

UCLA

UCLA Electronic Theses and Dissertations

Title

Essays on Financial Market Volatility and Real Economic Activity

Permalink

<https://escholarship.org/uc/item/5sc558cp>

Author

Choi, Sang Yup

Publication Date

2015

Peer reviewed|Thesis/dissertation

UNIVERSITY OF CALIFORNIA
Los Angeles

**Essays on Financial Market Volatility and Real
Economic Activity**

A dissertation submitted in partial satisfaction
of the requirements for the degree
Doctor of Philosophy in Economics

by

Sang Yup Choi

2015

© Copyright by
Sang Yup Choi
2015

ABSTRACT OF THE DISSERTATION

Essays on Financial Market Volatility and Real Economic Activity

by

Sang Yup Choi

Doctor of Philosophy in Economics

University of California, Los Angeles, 2015

Professor Aaron Tornell, Co-chair

Professor Roger E. Farmer, Co-chair

This dissertation studies how financial market volatility or uncertainty in the U.S. economy affects real economic activity both in the U.S. and other open economies. Chapter 1 critically examines a stylized fact about the effects of uncertainty shocks on the U.S. economy. A link between uncertainty and firms' investment, hiring, and production decisions has drawn much attention in contemporary discussions after the 2008 financial crisis. Bloom [2009] showed that uncertainty events, identified by spikes in stock market volatility, triggered immediate falls in output and employment, followed by rapid rebounds. I show that such stock market volatility shocks failed to produce this same pattern of responses after 1983. Chapter 2 studies the effects of risk aversion shocks, measured by increases in the VIX, on emerging market economies (EMEs). By estimating a structural vector autoregression (VAR) model, I find that, although risk aversion shocks do not have much impact on U.S. output, they do have a noticeable impact on the output of EMEs. To explain the contrast between the impact of risk appetite shocks on EMEs and the impact on the U.S. economy, a credit channel is proposed as a propagation mechanism. In the model, an increase in the VIX is translated to a risk-aversion shock that generates a "flight to quality." As international investors

pull their money from EMEs, borrowing costs increase and domestic credit falls as a consequence of credit market imperfections. Higher borrowing costs, in turn, lead to a fall in investment that causes a real depreciation and a decline in total output through sectoral linkages. Finally, Chapter 3, which is co-authored with Prakash Loungani, studies the effect of uncertainty shocks on unemployment dynamics by separating out the role of aggregate and sectoral channels. Using S&P500 data from the first quarter of 1963 through the third quarter of 2014, we construct a separate index to measure sectoral uncertainty and compare its effects on the unemployment rate with that of aggregate uncertainty in a standard VAR model, augmented by a local projection method. We find that aggregate uncertainty shocks lead to an immediate increase in unemployment, followed by swift reversals. In contrast, sectoral uncertainty shocks have a long-lasting impact on unemployment, with the peak impact occurring after two years. Our findings highlight an additional channel through which uncertainty shocks have persistent effects on unemployment by requiring substantial inter-industry labor reallocation.

The dissertation of Sang Yup Choi is approved.

Avanidhar Subrahmanyam

Jinyong Hahn

Roger E. Farmer, Committee Co-chair

Aaron Tornell, Committee Co-chair

University of California, Los Angeles

2015

To my wife, to my family

TABLE OF CONTENTS

1	Are the Effects of Bloom’s Uncertainty Shocks Robust?	1
1.1	Introduction	1
1.2	Data and Empirical Methodology	2
1.3	Empirical Findings	3
1.4	Robustness Checks	4
1.5	Conclusion	6
1.6	Appendix	6
1.6.1	Figures and Tables	6
2	The Impact of VIX Shocks on Emerging Market Economies: Flight to Quality Mechanism	15
2.1	Introduction	15
2.1.1	The Importance of VIX Shocks in Business Cycles: US vs. EMEs	18
2.2	Literature Review	19
2.3	The Model	21
2.3.1	The Domestic Economy	21
2.3.2	The International Asset Market	24
2.3.3	The Equilibrium of the Model	26
2.3.4	A Discussion of the Setup	31
2.4	Structural VARs	34
2.4.1	The Average Equilibrium Path	35
2.4.2	Identifying Structural Shocks	36

2.5	Estimating the Model	38
2.5.1	The Empirical Implementation of Structural VARs	38
2.5.2	Data	39
2.5.3	The Main Results	41
2.5.4	Robustness Checks	44
2.5.5	The Credit Channel	45
2.5.6	A Simulation of the Model	48
2.6	Conclusion	50
2.7	Appendix	52
2.7.1	Data Appendix	52
2.7.2	Proof	56
2.7.3	Figures and Tables	59
3	Uncertainty and Unemployment: The Effects of Aggregate and Sectoral Channels	84
3.1	Introduction	84
3.2	Measuring Uncertainty: Aggregate vs. Sectoral	87
3.2.1	Aggregate and Sectoral Uncertainty in a Simple Economy	87
3.2.2	Uncertainty Indices from the U.S. Stock Market	88
3.2.3	Data	89
3.3	Structural VARs	90
3.3.1	The Effects of Uncertainty Shocks	92
3.3.2	Interpretation of the Main Results: Different Channels of Uncertainty Shocks	94

3.3.3	Contribution of Uncertainty Shocks to Long-Term Unemployment during the Great Recession	95
3.4	Robustness Checks	95
3.4.1	Alternative Measure of Aggregate Uncertainty Shocks . . .	96
3.4.2	Impulse-Response Functions from a Local Projection Method	97
3.4.3	Inclusion of Additional Variables	98
3.4.4	Alternative Identifying Assumptions	99
3.4.5	Treatment of Non-stationarity	100
3.4.6	Different Lag Length	100
3.5	Conclusion	101
3.6	Appendix	101
3.6.1	Construction of the Sectoral Uncertainty Index	101
3.6.2	Figures and Tables	102
	Bibliography	122

LIST OF FIGURES

1.1	% deviation of industrial production from trend and dates of the uncertainty events	7
1.2	Response to uncertainty shocks (baseline result)	8
1.3	Theoretical wait-and-see behavior of a firm in response to uncertainty shocks.	9
1.4	Response to uncertainty shocks (before the Great Moderation) . .	10
1.5	Response to uncertainty shocks (during the Great Moderation) . .	11
1.6	Response to uncertainty shocks (data extension)	12
2.1	Output response to VIX shocks	60
2.2	Output response to VIX shocks in earlier periods	61
2.3	Flowchart of the model	62
2.4	Graphical description of the portfolio choice (loose VaR constraint)	63
2.5	Graphical description of the portfolio choice (tight VaR constraint)	64
2.6	The evolution of VIX	65
2.7	Responses to VIX shocks: The US and Korea	66
2.8	Historic decomposition of industrial production during the Great Recession	67
2.9	Responses to VIX shocks: 18 EMEs	68
2.10	Magnitude and statistical significance of response of country borrowing spreads	69
2.11	Magnitude and statistical significance of response of real exchange rates	70
2.12	Magnitude and statistical significance of response of domestic output	71

2.13	Robustness checks	72
2.14	Degree of credit market imperfections and the adverse impact on a credit market	73
2.15	Response of the 11 EMEs to VIX shocks in the extended VARs	74
2.16	Response of the US economy to VIX shocks in the extended VARs	75
2.17	Importance of the credit channel during the Great Recession	76
2.18	Counterfactual exercise during the global financial crisis	77
2.19	Bank lending standard and demand for bank loans	78
2.20	Sensitivity analysis on ρ	79
2.21	Sensitivity analysis on γ	80
3.1	Uncertainty index	103
3.2	Unemployment rate (%)	104
3.3	Response of the unemployment rate to various shocks in the baseline model	105
3.4	Effects of uncertainty shocks on the long-term unemployment rate	106
3.5	Effects of uncertainty shocks on the short-term unemployment rate	107
3.6	Contribution of uncertainty shocks to the long-term unemployment rate during the Great Recession	108
3.7	Sub-sample analysis	109
3.8	The effect of alternative measure of aggregate uncertainty shocks (economic policy uncertainty)	110
3.9	Robustness check: Impulse-response functions from a local projection method	111
3.10	Robustness check: Inclusion of additional variables	112

3.11 Robustness check: Different identifying assumptions	113
3.12 Robustness check: Various de-trending methods	114
3.13 Robustness check: Different lag lengths	115

LIST OF TABLES

1.1	Uncertainty events	13
1.2	Variance decompositions for the baseline VAR	14
2.1	Countries in the sample and the data coverage	81
2.2	Variance decomposition of the key variables	82
2.3	Calibration of the key parameters	83
3.1	Summary statistics	116
3.2	Decomposition of the unemployment rate for different durations (%)	117
3.3	Decomposition of the unemployment rate for different durations with local projections (%)	118
3.4	Industrial composition of the sectoral uncertainty index	119
3.5	Data description	120
3.6	Augmented Dickey-Fuller test	121

ACKNOWLEDGMENTS

I am deeply indebted to my advisors Aaron Tornell and Roger E. Farmer for their endless support throughout the Ph.D program at UCLA. Without their guidance, none of my achievement would have been possible. My work has been also benefited from the help of other committee members, Jinyong Hahn and Avaniidhar Subrahmanyam. They are truly talented economists and gifted advisors.

I am very grateful to Andrew Atkeson, Pablo Fajgelbaum, Gary Hansen, Kyle Herkenhoff, Zhipeng Liao, Prakash Loungani, and Pierre-Olivier Weill for their helpful comments and encouragement.

I would remember six years at UCLA with the warmest heart with Ana Luisa Araujo, Sean Fahle, Giang Ho, Byeonghyeon Jeong, Joonmo Kang, Vadim Khramov, Bo Kyung Kim, Daehyun Kim, Hyo Sang Kim, Young Ju Kim, Changsu Ko, Joseph Kuehn, Siwei Kwok, Chan Mang, Kenny Mirkin, Jaeok Park, Keyyong Park, Dmitry Plotnikov, Santiago Ignacio Sautua, Wei Shi, Marcus Studart, Miao Sun, Allen Tran, Kyle Woodward, Cong Xie, Yujing Xu, Yong Hyun Yang, and the faithful members of the student lunch seminar; Devin Buntun, Fernando Giuliano, Federico Grinberg, Andreas Gulyas, Jinwook Hur, Ioannis Kospentaris, Dennis Kuo, Giovanni Nicolo, Musa Orak, Liyan Shi, and Gabriel Zaourak. I am also thankful to Joonkyu Choi, Heechun Kim, Jinyeob Kim, Jongho Park, Kwangyong Park, Myungkyu Shim—the members of the Junior Scholar Club—for insightful discussions.

I met the love of my life, Eun Jin Shin, along the way, and her unconditional and sometimes unconventional support always kept me balanced along the right path. I am sincerely grateful to my parents and parents-in-law for their endless support. Finally, I appreciate continuing encouragement from my undergraduate advisors in Korea; Sunku Hahn, Youngse Kim, Ki Young Park, and Taeyoon Sung.

Generous financial support from the Department of Economics, the Graduate

Division, Yonsei International Foundation, and Ilsong Foundation is also gratefully acknowledged.

Chapter 1 is a version of the paper “Are the effects of Bloom’s uncertainty shocks robust?,” which was originally published in *Economics Letters*, Volume 119 (2013), pp. 216-220.

VITA

- 2007–2008 Exchange Student, University of California, Berkeley, Berkeley, California.
- 2009 B.A. (Economics), Yonsei University, Seoul, Republic of Korea.
- 2011 M.A. (Economics), University of California, Los Angeles, Los Angeles, California.

PUBLICATIONS

Choi, Sangyup. “Are the effects of Bloom’s uncertainty shocks robust?.” *Economics Letters* 119.2 (2013): 216-220.

CHAPTER 1

Are the Effects of Bloom’s Uncertainty Shocks Robust?

1.1 Introduction

Bloom [2009] shows that major uncertainty events trigger immediate falls in output and employment followed by rapid rebounds after the resolution of uncertainty, which he calls a result of “wait-and-see” dynamics. This paper shows that the wait-and-see mechanism is identified mostly by shocks that occurred between 1962 and 1982 and that the post-1983 data do not display the same dynamics.

Using data from 1962 through 2008, Bloom [2009] finds that 17 uncertainty events, identified by spikes in stock market volatility (SMV) index, had a significant impact on employment and output in the U.S. economy in the short run. Bloom [2009] explains this empirical finding in the context of a production model where uncertainty increases the region of inaction in hiring and investment decisions of firms facing non-convex adjustment costs. In this paper, I re-examine the effect of Stock Market Volatility (SMV) shocks studied in Bloom [2009] and check whether stylized wait-and-see dynamics in response to uncertainty shocks are robust over time. I divide the original sample period into two subsets (1962-1982 and 1983-2008) based on the generally accepted view¹ that 1983 is a breakpoint in the behavior of the U.S. economy. The period after 1983 is widely referred to

¹See Clarida et al. [2000], Lubik and Schorfheide [2004], and McConnell and Perez-Quiros [2000].

as the Great Moderation.

Surprisingly, I find that the effects of SMV shocks on the U.S. economy are different during the Great Moderation than in the period from 1962 to 1982. The impact of SMV shocks in the first period is consistent with Bloom’s baseline finding. During the Great Moderation, however, the effects of SMV shocks are inconsistent with theoretical wait-and-see dynamics.² Extending the data set to August 2012 does not alter this finding.

1.2 Data and Empirical Methodology

In this section I replicate Bloom’s results using the same data set.³ I use Hodrick–Prescott (HP) de-trended monthly variables of the log of the S&P 500 stock market index, a stock-market volatility indicator, the Federal Funds Rate, the log of average hourly earnings, the log of the consumer price index, the log of hours worked, the log of employment, and the log of industrial production of the period from 1962 to 2008. I divide the original sample into two periods (1962–1982 and 1983–2008) based on the widely reported finding that U.S. data display a structural break after 1983.

To check for the robustness of my finding in the later part of the paper, I extend Bloom’s original data to August 2012 to fully evaluate the effects of the 2008 financial crisis on the U.S. economy. This episode is not studied in Bloom’s original work. This extension of the data also allows me to analyze the effect of the recent stock market turmoil triggered by the Euro-zone crisis. Bloom [2009] constructs an indicator of large “exogenous” uncertainty shocks. This is a 0-1 variable that takes on a value of 1 if stock market volatility is more than 1.65 standard deviations

²Using German firm-level data, Bachmann and Bayer [2013] also suggest that time-varying firm level risk through wait-and-see dynamics is unlikely a major source of business cycle fluctuations.

³See Bloom [2009] for a detailed discussion about data and Vector autoregression (VAR).

above the HP de-trended series and 0 otherwise. Using Bloom's algorithm to directly compare my results with Bloom's, I add one more event (the October 2011, Euro-zone crisis).⁴ Table 1.6.1 shows the dates of uncertainty events for both periods.

I begin my analysis with a multi-variable VAR that includes 12 lags of the stock market index, uncertainty measured by stock market volatility, prices (wage and Consumer Price Index), interest rates, and real economic activity (output and employment). The ordering of the variables in the VAR follows Bloom [2009] to avoid any discrepancy that might arise from different identification methods.

1.3 Empirical Findings

Figure 1.1 summarizes my main results. This figure shows the percentage deviation of industrial production in manufacturing from its trend, together with the dates of the uncertainty events from Bloom [2009]. In the first sample (1962-1982), 6 out of 9 uncertainty shocks were immediately followed by a sharp decrease in industrial production, while in the second sample (1983-2008) only 2 out of 8 uncertainty shocks were followed by falls in industrial production. Except for the First Gulf War shock and the 2008 financial crisis, uncertainty shocks did not trigger a downturn in real economic activity in the second sample period. The rest of the paper will focus on establishing this finding more rigorously and checking its robustness.

Figure 1.6.1 shows my replication of Bloom's baseline impulse response of output and employment to his uncertainty shocks. This empirical finding is consistent with theoretical wait-and-see dynamics in response to an increase in uncertainty as in Figure 1.3.⁵

⁴In the later part of the paper, I use additional methods to check robustness of my results.

⁵In order to prove this is a robust finding, Bloom [2009] used different measures of uncertainty, different variables for his VAR, and different de-trending methods. However, the validity of his

However, once I divide the sample into two periods, I find that stylized wait-and-see dynamics do not hold during the second sample. The impulse response of industrial production and employment to uncertainty shocks during the first period (see Figure 1.4) is consistent with Bloom’s finding as in Figure 1.6.1.

In contrast, uncertainty shocks lose their negative impact in the second period as shown in Figure 1.5. In the short run, the response of both industrial production and employment during this period is not significantly different from zero. This observation implies that the wait-and-see mechanism is not consistent with the data after 1983.

This finding is confirmed when I look at forecast error variance decompositions. The standard error decompositions, presented in Table 1.6.1, indicate that SMV shocks play a much greater role in explaining the variation of output and employment in the first period. Specifically, at a six month horizon, more than 6 percent of the variance in industrial production and 10 percent of the variance in employment are attributable to innovations of SMV shocks during the first period. However, only 1 percent of output and employment variations are explained by the same shock during the second period. Such a pattern does not change when I extend my data through August of 2012.⁶

1.4 Robustness Checks

Here, I investigate my main finding in more detail to check its robustness. First, my finding could potentially be affected by the choice of a breakpoint in the sample. Perhaps the dramatic change in the impulse response functions in the second period is caused by the inclusion or exclusion of certain years or events. To check this possibility I consider various breakpoints. I confirm that my finding holds

VAR is still open to discussion. See Bachmann et al. [2013].

⁶Standard error decompositions for a trivariate case show an even sharper contrast.

for any breakpoint between 1980 and 1990.⁷ No matter when the second period starts, the negative impact of uncertainty shocks disappears. Second, Bloom [2009] does not fully evaluate the effect of the 2008 crisis on uncertainty dynamics because at the time he published his paper, the Great Recession had only just begun. Perhaps, the inclusion of the crisis will change the picture of uncertainty dynamics in the second period. This turns out not to be the case. When I include data through August 2012, I find that this extension of the data does not alter the main finding of the paper. Figure 1.6 indicates that a negative uncertainty impact still vanished even after the inclusion of the recent financial crisis.

Bloom [2009] uses two different measures of uncertainty: implied stock market volatility and realized stock market volatility. Despite the high correlation between these measures, they are different from a theoretical perspective. One is an ex-ante measure derived from the financial markets and the other is an ex-post measure of return volatility. The difference between the two volatilities is a time-varying variance risk premium that can be large in some periods. In this sense, the fact that stock market volatility is measured by realized volatility before 1986 and by Black-Scholes implied volatility (VXO) after 1986 may undermine my main result. However, I find that the structural break between the two periods cannot be attributed to a discontinuity in the volatility measure. To further explore this difference in measures of volatility, I redefine uncertainty events following Bloom's algorithm but using only realized volatility for the entire period.⁸ Although there are several changes in chosen events, the conclusion of this paper is reinforced.⁹ To conclude, after running thorough robustness checks, I confirmed that the impulse response of output and employment to SMV shocks is inconsistent with theoretical wait-and-see dynamics after 1983.

⁷Results from various breakpoints are available upon request.

⁸Bloom [2009] calculated realized volatility as the monthly standard deviation of the daily S&P500 index.

⁹Impulse response functions from uncertainty shocks defined by realized volatility alone are available upon request.

1.5 Conclusion

Bloom [2009] argues that the wait-and-see mechanism in response to uncertainty shocks can explain a large fraction of the post-war U.S. business cycle. Other recent works also confirm that uncertainty shocks, measured by the SMV index, are negatively correlated with future economic activity in the short run (Alexopoulos and Cohen [2009]; Fornari and Mele [2010]). Nevertheless, there are different explanations for the transmission mechanism of uncertainty shocks in the recent literature. For example, Gilchrist et al. [2014] emphasize the interaction of uncertainty and economic activity propagated through financial, rather than physical, friction. Basu and Bundick [2012] argue that nominal rigidities are the key to explaining uncertainty dynamics. Bachmann et al. [2013] suggest that endogenously expansionary monetary policy, rather than the wait-and-see channel, can be the transmission channel of uncertainty shocks.

I find that a strongly negative relationship between stock market volatility shocks and real economic activity in the short run disappeared in the early 1980s. A structural change in the response of output and employment to uncertainty shocks is robust to different measures of stock market volatility, variations in the choice of breakpoint, extension of the data, and different identification schemes for the VAR. It is beyond the scope of this paper to offer a theoretical explanation for this empirical finding. My finding, together with a regime switch in the U.S. monetary policy in the early 1980s, implies that at least the transmission mechanism from SMV shocks to the real economy changed after 1983.

1.6 Appendix

1.6.1 Figures and Tables

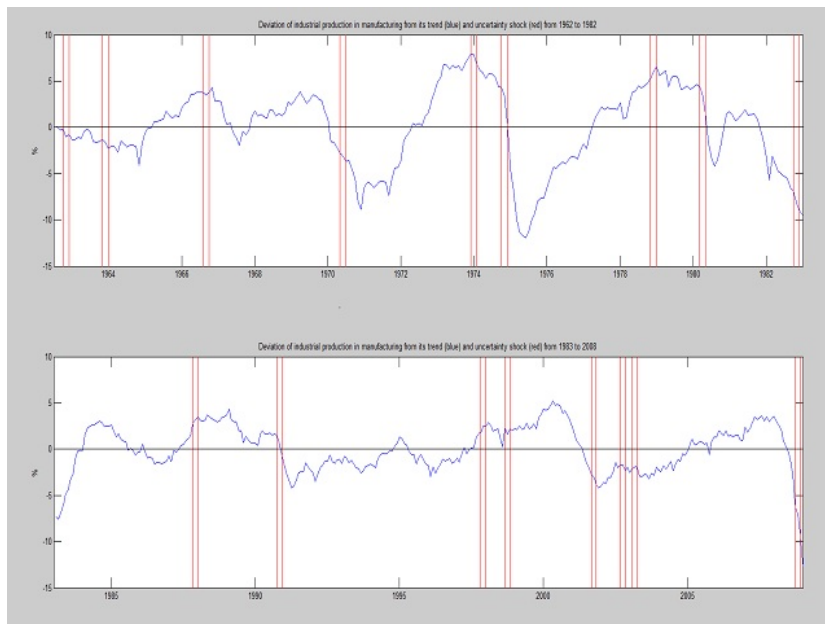


Figure 1.1: % deviation of industrial production from trend and dates of the uncertainty events

Notes: The top panel is for the period between 1962 and 1982, and the bottom panel is for the period between 1983 and 2008. The uncertainty events are taken from Bloom [2009].

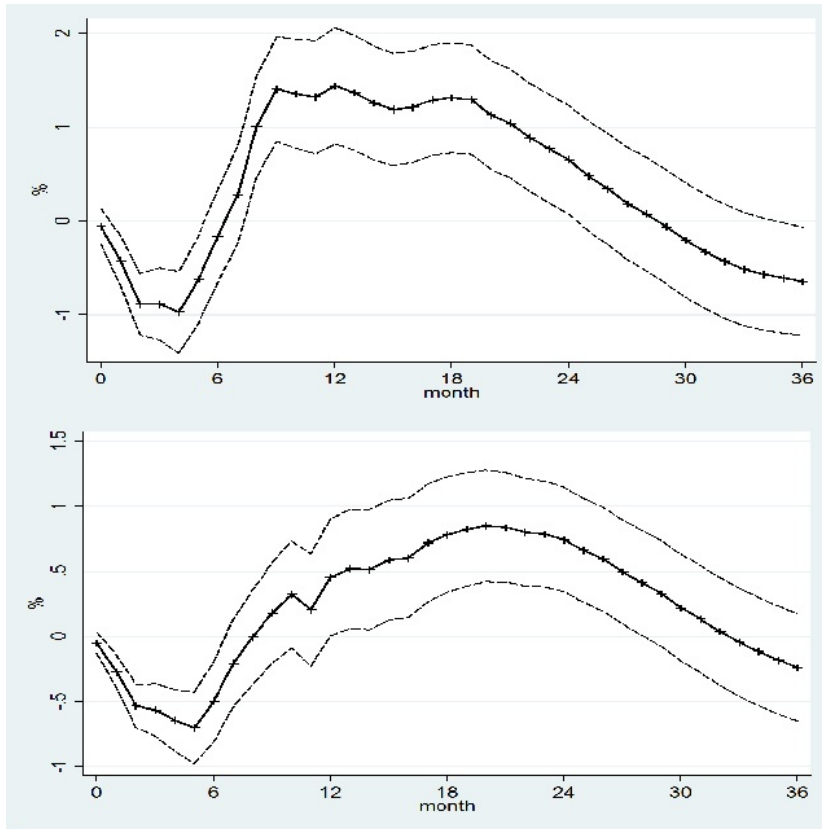


Figure 1.2: Response to uncertainty shocks (baseline result)

Notes: Impulse responses of industrial production (top) and employment (bottom) to the baseline uncertainty shocks from Bloom [2009].

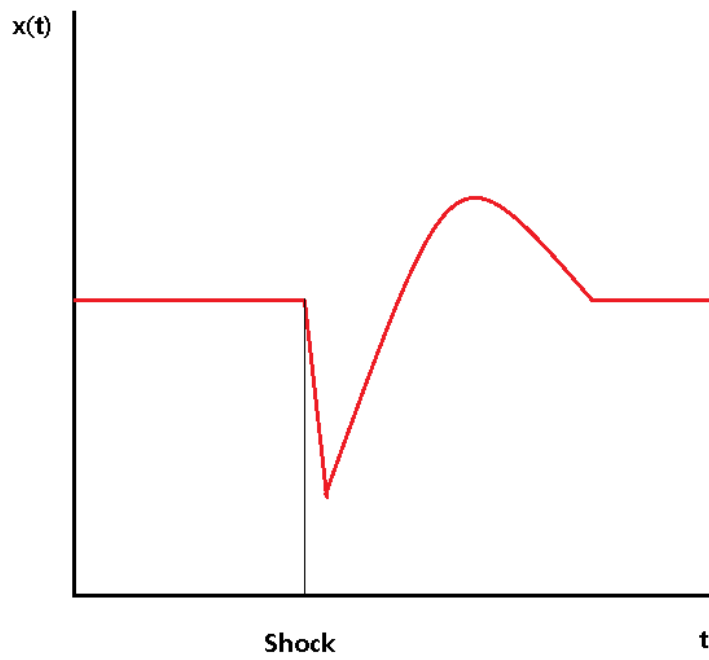


Figure 1.3: Theoretical wait-and-see behavior of a firm in response to uncertainty shocks.

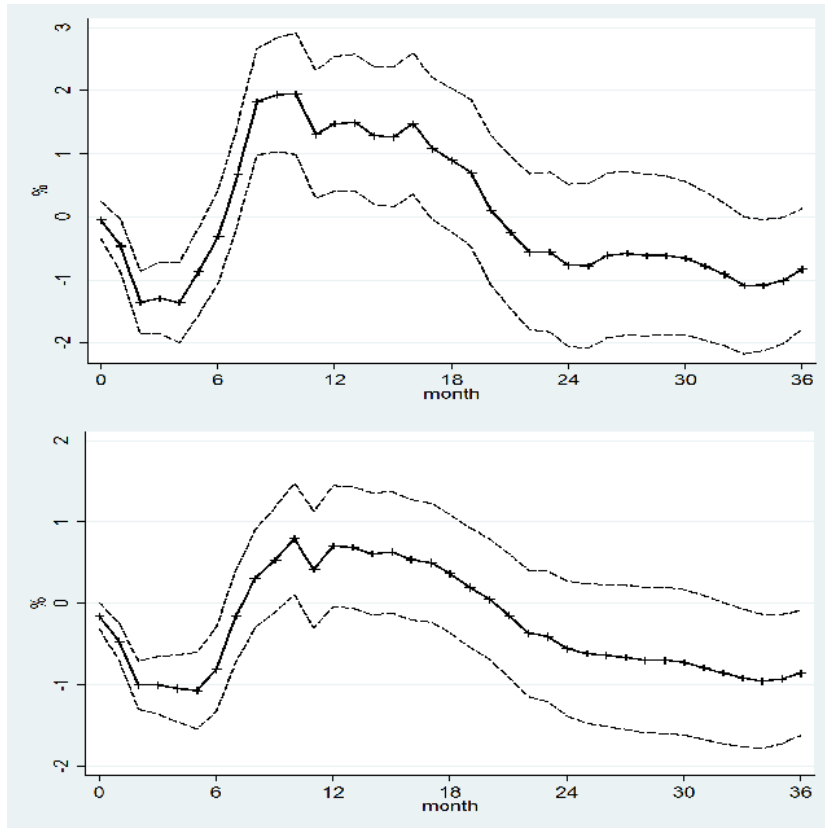


Figure 1.4: Response to uncertainty shocks (before the Great Moderation)
 Notes: Impulse responses of industrial production (top) and employment (bottom) to the base-line uncertainty shocks from 1962 to 1982.

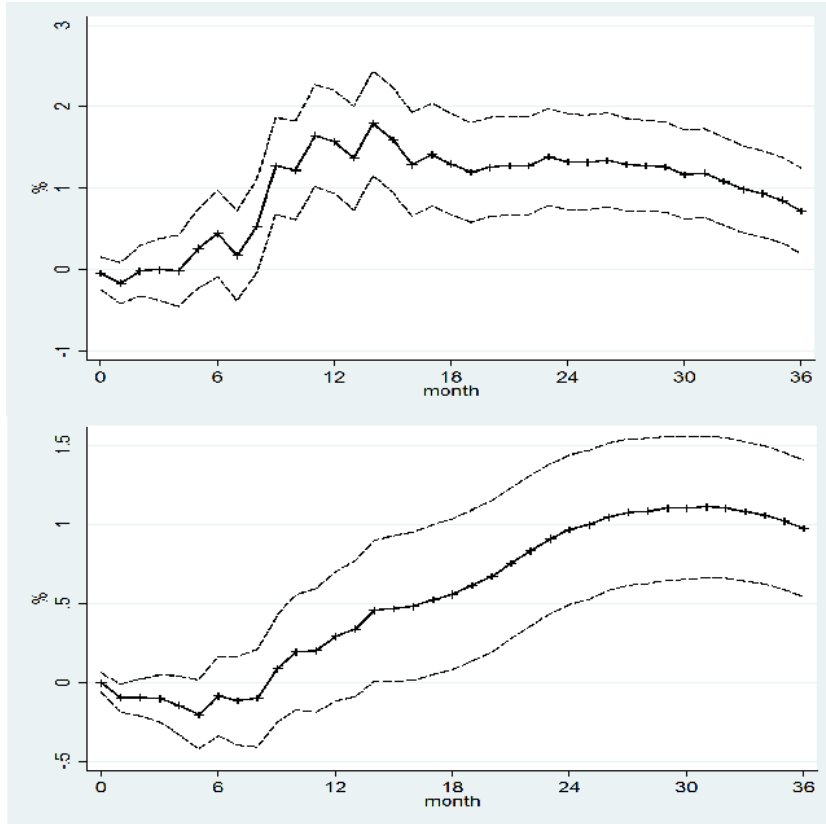


Figure 1.5: Response to uncertainty shocks (during the Great Moderation)
 Notes: Impulse responses of industrial production (top) and employment (bottom) to the base-line uncertainty shocks from 1983 to 2008.

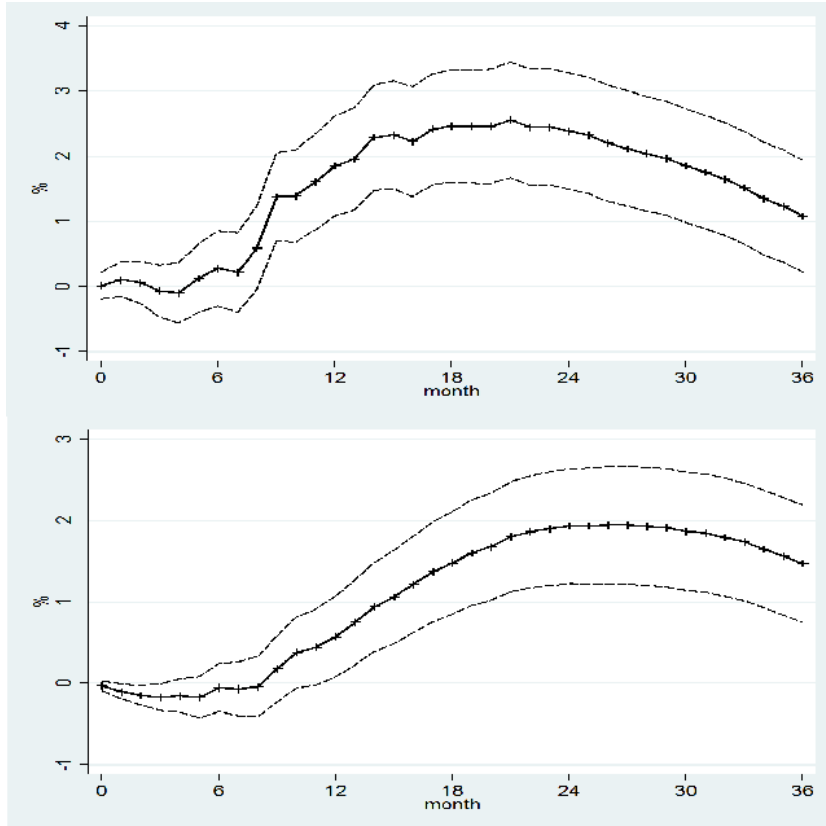


Figure 1.6: Response to uncertainty shocks (data extension)

Notes: Impulse responses of industrial production (top) and employment (bottom) to the baseline uncertainty shocks from 1983 to 2012.

Event (1st sample)	Date of the event	Event (2nd sample)	Date of the event
Cuban missile crisis	Oct 1962	Black Monday	Nov 1987
Assassination of JFK	Nov 1963	Gulf War I	Oct 1990
Vietnam buildup	Aug 1966	Asian crisis	Nov 1997
Cambodia and Kent State	May 1970	Russian, LTCM default	Sep 1998
OPEC I, Arab–Israeli War	Dec 1973	9/11 terrorist attack	Sep 2001
Franklin National	Oct 1974	Worldcom and Enron	Sep 2002
OPEC II	Nov 1978	Gulf War II	Feb 2003
Afghanistan, Iran hostages	Mar 1980	Credit crunch	Oct 2008
Monetary cycle turning point	Oct 1982	Euro-zone crisis*	Sep 2011

Table 1.1: Uncertainty events

Notes: * indicates the event added by the author.

Horizon	Industrial Production			Employment		
	1962-1982	1983-2008	1983-2012	1962-1982	1983-2008	1983-2012
1	1.24	0.07	0.09	0.12	1.39	0.00
2	1.15	0.06	0.05	0.13	0.89	0.01
3	1.16	0.05	0.03	2.95	0.52	0.03
6	6.71	1.01	0.15	10.68	1.35	1.52
9	6.75	1.25	0.48	9.54	1.07	0.81
12	11.34	1.04	2.55	8.39	2.96	0.87
15	13.76	1.16	4.61	9.66	2.87	1.71
18	16.79	1.93	6.25	12.21	2.48	3.02
24	14.74	4.56	9.11	11.39	1.98	6.48
30	12.02	8.92	11.48	8.39	3.21	10.91
36	11.86	11.78	12.36	7.75	5.76	14.61

Table 1.2: Variance decompositions for the baseline VAR

Notes: Numbers indicate the percentage of the variance of each variable explained by stock market volatility shock.

CHAPTER 2

The Impact of VIX Shocks on Emerging Market Economies: Flight to Quality Mechanism

2.1 Introduction

This paper studies the impact of increases in the VIX (hereafter VIX shocks) on emerging market business cycles.¹ I derive structural Vector Autoregressions (VARs) from an equilibrium model and estimate them with data from 18 emerging market economies (EMEs). From the structural VARs, I find that VIX shocks have a substantial impact on EMEs, but they do not have a significant impact on US output from 1994 to 2013. This new empirical finding helps understand high volatility of business cycles in EMEs.

To explain the contrasting impact of VIX shocks on EMEs from their impact on the US economy, I take the VIX as a measure of market sentiment that captures international investors' preference for safe assets (flight to quality). In the model, a stronger preference for safe assets is translated into higher borrowing costs in EMEs via credit market imperfections. More binding borrowing constraints in EMEs lead to a fall in investment that is followed by a real depreciation and a decline in total output via sectoral linkages. I propose this credit channel as a propagation mechanism of VIX shocks to EMEs, that is distinct from the wait-and-see mechanism under uncertainty interpretation of VIX shocks proposed by

¹The VIX is a measure of market expectations of near-term volatility conveyed by S&P 500 stock index option prices, often used as a barometer of investor sentiment and market volatility. See Whaley [2009] for the nontechnical summary of the VIX.

Bloom [2009].

The empirical results from the structural VARs across the 18 EMEs are consistent with the prediction of the model: A one standard deviation increase in the VIX is followed by a fall in industrial production, an increase in real lending rates, a decline in domestic credit, and a real depreciation, which are statistically and economically significant.

The model consists of two parts: an international asset market and a domestic economy. International investors allocate their wealth across three types of assets: (i) safe assets (US Treasury bills), (ii) risky assets from the US economy (US stocks), and (iii) risky assets from EMEs (emerging market risky bonds). They are subject to a Value-at-Risk (VaR) constraint under which the expected maximum loss should meet a predetermined VaR limit.

The domestic economy consists of two sectors: tradable and non-tradable. I model firms in the non-tradable sector as borrowing constrained, following the setup of Schneider and Tornell [2004]. Non-tradable sector firms can only borrow from domestic banks, and their borrowing is limited by their net worth due to contract enforceability problems. Domestic banks take on currency mismatch by borrowing in tradable goods from international investors and lending to non-tradable sector firms. These loans are denominated in units of non-tradable goods.² The only source of uncertainty is aggregate productivity shocks in the tradable sector. With currency mismatch, the realization of low productivity triggers a real depreciation, thereby leading domestic banks to default on their bonds. International investors diversify this exchange rate risk by investing in many different countries.

I model VIX shocks as an increase in the conditional variance of returns on US stocks. Under the VaR constraint, VIX shocks encourage international investors to reduce their demand for emerging market risky bonds to limit their downside

²This setup is intended to capture a common practice in EMEs that banks borrow in dollars and lend in local currencies (pesos).

risk as if a risk aversion shock does. As the supply of risky bonds remains the same, VIX shocks trigger a fall in the price of these bonds. A decrease in the bond price, in turn, is translated into more binding borrowing constraints at any level of non-tradable sector firms' net worth. Having less credit, non-tradable sector firms invest less, leading to a real depreciation via the non-tradable good market clearing condition. Although tradable sector firms are not financially constrained, sectoral linkages lead to a fall in total output.

I derive structural VARs from the recursive equilibrium of the model and estimate them with data from the 18 EMEs. The following three facts characterize my main results. First, I find that country borrowing spreads—the difference between domestic lending rates and the risk-free rate (3 month T-bill rates)—increase by 0.3% points following a one standard deviation shock to the VIX. Second, Real exchange rates depreciate by 0.7%. Third, domestic credit to private sector declines by 0.5% and industrial production declines by 0.7%. The fall in domestic credit and the increase in country borrowing spreads clearly indicate that VIX shocks are a negative credit supply shock to EMEs.

I numerically simulate the international asset market part of the model to gauge the quantitative effect of VIX shocks on domestic lending rates in EMEs via the above portfolio reallocation of international investors. When I calibrate key parameters of the model, I find that the model can replicate the empirical estimates from the structural VARs.

In contrast, the US economy shows sharply different responses to VIX shocks from the 18 EMEs. Following VIX shocks in a similarly identified structural VAR model, the risk-free real interest rate falls by 0.07% points, real exchange rate appreciates by 0.4%, domestic credit increases by 0.3%, and industrial production decreases by 0.1%. Further, the falls in the real interest rate and in industrial production are statistically insignificant.³ The qualitatively different pattern ob-

³This finding should be taken with caution. It does not controvert a well-known relation-

served in the behaviors of real interest rates, real exchange rates, and domestic credit of the 18 EMEs from the US economy is consistent with the flight to quality mechanism of this paper.

Recently, the VIX has become an empirical standard as a proxy for uncertainty. In academic literature, however, the “sentiment” interpretation of the VIX, which is common among financial market practitioners, has been largely ignored. The contrasting impact of VIX shocks on EMEs from their impact on the US economy is consistent with this interpretation and it suggests that the VIX may provide a useful barometer of risks to EMEs.

2.1.1 The Importance of VIX Shocks in Business Cycles: US vs. EMEs

I present the key finding of my paper that although VIX shocks do not have much impact on US output, they do have a noticeable impact on the output of EMEs for the last twenty years. Figure 2.1 presents the evidence for that claim.⁴ This result is consistent with the finding from Choi [2013] that the impact of uncertainty shocks, measured by exogenous spikes in US stock market volatility, on US manufacturing production and employment has substantially declined since 1983.

ship between fluctuations in a stock market and real activity through changes in future cash flow (Fama [1990]), changes in expectation (Benhabib and Farmer [1999]), or changes in news (Beaudry and Portier [2006]), as I only focus on “volatility”, not a level of the US stock market. The positive relationship between the level of a stock market and real activity in the US still remains strong (Farmer [2012]).

⁴Seeking the most parsimonious means of representation, the VAR model here only includes the VIX and the log level of industrial production without de-trending. The VIX is ordered first in a recursive identification, and the VARs are estimated with 6 lags. I obtain the strong correlation between the VIX and US output from estimating the same bivariate VARs for the earlier period. See Figure 2.2.

2.2 Literature Review

This paper is related mostly to three strands of literature. First, the recent empirical literature with a VAR analysis (Matsumoto [2011]; Akinci [2013]; Carrière-Swallow and Céspedes [2013]) finds substantial effects of VIX shocks on real activity such as output, consumption, and investment in EMEs, but it does not contrast fundamental differences between EMEs and the US economy. Other empirical works evaluate the effects of VIX shocks on sovereign spreads (González-Rozada and Yeyati [2008]; Ciarlone et al. [2009]), exchange rates (Cairns et al. [2007]; De Bock and Carvalho Filho [2013]), stock market (Chudik and Fratzscher [2011]), and capital flows (Ahmed and Zlate [2014]). However, they do not provide a theoretical framework to show how changes in these variables interact with real activity. I have sought to provide an integrated framework to study how VIX shocks affect financial markets and real economies both theoretically and empirically. As such, this analysis fills a gap in the literature.

The propagation mechanism of VIX shocks described in this paper shares a similar implication with other works. Similar to the propagation mechanism of risk shocks in Christiano et al. [2014], VIX shocks become an important driver of business cycles with the presence of financial friction. As in Gourio [2012], an increase in VIX leads risk-averse investors to invest less in risky assets. The market segmentation between safe and risky assets in Matsumoto [2011] resembles the interpretation in this paper of an international asset market. The credit channel as a propagation mechanism of VIX shocks in EMEs is similar to that in Carrière-Swallow and Céspedes [2013] who find that the effects of VIX shocks on investment and consumption in EMEs are substantially larger than those in advanced economies.

Second, the empirical results from this paper can increase understanding of the sources of volatile emerging market business cycles. On one hand, recent

international Real Business Cycle (RBC) literature (Neumeyer and Perri [2005]; Uribe and Yue [2006]; García-Cicco et al. [2010]; Mendoza and Yue [2012]; Hevia [2014]) concludes that volatile and counter-cyclical real interest rates in EMEs are the key to understanding their distinct business cycle fluctuations. This literature often explains volatile movements in the country premium component of real interest rates for EMEs in terms of the high degree of financial friction in these economies.

On the other hand, another stream of literature has exploited the financing asymmetry between the tradable and the non-tradable sectors prevalent in EMEs to explain their boom-bust cycles. Caballero and Krishnamurthy [2001] and Schneider and Tornell [2004] emphasize the role of collateral constraints faced by non-tradable sector firms in EMEs in the amplification of the negative shocks via a balance-sheet effect. This paper connects with the above studies by linking fluctuations in VIX—a source of shocks to real interest rates in EMEs—to the asymmetry between the tradable and the non-tradable sector in EMEs.

Finally, the introduction of the VaR constraint as a transmission mechanism of VIX shocks resembles prior works in the financial contagion literature. A financial crisis in one country is often transmitted to other economies without parallel deterioration in fundamentals of these economies. Regulations or risk management practices such as borrowing constraints, VaR constraints, margin requirements, and collateral constraints in a financial center are often blamed for financial contagion in EMEs both theoretically and empirically (Kaminsky and Reinhart [2000]; Kyle and Xiong [2001]; Kumar and Persaud [2002]; Kodres and Pritsker [2002]; Van Rijckeghem and Weder [2003]; Pavlova and Rigobon [2008]). The sentiment interpretation of VIX shocks in this paper can be supported by an outcome of the constrained maximization problem of international investors.

My international investors' portfolio reallocation mechanism is similar to that of Schinasi and Smith [2000], which shows how an increase in volatility of returns

on one risky asset can reduce the demand for other risky assets through the Value-at-Risk constraint. The VaR constraint has gained wide acceptance, not only from financial practitioners but also academics (Basak and Shapiro [2001]; Adrian and Shin [2014]). While I take the increase in VIX as a purely exogenous process, Bacchetta and Van Wincoop [2013] show that an increase in VIX can be an outcome of self-fulfilling shifts in risk.

2.3 The Model

I develop an equilibrium model in which there are two types of shock: VIX shocks and aggregate productivity shocks. A domestic economy consists of two sectors: tradable and non-tradable. The two-sector setup is required to understand the synchronized depreciation of EME exchange rates and spikes in VIX (De Bock and Carvalho Filho [2013]). Focusing on the EMEs' institutional features that are distinct from those of the US economy, I introduce credit market imperfections to the model following the framework of Schneider and Tornell [2004]. The model consists of four agents: non-tradable sector firms that are run by an overlapping generation of managers; tradable sector firms; domestic banks; and international investors. Figure 2.3 summarizes the key components of the model.⁵

2.3.1 The Domestic Economy

A tradable sector firm produces final consumption goods, and a non-tradable sector firm produces intermediate goods that are used as an input in the production of the tradable and the non-tradable sector. Using tradable goods as the numeraire, I denote the inverse of the real exchange rate by $p_t = \frac{p_t^N}{p_t^T}$, where p_t^N is the price of non-tradable goods and p_t^T is the price of tradable goods. The price of tradable

⁵I do not specify the problems of consumers (denoted by dashed circles in Figure 2.3) in the model. As the economy is small and open, the destination of tradable goods is not important for the main implication of the model.

goods is internationally fixed, so the price of non-tradable goods determines the real exchange rate.

Tradable Sector Firms

Tradable sector firms produce tradable goods by using a non-tradable sector input d_t and labor l_t , according to the following production function:

$$y_t^T = a_t d_t^\alpha l_t^{1-\alpha}, \quad (2.1)$$

where a_t is a binomial aggregate productivity shock, l_t is labor, and $\alpha \in (0, 1)$. For simplicity, I assume that supply of labor is inelastic, so $l_t = 1$ for every period.

There are two states (good, bad) for the realization of the aggregate productivity shock in the tradable sector: a and 0 , with the respective associated probabilities of $1 - u$ and u .⁶

$$a_t = \begin{cases} a & \text{with a probability } 1 - u \\ 0 & \text{with a probability } u \end{cases}$$

To ensure that the borrowing constraints of non-tradable sector firms always bind in equilibrium, the productivity of the tradable sector a_t is expected to shift in the finite future ($t = T$), following Schneider and Tornell [2004].⁷

$$a_t = \begin{cases} a \text{ or } 0 & \text{if } t < T \\ \bar{a} & \text{if } t = T, \end{cases}$$

where $a < \bar{a}$.

Non-tradable Sector Firms

Non-tradable sector firms are run by dynasties of managers who live through two periods. Non-tradable goods are produced using a non-tradable good as an

⁶The zero productivity in the bad state is just for simplicity, and any productivity lower than a would work as well.

⁷A large enough productivity shift in the final period induces a substantial real appreciation, encouraging non-tradable sector firms to take more debt along the equilibrium path.

input I_t , according to the following linear technology:

$$y_{t+1}^N = \theta I_t, \quad (2.2)$$

where θ is productivity of the non-tradable sector.

The investable funds of a non-tradable sector firm consist of the one-period debt (from a domestic bank) denominated in non-tradable goods—worth a total of b_t units of tradable goods—plus the firm’s net worth n_t in tradable goods. Therefore, the non-tradable sector firm’s budget constraint at time t , measured in tradable goods, is:

$$p_t I_t = n_t + b_t. \quad (2.3)$$

The time- t young manager inherits a net worth position n_t from her predecessor, and borrows b_t units of tradable goods by taking the non-tradable goods debt from a domestic bank. She promises to repay $(1 + i_t^D)b_t$ units of non-tradable goods at time $t + 1$, where i_t^D is the real lending rate that the domestic bank charges on the manager. At the end of the period t , the time- t old manager sells non-tradable goods and repays her debt from the previous period. Therefore, her profit in terms of tradable goods is

$$\pi_t(p_t) = p_t y_t^N - p_t(1 + i_{t-1}^D)b_{t-1}. \quad (2.4)$$

The time- t old manager distributes a fraction β of the profit (if positive) as a dividend to herself and passes on the rest $(1 - \beta)\pi_t(p_t)$ to her successor (time- $t + 1$ young manager):

$$n_{t+1} = (1 - \beta)\pi_t(p_t). \quad (2.5)$$

When a non-tradable sector firm becomes insolvent ($\pi_t(p_t) < 0$), all the revenue that the firm produces will dissipate, and a time- $t + 1$ young manager receives a small amount of government aid ϵ to start up. This situation, however, will not occur in equilibrium, as non-tradable sector firms find it optimal to hedge real exchange rate risks by borrowing in non-tradable goods only.

Domestic Banks

Domestic banks specialize in lending to non-tradable sector managers by borrowing from international investors through an emerging bond market. There are measure one of risk-neutral and competitive domestic banks. At period t , a domestic bank borrows from an emerging bond market by selling bonds at the price q_t , with the promise to repay one unit of tradable goods in the period $t + 1$, and then lends the borrowed funds to managers in non-tradable goods (i.e., they take on currency mismatch).

If the bank defaults on these bonds, international investors only collect Δ units of tradable goods per each unit of bonds purchased. For simplicity, I set $\Delta = 0$, so that emerging market bonds become completely worthless in the case of default, and defaulted banks are replaced by new banks. The emerging market bond price q_t determines the external cost of borrowing i_t faced by the domestic banks.⁸

$$1 + i_t \equiv \frac{1 - u}{q_t}. \quad (2.6)$$

2.3.2 The International Asset Market

International Investors

An international asset market is inhabited by a large number of identical two-period lived investors who will be represented by a representative investor. In period t , the representative investor is born with her exogenous wealth W_t in tradable goods, and maximizes the one-period expected returns from her portfolio investment. Her maximization problem is subject to the VaR constraint. The representative investor solves the following problem:

$$\max E_t R_{t+1}^P, \quad (2.7)$$

⁸The bond price q_t should be lower than $\frac{1-u}{R}$ because international investors are concerned about the trade-off between the returns and risk of the portfolio and these bonds bear default risk. Otherwise, international investors never purchase these bonds in the presence of safe assets, which guarantee the gross risk-free rate of R . If international investors are risk neutral, then $q_t = \frac{1-u}{R}$. Therefore, $\frac{1-u}{R} - q_t$ denotes risk premium.

subject to

$$\text{prob}\left(R_{t+1}^P < \underline{R}\right) \leq \gamma, \quad (2.8)$$

where R_{t+1}^P is the one-period gross rate of returns from the representative investor's portfolio. The VaR constraint (2.8) states that there is at most a γ percent chance of incurring losses that exceed $(1 - \underline{R})W_t$ between t and $t + 1$.

Under the joint normal distribution of perceived asset returns, which will be derived shortly, the constraint (2.8) can be written as

$$E_t R_{t+1}^P \geq \underline{R} + \Phi(1 - \gamma)\sqrt{\text{Var}_t R_{t+1}^P}, \quad (2.9)$$

where Φ denotes the cumulative distribution function of normal distribution and $\text{Var}_t R_{t+1}^P$ is the variance of the representative investor's portfolio.

International Asset Market Structure

An international asset market consists of three assets: safe assets (for example, US T-bills), US risky assets (US stocks), and EME risky assets (emerging market bonds). The emerging bond market consists of bonds supplied by domestic banks in N individual EMEs. When low productivity is realized with a probability u , domestic banks default on these bonds. Therefore, the expected returns and the variance of the returns from investing one unit of tradable goods by diversifying across N symmetric countries follow Lemma 2.3.1.

Lemma 2.3.1. (Returns Distribution of emerging market bonds)

Returns on emerging market bonds follow a normal distribution with the following mean and variance:

$$E_t R_{t+1}^F \equiv \mu_{F,t+1} = 1 + i_t,$$

$$\text{Var}_t R_{t+1}^F \equiv \sigma_{F,t+1}^2 = \frac{u(1 + i_t)^2}{1 - u},$$

where i_t also denotes the external cost of borrowing faced by borrowers in EMEs.⁹

⁹Note that i_t is a sufficient statistic for the expected returns and the variance of emerging market bonds due to the property of independently, identically distributed (i.i.d.) binomial distribution of aggregate productivity shocks.

Proof. For the proof, see 2.7.2.1 in Appendix. □

Under this representation of the expected returns on emerging market bonds, I attribute all the variations in the external cost of borrowing to the risk premium, as the physical probability of default is fixed in the model.

I also assume that the return process for US stocks is exogenous, and has a normal distribution with the following mean and variance:

$$E_t R_{t+1}^H \equiv \mu_{H,t+1}, \quad (2.10)$$

$$\text{Var}_t R_{t+1}^H \equiv \sigma_{H,t+1}^2.$$

The perceived returns on US stocks (H) and emerging market bonds (F) have conditional joint-normal distributions (with means $\mu_{j,t+1}$ and variances $\sigma_{j,t+1}^2$ for $j = H, F$) that are based on the period- t information set of the investors. The correlation of returns from two risky assets is $\rho > 0$.¹⁰ Denoting the portfolio weight on each asset by $\omega_{S,t}$, $\omega_{H,t}$, and $\omega_{F,t}$, the expected returns and the variance of the representative investor's portfolio are:

$$E_t R_{t+1}^P = \omega_{S,t} R + \omega_{H,t} E_t R_{t+1}^H + \omega_{F,t} E_t R_{t+1}^F = \mu_{P,t+1}, \quad (2.11)$$

$$\text{Var}_t R_{t+1}^P = \omega_{H,t}^2 \text{Var}_t R_{t+1}^H + \omega_{F,t}^2 \text{Var}_t R_{t+1}^F + \omega_{H,t} \omega_{F,t} \text{Cov}_t(R_{t+1}^H, R_{t+1}^F) = \sigma_{P,t+1}^2,$$

where $\omega_{S,t} + \omega_{H,t} + \omega_{F,t} = 1$ and R is the gross risk-free interest rate. Then (2.11) is used in the maximization problem of the representative investor (2.7).

2.3.3 The Equilibrium of the Model

For every period, investment and financing decisions are determined by the non-tradable sector managers' interactions with international investors via an emerging bond market.

¹⁰Positive correlations of asset returns are based on ample empirical evidence. If the correlations of asset returns are negative, then the VaR constraint is not necessary for the main result, and the simple mean-variance maximization will also deliver a reduced demand for emerging market bonds when the conditional variance of US stock returns increases.

Tradable Sector Firm's Profit Maximization

The profit maximization of unconstrained tradable sector firms, after the realization of the aggregate productivity shock, delivers the following demand function for non-tradable goods:

$$d_t(p_t) = \left(\frac{\alpha a_t}{p_t} \right)^{\frac{1}{1-\alpha}}. \quad (2.12)$$

Domestic Bank's Profit Maximization

In this economy, borrowing constraints occur in equilibrium because a young manager can divert investable funds after production, provided she incurs a cost proportional to her funds $h(n_t + b_t)$, where h is a measure of the contract enforceability, in advance and the firm is solvent in the next period ($\pi_{t+1}(p_{t+1}) \geq 0$). To model credit market imperfections in EMEs, I assume $h < R$.¹¹

Assumption 2.3.1. (Credit Market Imperfections)

In EMEs, a credit market is imperfect:

$$h < R.$$

As domestic banks take on currency mismatch, they should take account of the expected changes in the real exchange rate $\frac{1}{p_t}$ when they make a lending decision. The high-price state \bar{p}_{t+1} will be realized with a probability of $1 - u$, and the low-price state \underline{p}_{t+1} will be realized with a probability of u , as a result of the aggregate productivity realization. Therefore, from profit the maximization of domestic banks, domestic lending rates i_t^D must satisfy the following break-even condition:

$$E_t[p_{t+1}](1 + i_t^D) \equiv [(1 - u)\bar{p}_{t+1} + u\underline{p}_{t+1}](1 + i_t^D) = 1 + i_t. \quad (2.13)$$

¹¹This is because $R < 1 + i_t$, and $E_t[p_{t+1}](1 + i_t^D) = 1 + i_t$ in any equilibrium. If h is large enough that the condition $h \geq 1 + i_t$ is satisfied, then diversion becomes more expensive than the repayment, and the diversion costs have no effect on the lending decisions of domestic banks. I assume that this is the case for advanced economies, so borrowing constraints do not arise in advanced economies. I justify this assumption in light of suggestive evidence from bank loan-officer survey data (Section 4.5).

Therefore, domestic banks will finance the young manager only if the expected debt repayment does not exceed the diversion cost:

$$E_t[p_{t+1}](1 + i_t^D)b_t \leq h(n_t + b_t). \quad (2.14)$$

Interaction between a Domestic Economy and an International Asset Market

Demand for external credit by domestic banks and supply of external credit by international investors integrate a domestic economy with an international asset market. This is the main transmission channel of VIX shocks from the US stock market to EMEs. I derive the demand and the supply function of the external credit in the emerging bond market in turn.

Non-tradable Sector Firm's Maximization

As non-tradable sector managers cannot commit to repay their debt, no-diversion conditions (2.14) become borrowing constraints in equilibrium. If an investment yields an expected return that is higher than the opportunity cost of capital, the non-tradable sector firm will borrow up to an amount that makes the borrowing constraints (2.14) binding. Assumption 2.3.2 shows the condition for borrowing constraints to bind.

Assumption 2.3.2. In period t , the non-tradable sector productivity θ is sufficiently high:

$$\theta > \frac{p_t}{E_t p_{t+1}} h.$$

Given the external cost of borrowing i_t , binding borrowing constraints allow for the expression of the demand of external credit as a function of the time- t young manager's net worth.

Lemma 2.3.2. (Credit Demand Curve)

Demand of external credit from each economy increases with the young manager's net worth and decreases with the external cost of borrowing:

$$b_t = f(i_t, n_t; \theta_1) = (\mu(i_t) - 1)n_t, \quad (2.15)$$

where $\theta_1 = \{h\}$ is a set of relevant parameters of the model, and $\mu(i_t) = \frac{1}{1-h(1+i_t)^{-1}}$ is a leverage of non-tradable sector firms.

Proof. For the proof, see 2.7.2.2 in Appendix. □

Corollary 2.3.3. (Domestic Investment)

Investment by the non-tradable sector becomes:

$$I_t = \frac{\mu(i_t)}{p_t} n_t \quad (2.16)$$

Proof. For the proof, see 2.7.2.3 in Appendix. □

International Investor's Profit Maximization

When the representative investor determines her portfolio weights for each asset, she takes the expected returns from emerging market bonds $1 + i_t$ as given. Her decision on $\omega_{F,t}$, however, will affect i_t in equilibrium. The representative investor's demand for emerging market bonds is a function of the expected returns and the investor's wealth.¹²

Lemma 2.3.4. (Credit Supply Curve)

The representative investor's supply of credit b_t to each economy increases with the expected returns and her wealth:

$$b_t = g(i_t, W_t; \theta_2) = \frac{\omega_{F,t}(i_t; \theta_2)W_t}{N}, \quad (2.17)$$

where $\omega_{F,t}$ is a function of i_t and $\theta_2 = \{\mu_H, \sigma_H^2, \rho, R, \underline{R}, \gamma\}$, as in Appendix.

¹²Note that the representative investor's expected returns of investing in emerging market bonds equal to the external cost of borrowing by domestic banks.

Proof. For the proof, see 2.7.3 in Appendix. □

Market Clearing

The emerging bond market clears by i_t that equates the demand for external credit (2.15) to the supply of external credit (2.17). Therefore, the emerging bond market clearing condition is

$$(\mu(i_t) - 1)n_t = \frac{\omega_{F,t}(i_t; \theta_2)W_t}{N}. \quad (2.18)$$

Finally, the non-tradable goods market clearing condition is

$$d_t(p_t) + I_t(p_t) = y_t^N(I_{t-1}), \quad (2.19)$$

where $d_t(p_t)$ is derived from (2.12) and $I_t(p_t)$ is derived from (2.16). Because y_t^N is predetermined by the investment in the previous period, the realization of productivity shocks in the current period determines the price of non-tradable goods.

The following concept of equilibrium integrates the representative investor's portfolio allocation decision with the rest of the economy.

Definition 2.3.1. *An equilibrium of the model is a collection of stochastic processes*

$\{\omega_{S,t}, \omega_{H,t}, \omega_{F,t}, b_t, I_t, d_t, n_t, W_t, y_t^T, y_t^N\}$ that solves the maximization problem for international investors, non-tradable sector firms, tradable sector firms, and domestic banks, and a collection of prices $\{p_t^T, p_t^N, q_t, i_t, i_t^D\}$ such that:

(i) The emerging bond market clears by (2.18).

(ii) The non-tradable goods market clears by (2.19).

(iii) Internal funds evolve according to (2.5) for $t \geq 1$, and n_1 equals $(1 - \beta)p_0 y_0^N$ units of tradable goods. Young time-0 managers are endowed with n_0 units of tradable goods, and old time-0 managers are endowed with y_0^N units of non-tradable goods without debt.

Then, the following Proposition 2.3.5 fully characterizes the evolution of the key variables as a function of the state variable n_t .

Proposition 2.3.5. (Equilibrium Path of the Economy)

Given a non-tradable sector manager's net worth n_t , the equilibrium path of the key domestic variables is:

(i) Domestic credit b_t and the external cost of borrowing i_t are jointly determined by the emerging bond market equilibrium (2.18).

(ii) After the realization of a_t , investment I_t and the inverse of the real exchange rate p_t are jointly determined by (2.16).

(iii) The real exchange rate $\frac{1}{p_t}$, associated with the "good" ($\frac{1}{\bar{p}_t}$) and the "bad" states ($\underline{\frac{1}{p_t}}$), follows:

$$\left(\alpha a \frac{1}{\bar{p}_t}\right)^{\frac{1}{1-\alpha}} + \mu(i_t)n_t \frac{1}{\bar{p}_t} = y_t^N \quad \text{with a probability } 1 - u \quad (2.20)$$

$$\underline{\frac{1}{p_t}} = \frac{y_t^N}{\mu(i_t)n_t} \quad \text{with a probability } u.$$

(iv) n_t evolves according to:

$$\begin{aligned} n_{t+1} &= (1 - \beta) \left(p_t y_t^N - p_t (1 + i_{t-1}^D) b_{t-1} \right) \quad \text{for } t \geq 1 \\ &= (1 - \beta) p_t y_t^N \quad \text{for } t = 0 \end{aligned} \quad (2.21)$$

v) n_0 and y_0^N are given.

2.3.4 A Discussion of the Setup

In this section, I discuss how empirical regularities observed in EMEs are embedded in the structure of the model. As in the framework of Schneider and Tornell [2004], borrowing constraints in the non-tradable sector provide the key for propagating external shocks to EMEs. As the production of non-tradable goods takes one period, non-tradable sector firms have to borrow to finance their investment,

but they can only borrow from domestic banks. This is because non-tradable sector firms do not have export receivables that can be used as collateral to foreign lenders. Tradable sector firms, however, do not require external financing because they produce instantaneously by combining labor and intermediate goods. For further evidence of the asymmetry in financing opportunities in other EMEs, see Tornell and Westermann [2002] and Ranciere et al. [2010].

Given the particular interest toward the short-run dynamics of VIX shocks, ensuring a balanced growth path of the economy is not the main focus of this paper. As non-tradable sector managers accumulate net worth, the supply of emerging market bonds will dominate the demand from international investors in the limit, unless an infinite period maximization for international investors is considered. To obtain the closed-form solution for portfolio shares on emerging market bonds, I consider only the intertemporal decision in the period $t < T$. In this vein, the overlapping generation structure in the non-tradable sector has an advantage, in that financial decisions can be analyzed on a period-by-period basis. In particular, the equilibrium equations for investment and net worth do not include future prices.

As most existing models with risk-neutral international investors fail to capture empirical stylized facts in emerging bond markets (Lizarazo [2013]), I model them as effectively risk averse by imposing the VaR constraint.¹³ The introduction of risk-averse international investors has a similar implication on safe and risky asset prices as that discussed by Gourio [2012]. In Gourio [2012], risky asset prices fall because of an increased demand for precautionary savings, whereas in my analysis it is an outcome of the binding VaR constraint. Because international investors specialize in the emerging bond market, I assume that the relative sizes of the US Treasury bond market and the US stock market are much larger than the

¹³Empirical stylized facts include the high correlation of sovereign bond spreads across EMEs, countercyclical risk premium, and the high correlation between the investors' financial performance and their net foreign asset position in EMEs.

wealth of the representative investor. Therefore, the decision of the representative investor cannot affect the prices in these two markets. Although more a realistic description of the US stock market is feasible, I assume the exogenous return process to obtain a closed-form solution.¹⁴

The VaR constraint is essential for the one-to-one mapping from VIX to the shock in the model ($\sigma_{H,t+1}^2$), but it can be replaced by a more general form of a standard mean-variance utility-maximization problem by shocking the degree of the investor's risk aversion. A shock to the risk aversion can be identified by VIX under the assumption that VIX captures the time-varying risk aversion of investors (Bekaert et al. [2013]; Lizarazo [2013]; De Bock and Carvalho Filho [2013]).¹⁵ The VaR constraint, however, provides a simple explanation for why VIX shocks can be understood to act as risk aversion shocks.¹⁶

During the flight to quality episodes, asset markets in EMEs tend to suffer indiscriminately to a large extent (Pavlova and Rigobon [2008]). This is because international investors view risk in these assets as largely homogenous rather than country-specific. To capture this empirical regularity, I consider a framework in which the presence of risk encourages international investors to reduce their portfolio share in the emerging bond market, regardless of the individual realization of the aggregate productivity shock.¹⁷ The i.i.d. binomial distribution of the country-level aggregate productivity and the presence of a large number of countries imply that returns on the portfolio of emerging market bonds follow a normal distribution.

¹⁴See Basak and Shapiro [2001] and Adrian and Shin [2014] for more realistic setups for studying the asset market implication and the microfoundations of the VaR constraint.

¹⁵In a similar vein, Kumar and Persaud [2002] consider the direct impact of reduction in investors' risk appetite in a portfolio model to study pure financial contagion.

¹⁶As an alternative explanation, Gourio [2012] constructs a model in which VIX is driven by a disaster probability.

¹⁷Aside from a global push factor (homogenous risk), a local pull factor (country-specific risk) also plays an important role in shaping global capital flows (Fratzcher [2012]) and an international portfolio reallocation (Burger et al. [2014]). The cross-country empirical analysis in Section 4.5 describes the role played by country-specific risk in explaining the impact of VIX shocks on a domestic credit market.

2.4 Structural VARs

I derive in two steps the structural VARs that link VIX to domestic variables. The first step involves deriving a structural link between VIX and the emerging bond market variables. Then, the emerging bond market variables (country borrowing spreads $i_t^D - r_t$ and domestic credit b_t) are connected to the other domestic variables (the inverse of the real exchange rate p_t and domestic output y_t) from Proposition 2.3.5.

The Transmission Mechanism of VIX shocks

I consider the effect of VIX shocks on $i_t^D - r_t$ and b_t . In the model, I define a shock to VIX as a one period increase in the conditional variance of US stock returns; $\sigma_{H,t+1}^2$. As the risk-free interest rate is constant in the model and the domestic lending rate i_t^D is proportional to the external cost of borrowing i_t , it is sufficient to specify the evolution of i_t as a function of $\sigma_{H,t+1}^2$.

Proposition 2.4.1. (The Impact of VIX Shocks on the Emerging Bond Market)

An increase in VIX (i) decreases equilibrium domestic credit and (ii) increases the equilibrium external cost of borrowing.

$$\frac{\partial b_t}{\partial \sigma_{H,t+1}^2} < 0 \text{ and } \frac{\partial i_t}{\partial \sigma_{H,t+1}^2} > 0 \quad (2.22)$$

Proof. For the proof, see 2.7.2.5 in Appendix. □

Proposition 2.4.1 is derived from the emerging bond market clearing condition (2.18). It describes how VIX shocks affect a credit market in EMEs, and can be tested empirically. A sudden increase in the conditional variance of US stock returns makes US stocks more risky holding the same expected returns, and thus creates an incentive to reallocate the portfolio toward other risky assets (a substitution effect). However, any given portfolio of risky assets becomes more

risky, thus creating the incentive to reduce demand for all kinds of risky assets to respect the VaR constraint (an income effect). As described in Appendix, the income effect dominates the substitution effect when international investors are sufficiently leveraged as a result of the loose VaR constraint (corresponding to large γ). By way of the international investors' portfolio reallocation, VIX shocks act as a risk-aversion shock that reduces credit supply to EMEs. By exploiting the role of a structural parameter h (the degree of contract enforceability) in amplifying the impact of VIX shocks, another empirically testable prediction can be derived.

Corollary 2.4.2. (The Impact of VIX Shocks and Credit Market Imperfections)

VIX shocks have a more adverse impact on the external cost of borrowing in a country with a lower degree of contract enforceability:

$$\frac{\partial^2 i_t}{\partial h \partial \sigma_{H,t+1}^2} < 0 \tag{2.23}$$

2.4.1 The Average Equilibrium Path

By combining Proposition 2.4.1 with Proposition 2.3.5, the average equilibrium path that is needed to identify structural VARs becomes fully characterized. As the probability distribution of the aggregate productivity shock is i.i.d., there is no need to keep track of history to compute the average equilibrium path. I use \tilde{X}_t to denote the average value of X_t across two states (good and bad).

First, Proposition 2.4.1 has a clear implication on how VIX shocks affect domestic credit b_t and the external cost of borrowing i_t . b_t and i_t are affected contemporaneously by $\sigma_{H,t+1}^2$ alone, through the reduction of the demand for emerging market bonds. Note that the portfolio allocation decision of international investors occurs before the realization of the aggregate productivity shock

a_t , implying $i_t = \tilde{i}_t$ and $b_t = \tilde{b}_t$ for every t .¹⁸

Then, \tilde{b}_t and \tilde{i}_t recursively determines the inverse of the real exchange rate p_t . Once \tilde{b}_t and \tilde{i}_t are obtained, then the non-tradable good market clearing condition (2.19) pins down p_t . Depending on the realization of a_t , p_t takes a value of either \bar{p}_t or \underline{p}_t , and the probability of each state is fixed. The average equilibrium price path is

$$\tilde{p}_t = (1 - u)\bar{p}_t + u\underline{p}_t, \quad (2.24)$$

where \bar{p}_t and \underline{p}_t can be obtained from (2.20).

The last variable in the structural VARs is real GDP y_t , which is the value of domestic production of this economy in terms of tradable goods:

$$y_t = p_t I_t + y_t^T. \quad (2.25)$$

From the demand function of a tradable firm (2.12), it is clear that $d_t = \left(\frac{\alpha a}{\bar{p}_t}\right)^{\frac{1}{1-\alpha}}$ with a probability $1 - u$ and $d_t = 0$ with a probability u . Therefore, the average equilibrium path of y_t is

$$\tilde{y}_t = \tilde{p}_t \tilde{I}_t + \tilde{q}_t^T = \mu(\tilde{i}_t)\tilde{n}_t + (1 - u)a\left(\frac{\alpha a}{\bar{p}_t}\right)^{\frac{\alpha}{1-\alpha}}, \quad (2.26)$$

where \tilde{y}_t is contemporaneously affected by the other three variables.

2.4.2 Identifying Structural Shocks

The above sequence of actions traces the effects of a shock to $\sigma_{H,t+1}^2$ on domestic variables. This recursive structure of the average equilibrium path implies the VARs with a lower triangular structure. To evaluate the role of country-specific factors in explaining the impact of VIX shocks, I separately estimate the VARs with individual country data.¹⁹ The following representation summarizes

¹⁸For the same reason, n_t does not depend on the realization of a_t ($n_t = \tilde{n}_t$ for every t).

¹⁹₂₀s the number of variables in the structural VARs is relatively smaller than the length of time-series data (over 200 periods), a panel VAR model is not considered to allow heterogenous dynamics of VIX shocks.

the structural VARs:

$$AY_{i,t} = \sum_{k=1}^p B_k Y_{i,t-k} + \epsilon_{i,t}, \quad (2.27)$$

$$Y_{i,t} = \begin{pmatrix} \Delta\sigma_{H,t+1}^2 \\ \Delta\tilde{i}_{i,t}^D - r_t \\ \Delta\tilde{p}_{i,t} \\ \Delta\tilde{y}_{i,t} \end{pmatrix}, A = \begin{pmatrix} 1 & 0 & 0 & 0 \\ a_{21} & 1 & 0 & 0 \\ a_{31} & a_{32} & 1 & 0 \\ a_{41} & a_{42} & a_{43} & 1 \end{pmatrix}, \text{ and } \epsilon_{i,t} = \begin{pmatrix} \epsilon_{t+1}^{\sigma_H^2} \\ \epsilon_{i,t}^{i^D-r} \\ \epsilon_{i,t}^p \\ \epsilon_{i,t}^y \end{pmatrix}, \quad (2.28)$$

where Y is a vector of economic variables, i denotes countries, t indicates a time period, and Δ denotes a change in the variable.

Intuitive Description of the Mechanism

The propagation mechanism of VIX shocks in EMEs can be described intuitively using the structural VARs for guidance. First of all, given the current portfolio share and the perceived return process, international investors respond to a sudden increase in VIX by reducing their portfolio share on emerging market bonds $\omega_{F,t}$, which act as sudden stops from the perspective of EMEs. As VIX shocks only shift a credit supply curve, and not a demand curve, country borrowing spreads $i_t^D - r_t$ increase in EMEs.

Given the current level of net worth n_t , the increase in $i_t^D - r_t$ result in less investment I_t and a fall in p_t (real depreciation) by way of tighter borrowing constraints (2.16), which are often observed during sudden stop events. A real depreciation, independently from the realization of a_t at a country level, explains the coincidence of spikes in VIX and synchronized depreciation of emerging market currencies. A real depreciation also reduces the next-period net worth of managers n_{t+1} (balance-sheet effect) from (2.21). Finally, real GDP y_t falls from (2.25), and less investment I_t will lead, from (2.2), to a lower production of non-tradable goods y_{t+1}^N in the next period.

VIX will return to the pre-shock level after one period, so the VaR constraint

no longer binds at $t + 1$. Therefore, the external cost of borrowing i_{t+1} falls and domestic credit b_{t+1} increases at the given level of n_{t+1} , which reverses the vicious cycle described above. The overall contractionary effect, however, lasts more than one period because of the negative effects on n_{t+1} .²¹

2.5 Estimating the Model

2.5.1 The Empirical Implementation of Structural VARs

This section provides an empirical implementation of the structural VARs identified by (2.27) and (2.28). I identify a shock to $\sigma_{H,t+1}^2$ from a one standard deviation increase in the period- t value of VIX. Because VIX is a forward-looking volatility of US stock returns and $\sigma_{H,t+1}^2$ is the conditional variance of US stock returns known in period t , VIX_t is a time-consistent measure of $\sigma_{H,t+1}^2$. I place US output $y_{US,t}$ before VIX_t in $Y_{i,t}$ to control for a real disturbance from the US economy. Despite the strong evidence in Figure 2.1, I cannot fully rule out the possibility that fluctuations in VIX are an endogenous outcome of business cycles in the US economy (Bachmann et al. [2013]). This empirical implementation permits a conservative estimate to be made of the impact of VIX shocks that are controlled by the US output shocks.

In the empirical implementation, $Y_{i,t}$ and $\epsilon_{i,t}$ in (2.28) are replaced by their counterparts in (2.29). I impose further identifying restrictions by preventing feedback from domestic variables into the US variables ($B_{k,1,j} = B_{k,2,j} = 0$ for all $j \neq 1, 2$ and $k = 1, 2, \dots, p$). This restriction is consistent with a small open-

²¹Although the credit market imperfection mechanism of VIX shocks in this paper is similar to the financial accelerator mechanism of risk shocks (Christiano et al. [2014]), financial friction in this study only exists in EMEs. This particular modelling approach is motivated by the empirical breakdown in the relationship between VIX and US output. Therefore, I do not attempt to model the effect of VIX shocks on the real side of the US economy.

economy assumption in the model.²²

$$Y_{i,t} = (\Delta y_{US,t}, \Delta VIX_t, \Delta \tilde{i}_{i,t}^D - r_t, \Delta \tilde{p}_{i,t}, \Delta \tilde{y}_{i,t})', \quad (2.29)$$

$$\epsilon_{i,t} = (\epsilon_t^{y_{US}}, \epsilon_t^{VIX}, \epsilon_{i,t}^{i^D-r}, \epsilon_{i,t}^p, \epsilon_{i,t}^y)'$$

A Structural VAR Model of the US Economy

To compare the impact of VIX shocks on EMEs from the impact on the US economy, I implement a structural VAR model of the US economy parallel to that of EMEs. Under the international asset market segmentation, I include the risk-free rate in the structural VAR model of the US economy. The sign of responses of the risk-free rate and the US real exchange rate to VIX shocks is essential to verify the flight to quality mechanism. Following the notion of VIX shocks as a driver of the US business cycle in the prior literature, I place VIX_t before Y_t , and do not impose a small open-economy assumption:

$$Y_t = (\Delta VIX_t, \Delta r_t, \Delta p_{US,t}, \Delta y_{US,t})', \quad (2.30)$$

$$\epsilon_t = (\epsilon_t^{VIX}, \epsilon_t^r, \epsilon_{US,t}^p, \epsilon_t^{y_{US}})'$$

The empirical results from the US economy may contain the wealth effect (Kyle and Xiong [2001]) of VIX shocks through a fall in W_t , as the high volatility of stock returns is more often accompanied by a crash in a stock market than a rally (Whaley [2009]). Taking into account this additional effect, the estimates from the following VAR should be taken as an upper bound on the quantitative importance of VIX shocks on the US economy.²³

2.5.2 Data

This section describes macroeconomic data of the 18 EMEs and the US economy used in the estimation of structural VARs. I employ monthly macroeconomic

²²Relaxing this assumption does not change the main results.

²³Once the level of the US stock market is controlled in VARs to control for the wealth effect, as in Bloom [2009], I even obtain positive effects of VIX shocks on US output, further questioning the role of VIX shocks as a US business cycle driver. See Figure 6 in Choi [2013] for this finding.

data throughout the structural VARs, focusing on the short-run nature of VIX shocks (Bloom [2009]; Bachmann et al. [2013]; Gourio et al. [2013]). The choices of sample countries and sample periods are mainly restricted by the availability of monthly data. Table 2.7.3 lists the 18 EMEs studied in the paper with their sample coverage. As my analysis is not restricted to a certain regional group of countries or crisis episodes, the following empirical results gain a general implication.

Most empirical studies on EMEs use quarterly variables due to the limited availability of data, but using monthly variables has four main advantages toward studying the impact of VIX shocks in the context of structural VARs. First, it helps discover relevant short-run dynamics because jumps in VIX typically last only for a few months. Aggregation into the quarterly frequency would smooth out much of the variation (Fernández-Villaverde and Guerrón-Quintana [2011]). Second, using higher-frequency variables mitigates the identification issue when zero contemporaneous restrictions are used for structural interpretation. Zero contemporaneous restrictions on financial variables in quarterly data are difficult to justify. Third, it allows inclusion of more lags in the VAR system, which helps alleviate the serial correlation issue. Finally, the quarterly GDP data may not correctly capture behaviors of a private sector because of countercyclical government expenditure.

To measure domestic production at the monthly frequency, I use industrial production index. By using real effective exchange rates to measure real exchange rates, an increase in the real effective exchange rates indicates a real appreciation. I measure country borrowing spreads by the difference between domestic real lending rates and the real risk-free rate.²⁴ Therefore, the baseline model contains

²⁴Although spreads from J.P. Morgan’s Emerging Markets Bond Index Plus (EMBI+), corresponding to $i_t - r_t$ in the model, are often used to measure country spreads in EMEs (for example, Uribe and Yue [2006]; Neumeyer and Perri [2005]; Akinci [2013]), I do not use them for two reasons: (i) the EMBI+ index does not cover as many countries as bank lending rates, and (ii) it has substantially different starting and ending dates across countries, preventing a meaningful cross-country comparison. For example, the EMBI+ index for South Africa has only been available since 2002, and the index for Korea was no longer available after 2006. Neverthe-

five variables, ordered as follows: the log of the US industrial production, VIX, country borrowing spreads, the log of domestic real effective exchange rates, and the log of domestic industrial production. Appendix B.1 provides a complete description of and sources of the data used in the analysis. Figure 2.6 describes the evolution of VIX during the sample period.²⁵

All the variables in the structural VARs are de-trended using a Hodrick-Prescott (HP) filter at the monthly frequency, so as to obtain a stationary series. I choose the appropriate lag-length of the six lags for all countries in the sample, as the Akaike information criterion typically suggests a lag-length between 3 and 6. Then, the model is estimated by maximum likelihood for each of the countries in the sample. Standard errors are estimated using a parametric bootstrapping procedure with 200 repetitions.

2.5.3 The Main Results

Figure 2.7 summarizes the main results from the structural VARs of EMEs and the US economy. The main results highlight the distinct impact of VIX shocks on EMEs from the impact on the US economy. Because displaying impulse responses for every country would be too exhaustive, I first compare the results from Korea with those from the US, to demonstrate the different responses to VIX shocks. Then, I run the VARs of the rest of the countries individually, to confirm whether EMEs share the results from Korea.

The response of key domestic variables in Korea is consistent with the prediction of the model. VIX shocks are followed by an increase in country borrowing spreads and a real depreciation. A substantial fall in Korean output confirms

less, Akinci [2013] finds, from structural VARs on 6 EMEs, a similar degree of increase (0.3%) in the EMBI+ spreads after a one standard deviation increase in VIX.

²⁵Bloom [2009]—further extended by Choi [2013]—identifies 17 exogenous events that led a spike in VIX since 1962. Among 7 exogenous events during the sample period in this analysis, only one event (Asian Crisis) is directly driven by EMEs, suggesting the implausibility of the reverse causality (fluctuations in VIX are driven by EME business cycles).

the results from the bivariate VARs, as described in the Introduction. All of the responses of these variables are statistically and economically significant.

In the US, however, the response of key domestic variables is dramatically different. The risk-free interest rate decreases (although insignificantly) by 0.07%, and real exchange rates appreciate by 0.4%. A fall in the risk-free rate is key to distinguishing a VIX shock from a typical liquidity shock, as a typical liquidity shock has a symmetric effect on both safe and risky assets (Chudik and Fratzscher [2011]; Matsumoto [2011]; Gourio [2012]). VIX shocks have no impact on US output in either the large scale VARs or the bivariate VARs.²⁶

Once the flight to quality mechanism is considered, the opposite behaviors of price variables between two economies are easy to understand: As long as US treasury bonds and US dollars serve as a reliable safe haven, the US economy will be the destination for the withdrawn funds from EMEs. Unless the supply of safe assets is perfectly inelastic (although the model assumes so for simplicity), their price would increase. This result reinforces the importance of considering an international asset market to understand the transmission channel of VIX shocks to EMEs.

Figure 2.8 further shows that a sharp increase in VIX during the 2008-09 global financial crisis was more relevant for EMEs than the US economy. Although the US housing crisis has negatively affected US output since the beginning of 2008, VIX remained low until the bankruptcy of Lehman Brothers in October, 2008. This timing inconsistency is pointed out by Schwert [2011], who has a skeptical view on stock market volatility as a leading indicator during the Great Recession. Moreover, VIX shocks only explain a small part of the decline in US output during the Great Recession, a finding in line with Born et al. [2014] and Caldara et al. [2014]. In Korea, however, a larger fraction (1/4) of output decline is explained by

²⁶VIX shocks may have a significant impact in a non-linear manner on US output during recessions as shown in Caggiano et al. [2014]. However, I do not consider this possibility, as I compare only the first-order impact of VIX shocks in EMEs with that in the US economy.

VIX shocks and a sharp fall in output follows the spike in VIX.²⁷ This is consistent with the observation that the US housing crisis expanded to the global scale only after the collapse of US financial markets.

To represent the results from the 18 EMEs visually, Figure 2.9 shows the average and the median responses of the 18 EMEs with an interquartile range for the point estimates.²⁸ The results across countries differ to a large degree in terms of magnitudes, but the case of Korea is representative of the qualitative patterns.

2.5.3.1 Cross-Country Comparison of the Empirical Results

From the comparison of the responses between the US economy and the average pattern from the 18 EMEs, I find that the impact of VIX shocks is qualitatively different for EMEs and the US economy. The next questions to ask are: (i) How important are VIX shocks in explaining economic fluctuations in EMEs? and (ii) Which countries are particularly susceptible to VIX shocks and which are not?

Table 2.7.3 summarizes the variance decomposition of the domestic variables from the structural VARs at the 36-month horizon for each country in the sample. While VIX shocks only explain insignificant and small (1%, 5%, and 2%) variances in the real interest rate, the real effective exchange rate, and industrial production, respectively, much larger fractions of domestic variables in the 18 EMEs are explained by VIX shocks, even after controlling for US output shocks. As the numerous shaded areas in the second to the fourth column of Table 2.7.3 indicate, the fraction explained by VIX shocks is comparable to that of US output shocks, which are among the most important exogenous shocks to EMEs.

²⁷This finding is consistent with Chudik and Fratzscher [2011], who state that EMEs have been more strongly affected by risk-appetite shocks—measured by VIX—than have advanced economies during the global financial crisis.

²⁸I do not plot confidence intervals for the average and the median response because VIX shocks are not i.i.d. across countries. Common shocks to all the countries result in correlated error among countries, preventing a straightforward estimation of standard errors. See Carrière-Swallow and Céspedes [2013] for an alternative representation under similar circumstances.

Figures 2.10-2.12 illustrate the empirical estimates and the statistical significance of these estimates. The empirical estimates for each country are based on the minimum (or, for country borrowing spreads, the maximum) of the estimates within the 36-month horizon. Although the US is a source of VIX shocks, the impact of these shocks on every EME is greater than it is on the US economy.

2.5.4 Robustness Checks

In this section, I explore whether the baseline results are robust to changes in the specification of the empirical model. First of all, HP-filtering of data is subject to a critique. Bachmann et al. [2013] criticize the VARs used in Bloom [2009] because filtering prior to estimation removes, by construction, persistent or permanent effects of VIX shocks. To address this potential issue, I estimate the same structural VARs with levels of each variable, as recommended by Sims et al. [1990]. The exceptions are industrial production series, which are non-stationary for every country in the sample. For output series, I use linear de-trending to obtain stationary series.

Second, the choice of Cholesky ordering of the variables is critical in identifying orthogonal shocks. Although I derive a recursive structure from the equilibrium model, a potential mis-specification issue still remains. Therefore, I place the exogenous block $(\Delta y_{US,t}, \Delta VIX_t)'$ after the domestic block $(\Delta \tilde{i}_{i,t}^D - r_t, \Delta \tilde{p}_{i,t}, \Delta \tilde{y}_{i,t})'$ in $Y_{i,t}$ of (2.29).

Third, the sample period examined for this analysis only covers the last 20 years. This being the case, I should check the possibility that the main results are driven simply by the extreme event of the 2008-09 global financial crisis. Therefore, I re-estimate the VARs using the period between 1994 and 2007.

Last, although I have applied the Akaike criterion to consistently select the appropriate lag lengths, some residual serial correlation may still be present. Tak-

ing into account the monthly nature of the data, I re-estimate the VARs with 12 lags.

Figure 2.13 shows the response of the key domestic variables under alternative specifications. To save space, I include the results from the US and Korea only. The online Appendix of this paper includes the individual impulse response functions of all 18 countries, along with the results from robustness checks. As the response of the key variables under different specifications resembles Figure 2.7, I conclude that the main results are not sensitive to these issues.

2.5.5 The Credit Channel

I have shown the strong negative impact of VIX shocks on the 18 EMEs. Credit market imperfections, leading to binding borrowing constraints in EMEs, are key factor affecting the function of the credit channel. This section further investigates the credit channel as a propagation mechanism of VIX shocks to EMEs.

In the model, contract enforceability h is an important structural parameter that distinguishes EMEs from the US economy and also governs the degree of credit market imperfections among EMEs. As shown in Corollary 2.4.2, the negative relationship between the degree of contract enforceability and the magnitude of the impact of VIX shocks on the external cost of borrowing is expected. To gauge the magnitude of the impact, I use the maximum increase in country borrowing spreads within the 36-month horizon from Figure 2.10.

I measure country-level contract enforceability by employing four different indexes. There are two direct measures of h : (i) the strength of legal rights index from the World Bank Indicator, and (ii) the efficiency of debt enforcement index from Djankov et al. [2008]. In both indexes, a higher score indicates higher h . There are two indirect measures of h , taking into account the consequence of low contract enforceability in EMEs: (i) the financial depth index as measured by the

domestic credit provided by financial sector as a percentage of GDP, from the World Bank Indicator, and (ii) the financial dollarization index, from the 2010 updated database by Yeyati [2006]. Appendix summarizes the construction of these indexes. Figure 2.14 shows a negative relationship between the measures of credit market imperfections and the magnitude of impact on the external cost of borrowing.

Because domestic credit and the external cost of borrowing are jointly determined in the model, I only employ the external cost of borrowing in the baseline VAR model. If VIX shocks act as a negative credit demand shock, however, domestic credit and the external cost of borrowing would move in the same direction. To identify the credit channel, I add a variable for measuring the deviation of domestic credit from the trend Δb_t toward the domestic block of (2.29). To measure b_t , I use domestic credit provided to the private sector by deposit-money banks, from the International Monetary Fund (IMF) International Financial Statistics (IFS), line 22D. Due to the limited availability of consistent data, I only include 11 countries for this extension: Argentina, Chile, Indonesia, Korea, Malaysia, Mexico, the Philippines, Russia, Taiwan, Thailand, and Turkey.

Figure 2.15 shows the average and the median responses of four domestic variables to a one standard deviation increase in VIX. These results further confirm the prediction of the model. While country borrowing spreads immediately spike after the shock, domestic credit declines rather gradually from the trend, implying that an adjustment in the price occurs faster than that the adjustment in the quantity. The responses of country borrowing spreads and domestic credit indicate that VIX shocks are a negative credit supply shock to EMEs.

To demonstrate that this is not the case for the US economy, I conduct a similar analysis by including Δb_t in (2.30). I measure b_t by Commercial and Industrial (C&I) loans from all commercial banks because data from IFS line 22D

are not available for the US at the monthly frequency.²⁹ Figure 2.16 shows that VIX shocks do not have a negative impact (in fact, they have a positive impact) on the domestic credit of the US economy.³⁰

Finally, I gauge the importance of the credit channel in explaining output drops during the 2008-09 global financial crisis by conducting a counterfactual exercise. For the 11 countries with the full data availability, I compare counterfactual changes in output when the credit channel is shut down to the actual changes in the data. I conduct this counterfactual exercise by assuming that country borrowing spreads and domestic credit are constant at the pre-crisis level.

The average of the simulation results for the 11 countries in (shown in Figure 2.17) indicates that about a quarter of the average 8% decline of output from its trend in the 11 countries is explained by the credit channel.³¹ Individual results from the 11 countries are summarized in Figure 2.18.

Suggestive evidence from an independent source of the survey data further supports the credit channel as a propagator of VIX shocks in EMEs. The key assumption in the model is low contract enforceability in EMEs, which translates into tighter borrowing constraints on the impact of VIX shocks. In the US economy where financial friction is less relevant, this mechanism should not work.

The top panel in Figure 2.19 shows that changes in the index of bank tightening standards for business loans is strongly countercyclical and positively correlated

²⁹Nevertheless, the correlation between C&I loans at the quarterly frequency and IFS line 22D is above 0.9.

³⁰This result should be taken with caution, as the initial increase in domestic credit is followed by a persistent decline after one year when the level of C&I loans are used in the alternative specification. This response is consistent with findings from Bassett et al. [2014], which show that US firms draw their existing lines of credit rather than by borrowing through newly issued loans. Nevertheless, the different short-run response of domestic credit to VIX shocks from EMEs to the US economy still suggests that the credit channel plays a more important role in EMEs.

³¹The residual fraction of output declines during the global financial crisis may be explained by the recent findings from Novy and Taylor [2014]. These show that a fall in US import in response to VIX shocks is much larger than that in US industrial production. It is plausible that the supply and demand sides of trade with the US are negatively affected by the credit channel in exporting countries and the wait-and-see channel in the US.

with VIX (US: 0.73 and Korea: 0.61) in both countries. In this part of the figure, an increase denotes bank tightening of constraints. The bottom panel shows that changes in the index of demand for bank loans from the business sector in the two countries follow the exact opposite pattern. Whereas demand for bank loans is procyclical and negatively correlated with VIX in the US, it is countercyclical and positively correlated with VIX in Korea, implying that observed declines in domestic credit are mainly driven by the supply side.³²

This opposite pattern between two countries is consistent with the observation of Bernanke et al. [1996] that demand for short-term credit may be countercyclical, so as to finance unintended inventory buildup or other fixed obligations if the financial accelerator fully operates through financial friction. Therefore, the Korean bank loan survey suggests that the observed decline in domestic credit and output in EMEs is unlikely driven by firms' wait-and-see behaviors.

2.5.6 A Simulation of the Model

The qualitative predictions of the model on key domestic variables are well matched by data from the 18 EMEs. However the model is silent about the quantitative prediction for VIX shocks on these variables. I simulate the international asset market part of the model to predict the quantitative effects of VIX shocks on the external cost of borrowing i_t .

Instead of assuming an arbitrary process for the evolution of international investors' wealth W_t , I set the ratio between W_t and n_t so as to obtain the equilibrium value of i_t to match data. The purpose of this exercise is to demonstrate that the empirical estimates from the structural VARs can be replicated by the in-

³²For the US, data are taken from the Federal Reserve Board's Senior Loan Officer Opinion Survey on Bank Lending Practices (SLOOS). For Korea, comparable data are taken from the Bank of Korea Economic Statistics System. See Appendix for a description of how each index is constructed. Korean survey data are only available since 2002, while the US data are available since 1990.

ternational investors' portfolio reallocation mechanism under the parametrization of which is consistent with data.

First, I set the structural parameters of the model to satisfy the condition for binding borrowing constraints: $u = 0.01$, $h = 1.01$, and $\theta = 1.1$.³³ Then, I set the gross risk-free interest rate R to be 1.03 and expected returns on US stocks μ_H to be 1.08, which is consistent with the equity premium of 5%. To obtain a reasonable Sharpe ratio on US stocks I set the standard deviation on returns σ_H to be 0.1. This results in a Sharpe ratio of 0.5. For emerging market bonds, I set μ_F to be 1.09 and σ_F to be 0.1, so they have a Sharpe ratio of 0.6. I set \underline{R} equal to 0.95 to have an interior solution.

I set the correlation of two risky assets ρ to be 0.25 and set the value of $\gamma = 0.17$ for the leverage of international investors to be 3. As discussed in Schinasi and Smith [2000], the leverage of international investors is essential for the proposed mechanism to work when the correlation between two risky assets is positive. Under this reasonable parametrization, I set the ratio between $\frac{W_t}{N}$ and n_t to be 4.78 so that equilibrium values of μ_F and σ_F are indeed 1.09 and 0.1. Table 2.7.3 summarizes key parameter values used in this exercise.

I simulate the model by increasing σ_H from 0.1 to 0.2 and trace out its effect on i_t . Consistent with the qualitative prediction from Proposition 2.4.1, the increase in σ_H reduces $\omega_{H,t}$ from 1.69 to 0.20 and reduces $\omega_{F,t}$ from 2.29 to 2.19, which corresponds to a 4.6% decrease in demand for emerging market bonds. As a result, international investors de-leverage from 3.00 to 1.39. A 4.6% decline in demand for emerging market bonds drives up i_t from 9% to 9.43%, which corresponds to a 0.43% increase in country borrowing spreads.

Changes in i_t decrease with ρ as the substitution effect becomes stronger and increase with γ as international investors take more leverage. As the time-varying

³³A default probability of 1% makes sense if investors receive nothing ($\Delta = 0$) in the case of default.

nature of the asset correlation and leverage ratio make it impossible to draw a precise quantitative prediction of VIX shocks on i_t , I provide changes in i_t under the admissible range of two parameters ρ and γ in Figures 2.20 and 2.21.

2.6 Conclusion

Contributing to the growing literature on risk or uncertainty shocks as a new driver of business cycle fluctuations, I have presented an internally consistent model that explains the negative impact of VIX shocks on EMEs. In my model, an increase in VIX is translated into an increase in risk aversion of international investors when they are subject to the VaR constraint. With the presence of credit market imperfections in EMEs, a risk-aversion shock acts as a negative credit supply shock, and has adverse effects on these economies. Structural VARs derived from the model allow me to identify shocks to VIX and trace their impact on real interest rates, domestic credit, real exchange rates, and domestic output. My empirical results are consistent with the predictions of the model, highlighting the flight to quality mechanism in the propagation of VIX shocks to EMEs.

This paper has timely implications for two different contemporary economic discussions. Recent studies (Bloom [2009]; Bachmann et al. [2013]; Gourio et al. [2013]; Mathy [2014]) document a tight historical relationship between uncertainty, measured by stock market volatility, and real activity in the US economy. However, this relationship has broken down in recent years (Choi [2013]). As demonstrated in this paper, the contrasting impact of VIX shocks on the US economy versus EMEs casts doubt on US stock market volatility (or VIX) as the best proxy for uncertainty in the US economy. This paper suggests that it would be fruitful to look for measures of time-varying uncertainty that are independent of VIX.³⁴ This paper suggests that it would be fruitful to look for measures of

³⁴There are a few recent works in the related literature that potentially explain the breakdown of the relationship in the US economy. First, Caldara et al. [2014] purge uncertainty

time-varying uncertainty that are independent of VIX.³⁵

The impact of VIX shocks on EMEs, as contrasted to their impact on the US economy, demonstrates a fundamental difference between two economies. As the Federal Reserve recently declared to slow down its quantitative easing, many economists and policymakers are concerned about the adverse effect of an exit from unconventional monetary policy on EMEs (Sahay et al. [2014]). If the exit from unconventional monetary policy in the future is accompanied by spikes in VIX, policymakers in EMEs should note that VIX serves as a real-time barometer of these economies, independently from a real side of the US economy. Unlike the uncertainty interpretation of VIX shocks (Bloom [2009]), in which policy intervention is ineffective when uncertainty is high, the flight to quality mechanism in this paper recommends that EME policymakers counteract an expected negative credit supply shock by providing liquidity in a timely manner.

shocks—measured by VIX—from financial shocks—measured by the excess bond premium—and find that the effect of uncertainty shocks on GDP is significant only if it is transmitted through a financial channel. Second, Cesa-Bianchi and Fernandez-Corugedo [2014] provide a theoretical prediction that uncertainty shocks can generate a sizable impact on economic activity only when transmitted through the credit channel.

³⁵For example, Bachmann et al. [2013] construct a survey-based measure of uncertainty from the cross-sectional standard deviation of forecast error made by firms. Baker et al. [2013] measure economic policy uncertainty mostly based on the frequency of newspaper references to policy uncertainty. Leduc and Liu [2013] construct an uncertainty index from the University of Michigan Survey of Consumers on durable good purchases. Jurado et al. [2015] measure uncertainty from the unforecastable component of a large number of economic indicators.

2.7 Appendix

2.7.1 Data Appendix

2.7.1.1 Macroeconomic Data

Daily historical price data for VIX are taken from the Chicago Board Options Exchange (CBOE) and averaged to produce monthly data. For the period between 1962 and 1985, when VIX is not available, I employ a realized volatility of S&P500 returns from Bloom [2009]. Industrial production, Consumer Price Index (CPI), the 3-month T-bill rates, and commercial and industrial (C&I) loans from all commercial banks are extracted from the Federal Reserve Economic Data (FRED). Industrial production is seasonally adjusted using X-12 ARIMA. The real interest rate is measured by the difference between the 3-month T-bill rate and the expected inflation rate. Following Schmitt-Grohé and Uribe [2011], the expected inflation rate is measured by the fitted component of a regression of an inflation rate onto a constant and three lags. The inflation rate is measured by $\log\left(\frac{P_t}{P_{t-12}}\right) \times 100\%$, where P_t is the monthly Consumer Price Index. C&I loans is deflated by the CPI to obtain real domestic credit used in the extended VARs in Section 4.5.

Following Tornell and Westermann [2002], I measure country borrowing spreads by the difference between domestic real lending rates and the US real interest rate. Domestic real lending rates are measured by the difference between nominal domestic lending rates and expected inflation rates. For consistency, the expected inflation rates are measured by the same method used in the US economy. The monthly Consumer Price Index is adopted from the IMF International Financial Statistics (IFS) line 64, except for Taiwan (Central Bank of the Republic of China). For all countries except Brazil, Poland, Singapore, Taiwan, and Turkey, domestic bank lending rates are taken from the IFS line 60P. For Brazil, Poland,

and Singapore, where bank lending rates are not available, I use money market rates (IFS line 60B), and I use deposit rates (IFS line 60L) for Turkey. For Taiwan, domestic bank lending rates are taken from the Central Bank of the Republic of China.

Various sources of data to measure domestic output at the monthly frequency are employed. For the Czech Republic, Hungary, Indonesia, Korea, Malaysia, Mexico, and Poland, output is measured by industrial production from the IFS line 66. For Brazil, Chile, Indonesia, South Africa, Israel, and Russia, industrial production is taken from the OECD Monthly Economic Indicator (MEI). For the Philippines and Singapore, where industrial production is not available, manufacturing production is taken from the IFS line 66EY. For Argentina, I use the Industrial Monthly Estimator from the Central Bank of Argentina database of Macroeconomic RADAR. For Taiwan, the industrial production index is taken from the Central Bank of the Republic of China. For Thailand, the manufacturing index is taken from the Bank of Thailand. All the output data are seasonally adjusted using X-12-ARIMA.

For all countries, real exchange rates are measured by Real Effective Exchange Rate (REER) indices from the Bank for International Settlements (BIS). REER indices are the geometric weighted averages of bilateral exchange rates adjusted by relative consumer prices. The weighting pattern is time-varying, and the most recent weights are based on trade in 2008-10. I use broad indices comprising 61 economies.

For all countries where consistent domestic credit data are available, domestic credit is measured by the domestic credit to the private sector by deposit-money banks (IFS line 22D), except for Taiwan (Central Bank of the Republic of China). Domestic credit is deflated by the CPI to obtain the real domestic credit used in the extended VARs in Section 4.5.

2.7.1.2 Indicators of Credit Market Imperfections

The strength of legal rights index measures the degree to which collateral and bankruptcy laws protect the rights of borrowers and lenders. The index ranges from 0 to 10, with higher scores indicating that these laws are better designed to expand access to credit. These data sets are extracted from the World Development Indicator. The yearly average between 2004 and 2012 is used in the analysis. The index for Taiwan is not available.

The efficiency of debt enforcement index is taken from the database by Djankov et al. [2008]. The authors use the data on time, cost, and the likely disposition of assets to construct a measure of the efficiency of debt enforcement in 88 countries. See Djankov et al. [2008] for further details about the data.

Domestic credit provided by the financial sector includes all credit to various sectors on a gross basis, with the exception of credit to the central government, which is net. The financial sector includes monetary authorities and deposit-money banks, as well as other financial corporations where data are available. Data are taken from the World Development Indicator, and the yearly average between 1994 and 2012 is used in the analysis. The data for Taiwan are not available.

The financial dollarization index is taken from the 2010 updated version of Yeyati [2006]. The index is measured by the ratio of deposit dollarization to total deposits. The yearly average between 1994 and 2010 is used in the analysis. The index for Taiwan is not available. See Yeyati [2006] for details of the data.

2.7.1.3 Bank Loan Officer Survey Data

The US bank loan officer survey data are gathered from the Federal Reserve Board's Senior Loan Officer Opinion Survey on Bank Lending Practices (SLOOS). Each quarter, the Federal Reserve surveys the opinions of senior loan officers at

commercial banks. On the credit supply side, this survey has queried banks about changes in their lending standards for the major categories of loans to households and businesses. On the credit demand side, it has queried banks as to whether they have experienced a change in loan demand from households and businesses. The survey is usually conducted four times per year by the Federal Reserve Board, and up to 80 US commercial banks participate in each survey. I only report changes in the lending standards and the loan demand from business sectors at the aggregate level. See Bassett et al. [2014] for a complete description of the panel selection criteria, wording of individual questions, and methods used to conduct the survey.

The source of Korean bank loan officer survey data is the Bank of Korea's Survey on Financial Institution Lending Practices. The index is based on a survey of up to 38 domestic banks, and is conducted every quarter. The main questionnaires in the survey are similar to those in the SLOOS. The index is constructed by the weighted average of the number of respondents, as follows:

$$DI = (1 \times \# \text{ of substantial increase} + 0.5 \times \# \text{ of somewhat increase}) \\ - (1 \times \# \text{ of substantial decrease} + 0.5 \times \# \text{ of somewhat decrease}) \quad (2.31)$$

For the lending standard survey, a reading above zero means the number of banks that restricted their lending compared to the last quarter outnumbered the number of lenders that eased their lending. For the loan demand survey, a reading above zero means the number of banks that experienced increased loan demand from the business sector compared to the last quarter outnumbered the number of lenders that were faced with reduced loan demand. Consistent with the SLOOS data, I only report changes in the lending standards and the loan demand from business sectors.

2.7.2 Proof

2.7.2.1 Proof of Lemma 2.3.1

Proof. Because aggregate productivity shocks are independent across N countries, a u -share of N countries in the portfolio experience the low productivity shock and default on their bonds at the end of every period. All countries are symmetric before the realization of the shocks, so they have the same bond price q_t . As international investors diversify the default risk by investing an equal share in each of the N countries, the return distribution of the portfolio of N countries follows a normal distribution with the following mean and variance by the law of large numbers:

$$E_t[R_{t+1}^B] = \frac{1}{N} \sum_{i=1}^N \frac{1-u}{q_t} = \frac{1-u}{q_t} = 1 + i_t,$$

$$Var_t[R_{t+1}^B] = E_t[R_{t+1}^{B2}] - \left(E_t[R_{t+1}^B]\right)^2 = \frac{1}{N} \sum_{i=1}^N \frac{1-u}{q_t^2} - \left(\frac{1-u}{q_t}\right)^2 = \frac{u(1-u)}{q_t^2} = \frac{u(1+i_t)^2}{1-u}$$

□

2.7.2.2 Proof of Lemma 2.3.2

Proof. Given $h < R$, the no-diversion condition (2.14) becomes the borrowing constraint in equilibrium. If Assumption 2.3.2 holds, borrowing constraints are binding. For the first equality, combine the budget constraint of manager (2.3) with the no-diversion condition (2.14) and substitute with the break-even condition of domestic banks (2.13). For the second equality, use the definition of the external cost of borrowing (2.6). □

2.7.2.3 Proof of Corollary 2.3.3

Proof. Once b_t is obtained from (2.15), it directly follows from the budget constraint of manager (2.3). □

2.7.2.4 Proof of Lemma 2.3.4

Proof. Because of the symmetry before the realization of the aggregate productivity shock, the representative investor's portfolio share on the emerging bond market $\omega_{F,t}$ is evenly distributed among N countries. To derive $\omega_{F,t}$, the portfolio allocation problem must be solved under the VaR constraint. In a mean-standard deviation space (Figure 2.4), all mean-variance efficient portfolios lie on the straight line with the vertical intercept R and the slope $\frac{\mu_{P,t+1}^* - R}{\sigma_{P,t+1}^*}$, where $\mu_P^* - R = \frac{\mu_H \mu_H^e \sigma_F^2 + \mu_F \mu_F^e \sigma_H^2 - \sigma_{HF}(\mu_H \mu_F^e + \mu_H \mu_F^e)}{\mu_H^e \sigma_B^2 + \mu_F^e \sigma_H^2 - \sigma_{HF}(\mu_H^e + \mu_F^e)}$ and $\sigma_P^* = \frac{\left((\mu_H^2 \sigma_F^2 - \mu_F^2 \sigma_{HF})^2 \sigma_H^2 + (\mu_F^2 \sigma_H^2 - \mu_H^2 \sigma_{HF})^2 \sigma_F^2 + 2(\mu_H^2 \sigma_F^2 - \mu_F^2 \sigma_{HF})(\mu_F^2 \sigma_H^2 - \mu_H^2 \sigma_{HF}) \sigma_{HF} \right)^{\frac{1}{2}}}{\mu_H^e \sigma_F^2 + \mu_F^e \sigma_H^2 - \sigma_{HF}(\mu_H^e + \mu_F^e)}$ are the solutions for the mean-variance portfolios (after dropping a time subscript) and $\mu_i^e = \mu_i - R$ for $i = H, F$. The constraint (2.9) draws the straight line on a mean-standard deviation space, with the intercept \underline{R} and the slope $\Phi(1 - \gamma)$. This portfolio selection problem has an interior solution if the two straight lines intersect each other and the intercept of the constraint is greater than that of the tangency portfolio. To obtain an interior solution, the following parametric assumptions are made:

- (i) $R > \underline{R}$
- (ii) $\Phi(1 - \gamma) > \frac{\mu_{P,t+1}^* - R}{\sigma_{P,t+1}^*}$.

Under this condition, the closed-form solution for the optimal portfolio shares on each asset can be derived by solving the portfolio problem (2.7), subject to (2.9):

$$\omega_H = \frac{z(R - \underline{R})(\mu_H^e \sigma_F^2 - \mu_H^e \sigma_{HF})}{(\Phi(1 - \gamma) - z)(\mu_H^{e2} \sigma_F^2 + \mu_F^{e2} \sigma_H^2 + 2\mu_H^e \mu_F^e \sigma_{HF})}. \quad (2.32)$$

and

$$\omega_F = \frac{z(R - \underline{R})}{(\Phi(1 - \gamma) - z)\mu_F^e} - \frac{\mu_H^e}{\mu_F^e} \omega_H, \quad (2.33)$$

where $z = \frac{\mu_P^* - R}{\sigma_P^*}$. When an asset S and an asset H follow exogenous return process and the representative investor takes the price of an asset F as given, the optimal

asset position directly follows the Appendix in Schinasi and Smith [2000]. \square

2.7.2.5 Proof of Proposition 2.4.1

Proof. I only consider the proof for (i) as the proof for (ii) is analogous. I can rewrite (i) as follows:

$$\frac{\partial b_t}{\partial \sigma_{H,t+1}^2} = \underbrace{\frac{\partial \omega_{F,t}}{\partial \sigma_{H,t+1}^2}}_{<0} \underbrace{\frac{\partial b_t}{\partial \omega_{F,t}}}_{>0} < 0$$

For a technical proof of the first partial derivative in Proposition 2.4.1, see the proof of Proposition 2 in the Appendix of Schinasi and Smith [2000]. Here, instead is a graphical explanation using the mean-standard deviation space in Figure 2.4. Given any initial asset returns distribution, the optimal portfolio is located on the intersection of the tangency portfolio and the VaR constraint (point B). A VIX shock increases the standard deviation of the tangency portfolio, holding the mean of the tangency portfolio constant by shifting the risky portfolio from the point A to the point A' . This makes the slope of the tangency portfolio $\frac{\mu_{P,t+1}^* - R}{\sigma_{P,t+1}^*}$ flatter. The point A' , however, is located below the VaR constraint, violating the VaR constraint. The representative investor must adjust the portfolio share to respect the VaR constraint, which requires moving to the point B' . Compared to the point B , the point B' is associated with the portfolio of lower mean and standard deviation.

The slope of the VaR constraint $\Phi(1 - \gamma)$ implies that the increase in the expected returns is required to compensate the increased risk (the standard deviation of the portfolio) on the impact of VIX shocks. First, if the representative investor is subject to the loose VaR constraint (large γ), then it requires a small increase in the expected returns per unit risk. Because the income effect dominates the substitution effect, the representative investor increases the share on a safe asset by a large amount. In this case, not only demand for US stocks but emerging market bonds would decrease. Second, if they are subject to the tight

VaR constraint, then it requires a large increase in the expected returns per unit risk. In this case, the substitution effect dominates the income effect, so that there would be an increase in demand for emerging market bonds. Figure 2.4 shows the case for the former, and Figure 2.5 shows the case for the latter. The sufficient condition for the former case is:

$$\Phi(1 - \gamma) < \frac{2\mu_{H,t+1}^e \mu_{F,t+1}^e \sigma_{P,t+1}^*}{\left(\mu_{F,t+1}^e \sigma_{H,t+1}^2 + \mu_{H,t+1}^e \sigma_{HF,t+1}\right) \left(\mu_{H,t+1}^e \sigma_{F,t+1}^2 + \mu_{F,t+1}^e \sigma_{HF,t+1}\right)}.$$

The second partial derivative follows from (2.17). Similarly, the proof for (ii) follows:

$$\frac{\partial i_t}{\partial \sigma_{H,t+1}^2} = \underbrace{\frac{\partial \omega_{F,t}}{\partial \sigma_{H,t+1}^2}}_{<0} \underbrace{\frac{\partial q_t}{\partial \omega_{F,t}}}_{>0} \underbrace{\frac{\partial i_t}{\partial q_t}}_{<0} > 0$$

The last partial derivative follows from (2.6). □

2.7.3 Figures and Tables

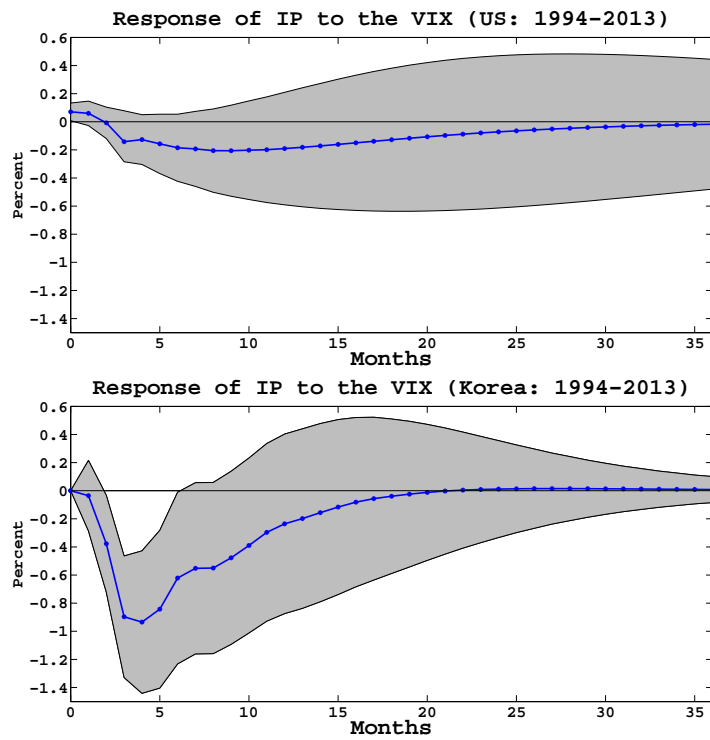


Figure 2.1: Output response to VIX shocks

Notes: This figure plots the response of industrial production of the US (top) and Korea (bottom) between January 1994 and December 2013 to a one standard deviation shock to the VIX in the bivariate VARs using the VIX and the log of industrial production. The shaded areas are 90% bootstrap confidence interval.

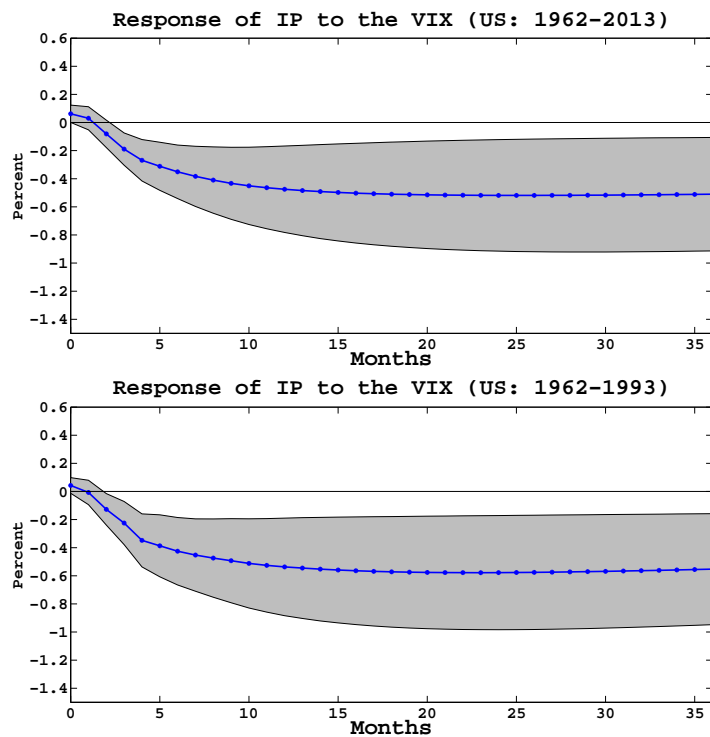


Figure 2.2: Output response to VIX shocks in earlier periods

Notes: This figure plots the response of industrial production of the US between July 1962 and December 2013 (top) and between July 1962 and December 1993 (bottom) to a one standard deviation increase in the VIX from the bivariate VARs using the monthly VIX and the log of industrial production. The shaded areas are 90% bias-corrected bootstrap confidence interval.

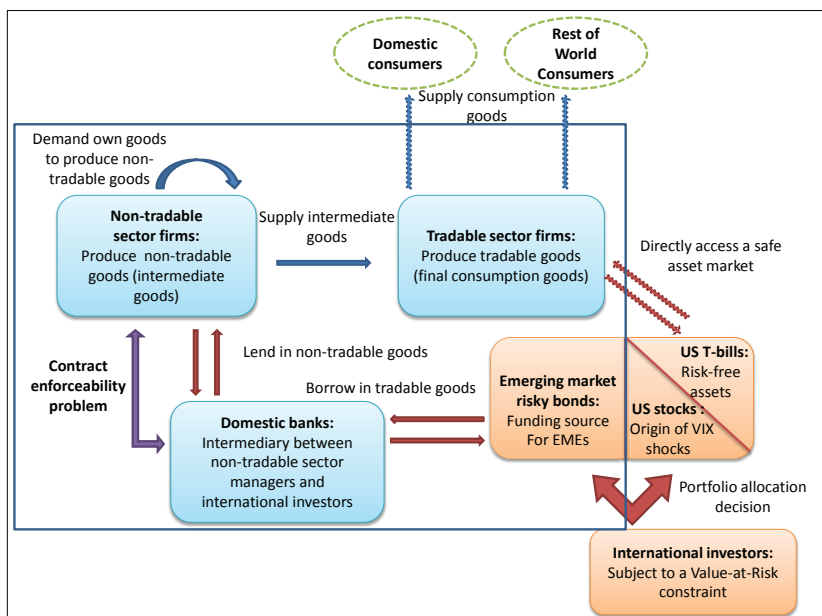


Figure 2.3: Flowchart of the model

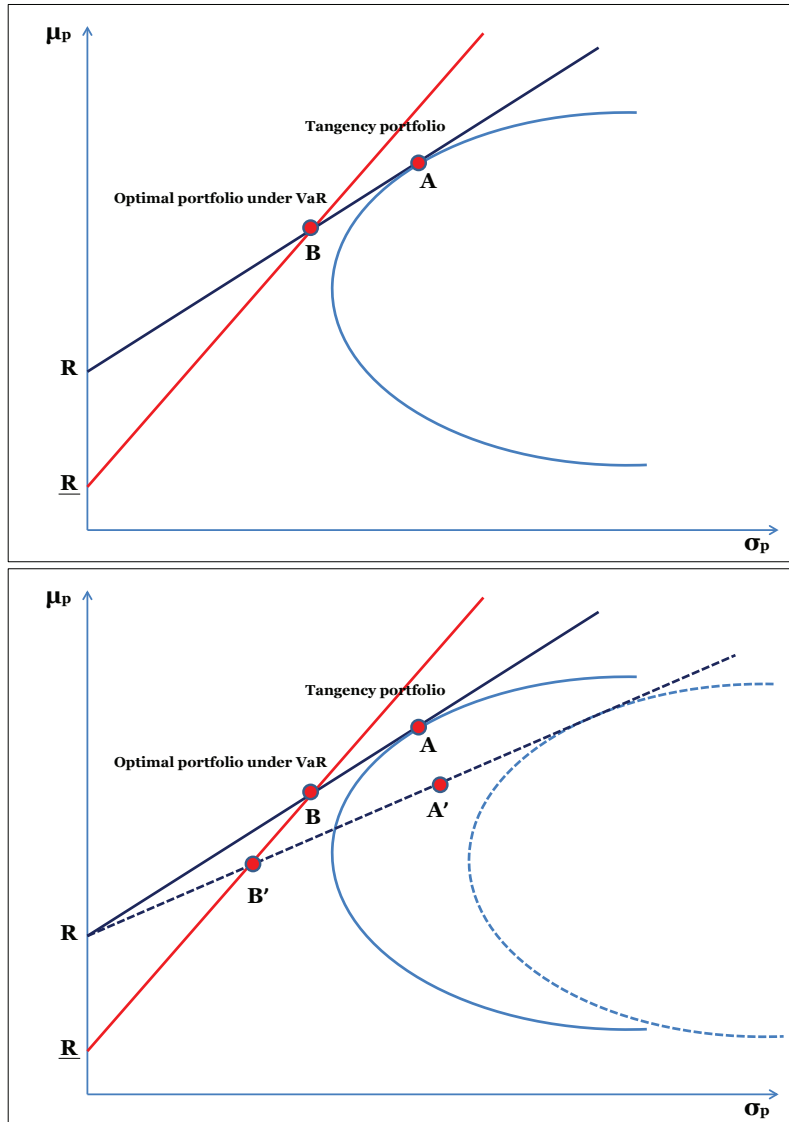


Figure 2.4: Graphical description of the portfolio choice (loose VaR constraint)
 Notes: This figure plots the optimal portfolio choice of the representative investor (top) and the reallocation after a VIX shock (bottom) when investors are highly leveraged by taking the loose VaR constraint.

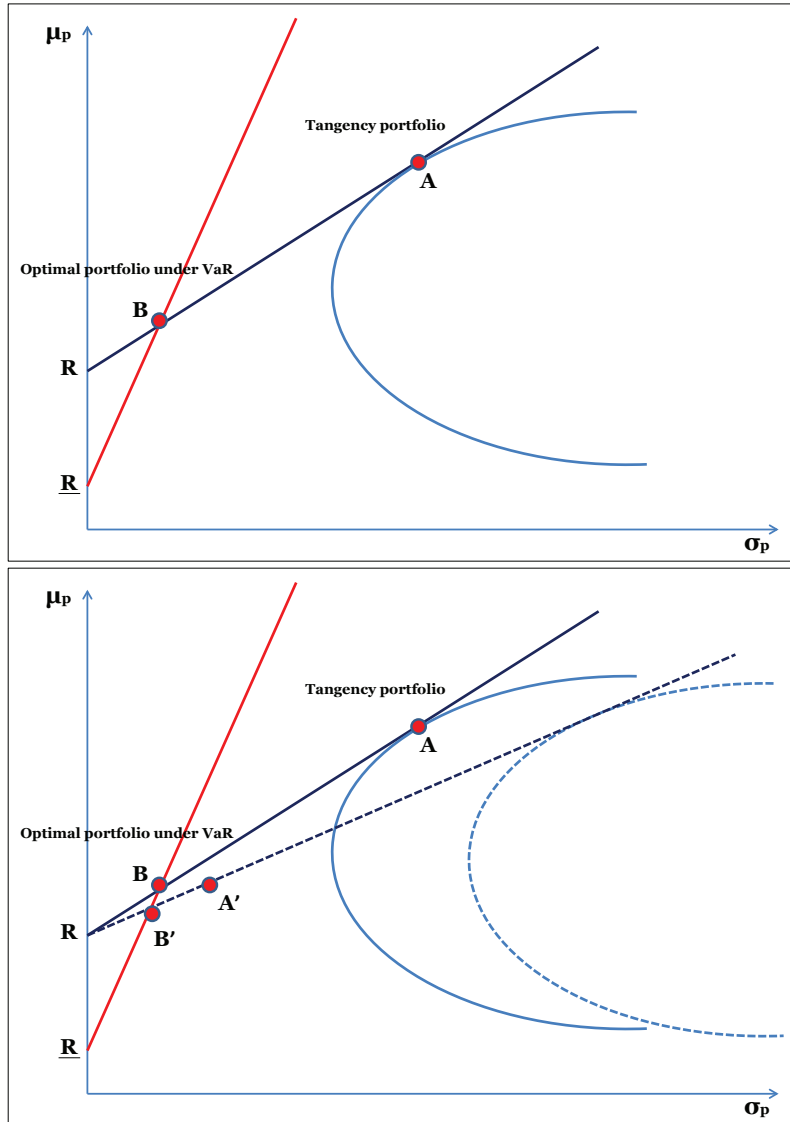


Figure 2.5: Graphical description of the portfolio choice (tight VaR constraint)
 Notes: This figure plots the optimal portfolio choice of the representative investor (top) and the reallocation after a VIX shock (bottom) when investors are not sufficiently leveraged by taking the tight VaR constraint.

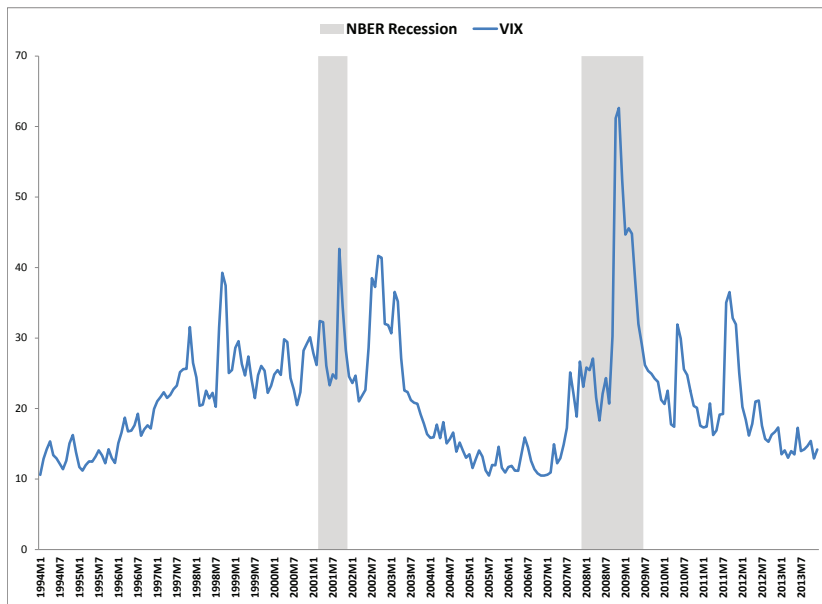


Figure 2.6: The evolution of VIX

Notes: This figure plots the evolution of VIX between January, 1994 and December, 2013.

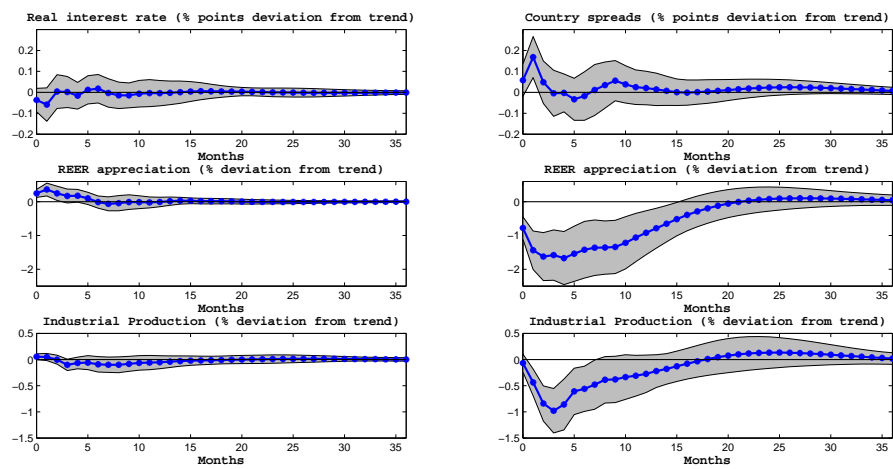


Figure 2.7: Responses to VIX shocks: The US and Korea

Notes: This figure plots the response of real interest rates (country borrowing spreads for Korea), real effective exchange rates, and industrial production of the US (left) and Korea (right) to a one standard deviation increase in VIX.

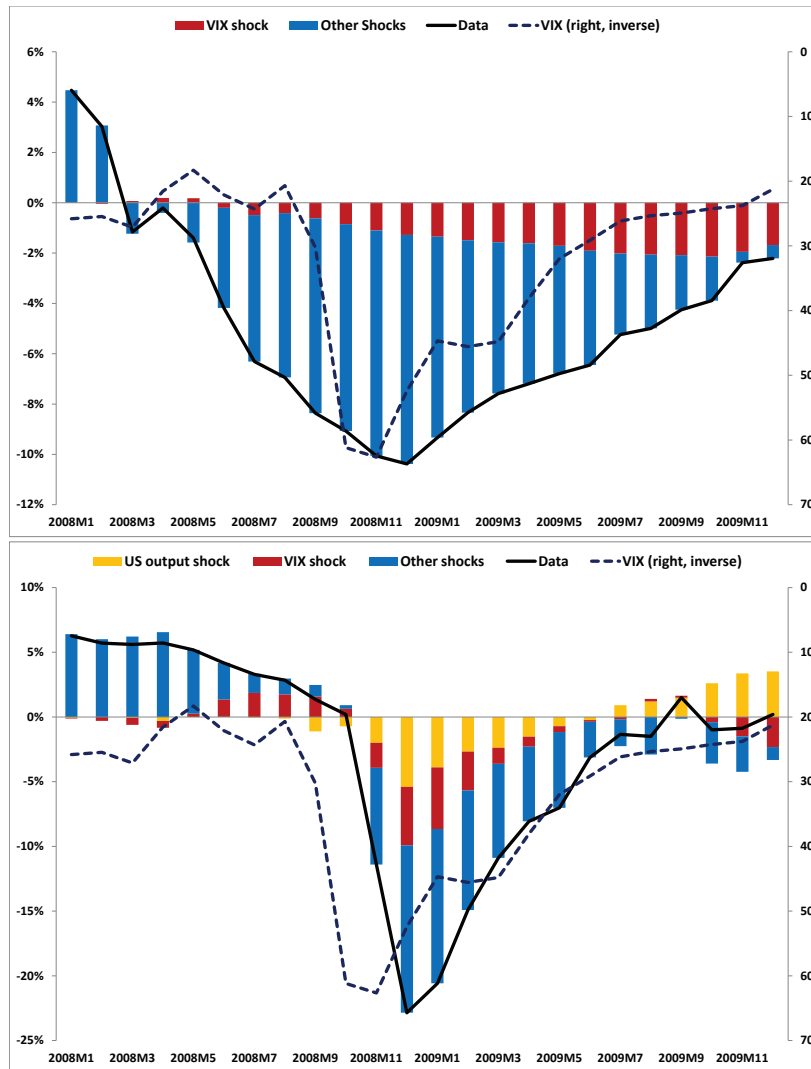


Figure 2.8: Historic decomposition of industrial production during the Great Recession

Notes: This figure plots the contribution of VIX shocks to changes in industrial production during the Great Recession for the US (left) and Korea (right). The solid lines indicate actual data; the blue bars indicate the simulated fluctuations in industrial production when all shocks except VIX shocks (US output shocks and VIX shocks for Korea) are turned on; and the red bars indicate the simulated fluctuations in industrial production conditional on the estimated VIX shocks alone.

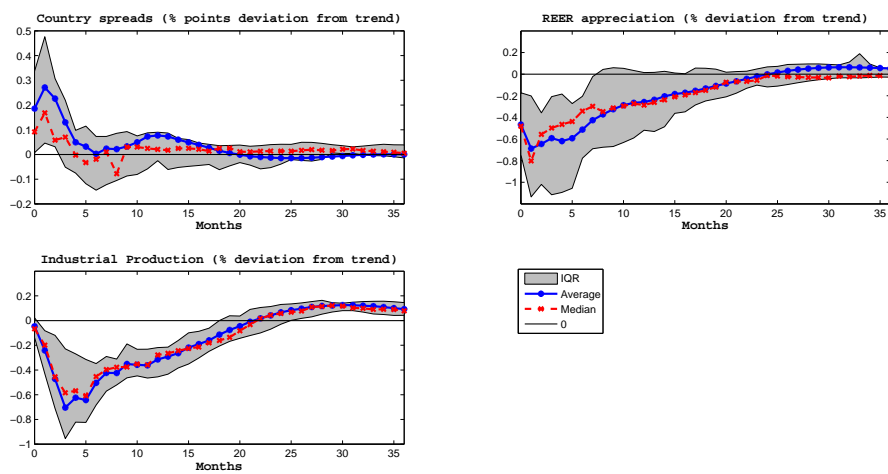


Figure 2.9: Responses to VIX shocks: 18 EMEs

Notes: This figure plots the average (blue) and the median (red) responses of three macroeconomic variables (country borrowing spreads, real effective exchange rates, and industrial production) from the 18 EMEs in the sample and corresponding IQR to a one standard deviation increase in VIX.

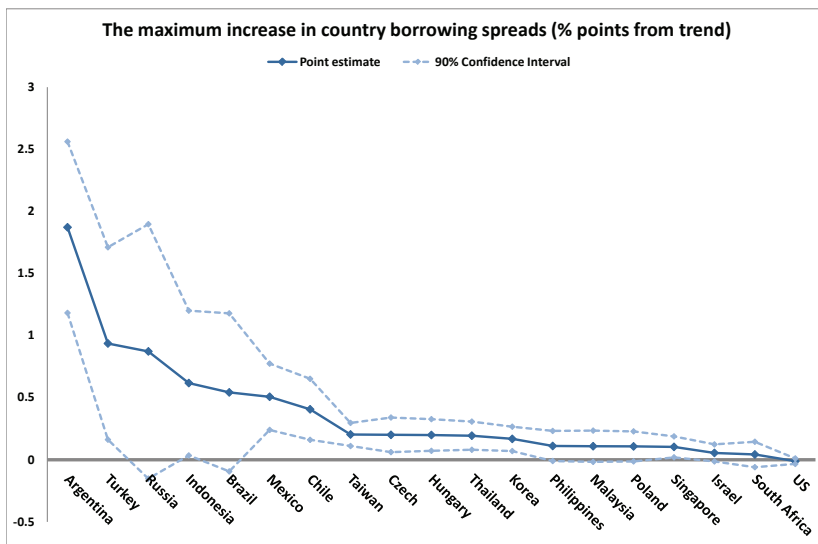


Figure 2.10: Magnitude and statistical significance of response of country borrowing spreads

Notes: This figure plots the point estimates of the maximum increase in country borrowing spreads within the 36-month horizon after VIX shocks, with corresponding 90% confidence intervals.

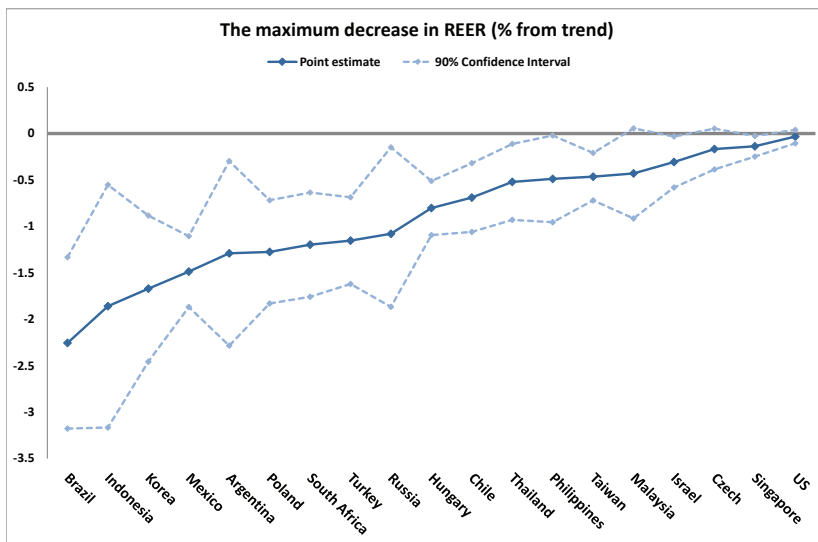


Figure 2.11: Magnitude and statistical significance of response of real exchange rates

Notes: This figure plots the point estimates of the maximum decrease in real exchange rates within the 36-month horizon after VIX shocks, with corresponding 90% confidence intervals.

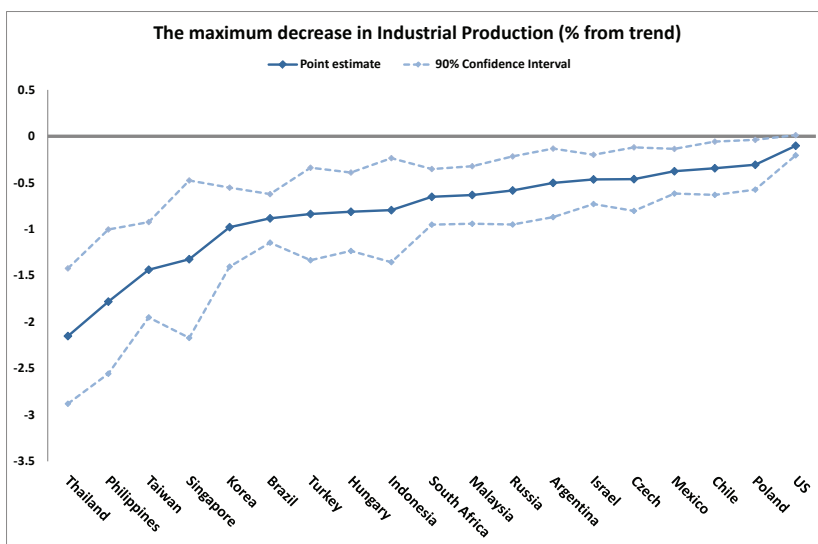


Figure 2.12: Magnitude and statistical significance of response of domestic output
 Notes: This figure plots the point estimates of the maximum decrease in domestic output within the 36-month horizon after VIX shocks, with corresponding 90% confidence intervals.

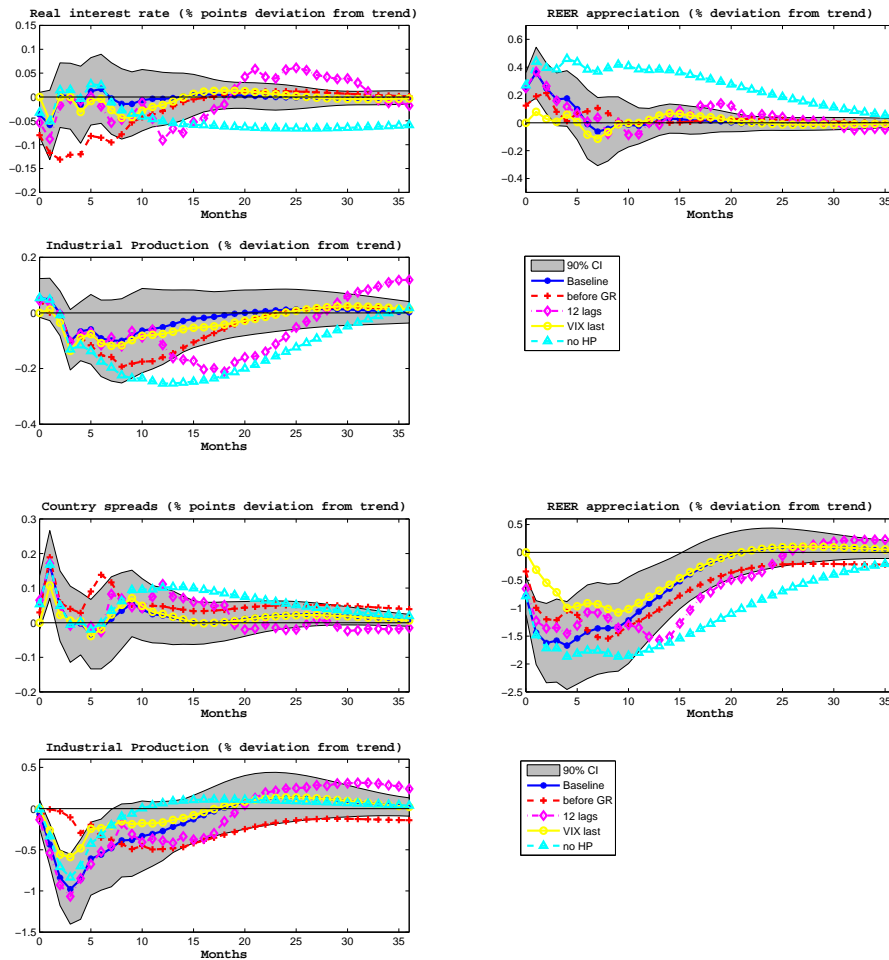


Figure 2.13: Robustness checks

Note: This figure plots the results from robustness checks for the US (top) and Korea (bottom). Shaded area indicates 90% confidence interval for the baseline specification. “before GR” denotes the baseline VAR with data from 1994 and 2007, “12 lags” denotes the baseline VAR but using 12 lags instead of 6 lags, “VIX last” denotes the VAR with the exogenous block placed after the domestic block to obtain conservative estimates of VIX shocks, and “no HP” denotes the VAR without using HP-filter.

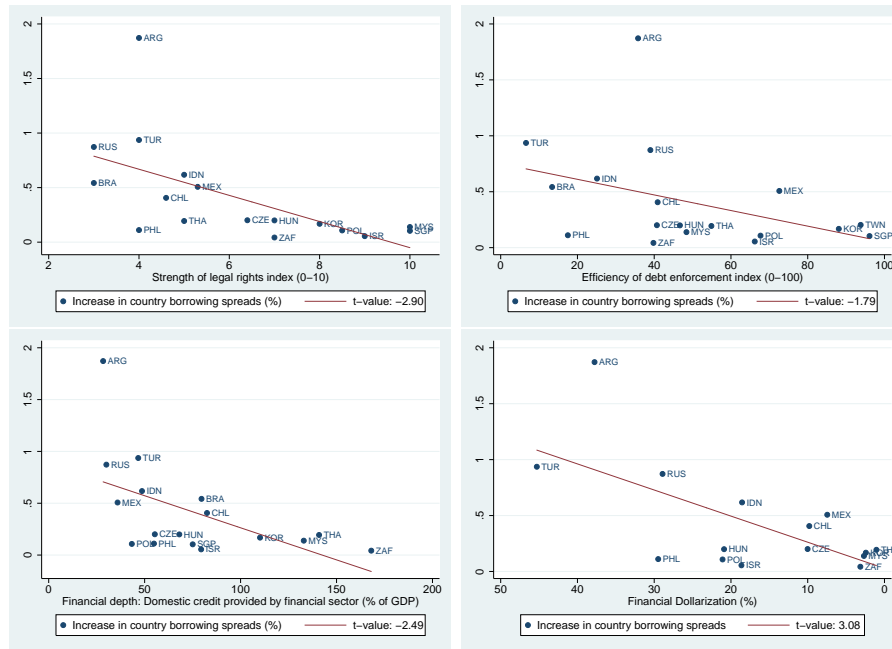


Figure 2.14: Degree of credit market imperfections and the adverse impact on a credit market

Notes: This figure shows a correlation between the degree of credit market imperfections, measured by four different indexes, and changes in country borrowing spreads in EMEs with the corresponding t-values.

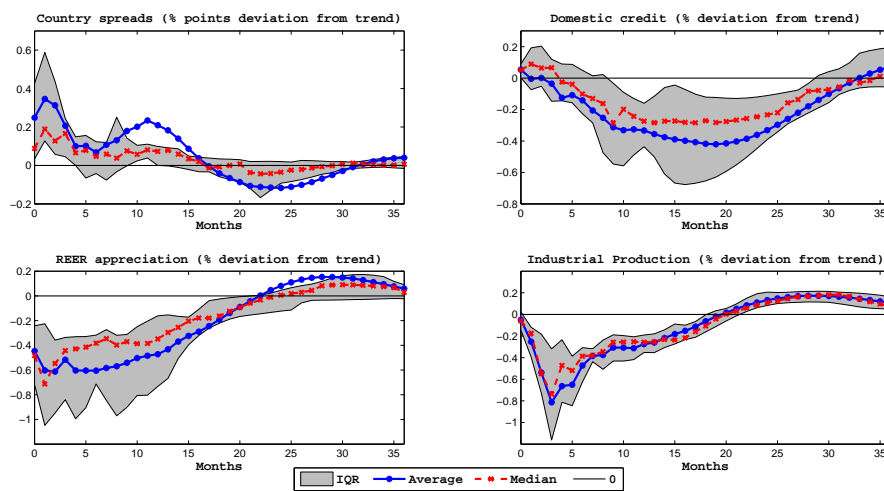


Figure 2.15: Response of the 11 EMEs to VIX shocks in the extended VARs
Notes: This figure plots the average (blue), the median (red), and the IQR (shaded area) of the response of four domestic variables (country borrowing spreads, domestic credit, real effective exchange rates, and industrial production) in the 11 selected EMEs to a one standard deviation increase in VIX.

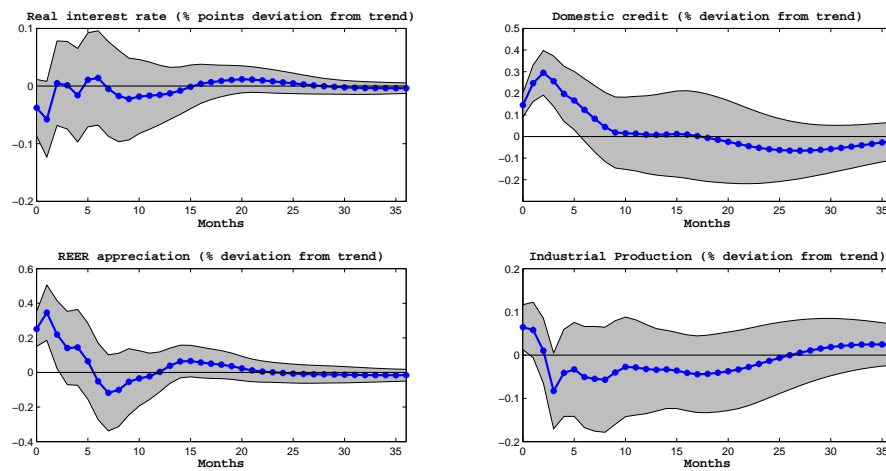


Figure 2.16: Response of the US economy to VIX shocks in the extended VARs
 Notes: This figure plots the response of the real interest rate, domestic credit, real effective exchange rates, and industrial production of the US economy to a one standard deviation increase in VIX.

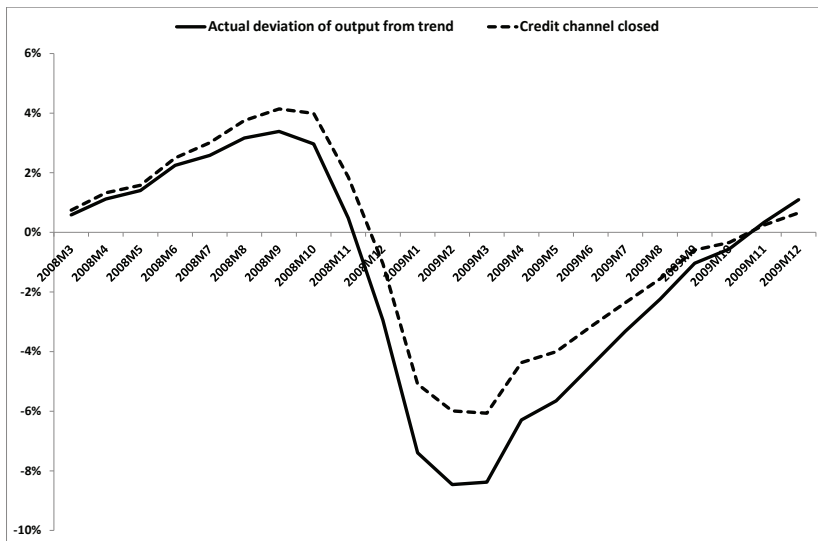


Figure 2.17: Importance of the credit channel during the Great Recession
Notes: This figure plots the average of actual deviation in output (solid) and counterfactual deviation in output by shutting down the credit channel (dashed) from its trend during the global financial crisis period from the 11 countries.

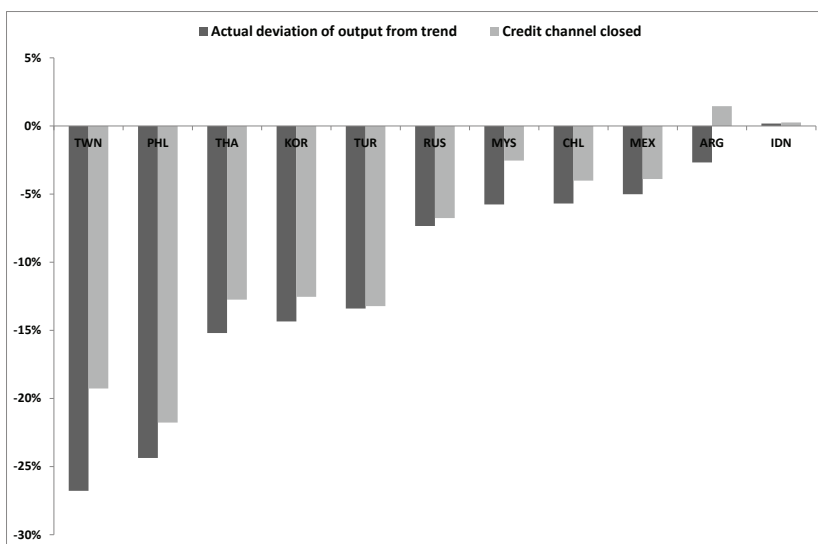


Figure 2.18: Counterfactual exercise during the global financial crisis

Notes: This figure plots actual deviation in industrial production (black) and counterfactual deviation in industrial production (gray) from its trend of the 11 countries.

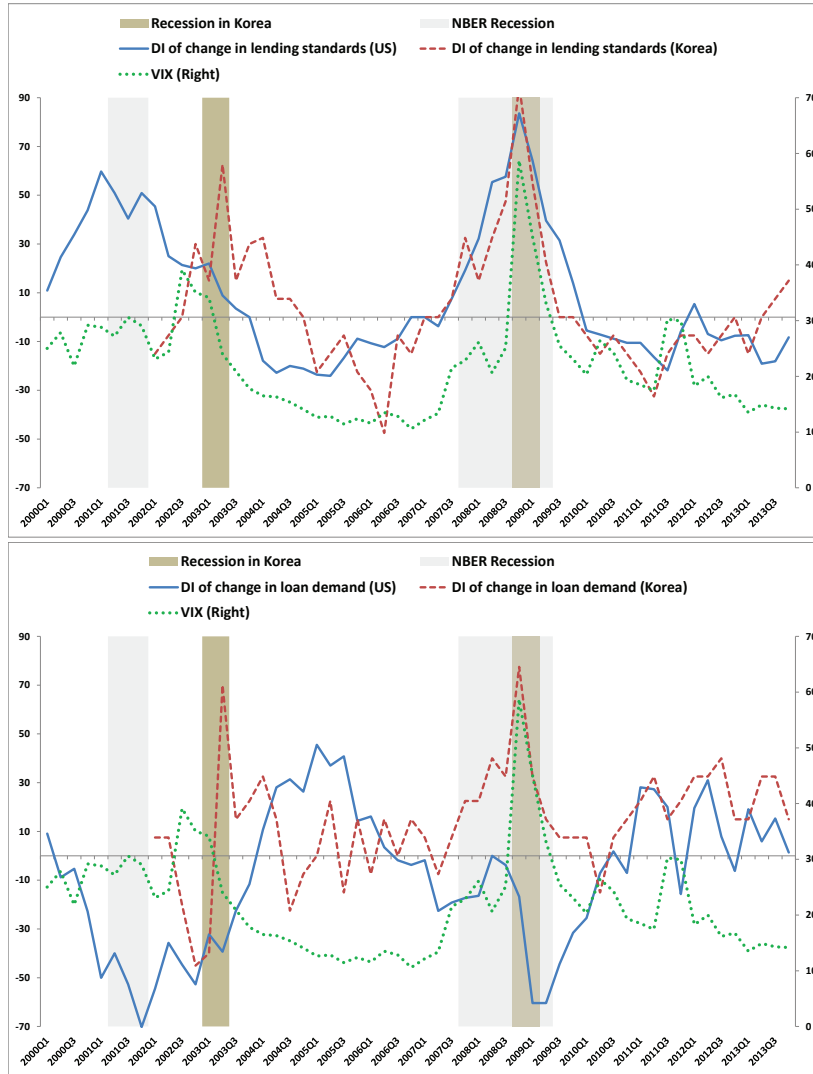


Figure 2.19: Bank lending standard and demand for bank loans

Notes: This figure plots the evolution of the index for bank tightening standard for business loans (top) and demand for bank loans (bottom) in the US (solid blue) and Korea (dashed red) from bank loan officer survey data. Survey data from Korea is only available since 2002. Two shaded regions represent recession dates of each country.

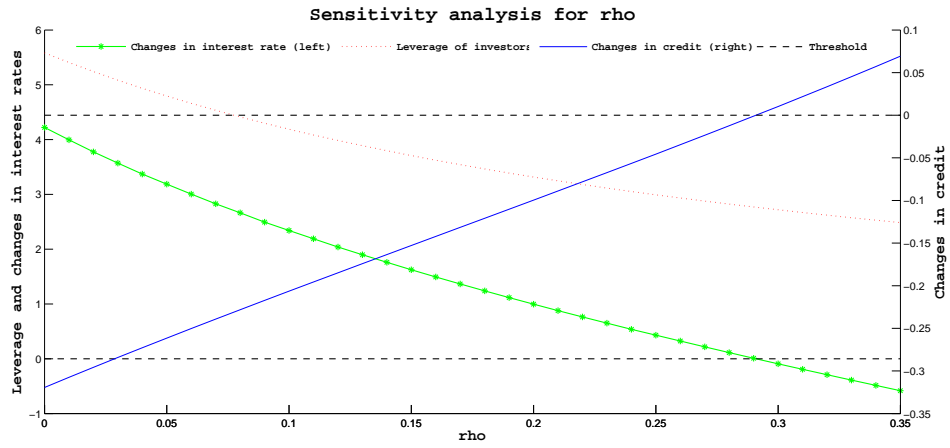


Figure 2.20: Sensitivity analysis on ρ

Notes: Two dashed lines indicate the threshold values of $\rho < 0.29$ holding $\gamma = 0.17$ to have the fall in international investors' demand for emerging market bonds $\omega_{F,t}$.

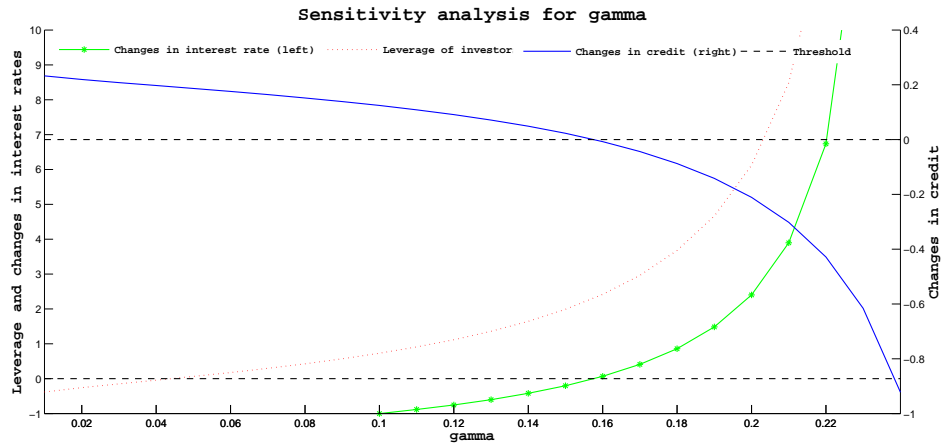


Figure 2.21: Sensitivity analysis on γ

Notes: Two dashed lines indicate the threshold values of $\gamma > 0.16$ holding $\rho = 0.25$ to have the fall in international investors' demand for emerging market bonds $\omega_{F,t}$.

Countries	Coverage	Countries	Coverage
Argentina	1994M1-2013M12	Philippines	1994M1-2013M12
Brazil	1996M1-2013M12	Poland	1994M1-2013M12
Chile	1994M1-2013M12	Russia	1996M1-2013M12
Czech	1994M1-2013M12	Singapore	1997M1-2013M12
Hungary	1994M1-2013M12	South Africa	1994M1-2013M12
Indonesia	1994M1-2013M12	Taiwan	1994M1-2013M12
Israel	1994M1-2013M12	Thailand	1994M1-2013M12
Korea	1994M1-2013M12	Turkey	1995M1-2013M12
Malaysia	1994M1-2013M12	US	1994M1-2013M12
Mexico	1996M1-2013M12		

Table 2.1: Countries in the sample and the data coverage

Notes: The choice of sample countries and sample periods is mainly restricted by the monthly data availability.

Response	VIX			US output		
	Country spreads	REER	Domestic output	Country spreads	REER	Domestic output
Argentina	17.10*	11.69	10.99	16.32	13.48	16.25
Brazil	8.30	27.91*	32.49*	11.67	3.82	18.01
Chile	9.33*	11.86*	9.13*	14.62	12.89*	16.22*
Czech	14.59	7.76	12.69	5.69	19.97	23.57*
Hungary	4.56	16.60	20.96	10.73	2.56	43.92*
Indonesia	4.62	9.19	6.20	11.37	6.59	5.11
Israel	1.55	2.41	12.56	4.56	16.42*	27.16*
Korea	4.25	36.81*	15.65	4.15	12.67*	10.80
Malaysia	4.77	7.45	19.74*	4.26	17.37	11.71
Mexico	10.48*	33.31*	22.98*	12.58	4.73	41.05*
Philippines	1.87	9.46	17.44*	2.43	9.37	15.10*
Poland	8.07	27.24*	7.18	5.88	4.78	17.55*
Russia	4.88	5.00	11.35	4.50	3.11	33.34*
Singapore	14.12*	2.82	6.88	4.98	18.28*	10.44
South Africa	4.86	9.76	27.86*	24.22*	5.83	16.36
Taiwan	10.10	25.52*	17.28*	2.97	8.03	47.95*
Thailand	14.44	6.03	25.87*	0.42	26.61*	9.90
Turkey	2.29	6.44	15.54*	13.13	4.65	30.62*
EME Average	7.68	14.29	16.27	8.58	10.62	21.95
	Real inter- est rates	REER	Domestic output			
US	0.69	5.30	1.98			

Table 2.2: Variance decomposition of the key variables

Notes: For EMEs, each statistic denotes the portion of the variance of forecasting error in each variable explained by a one standard deviation shock to VIX and US industrial production. For the US, each statistic denotes the portion by VIX only. I only report the variance decomposition at 36-month horizon to save space. All the numbers are in percentage and the shaded area indicates statistical significance at 10%.

Parameter	Definition	Value	Note
R	Gross risk-free rate	1.03	Risk-free rate of US treasury bonds
μ_H	Expected returns on US stocks	1.08	Equity premium of 5%
σ_H	Standard deviation of the returns on US stocks	0.1	Sharpe ratio of 0.5
μ_F	Expected returns on emerging market bonds	1.09	Interest rates on EME bonds
σ_F	Standard deviation of the returns on emerging market bonds	0.1	Sharpe ratio of 0.6
u	Crisis probability	0.01	Crisis every 100 period
h	Contract enforceability	1.01	Taken from Schneider and Tornell [2004]
θ	Non-tradable sector probability	1.1	Taken from Schneider and Tornell [2004]

Table 2.3: Calibration of the key parameters

CHAPTER 3

Uncertainty and Unemployment: The Effects of Aggregate and Sectoral Channels

3.1 Introduction

The sharp rise in the U.S. unemployment rate since 2007 has triggered a debate about the driving factors of persistent unemployment. In the third quarter of 2014 (2014Q3), the long-term unemployment rate remained above 2%, significantly higher than the 0.7% rate recorded in 2007. Economic uncertainty is among the possible factors blamed for the sluggish recovery of the U.S. labor market. Bloom's [2009] seminal work shows that, in the presence of adjustment costs in factors of production, uncertainty shocks through a wait-and-see mechanism can be a driver of the U.S. business cycle. The wait-and-see channel alone, however, is not fully capable of explaining a persistent increase in the unemployment rate, because this channel is known to have a short-term impact followed by swift reversals.

This paper focuses on independent roles of two kinds of uncertainty (aggregate and sectoral) shocks on unemployment, which are largely ignored in the literature due to a positive correlation between empirical measures of uncertainty. If uncertainty shocks affect unemployment through an additional channel, a persistent increase in the unemployment rate remains consistent with the uncertainty-based explanation. To test this hypothesis, we decompose U.S. stock market data in order to construct measures of aggregate and sectoral uncertainty, and estimate structural vector autoregressions (VARs) of the U.S. economy from 1963Q1 to

2014Q3.

Our main finding is that the two types of uncertainty shocks have different effects on the U.S. labor market despite the positive correlation of their empirical proxies. Aggregate uncertainty shocks—measured by the volatility of aggregate stock returns—lead to an immediate but short-lived increase in the unemployment rate. In contrast, sectoral uncertainty shocks—measured by the cross-industry dispersion of stock returns—have more significant, persistent effects on the unemployment rate and are especially important in explaining the long-term unemployment rate (27 weeks and over). The substantial increase in the long-term unemployment rate since 2007 can largely be attributed to sectoral, not aggregate, uncertainty.

According to Bloom’s [2009] explanation, the option value of waiting increases when uncertainty is high, prompting firms to freeze hiring and firing decisions. This mechanism is distinct from the effect of the traditional business cycle on unemployment. Bloom [2009] constructs an uncertainty index based on the monthly volatility of the aggregate stock market index. While modeling both aggregate and idiosyncratic uncertainty, Bloom [2009] assumes that the same stochastic process drives both, so he empirically evaluates the effect only of aggregate uncertainty shocks.

We claim that this wait-and-see channel is not the only mechanism through which uncertainty shocks affect unemployment in the presence of labor market frictions and that ignoring this second channel could result in substantially underestimating the effect of uncertainty shocks on the unemployment rate. Sectoral uncertainty shocks resulting in greater productivity dispersion across industries can have an independent effect on unemployment through a re-allocation mechanism to the extent that workers accumulate industry-specific skills similar to that proposed by Lilien [1982].

We provide three new empirical findings. First, the unemployment rate responds in sharply different dynamic ways to aggregate uncertainty and sectoral

uncertainty shocks. Whereas aggregate uncertainty shocks have short-lived effects on the unemployment rate (peaking in two quarters and becoming negative after four quarters), sectoral uncertainty shocks have more persistent effects (peaking in 10 quarters and becoming statistically insignificant after four years). Moreover, the short-term unemployment rate (less than five weeks) decreases after aggregate uncertainty shocks, but increases after sectoral uncertainty shocks, further suggesting that different mechanisms lie behind each of the uncertainty shocks.

Second, the share of unemployment fluctuations attributed to sectoral uncertainty shocks increases significantly when moving from short-term to long-term unemployment and moving from short to long horizons. Aggregate uncertainty shocks exhibit, if anything, an opposite pattern. These results reinforce the findings from our baseline analysis.

Finally, the spike in both aggregate and sectoral uncertainty during the Great Recession helps explain why long-term unemployment has been such a prominent feature of its aftermath. A large fraction of the persistent increase in the long-term unemployment rate can be explained by the long lasting effects of sectoral uncertainty shocks during this period. Therefore, this finding complements the recent findings of Caldara et al. [2014] that uncertainty shocks played a minor role in employment fluctuations during the Great Recession when considering only aggregate uncertainty shocks.

With a battery of robustness checks, we confirm that our results are not driven by a structural break in the sample period, the use of particular proxies of aggregate uncertainty, identifying assumptions in structural VARs, omitted variable bias, mistreatment of non-stationarity, selection of lag length, or errors in estimating impulse-response functions. Instead, the qualitatively different effects of the two types of uncertainty shocks on the unemployment rate are a robust feature.

The remainder of this paper is organized as follows. Section 2 provides a simple economic framework in which two types of uncertainty shocks can have different

effects on a labor market, and presents indices of each of uncertainty. In Section 3, we detail our structural VAR model and share our baseline results, including those from an alternative measure of aggregate uncertainty. Section 4 presents a battery of robustness checks, including the local projection method proposed by Jordà [2005] to guard against the model misspecification. In Section 5, we present our conclusions.

3.2 Measuring Uncertainty: Aggregate vs. Sectoral

3.2.1 Aggregate and Sectoral Uncertainty in a Simple Economy

We closely follow the setup in Bloom et al. [2012] that defines uncertainty as an increase in the variance of underlying shocks to the economy. We put additional emphasis on the potential role of sectoral uncertainty in order to construct a structural interpretation of our empirical results. For example, we assume that a representative firm¹ in an industry i produces output in period t , according to the following production function:

$$y_{i,t} = A_t f(k_{i,t}, l_{i,t}), \quad (3.1)$$

where $k_{i,t}$ and $l_{i,t}$ represent idiosyncratic capital and labor employed by the firm, respectively. In this case, each firm's productivity can be understood as the product of two separate processes: an aggregate (or macro) component, A_t , and a sectoral (or industry) component, $z_{i,t}$. Further, the aggregate and sectoral components follow an autoregressive process:

$$\ln(A_t) = \rho^A \ln(A_{t-1}) + \sigma_{t-1}^A \epsilon_t, \quad (3.2)$$

¹In principle, we can consider firm-level uncertainty within each industry and its effect on unemployment through an intra-industry re-allocation mechanism separate from the inter-industry re-allocation mechanism. However, we do not have a sufficient number of firms for many industries, leading to very noisy firm-level uncertainty. Moreover, Shin [1997] finds that inter-industry labor re-allocation accounts for a larger share of unemployment fluctuations than intra-industry re-allocation. Therefore, we focus only on sectoral uncertainty.

$$\ln(z_{i,t}) = \rho^z \ln(z_{i,t-1}) + \sigma_{t-1}^z \epsilon_{i,t},$$

where σ_t^A and σ_t^z stand for time-varying aggregate and sectoral uncertainty, and ϵ_t and $\epsilon_{i,t}$ are i.i.d. shocks that follow a standard normal distribution.² Increases in aggregate uncertainty imply that all firms are equally affected by more volatile shocks, whereas increases in sectoral uncertainty suggest a larger productivity dispersion across sectors. These two types of shocks are driven by different statistics. Volatility in A_t leads to higher variability in aggregate variables, such as GDP growth and the S&P500 index, while volatility in $z_{i,t}$ implies larger cross-sectional dispersion of industry-level output, sales, and stock market returns.

3.2.2 Uncertainty Indices from the U.S. Stock Market

We use two empirical proxies constructed from the U.S. stock market to evaluate the effects of uncertainty shocks on unemployment. Rising uncertainty can be an endogenous outcome of negative development in the real economy rather than an independent driver of business cycles (Bachmann and Bayer [2013]; Bachmann et al. [2013]). Therefore, existing measures of uncertainty are typically purged from the impacts of other variables when evaluating their effects on macroeconomic variables. For example, Bloom [2009] controls for the level of U.S. stock market in his VAR to separate second and first moment shocks. The advantage of our uncertainty indices is that we can purge them using the same variable (U.S. stock price).

For the aggregate uncertainty index, we take Bloom’s [2009] uncertainty index that combines realized volatility until 1985 and an implied volatility index (VXO) from 1986 onward, in line with prior literature (Bloom [2009]; Leduc and Liu [2013]; Bachmann et al. [2013]; Caggiano et al. [2014]; Caldara et al. [2014]).³

²In his definition of uncertainty, Bloom [2009] assumes that aggregate (or macro) uncertainty and idiosyncratic (or micro) uncertainty are driven by the same stochastic process ($\sigma_t^A = \sigma_t^z = \sigma_t$), based on the positive correlation between empirical proxies.

³In a previous version of this paper, we considered realized volatility for the whole period

Then, we construct the sectoral uncertainty index using industry-level quarterly stock returns, following Loungani et al. [1990] and Brainard and Cutler [1993] who employ dispersion in industry-level stock returns to test Lilien’s [1982] sectoral shift hypothesis. Drawn from the same underlying source of the U.S. stock market, this index becomes a natural counterpart to aggregate uncertainty measured by aggregate stock market volatility. To address the potential problem of industry returns with different sensitivity to market returns (i.e., different betas),⁴ we first regress industry returns $R_{i,t}$ on market returns R_t : $R_{i,t} = \alpha_i + \beta_i R_t + \epsilon_{i,t}$. We then calculate the dispersion of excess returns: $\eta_{i,t} = \hat{\alpha}_i + \hat{\epsilon}_{i,t}$. After controlling for different betas, the sectoral uncertainty index is defined as:

$$SU_t = \left(\sum_{i=1}^n w_i (\eta_{i,t} - \bar{\eta}_t)^2 \right)^{\frac{1}{2}}, \quad (3.3)$$

where $\bar{\eta}_t$ is the average excess returns in period t and w_i is a weight based on the industry’s share of total employment.⁵

3.2.3 Data

This section describes the statistical and cyclical properties of both uncertainty indices. Figure 3.1 shows the behavior of the two measures of uncertainty from 1963Q1 to 2014Q3 based on a quarterly frequency.⁶ Both measures are counter-cyclical and increase sharply during the Great Recession. Despite the moderate correlation (0.53) between the two indices, they diverge from one another in several instances, implying potentially different roles in shaping labor market dynamics.

and obtained very similar results. To ease comparison with prior literature, we directly import Bloom’s [2009] index.

⁴Noting that some industry stock returns might be more cyclically sensitive, Brainard and Cutler [1993] introduce a modified two-step measure in attempt to eliminate these cyclical effects. Our main results do not depend on whether we use returns, as in Loungani et al. [1990], or excess returns, as in Brainard and Cutler [1993].

⁵See the appendix for details on measuring employment shares.

⁶See Table 3.6.2 in the appendix for a description of the main variables used in the analysis. To ease comparison, we normalize both uncertainty indices so that they have the same mean and variance.

Table 3.6.2 presents the higher moments of both uncertainty indices and their correlations with changes in other macroeconomic variables. The persistence of the aggregate uncertainty index, measured by the AR(1) coefficient, is larger than that of the sectoral uncertainty index.⁷ The cyclical properties of the two indices are quite similar. If anything, the pair-wise correlations indicate that the aggregate uncertainty index is more countercyclical than the sectoral uncertainty index.

Table 3.6.2 in the appendix provides the results for the Augmented Dickey-Fuller (ADF) test on the variables of interest. In sum, we cannot reject a unit root process for every macroeconomic variable, indicating the potential presence of cointegration. The ADF test in first-difference shows that all macroeconomic variables follow an I(1) process.

Figure 3.2 shows the main subject of interest—the history of the overall unemployment rate during the sample period—and the long-term unemployment rate. The unprecedented increase in the long-term unemployment rate during the Great Recession stands out, so we pay extra effort to explaining its contributing factors.

3.3 Structural VARs

In this section, we present the results from the structural VARs estimated using quarterly U.S. data from 1963Q1 to 2014Q3. The baseline model includes six variables: the real GDP, year-to-year CPI inflation rate, the Federal Funds rate, level of the U.S. stock market index (S&P500), and each of our uncertainty indices. Following Bloom [2009], we control for the S&P500 index to rule out a spurious relationship between uncertainty and unemployment driven by the negative relationships between stock market volatility and stock prices (Campbell and Hentschel [1992]) and stock prices and the unemployment rate (Farmer [2012]).

⁷The higher persistence of the aggregate uncertainty index indicates that our main results are not simply driven by more persistent sectoral uncertainty shocks.

The system is identified following a standard recursive ordering procedure. The variables in the system are ordered as follows: real GDP (y_t); unemployment rate (u_t); inflation rate (π_t); stock market index (sp_t), each of the uncertainty indices (unc_t), which enter the baseline VAR model in turn;⁸ and the Federal Funds rate (r_t). Thus, we write our VAR system as follows:

$$AY_t = \sum_{k=1}^p B_k Y_{t-k} + \epsilon_t, \quad (3.4)$$

$$Y_t = \left(y_t, u_t, \pi_t, sp_t, unc_t, r_t \right)',$$

where ϵ_t is the vector of structural shocks.

This recursive ordering is based on the assumption that GDP, inflation, and the unemployment rate are classified as slow-moving variables, while our uncertainty indices constructed from the stock market are fast-moving variables, based on the classification of Bernanke et al. [2005]. According to this identifying assumption, our uncertainty indices can respond contemporaneously to innovations to real GDP and the unemployment rate, whereas these real variables respond only to innovations to uncertainty with a lag. This identifying assumption is desirable because our main question is whether uncertainty shocks have an effect on the unemployment rate independent from business cycles.

We estimate our baseline VAR model with levels of variables because a large body of literature on the issue suggests that even if the variables have unit roots, it is still desirable to estimate a structural VAR in level (Sims et al. [1990]; Lin and Tsay [1996]).⁹ While the Akaike Information Criterion (AIC) suggests six lags and the Schwartz Bayesian Information Criterion (SBIC) suggests two lags, we

⁸In a previous version of this paper, we include both uncertainty indices in structural VARs to evaluate marginal effects on the unemployment rate. However, there is no clear theory to justify a zero restriction between innovations to the two types of uncertainty, so we consider each uncertainty index in turn. The main results do not depend on this change.

⁹In principle, a VAR specified in first differences assumes that variables are not cointegrated. If there is cointegration, then such a model is misspecified.

set the lag length in the baseline model at four because of the quarterly frequency of data.

3.3.1 The Effects of Uncertainty Shocks

Figure 3.3 shows the effects of various shocks on the unemployment rate in the baseline structural VAR model, along with the associated 90% confidence intervals, using a parametric bootstrapping procedure with 200 repetitions. The signs of the responses by the unemployment rate to other macroeconomic variables are consistent with what standard economic theories suggest.

The unemployment rate rises after an increase in both uncertainty indices, but the dynamics are quite different. On one hand, an increase of one standard deviation in the aggregate uncertainty index immediately leads to a 0.03 percentage point increase in the unemployment rate, followed by an insignificant decrease after three quarters. The shape of the unemployment rate's response to uncertainty shock is a mirror image of the response of the level of employment to uncertainty shocks (a sharp drop in six months followed by a rebound and an overshoot) in Bloom [2009]. On the other hand, an increase of one standard deviation in the sectoral uncertainty index leads to a 0.15 percentage point increase in the unemployment rate, which remains significant and positive for four years. Sectoral uncertainty shocks, therefore, have more significant and persistent effects on the unemployment rate than aggregate uncertainty shocks.

We further investigate the different effects of the two uncertainty indices by illustrating the dynamic responses of the long- and short-term unemployment rates. We re-estimate our VAR model by replacing the unemployment rate with the long- and short-term unemployment rates in turn. Figure 3.4 shows a pattern similar to that of the overall unemployment rate: Only sectoral uncertainty shocks have a persistent effect on the long-term unemployment rate. Interestingly, Figure 3.5

shows that the short-term unemployment rate (or the separation rate) actually falls after aggregate uncertainty shocks, but increases after sectoral uncertainty shocks, suggesting that the uncertainty shocks affect the labor market through different channels.¹⁰

The forecast error variance decomposition of the unemployment rate provides further evidence of the two uncertainty shocks' relative importance in explaining fluctuations in unemployment. Table 3.6.2 shows the variance in forecast errors explained by each of the uncertainty shocks for unemployment of different durations over 20 quarters. Aggregate uncertainty shocks explain only 1.3%, but sectoral uncertainty shocks explain approximately 16% of the variance in the unemployment forecast errors at 20 quarters.

The share of variation in unemployment explained by sectoral uncertainty shocks has two interesting properties. First, it increases monotonically with the duration of unemployment. Sectoral uncertainty shocks account for 3% of the variation in the short-term unemployment rate. When unemployment lasts longer than 26 weeks, though, sectoral uncertainty shocks account for more than 25% of the variance in the forecast errors. Second, as forecasting horizon increases, the variation explained by sectoral uncertainty shocks increases monotonically. Aggregate uncertainty shocks, however, account for only a minor fraction of the variation in unemployment and do not show any persistent or regular pattern.

¹⁰footnotesize Note that, by design, changes in the short-term unemployment rate are not driven by changes in the job finding rate. Whether or not short-term (less than five weeks) unemployed workers find a job has the same effect on the short-term unemployment rate (If they do not find a job they simply move to the next unemployment category of 5-14 weeks, so they are no longer considered short-term unemployed). Therefore, a decrease in the short-term unemployment rate is the result of a decline in the separation rate, consistent with the prediction of the wait-and-see mechanism; firms facing aggregate uncertainty neither hire nor fire.

3.3.2 Interpretation of the Main Results: Different Channels of Uncertainty Shocks

This section discusses the economic explanation for our empirical results: the temporary effects of aggregate uncertainty shocks and the persistent effects of sectoral uncertainty shocks on unemployment. In the first channel, greater uncertainty increases the real option value of waiting, so firms scale back their investment and hiring plans (Dixit [1994]; Bloom [2009]) in the presence of factor adjustment costs. This channel predicts that the marginal effect on the unemployment rate will be temporary once business cycle effects are considered. Considering this channel alone, however, might lead to underestimating the effect of uncertainty shocks on unemployment. Considering this channel alone, however, might lead to underestimating the effect of uncertainty shocks on unemployment.

The second channel we consider in this paper is an immediate consequence of increases in sectoral uncertainty on the aggregate economy. According to the setup presented in section 2.1, increases in sectoral uncertainty in the preceding period result in the different fortunes of the winning industries and losing industries in the present period. If there are any barriers to inter-industry labor re-allocation, sectoral uncertainty can have a persistent effect on unemployment independent from the wait-and-see channel.

Both channels predict a change in the unemployment rate in the same direction; therefore, contrasting their short- and long-term effects is necessary to identify different channels. Indeed, the impulse response functions and forecast error variance decomposition of unemployment at different durations capture sharply different dynamics. The contrasting responses of the short-term unemployment rate to the two types of uncertainty shocks, in particular, clearly indicate that both channels of uncertainty shocks based on Bloom [2009] and Lilien [1982] contribute to explaining unemployment dynamics.

3.3.3 Contribution of Uncertainty Shocks to Long-Term Unemployment during the Great Recession

We use the estimated VAR to examine fluctuations in long-term unemployment during the Great Recession. Long-term unemployment accounted for only 18% of total unemployment in the 2007Q4, but still remained high, at 32%, in the 2014Q3, long after the official end of the Great Recession.

Figure 6 shows a plot of the long-term unemployment rate since early 2008 and the contributions of the two types of uncertainty. The base period chosen is the 2007Q4, declared the official start of the recession by the U.S. National Bureau of Economic Research. The forecast horizon extends to the 2014Q3. The line labeled “baseline projection” plots the conditional expectation for the long-term unemployment rate over these 27 quarters, as of 2007Q4. The contribution of each type of uncertainty shocks is measured by the VAR forecast for the long-term unemployment rate if the orthogonalized aggregate and sectoral uncertainty shocks from 2008Q1 to 2014Q3 had been known at the end of 2007. Sectoral uncertainty shocks emerge as quite important in explaining the deviation of the realized long-term unemployment rate from the baseline forecast, while aggregate uncertainty shocks contribute little.¹¹

3.4 Robustness Checks

To support our main findings, we perform a battery of robustness checks. To highlight the subject of interest, we report results only for the unemployment

¹¹For this analysis, we estimate the 7-variable VAR model with both types of uncertainty. To obtain conservative results, we place the aggregate uncertainty index before the sectoral uncertainty index in the VAR system. The switch of ordering magnifies the difference between the two uncertainty shocks. This finding is in line with the historical decomposition of aggregate uncertainty shocks by Caldara et al. [2014], which finds that uncertainty shocks—measured by aggregate stock market volatility—account for only a minor fraction of the employment decrease during the Great Recession.

rate.

3.4.1 Alternative Measure of Aggregate Uncertainty Shocks

To support the existence of two independent channels for uncertainty shocks, we consider another measure of aggregate uncertainty which does not rely on stock market data. We employ the economic policy uncertainty index developed by Baker et al. [2013], a widely used measure of uncertainty in recent literature.

By design, this measure of uncertainty does not incorporate any sector-level dispersion.¹² If alternative aggregate uncertainty shocks lead to different unemployment dynamics than our preferred aggregate uncertainty shocks, then the wait-and-see vs. re-allocation mechanism might not be a correct interpretation of our empirical findings. The economic policy uncertainty index is available only from 1985, so we restrict our analysis to the common sample from 1985Q1 to 2014Q3.

Beetsma and Giuliadori [2012] and Choi [2013] find that the effect of uncertainty shocks—measured by aggregate stock market volatility—on the real economy has substantially decreased since 1984. Therefore, this common sample analysis serves a natural sub-sample robustness check for our findings. We further drop the Great Recession period and re-estimate our VAR model with data from 1985Q1 to 2007Q4 in order to isolate the dominant effects of the Great Recession.

Two results from this analysis stand out. First, the results reported in the left panel of Figure 3.7 are consistent with the findings of Beetsma and Giuliadori [2012] and Choi [2013] because the effect of aggregate uncertainty shocks declines. However, sectoral uncertainty shocks still have persistent effects on the unemployment rate, as shown in the right panel of Figure 3.7. Moreover, in Figure 3.8, we confirm the short-term impact of aggregate uncertainty shocks on the unemploy-

¹²See Baker et al. [2013] for further details on the economic policy uncertainty index.

ment rate even when the alternative measure is used.¹³

3.4.2 Impulse-Response Functions from a Local Projection Method

Despite the stark differences reported in the previous section, impulse-response functions from standard VARs might have substantial errors on longer horizons Phillips [1998]. This is because the impulse responses in a standard VAR model are derived iteratively, moving forward period-by-period, relying on the same set of original VAR parameter estimates. This iterative process magnifies any model misspecification. A local projection method proposed by Jordà [2005] is known to be robust to the misspecification problem. We re-evaluate the effects of both uncertainty shocks on the unemployment rate by applying local projections. We do not treat this alternative as a panacea, though, and also perform conventional robustness checks on our results.

We refer to Jordà [2005] for details on the local projection method and here briefly illustrate how we compute impulse-response functions. Impulse responses are defined as the revision to the best mean-squared-error predictor when a shock hits, without reference to the unknown data-generating process. Following Jordà [2005], we define the impulse response at time $t + s$ arising from the experimental shocks in $d_{i,t}$ at time t as:

$$IR(t, s, d_{i,t}) = \frac{\partial y_{t+s}}{\partial \delta_t} = E[y_{t+s} | \delta_t = d_{i,t}; X_t] - E[y_{t+s} | \delta_t = 0; X_t] \quad (3.5)$$

for $i = 0, 1, 2, \dots, n$; $s = 0, 1, 2, \dots$; $X_t = (y_{t-1}, y_{t-2}, \dots)'$, where operator $E[.]$ is the best mean-squared error predictor, y_t is an n -dimensional vector of the variables of interest, and d_t is a vector additively conformable to y_t . The expectations are formed by linearly projecting y_{t+s} onto the space of X_t :

$$y_{t+s} = \alpha^s + B_1^{s+1} y_{t-1} + B_2^{s+1} y_{t-2} + \dots + B_p^{s+1} y_{t-p} + U_{t+s}^s, \quad (3.6)$$

¹³When we also use the news component of the policy uncertainty index (quantifying newspaper coverage on economic policy uncertainty) we obtain similar results.

where α^s is a vector of constants and B_j^{s+1} are coefficient matrices at lag j and horizon $s + 1$. For every horizon $s = 0, 1, 2, \dots, h$, a projection is performed to estimate the coefficients in B_j^{s+1} . The estimated impulse-response functions are denoted by $\hat{IR}(t, s, d_i) = \hat{B}_1^s d_{i,t}$, with the normalization $B_1^0 = I$. Thus, an innovation to the i -th variable in the vector y_t produces an impulse response of \hat{B}_1^s . The impulse responses from local approximations are calculated from univariate least squares regressions for each variable at every horizon.

Figure 3.9 shows the response of the unemployment rate to the two types of uncertainty shocks when linear local projections are applied.¹⁴ To be consistent with our baseline model, we first fix the lag length at four. Then, we allow optimal lag lengths at every forecasting horizon h . The local projection method yields even starker differences in the effects of the two types of uncertainty shocks on the unemployment rate. Table 3.6.2 shows a forecast error variance decomposition under the local projection method. Our conclusions about temporary and persistent effects do not depend on any particular estimation technique.

3.4.3 Inclusion of Additional Variables

Our baseline VAR model with six variables might have omitted important factors affecting unemployment through different channels, thereby exaggerating differences in the effects of the two uncertainty shocks on unemployment. Oil price shocks are a first potential candidate for explaining a persistent increase in unemployment (Loungani [1986]; Davis and Haltiwanger [2001]). The mechanism through which oil price shocks affect unemployment has much in common with the re-allocation mechanism of sectoral uncertainty shocks proposed in this paper. If our sectoral uncertainty index detects sharp changes in oil prices (especially during the Great Recession), traditional oil price shocks might mask sectoral uncertainty shocks.

¹⁴We use Jorda's Gauss code for this exercise.

Second, credit spreads are also known to be a robust business-cycle indicator. Moreover, increases in our uncertainty indices are frequently associated with a widening of credit spreads (Gilchrist et al. [2014]; Caldara et al. [2014]; Nodari [2014]). If our sectoral uncertainty shocks really capture an additional labor reallocation channel, the inclusion of credit spreads should not affect our main results. Therefore, we add the volatility of crude oil prices (West Texas Intermediate) and Moody’s Baa- and Aaa-rated corporate bond yields to our baseline VAR model in turn, in order to estimate 7-variable VARs.¹⁵ We place the oil price volatility variable before inflation rate and Baa-Aaa spreads before our uncertainty indices.¹⁶ Figure 3.10 shows that sectoral uncertainty shocks have additional effect on unemployment beyond oil price shocks and credit spread shocks.

3.4.4 Alternative Identifying Assumptions

Although we employ a standard recursive ordering which follows conventional economic theories, imposing a lag on the response of the unemployment rate to uncertainty shocks might have resulted in limited effects from aggregate uncertainty shocks. To explore this possibility, we employ a common identification scheme in the literature (Bloom [2009]; Bachmann et al. [2013]; Baker et al. [2013]; Caggiano et al. [2014]; Jurado et al. [2015]; Nodari [2014]) by placing uncertainty indices before real variables in a recursive ordering. This alternative identification scheme imposes the following ordering: $Y_t = (sp_t, unc_t, r_t, \pi_t, u_t, y_t)$.

In addition, the baseline VAR model with six variables might not have a tight relationship with structural shocks. In the spirit of Okun’s Law (Blanchard [1989]; Ball et al. [2013]), we adapt a parsimonious VAR model which includes only four

¹⁵Similar to our aggregate uncertainty index, oil price volatility is constructed from quarterly standard deviation of daily returns on oil prices. As we have daily prices only from 1986, this robustness check is conducted for the period from 1986Q1 to 2014Q3.

¹⁶The ordering of additional variables in structural VARs barely affects the main result. The use of the level of oil prices and spreads between the Baa- and the 10-year Treasury constant maturity rates yields similar results.

variables: y_t, sp_t, unc_t, u_t . Figure 3.11 shows that qualitative results reported in Figure 3.3 do not depend heavily on alternative specifications.

3.4.5 Treatment of Non-stationarity

As Table 3.6.2 suggests, most of the variables of interest follow an I(1) process. Although we consistently use the level for each variables suggested by Sims et al. [1990] and Lin and Tsay [1996], our main results might depend on how we treat trends in variables. Therefore, we re-estimate our baseline VAR model with 1) variables in first differences and 2) HP-filtered variables. Figure 3.12 shows that various de-trending methods yield qualitatively similar results as the baseline estimation. Although the persistence of both uncertainty shocks becomes equally weaker,¹⁷ sectoral uncertainty shocks still have more persistent effects on the unemployment rate.

3.4.6 Different Lag Length

In addition to applying the local projection method, we further check for possible misspecification in a lag structure. Based on suggestions from the AIC and SBIC, we re-estimate the VAR model with 1) two lags and 2) six lags. Figure 3.12 confirms that the different qualitative features of the responses by the unemployment rate do not depend on lag length.¹⁸

¹⁷Note that, by design, de-trending data precludes the persistent or permanent effects of uncertainty shocks (Lin and Tsay [1996]; Bachmann et al. [2013]).

¹⁸Although aggregate uncertainty shocks seem to have more persistent effect on the unemployment rate when two lags are used, the impact becomes statistically insignificant after three quarters.

3.5 Conclusion

This paper contributes to the growing literature on measuring uncertainty and quantifying its macroeconomic effects. We provide novel empirical evidence indicating that aggregate and sectoral uncertainty shocks have different effects on U.S. unemployment. Aggregate uncertainty has short-lived effects whereas sectoral uncertainty has more persistent effects. The results from the forecast error variance decomposition of unemployment at different durations suggest that sectoral uncertainty is especially relevant to understanding the dynamics of long-term unemployment.

Economic theory suggests that uncertainty can result in higher unemployment through various channels. By analyzing different dimensions of uncertainty (aggregate and sectoral), we show that each type of uncertainty shocks has effects on the U.S. unemployment rate, consistent with the predictions made by different channels (wait-and-see and reallocation). To strengthen the independent channels through which aggregate and sectoral uncertainty affect unemployment, developing an integrated model that jointly evaluates both types of uncertainty would be a fruitful direction for future research.

3.6 Appendix

3.6.1 Construction of the Sectoral Uncertainty Index

This section describes in detail how we construct the sectoral uncertainty index using the similar methodologies of Loungani et al. [1990] and Brainard and Cutler [1993]. Given the data constraints, our baseline series covers 1963Q1 to 2014Q3. This exercise presents three main challenges. First, industry subgroups are added and deleted over the lifetime of the S&P500 Composite Index; therefore, we obtain a list of the dates of changes in the S&P.

Second, weights are based on the BLS employment data which use SIC industry codes; however, the S&P500 industry-level indices do not correspond exactly to the SIC industry codes. Therefore, we determine the weight by two-digit SIC codes and divide it equally among the component industries at the end of the sample period. We match the two-digit SIC codes of individual firms with each S&P500 industry index. For example, at the end of the sample period, one S&P500 industry consists of 10 firms: six firms in one two-digit industry, three firms in another two-digit industry, and one firm in a third two-digit industry. We calculate the employment share of the S&P500 industry as the weighted average of the employment share of the three two-digit SIC industries for each period. In this case, the weights for the industries are 0.6, 0.3, and 0.1.

Third, disaggregated industry-level employment data are consistently available only after 1990; therefore, we use the average of the employment share of two-digit SIC codes from 1990 to 2009. Our weights are not time-varying and can be subject to bias in a time trend. However, the sectoral uncertainty index based on the average employment share has a high correlation with the unweighted index. Our index contains only S&P500 industry indexes included in the composite at the end of the sample period. Among these industries, we excluded S&P500 industries added to the S&P500 Composite, resulting in 50 U.S. industries at the end of the sample period. In sum, our main results are robust when using any index because the correlation between indices based on different employment weights exceeds 0.9. Table 3.6.2 shows the name of industry, S&P500 industry code, starting date, and employment share, when applicable.

3.6.2 Figures and Tables

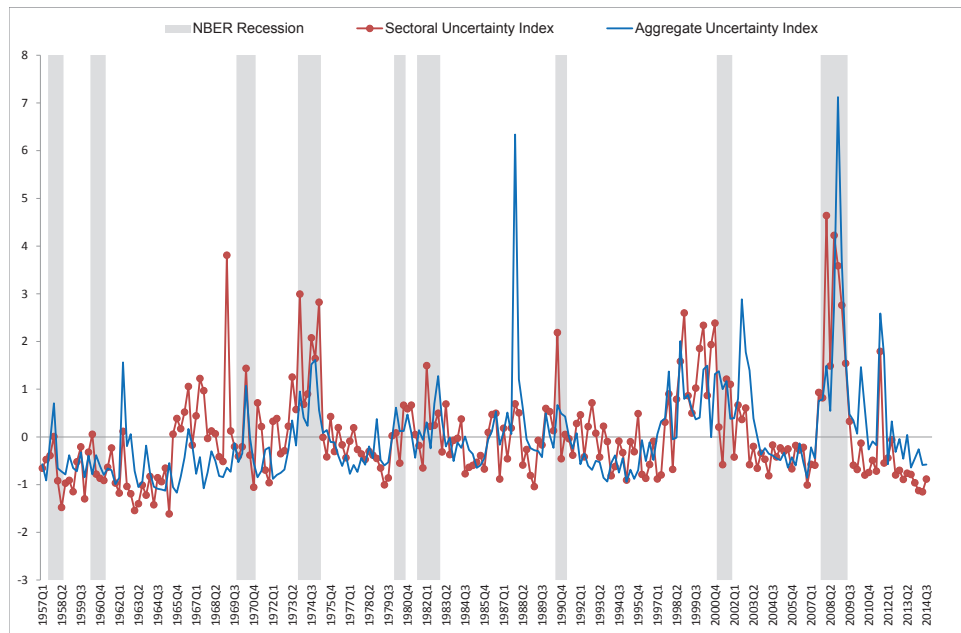


Figure 3.1: Uncertainty index

Notes: The shaded areas represent NBER recessions.

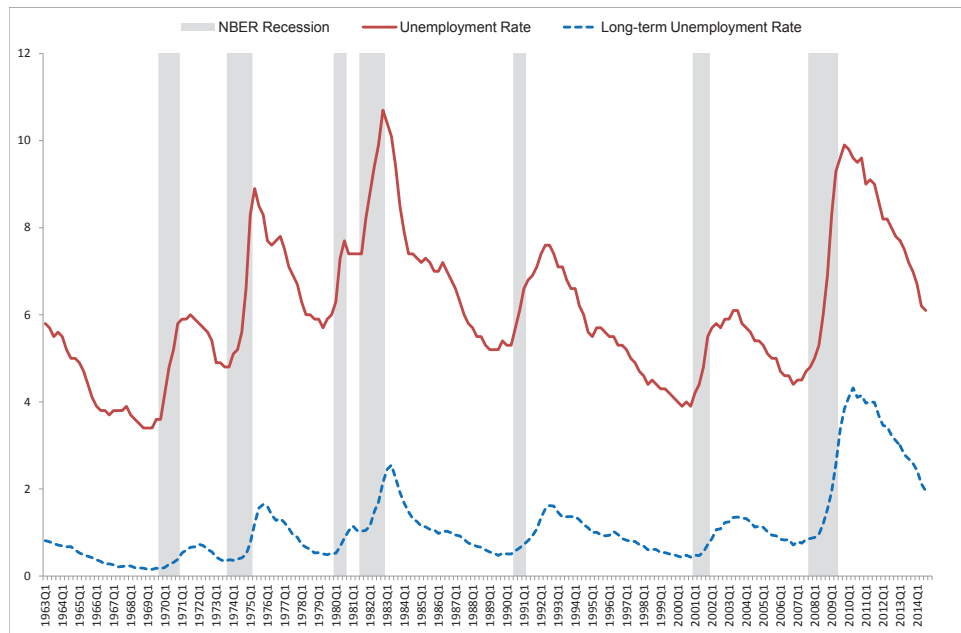


Figure 3.2: Unemployment rate (%)

Notes: The shaded areas represent NBER recessions.

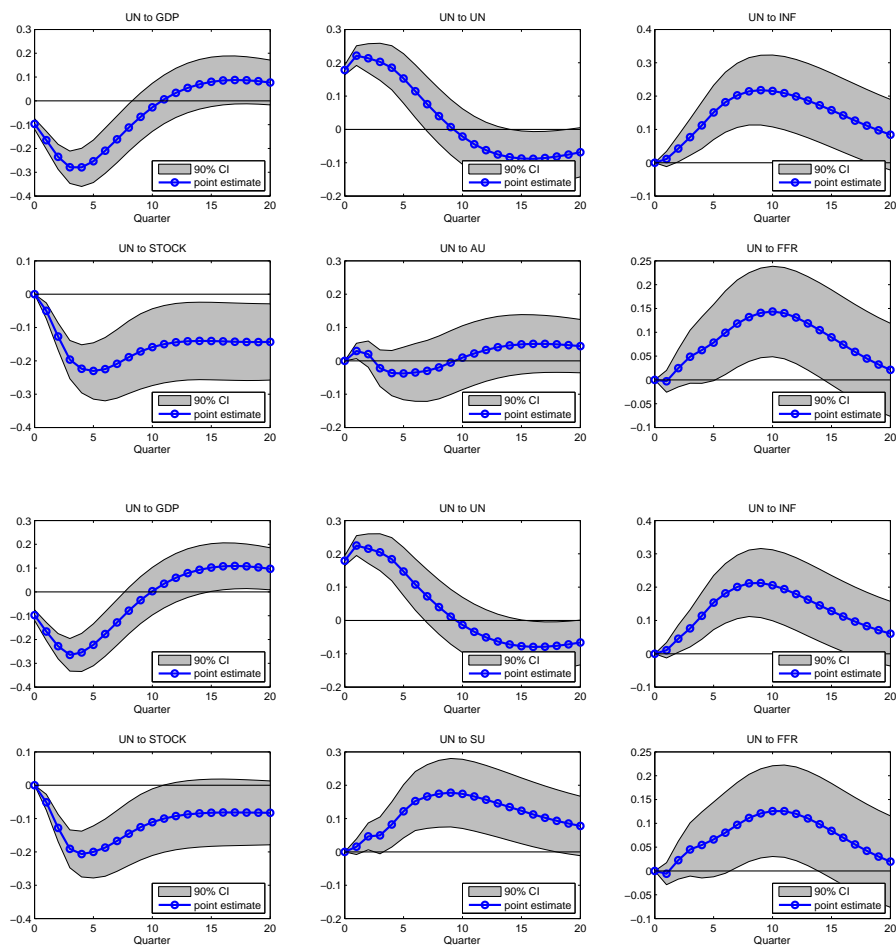


Figure 3.3: Response of the unemployment rate to various shocks in the baseline model

Notes: baseline model with aggregate uncertainty (top), baseline model with sectoral uncertainty (bottom)

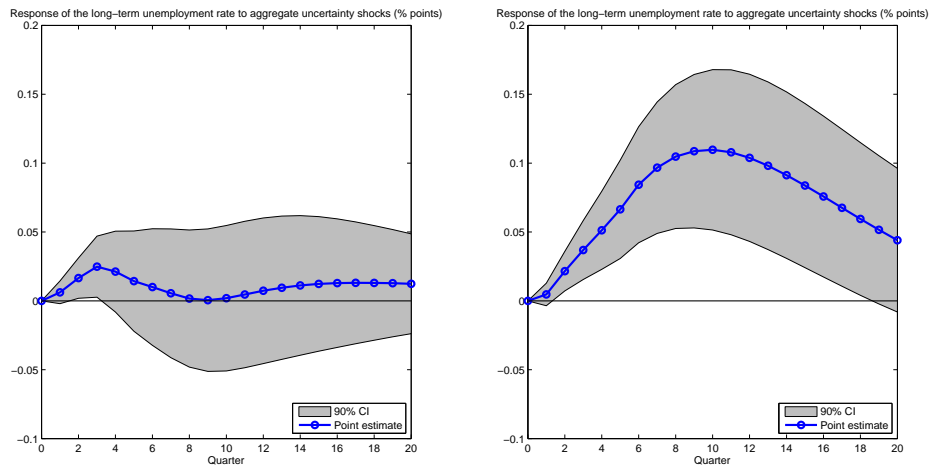


Figure 3.4: Effects of uncertainty shocks on the long-term unemployment rate

Notes: aggregate uncertainty (left), sectoral uncertainty (right)

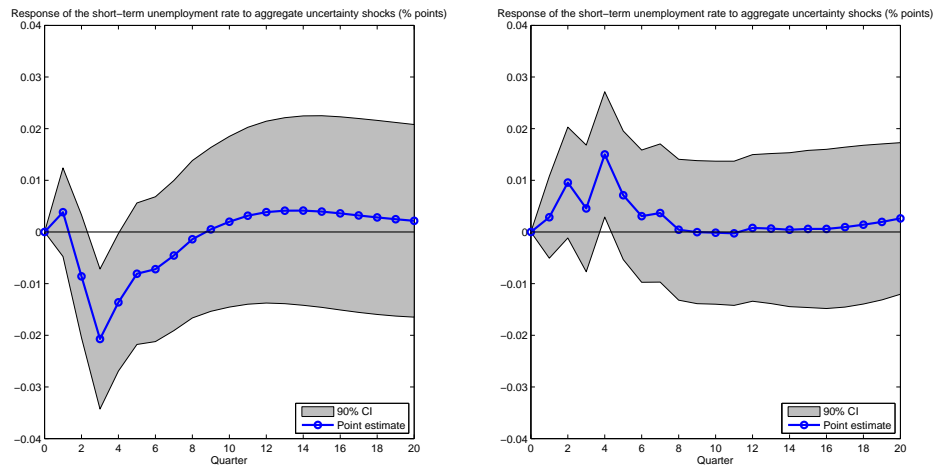


Figure 3.5: Effects of uncertainty shocks on the short-term unemployment rate

Notes: aggregate uncertainty (left), sectoral uncertainty (right)

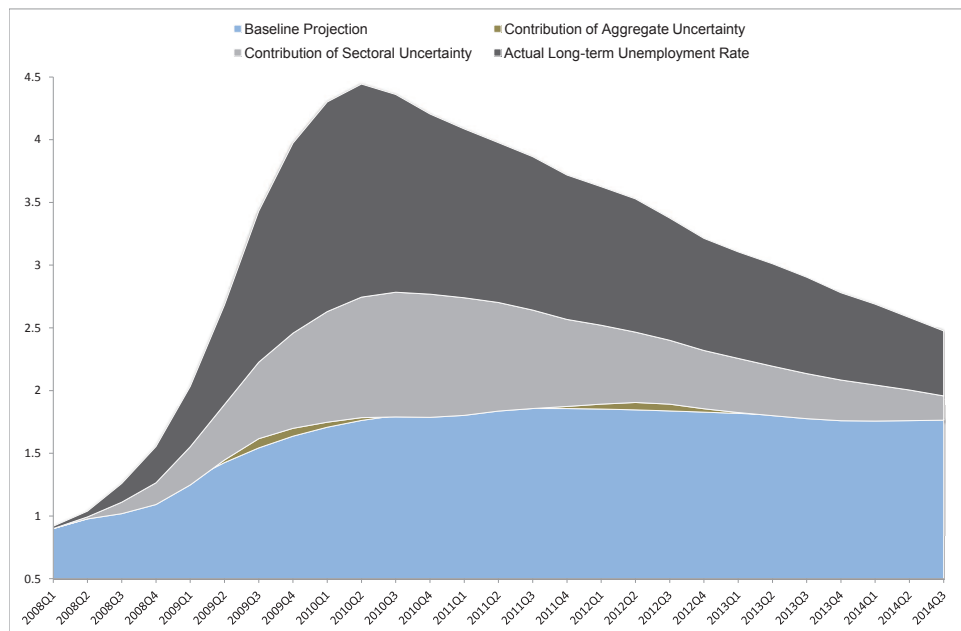


Figure 3.6: Contribution of uncertainty shocks to the long-term unemployment rate during the Great Recession

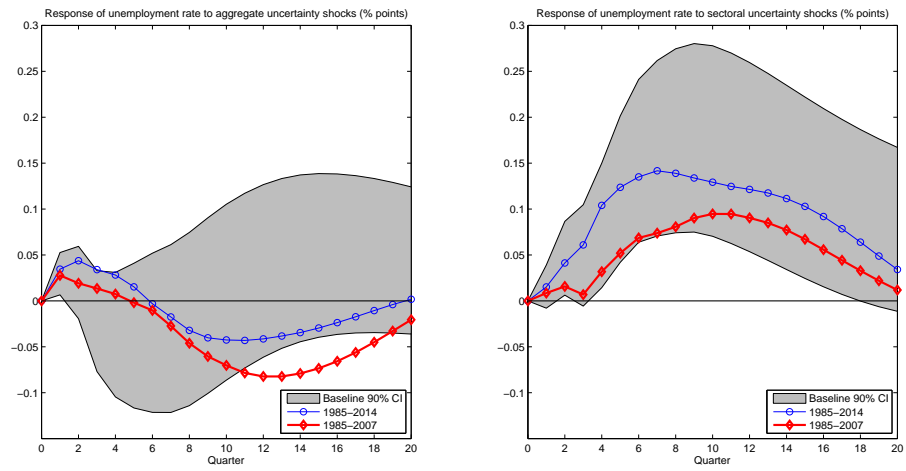


Figure 3.7: Sub-sample analysis

Notes: aggregate uncertainty (left), sectoral uncertainty (right)

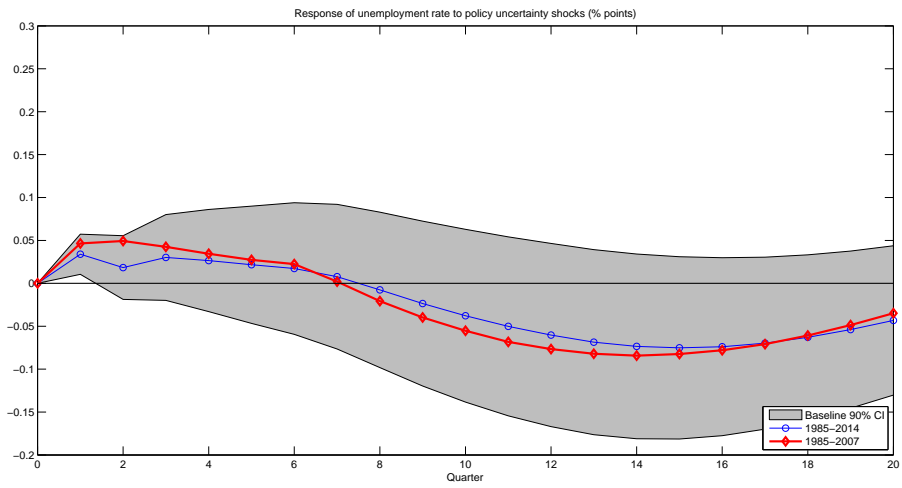


Figure 3.8: The effect of alternative measure of aggregate uncertainty shocks (economic policy uncertainty)

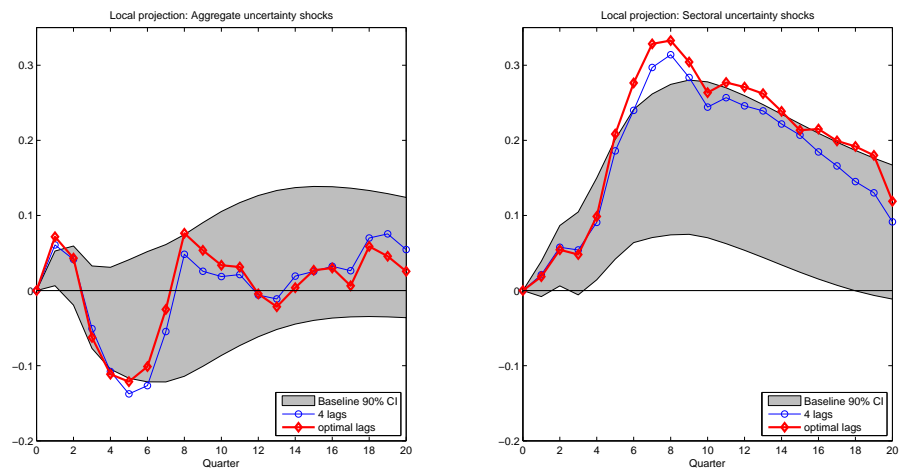


Figure 3.9: Robustness check: Impulse-response functions from a local projection method

Notes: aggregate uncertainty (left), sectoral uncertainty (right)

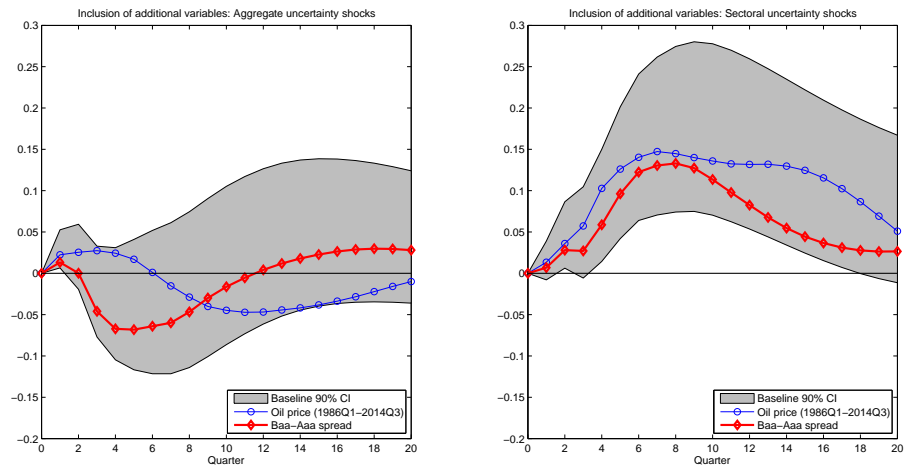


Figure 3.10: Robustness check: Inclusion of additional variables

Notes: aggregate uncertainty (left), sectoral uncertainty (right)

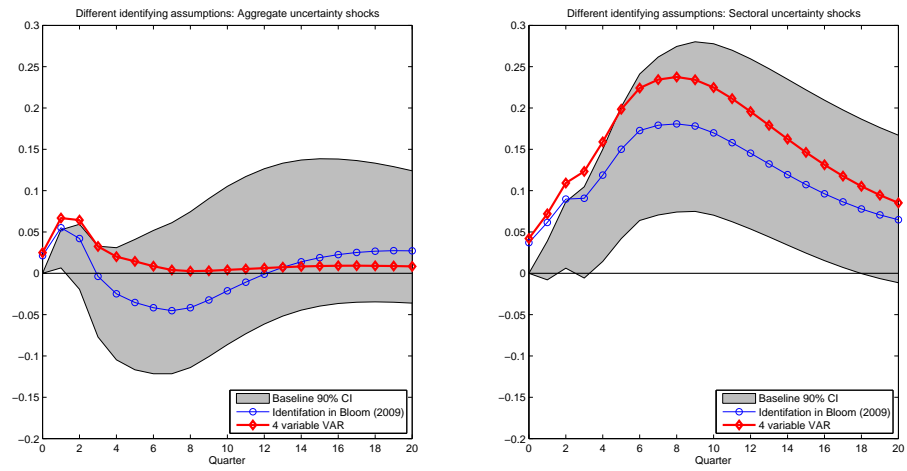


Figure 3.11: Robustness check: Different identifying assumptions

Notes: aggregate uncertainty (left), sectoral uncertainty (right)

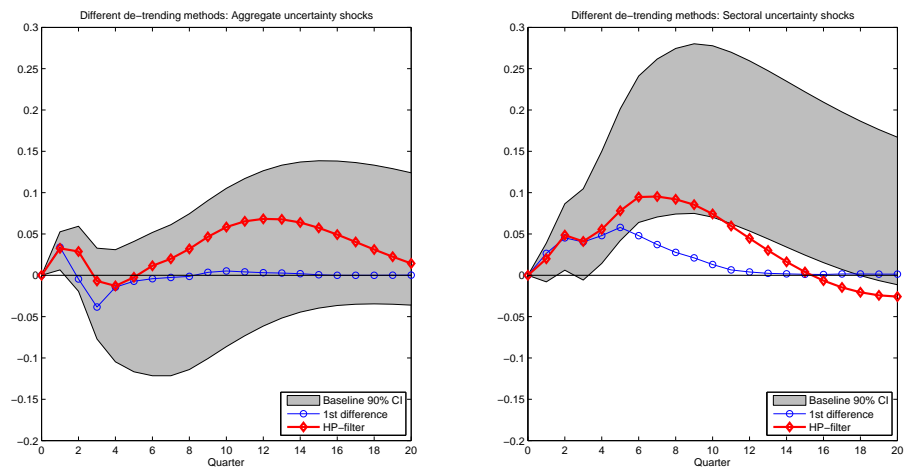


Figure 3.12: Robustness check: Various de-trending methods

Notes: aggregate uncertainty (left), sectoral uncertainty (right)

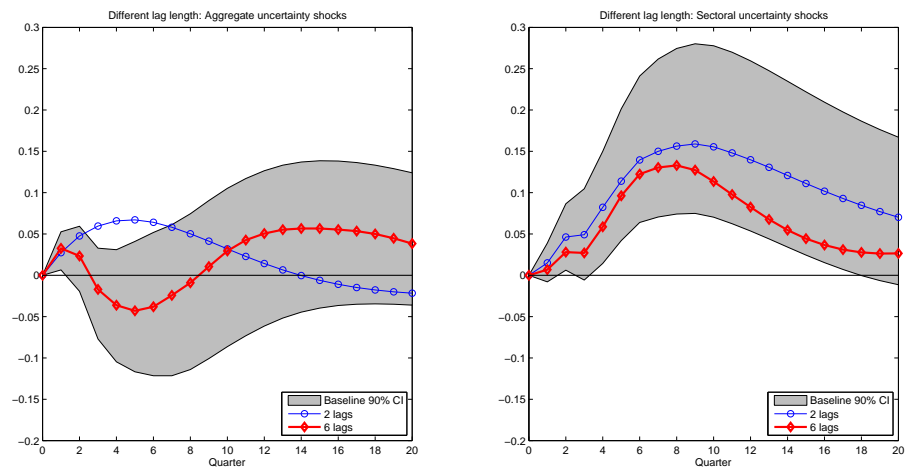


Figure 3.13: Robustness check: Different lag lengths

Notes: aggregate uncertainty (left), sectoral uncertainty (right)

Variable	Sectoral Uncertainty Index	Aggregate Uncertainty Index
Skewness	1.67	1.83
Kurtosis	6.75	9.14
1st Order Autocorr.	0.51	0.74
Corr w/ changes in real GDP	-0.27	-0.41
Corr w/ changes in inflation rate	0.08	0.01
Corr w/ changes in SP500	-0.39	-0.47
Corr w/ changes in unemployment rate	0.29	0.37
Corr w/ changes in Federal Funds Rate	-0.14	-0.22
Corr w/ changes in Crude oil price	0.09	0.16
Corr w/ Crude oil price volatility*	0.43	0.48
Corr w/ changes in Baa-Aaa spreads	0.24	0.48
Corr w/ aggregate uncertainty index	0.53	1

Table 3.1: Summary statistics

Notes: * refers for the period between 1986Q1 and 2014Q3.

horizon (quarter)	Less than 5 weeks	5 to 14 weeks	15 to 26 weeks	27+ weeks	Total
Aggregate Uncertainty					
4	2.71	1.18	0.98	1.22	0.43
8	2.48	2.71	1.12	0.61	0.64
12	1.58	2.11	1.00	0.41	0.53
16	1.28	1.81	1.04	0.44	0.86
20	1.12	1.70	1.11	0.55	1.26
Sectoral Uncertainty					
4	0.58	0.38	3.25	3.01	1.21
8	1.75	3.01	9.13	11.44	7.83
12	2.58	4.70	12.95	19.67	14.02
16	3.05	5.39	13.49	23.63	16.23
20	3.66	6.10	13.31	25.01	16.76

Table 3.2: Decomposition of the unemployment rate for different durations (%)

horizon (quarter)	Less than 5 weeks	5 to 14 weeks	15 to 26 weeks	27+ weeks	Total
Aggregate Uncertainty					
4	3.44	3.26	1.50	0.76	0.81
8	3.41	3.54	2.18	0.53	1.10
12	2.83	2.94	2.12	0.40	0.82
16	4.76	3.01	2.17	1.52	0.75
20	5.37	3.81	2.45	2.87	0.83
Sectoral Uncertainty					
4	0.73	0.11	2.70	4.17	1.51
8	5.26	8.00	12.20	12.08	12.70
12	4.80	8.35	13.01	17.60	17.11
16	6.57	10.53	12.86	18.22	19.45
20	5.96	10.12	12.37	18.39	19.15

Table 3.3: Decomposition of the unemployment rate for different durations with local projections (%)

SP500 Industry	SP500 Code	Starting period in GFD	Average Employment Share between 1990 and 2009 (%)	Employment Share in 2009 (%)
SP500 Aerospace and Defense	201010	May 18, 1928	3.093	2.162
SP500 Air Freight and Couriers	2031	January 6, 1965	3.702	3.318
SP500 Airlines	2032	May 18, 1928	0.354	0.277
SP500 Aluminum	15141	January 31, 1935	0.685	0.415
SP500 Apparel, Accessories, Luxury Goods	25231	November 30, 1913	1.451	0.353
SP500 Automobile Parts and Equipment	25111	January 7, 1970	1.403	1.586
SP500 Automobiles	251020	January 31, 1912	1.341	1.083
SP500 Brewers	30211	January 31, 1934	2.022	1.642
SP500 Building Products	2012	September 30, 1916	3.023	2.982
SP500 Chemicals Composite	1511	May 31, 1902	2.361	1.712
SP500 Commercial Banks	4011	January 31, 1941	0.674	0.471
SP500 Computer Hardware	45202010	March 31, 1911	0.751	0.864
SP500 Consumer Finance	40221	January 31, 1935	2.278	2.300
SP500 Department Stores	25531	October 31, 1909	3.413	3.319
SP500 Diversified Metals and Mining	15142	January 31, 1941	0.193	0.113
SP500 Drug Retail	30111	January 7, 1970	2.664	2.544
SP500 Electric Utilities	551010	January 31, 1918	1.245	1.209
SP500 Electrical Equipment	2014	January 31, 1918	1.194	0.699
SP500 Environmental Services	20201050	January 31, 1965	0.312	0.422
SP500 Food Retail	30113	October 31, 1909	1.525	2.016
SP500 Footware	25232	August 31, 1915	0.696	0.503
SP500 Gas Utilities	551020	January 31, 1941	0.895	0.704
SP500 General Merchandise	25503020	January 8, 1969	4.811	6.571
SP500 Gold	15143	January 31, 1941	0.070	0.044
SP500 Health Care Equipment	35101010	January 6, 1965	1.287	1.204
SP500 Homebuilding	25213	January 6, 1965	2.688	2.383
SP500 Hotels, Resorts and Cruise Lines	25312	January 6, 1965	5.607	6.597
SP500 Household Products	303010	December 31, 1925	0.295	0.248
SP500 Integrated Telecommunications	50112	January 31, 1871	2.137	2.209
SP500 Leisure Products	25221	January 6, 1965	0.496	0.362
SP500 Life and Health Insurance	40312	January 31, 1941	2.041	2.393
SP500 Machinery	201060	June 30, 1900	2.746	2.049
SP500 Metal and Glass Containers	15103010	December 31, 1925	2.942	2.958
SP500 Movies and Entertainment	25413	May 31, 1919	0.147	0.162
SP500 Multi-line Insurance	40313	January 3, 1968	0.795	0.784
SP500 Oil and Gas Equipment	10112	January 31, 1941	2.621	2.767
SP500 Oil, Gas and Consumable Fuels	101020	September 30, 1910	3.835	3.073
SP500 Packaged Foods and Meats	30202030	January 31, 1926	2.661	2.428
SP500 Paper and Forest	1515	August 31, 1898	1.004	0.572
SP500 Paper Packaging	15103020	January 31, 1941	1.118	0.686
SP500 Personal Products	3032	January 2, 1957	0.676	0.488
SP500 Pharmaceuticals	352020	November 30, 1916	6.761	9.579
SP500 Property and Casualty Insurance	40314	January 31, 1926	1.675	1.665
SP500 Publishing	25414	January 31, 1941	2.497	2.968
SP500 Railroads	20304010	January 31, 1871	0.464	0.370
SP500 Restaurants	25301040	January 6, 1965	11.753	13.555
SP500 Semiconductors	45205020	January 8, 1969	2.142	2.174
SP500 Soft Drinks	30213	January 31, 1926	0.060	0.045
SP500 Steel	15145	January 31, 1887	0.915	0.570
SP500 Tobacco	3023	January 31, 1912	0.295	0.243

Table 3.4: Industrial composition of the sectoral uncertainty index

Variable	Note	Source
Real GDP	Billions of Chained 2009 Dollar: Available from 1963Q1 to 2014Q3	Federal Reserve Economic Data
Unemployment Rate	Quarterly average of monthly data at different durations: Available from 1963Q1 to 2014Q3	Bureau of Labor Statistics
Inflation Rate	Year-to-year growth rate of CPI: Available from 1963Q1 to 2014Q3	Federal Reserve Economic Data
Federal Fund Rate	Quarterly average of monthly data: Available from 1963Q1 to 2014Q3	Federal Reserve Economic Data
Crude Oil Price Volatility	Quarterly standard deviation of daily returns of Crude oil price: Available from 1986Q1 to 2014Q3	Federal Reserve Economic Data
Baa-Aaa Spreads	Moody's Baa - Aaa Corporate Bond Yield: Available from 1963Q1 to 2014Q3	Federal Reserve Economic Data
Aggregate Uncertainty Index	Quarterly average of Bloom's monthly uncertainty index	Bloom (2009)
Sectoral Uncertainty Index	Cross-sectoinal dispersion of quar- terly SP500 industrial returns: Availabe from 1963Q1 to 2014Q3	Global Financial Data
Economic Policy Uncertainty Index	Quarterly average of monthly data: Available from 1985Q1 to 2014Q3	Baker, Bloom and Davis (2012)

Table 3.5: Data description

Variable	Test statistics	p-value
Levels		
Real GDP	-1.463	0.8414
Unemployment Rate	-1.493	0.8316
Inflation Rate	-2.44	0.3587
Federal Fund Rate	-2.456	0.5992
S&P500	-2.004	0.3502
Crude Oil Price	-2.328	0.4186
Baa-Aaa Spreads	-3.336	0.0605
Aggregate Uncertainty Index	-5.642	0
Sectoral Uncertainty Index	-8.104	0
First differences		
Real GDP	-10.507	0
Unemployment Rate	-6.655	0
Inflation Rate	-9.749	0
Federal Fund Rate	-11.288	0
S&P500	-13.135	0

Table 3.6: Augmented Dickey-Fuller test

BIBLIOGRAPHY

- Adrian, Tobias and Shin, Hyun Song. Procyclical leverage and value-at-risk. *Review of Financial Studies*, 27(2):373–403, 2014.
- Ahmed, Shaghil and Zlate, Andrei. Capital flows to emerging market economies: A brave new world? *Journal of International Money and Finance*, 2014.
- Akıncı, Özge. Global financial conditions, country spreads and macroeconomic fluctuations in emerging countries. *Journal of International Economics*, 91(2): 358–371, 2013.
- Alexopoulos, Michelle and Cohen, Jon. Uncertain times, uncertain measures. *University of Toronto Department of Economics Working Paper*, 352, 2009.
- Bacchetta, Philippe and Van Wincoop, Eric. Sudden spikes in global risk. *Journal of International Economics*, 89(2):511–521, 2013.
- Bachmann, Rüdiger and Bayer, Christian. ‘Wait-and-see’ business cycles? *Journal of Monetary Economics*, 60(6):704–719, 2013.
- Bachmann, Rüdiger, Elstner, Steffen, and Sims, Eric R. Uncertainty and economic activity: Evidence from business survey data. *American Economic Journal: Macroeconomics*, 5(2):217–49, 2013.
- Baker, Scott R, Bloom, Nicholas, and Davis, Steven J. Measuring economic policy uncertainty. *Manuscript*, 2013.
- Ball, Laurence M, Leigh, Daniel, and Loungani, Prakash. Okun’s law: Fit at fifty? *NBER Working Papers*, 2013.
- Basak, Suleyman and Shapiro, Alexander. Value-at-risk-based risk management: Optimal policies and asset prices. *Review of Financial studies*, 14(2):371–405, 2001.

- Bassett, William F, Chosak, Mary Beth, Driscoll, John C, and Zakrajšek, Egon. Changes in bank lending standards and the macroeconomy. *Journal of Monetary Economics*, 2014.
- Basu, Susanto and Bundick, Brent. Uncertainty shocks in a model of effective demand. *NBER Working Papers*, 2012.
- Beaudry, Paul and Portier, Franck. Stock prices, news and economic fluctuations. *American Economic Review*, 96(4):1293–1307, 2006.
- Beetsma, Roel and Giuliodori, Massimo. The changing macroeconomic response to stock market volatility shocks. *Journal of Macroeconomics*, 34(2):281–293, 2012.
- Bekaert, Geert, Hoerova, Marie, and Lo Duca, Marco. Risk, uncertainty and monetary policy. *Journal of Monetary Economics*, 60(7):771–788, 2013.
- Benhabib, Jess and Farmer, Roger E. Indeterminacy and sunspots in macroeconomics. *Handbook of Macroeconomics*, 1:387–448, 1999.
- Bernanke, Ben, Gertler, Mark, and Gilchrist, Simon. The financial accelerator and the flight to quality. *The Review of Economics and Statistics*, 78(1):1–15, 1996.
- Bernanke, Ben S, Boivin, Jean, and Eliasziw, Piotr. Measuring the effects of monetary policy: A factor-augmented vector autoregressive (favar) approach. *The Quarterly Journal of Economics*, 120(1):387–422, 2005.
- Blanchard, Olivier Jean. A traditional interpretation of macroeconomic fluctuations. *The American Economic Review*, pages 1146–1164, 1989.
- Bloom, Nicholas. The impact of uncertainty shocks. *Econometrica*, 77(3):623–685, 2009.

- Bloom, Nicholas, Floetotto, Max, Jaimovich, Nir, Saporta-Eksten, Itay, and Terry, Stephen J. Really uncertain business cycles. 2012.
- Born, Benjamin, Breuer, Sebastian, and Elstner, Steffen. Uncertainty and the great recession. *Manuscript*, 2014.
- Brainard, S Lael and Cutler, David M. Sectorial shifts and cyclical unemployment reconsidered. *The Quarterly Journal of Economics*, pages 219–243, 1993.
- Burger, John D, Sengupta, Rajeswari, Warnock, Francis E, and Warnock, Veronica Cacadac. US investment in global bonds: As the Fed pushes, some EMEs pull. *NBER Working Paper*, 2014.
- Caballero, Ricardo J and Krishnamurthy, Arvind. International and domestic collateral constraints in a model of emerging market crises. *Journal of Monetary Economics*, 48(3):513–548, 2001.
- Caggiano, Giovanni, Castelnuovo, Efrem, and Groshenny, Nicolas. Uncertainty shocks and unemployment dynamics in us recessions. *Journal of Monetary Economics*, 67:78–92, 2014.
- Cairns, John, Ho, Corrinne, and McCauley, Robert. Exchange rates and global volatility: implications for asia-pacific currencies. *BIS Quarterly Review*, 2007: 41–52, 2007.
- Caldara, Dario, Fuentes-Albero, Cristina, Gilchrist, Simon, and Zakrajsek, E. The macroeconomic impact of financial and uncertainty shocks. *Manuscript*, 2014.
- Campbell, John Y and Hentschel, Ludger. No news is good news: An asymmetric model of changing volatility in stock returns. *Journal of financial Economics*, 31(3):281–318, 1992.

- Carrière-Swallow, Yan and Céspedes, Luis Felipe. The impact of uncertainty shocks in emerging economies. *Journal of International Economics*, 90(2):316–325, 2013.
- Cesa-Bianchi, Ambrogio and Fernandez-Corugedo, Emilio. Uncertainty in a model with credit frictions. *Bank of England Working Paper*, 2014.
- Choi, Sangyup. Are the effects of Bloom’s uncertainty shocks robust? *Economics Letters*, 119(2):216–220, 2013.
- Christiano, Lawrence J, Motto, Roberto, and Rostagno, Massimo. Risk shocks. *American Economic Review*, 104(1):27–65, 2014.
- Chudik, Alexander and Fratzscher, Marcel. Identifying the global transmission of the 2007–2009 financial crisis in a gvar model. *European Economic Review*, 55(3):325–339, 2011.
- Ciarlone, Alessio, Piselli, Paolo, and Trebeschi, Giorgio. Emerging markets’ spreads and global financial conditions. *Journal of International Financial Markets, Institutions and Money*, 19(2):222–239, 2009.
- Clarida, Richard, Gali, Jordi, and Gertler, Mark. Monetary policy rules and macroeconomic stability: Evidence and some theory. *Quarterly Journal of Economics*, pages 147–180, 2000.
- Davis, Steven J and Haltiwanger, John. Sectoral job creation and destruction responses to oil price changes. *Journal of Monetary Economics*, 48(3):465–512, 2001.
- De Bock, Reinout and Carvalho Filho, Irineu E. The behavior of currencies during risk-off episodes. *IMF Working Papers*, 2013.
- Dixit, Avinash K. *Investment under uncertainty*. Princeton university press, 1994.

- Djankov, Simeon, Hart, Oliver, McLiesh, Caralee, and Shleifer, Andrei. Debt enforcement around the world. *Journal of Political Economy*, 116(6), 2008.
- Fama, Eugene F. Stock returns, expected returns, and real activity. *The Journal of Finance*, 45(4):1089–1108, 1990.
- Farmer, Roger E. The stock market crash of 2008 caused the Great Recession: Theory and evidence. *Journal of Economic Dynamics and Control*, 36(5):693–707, 2012.
- Fernández-Villaverde, Jesús and Guerrón-Quintana, Pablo. Risk matters: The real effects of volatility shocks. *American Economic Review*, 101:2530–2561, 2011.
- Fornari, Fabio and Mele, Antonio. Financial volatility and economic activity. *Journal of Financial Management Markets and Institutions*, 1(2):155–196, 2010.
- Fratzscher, Marcel. Capital flows, push versus pull factors and the global financial crisis. *Journal of International Economics*, 88(2):341–356, 2012.
- García-Cicco, Javier, Pancrazi, Roberto, and Uribe, Martín. Real business cycles in emerging countries? *American Economic Review*, 100(5):2510–2531, 2010.
- Gilchrist, Simon, Sim, Jae W, and Zakrajšek, Egon. Uncertainty, financial frictions, and investment dynamics. *NBER Working Papers*, 2014.
- González-Rozada, Martín and Yeyati, Eduardo Levy. Global factors and emerging market spreads. *The Economic Journal*, 118(533):1917–1936, 2008.
- Gourio, François. Disaster risk and business cycles. *The American Economic Review*, 102(6):2734–2766, 2012.
- Gourio, Francois, Siemer, Michael, and Verdelhan, Adrien. International risk cycles. *Journal of International Economics*, 89(2):471–484, 2013.

- Hevia, Constantino. Emerging market fluctuations: what makes the difference? *Journal of International Economics*, 2014.
- Jordà, Òscar. Estimation and inference of impulse responses by local projections. *American economic review*, pages 161–182, 2005.
- Jurado, Kyle, Ludvigson, Sydney C, and Ng, Serena. Measuring uncertainty. *American Economic Review*, 105(3):1177–1216, 2015.
- Kaminsky, Graciela L and Reinhart, Carmen M. On crises, contagion, and confusion. *Journal of International Economics*, 51(1):145–168, 2000.
- Kodres, Laura E and Pritsker, Matthew. A rational expectations model of financial contagion. *The Journal of Finance*, 57(2):769–799, 2002.
- Kumar, Manmohan S and Persaud, Avinash. Pure contagion and investors' shifting risk appetite: Analytical issues and empirical evidence. *International Finance*, 5(3):401–436, 2002.
- Kyle, Albert S and Xiong, Wei. Contagion as a wealth effect. *The Journal of Finance*, 56(4):1401–1440, 2001.
- Leduc, Sylvain and Liu, Zheng. Uncertainty shocks are aggregate demand shocks. *Federal Reserve Bank of San Francisco Working Paper*, 10, 2013.
- Lilien, David M. Sectoral shifts and cyclical unemployment. *The Journal of Political Economy*, pages 777–793, 1982.
- Lin, Jin-Lung and Tsay, Ruey S. Co-integration constraint and forecasting: An empirical examination. *Journal of Applied Econometrics*, 11(5):519–538, 1996.
- Lizarazo, Sandra Valentina. Default risk and risk averse international investors. *Journal of International Economics*, 89(2):317–330, 2013.

- Loungani, Prakash. Oil price shocks and the dispersion hypothesis. *The Review of Economics and Statistics*, pages 536–539, 1986.
- Loungani, Prakash, Rush, Mark, and Tave, William. Stock market dispersion and unemployment. *Journal of Monetary Economics*, 25(3):367–388, 1990.
- Lubik, Thomas A and Schorfheide, Frank. Testing for indeterminacy: an application to us monetary policy. *American Economic Review*, pages 190–217, 2004.
- Mathy, Gabriel. Stock market jumps and uncertainty shocks during the Great Depression. *Manuscript*, 2014.
- Matsumoto, Akito. Global liquidity: Availability of funds for safe and risky assets. *IMF Working Papers*, pages 1–36, 2011.
- McConnell, Margaret M and Perez-Quiros, Gabriel. Output fluctuations in the united states: What has changed since the early 1980's? *American Economic Review*, 90(5):1464–1476, 2000.
- Mendoza, Enrique G and Yue, Vivian Z. A general equilibrium model of sovereign default and business cycles. *The Quarterly Journal of Economics*, 127(2):889–946, 2012.
- Neumeyer, Pablo A and Perri, Fabrizio. Business cycles in emerging economies: the role of interest rates. *Journal of Monetary Economics*, 52(2):345–380, 2005.
- Nodari, Gabriela. Financial regulation policy uncertainty and credit spreads in the us. *Journal of Macroeconomics*, 41:122–132, 2014.
- Novy, Dennis and Taylor, Alan M. Trade and uncertainty. *NBER Working Paper*, 2014.

- Pavlova, Anna and Rigobon, Roberto. The role of portfolio constraints in the international propagation of shocks. *The Review of Economic Studies*, 75(4): 1215–1256, 2008.
- Phillips, Peter CB. Impulse response and forecast error variance asymptotics in nonstationary vars. *Journal of Econometrics*, 83(1):21–56, 1998.
- Ranciere, Romain, Tornell, Aaron, and Vamvakidis, Athanasios. Currency mismatch, systemic risk and growth in emerging europe. *Economic Policy*, 25(64): 597–658, 2010.
- Sahay, Ratna, Arora, Vivek, Arvanitis, Thanos, Faruquee, Hamid, N'Diaye, Papa, and Griffoli, Tommaso Mancini. Emerging market volatility: Lessons from the taper tantrum. *IMF Staff Discussion Note*, 2014.
- Schinasi, Garry J and Smith, R Todd. Portfolio diversification, leverage, and financial contagion. *IMF Staff Papers*, 47(2):159, 2000.
- Schmitt-Grohé, Stephanie and Uribe, Martin. Pegs and pain. *NBER Working Paper*, 2011.
- Schneider, Martin and Tornell, Aaron. Balance sheet effects, bailout guarantees and financial crises. *The Review of Economic Studies*, 71(3):883–913, 2004.
- Schwert, G William. Stock volatility during the recent financial crisis. *European Financial Management*, 17(5):789–805, 2011.
- Shin, Kwanho. Inter-and intrasectoral shocks: effects on the unemployment rate. *Journal of Labor Economics*, pages 376–401, 1997.
- Sims, Christopher A, Stock, James H, and Watson, Mark W. Inference in linear time series models with some unit roots. *Econometrica: Journal of the Econometric Society*, pages 113–144, 1990.

- Tornell, Aaron and Westermann, Frank. The credit channel in middle income countries. *NBER Working Paper*, 2002.
- Uribe, Martin and Yue, Vivian Z. Country spreads and emerging countries: Who drives whom? *Journal of International Economics*, 69(1):6–36, 2006.
- Van Rijckeghem, Caroline and Weder, Beatrice. Spillovers through banking centers: a panel data analysis of bank flows. *Journal of International Money and Finance*, 22(4):483–509, 2003.
- Whaley, Robert E. Understanding the VIX. *The Journal of Portfolio Management*, 35(3):98–105, 2009.
- Yeyati, Eduardo Levy. Financial dollarization: evaluating the consequences. *Economic Policy*, 21(45):61–118, 2006.