Conventional Monetary Policy Transmission during Financial Crises: An Empirical Analysis

Not-for-publication Online Appendix

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Abstract

This not-for-publication online appendix includes three appendices. Appendix A presents some details of the proposed Gibbs sampler and Appendix B lists the data set used. Appendix C contains an extended discussion of robustness for the results reported in the main text. First, it provides additional evidence for the differences between the two regimes. Second, Appendix C reports the results for alternative measures of financial stress, alternative identifications of the monetary policy shock, and alternative prior choices for the non-linear parameters.

JEL classification: C11; C32; E32; E44; G01

Keywords: Factor models; Smooth transition; Financial crisis; Monetary policy transmission

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A Details of Gibbs Sampler

This appendix presents some details about the proposed Gibbs sampler. It derives the likelihood of the STFM, lays down the Kalman filter and smoother algorithm used to estimate the factors and discusses convergence.

A.1 Likelihood

Under the normality assumptions, the likelihood of the model can be expressed as

$$\begin{aligned} L(\Lambda, f, D, H, Q, \nu) \quad \propto \quad & |H|^{T/2} \exp\left\{-\frac{1}{2} tr\left[(X - F\Lambda)' H^{-1} (X - F\Lambda)\right]\right\} \times \\ & |Q|^{T/2} \exp\left\{-\frac{1}{2} tr\left[(F - W^{ST} D)' Q^{-1} (F - W^{ST} D)\right]\right\}, \end{aligned} \tag{1}$$

where the first factor of the product is the likelihood of the observation equation and the second factor is the likelihood of the measurement equation. After some manipulations, I can rewrite the likelihood in the standard way as

$$\begin{aligned} L(\Lambda, f, D, H, Q, \nu) \quad \propto \quad & |H|^{T/2} \exp\left\{-\frac{1}{2} (\lambda - \hat{\lambda})' (H^{-1} \otimes F'F)(\lambda - \hat{\lambda})\right\} \times \\ & \exp\left\{-\frac{1}{2} tr\left[(X - F\hat{\Lambda})' H^{-1} (X - F\hat{\Lambda})\right]\right\} \times \\ & |Q|^{T/2} \exp\left\{-\frac{1}{2} (d - \hat{d})' (Q^{-1} \otimes W^{ST\prime} W^{ST})(d - \hat{d})\right\} \times \\ & \exp\left\{-\frac{1}{2} tr\left[(F - W^{ST} \hat{D})' Q^{-1} (F - W^{ST} \hat{D})\right]\right\}. \end{aligned} \tag{2}$$

Now the likelihood of each equation in the model given in (6) and (7) (in the main text) can be seen to be the product of an inverse Wishart density for H and Q, respectively, and a normal density for λ and d, respectively.

A.2 The Kalman Filter and Smoother Algorithm

Let $X^t = (x_1, x_2, ..., x_t)$, $\bar{F}^t = (\bar{f}_1, \bar{f}_2, ..., \bar{f}_t)$ and $\bar{D}^t = (\bar{D}_1, \bar{D}_2, ..., \bar{D}_t)$ be the history from period 1 to t of x_t, $\bar{f}_t$ and $\bar{D}_t$, which are from the state space representation given by Equation (10) of the main text. As in Carter and Kohn (1994) the conditional distribution of the whole history of the factors at time t is

$$p\left(\bar{F}^T|X^T,\bar{D}^T,\bar{\Lambda},\bar{Q},H,\nu\right)=p\left(\bar{f}_T|X^T,\bar{D}^T,\bar{\Lambda},\bar{Q},H,\nu\right)\prod_{t=1}^{T-1}p\left(\bar{f}^t|\bar{f}_{t+1},X^t,\bar{D}^t,\bar{\Lambda},\bar{Q},H,\nu\right). \quad (3)$$

Since the state space model in (10) is linear and Gaussian, the distribution of the factors is given by

$$\begin{aligned}\bar{f}_T|X^T,\bar{D}^T,\bar{\Lambda},\bar{Q},H,\nu &\sim N\left(\bar{f}_{T|T},P_{T|T}\right) && (4)\\ \bar{f}_t|\bar{f}_{t+1},X^t,\bar{D}^t,\bar{\Lambda},\bar{Q},H,\nu &\sim N\left(\bar{f}_{t|t+1},P_{t|t+1}\right)\quad t=T-1,...,1. && (5)\end{aligned}$$

First, I run the Kalman filter to obtain $\bar{f}_{T|T}$ and $P_{T|T}$. Starting with $\bar{f}_{0|0}=\mathtt{0}_{r\times p}$ and $P_{0|0}=I_{r\times p}$, the Kalman filter recursion over $t=1,...,T$ is given by

$$\begin{aligned}\bar{f}_{t|t-1} &= \bar{D}_t\bar{f}_{t-1|t-1} && (6)\\ P_{t|t-1} &= \bar{D}_tP_{t-1|t-1}\bar{D}_t'+\bar{Q}\\ \bar{f}_{t|t} &= \hat{\bar{f}}_{t|t-1}+P_{t|t-1}\bar{\Lambda}'\left(\bar{\Lambda}P_{t|t-1}\bar{\Lambda}'+H\right)^{-1}\left(x_t-\bar{\Lambda}\bar{f}_{t|t-1}\right)\\ P_{t|t} &= P_{t|t-1}-P_{t|t-1}\bar{\Lambda}'\left(\bar{\Lambda}P_{t|t-1}\bar{\Lambda}'+H\right)^{-1}\bar{\Lambda}P_{t|t-1}.\end{aligned}$$

Then, having the draw of $\bar{f}^T$ and the results of the filter, I run the Kalman smoother to obtain $\bar{f}_{T-1|T}$ and $P_{T-1|T}$. This backward updating provides me with a draw of $\bar{f}_{T-1}$, and in the next updating step with a draw of $\bar{f}_{T-2}$, and so on until I arrive at $\bar{f}_1$. More specifically, the Kalman smoother steps for $t=T-1,...,1$ are as follows:

$$\begin{aligned}\bar{f}_{t|t+1} &= \bar{f}_{t|t}+P_{t|t}\bar{D}_t'\left(\bar{D}_tP_{t|t}\bar{D}_t'+\bar{Q}\right)^{-1}\left(\bar{f}_{t+1}-\bar{D}_t\bar{f}_{t|t}\right) && (7)\\ P_{t|t+1} &= P_{t|t}+P_{t|t}\bar{D}_t'\left(\bar{D}_tP_{t|t}\bar{D}_t'+\bar{Q}\right)^{-1}\bar{D}_tP_{t|t}.\end{aligned}$$

If the lag order p exceeds one, then lags of the factors appear in $\bar{f}_t$ and $\bar{Q}$ is singular. In this case in the Kalman smoother steps, rather than conditioning on the full vector $\bar{f}_{t+1}$ when drawing $\bar{f}_t$, I only can use the first p elements of $\bar{f}_{t+1}$. See Kim and Nelson (1999) for more details.

A.3 Convergence

To make sure that the results are based on converged simulations, I follow various strategies. First, all my results are based on 20,000 draws of the Metropolis-within-Gibbs sampler, where the first 4,000 draws are discarded as burn-in. Second, I thin the draws by considering only every fourth draw to reduce possible autocorrelations of the sequence (since I have a Metropolis-Hastings step). Third, the Gibbs sampler is run several times to compare the results obtained each time assuring that the chain is converging to the same stationary distribution. Moreover, I assess convergence visually by checking the trace plots, which show the evolution of draws of the parameters and the log-likelihood. This is helpful for checking whether there are jumps in the level and variance of the respective parameter. Furthermore, to assure that the Gibbs sampler has moved to its target distribution, I compare the estimated factors obtained in the first half of simulations against the ones obtained in the second half of the sample as small deviations show that the simulated chain has converged. Finally, to assess the precision of the Gibbs sampler, I check the estimated factors along with their 95% confidence bands. I find that the estimated factors of the first and second halves of the simulations are nearly identical and the bands of the estimated factors are tight. Therefore, the chain seems to converge properly.

B Data

Series	Mnemonic	Description	Transformation
1	GDPC1	Real Gross Domestic Product, 1 Decimal	5
2	GDPDEF	Gross Domestic Product: Implicit Price Deflator	6
3	CPIAUCSL	Consumer Price Index For All Urban Consumers: All Items	6
4	FEDFUNDS	Effective Federal Funds Rate	2
5	GNPC96	Real Gross National Product	5
6	NICUR/GDPDEF	National Income/GDPDEF	5
7	DPIC96	Real Disposable Personal Income	5
8	OUTNFB	Nonfarm Business Sector: Output	5
9	FINSLC1	Real Final Sales of Domestic Product	5
10	FPIC1	Real Private Fixed Investment	5
11	PRFIC1	Real Private Residential Fixed Investment	5
12	PNFIC1	Real Private Nonresidential Fixed Investment	5
13	GPDIC1	Real Gross Private Domestic Investment	5
14	PCECC96	Real Personal Consumption Expenditures	5
15	PCNDGC96	Real Personal Consumption Expenditures: Nondurable Goods	5
16	PCDGCC96	Real Personal Consumption Expenditures: Durable Goods	5
17	PCESVC96	Real Personal Consumption Expenditures: Services	5
18	GPSAVE/GDPDEF	Gross Private Saving/GDP Deflator	5
19	FGCEC1	Real Federal Consumption Expenditures & Gross Investment	5
20	FGEXPND/GDPDEF	Federal Government: Current Expenditures/GDP deflator	5
21	FGRECPT/GDPDEF	Federal Government Current Receipts/GDP deflator	5
22	FGDEF	Federal Real Expend-Real Receipts	2
23	CBIC1	Real Change in Private Inventories	1
24	EXPGSC1	Real Exports of Goods & Services	5
25	IMPGSC1	Real Imports of Goods & Services	5
26	CP/GDPDEF	Corporate Profits After Tax/GDP deflator	5
27	NFCPATAX/GDPDEF	Nonfinancial Corporate Business: Profits After Tax/GDP deflator	5
28	CNCF/GDPDEF	Corporate Net Cash Flow/GDP deflator	5
29	DIVIDEND/GDPDEF	Net Corporate Dividends/GDP deflator	5
30	HOANBS	Nonfarm Business Sector: Hours of All Persons	5
31	OPHNFB	Nonfarm Business Sector: Output Per Hour of All Persons	5
32	UNLPNBS	Nonfarm Business Sector: Unit Nonlabor Payments	5
33	ULCNFB	Nonfarm Business Sector: Unit Labor Cost	5
34	WASCUR/CPI	Compensation of Employees: Wages & Salary Accruals/CPI	5
35	COMPNFB	Nonfarm Business Sector: Compensation Per Hour	6
36	COMPRNFB	Nonfarm Business Sector: Real Compensation Per Hour	5
37	GDPCTPI	Gross Domestic Product: Chain-type Price Index	6
38	GNPCTPI	Gross National Product: Chain-type Price Index	6
39	GNPDEF	Gross National Product: Implicit Price Deflator	6
40	INDPRO	Industrial Production Index	5
41	IPBUSEQ	Industrial Production: Business Equipment	5
42	IPCONGD	Industrial Production: Consumer Goods	5
43	IPDCONGD	Industrial Production: Durable Consumer Goods	5
44	IPFINAL	Industrial Production: Final Products (Market Group)	5
45	IPMAT	Industrial Production: Materials	5
46	IPNCONGD	Industrial Production: Nondurable Consumer Goods	5
47	AWHMAN	Average Weekly Hours: Manufacturing	2
48	AWOTMAN	Average Weekly Hours: Overtime: Manufacturing	2
49	CIVPART	Civilian Participation Rate	2
50	CLF16OV	Civilian Labor Force	5
51	CE16OV	Civilian Employment	5
52	USPRIV	All Employees: Total Private Industries	5
53	USGOOD	All Employees: Goods-Producing Industries	5
54	SRVPRD	All Employees: Service-Providing Industries	5

Table 1: *Transformations of* x_t*:* $1 = x_t$, $2 = \Delta x_t$, $5 = \Delta \log x_t$, $6 = \Delta^2 \log x_t$

Continued...

Series	Mnemonic	Description	Transformation
55	UNEMPLOY	Unemployed	5
56	UEMPMEAN	Average (Mean) Duration of Unemployment	5
57	UNRATE	Civilian Unemployment Rate	2
58	HOUST	Housing Starts: Total: New Privately Owned Housing Units Started	5
59	M1SL	M1 Money Stock	6
60	M2MSL	M2 Minus	6
61	M2SL	M2 Money Stock	6
62	BUSLOANS	Commercial and Industrial Loans at All Commercial Banks	6
63	CONSUMER	Consumer (Individual) Loans at All Commercial Banks	6
64	LOANINV	Total Loans and Investments at All Commercial Banks	6
65	REALLN	Real Estate Loans at All Commercial Banks	6
66	TOTALSL	Total Consumer Credit Outstanding	6
67	CPIULFSL	Consumer Price Index for All Urban Consumers: All Items Less Food	6
68	CPILEGSL	Consumer Price Index for All Urban Consumers: All Items Less Energy	6
69	CPILFESL	Consumer Price Index for All Urban Consumers: All Items Less Food & Energy	6
70	CPIENGSL	Consumer Price Index for All Urban Consumers: Energy	6
71	CPIUFDSL	Consumer Price Index for All Urban Consumers: Food	6
72	PPICPE	Producer Price Index Finished Goods: Capital Equipment	6
73	PPICRM	Producer Price Index: Crude Materials for Further Processing	6
74	PPIFCG	Producer Price Index: Finished Consumer Goods	6
75	PPIFGS	Producer Price Index: Finished Goods	6
76	OILPRICE	Spot Oil Price: West Texas Intermediate	6
77	USNEDG	US Manufacturers new Orders of durable Goods	5
78	USNOCG	US New Orders of Consumer Goods & Materials	5
79	NAPMNOI	US ISM Manufacturer Survey: New Orders Index	1
80	USCYLEAD	US the Conference Board Leading Economic Indicators Index	5
81	GEXPND/GDPDEF	Government Current Expenditures/ GDP deflator	5
82	GRECPT/GDPDEF	Government Current Receipts/ GDP deflator	5
83	GDEF	Governnent Real Expend-Real Receipts	2
84	GCEC1	Real Government Consumption Expenditures & Gross Investment	5
85	TB3MS	3-Month Treasury Bill: Secondary Market Rate	2
86	TB6MS	6-Month Treasury Bill: Secondary Market Rate	2
87	GS1	1-Year Treasury Constant Maturity Rate	2
88	GS10	10-Year Treasury Constant Maturity Rate	2
89	AAA	Moody's Seasoned Aaa Corporate Bond Yield	2
90	BAA	Moody's Seasoned Baa Corporate Bond Yield	2
91	MPRIME	Bank Prime Loan Rate	2
92	GS10-FEDFUNDS		1
93	GS1-FEDFUNDS		1
94	BAA-AAA	Default Rate Spread	1
95	MPRIME-TB3MS	External Finance Premium	1
96	MPRIME-TB6MS	Bank Prime Loan Rate minus 6-Month Treasury Bill	1
97	US500STK	US Standard & Poor's Index of 500 common Stocks	5
98	USSHRPRCF	US Dow Jones Industrial Share Price Index	5
99		Realized Volatility of S&P 500 Index	1
100	LIBOR3M	3-Month US Deposit London Offer	2
101	LIBOR6M	6-Month US Deposit London Offer	2
102	LIBOR3M-FEDFUNDS		1
103	LIBOR3M-TB3M	TED spread	1
104	NYSE	US NYSE Composite Index	5
105		Realized Volatility of NYSE Index	1
106	EXCRESNS	Excess Reserves of Depository Institutions	5
107	ADJRESSL	Adjusted Monetary Base	5
108		Real Net Taxes	5

Table 1 (Continued): *Transformations of* x_t*:* $1 = x_t$, $2 = \Delta x_t$, $5 = \Delta \log x_t$, $6 = \Delta^2 \log x_t$

C Robustness of Results

C.1 Additional Evidence on Differences between the two Regimes

In this section, I provide an additional way of testing the hypothesis that the impulse responses are equal in the financial crises regime and the normal regime. In addition to standard confidence bands of the differences between impulse responses in the two regimes, here I use empirical distribution functions. Figures C1 and C2 show the empirical distribution functions for the maximum difference of the responses in the high and low financial stress regimes. x denotes the value of the maximum difference at each draw of the Gibbs sampler (after thinning). The maximum of the median difference across horizons is used. Evidence for regime-dependent transmission of monetary policy shocks is reinforced. As for GDP, employment, investment, and industrial production, the maximum difference between the two regimes is positive with a probability of 90% (80% in the case of consumption and new orders). Similar probabilities are reached for differences between responses of financial variables. For example, the maximum difference between the responses of the EFP is negative with a probability of 90% and the differences between responses of the stock price indices are positive with a probability of around 80%.

C.2 Alternative Financial Condition Indices

In the main text, I used the purged version of the financial conditions index (FCI) constructed by Hatzius et al. (2010). Here I perform a robustness exercise to check for robustness of results to the choice of the FCI. More specifically, I employ the unpurged version of the Hatzius et al. (2010) FCI and the Federal Reserve Bank of Chicago National Financial Conditions Index (NFCI).[1]

First, I use the unpurged version of the FCI by Hatzius et al. (2010), which is the first principal component of the 45 financial indicators they used. Results obtained are robust to this alternative version of the FCI. Impulse responses for the macroeconomic as well as financial variables follow very similar patterns. Figure C3 reports the differences between impulse responses. An expansionary monetary policy shock increases macroeconomic vari-

[1] As requested by the STFM, all indices enter standardized in the model. Therefore, I used the same non-linear parameter priors as for the benchmark estimation in the main text. However, as it is the case for the baseline model, results for the alternative indices are robust to reasonable choices of the non-linear parameter priors.

ables such as GDP, employment, consumption, investment and industrial production by more during times of high financial stress than it does during normal times. As for the financial variables, the EFP, stock prices, and loans react more to a monetary policy shock during financial crises.

The FCIs constructed by Hatzius et al. (2010) have one major advantage over other indices since they date back to 1970. Most of the other indices measuring financial conditions start in the 1990s.[2] This makes them difficult to employ in my setting, since, with a maximum of 20 years of data, it becomes rather difficult to identify the financial crises regime. However, the NFCI constructed by the Federal Reserve Bank of Chicago starts in 1973 and, thus, I can employ it as an alternative choice of the transition variable in the STFM. The NFCI is a weighted average of a large number of variables measuring financial activity each expressed relative to their sample averages and scaled by their sample standard deviations. Results obtained by using the NFCI are very similar to the ones obtained from the Hatzius et al. (2010) index. Figure C4 reports the difference of impulse responses between the high financial stress regime and the normal regime. Again, the credit channel seems to be asymmetric with the EFP, stock prices and bank loans reacting by more during financial crises.

In sum, results and conclusions seem to be robust to the choice of the transition variable measuring financial stress.

C.3 Identification of the Monetary Policy Shock

By construction, in the STFM the number of structural shocks equals the number of common factors. Therefore, assessing the results obtained by using alternative identifications, at the same time allows me to assess the robustness to the number of factors. Here, I discuss the robustness of results to a Cholesky scheme including three and six variables, i.e., $r = 3$ and $r = 6$.

First, Figure C5 shows results obtained for the STFM including three factors. In that case, I ordered the federal funds rate third and GDP and the GDP deflator are ordered before. Responses and their differences to a conventional monetary policy shock are very

[2] For example, the Federal Reserve Bank of St. Louis Financial Stress Index starts in 1993, the Federal Reserve Bank of Kansas City Financial Stress Index in 1990, the Goldman Sachs Financial Conditions Index in 1990, and the Bloomberg Financial Condition Index in 1991.

similar to the ones obtained from the baseline model. Second, Figure C6 plots differences between responses obtained in a STFM with 6 factors. In this specification, six variables enter the Cholesky identification. In principle any of the variables contained in the data set can be chosen and ordered adequately. For example, any variable that is slow moving could be ordered before the federal funds rate and any variables that are fast moving such as financial variables could be ordered after. Here, I choose the S&P 500 index and its realized volatility to be ordered after the federal funds rate. Again, results are robust to this ordering.[3]

C.4 Prior Choices

Since the threshold parameter provides the point around which the dynamics of the model change, I also experiment with choosing different prior means of c, i.e., $m_c = \{-1.3, -1.2, -1.1, -1.0, -0.9, -0.8\}$. Results are robust to these prior choices and, for brevity, I only discuss results for $m_c = -1.0$ and $m_c = -1.3$ in this section. Choosing a prior mean for c of -1.0 does not change the results or main conclusion of this paper. Impulse responses and their respective difference to a conventional monetary policy shock look very similar to the ones described in the main text. Figure C7 plots the difference between responses in the financial crises and the normal regime and confirms that conclusions reached in the main text remain the same. There is a positive difference between the responses of macroeconomic variables. Moreover, differences are negative for the EFP and positive for stock prices and commercial and industrial loans. A similar picture arises for a prior choice of $m_c = -1.3$. However, bands around the response in the financial stress regime are much wider yielding wider bands for the difference between responses in the high financial stress and normal regime. In sum, median responses are very similar for the different prior choices of c, however as the prior mean of c decreases, confidence bands in the financial crises regime get wider since they are based on lesser and lesser data in the financial crises regime.

[3]In the STFM, which is based on the factor model by Forni et al. (2009), the structural shocks are identified by imposing restrictions on variables contained in x_t per se. An alternative way of identifying structural shocks in factor models is along the lines of FAVAR models, e.g., Bernanke et al. (2005). In those models, structural shocks are identified by imposing restrictions on the factors which are characterized as slow and fast moving factors. The way employed here has the advantage that I can stay agnostic about the interpretation of the factors (whether they are purely financial or related to the business cycle). Since identification is achieved by restricting variables per se, that are established for achieving identification in the SVAR literature, the factor are rather a statistical tool to model the dynamics of the system.

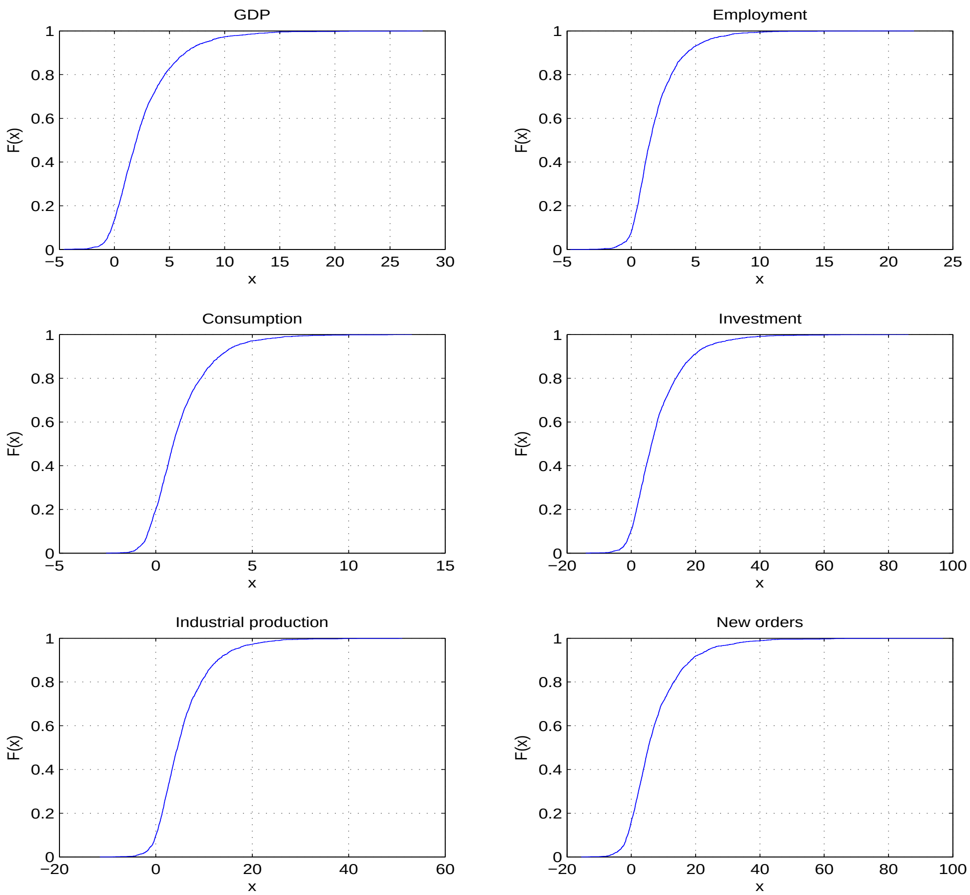

Figure C1: *This figure plots the empirical distribution function of the maximum difference between the impulse responses of macroeconomic variables in the high financial stress regime and the normal regime. x denotes the value of the maximum difference at each draw of the Gibbs sampler (after thinning). The maximum of the median difference across horizons is used.*

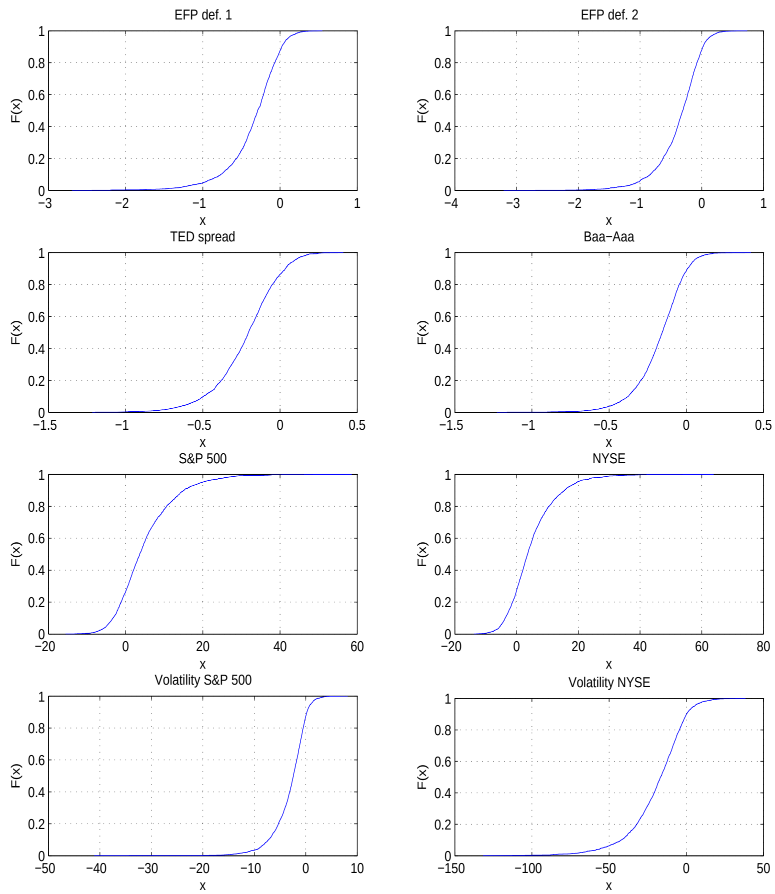

Figure C2: *This figure plots the empirical distribution function of the maximum difference between the impulse responses of financial variables in the high financial stress regime and the normal regime. x denotes the value of the maximum difference at each draw of the Gibbs sampler (after thinning). The maximum of the median difference across horizons is used.*

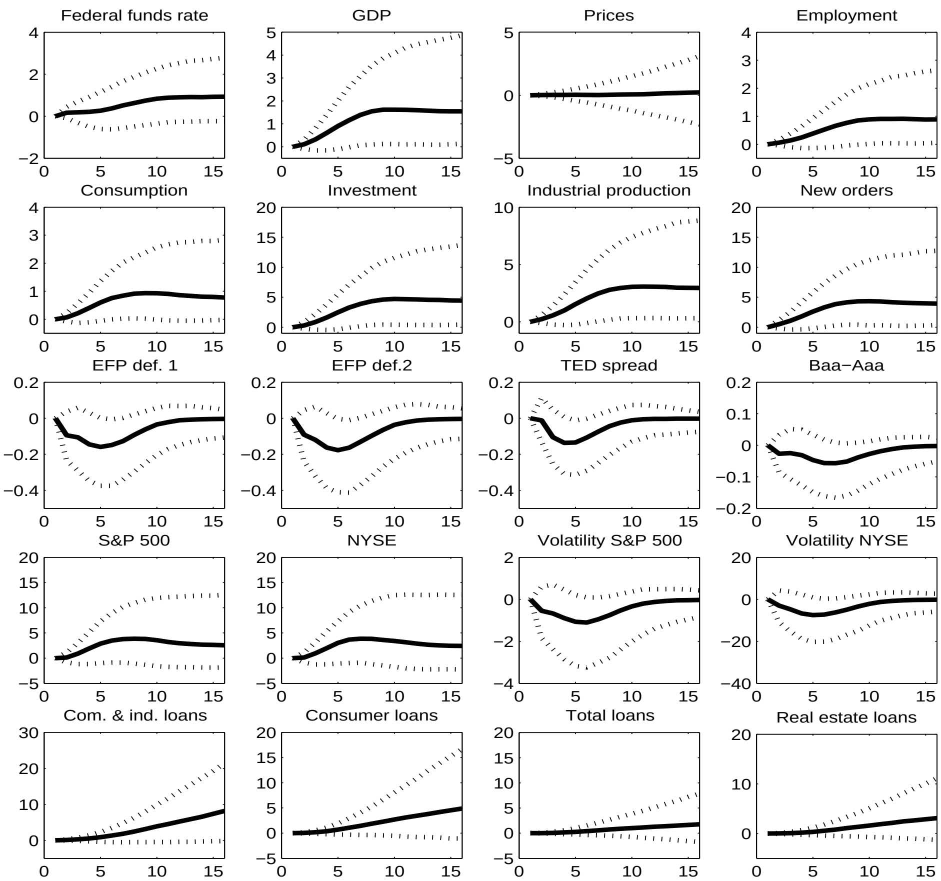

Figure C3: *This figure plots the difference between impulse responses in the high financial stress regime and the normal regime for the STFM using the unpurged FCI of Hatzius et al. (2010) as transition variable. Solid lines indicate the median and dotted lines the 68% confidence bands.*

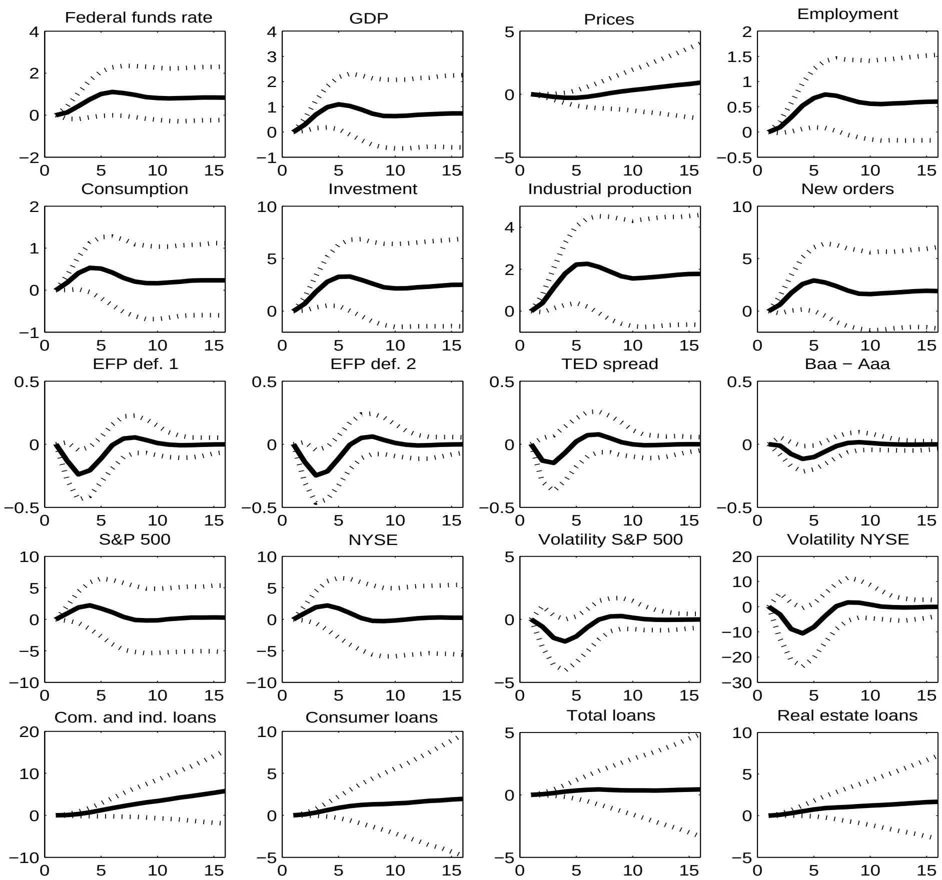

Figure C4: *This figure plots the difference between impulse responses in the high financial stress regime and the normal regime for the STFM using the NFCI as transition variable. Solid lines indicate the median and dotted lines the 68% confidence bands.*

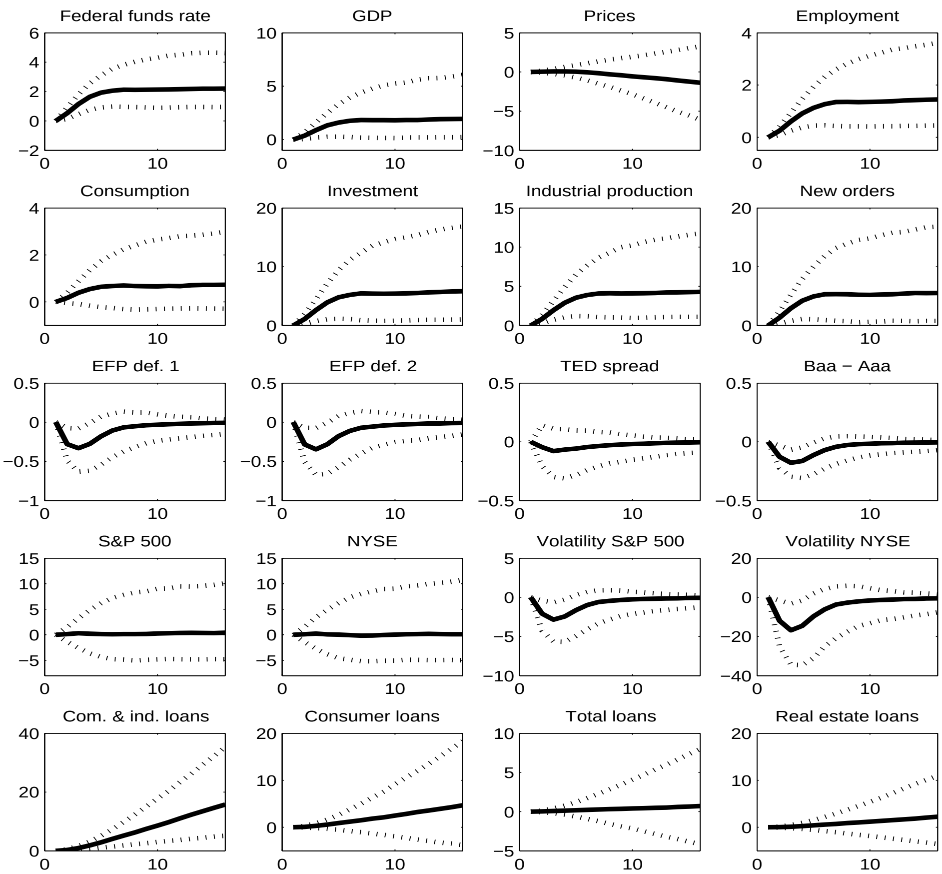

Figure C5: *This figure plots the difference between impulse responses in the high financial stress regime and the normal regime for the STFM containing three factors. Solid lines indicate the median and dotted lines the 68% confidence bands.*

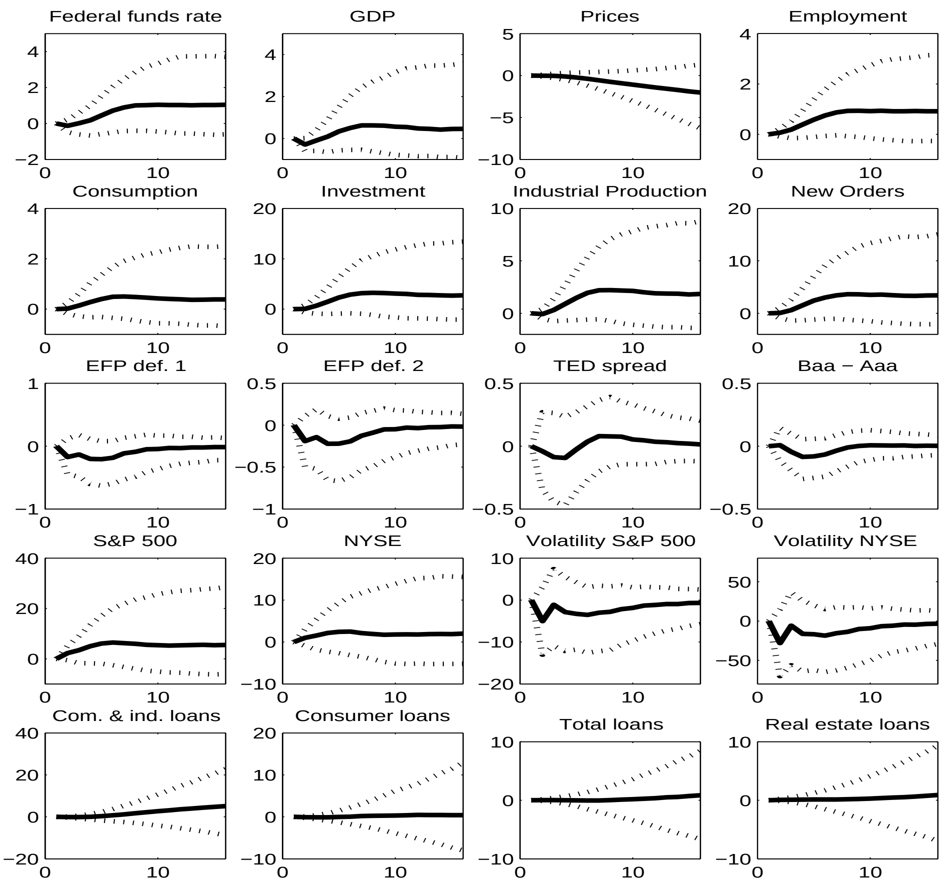

Figure C6: *This figure plots the difference between impulse responses in the high financial stress regime and the normal regime for the STFM containing six factors. Solid lines indicate the median and dotted lines the 68% confidence bands.*

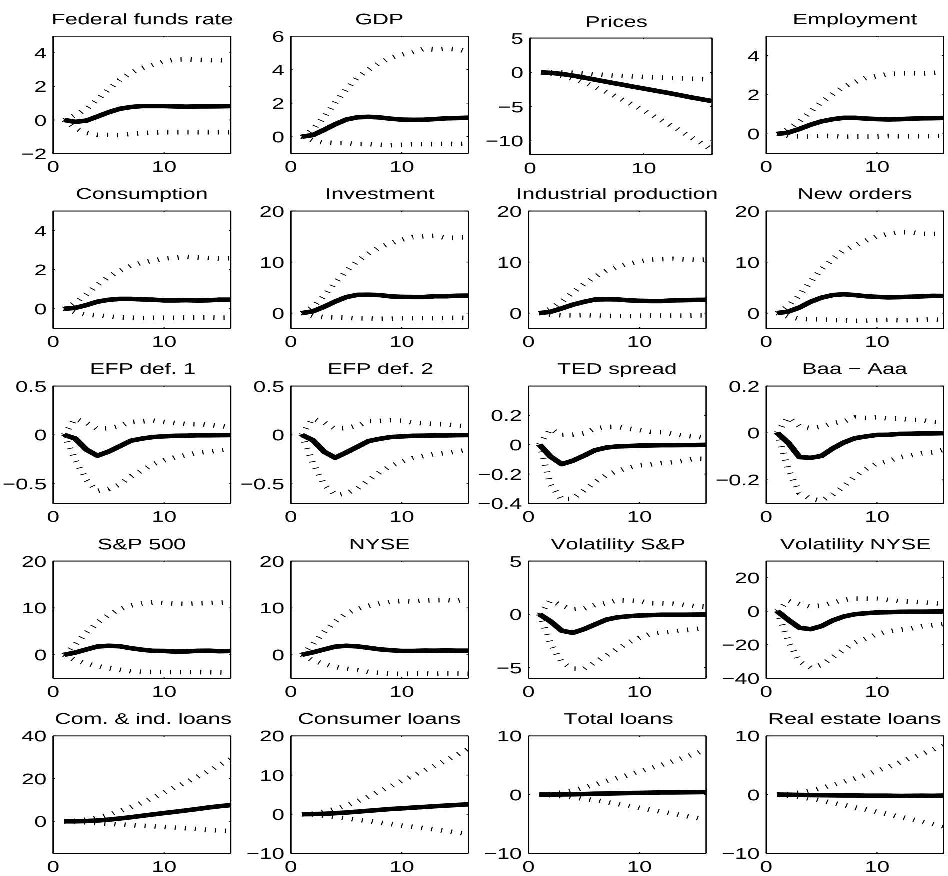

Figure C7: *This figure plots the difference between impulse responses in the high financial stress regime and the normal regime for the STFM assuming an alternative prior for the threshold parameter, i.e.,* $m_c = -1.0$*. Solid lines indicate the median and dotted lines the 68% confidence bands.*

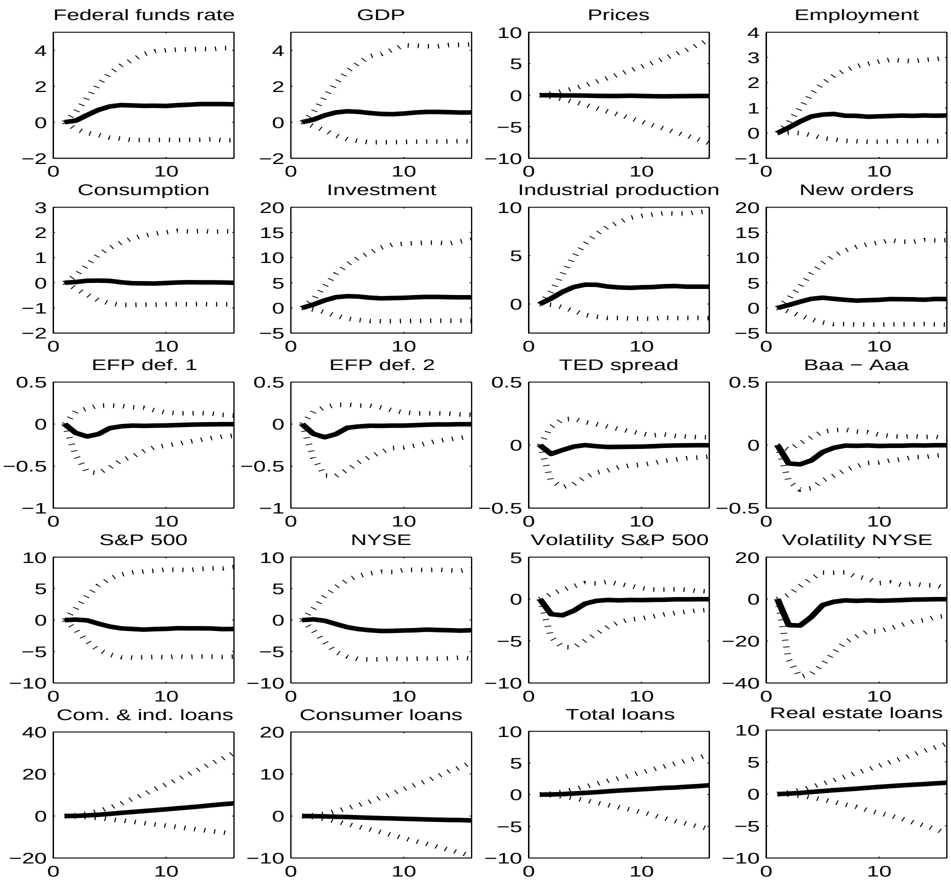

Figure C8: *This figure plots the difference between impulse responses in the high financial stress regime and the normal regime for the STFM assuming an alternative prior for the threshold parameter, i.e., $m_c = -1.3$. Solid lines indicate the median and dotted lines the 68% confidence bands.*

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