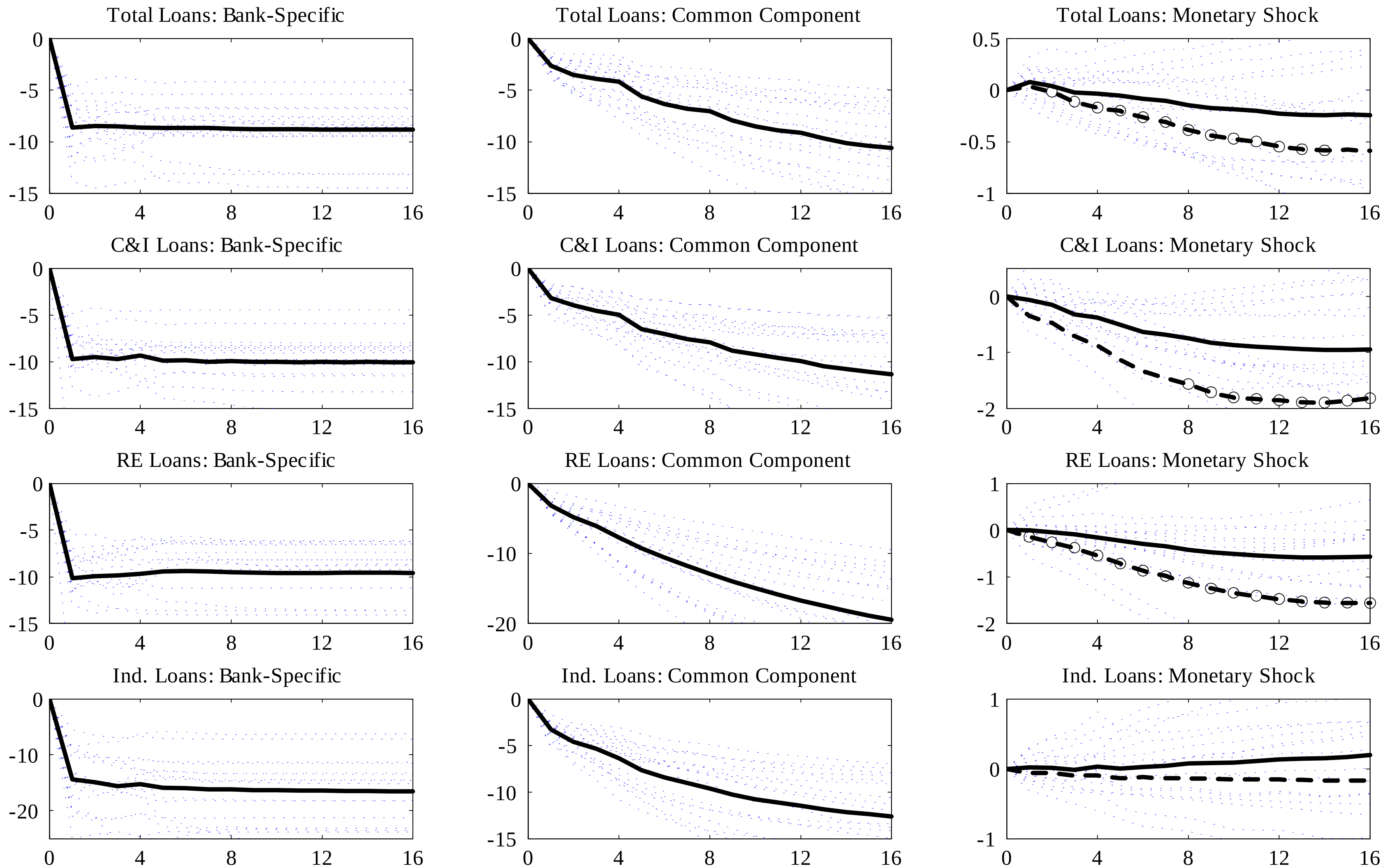

Figure 4: Estimated impulse responses of lending variables (in %) for large banks to a bank-specific shock e_{it} of one standard deviation (left column), a common shock $\lambda_i' C_t$ of one standard deviation (middle column), and an identified monetary policy shock (right column). The monetary shock is a surprise of 25 basis points in the Federal funds rate. The thick solid lines represent unweighted average responses, while the thick-dashed lines represent the response of aggregate lending for large banks.

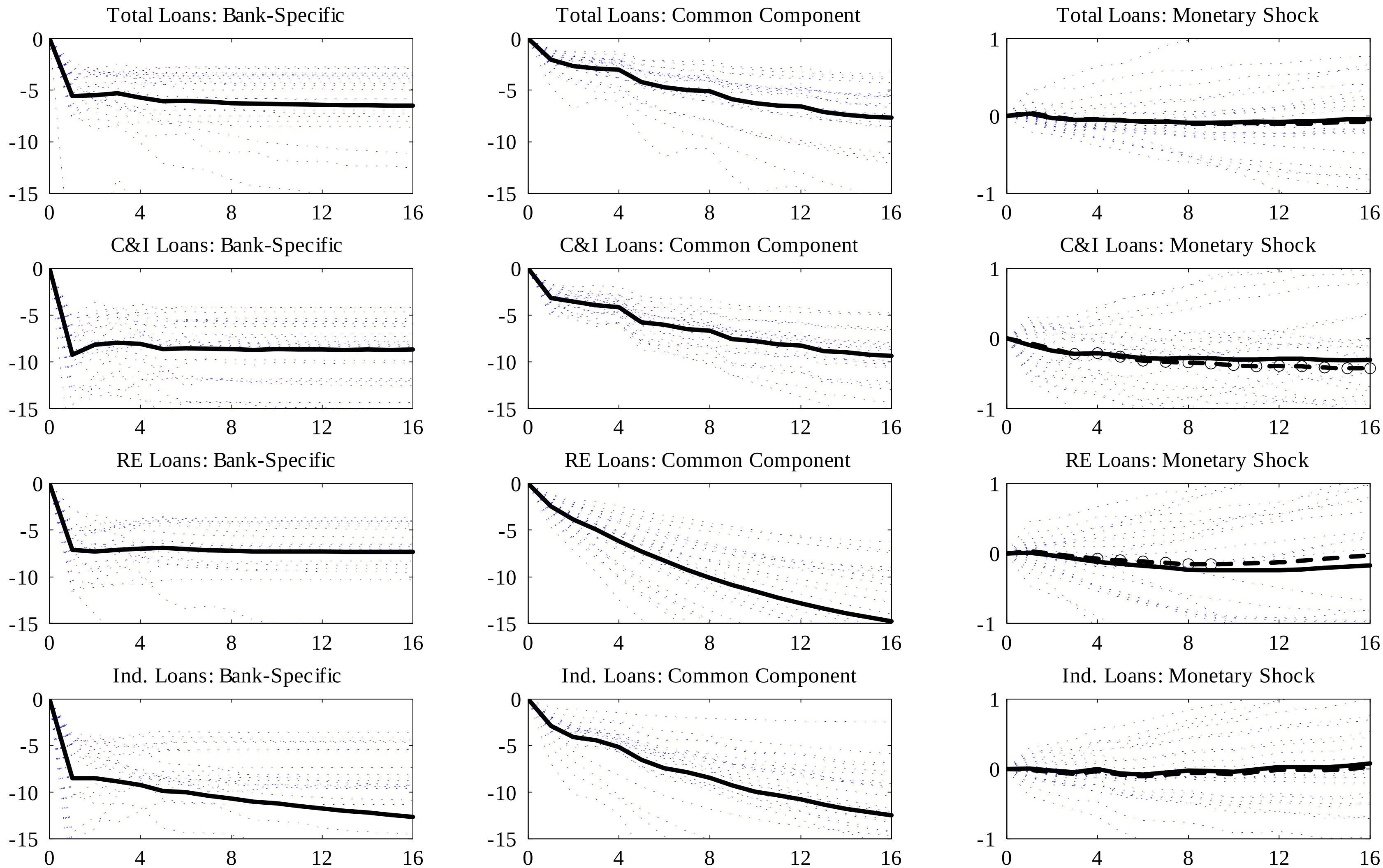

Figure 5: Estimated impulse responses of lending variables (in %) for middle banks to a bank-specific shock e_{it} of one standard deviation (left column), a common shock $\lambda_i' C_t$ of one standard deviation (middle column), and an identified monetary policy shock (right column). The monetary shock is a surprise of 25 basis points in the Federal funds rate. The thick solid lines represent unweighted average responses, while the thick-dashed lines represent the response of aggregate lending for middle banks.

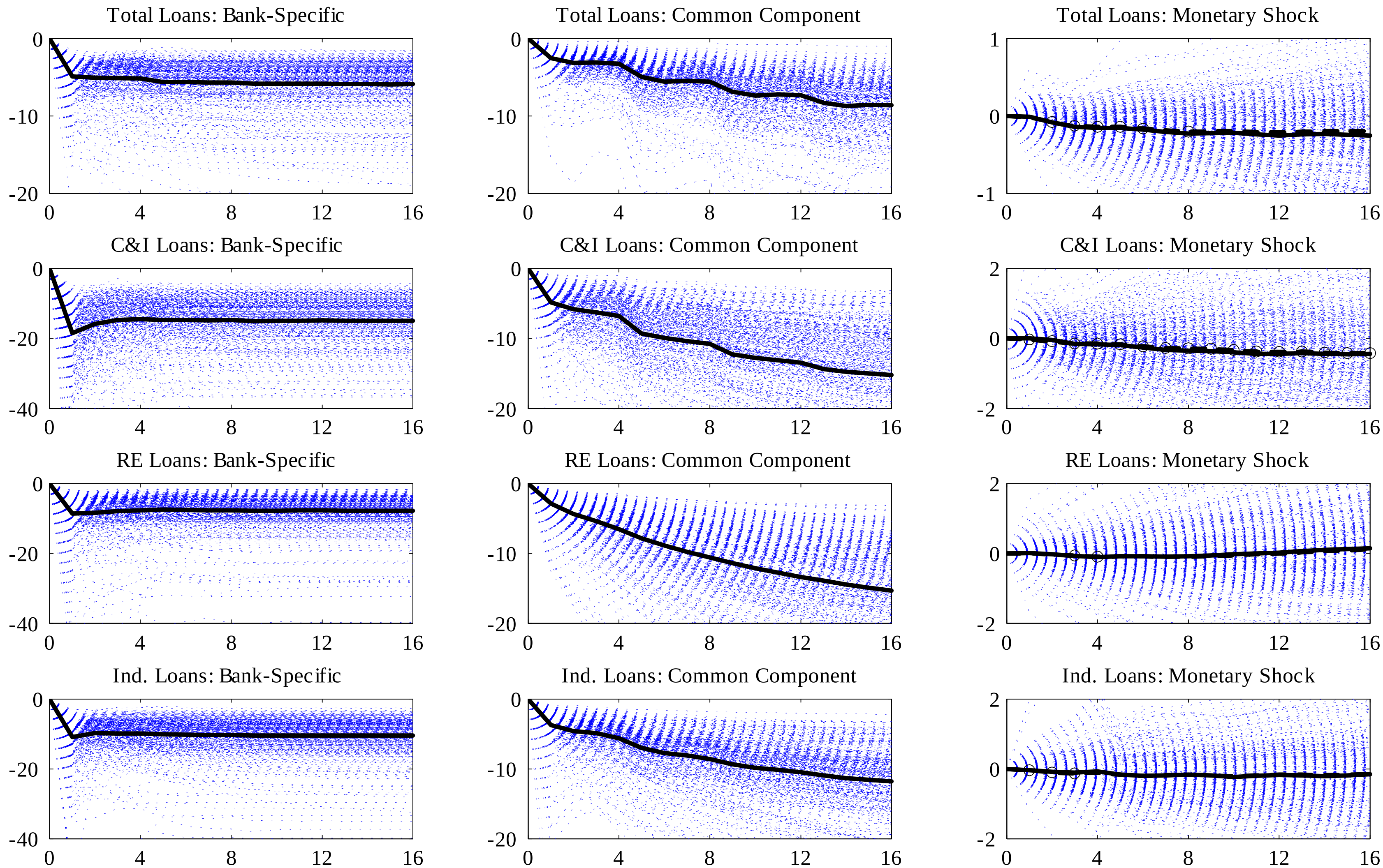

Figure 6: Estimated impulse responses of lending variables (in %) for small banks to a bank-specific shock e_{it} of one standard deviation (left column), a common shock $\lambda_i' C_t$ of one standard deviation (middle column), and an identified monetary policy shock (right column). The monetary shock is a surprise of 25 basis points in the Federal funds rate. The thick solid lines represent unweighted average responses, while the thick-dashed lines represent the response of aggregate lending for small banks.

Table 2: Volatility of Bank Lending, Post-1984

		Disaggregates				Aggregates			
		x_{it}	Common	Specific	R^2	x_{it}	Common	Specific	R^2
Total Loans	All	5.73	2.28	5.13	0.19	3.37	1.79	2.85	0.28
	Large	9.32	2.52	8.93	0.08	3.55	1.84	3.03	0.27
	Medium	5.75	1.90	5.40	0.12	2.18	1.49	1.59	0.47
	Small	5.58	2.29	4.96	0.20	1.10	1.02	0.43	0.84
C&I Loans	All	17.53	5.06	16.68	0.10	3.98	2.15	3.35	0.29
	Large	10.31	3.34	9.66	0.14	4.14	2.18	3.52	0.28
	Medium	9.76	3.50	9.02	0.15	3.03	2.11	2.18	0.48
	Small	18.28	5.22	17.41	0.09	2.09	1.66	1.26	0.63
Real Estate	All	8.30	2.33	7.90	0.11	3.91	2.20	3.23	0.32
	Large	11.54	2.97	11.10	0.08	4.28	2.38	3.56	0.31
	Medium	7.24	1.90	6.95	0.09	2.00	1.08	1.68	0.29
	Small	8.23	2.33	7.82	0.11	0.96	0.63	0.73	0.43
Individual	All	11.65	3.68	10.85	0.13	4.01	1.02	3.87	0.07
	Large	16.02	3.71	15.48	0.07	4.35	1.02	4.23	0.05
	Medium	9.39	2.64	8.94	0.12	2.73	1.36	2.37	0.25
	Small	11.60	3.73	10.78	0.13	1.56	1.38	0.72	0.78

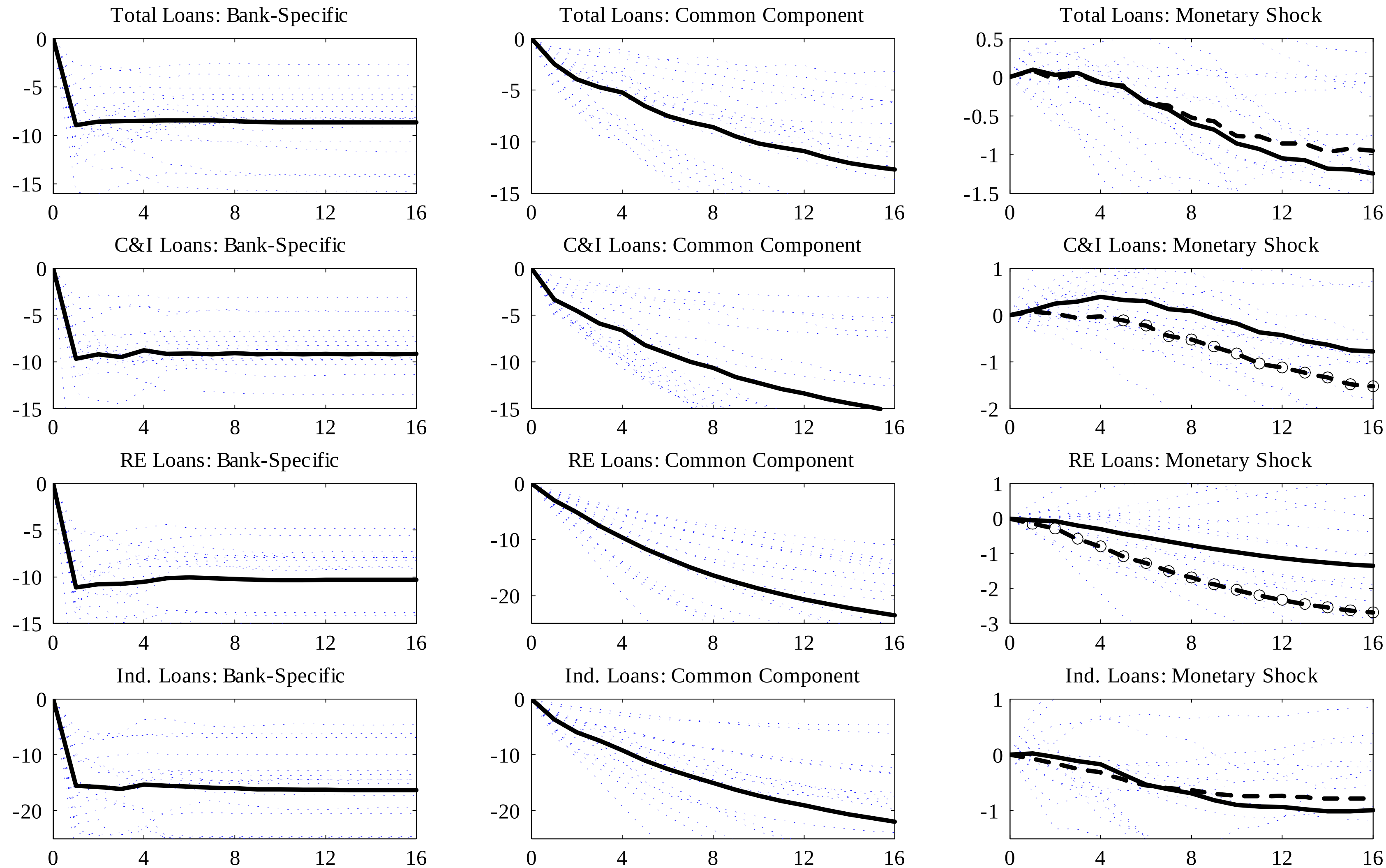

Figure 7: (Post-1984) Estimated impulse responses of lending variables (in %) for large banks to a bank-specific shock e_{it} of one standard deviation (left column), a common shock $\lambda_i' C_t$ of one standard deviation (middle column), and an identified monetary policy shock (right column). The monetary shock is a surprise of 25 basis points in the Federal funds rate. The thick solid lines represent unweighted average responses, while the thick-dashed lines represent the response of aggregate lending for large banks.

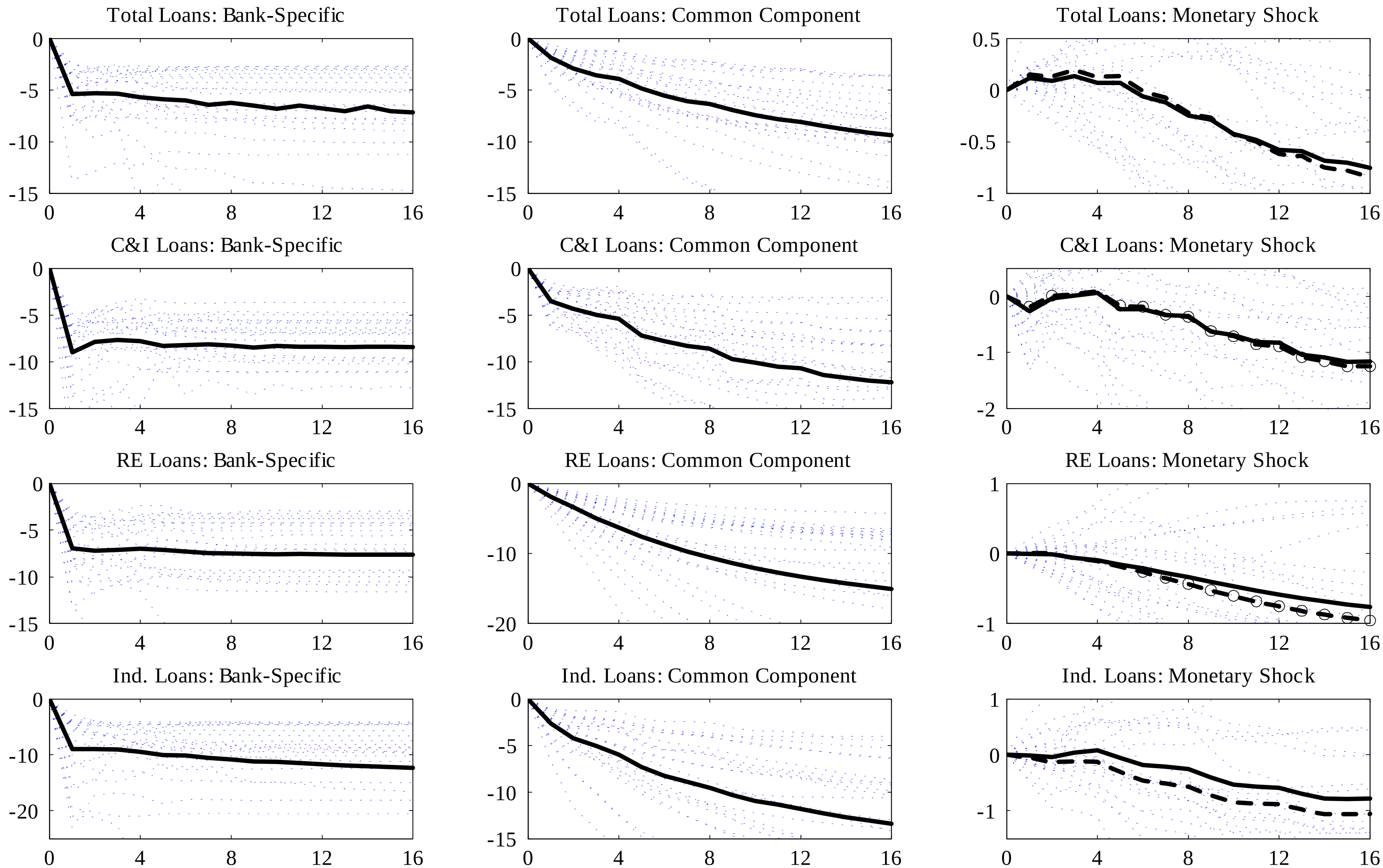

Figure 8: (Post-1984) Estimated impulse responses of lending variables (in %) for middle banks to a bank-specific shock e_{it} of one standard deviation (left column), a common shock $\lambda_i' C_t$ of one standard deviation (middle column), and an identified monetary policy shock (right column). The monetary shock is a surprise of 25 basis points in the Federal funds rate. The thick solid lines represent unweighted average responses, while the thick-dashed lines represent the response of aggregate lending for middle banks.

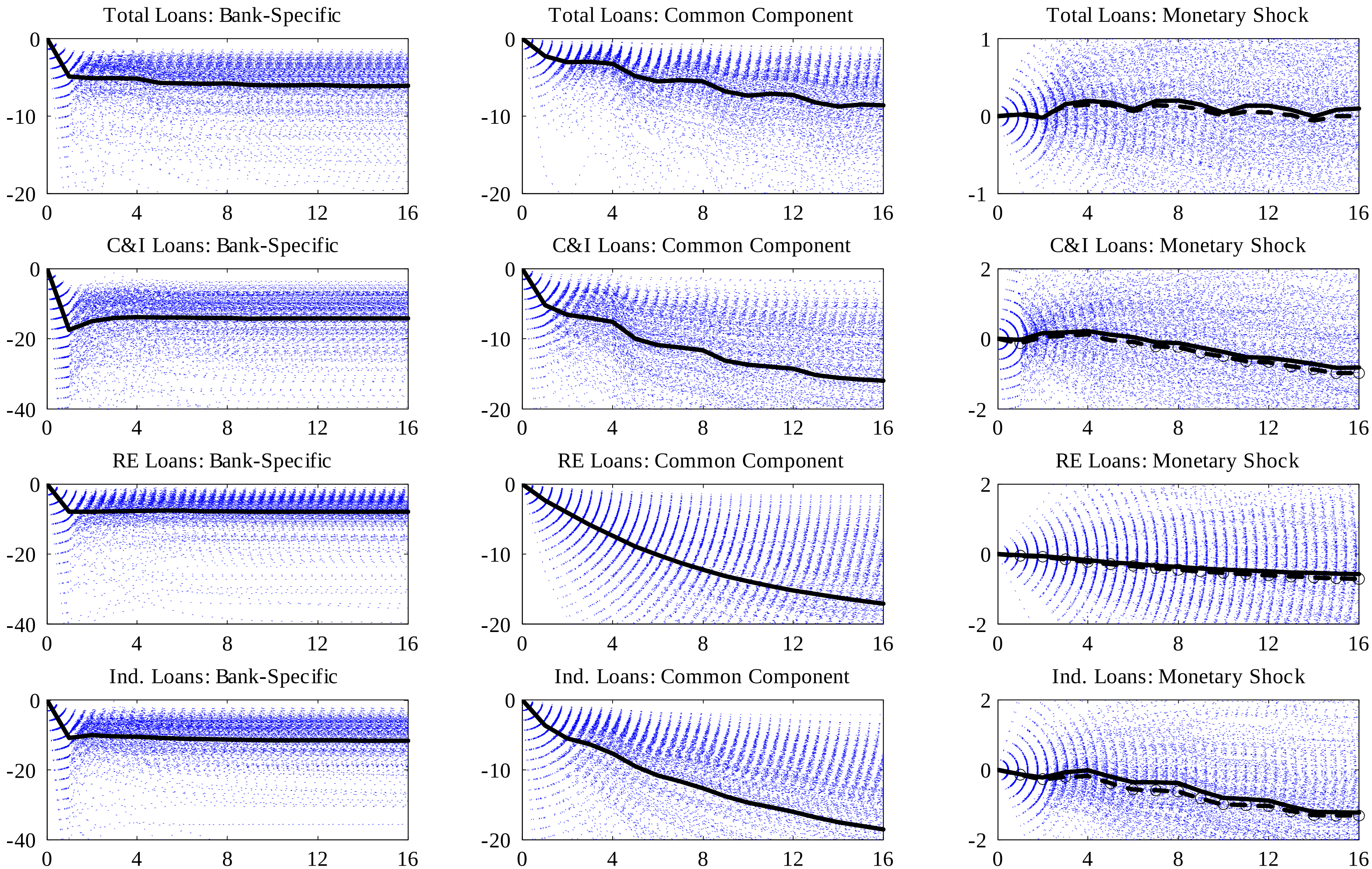

Figure 9: (Post-1984) Estimated impulse responses of lending variables (in %) for small banks to a bank-specific shock e_{it} of one standard deviation (left column), a common shock $\lambda_i' C_t$ of one standard deviation (middle column), and an identified monetary policy shock (right column). The monetary shock is a surprise of 25 basis points in the Federal funds rate. The thick solid lines represent unweighted average responses, while the thick-dashed lines represent the response of aggregate lending for small banks.