Monetary Policy Uncertainty and the Transmission of Monetary Policy Shocks to Financial Markets

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Abstract

We study how monetary policy uncertainty affects the transmission of monetary policy shocks to financial markets via the credit channel . In particular we estimate a Factor Augmented Threshold VAR (FTVAR) model using bayesian methods. Excess returns are on industry- and size-sorted portfolios. Our results show that monetary policy uncertainty affects the transmission of monetary policy shocks to financial markets. We find that monetary policy uncertainty has heterogeneous effects on the transmission of monetary policy shocks on firms.

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1 Introduction

Financial markets are an important channel in the transmission of monetary policy to the real economy and one particular channel through wich monetary policy affects the stock market is the credit channel, either in the form of the balance sheet channel or in the form of the bank lending channel. The balance sheet channel postulates that a contractionary monetary policy raises a firms cost associated with external finance such as agency costs or informational costs (see e.g. Bernanke, Gertler, and Gilchrist (1999), Bernanke and Gertler (1989)). Alternatively it reduces the value of a firms assets that can be used as a collateral for borrowing. Or, in other words, a raise in interest rates reduces investments and therefore future earnings. In the form of the bank lending channel a contractionary monetary policy increases a banks funding costs and therefore reduces lending. Empirical evidence from time series studies and event studies provide support for the importance of the credit channel for asset returns (see e.g. Lucca and Moench (2015), Maio (2013), Patelis (1997)). Given the importance of the credit channel for affecting asset returns one may suspect that uncertainty around monetary policy would also affect asset returns.

A recent strand of literature investigates the role of policy uncertainty for macroeconomic variables and finds that policy uncertainty affects real and financial variables negatively. For instance, Bloom (2009) argues that policy uncertainty reduces investments as firms will adopt a wait-and-see policy and stop investing until they know which policy is adapted. The real option value of this wait-and-see strategy increases with uncertainty. Resolving uncertainty generates an investment boom as firms continue the delayed projects with the size of the boom depending on the adapted strategy and a more favorable policy generates a larger boom. Hence, in periods with low policy uncertainty we should see a smaller boom generated by the resolution of policy uncertainty. In addition to the macroeconomic literature there is also an emerging literature studying the effects of policy uncertainty on asset returns and risk premia. Pastor and Veronesi (2012) and Pástor and Veronesi (2013) study the theoretical implications of policy and political uncertainty on financial markets. They argue that policy uncertainty affects asset prices negatively in the sense that higher uncertainty decreases prices and increase risk premia with empirical evidence supporting these predictions from theoretical models (see e.g., Brogaard and Detzel (2015), Brogaard et al. (2015), Liu, Shu, and Wei (2017))

Considering the importance of monetary policy for the economy a crucial question is how uncertainty about monetary policy affects the transmission of monetary policy shocks to the economy. The aim of this paper is to study how monetary policy uncertainty affects the transmission of monetary policy shocks. An important aspect of our analysis is that we look at the response of stock returns to monetary policy shocks at a disaggregated level. In particular we look at firms disaggregated to the industrial level as well as firms sorted by size. The analysis proceeds in two steps. First, we use a simple regression model to study the static effects of monetary policy and monetary policy uncertainty on asset returns. In the second step we study the dynamic effects in a Factor-Augmented Threshold Vector Autoregression (FTVAR). The FTVAR enables us to distinguish between periods of high uncertainty and low uncertainty. The FTVAR is a non-linear generalization of the Factor-Augmented VAR proposed by Bernanke, Boivin, and Eliasz (2005). A similar model using the Smooth-Transition framework has been introduced by Popp and Zhang (2016) and by Huber and Fischer (2015) in a Markov-Switching framework.

Looking at disaggregated returns and not only market returns is motivated by the following observation. The credit channel implies that a firms' capital structure may be an important determinant of the effect of monetary policy on asset returns. In particular firms with a weak capital structure, in the sense that they have high debt and low equity, should be more affected by negative monetary policy shocks than firms with a strong capital structure. And while capital structures across firms may be heterogeneous, firm size is positively correlated with leverage in the sense that larger firms are more leveraged (see Titman and Wessels (1988), Rajan and Zingales (1995) or Fama and French (2002)). Furthermore, as shown by Bordo, Duca, and Koch (2016) economic policy uncertainty affects the credit channel via bank lending as policy uncertainty has a negative impact on loan growth of banks. Thus, one expects that the effects of policy uncertainty vary with firms characteristics' such as size of the firm.

The rest of the paper is structured as follows. In section 2 we do an event study. In Section 3 we discuss the FTVAR model. In Section 4 we discusses the dynamic effects of monetary policy shocks and Section 5 concludes the paper

2 A First Look at the Effects of Monetary Policy and Monetary Policy Uncertainty

Our analysis with using an event-study similar to Maio (2013) (other authors?) adding monetary policy uncertainty and including the interaction between the federal funds rate and monetary policy uncertainty to capture how monetary policy uncertainty affects the transmission of monetary policy. We first describe the data used in section 2.1 and the use of the federal funds rate is discussed in Section 2.2 we discuss the use of the federal funds rate and in Section 2.3 we discuss the results.

2.1 Data

Uncertainty about monetary policy is measured using the news-based monetary policy uncertainty index[1] by Baker, Bloom, and Davis (2016). To measure monetary policy uncertainty they perform a word search in selected news papers and count how often a combinantion of selected key words is used. These key words include (i) ’uncertainty’ or ’uncertain’, (ii) ’economic’ or ’economy’ and (iii) ’federal reserve’, ’fed funds rate’, ’monetary policy’ and some more. The first two groups of the key words refer to uncertainty and the economy and the last group refers to monetary policy. Only if an article contains key words from all three categories they are counted. To account for the varying volume of news articles these counts are scaled by the total number of news articles in the same paper and month. Baker, Bloom, and Davis (2016) then normalize the uncertainty index to have a mean 100 for the period from 1985 to 2009 and a higher value means higer monetary policy uncertainty. For our empirical exercise we normalize the whole series to have 0 mean and a standard devia-

[1] Data can be downloaded from http://www.policyuncertainty.com/

tion of 1. A similar news-based measure of monetary policy uncertainty with a different set of keywords has been proposed by Husted, Rogers, and Sun (2017).

Another way to capture uncertainty has been proposed by Patton and Timmermann (2010). They use the forecast dispersion available in the survey of professional forecasters as a proxy for uncertainty. Apart from the lower frequency of the survey this method does not capture directly uncertainty about monetary policy but only uncertainty about macroeconomic variables that are affected by monetary policy, for instance inflation. Furthermore, as pointed out by Lahiri and Sheng (2010), it is also a bad empirical proxy for uncertainty.

Excess returns are formed on the basis of 10 size-sorted portfolios. These portfolios are constructed in each year at the end of June. In particular the portfolio in June of year t the portfolio for July in year t until June in year $t+1$ is formed and includes all NYSE, AMEX, and NASDAQ stocks for which market equity data is available in June of year t. Excess returns are then measured as the 1-month return over the 1-month riskfree rate. In addition to size-sorted portfolios we also look at portfolios sorted on the Book-to-Market ratio. As argued by Fama and French (1995) a high book-to-market ratio is an indicator for sustained distress. Hence, firms with a high book-to-market should be more sensitive to monetary policy. All three data sets, i.e. size sorted portfolios and the 1-month riskfree interest rate are from Kenneth Frenchs Data library.[2] Table 1 provides industry definitions as well as mean and standard deviation of portfolios.

For the regression we add variables that indicate the state of the business cycle which are downloaded from the Federal Reserve Economic Database. These variables are BILL, the yield on the 3-month Treasury bill. RREL is the BILL minus the 12-month rolling average and TERM is the difference between the yield on the 10 year Treasury Bond and the yield on the 3 month Treasury bill. DEF is the difference between the Moody's BAA corporate bond yield and the Moody's AAA corporate bond yield. We also include the Chicago National Financial Activity Index and the log dividend/price ratio of the S&P 500 using

[2] Data is available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Table 1: Descriptive statistics: Industryportfolios

Abbreviation	Industry Definition	Mean	Standard deviation
NoDur	Consumer Non-Durables	0.0116	0.0409
Dur	Consumer Durables	0.0087	0.0681
Manuf	Manufacturing	0.0112	0.0532
Enrgy	Oil, Gas, and Coal Extraction and Products	0.0096	0.0533
Chems	Chemicals and Allied Products	0.0107	0.045
BusEq	Business Equipment	0.0104	0.0687
Telcm	Telephone and Television Transmission	0.0095	0.0506
Utils	Utilities	0.0093	0.0395
Shops	Wholesale, Retail and Some Services	0.0105	0.0484
Hlth	Healthcare, Medical Equipment, and Drugs	0.0117	0.0463
Money	Finance	0.0103	0.055
Other	Other	0.008	0.0502

Note: Abbreviation, Industrydefinition and mean and standard deviation for the 12 industry portfolios.

Table 2: Descriptive Statistics for size-sorted portfolios

(a) Book-to-Market Ratio

Decile	Mean	Standard Deviation
1st Dec	0.0095	0.0493
2nd Dec	0.0106	0.045
3rd Dec	0.0113	0.0448
4th Dec	0.0101	0.0458
5th Dec	0.0105	0.0446
6th Dec	0.0109	0.0432
7th Dec	0.0096	0.0461
8th Dec	0.0099	0.0463
9th Dec	0.0121	0.0493
10th Dec	0.0118	0.0628

(b) Market Equity

Decile	Mean	Standard Deviation
1st Dec	0.0101	0.0589
2nd Dec	0.0104	0.0625
3rd Dec	0.0113	0.0584
4th Dec	0.0103	0.0564
5th Dec	0.0109	0.0551
6th Dec	0.011	0.0509
7th Dec	0.0113	0.0497
8th Dec	0.0111	0.0497
9th Dec	0.0109	0.0456
10th Dec	0.0096	0.0426

(c) Operating Profit

Decile	Mean	Standard Deviation
1st Dec	0.0062	0.0682
2nd Dec	0.0081	0.0539
3rd Dec	0.009	0.0487
4th Dec	0.0099	0.0456
5th Dec	0.0098	0.0478
6th Dec	0.0098	0.0423
7th Dec	0.0095	0.045
8th Dec	0.0113	0.0433
9th Dec	0.0112	0.0434
10th Dec	0.0107	0.0441

(d) Investments

Decile	Mean	Standard Deviation
1st Dec	0.0111	0.0513
2nd Dec	0.0122	0.0467
3rd Dec	0.0105	0.0405
4th Dec	0.011	0.0404
5th Dec	0.0108	0.042
6th Dec	0.0101	0.0424
7th Dec	0.0106	0.0436
8th Dec	0.0104	0.0468
9th Dec	0.0105	0.054
10th Dec	0.0072	0.0582

Table 3: Mean and standard deviation of variables

Variable	Mean	Standard Deviation	min	max
ΔFFR	0	0.0053	-0.0663	0.0306
T-Bill	3.4968	3.1728	0.01	16.3
DEF	1.1831	0.7016	0.32	5.64
TERM	1.8466	1.0911	-0.7	4.15
CFNAI	-0.0001	1	-5.13	2.74
MPU	0	0.9993	-1.3187	5.3797
log(D/P)	-3.8258	0.3272	-4.5021	-3.1205

data from Robert Shiller[3]

For the VAR in later section we use a different set of variables that indicate the state of the business cycle and which is in line with the macroeconomic literature on monetary policy. These variables are Industrial Production, the Consumer Price Index. This data is downloaded from the Federal Reserve Economic Database.

2.2 Measuring Monetary Policy

As a proxy for monetary policy actions we use the changes in the federal funds rate

$$\Delta FFR_t = FFR_t - FFR_{t-1} \tag{1}$$

This measure of monetary policy actions has been used by Thorbecke (1997), Patelis (1997), Maio (2013) and Galí and Gambetti (2015), among others and is also widely used in the macroeconomic literature as a proxy for monetary policy (see e.g. Bernanke and Blinder (1992))

In the literature, there are two other ways to identify monetary policy shocks. One way is to use market-based expectations about the federal funds rate by using financial market instruments that are linked to the policy instrument. Federal Funds Futures have been proposed by Kuttner (2001). Federal Funds Futures have been introduced in 1988 and their price is based on the average Federal Funds Rate over a month. Hence, federal funds futures reflect expectations about upcoming changes in the federal funds rate. There-

[3]The data can be downloaded from http://www.econ.yale.edu/~shiller/data.htm

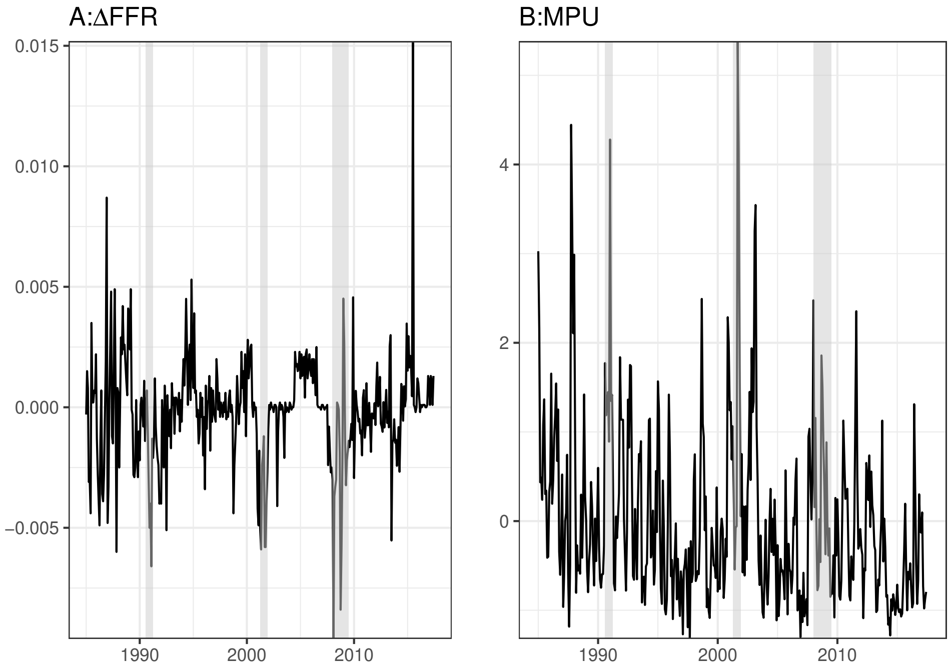

Figure 1: Figure plotting monetary policy uncertainty (Panel B) and the change in the federal funds rate as a proxy for monetary policy (Panel A). The sample period is 1985:01-2017:6. Shaded areas indicate NBER-recessions.

fore, announcements of changes in the interest rate can be decomposed into an expected change and an unexpected change. For our purpose, which is to estimate a VAR-Model, we need a regular time series. As the FOMC does not meet at regularly this measure cannot be used in a VAR-Model. Additionally, by using the changes in the federal funds rate, we are able to use a longer time series which gives us more precise estimates. Another financial market instrument used in the literature and with a similar interpretation as Federal Funds Futures are eurodollar futures (Cochrane and Piazzesi (2002)).

By using high-frequency data the event-study literature can pinpoint the exact time of monetary policy announcements and study its impact on financial markets (see e.g. Rigobon and Sack (2004)). This has the obvious advantage that it is very unlikely that any other information than monetary policy announcements would affect returns. The obvious downside is that as with federal funds futures, i.e. changes are not made at regular spaced intervals and thus cannot be used in a time-series context.

To estimate the contemporaneous actions of monetary policy on asset returns, the literature uses the following regression:

$$r_t^i = a^i + b^i \Delta FFR_t + \epsilon_{i,t}. \tag{2}$$

With r_t^i the return in excess of the 1-month risk-free rate for industry i. This baseline regression does not capture monetary policy uncertainty and how monetary policy uncertainty affects the transmission of monetary policy shocks. Therefore, we run the following regression

$$r_t^i = a^i + b_1^i \Delta FFR_t + b_2^i MPU_t + b_3 \Delta FFR_t \times MPU_t + \delta X_t + \epsilon_t \tag{3}$$

The interpretation of this regression equation is straightforward, i.e. b_1 and b_2 capture the effects of a monetary policy shock and monetary policy uncertainty, respectively, while b_3 estimates how returns are affected by a monetary policy shock given a level of monetary policy uncertainty. And X_t represents additional control variables.

Our sample period covers all months between 1985 : 1 and 2017 : 6. As discussed above we use the changes in the federal funds rate as a proxy for monetary policy actions. Between 1974 and 1979 the Federal reserve conducted monetary policy through a federal funds rate targeting procedure.[4] Additionally, in the late 1980s returned to an explicit federal funds rate targeting procedure. In recent years, the federal funds rate has been close to the zero lower bound. To include these periods we use the shadow rate by Wu and Xia (2016). Figure 1 shows monthly changes in the federal funds rate. One can see that monthly changes in the federal funds rate are rather small and reflect a 'gradualism' approach to monetary policy during the Greenspan era.

Figure 2 shows the the relationship between the change in the federal funds rate and excess returns (Panel A) and Monetary Policy Uncertainty and excess returns (Panel B). Excess returns are monthly returns of the S&P500 (downloaded from Shillers Homepage) minus the 1 month nominal interest rate. To

[4] The target rate was kept secret, however open market operations revealed the target rate. Cook and Hahn (1989) compile 76 target changes using the *Wall Street Journal*

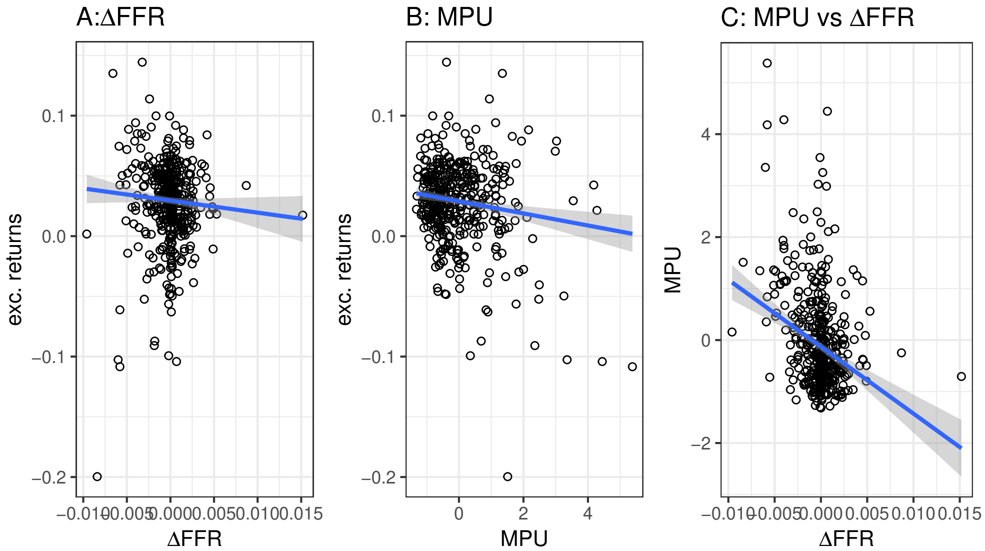

Figure 2: Scatterplot showing the relation between a change in the federal funds rate and excess returns and uncertatinty about Monetary Policy and Excess Returns on Market Portfolio (Panels A and B). Panel C shows the relation between monetary policy uncertainty and changes in the federal funds rate. Regression lines are fitted using Robust Regression (M-estimator).

accomodate for the clearly visible outliers in returns the regression line is fitted using robust regression. In both panels the regression line has a negative slope, i.e. a larger change in the federal funds rate or higher uncertainty implies smaller returns. Finally, Panel C shows the relation between changes in the federal funds rate (x-axis) and monetary policy uncertainty (y-axis). A high monetary policy uncertainty is associated with decreases in the federal funds rate, while low monetary policy uncertainty is associated with increases in the federal funds rate. The reason for this is that during recessions monetary policy uncertainty is high and the Fed is lowering interest rates.

2.3 Results

2.3.1 Portfolios based on Industry

Table 4 shows the regression results for portfolios sorted by Industry. For most industries the coefficients for the monetary policy shock is negative, implying

Table 4: Regression Results for Portfolios sorted by Industry

	ΔFFR	MPU	$\Delta FFR \times MPU$	T-Bill	Default	TERM	RREL	CFNAI	log(D/P)
NoDur	-0.8596	0.0025	-0.3738	-0.0018	0.0014	-0.0043	-0.0033	0.0063	0.0237 **
	(1.2352)	(0.0021)	(0.7506)	(0.0012)	(0.009)	(0.0032)	(0.0154)	(0.0045)	(0.0104)
Durbl	-1.7748	0.0053	0.1716	-0.0054 ***	0.0081	-0.0096 **	0.0379 *	0.013	0.0319 **
	(1.7694)	(0.004)	(1.3754)	(0.0016)	(0.015)	(0.0042)	(0.0211)	(0.0086)	(0.0126)
Manuf	-1.3921	0.0043	-0.3072	-0.004 ***	0.0047	-0.0089 ***	0.0319 *	0.0136 **	0.0242 **
	(1.532)	(0.003)	(1.1297)	(0.0013)	(0.0114)	(0.0033)	(0.0187)	(0.0067)	(0.0099)
Enrgy	-1.6729	0.0022	0.1402	-0.002	0.013	-0.0082 ***	0.0301 *	0.0172 ***	0.009
	(1.1281)	(0.0032)	(0.7933)	(0.0014)	(0.0104)	(0.0032)	(0.018)	(0.0058)	(0.0095)
Chems	-1.8964	0.0048 *	0.2364	-0.0033 ***	0.0003	-0.0064 **	0.0097	0.0276 ***	0.0276
	(1.3446)	(0.0026)	(0.9387)	(0.0012)	(0.0098)	(0.0029)	(0.0148)	(0.0052)	(0.0092)
BusEq	-0.173	0.0043	-1.34	-0.0059 **	-0.0082	-0.0127 ***	0.0556 ***	0.0083	0.0381 *
	(1.9987)	(0.0038)	(2.2317)	(0.0023)	(0.0148)	(0.0048)	(0.0202)	(0.0072)	(0.0207)
Telcm	-0.7227	0.0044	1.4452	-0.0045 ***	-0.0005	-0.0093 ***	-0.0033	0.0396 ***	0.0396
	(1.2945)	(0.0034)	(0.9174)	(0.0014)	(0.0092)	(0.0035)	(0.0166)	(0.0054)	(0.0134)
Utils	-0.3593	0.0023	0.1144	-0.0015	-0.0036	-0.0025	-0.0086	0.0064	0.0115
	(1.1551)	(0.0025)	(0.6579)	(0.0012)	(0.0081)	(0.0027)	(0.0159)	(0.0048)	(0.0109)
Shops	-1.431	0.0064 **	-0.0744	-0.0038 ***	-0.0054	-0.0084 **	0.0285	0.0291 ***	0.0291
	(1.3042)	(0.0028)	(0.8886)	(0.0013)	(0.0093)	(0.0036)	(0.0199)	(0.0049)	(0.0097)
Hlth	-1.3963	0.0027	0.0132	-0.0029 **	-0.0068	-0.009 ***	0.0012	0.0324 ***	0.0324
	(1.3671)	(0.0025)	(0.8625)	(0.0013)	(0.0089)	(0.0035)	(0.0155)	(0.0045)	(0.0104)
Money	0.0679	0.006 **	0.5818	-0.0033 **	-0.0112	-0.0056	0.0072	0.0061	0.0265 **
	(1.5522)	(0.0029)	(1.0729)	(0.0015)	(0.0142)	(0.0035)	(0.0187)	(0.0069)	(0.0119)
Other	-1.7633	0.0062 **	-0.04	-0.0033 ***	-0.0042	-0.0104 ***	0.0248	0.0377 ***	0.0377
	(1.3599)	(0.0029)	(1.0362)	(0.0013)	(0.0112)	(0.0034)	(0.0178)	(0.006)	(0.0105)

Note: *p<0.1;**p<0.05;***p<0.01. Standard errors are calculated using Newey-West standard errors using 5 lags.

that an increase in the federal funds rate results in a decline in asset returns. In particular 'Durbl', 'Chems', 'Shops' react most strongly to changes in the federal funds rate and an increase of 100 basis points in the federal funds rate results in a decline of up to 76 points in asset returns for 'Chems'. In contrast there are also industries that react positively to a change in the federal funds rate. These industries are 'BusEq', 'TelCm', 'Utils', 'Money'.

Surprisingly, monetary policy uncertainty have small positive effects on monthly returns, i.e. an increase in monetary policy uncertainty increases asset returns. One reason might be that monetary policy uncertainty and changes in the federal funds rate a negatively correlated, i.e. a higher monetary policy occurs when the federal funds rate is lowered.

For the interaction term we see that, in general, a an increase in monetary policy uncertainty also increases the effects of changes in the federal funds rate. Or, in other words, a higher monetary policy uncertainty exacerbates the negative effects of an increase in the federal funds rate.

However, a caveat of these results is that there is a high statistical uncer-

Table 5: Regression Results for Portfolios sorted by Market Equity

	ΔFFR	MPU	$\Delta FFR \times MPU$	T-Bill	Default	TERM	RREL	CFNAI	log(D/P)
1st Dec	-2.1489	-0.0118 **	0.2149	0.0018	-0.0107	0.0434 **	-0.0033	-0.005	-0.0148
	(1.8605)	(0.0051)	(1.4055)	(0.0019)	(0.0198)	(0.0036)	(0.0171)	(0.0058)	(0.0143)
2nd Dec	-2.8626	-0.0122 **	0.6472	0.0019	-0.0105	0.0487 ***	0.0379 *	-0.0058	-0.0113
	(2.0628)	(0.005)	(1.5299)	(0.0017)	(0.018)	(0.0034)	(0.0186)	(0.0061)	(0.0128)
3rd Dec	-2.1891	-0.0109 **	0.8386	0.0004	-0.014	0.0459 ***	0.0319 *	-0.0062	0.0031
	(1.7806)	(0.0049)	(1.5279)	(0.0015)	(0.0171)	(0.003)	(0.0169)	(0.0053)	(0.0117)
4th Dec	-2.867	-0.0106 **	0.9127	0.0004	-0.0129	0.0426 **	0.0301 *	-0.0054	0.0041
	(1.7661)	(0.0049)	(1.4656)	(0.0014)	(0.0164)	(0.0029)	(0.0173)	(0.0052)	(0.0113)
5th Dec	-2.9537 *	-0.0112 **	0.7155	0.0002	-0.0104	0.038 **	0.0097	-0.0035	0.0072
	(1.5812)	(0.0047)	(1.4558)	(0.0014)	(0.0164)	(0.0029)	(0.0162)	(0.0052)	(0.0111)
6th Dec	-3.2295 **	-0.0099 **	0.9127	-0.0005	-0.0119	0.0391 ***	0.0556 ***	-0.0035	0.0115
	(1.3984)	(0.0043)	(1.2702)	(0.0013)	(0.014)	(0.0027)	(0.0147)	(0.0046)	(0.0101)
7th Dec	-2.9351 **	-0.0106 **	0.9729	0.0005	-0.0097	0.0434 **	-0.0033	-0.0027	0.0052
	(1.3753)	(0.0044)	(1.3055)	(0.0014)	(0.0148)	(0.0027)	(0.0142)	(0.0045)	(0.0107)
8th Dec	-3.2729 **	-0.0098 **	1.5079	0.0004	-0.0106	0.0377 **	-0.0086	-0.003	0.0046
	(1.3755)	(0.0042)	(1.2535)	(0.0013)	(0.0139)	(0.0026)	(0.0147)	(0.0046)	(0.0103)
9th Dec	-3.1725 **	-0.0081 **	1.5602	-0.0003	-0.0122	0.0266 *	0.0285	-0.002	0.0108
	(1.3327)	(0.004)	(1.1904)	(0.0011)	(0.0145)	(0.0024)	(0.0142)	(0.0044)	(0.0091)
10th Dec	-2.6201 **	-0.0077 **	1.3042	-0.0008	-0.0144	0.0279 **	0.0012	-0.0021	0.0194 **
	(1.1534)	(0.0036)	(0.9493)	(0.001)	(0.0114)	(0.0022)	(0.0127)	(0.0043)	(0.0084)

Note: *p<0.1;**p<0.05;***p<0.01. Standard errors are calculated using Newey-West standard errors using 5 lags.

tainty for the estimates of the coefficients. Therefore, the results should be treated cautiosly.

2.3.2 Portfolios sorted by size

Table 5 shows the regression results for the portfolios sorted by market equity. The coefficient for the change in the federal funds rate is negative for all portfolios. Therefore an increase in the federal funds rate decreases monthly asset returns. The strongest effect of a change in the federal funds rate is for the assets in thee 6th decile and the smallest effects are for the smallest 10% of firms and largest 10% firms. Otherwise there seems to be no no relation between the size of the firm and the effects of a change in the federal funds rate.

For monetary policy uncertainty the coefficient for all sizes are negative. Furthermore, the coefficient declines with the size of the firm. Which means that larger firms are usually less affected by monetary policy uncertainty than smaller firms, because large firms may be less financially constrained than small firms.

For all size-sorted portfolios the interaction term is positive. Furthermore, the coefficient increases with firm size. Thus, the reaction to changes in the

Table 6: Regression Results for Portfolios sorted by Book-to-Markt Ratio

	ΔFFR	MPU	$\Delta FFR \times MPU$	T-Bill	Default	TERM	RREL	CFNAI	log(D/P)
1st Dec	-1.336	-0.008 **	0.9696	-0.0007	-0.0163	0.039 **	-0.0033	-0.0063	0.0203 **
	(1.3749)	(0.004)	(1.0525)	(0.001)	(0.0137)	(0.0025)	(0.0153)	(0.0051)	(0.0103)
2nd Dec	-2.3803 **	-0.0086 **	0.6119	-0.0001	-0.013	0.0324 **	0.0379 *	-0.0033	0.0142 *
	(1.0544)	(0.004)	(0.9914)	(0.0009)	(0.0101)	(0.0024)	(0.014)	(0.0044)	(0.0086)
3rd Dec	-2.7687 **	-0.0084 **	0.9794	-0.0004	-0.0109	0.0284 **	0.0319 *	-0.0025	0.0122
	(1.2642)	(0.0041)	(1.0405)	(0.0008)	(0.0107)	(0.0021)	(0.0136)	(0.0047)	(0.0079)
4th Dec	-3.1382 **	-0.0092 **	1.1272	0.0003	-0.007	0.0224	0.0301 *	0	0.0067
	(1.3245)	(0.004)	(1.0269)	(0.0008)	(0.0119)	(0.0022)	(0.0148)	(0.0047)	(0.0078)
5th Dec	-2.7956 *	-0.0084 **	1.7597 **	0.0003	-0.0105	0.0198	0.0097	-0.0033	0.0061
	(1.4303)	(0.0039)	(0.887)	(0.001)	(0.0128)	(0.0021)	(0.0132)	(0.0044)	(0.0086)
6th Dec	-3.0972 ***	-0.0076 *	1.1227	-0.0001	-0.009	0.0144	0.0556 ***	0.001	0.0064
	(1.0886)	(0.0039)	(0.9253)	(0.001)	(0.0106)	(0.0022)	(0.0144)	(0.0042)	(0.009)
7th Dec	-2.4614 *	-0.0055	1.5614	0.0001	-0.0108	0.039	-0.0033	0.0013	0.0065
	(1.3671)	(0.0034)	(1.1221)	(0.001)	(0.0142)	(0.0023)	(0.0139)	(0.0046)	(0.0099)
8th Dec	-2.652 *	-0.0057	1.541	-0.0005	-0.0217	0.0059	-0.0086	-0.0019	0.0096
	(1.5861)	(0.0038)	(1.1278)	(0.0011)	(0.0173)	(0.0024)	(0.0148)	(0.0041)	(0.0098)
9th Dec	-3.0993 **	-0.008 **	1.7892 *	0	-0.0193	0.0182	0.0285	-0.0049	0.011
	(1.3981)	(0.0035)	(0.9841)	(0.0013)	(0.0155)	(0.0032)	(0.0143)	(0.0044)	(0.0117)
10th Dec	-3.6787 *	-0.0118 **	1.4911	0.0012	-0.0124	0.0327 *	0.0012	-0.0012	0.0008
	(1.9873)	(0.0046)	(1.5533)	(0.0017)	(0.0226)	(0.0035)	(0.0187)	(0.0056)	(0.013)

Note: *p<0.1;**p<0.05;***p<0.01. Standard errors are calculated using Newey-West standard errors using 5 lags.

federal funds rate to monetary policy uncertainty increases with firm size. As the coefficient for the interaction is positive and much larger than the coefficient for monetary policy uncertainty a higher monetary policy uncertainty implies that an increase in the federal funds rate is associated with a smaller decline in returns.

Furthermore, for changes in the federal funds rate and monetary policy uncertainty and most of the coefficients are statistically significant while coefficients for the interaction terms are all insignificant. Yet, these coefficients are much larger than the coefficient for monetary policy uncertainty.

Table 6-8 show the result for portfolios sorted by book-to-market ratio, investments and operating profits. We have similar observation as with portfolios based on market equity. In particular, asset returns react negatively to higher monetary policy uncertainty and to increase in the federal funds rate. Furthermore, the interaction term is again positiv indicating that higher monetary policy uncertainty increases the effects of monetary policy shocks.

Table 7: Regression Results for Portfolios sorted by Investment

	ΔFFR	MPU	$\Delta FFR \times MPU$	T-Bill	Default	TERM	RREL	CFNAI	log(D/P)
1st Dec	-2.5736 **	-0.0086 *	1.2589	-0.0004	-0.0104	0.0402 ***	-0.0033	-0.0025	0.0061
	(1.294)	(0.0045)	(1.1573)	(0.0011)	(0.016)	(0.0026)	(0.0149)	(0.0049)	(0.0093)
2nd Dec	-2.3231 *	-0.006	1.4247	-0.0006	-0.0089	0.0206	0.0379 *	0.0002	0.0131
	(1.2881)	(0.0038)	(1.0731)	(0.001)	(0.0135)	(0.0023)	(0.0128)	(0.0044)	(0.0081)
3rd Dec	-2.7586 **	-0.0078 **	1.4925 *	0.0004	-0.0072	0.0177	0.0319 *	-0.0006	0.0073
	(1.2294)	(0.0036)	(0.7846)	(0.0009)	(0.0088)	(0.0021)	(0.0122)	(0.004)	(0.0081)
4th Dec	-1.959 *	-0.0077 **	0.2603	0.0003	-0.0107	0.0153	0.0301 *	-0.0014	0.0081
	(1.0418)	(0.0033)	(0.7931)	(0.0009)	(0.0099)	(0.002)	(0.0119)	(0.0036)	(0.007)
5th Dec	-2.3372 **	-0.0077 **	1.0072	0	-0.0071	0.0139	0.0097	-0.0018	0.0073
	(1.1253)	(0.0031)	(1.0162)	(0.0009)	(0.0123)	(0.0021)	(0.012)	(0.0038)	(0.0076)
6th Dec	-2.4201 **	-0.0068 *	1.2214	-0.0003	-0.0136	0.0233 *	0.0556 ***	-0.0018	0.0115
	(1.1512)	(0.0036)	(0.9223)	(0.0009)	(0.0113)	(0.0022)	(0.0136)	(0.0044)	(0.008)
7th Dec	-2.2876 *	-0.0071 *	0.7891	0.0006	-0.0117	0.0402 **	-0.0033	-0.0013	0.0045
	(1.1809)	(0.0039)	(0.8825)	(0.0009)	(0.0102)	(0.0021)	(0.0136)	(0.0046)	(0.0078)
8th Dec	-1.9	-0.0073 *	1.2563	0.0004	-0.0122	0.0327 **	-0.0086	-0.0023	0.0049
	(1.3585)	(0.004)	(1.0555)	(0.0009)	(0.0149)	(0.0021)	(0.0139)	(0.0044)	(0.0087)
9th Dec	-1.3827	-0.0091 **	0.9648	-0.0004	-0.0176	0.0465 ***	0.0285	-0.0059	0.0167
	(1.3588)	(0.0044)	(1.1696)	(0.001)	(0.0141)	(0.0025)	(0.0164)	(0.0053)	(0.0116)
10th Dec	-2.6752 *	-0.012 ***	0.7235	-0.001	-0.0211	0.0602 ***	0.0012	-0.0075	0.0284 **
	(1.375)	(0.0044)	(1.3113)	(0.0012)	(0.0155)	(0.0031)	(0.0187)	(0.0057)	(0.0126)

Note: *p<0.1;**p<0.05;***p<0.01. Standard errors are calculated using Newey-West standard errors using 5 lags.

Table 8: Regression Results for Portfolios sorted by Operating Profits

	ΔFFR	MPU	$\Delta FFR \times MPU$	T-Bill	Default	TERM	RREL	CFNAI	log(D/P)
1st Dec	-2.3405	-0.0124 **	0.6894	-0.0009	-0.0192	0.0581 **	-0.0033	-0.0043	0.0201
	(1.6098)	(0.0056)	(1.5198)	(0.0018)	(0.0208)	(0.004)	(0.0231)	(0.006)	(0.0175)
2nd Dec	-2.4371 *	-0.01 **	1.0432	-0.0005	-0.0123	0.0418 ***	0.0379 *	-0.0017	0.0164
	(1.3743)	(0.0046)	(1.3215)	(0.0013)	(0.0162)	(0.0029)	(0.015)	(0.0053)	(0.0112)
3rd Dec	-2.5531 **	-0.0106 ***	0.6428	-0.0006	-0.0163	0.0328 **	0.0319 *	-0.001	0.0189 **
	(1.1658)	(0.0037)	(1.0061)	(0.0011)	(0.0128)	(0.0023)	(0.0146)	(0.0043)	(0.0095)
4th Dec	-1.6125	-0.0099	0.7112	0	-0.0077	0.0291 **	0.0301 *	-0.0019	0.0065
	(1.3038)	(0.0035)	(1.0812)	(0.0009)	(0.0125)	(0.0023)	(0.0122)	(0.0041)	(0.0083)
5th Dec	-2.821 *	-0.0081 **	1.2255	-0.0008	-0.0143	0.0273 *	0.0097	-0.0006	0.0172 **
	(1.4791)	(0.0039)	(1.1151)	(0.0009)	(0.0165)	(0.0022)	(0.0143)	(0.0042)	(0.0079)
6th Dec	-2.2546 *	-0.0063 *	1.399 *	0	-0.01	0.0255 *	0.0556 ***	-0.0009	0.0076
	(1.1867)	(0.0034)	(0.7933)	(0.0008)	(0.01)	(0.0021)	(0.0131)	(0.0043)	(0.0072)
7th Dec	-1.8383	-0.0076 **	1.196	-0.0005	-0.0124	0.0581 **	-0.0033	-0.0009	0.0149 *
	(1.2914)	(0.0036)	(0.9794)	(0.0009)	(0.0128)	(0.002)	(0.0139)	(0.0045)	(0.0087)
8th Dec	-2.2889 **	-0.0079 **	0.9136	0.0001	-0.0154	0.029 **	-0.0086	-0.0055	0.0107
	(1.0773)	(0.0034)	(0.8731)	(0.0008)	(0.0099)	(0.002)	(0.0125)	(0.004)	(0.0078)
9th Dec	-2.6036 ***	-0.0079 **	0.6677	0	-0.0136	0.0263 **	0.0285	-0.0027	0.0148 *
	(0.9631)	(0.0038)	(0.9445)	(0.0009)	(0.0105)	(0.0022)	(0.0131)	(0.0046)	(0.0078)
10th Dec	-2.0267	-0.0074 *	1.2751	-0.0004	-0.0126	0.0258 **	0.0012	-0.005	0.0163 **
	(1.241)	(0.004)	(1.0515)	(0.0008)	(0.0123)	(0.0023)	(0.0131)	(0.0049)	(0.0076)

Note: *p<0.1;**p<0.05;***p<0.01. Standard errors are calculated using Newey-West standard errors using 5 lags.

3 Econometric Model

3.1 The Factor Augmented Threshold VAR Model

Time-Varying parameter models are popular in modern empirical macroeconomics (see e.g. Primiceri (2005)) and Galí and Gambetti (2015) uses a TVP-VAR to provide some evidence that monetary policy may contribute to bubbly asset prices. Korobilis (2013) extends the TVP-Model to a TVP-FAVAR model.

An underlying assumption of models with time-varying parameters is that of smooth parameter changes. However, there is ample evidence (see e.g. Ang and Timmermann (2012) for a survey) that changes in financial happen suddenly. To capture those sudden breaks in financial markets we use a threshold VAR and the changes in the parameters is conditioned on endogeneous variables. In particular, the joint dynamics of $c_t = (y_t, f_t)$ are given by

$$c_t = \begin{cases} k^1 + \sum_{j=1}^{p} A_j^1 c_{t-j} + \epsilon_t^1 & \text{if } c_{t-d}^i > \bar{c} \quad \epsilon_t^1 \sim N(0, \Sigma^1) \\ k^2 + \sum_{j=1}^{p} A_j^2 c_{t-j} + \epsilon_t^2 & \text{if } c_{t-d}^i \leq \bar{c} \quad \epsilon_t^2 \sim N(0, \Sigma^2) \end{cases} \tag{4}$$

With c^i as the threshold variable and $\bar{c}$ as the threshold and d as the delay. The regime specific shocks ϵ_t^1 and ϵ_t^2 are normally distributed zero mean and regime dependent covariance matrices Σ^1 and Σ^2.

The unobserved factors are extracted from a large panel of M indicators, x_t, that contain important information about the fundamentals of asset returns. The factors in the panel are related by an observation equation of the form

$$x_t = \begin{cases} \Lambda_1^f f_t + \Lambda_1^y y_t + u_t^1 & \text{if } c_{t-d}^i > \bar{c} \quad u_t^1 \sim N(0, W^1) \\ \Lambda_2^f f_t + \Lambda_2^y y_t + u_t^2 & \text{if } c_{t-d}^i \leq \bar{c} \quad u_t^2 \sim N(0, W^2) \end{cases} \tag{5}$$

Intuitively, the model describes a combination of two linear FAVARs and in our model we use monetary policy uncertainty as the threshold variable. Therefore, in regime 1 we have the dynamics of an economy during high monetary policy uncertainty and regime 2 describes the dynamics during low monetary policy uncertainty.

3.2 Data

In our model the vector Y_t^s contains 5 variables plus the N extracted factors from the return series. These five variables are industrial production, inflation as measured in changes of the consumer price index and changes in the federal funds rate. Industrial production and inflation typically used to identify structural shocks of monetary policy. Monetary Policy, Monetary Policy Uncertainty and returns are the same as in the previous section. The vector Y_t is therefore as follows:

$$Y_t = [\Delta Ip_t, \Delta\pi_t, MPU_t, \Delta FFR_t, f_t^1, \ldots, f_t^N], \tag{6}$$

with ΔIp_t as the changes in industrial production, $\Delta\pi_t$ as inflation, MPU_t as Monetary Policy Uncertainty and ΔFFR_t as the change in the federal funds rate. The factors on stock returns are $f_t^1, \ldots, f_t^N$.

3.3 Estimation

The factor-augmented threshold var is estimated via a two-step procedure. First, we extract the factors from portfolio returns using principal component analysis then we estimate the threshold VAR which is estimated using MCMC methods.

1. sample delay parameter d
2. Sample threshold value $\bar{c}$
3. Conditional on the delay parameter d and the threshold value d split the sample into two subsample. For each subsample:
4. Sample Λ based on Y_t, $A^{s_t,(n)}$,Y_t, $\tilde{s}_T$ and $\Sigma^{s_t,(n-1)}$
5. Sample $A^{s_t,(n)}$ based on Y_t, $\tilde{s}_T$ and $\Sigma^{s_t,(n-1)}$
6. Sample $\Sigma^{s_t,(n)}$ based on $A^{s_t,(n)}$, Y_t and $\tilde{s}_T^{(n)}$.

7. Repeat steps 1-5 $n_1 + n_2$ times.

For steps 4 we use a SSVS-prior on the measurement equation.

Given the estimated model we also have to compute Impulse-Response Functions. In contrast to linear models where one set of impulse-response functions is sufficient to characterize the model in non-linear models several complications arise. For instance, a non-linear model is sensitive to initial conditions and the magnitude of the shock. Furthermore, impulse response functions are also history-dependent (see Potter (2000) for a discussion). To construct impulse-response functions for non-linear models we follow Koop, Pesaran, and Potter, 1996. They define the impulse response function as a change in the conditional expectation of Y_{t+k} as a result of knowing the exogeneous shock U_t:

$$E[Y_{t+k}|H_{t-1}, U_t] - E[Y_{t+k}|U_t] \tag{7}$$

with H_{t-1} being the history up to period $t-1$ and both conditional expectations are computed by simulating the model. The algorithm to compute non-linear impulse response functions is outlined in Appendix A

3.4 Priors

State Equation

For the state equation (4) we use an uninformative prior.

Measurement Equation

For the measurement equation (5) we use an SSVS-prior on the factor loadings Λ^f and Λ^y. For ease of notation we write collect Λ^y and Λ^f in one matrix Λ. For each element j of $\lambda = vec(\Lambda)$ we have the following:

$$\lambda_j|1_j \sim N(0, \phi_0^2)1_j + N(0, \phi_1^2)(1 - 1_j) \tag{8}$$

with 1_j being a binary random variable that takes the values 0 and 1 and ϕ_0^2 and ϕ_1^2 being hyperparameters controlling the tightness of priors. We assume that $\phi_1^2 >> \phi_0^2$. Thus, if $1_j = 1$ then a large ϕ_1^2 implies a rather uninformative prior whereas, if $1_j = 0$ we have a tighter prior centered around 0.

Furthermore, we impose a bernoulli prior on 1_j:

$$1_j = Bernoulli(\rho_j) \tag{9}$$

with $Prob(1_j = 0) = \rho_j$ the probability that a variable is included in the measurement equation.

The last part of the measurement equation is an inverse gamma prior on the innovation variance, i.e.

$$\epsilon_j = IG(\alpha_j, \beta_j), \tag{10}$$

with α_j being the prior shape and β_j denotes the prior scale parameter.

3.5 Identification

The model outlined above is not fully identified and therefore cannot be estimated. To estimate the model we need to impose two restrictions. The first restriction is related to the factors and the second restriction is related to the structural identification of shocks.

Factors

Without restrictions on factors and factor loadings they are not uniquely identified. Similar to Bernanke, Boivin, and Eliasz (2005) we restrict the upper $K \times K$-block to be an identity matrix and the upper $q \times n$ block of to be zero.

Structural Identification

The usual assumption is in the literature is to use a Cholesky factorization. With a Cholesky factorization the ordering of the variables becomes important. In our empirical exercise we have ordered the monetary policy variable ahead of stock returns. Hence, implying that monetary policy does not react contemporeanously to stock returns.

While there are no official policies that forces a central bank to react to changes in the stock market, this assumption is questionable as there have been several instance when the Federal Reserve did react to large changes in the stock market. For example, the Fed lowered the Federal Funds Rate after the 1987 stock market crash.[5] In addition to anecdotal evidence, there is also empirical evidence that argue that the Feds monetary policy to changes in financial markets[6] and that it is inappropriate to use a Cholesky-factorization to identify stock market reactions to monetary policy (Bjørnland and Leitemo (2009)).

However, the literature typically uses quarterly data which makes it more likely that the FED reacts to changes on financial markets within the period. We, on the other hand, use monthly data which makes it much less likely that the FED reacts to changes in financial markets within the period. Hence, we feel comfortable to use only a recursive identification.

4 Results

4.1 Factors

To estimate the number of factors we rely on Bai and Ng (2007). To use their method we don't have to estimate the factors to determine the suitable number of factors. Our results indicate that all return series are best summarized by two factors.

Figure 3 plots the first factor from all five series and compares it with the returns on the S&P500. It is easy to see that all three factors are roughly the same. Furthermore, the graph also suggests that the returns series is highly correlated with the factors, indicating that the SP500 captures the whole market reasonably well.

[5] Blinder and Reis (2005) discusses other events on financial markets and the Feds decisions as well as the rationale behind those decisions

[6] This is not, however, not true for all central banks. For instance Bohl, Siklos, and Werner (2007) find only weak evidence that the Bundesbank reacted to financial markets

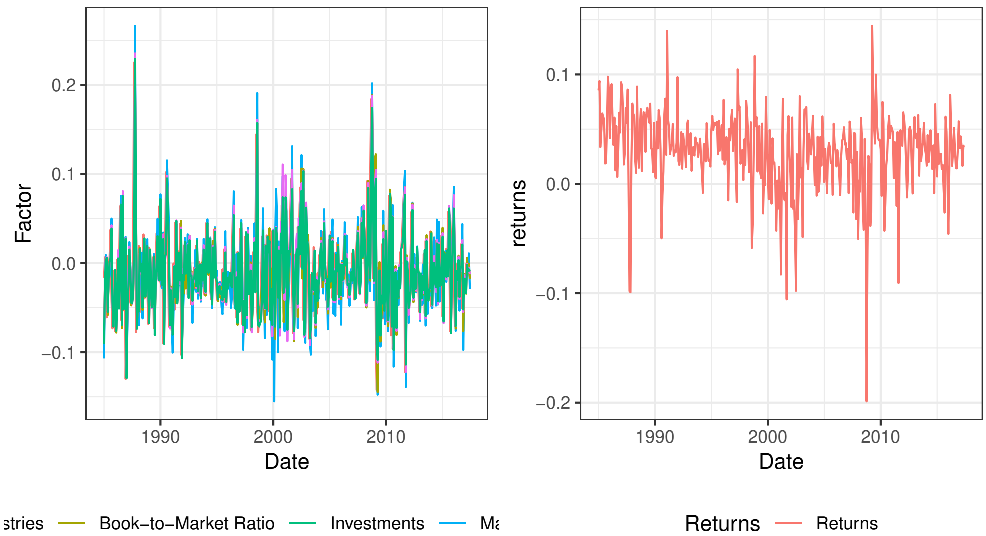

Figure 3: Factor evolution and returns for the SP500. The left panel shows the evolution of the factor for the three portfolios. In the right panel the returns on the S&P500 are plotted.

4.2 Responses to Monetary Policy shocks

4.2.1 Portfolios sorted by Industry

Figure 4 shows the impulse-response functions for excess returns to a shock to monetary policy. Excess returns are on portfolios sorted by Industry. In general, the responses to a monetary policy shock are heterogeneous across firms. In general, responses to monetary policy shocks are heterogeneous in size and sign across industries. Most industries react negatively to an increase in the federal funds rate, regardless whether the economy is in a high uncertainty regime or low uncertainty regime. Yet the regime affects the size of the initial reaction to a monetary policy shock. For most industries the initial reaction to a monetary policy shock is less negative in regimes with high monetary policy uncertainty than in regimes with low monetary policy uncertainty. Furthermore, after initial response excess returns quickly return to the steady state or, in other words, independent of the regime the effects of monetary policy shocks are not long-lived. To some extent this can be explained by the fact that in high uncertainty regimes monetary policy is typically more accomodating

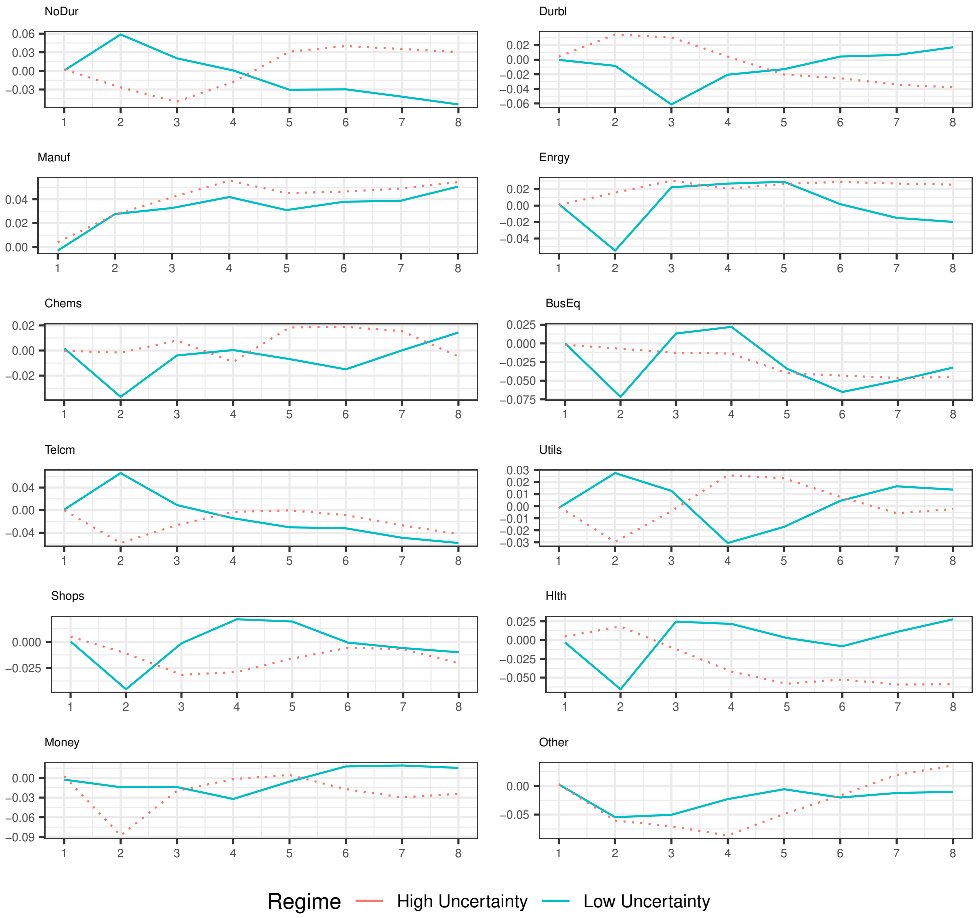

Figure 4: Impulse-Response Functions for for Monetary Policy shocks for Portfolios sorted by Industry

in the sense that the Federal Reserve decreases the federal funds rate which has a positive impact on returns.

4.2.2 Portfolios sorted by Size

Figures 5 to 8 whos the impulse-response functions of asset returns to monetary policy shocks for size-sorted portfolios. As with industry-sorted portfolios response to monetary policy shocks are heterogeneous in size and sign. Furthermore, the reaction also depends on the uncertainty regime. For instance, consider the 10th decile of firms sorted by the book-to-market ratio. A high book to market ratio implies that a company may be in financial distress and

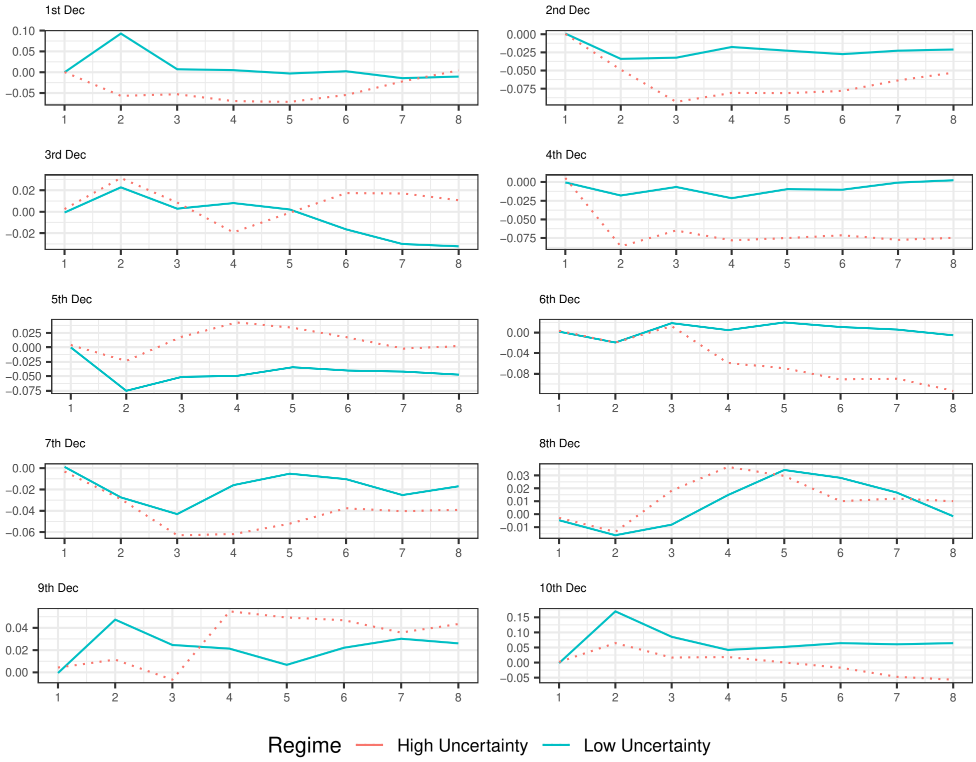

Figure 5: Impulse-Response Functions for for Monetary Policy shocks for Portfolios sorted by Book-to-Market Ratio

thus are in particular affected by reduced bank lending. The monetary policy shock resolves this uncertainty and thus bank lending increases and even though the monetary policy shock is contractionary and thus at the same time reduces the borrowing capacity of firms the initial reaction to a monetary policy shock are positive returns. Hence, the effects of resolving uncertainty are larger than the effects of a contractionary monetary policy.

4.3 The Impact of Uncertainty Shocks

4.3.1 Portfolios based on Industry

Figure 4 shows the response of excess returns to a shock in monetary policy uncertainty. As with monetary policy shocks responses are heterogeneous in size and sign across industries. Additionally, the reaction to uncertainty shocks

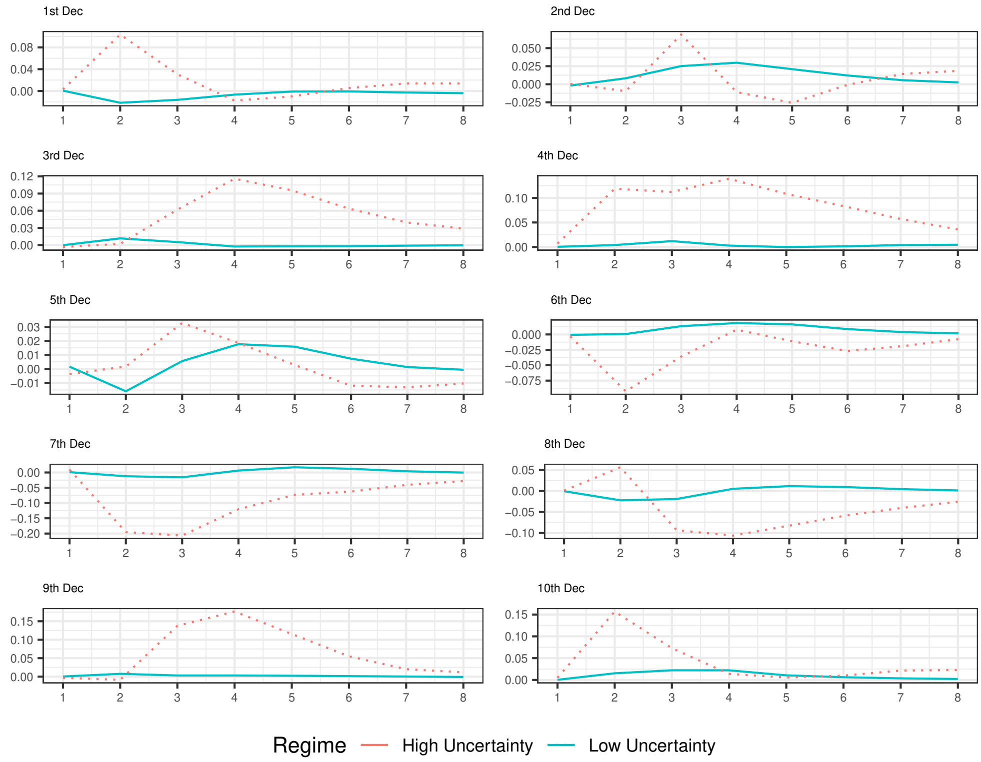

Figure 6: Impulse-Response Functions for Monetary Policy shocks for Portfolios sorted by Market Equity

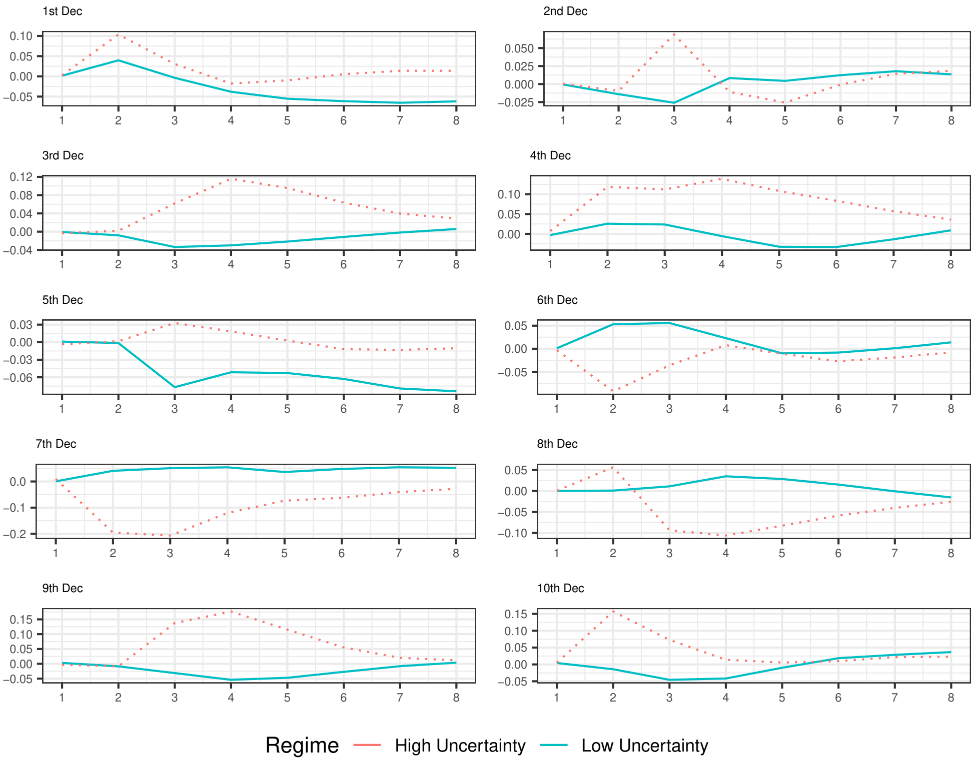

Figure 7: Impulse-Response Functionsfor Monetary Policy shocks for Portfolios sorted by Investment

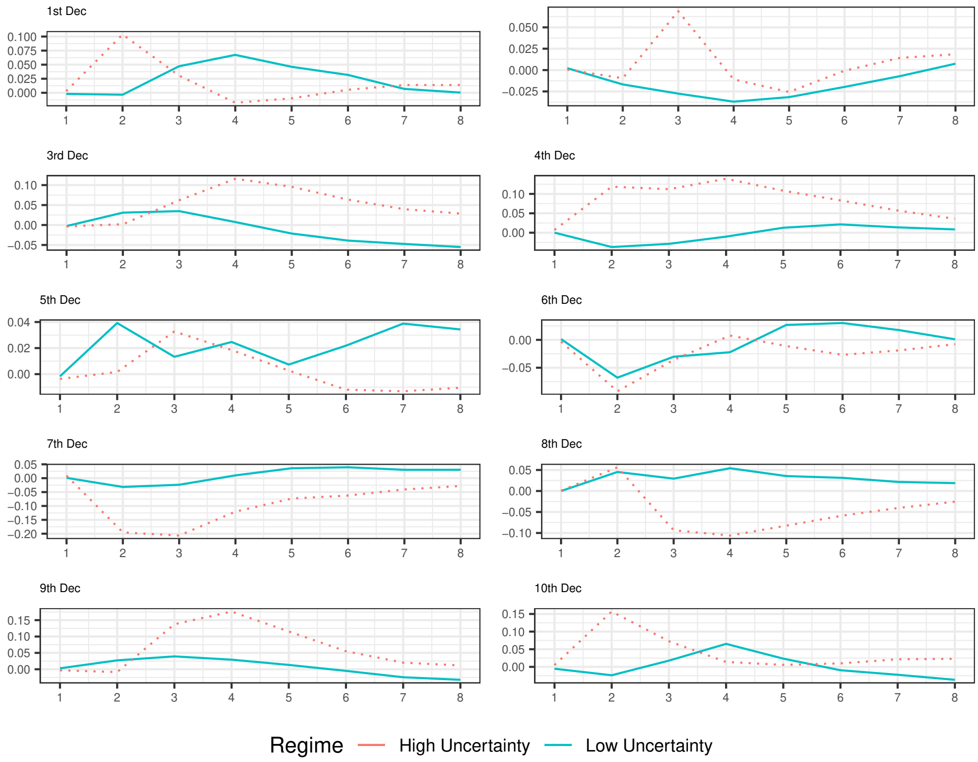

Figure 8: Impulse-Response Functions for Monetary Policy shocks for Portfolios sorted by Operating Profits

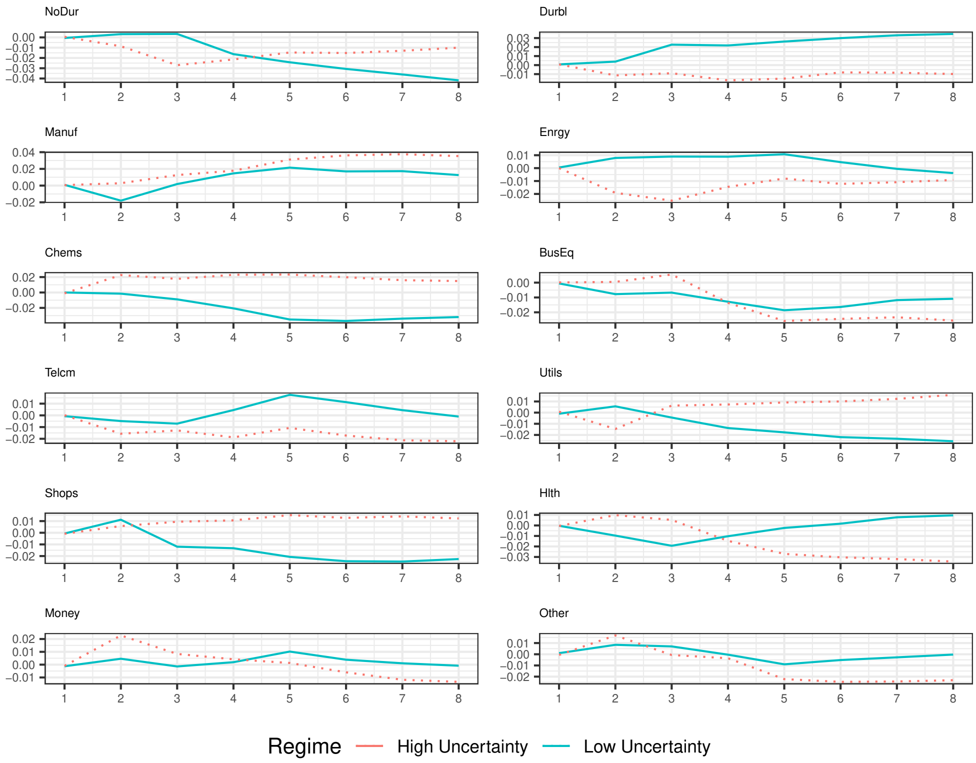

Figure 9: Impulse response functions for uncertainty shocks for portfolios sorted by Industry

is different across regimes. For instance, stocks in 'Chems' have a negative reaction to uncertainty in a high uncertainty regime while there is no initial reaction to an uncertainty shock in a low uncertainty regime. Uncertainty shocks in a high uncertainty regime may indicate a deepening of a recession and as the chemical industry is highly cyclical returns are strongly affected by an uncertainty shock in a period of high monetary policy uncertainty.

4.3.2 Portfolios based on Size

Figures 10 to 13 show the impulse-response to uncertainty shocks for size-sorted portfolios. We make similar observations as before, i.e. size and sign of initial response are heterogeneous across firm sizes and they also differ across uncertainty regimes.

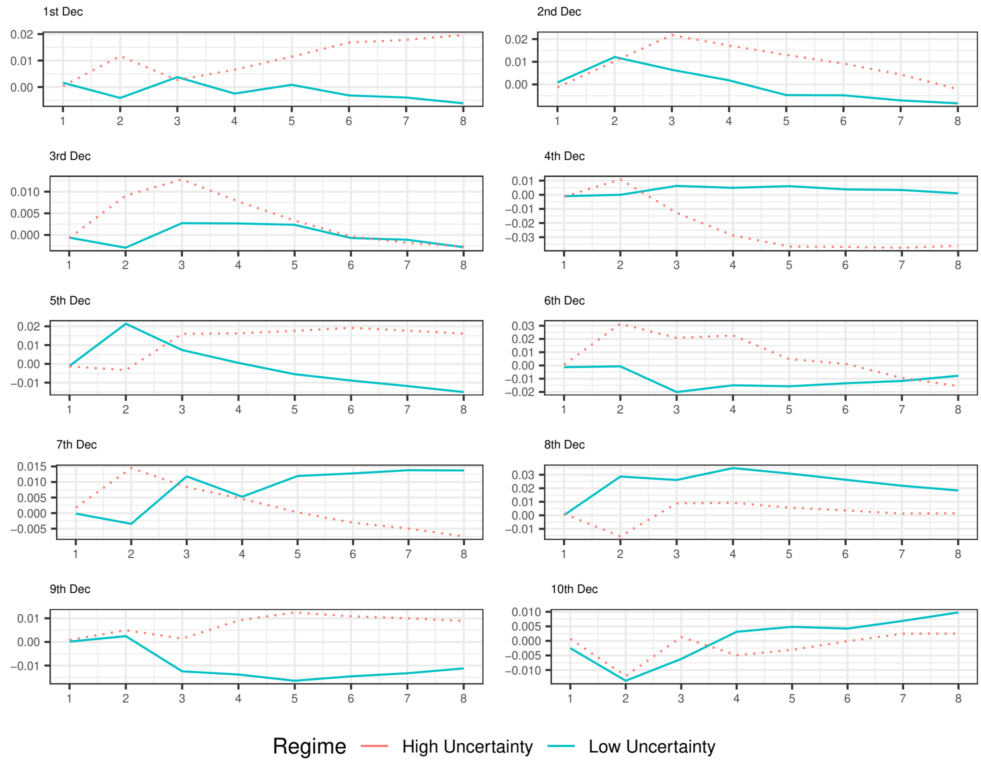

Figure 10: Impulse response functions for uncertainty shocks for portfolios sorted by Book-to-Market Ratio

5 Conclusion

This paper studied how monetary policy uncertainty affects the transmission of monetary policy shocks to financial markets by using industry- and size sorted portfolios and a Factor Augmented Threshold VAR model to separate the economy in a regime with low uncertainty and one with high uncertainty. We found that monetary policy uncertainty does affect the transmission of monetary policy shocks, but the effects of monetary policy uncertainty are very heterogeneous across industries and firm sizes as is consistent with the literature. One key result is that a monetary policy shock in a high uncertainty regime is often associated with a positive initial response.

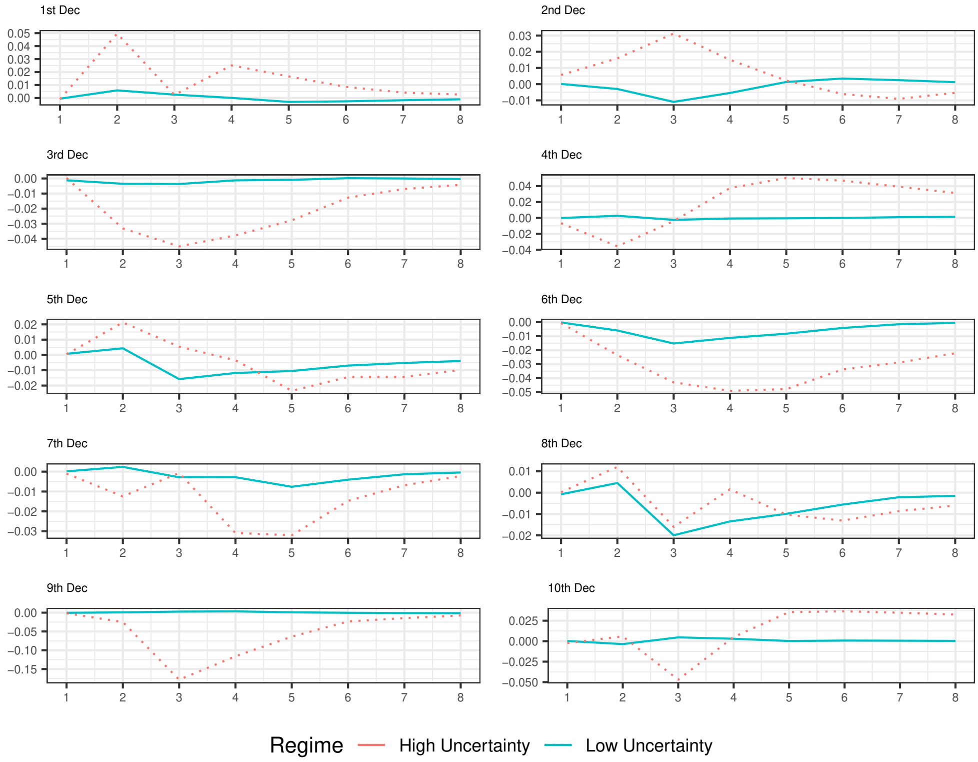

Figure 11: Impulse response functions for uncertainty shocks for portfolios sorted by Market Equity

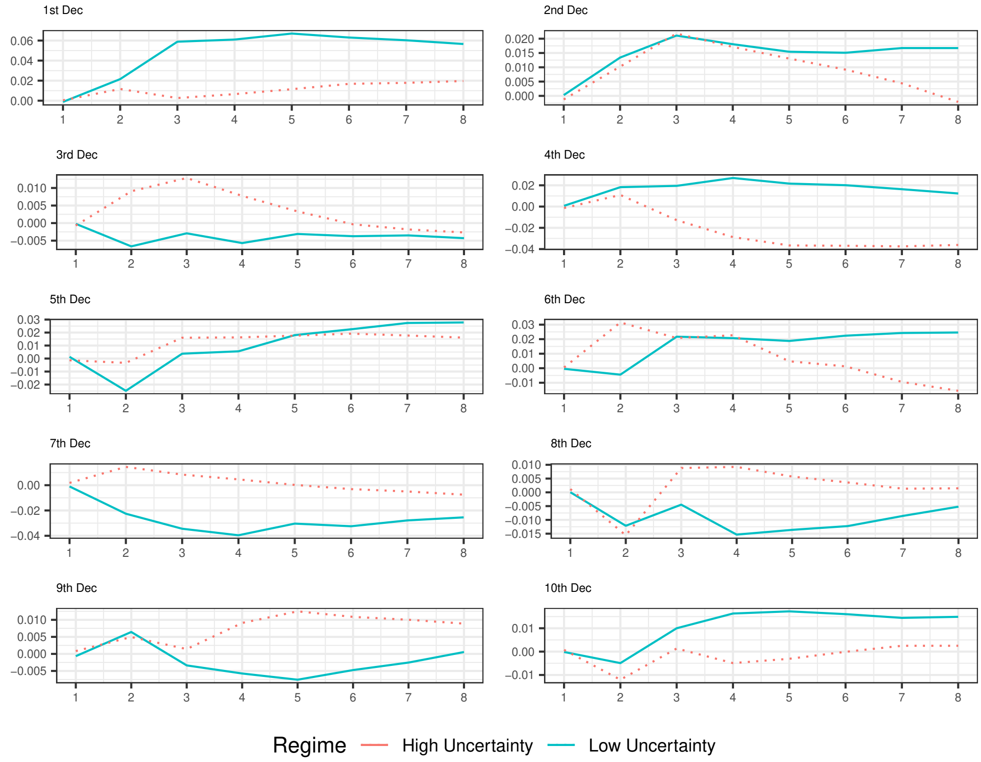

Figure 12: Impulse response functions for uncertainty shocks for portfolios sorted by Investment

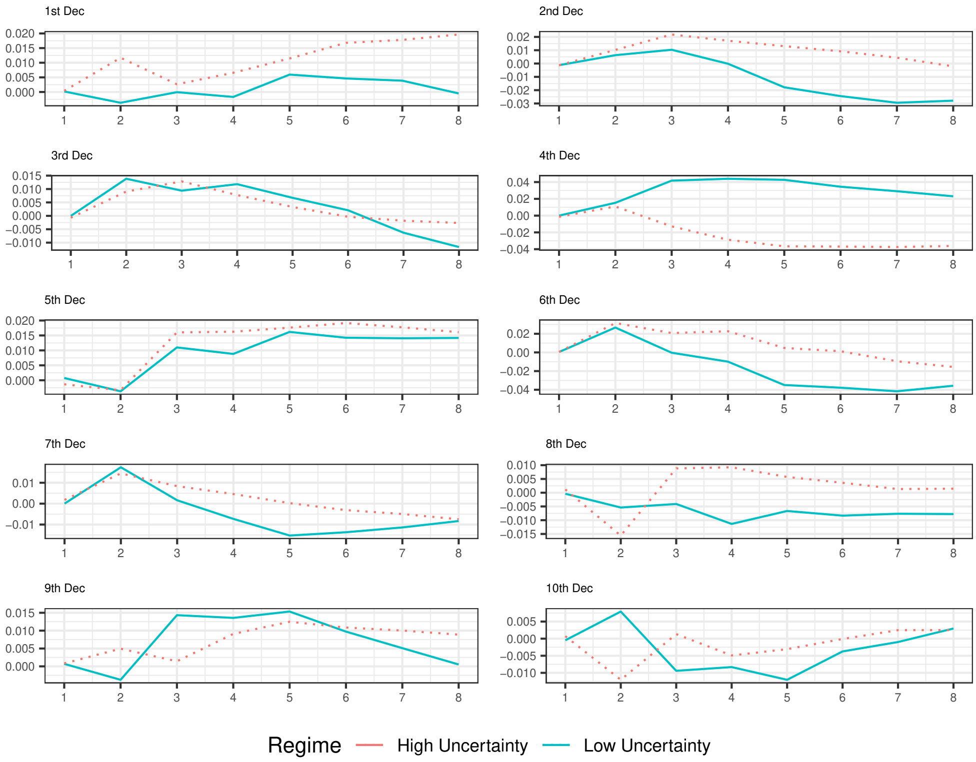

Figure 13: Impulse response functions for uncertainty shocks for portfolios sorted by Operating Profit

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A Algorithm to compute nonlinear impulse response functions

1. The shocks for periods 0 to q are drawn from a multivariate normal distribution
2. For an initial value the sequence of shocks is used to compute conditional forecasts
3. Repeat step 2 with an initial shock to a variable of one standard deviation
4. The difference between the forecasts from step 2 and 3 is the impulse-response functions. Repeat this 50 times for each inital condition.
5. Repeat steps 2-4 for each initial condition. Final impulse response functions are the average over all initial conditions in of all regimes.