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이 논문을 경제학 박사 학위논문으로 제출함

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Abstract

The financial economy has grown rapidly with technology development. Financial assets are becoming more accessible to people, and this is increasing the impact of the financial economy on the real economy. Thus, many studies are needed to analyze the more accurate impact of the financial economy. This dissertation aims to analyze the financial economy with three separate essays.

The first chapter analyzes how bond market development affects the pass-through of monetary policy to bank lending rates by using panel data of 36 countries. As the measure of bond market development, we use the ratio of outstanding bonds to GDP. Results show that the degree of monetary policy pass-through to lending rates are significantly changed by bond market development. The effect of bond market development is robust under various specifications of the empirical model.

The second chapter studies asymmetric responses of economic agents to the uncertainty shock. Using a smooth local projection (SLP) method, study shows that macro variables have asymmetric responses to the increasing and decreasing VXO shocks and calibrate the asymmetric uncertainty shock process in a DSGE model using the empirical result. Model estimation results show that a positive uncertainty shock have lower persistence and higher volatile than a negative uncertainty shock. Furthermore, price stickiness and risk aversion affect asymmetry of responses to uncertainty shocks.

The third chapter analyzes the dynamic relationship between the US stock and treasury bonds while considering spillover effects. Moving average terms and stock volume changes are used to measure the risk spillover and financial information spillover, respectively. Empirical results show three important implications in US financial markets. First, the stock market return and volatility decrease the bond market return, whereas the bond market return and volatility have no effects on the stock return. Second, spillover effects are observed in US financial markets and spillover effects vary depending on market conditions. Third, spillover effects affect the conditional second moments relations between the stock and bond returns. The findings provide an important implication for financial portfolio investors and policy makers.

Keyword: The financial economy, Monetary policy pass-through, Uncertainty, Smooth local projection, DSGE model, Stock-bond relations
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Table of Contents

ABSTRACT .... **I**

TABLE OF CONTENTS .... **III**

LIST OF TABLES .... **V**

LIST OF FIGURES .... **VII**

CHAPTER 1. Bond Market Development and Monetary Policy Pass-Through to Bank Lending Rates **1**

1.1. INTRODUCTION 1

1.2. DATA AND METHODOLOGY 5

1.2.1. Empirical Methodology 5

1.2.2. Data 6

1.3. BASELINE MODEL RESULTS 9

1.4. EXTENDED ANALYSIS 11

1.5. CONCLUSION 20

CHAPTER 2. Asymmetric uncertainty shocks in a DSGE model **24**

2.1. INTRODUCTION 24

2.2. EMPIRICAL WORKS 27

2.3. DSGE MODEL 32

2.4. RESULT 42

2.5. FURTHER ANALYSIS 43

2.6. CONCLUSION 45

CHAPTER 3. Dynamic relationships between stocks and treasury bonds with spillover effects: Evidence from US financial markets **48**

3.1. INTRODUCTION 48

3.2. LITERATURE REVIEW 50

3.3. DATA 53

3.4. METHODOLOGY AND RESULTS 54

3.4.1. Univariate EGARCH (1,1)-M models 54

3.4.2. Multivariate EGARCH (1,1)-M models 56
3.5. CONCLUSIONS 69

REFERENCES **72**

TABLES **72**

FIGURES **110**

APPENDIX **135**

ABSTRACT IN KOREAN **142**

List of Tables

[Table 1.1] Summary Statistics 79
[Table 1.2] Summary Statistics of the Measure of Bond Market Development 80
[Table 1.3] Correlation Matrix 81
[Table 1.4] Results of Baseline Model 1 (Random vs. Individual Fixed Effects) 82
[Table 1.5] Results of Baseline Model 1(Individual Fixed Effects vs. Individual and Time Fixed Effects) 83
[Table 1.6] Results of Baseline Model 2 (Random vs. Individual Fixed Effects) 84
[Table 1.7] Results of Baseline Model 2 (Individual Fixed Effects vs. Individual and Time Fixed Effects) 85
[Table 1.8] Results of Model with Macro Variables 1 86
[Table 1.9] Results of Model with Macro Variables 2 87
[Table 1.10] Results of the model with the financial corporate bond market index 88
[Table 1.11] Results of the model with the non-financial corporate bond market index. 89
[Table 1.12] Results of the model with subgroup countries (Financial bond) 90
[Table 1.13] Results of the model with subgroup countries (Nonfinancial bond) 91
[Table 1.14] Results of the Model with Lagged Effects 92
[Table 1.15] Results of the model with bank characteristic measurements.. 93
[Table 2.1] Testing the asymmetry of the response 94

[Table 2.2] Testing the asymmetry of the response (Multipliers)............ 95
[Table 2.3] Parameter values 96
[Table 2.4] Empirical and model-implied volatility 97
[Table 3.1] Summary Statistics.. 98
[Table 3.2] EGARCH (1,1)-M Model Estimation Results 99
[Table 3.3] Multivariate EGARCH (1,1)-M Model Estimation Results .. 100
[Table 3.4] Multivariate EGARCH (1,1)-M Model with Stock Volume Changes Estimation Results 101
[Table 3.5] Multivariate EGARCH (1,1)-M with Spillovers Model Estimation Results 102
[Table 3.6] Multivariate EGARCH-M Spillover Model Estimation Results (Crisis periods) 103
[Table 3.7] Multivariate EGARCH-M Spillover Model Estimation Results (Non-crisis periods) 104
[Table 3.8] Correlations between the Stock Market and Bond Markets .. 105
[Table 3.9] Difference among DCCs 106
[Table 3.10] Portfolios Conditional Risk.. 107
[Table 3.11] Portfolios Conditional Risk (Crisis periods) 108
[Table 3.12] Portfolios Conditional Risk (Non-crisis periods)............ 109

List of Figures

[Figure 1.1] Bond Market Development 110

[Figure 2.1] Chicago Board Options Exchange (CBOE) Standard & Poor's 100 volatility index (VXO) 119

[Figure 2.2.1] Empirical impulse response to VXO shocks 120

[Figure 2.2.2] Empirical impulse response to VXO shock.................. 121

[Figure 2.3] The mean value of the output multipliers........................ 122

[Figure 2.4.1] Model implied responses to uncertainty shocks 123

[Figure 2.4.2] Model implied responses to uncertainty shocks 124

[Figure 2.5] Distance of VXO between responses to asymmetry shocks 125

[Figure 2.7] Distance of key macro variables between responses to asymmetry shocks (Habit persistence) 127

[Figure 2.8] Distance of key macro variables between responses to asymmetry shocks (Risk aversion).. 128

[Figure 2.9] Distance of key macro variables between responses to asymmetry shocks (Extreme model vs Baseline model)...................... 129

[Figure 3.1] Stock index and bond excess yields 130

[Figure 3.2] Correlations between the stock and thirty-year bond markets . 131

[Figure 3.3] Correlations between the stock and ten-year bond markets . 132

[Figure 3.4] Correlations between the stock and one-year bond markets 133

[Figure 3.5] Correlations between the stock and bond markets 134

Chapter 1. Bond Market Development and Monetary Policy Pass-Through to Bank Lending Rates

1.1. Introduction

The monetary policy of central banks can have a significant effect on the economy in the short run. When monetary policy action takes the form of policy rate adjustment, its impact will be transmitted to the economy via various channels. For example, the policy rate changes will affect the exchange rate (i.e. exchange rate channel), bond yield and stock market index (i.e. capital market channel), and bank lending rates (i.e. bank lending channel). In this paper, we are interested in the bank lending channel (1995) [e.g. Bernanke and Gertler (1995) and Kashayp and Stein (1994)]. In particular, we empirically analyze whether bond market development improves the pass-through of monetary policy to bank lending rates.

There are two channels that the bond market development can affect the degree of monetary policy pass-through to bank lending rates.

First, the degree of pass-through likely increase as the bond market develops in the firm financing channel. Suppose that the central bank cuts the interest rate. Lower interest rates reduce bond yields, which in turn induces banks to cut their lending rates. The extent to which the banks will cut their lending rates in response to changes in bond yields depends on the level of bond market development. If the bond market is relatively small and underdeveloped, the response of banks will be limited. On the other hand, if the bond market is large and well developed, lower bond yields will exert more pressure on banks to reduce their lending rates since bond markets pose a greater competitive threat to banks.

Second, the degree of pass-through likely move either ways as the bond market develops in the bank financing channel. Banks can raise funds for a loan from interbank transactions and the bond market. When the central bank raises the interest rate, both call rates and bank bond issuance rates rise. Rising call rates and bank bond issuance rates increase the cost of bank financing. Higher call rates increase the incentive for banks to raise funds from the bond market (i.e. funding substitution effect). As the bond market is large and well developed, bank ease to raise funds from the bond market. Therefore, banks have an incentive not to raise lending rates as much as the rise in policy rates. However, higher bank bond issuance rates decrease an incentive for funding from the bond market (i.e. funding cost effect). In this case, bond market issuance rates increase as much as the rise in policy rates as the bond market is well developed. Therefore, the bond market becomes less attractive for banks to financing. It is not clear which effects dominated and may vary depending on market conditions. Suppose the bond market is large and well developed. If the bank mainly raises its funds through interbank transactions, the bond market become a competitor for bank financing and funding substitution effect dominate the funding cost effect. Therefore, the degree of pass-through likely decrease. On the other hand, if the bank mainly raises its funds from the bond market, the funding cost effect dominate the funding substitution effect and the degree of pass-through likely increase.

In this paper, we empirically investigate how bond market development influences the pass-through of monetary policy to bank lending rates by running panel regressions using monthly lending and call rates data and quarterly bond markets data from 36 countries. Our dataset is an unbalanced panel which begins in different periods but ends in June 2019. Our sample includes US financial crisis and EU debt crisis periods.

Therefore, we use the call rates instead of monetary policy rates to avoid zero lower bound and consider quantitative easing. To measure the degree of bond market development, we employ the ratio of total outstanding bonds to GDP. This measure captures the depth of the bond market, and it is a widely used indicator of bond market development—for example, World Bank (2006) and Park, Shin and Tian (forthcoming).

In our empirical analysis, we first measure the degree of monetary policy pass-through to bank lending rates by regressing lending rate changes on call rate changes. Then, to investigate the effects of bond market development on the degree of pass-through, we add the cross-term of call rate changes and the effects of bond market development. A positive coefficient on the cross-term implies that bond market development strengthens the degree of monetary policy pass-through to bank lending rate. To investigate the robustness of our results, we extend our analysis in various directions. More specifically, we control for key macro variables such inflation rate and growth rate as well as dynamic interactions among variables. In addition, we investigate the role of financial corporate and non-financial corporate bonds.

There are some past studies on monetary policy pass-through to lending rates. Salachas, Laopodis, and Kouretas (2017) assessed the influence of monetary policy on the bank-lending channel before and after global financial crisis. They find that the central bank's interest rates had a significant effect on bank lending rates during before the crisis, but the effect weakened after the crisis. Cottarelli and Kourelis (1994) developed a systematic measure for the degree of responsiveness of bank lending rates to money market rates. Donnay and Degryse (2001) investigated the pass-through of money market rate to several bank lending rates in twelve European countries during 1980-2000. Using bank-level data from eighteen Asian and Latin American economies in 1996-2006, Olivero, Li and Jeon (2011, A) find that as concentration in banking increases, the bank lending channel is weakened, rendering monetary policy transmission less effective. Blot and Labondance (2013) examined how the global financial crisis affected the pass-through from money market rates to bank lending rates in the eurozone. Altavilla, Canova, and Ciccarelli (2020) analyzed the pass-through of monetary policy measures to lending rates to households and firms in the euro area using bank level datasets.

However, relatively few studies investigated determinants of the degree of pass-through. Olivero, Li, and Jeon (2011, B) investigated the effects of banking competition on the pass-through. Cottarelli and Kourelis (1994) examined the role of the structural features of the financial system, such as the existence of barriers to competition, the degree of development of financial markets, and the ownership structure of the banking system. Altavilla, Canova, and Ciccarelli (2020) considered banks' characteristics such as the capital ratio, exposure to domestic sovereign debt, percentage of non-performing loans, and stability of funding structure.

In addition, some studies analyzed the influence of nonfinancial corporate bond on monetary policy pass-through to lending rates through the firm financing channel. Becker and Ivashina (2014) find firm-level evidence of substitution between bank loans and nonfinancial corporate bonds as credit conditions tighten. Crouzet (2019) and, Holm-Hadulla and Thürwächter (2021) investigate the relative role of corporate bonds and bank loans in the debt structure. They show that the firm financing choice between corporate bond and bank loans affects the monetary policy pass-through to the economy. Furthermore, they find that certain shocks (e.g.

monetary policy shock) or risk (e.g. liquidation risk) affect bond financed debt structure. Ippolito, Ozdagli, and Perez-Orive (2018) illustrates the importance of large-scale asset purchases in the firm financing channel. Their findings show that the bank debt has much less important role in the monetary policy pass-through during the unconventional monetary policy period. But no past studies analyzed the influence of bond market development on monetary policy pass-through to lending rates and effects from the bank financing channel, which is what we do in this paper and this is the primary contribution of our paper to the literature.

The rest of this paper is organized as follows. Section 2 explains the empirical methodology and the data. Section 3 reports the results from the baseline model. Section 4 reports the results of extended analysis. Section 5 concludes the paper.

1.2. Data and Methodology

In this section, we describe our empirical framework.

1.2.1. Empirical Methodology

To investigate monetary policy pass-through to lending rates, we first consider the following basic panel regression.

$$\Delta LR_{it} = \alpha_i + \delta_t + \beta \Delta CR_{it} + e_{it} \tag{1}$$

where *LR* and *CR* are bank lending and call rates, respectively, α_i and δ_t are individual and time fixed effects, respectively, and *i* and *t* are indices for individual country and time. ΔCR represents the short-term interest rate changes due to monetary policy actions. In the regression, β captures the degree of monetary policy pass-through to lending rates. For example, if β = 0, the call rate changes induced by monetary policy actions do not pass through to lending rates at all. At the other extreme, if β = 1, the call rate changes pass through one-to-one to lending rates. Individual fixed effect is included to control for country specific factors that affect the lending rates of each country. In addition, time fixed effect is included to control for common global factors that affect the lending rates of all countries. For example, global financial and business cycles may affect the lending rates of all countries.[1]

To further investigate the role of bond market development in the pass-through of monetary policy to lending rates, we consider the following panel regression which adds a cross-term of the measure of bond market development and change in call rates.

$$\Delta LR_{it} = \alpha_i + \delta_t + \beta \Delta CR_{it} + \gamma BM_{it} \Delta CR_{it} + e_{it} \qquad (2)$$

where *BM* is the measure of bond market development. In this regression, $\beta + \gamma BM$ is the degree of monetary policy pass-through and γ captures the role of bond market development. If the estimated γ is positive and significant, the degree of monetary policy pass-through increases as bond market development increases. But if it is insignificant, the influence of bond market development on the degree of monetary policy pass-through is unclear.

1.2.2. Data

[1] For example, Rey (2013) emphasized the role of global financial cycles on domestic financial condition.

Our dataset consists of monthly call rates (CR) and bank lending rates (LR) for the 36 countries that are listed in Table 2. In the extended analysis, we also include monthly data on consumer price index (CPI) and industrial production index (IP). Call rates and lending rates are obtained from International Financial Statistics, OECD Statistics, and CEIC Database. CPI and IP are collected from OECD Statistics and World Bank Metadata sets.

The ratio of outstanding total bonds to GDP is used as the measure of bond market development (BM). The outstanding total bond data and GDP are obtained from the Bank for International Settlements (BIS) and World Bank metadata sets, respectively. They are quarterly data series. The same value is used for three months in each quarter. However, this is unlikely to cause much of problem because monthly changes in the bond to GDP ratio are relatively small. Compared to other data series, the outstanding total bond data is available for relatively short sample periods. Therefore, the sample period, which differ across countries, is dictated by the availability of outstanding total bond data. The longest sample periods run from 1987 to 2019. See Table 2 for the sample period of each country.

Table 1.1 shows the summary statistics - i.e. number of observations, mean, standard deviation, median, and minimum and maximum values - of variables in 1987-2019. Lending rates tend to be higher than call rates. The averages are 6.16 and 3.36, respectively, and the medians are 5.21 and 2.33, respectively. The standard deviation of LR, 4.815, is slightly larger than that of CR, 4.466. However, the standard deviation of ΔLR, 0.537, is slightly smaller than that of ΔCR, 0.585. The standard deviations of ΔLR and ΔCR suggest that they are directly comparable because the numbers are not too different.

The mean and the median of the ratio of bonds to GDP are 4.06 and 3.88, respectively, which suggests that the share of total bonds outstanding in GDP is approximately 400% in our sample. The standard deviation of the ratio of bonds to GDP is 2.18. The maximum and minimum are 11.441 and 0.216, respectively. The standard deviation, the maximum, and the minimum of the ratio of bond to GDP suggests that there is enough variation in the sample to investigate the influence of the bonds to GDP ratio.

Table 1.2 shows the summary statistics (period, observations, mean, standard deviation, and minimum and maximum values) of bond market development measures for all countries in the sample. Japan and Netherland show the highest numbers. Japan has the highest mean value (8.30). Netherland has the second highest mean value (7.341) and the highest maximum observation (11.441). In addition, countries such as Austria, Belgium, Italy, Sweden, the U.K., and the U.S. have mean values that are larger than 5.0. On the other hand, Estonia has the lowest mean value (0.330), and the lowest minimum observation (0.216). Bulgaria and Peru have means value smaller than one, 0.736 and 0.887, respectively. Countries like Latvia, Lithuania, and Turkey have mean value that are smaller than 1.5.

Figure 1.1 shows time series figures of the bond market development measures for each country. The measure tends to increase over time in many countries, including Australia, Bulgaria, Canada, Estonia, Finland, Greece, Japan, Malaysia, Netherlands, Norway, Peru, Singapore, Slovenia, Sweden, Thailand, UK, and US. However, the bond market development measure declines during the sample period in some countries, including Croatia, France, Germany, Lithuania, the Philippines, and Turkey.

Table 1.3 shows the correlations among the variables. The correlation between lending rates and call rates is 0.758, which suggests a strong linear relation. In this paper, we seek to identify the source of such a strong relation. Both the lending and call rates have positive correlation with inflation rate, 0.147 and 0.122, respectively. The correlations of these two rates with the measure of bond market development and IP (industrial production) growth rate are close to zero. The correlation between the inflation rate and the measure of bond market development is -0.161. The correlations of IP growth rate with the measure of bond market development and CPI inflation rate are close to zero.

1.3. Baseline Model Results

In this section, we report and discuss the results for our baseline model. Tables 1.4 and 1.5 show the results of the basic panel regressions of bank lending rate on call rate [equation (1)]. Table 1.4 reports the results of the random effects and individual fixed effects models. The results show that estimated coefficients are similar in the two models, 0.696 and 0.692, respectively for random effects and individual fixed effects. The estimated coefficients of call rates are significant at 1% level in both models. The positive coefficient implies that changes in call rates affects changes in lending rates positively with a degree of pass-through of 0.69-0.70. The last row of Table 1.4 reports the result of the Hausman test, which suggests that fixed effects model is preferred to random effects model.

Table 1.5 compares the results of the individual fixed effects model and the results of the model with both individual and time-fixed effects. The estimated coefficient (0.692) is the same in both models, and they are statistically significant at 1% level. The last row of Table 1.5 reports the result of the F test for time fixed effects. The test result suggests that the model with both individual and time effects is preferred because the null hypothesis of no time fixed effect term is rejected at the 10% level.

Tables 1.6 and 1.7 show the result for the regressions with cross-term of the measure of bond market development and changes in CR [equation (2)]. Table 1.6 reports the results of the random effects and (individual) fixed effects model. The estimated coefficients of the call rate and the cross term of changes in the call rate and the measure of bond market development are similar in two models. The estimated coefficients of the call rate are 0.633and 0.630, respectively, in the random effects and fixed effects models. The estimated coefficients of the cross-term are 0.034 in both models. All estimated coefficients are significant at 1% level. The results of Hausman test suggests that fixed effects model is preferred to random effects model.

Table 1.7 compare the results for the individual fixed effects model versus the model with both individual and time-fixed effects. The estimated coefficients are similar, 0.630 and 0.621, respectively, for the model with individual fixed effects and that the model with both effects. The estimated coefficient of the cross-term is 0.034 and 0.040, respectively, for the model with individual fixed effects and that the model with both effects. Table 1.7 also reports the result of the F test for time fixed effects. The F test result suggests the model with both individual and time fixed effects is preferred because the null hypothesis of no time fixed effect term is rejected at 5% level.

In all cases, the estimated coefficient of the cross-term is positive and statistically significant at 1% level. This implies that the degree of pass-through of monetary policy to bank lending rates increases as bond market develops. The estimated coefficient of 0.04, for example, suggests that the degree of pass-through increases by 0.04 when the ratio of bonds to GDP increases by 1. As the bond market develops, changes in policy rates would have a stronger impact on the bond market interest rate. Then, changes in bond yield would exert more pressure on commercial banks to adjust their lending rates in response to policy rate changes. Therefore, the degree of pass-through of the policy rate to bank lending rates likely increase as the bond market develops.

In these models [equation (2)], the estimated coefficients of changes in call rates, ranging from 0.62 to 0.64, are slightly smaller than those in the previous models without the cross term [equation (1)], which range from 0.69 to 0.70. This is not surprising because the cross-term captures the additional explanatory power of bond market development measure on the degree of monetary policy pass-through to bank lending rates.

1.4. Extended Analysis

In this section, we report and discuss the results of various extensions. First, we extend the baseline model to include key macro variables such as inflation rate and output growth rate. Bank lending rates are likely to be affected by key macro variables such as inflation rate and output growth rate. In addition, monetary policy endogenously reacts to such key macro variables. To account for such third variable effects, we explicitly include inflation rate and output growth rate in the panel regression as follows.

$$\Delta LR_{it} = \alpha_i + \delta_t + \beta \Delta CR_{it} + \gamma BM_{it} \Delta CR_{it} + \theta \Delta CPI_{it} + \mu \Delta IP_{it} + e_{it}$$

(3)

where CPI and IP are consumer price index and industrial production, respectively. In this panel regression, $\beta + \gamma BM$ is the degree of monetary policy pass-through and γ captures the role of bond market development.

Table 1.8 shows the results. In this and following extended analyses, we report the results for the model with individual fixed effect and the model with both individual and time fixed effects only. This is because fixed effects model is preferred to random effects model in the case of the baseline model. In both models, the estimated coefficient of inflation rate is significant, but the estimated coefficient of IP growth rate is not. In both models, the estimated coefficient of CPI inflation rate is 0.048, which is statistically significant at 1% level.

More importantly, even after controlling for the macroeconomic variables, the results are very similar to those of the baseline model, especially the one with cross-term [equation (2)]. The estimated coefficient of the call rate is 0.628 and 0.618, respectively, in the model with individual fixed effect and the model with both individual and time fixed effects. The estimated coefficient of the cross-term is 0.032 and 0.040, respectively, in the model with individual fixed effect and the model with both individual and time fixed effects. These estimated coefficients of the cross-term are essentially the same as those in the baseline model.

In addition, we also consider the regression that includes changes in CPI inflation rate and changes in IP growth rate instead of CPI inflation rate and IP growth rate, as in equation (4). If the interest rate depends on inflation rate and IP growth rate, then, changes in the interest rate may depend on changes in inflation rate and changes in IP growth rate.

$$\Delta LR_{it} = \alpha_i + \delta_t + \beta \Delta CR_{it} + \gamma BM_{it} \Delta CR_{it} + \theta \Delta\Delta CPI_{it} + \mu \Delta\Delta IP_{it} + e_{it}$$

(4)

Table 1.9 reports the results. The estimated coefficients of changes in CPI inflation rate and changes in IP growth rate are insignificant. The estimated coefficient of call rate is 0.630 and 0.621, respectively, in the model with individual fixed effect and the model with both individual and time fixed effects. The estimated coefficient of the cross-term is 0.034 and 0.040, respectively, in the model with individual fixed effects and the model with both individual and time fixed effects. These estimated coefficients are very similar to the baseline model.

To summarize, the baseline result remains robust even when we include key macroeconomic variables in the analysis. As the bond market develops, the degree of monetary policy pass-through to bank lending rates increase. The degree of pass-through increases by 0.04 when the ratio of bonds to GDP increases by 1.

Second, we use subgroups of bond and country data to investigate changes in bond market effects due to bond types and country characteristics. Financial corporate bonds and nonfinancial corporate bonds differently affect the degree of monetary policy pass-through to bank lending rates. In the nonfinancial corporate bond market, a firm financing channel effect is dominated and the degree of pass-through likely increase as the nonfinancial corporate bond market develops. On the other hand, the degree of pass-through may increase or decrease as the financial corporate bond market develops because of funding substitution and cost effects. To account bond characteristic effects, we use financial corporate bond and nonfinancial corporate bond markets development index instead of the bond market index in the basic panel regression [equation 2].

Table 1.10 and 1.11 show results of the financial corporate bond market index and the nonfinancial corporate bond market index, respectively. In table 1.10, the estimated coefficient of the call rate is 0.758 and 0.770, respectively, in the model with individual fixed effect and the model with both individual and time fixed effects. The estimated coefficient of the financial corporate bond cross-term is -0.253 and -0.290, respectively, in the model with individual fixed effect and the model with both individual and time fixed effects. Unlike the result of the baseline model, the degree of passthrough decreases as the financial corporate bond market develops.

Table 1.11 reports the results of nonfinancial corporate bond market. The estimated coefficient of the call rate is 0.529 and 0.536, respectively, in the model with individual fixed effect and the model with both individual and time fixed effects. The estimated coefficient of the financial corporate bond cross-term is 0.242 and 0.224, respectively, in the model with individual fixed effect and the model with both individual and time fixed effects. The results support that the nonfinancial bond market development effect is bigger than the total bonds effect.

As a result, estimation results show that changes in the degree of pass-through varies depending on the type of bonds. In a nonfinancial corporate bond market, nonfinancial corporate firms mainly issue the corporate bond and borrow money from the bond market. Therefore, the firm financing channel effect dominates other effects and the degree of pass-through increases as the nonfinancial bond market develops. On the other hand, financial corporate firms mainly issue the corporate bond in a financial corporate bond market. If funding substitution effects are dominated, the degree of pass-through decreases as the financial bond market develops. On the other hand, the degree of pass-through increases as the financial bond market develops when funding cost effects are dominated. In our empirical results, the degree of pass-through decreases by -0.3 when the ratio of financial corporate bonds to GDP increases by 1. Our results establish that funding substitution effects are dominated in financial corporate bond markets in the whole country sample.

In addition, we divide the country sample into two subgroups, market-based and bank-based countries, to measure the changes in estimation results. The bank-based countries who have bank-based financial system such as Germany. Bank play a leading role in financial markets in bank-based countries. In market-based countries such as the United States, securities markets share center stage with banks in financial markets (Demirgüç-Kunt and Levine, 1999). We calculate the domestic assets of deposit money banks/market capitalization to divide the country sample into market-based and bank-based as Demirgüç-Kunt and Levine (1999) proposes. In our samples, seven countries (Belgium, Chile, Hong Kong, Peru, Philippines, Singapore and the United States) belong in market-based countries and the rest are in bank-based countries. We estimate the basic panel regression [equation 2] with a financial corporate bond market index and a nonfinancial corporate bond market index using the subgroup country sample.

Table 1.12 reports the results of the financial bond market. Panel A and B report the estimation results of market-based countries and bank-based countries, respectively. In panel A, the estimated coefficient of the call rate is -0.236 and -0.159, respectively, in the model with individual fixed effect and the model with both individual and time fixed effects. The estimated coefficient of the financial corporate bond cross-term is 0.274 and 0.203, respectively, in the model with individual fixed effect and the model with both individual and time fixed effects. Contrary to the results of the whole country sample, the degree of the pass-through increases as the financial bond market develops in market-based countries. In panel B, the estimated coefficient of the call rate is 0.787 and 0.796, respectively, in the model with individual fixed effect and the model with both individual and time fixed effects. The estimated coefficient of the financial corporate bond cross-term is -0.195 and -0.224, respectively, in the model with individual fixed effect and the model with both individual and time fixed effects. These estimated coefficients are very similar to the results of the whole country sample.

Table 1.13 reports the results of the nonfinancial bond market. Panel A and B report the estimation results of market-based countries and bank-based countries, respectively. In panel A, the estimated coefficient of the call rate is -0.030 and -0.007, respectively, in the model with individual fixed effect and the model with both individual and time fixed effects. The F-test does not reject the null hypothesis of no time fixed effect; however, estimated coefficient of the call rate is not significant considering the time fixed effect. The estimated coefficient of the nonfinancial corporate bond cross-term is 0.502 and 0.353, respectively, in the model with individual fixed effect and the model with both individual and time fixed effects. The results support that the degree of the pass-through increases as the nonfinancial bond market develops in market-based countries. In panel B, the estimated coefficient of the call rate is 0.679 in the model with individual fixed effect and the model with both individual and time fixed effects. The estimated coefficient of the nonfinancial corporate bond cross-term is 0.028 and 0.044, respectively, in the model with individual fixed effect and the model with both individual and time fixed effects. Unlike the previous results in the whole country sample, nonfinancial bond market cross terms are not statistically significant in a bank-based countries sample.

To summarize, the impact of the bond market on the degree of the pass-through depend on the type of bond and the financial system. In market-based countries, the degree of the pass-through increases as the financial corporate and nonfinancial corporate bond markets develop. In contrast, the degree of the pass-through decreases as the financial bond market develops but the nonfinancial bond market has no effect on the degree of the pass-through in bank-based countries. Our empirical results suggesting, firm financing channel and funding cost effects are prominent in market-based countries. In market-based countries, bond markets share center stage with banks in the financial market. Higher the role of bond markets increases the portion of bond markets in loan funds, which in turn induces the funding cost effect to dominate the funding substitution effect. However, bond market effects are different in bank-based countries. Empirical results suggest that the funding substitution effect is stronger than the funding cost effect and the firm financial channel effect is not statistically significant in bank-based countries.

Third, we add some lagged variables to the model. Monetary policy pass-through to lending rate may persist longer than a month. In addition, there may be some dynamic interactions among the variables. Therefore, we add lagged values of all variables in the baseline model - i.e. changes in lending rate, changes in call rate, and the cross term of changes in call rate and the measure of bond market development. We estimate the following equation.

$$\Delta LR_{it} = \alpha_i + \delta_t + \omega \Delta LR_{it-1} + \beta \Delta CR_{it} + \gamma BM_{it} \Delta CR_{it} + \theta \Delta CR_{it-1} + \mu BM_{it-1} \Delta CR_{it-1} + e_{it} \tag{5}$$

As in the previous cases, we estimate the individual time fixed model and the model with both individual and time fixed effect. In addition, we estimate the model by using the Arellano and Bond (1991) method to address potential bias due to lagged dependent variables.

Table 1.14 shows the estimation results. The estimated coefficients of current call rate are significant at 1% level in all cases, as in the baseline model. The estimated values are 0.643, 0.624, and 0.593, respectively, in the model with individual fixed effect, the model with individual and time fixed effects, and the model estimated by the Arellano and Bond (1991) method, respectively. The estimated coefficients of the current cross term with the ratio of bonds to GDP are also positive and significant at 1% level, 0.029, 0.044, and 0.060, respectively in the model with individual fixed effects, the model with individual and time fixed effects, and the model estimated by the Arellano and Bond (1991) method. This result re-confirms that monetary policy pass-through to bank lending rate increases as bond market develops, as in the baseline model.

The estimated coefficients of lagged call rate are close to zero and insignificant. The estimated coefficients of lagged lending rate are negative and significant at 1% level. Most interestingly, the estimated coefficient of lagged cross-term with the ratio of bonds to GDP is positive and significant, 0.059, 0.061, and 0.074, in the model with individual fixed effects, the model with both individual and time fixed effects, and the model estimated by the Arellano and Bond (1991) method. That is, changes in call rates affect lending rates gradually, both contemporaneously and with a lag, when we look at monthly data. More interestingly, the estimated coefficient on lagged cross-term is even larger than the estimated coefficient on current cross-term. This suggests that bond market development may play an even bigger role in lagged monetary policy pass-through than contemporaneous monetary policy-through.

Fourth, we add bank market characteristic variables in the model for the robustness check of the bond market effect. We use 3 bank asset concentration ratio and Lerner index which represents the bank market competition for bank market characteristic variables. Bank market characteristic variables are obtained from World Bank Metadata sets. Only yearly data series are available. Therefore, we assume that bank market characteristics are maintained for a year and the same value used for twelve months in each year. We estimate the following equation.

$$\Delta LR_{it} = \alpha_i + \delta_t + \beta \Delta CR_{it} + \gamma BM_{it} \Delta CR_{it} + \theta \Delta CPI_{it} + \mu Con_{it} \Delta CR_{it} + \rho Com_{it} \Delta CR_{it} + e_{it} \tag{3}$$

where ΔLR, ΔCR, BM and ΔCPI represent changes in lending rates, call rates, the measure for the bond market development (bonds/GDP) and CPI inflation rates, respectively. Δ Con and Δ Com represent bank market characteristic which are 3 bank asset concentrations and competition indexes (i.e. Lerner index), respectively. In this panel regression, $\beta + \gamma BM + \mu Con + \rho Com$ is the degree of monetary policy pass-through and γ, μ and ρ capture the role of bond market development, bank market concentration and bank market competition, respectively.

Table 1.15 shows the estimation results. Most interestingly, the estimated coefficient of cross-term with the ratio of bonds to GDP is positive and significant, 0.071 and 0.051, in the model with individual fixed effects, and the model with both individual and time fixed effects. These estimated coefficients slightly increase to the baseline model but are statistically significant. Estimated coefficients of bank market characteristic variables are also statistically significant. The estimated coefficient of cross-term with the bank market concentration index is negative, -0.004 and -0.005, in the model with individual fixed effects, and the model with both individual and time fixed effects. A bank market concentration index is measured by ratio of sum for three largest banks assets to total banks assets. Higher bank market concentration index means that bank assets are concentrated and decreases the degree of the pass-through. The estimated coefficient of cross-term with the bank market competition index is positive, -0.893 and 0.888, in the model with individual fixed effects, and the model with both individual and time fixed effects. A bank market competition is measured by the Lerner index. The Lerner index shows the market power in the banking market. It is calculated by the gap between output price and marginal costs. Therefore, higher values of the Lerner index indicate that bank markets have less competition. Consequently, our empirical results are consistent with those of the literatures (Cottarelli and Kourelis, 1994; OLIVERO, et al, 2011a; OLIVERO, et al, 2011b). The degree of the pass-through decreases as the bank market becomes higher concentration and competition.

1.5. Conclusion

The monetary policy decisions of central banks can have a potent impact on the economy in the short run. For example, during the COVID-19 pandemic, the central banks of many major economies have eased their monetary policy stance in a bid to support growth. The impact of monetary policy on the economy depends on the extent to which monetary policy action impacts a key economic variable. One common policy action of central banks is to adjust the policy rate, which affects the bank lending rate, along with the exchange rate and bond yield and stock market index. Bank lending rate affects consumption, investment, and aggregate demand since it is the cost of borrowing for companies and households.

In this paper, we examine the extent to which a policy rate hike or cut passes through to bank lending rates. More specifically, we look at how bond market development affects the pass-through. There is a sizable empirical literature on monetary policy pass-through and a more limited literature on the determinants of the pass-through. However, no past studies examine the role of bond market, which is what we do here and this is the primary contribution of our paper to the literature. As the bond market develops, we can expect two channels that affect the degree of monetary policy pass-through to bank lending rates.

First, in the firm financing channel, central bank's policy rate changes to have a bigger impact on bond yields, which in turn will have a bigger impact on the banks' lending rate. Furthermore, more developed bond markets pose a greater competitive threat to banks. Therefore, bond market development may strengthen the pass-through of the central bank's policy rates to commercial banks' lending rates.

Second, in the bank financing channel, central bank's policy rate changes to have a bigger impact on bank financing costs. Higher policy rate increase both interbank transactions and bank bond issuance rates.

Therefore, there are two effects, the funding substitution effect and the funding cost effect, and which effect dominates determines the effect of the degree of the pass-through.

In this paper, we empirically examine whether and to what extent bond market development increases the pass-through. For our analysis, we use a widely used measure of bond market development, namely the ratio of total outstanding bonds to GDP. We perform panel regressions on data from 36 advanced economies and emerging markets. Our evidence indicates that a more developed bond market strengthens the extent to which policy rate cuts or hikes by the central bank are passed through to the lending rates of commercial banks. More specifically, the responsiveness of lending rate changes to a 1% change in call rate increases by 0.03 to 0.04% within a month when the ratio of bonds to GDP increases by 1. Furthermore, the positive impact of bond market development on monetary policy pass-through remains robust under various specifications of the empirical model.

Our findings are especially relevant for emerging markets which have experienced a rapid expansion of bond markets since around 2005 when the markets were still small and underdeveloped. The bond market, which is integral to a diversified and well-balanced financial system, has long been neglected in emerging markets. Therefore, an important benefit of a well-developed bond market for emerging markets is that it contributes to financial stability. For example, Park, Shin and Tian (forthcoming) find evidence that bond market development promoted financial stability of emerging markets. IMF (2016) highlights the role of bond markets as a source of funding for long-term investments such as infrastructure.

Our main finding that bond market development strengthens monetary policy pass-through to bank lending rates points to another potential of well-developed bond markets for emerging markets. Compared to advanced economies, emerging markets have less experience and capacity of using monetary policy to influence the economy. In addition, they tend to have less sophisticated instruments and more broadly, less capacity for monetary policy. Bond market development can be beneficial in and of itself for the financial stability and growth of emerging markets. Our analysis suggests that it may yield a significant additional benefit, namely strengthened capacity to wield monetary policy to stabilize the economy.

Chapter 2. Asymmetric uncertainty shocks in a DSGE model

2.1. Introduction

An uncertainty of economy has become a substantial issue in macroeconomics recently. Specially, the uncertainty highly rises when unexpected events occurred such as the COVID-19 pandemic and 2007-2009 financial crisis. Jerome Powel, the Fed chairman, mentioned about facing the new level of uncertainty by the COVID-19 in his May 21st, 2020 speech.[2] Also, the Federal Open Market Committee (FOMC) minutes continued to address the importance of uncertainty in recessions periods.[3] It is inherently difficult to measure uncertainty in the sense that hard to know the subjective probability distribution of the future behavior by the economic agents. However, many studies suggest VXO as one of the uncertainty measures[4]. Figure 2.1 shows the VXO index of the 30-day implied volatility on the Standard & Poor's 100 stock market index. It is estimated by values of options on the Standard & Poor's 100 index and represents the expectation of volatility over the next 30 days. As figure

[2] The FED chairman, Jerome Powell, mentioned about the new level of uncertainty in May 21st ,2020 speech noting "We are now experiencing a whole new level of uncertainty, as questions only the virus can answer complicate the outlook".

[3] The Federal Open Market Committee (FOMC) noted that "Several participants reported that uncertainty about the economic outlook was leading firms to defer spending projects until prospects for economic activity became clearer." (April 2008), "Participants noted an improvement in business sentiment in many districts, but contacts remained quite uncertain about the timing and extent of the recovery; elevated uncertainty was said to be inhibiting capital spending in many cases." (June 2009) and "A number of business contacts indicated that they were holding back on hiring and spending plans because of uncertainty about future fiscal and regulatory policies." (September 2010).

[4] In Bloom (2009), paper shows that a number of different measures of uncertainty are highly correlated with the stock volatility. Caggiano et al. (2014), Leduc and Liu (2016), Basu and Bundick (2017) and Altig et al. (2020) use the stock volatility as uncertainty measures.

shown, VXO index dramatically increased in recession periods while gradually decreased in recovery periods.

In this article, we study asymmetry response of economic agents to the uncertainty shock. Unexpected events can be a good event or a bad event. Bad events like COVID-19 or Lehman Brothers failure negatively affect the economy and cause the rising in economy uncertainty. In contrast, development of Vaccine or start of the proper monetary policy and fiscal support can be good events and decrease the economy uncertainty consequently. For the most part, people prefer the certain situation than an uncertain situation[5]. Due to an uncertainty aversion, economic agents can react differently to good and bad events. For instance, households reduce consumption due to precautionary saving motives when uncertainty increases. Suppose uncertainty decreases to same level of increases, it must be recovered by the same level in a symmetry response situation. However, if agents have an uncertainty aversion, households have motive for save more than a symmetric case, even if uncertainty shocks increase the same level of a symmetric case. As a result, it may be recovered slower than a symmetric case in a asymmetric response situation. Asymmetric responses to the uncertainty shock of economic agents lead asymmetric responses to the uncertainty shock of macro variables. For good events with decreasing uncertainty, the decrease may be small, or the rate of decrease may be gradual, and for bad events with increasing uncertainty, the increase may be large, and the rate of increase may be steep.

Some previous studies have proposed an asymmetric response to exogenous shock in business cycles. Devereux and Siu (2007) shows the asymmetric business cycles and the asymmetric changes from monetary policy shocks with a model adopting state dependent pricing. Berger and Vavra (2015) find the empirical evidence for the asymmetric response of

[5] Ellsberg paradox.

durable consumptions to income shock. They show that the estimated response in boom is almost twice as large as in recessions. Similarly, Ferraro (2018) shows the difference of response to technology shock between normal periods and recessions. In addition, the paper explains the asymmetry of business cycles and IRF through a model with search frictions and heterogeneity in productivity.

Despite the existence of many literatures about the asymmetry in business cycles, there are rarely studies about the relation between uncertainty and asymmetry response of macro variables. Grier et al. (2004) use the multivariate GARCH model to show the asymmetric response of output growth and inflation. Their results support that growth uncertainty and inflation uncertainty which are measured by volatilities of each variables decrease the output growth and inflation. Furthermore, they show the asymmetric response to positive and negative shocks in same magnitude. Bloom (2014) mentions that uncertainty appear to rise sharply in recessions and fall in booms. Although of the weak the econometric evidence, it suggests that higher uncertainty worsened the recessions and sluggish recovery. These features indicate that the uncertainty have asymmetry effects on the real business cycles with delaying recovery and cause the asymmetry movement of uncertainty measures.

In this paper, we find empirical evidence for asymmetric effects of uncertainty to real economic. Also, we specify and estimate a dynamic stochastic general equilibrium (DSGE) model with asymmetric uncertainty. We follow the calibration method which is Basu and Bundick (2017) used. First, we get an asymmetry impulse response function (IRF) from non-linear regressions then calibrate DSGE model variables with that IRF results. Unlike the previous research, our model allows for the asymmetric effects of uncertainty in agents discount rate. An increasing uncertainty like the recession period has the greater effect on the economy than a decreasing uncertainty like the economic boom period due to asymmetric reaction of agents. Previous DSGE models do not capture asymmetric effects and only allow for symmetric reactions with positive and negative uncertainty shocks on the economy.[6]

This paper is organized as follows. Section 2 reports estimation results of empirical works with the nonlinear regression model. In section 3, we explain the DSGE model with asymmetric uncertainty and calibration method. In section 4, we discuss calibration results of the DSGE model and compare with empirical works. Section 5 provides further analysis of asymmetric uncertainty. Section 6 concludes.

2.2. Empirical works

For getting asymmetry impulse response functions (IRFs), we adopt the Smooth Local Projection (SLP) method (Barnichon and Brownlees, 2019). Many relate works use Vector Autoregressions (VAR) and Local Projection (LP) (Jorda, 2005) for the estimation of impulse responses (IR). VAR and LP have pros and cons: If the model is correctly specified then VAR approach is more efficient then LP approach but if not, then LP approach is more robust than VAR approach (Barnichon and Brownlees, 2019). Furthermore, VAR approach recursively estimate the response so there is much difficulty when an asymmetry term is added in the model. However, LP approach estimates the full length of responses at once, so it has the advantage for adding the asymmetry term in the model. Specially, SLP which is LP method with Penalized B-splines is more

[6] Ilut and Schneider (2014) models New Keynesian model with uncertainty in total factor productivity (TFP). Leduc and Liu (2016) use DSGE model with uncertainty in aggregate technology and calibrate the model with Michigan survey data. Basu and Bundick (2017) use DSGE model with uncertainty in household discount rate and calibrate the model with empirical IRF. In Bloom et al. (2018), they consider two components of uncertainty. They use aggregate part and idiosyncratic part as TFP uncertainty in the DSGE model to show the effects of aggregate shocks and idiosyncratic shocks.

flexible and more precise than LP approaches. So, we use the SLP method for estimation of asymmetric impulse responses in our models.

In our empirical model, we define the non-linear local projection regressions as follows:

$$y_{t+h} = \beta_{(h)} VXO_t + \gamma_{(h)} VXO_t^+ + \sum_{i=1}^{P} \delta_{i(h)} x_{it} + u_{(h)t+h}, \tag{1}$$

where t represents the time for $t = 1 \cdots T$ and h represents the IRF length for $h = 1 \cdots H$. P is the number of regressors except VXO, VXO^+ and a constant. y_{t+h} is an dependent variable observed at period $t+h$. VXO_t and VXO_t^+ represent implied stock volatility (VXO) term and non-linear term for capturing the asymmetric effect of VXO. We set VXO_t^+ as follows:

$$VXO_t^+ = \begin{cases} VXO_t & (VXO_{t+1} \geq VXO_t) \\ 0 & (VXO_{t+1} \leq VXO_t) \end{cases}$$

x_{it} are independent variables such as GDP, consumptions, investments, working hours, money stock (M2), inflations and policy rates[7]. $u_{(h)t+h}$ is a residual. Dependent variables are also same variables which is used in x_{it} and VXO. Details for data are in the "Data appendix". To get a smooth asymmetric IRF, we use a linear B-splines basis function expansion to approximate the coefficients. For example, we estimated the $\beta_{(h)}$ as follows:

7 We us Wu-Xia shadow rate for policy rates. Additionally, all variables are HP-filtered to get stationary series except the inflation variable.

$$\beta_{(h)} \approx \sum_{k=1}^{K} b_k B_k(h), \tag{2}$$

where $B_k(h)$ are B-spline basis functions for $k = 1 \cdots K$ and b_k for $k = 1 \cdots K$ is a parameter and K is the number of knots. Then non-linear local projection equations (1) can be approximated as follows:

$$y_{t+h} \approx \sum_{k=1}^{K} a_k B_k(h) + \sum_{k=1}^{K} b_k B_k(h) VXO_t + \sum_{k=1}^{K} c_k B_k(h) VXO_t^{+} + \sum_{i=1}^{P} \sum_{k=1}^{K} d_{i,k} B_k(h) w_{it} + u_{(h)t+h}, \tag{3}$$

and equations (2) and (3) can be rewritten as follows:

$$\beta_{(h)} \approx \sum_{k=1}^{K} b_k B_k(h) = b' B(h), \tag{4}$$

$$\begin{aligned} y_{t+h} &= a'B(h) + b'B(h)VXO_t + c'B(h)VXO_t^{+} + \sum_{i=1}^{P} d_i' B(h) w_{it} + u_{(h)t+h} \\ &= \theta'(x_t \otimes B(h)) + u_{(h)t+h}, \end{aligned} \tag{5}$$

where $a'(= (a_1, \cdots, a_K))$, b' , c' , d_i' are vectors of parameters and $B(h) = (B_1(h), \cdots, B_K(h))'$ is a vector of B-spline basis functions. $x_t = (VXO_t, VXO_t^{+}, w_{1t}, \cdots, w_{Pt}, 1)'$ is a vector of regressors and $\theta' = (b', c', d_1', \cdots, d_P', a')$ is a vector of corresponding regressors coefficients. As a result, we let $\overline{x}_{t,h} = x_t \otimes B(h)$ and rearrange the equation (5) then the equation (5) is in matrix notations as follows:

$$\begin{aligned} &y = \overline{x}\theta + u, u \sim N(0_{HT}, I_T \otimes \Sigma), \\ &y = (y_{(1)} \cdots y_{(T)})', \overline{x} = (\overline{x}_{(1)} \cdots \overline{x}_{(T)})', u = (u_{(1)} \cdots u_{(T)})', \end{aligned} \tag{6}$$

where $y_{(t)} = (y_{t+1}, \cdots, y_{t+H})$, $\overline{x}_{(t)} = (\overline{x}_{t,1} \cdots \overline{x}_{t,H})$ and $u_{(t)} = (u_{(1),t+1}, \cdots, u_{(H),t+H})'$ for $t = 1 \cdots T$ and $h = 1 \cdots H$. Σ is a covariance matrix and $N(C, D)$ is a multivariate normal distribution with mean C and covariance D.

For testing asymmetries in the IRF, we use the IRF-based Wald test proposed by Killan and Vigfusson (2011). We test the null hypothesis as follows:

$$H_0 : I_y(h, \delta) = -I_y(h, -\delta) \quad \forall h = 1, \ldots, H$$

where $I_y(h, \delta)$ is the response of y_t to an shocks in VXO_t of size δ at horizon h.

Figure 2.2.1 and 2.2.2 plot the estimated response to the positive and negative VXO shocks. Figure plots the mirror image of negative shock. The size of shock is one standard deviation of VXOs, and it is 24.7%. After the one period, a positive shock decreases to 11.6% and a negative shock decreases to 12.2%. In VXO case, the response to a negative shock is above the response to a positive shock in whole periods. Furthermore, the response to a positive shock decreases to zero after 5 periods while the response to a negative shock decreases to zero after 6 periods, implying that recovery speed of s positive shock is faster than to a negative shock. Macro variables have similar characteristic in responses to VXO shock except inflation. After the one period, all responses to the positive shock are smaller than responses to the negative shock. However, positive shock responses recovery faster than negative shock responses and move upwards except the inflation case. In inflation case, the negative shock responses are above the positive shock responses.

Table 2.1 reports test results of asymmetries in the IR. We perform the IRF-based Wald test and the table reports Chi-squared test statistics which has the null hypothesis of no difference between IRs to positive and negative VXO shocks. IRs are estimated and tested every 4 quarters. H represents the length of responses and the degree of freedom of Chi-squared test depends on the length of IR. Test results imply that there are asymmetry responses to the positive and negative VXO shocks except the inflation and policy rate. Output and consumption have asymmetry responses to positive and negative VXO shocks in all sample length of IR while VXO, Investment and working hours have asymmetry responses after 12 periods. However, test results suggest that inflation and policy rate response have no asymmetry in responses to the VXO shocks until 20 periods.

In addition, we compare the multipliers to determine whether the macro variable response is an asymmetric response to the VXO shock or a difference due to a change in the VXO response. We calculate the multipliers by ratio of the size of a macro variable response to the size of a VXO response. Table 2.2 reports the mean value of the multipliers. Table shows the multiplier every 4 quarters. All macro variables multipliers have lower mean values to a positive VXO shock than a negative VXO shock in 4 quarters. After 4 or 5 quarters, the mean values of multipliers to a negative shock become lower than to a positive shock. Figure 2.3 plots the changes in the mean value of the output multipliers. Results suggest that macro variables responses have asymmetric responses to the VXO shock.

Moreover, we add the stock price in basic local projection equations as the macro variables to control the stock price effect. Appendix B plots the estimated response to the positive and negative VXO shocks with the stock price. The figure shows that VXO and macro variables have asymmetric responses to a VXO shock and essentially the same characteristic with responses in the baseline model.

2.3. DSGE model

In section 2.3, we describe the baseline DSGE model which is used in our analysis of asymmetry uncertainty shocks. The model consists with Epstein-Zin preference households, intermediate goods producers, final goods producers and a central bank that follows a Taylor rule. Also, we allow sticky prices in a model with using Rotemberg (1982) price-setting. Exogenous shocks are in the household discount rate and the technology. As in Basu and Bundick (2011), the household discount rate shock has a time varying second moment and we allow the asymmetry on it.

Households

The representative household maximizes Epstein-Zin preference style lifetime utility with Cobb-Douglas functions over streams of consumption C_t and leisure $1-N_t$. The household maximizes lifetime utility by solving the following problem:

$$V_t = \max\left[a_t (C_t^{\eta}(1-N_t)^{1-\eta})^{(1-1/\psi)} + \beta(\mathbb{E}_t V_{t+1}{}^{1-\sigma})^{(1-1/\psi)/(1-\sigma)} \right]^{1/(1-1/\psi)},$$

$$s.t. \quad C_t + \frac{P_t^{Equity}}{P_t} S_{t+1} + \frac{1}{R_t^R} B_{t+1} \le \frac{W_t}{P_t} N_t + \left(\frac{D_t^{Equity}}{P_t} + \frac{P_t^{Equity}}{P_t}\right) S_t + B_t,$$

where β and a_t are the discount rates of the household. σ is risk aversion parameter and ψ is the elasticity of intertemporal substitution and we set $\theta_V = (1-\sigma)/(1-1/\psi)^{-1}$. The household earns money by supplying labor N_t to intermediate goods firms and owning intermediate goods firms stocks S_t and one-period riskless bonds B_t. The labor incomes, stock prices and dividends are W_t, P_t^{Equity} and D_t^{Equity} respectively. The riskless bonds have the gross one-period risk-free interest rate R_t^R and P_t is the price level. The household divides earnings into consumption C_t and holdings of financial assets S_{t+1} and B_{t+1} for next period. The household chooses $C_{t+s}, N_{t+s}, B_{t+s+1}$ and S_{t+s+1}, for $s = 0,1,\cdots$ to maximize its lifetime utility. Furthermore, a model induces a stochastic discount factor M between t and t+1 as follows:

$$M_{t+1} = \left(\frac{\partial V_t / \partial C_{t+1}}{\partial V_t / \partial C_t} \right) = \left(\beta \frac{a_{t+1}}{a_t} \right) \left(\frac{C_{t+1}{}^{\eta} (1-N_{t+1})^{1-\eta}}{C_t{}^{\eta} (1-N_t)^{1-\eta}} \right)^{1-\sigma/\theta_v} \left(\frac{C_t}{C_{t+1}} \right) \left(\frac{V_{t+1}^{1-\sigma}}{\mathbb{E}_t \left[V_{t+1}{}^{1-\sigma} \right]} \right)^{1-1/\theta_V}$$

.

The Representative Intermediate Goods Producers

During the period, the representative intermediate goods producing firm i($i \in [0,1]$) rents labor $N_t(i)$ from the representative household and owns capital stocks $K_t(i)$ to produce intermediate goods $Y_t(i)$. For price stickiness, we adopt the Rotemberg (1987) style price setting. As mentioned in Oh (2020), uncertainty shocks raise inflation in a model with Calvo style price setting because firms have precautionary pricing motive in Calvo (1983) style price setting. In our empirical results, inflations response opposite ways to VXO shocks in first period thus we adopt the Rotemberg style price setting. The intermediate goods producing firm faces a quadratic cost of adjusting its price between the periods as follows:

$$\frac{\phi_P}{2}\left[\frac{P_t(i)}{\Pi P_{t-1}(i)}-1\right]^2 Y_t$$

where ϕ_P is the size of the price adjustment cost and Π represent the steady state inflation rate.

In addition, the capital stock evolves as follows:

$$K_{t+1}(i)=\left(1-\delta\right)K_t(i)+\left(1-\frac{\phi_I}{2}\left(\frac{I_t(i)}{I_{t-1}(i)}-1\right)^2\right)I_t(i)$$

Where δ is the depreciation rate and ϕ_I is investment adjustment cost as proposed by Christiano et al. (2005).

The representative intermediate goods producing firm i produces its goods using the following Cobb-Douglas production function:

$$Y_t(i)\leq\left[K_t(i)\right]^{\alpha}\left[Z_t N_t(i)\right]^{1-\alpha}-\Phi$$

Where α and Φ denote capital income share and the fixed cost, respectively. Z_t is an exogenous labor productivity shock.

Finally, the representative intermediate goods producing firm i maximizes discounted cash flows using the household's stochastic discount factor:

$$\max \mathbb{E}_t\sum_{s=0}^{\infty}\left(\frac{\partial V_t/\partial C_{t+s}}{\partial V_t/\partial C_t}\right)\left[\frac{D_{t+s}(i)}{P_{t+s}}\right]$$

subject to the production function and the capital accumulation equation. The representative intermediate goods producing firm's cash flows in time t is given by:

$$\frac{D_t(i)}{P_t} = P_t(i)Y_t(i) - \frac{W_t}{P_t}N_t(i) - I_t(i) - \frac{\phi_P}{2}\left[\frac{P_t(i)}{\Pi P_{t-1}(i)} - 1\right]^2 Y_t \, .$$

Each intermediate good producing firm finances its capital stock with risk-less bonds. The bonds pay the one-period real risk free interest rate R_t^R and sizes are a percentage ν of its capital stock, $B_t(i) = \nu K_t(i)$. After financing, firm divide cash flows between to bond holders and equity holders as follows:

$$\frac{D_t(i)}{P_t} = \frac{D_t^{Equity}(i)}{P_t} + B_t(i) - \frac{1}{R_t^R}B_{t+1}(i) \, .$$

Leverage allows the volatile movement of the price of equity. We compute the equity return and the expected conditional volatility of the return as follows:

$$R_{t+1}^{Equity} = \frac{D_t^{Equity} + P_t^{Equity}}{P_t^E} \, ,$$

$$V_t^{Equity} = 100 * \sqrt{4 * (\mathbb{E}_t((R_{t+1}^{Equity})^2) - \mathbb{E}_t(R_{t+1}^{Equity})^2)} \, .$$

Final Goods Producers

The representative final goods producing firm uses $Y_t(i)$ units of each intermediate goods from the intermediate goods producing firm i, to produce Y_t units of the final goods using the constant returns to scale technology as follows:

$$\left[\int_0^1 Y_t(i)^{(\theta_\mu-1)/\theta_\mu}\, di\right]^{\theta_\mu/(\theta_\mu-1)} \geq Y_t ,$$

where θ_μ is elasticity of substitution parameter and $\theta_\mu > 1$. The final goods producing firm buys the intermediate good at nominal price $P_t(i)$ and sells the final good at nominal price P_t. So, the final goods producing firm chooses Y_t and $Y_t(i)$ for all $i \in [0,1]$ to maximize its profit which are given by

$$P_t Y_t - \int_0^1 P_t(i) Y_t(i) di$$

subject to the constant returns to scale production function. The first order condition for its optimization problems as follows:

$$Y_t(i) = \left[\frac{P_t(i)}{P_t}\right]^{-\theta_\mu} Y_t .$$

The final goods market is perfectively competitive, thus the final goods producing firm earns zero in equilibrium. From the zero-profit condition, we derive the aggregate price index as follows:

$$P_t = \left[\int_0^1 P_t(i)^{1-\theta_\mu}\, di\right]^{1/(1-\theta_\mu)} .$$

Monetary Policy and Equilibrium

In the equilibrium, all intermediate goods producing firms make identical decisions, so that firms choose the same price $P_t(i) = P_t$ and employ the same amount of labor $N_t(i) = N_t$. Also firms choose the same amount of capital $K_t(i) = K_t$, investment $I_t(i) = I_t$ and (utilization rate $U_t(i) = U_t$). As a result, firms have the same financing decision so they have same amount of cash flows $D_t(i) = D_t$, bonds $B_t(i) = B_t$ and dividend $D_t^E(i) = D_t^E$. Gross inflation is $\Pi_t = P_t / P_{t-1}$. Equations for first order conditions are summarized in Appendix C. We assume that the central bank sets the nominal interest rate R_t to stabilize inflations π_t and output growth y_t with the following Taylor(1993) rule:

$$r_t = r + \rho_\pi (\pi_t - \pi) + \rho_y y_t ,$$

where $r_t = \ln(R_t), \pi_t = \ln(\Pi_t)$ and $y_t = \ln(Y_t / Y_{t-1})$. r, π are steady state of r_t and π_t respectively. ρ_π and ρ_y are response coefficients. The central bank raises the nominal interest rate in response to rising of output or inflations. Also, we include following Euler equation for nominal interest rate equilibrium conditions:

$$1 = R_t \mathbb{E}_t \left\{ M_{t+1} \left(\frac{1}{\Pi_{t+1}} \right) \right\}.$$

For final goods clearing, we include final goods constraint as follows:

$$Y_t = C_t + I_t - \frac{\phi_P}{2}\left[\frac{P_t}{\Pi P_{t-1}} - 1\right]^2 Y_t$$
.

Exogeneous Shock Processes

A preference shock and a technology shock processes are the autoregressive process as follows:

$$a_t = (1-\rho_a)a + \rho_a a_{t-1} + \sigma_{t-1}^a \varepsilon_t^a,$$
$$\sigma_t^a = (1-\rho_{\sigma^a} - \rho_{\sigma^a}^+)\sigma^a + (\rho_{\sigma^a} + \rho_{\sigma^a}^+)\sigma_{t-1}^a + (\sigma_{\sigma^a} + \sigma_{\sigma^a}^+)\varepsilon_t^{\sigma^a},$$
$$Z_t = (1-\rho_Z)Z + \rho_Z Z_{t-1} + \sigma^Z \varepsilon_t^Z,$$
$$\varepsilon_t^a, \varepsilon_t^{\sigma^a}, \varepsilon_t^Z \sim N(0,1),$$

where a_t is the stochastic process of household discount factors and Z_t is a labor productivity shock. σ_t^a is stochastic volatility process term of household discount factors and is varying over time. ρ_a, ρ_{σ^a}, and ρ_Z are persistence of each shock process. $N(0,1)$ represents the standard normal distribution. ε_t^a and ε_t^Z are first moment shocks and $\varepsilon_t^{\sigma^a}$ is the second moment shock of household discount factors. $\varepsilon_t^{\sigma^a}$ captures the innovation to the volatility of household discount factors and it refers the uncertainty shock. σ^{σ^a} and σ^Z represents standard deviation of shock $\varepsilon_t^{\sigma^a}$ and ε_t^Z respectively. Furthermore, we add $\rho_{\sigma^a}^+$ and $\sigma_{\sigma^a}^+$ terms in second moment shock process to capture asymmetry effect of the uncertainty shocks as follows:

$$\rho_{\sigma^a}^{+} = \begin{cases} \rho_{\sigma^a}^{+} & (\varepsilon_t^{\sigma^a} \geq 0) \\ 0 & (\varepsilon_t^{\sigma^a} < 0) \end{cases}, \quad \sigma_{\sigma^a}^{+} = \begin{cases} \sigma_{\sigma^a}^{+} & (\varepsilon_t^{\sigma^a} \geq 0) \\ 0 & (\varepsilon_t^{\sigma^a} < 0) \end{cases}.$$

ρ_a and σ^{σ^a} capture the persistence and the magnitude of uncertainty shocks, respectively. If $\rho_{\sigma^a}^{+}$ and $\sigma_{\sigma^a}^{+}$ are negative, a positive uncertainty shock recovers faster and is more volatile than a negative uncertainty shock.

Calibration and Estimation

Our calibration method follows Chiristiano et al. (2005) and Basu and Bundick (2017) methods. We divide parameters into two groups. Parameters in the first group are calibrated using steady state relations or results from previous studies. We calibrate the model to quarterly frequency. We choose the Households Cobb-Douglas aggregator η such that the model has a Frisch labor elasticity of 2. For assumption of competitive goods market, fixed cost of production for the intermediate producing firm Φ is calibrated to make the profit zero in the steady state of the model. We calibrate discount factor β=0.994, risk aversion σ=80 and intertemporal elasticity of substitution ψ=0.95, which are line with the Basu and Bundick (2017). In our model, firm's capital has no capital utilization but investment adjustment cost. We calibrate a parameter which control the investment adjustment cost ϕ_I=1.58. Rotemberg price adjustment cost parameter ϕ_P is 100 which implies prices are changed about once every four quarter. Firm's Cobb-Douglas parameter α, capital depreciation rate δ, demand elasticity θ_μ and share of bonds in capital ν are 0.333, 0.025, 6 and 0.9 respectively. In monetary policy parameter settings, we calibrate the steady state inflation rate as 1.005 which implies the annual rate is 2%. Coefficients of inflation target and output growth target in monetary policy are set as 1.5 and 0.2, respectively.

Parameters in the second group are estimated by following the method of Basu and Bundick (2017). We compute a model implied volatility index from the expected conditional volatility of the stock return as a model implied volatility index, and closely matches the log VXO movements from our empirical results.

To estimate parameters, we solve following problems and use the solution as our estimators:

$$J=\min_{\gamma}\sum_{s\in\{+,-\}}\left[\hat{IRF}_s-IRF_s(\gamma)\right]' V_s^{-1}\left[\hat{IRF}_s-IRF_s(\gamma)\right]+\hat{W}\left[\hat{Std}-Std(\gamma)\right]' W^{-1}\left[\hat{Std}-Std(\gamma)\right]$$

where $\hat{IRF}_i$ and $IRF_i(\gamma)$ are empirical IRF and model implied IRF[8]with estimated parameters γ ($\equiv(\rho_a,\sigma^a,\rho_{\sigma^a},\rho^+_{\sigma^a},\sigma_{\sigma^a},\sigma^+_{\sigma^a},\rho_Z,\sigma^Z)$). Sign indicator s represents the direction of uncertainty shock so + means the increasing uncertainty and – means the decreasing uncertainty. V_s is a variance matrix of the empirical IRF along the main diagonal. $\hat{Std}$ is an unconditional standard deviation vector of output, consumption, investment and house worked in the data, and $Std(\gamma)$ is a model implied standard deviation vector of them. To calculate the model implied standard deviation, we calculate in the following ways. First, we simulate large enough sample of key macro variables (output, consumption, investment and working hours). Second, the model implied sample is divided by the sample length of the data to make multiple samples of the same length with data used in empirical analysis. At last, we calculate the

[8] We use generalized impulse response functions (GIRF) which proposed by Koop et al. (1996).

average of the standard deviation of all divided samples for the model implied standard deviation. W is the diagonal matrix with the empirical unconditional variance of output, consumption, investment, house worked and stock returns along its main diagonal. $\hat{W}$ is the weight scalar to equalize the matching IRF part and the unconditional moments part.

To solve this problem, we use the Dynare software package (Adjemian et al., 2011). As mentioned in Fernandez-Villaverde et al. (2011), we need more than a third-order approximation of the policy functions of the DSGE model to find the second moment shock effects on IRF. Dynare provides the third order Taylor series approximation options and compute the rational expectations around the deterministic steady state (SS) of the model. Also, we use the deviation from the stochastic SS as a model implied IRF.[9]

In addition, we derive two model implied IRFs ($IRF_i(\gamma)$) to show the asymmetry of uncertainty. Unfortunately, calculating the asymmetry shock effects is not provided in Dynare so we need to make two 'MOD' (which are Dynare programming files) files of different situations, increasing uncertainty and decreasing uncertainty, for deriving the two different IRFs.[10] In addition, we also calculate the model implied moments with using the different third-order results. First, we extract random series from all exogeneous shocks. Second, we separate the increasing and the decreasing uncertainty shocks ($\varepsilon_t^{\sigma^a}$). Third, we set the initial point at stochastic steady states and calculate the random path of target variables (output, consumption, investment and house worked) with

[9] In Basu and Bundick (2017), they use 400 periods for deriving the stochastic steady states, but we think that it is too short. So, we extend it to 10,000 periods.

[10] The magnitude of shock is $\sigma_{\sigma^a} + \sigma_{\sigma^a}^{+}$ for the positive uncertainty shock in the first MOD file and σ_{σ^a} for the negative uncertainty shock in the second MOD file. In the same way, persistence of uncertainty are $\rho_{\sigma^a} + \rho_{\sigma^a}^{+}$ and ρ_{σ^a} in the first MOD file and the second MOD file, respectively. Other parameters of γ are unchanged in both MOD files.

two different third-order result from two MOD files. Finally, we calculate standard deviations of target variables.

2.4. Result

Table 2.3 shows the calibrated and estimated parameters of our model. Preference and labor productivity shock persistence parameters are close to unity, indicating that preference and labor productivity have strong persistence to the shock. Uncertainty shock's persistence parameter is 0.625 and the asymmetry coefficient of uncertainty shock persistence have negative value (-0.086). Results indicate that the positive uncertainty shock have lower persistence than the negative uncertainty shock. The lower persistence implies the faster recovery from the shock. The result of the estimated parameter is consistent with the results of the empirical result that the uncertainty measure, VXO, the positive shock recovers faster than the negative shock. Furthermore, the volatility parameter of uncertainty shock is 0.008 and asymmetry volatility parameter of uncertainty shock is 0.002. The result implies that the positive uncertainty shock is more volatile than the negative uncertainty shock. In VXO data, the standard deviation of the increasing VXO changes is higher than that of the decreasing VXO changes[11].

Table 2.4 shows the second moment values of key macro variables which are output, consumption, investment and working hours, calculated from the data and model. To calculate the standard deviation from the data, we use the cyclic component of HP-filtered variables. Model implied standard deviation is calculated in the same method as

[11] In quarterly frequency data, a standard deviation value of increasing VXO changes and that of decreasing VXO changes are 6.39 and 3.48, respectively. As the frequency of the data increases, the standard deviation value decreases. However, the standard deviation of increasing VXO changes is higher than those of decreasing VXO changes in monthly and daily frequency data. (Appendix D)

described in section 3. Estimation results support that our model closely matches the volatility of all key macro variables.

Figure 2.4.1 and 2.4.2 plots the model implied response to the positive and negative uncertainty shocks. Figure plots the mirror image of the negative shock. The size of shocks is one standard deviation of preference uncertainty, and values are 0.01 and 0.008 for the positive shock and negative shock, respectively. The blue solid line and black dashed line represent the impulse response to a positive and a negative shock, respectively. The first graph shows responses of VXO to uncertainty shocks. As the empirical result, the response of VXO to the positive shock recovery faster than that to the negative shock. In empirical result, the size of responses in the first period is 10.89% and 11.04% for the positive shock and negative shock, respectively. In model implied responses, the size of responses in the first period is 11.71% and 11.83% for the positive shock and negative shock, respectively. Furthermore, macro variables have similar characteristic in empirical results except inflation and the policy rate. Graphs of key macro variables, output, consumption, investment, and working hours, show that responses to the positive shock are smaller than those to the negative shock but positive shock responses recovery faster than negative shock responses. In inflation and policy rate cases, the response to the positive shock is bigger than that to the negative shock in starting point, but it continues to be smaller after the first period.

2.5. Further analysis

In this section, we investigate which factor can deepen the asymmetry. We calculate the difference between macro-variables responses to a positive and a negative uncertainty shock. We consider three factors that can influence the decision of the economic agent: price rigidity, consumption habit and risk aversion. We calculate the distance of responses as follows:

$$Dist(\gamma) = IRF_{+}(\gamma) - IRF_{-}(\gamma).$$

Figure 2.5 shows the distance of VXO responses to asymmetric uncertainty shocks. The first, second, and third figures represent the change in distance with price rigidity, habit persistency, and risk aversion changes. The VXO distance falls as price rigidity rises and rises as habit persistence rises. However, VXO distance does not change with risk aversion.

Figure 2.6, 2.7 and 2.8 show the distance of key macro variables, output, consumption, investment and working hours, to asymmetric uncertainty shocks with price rigidity, habit persistency, and risk aversion changes.

Comparing the response of the first period in figure 2.6, it is the smallest when price rigidity is 100 except the investment distance. However, unlike the VXO result, the absolute distance between responses of key macro variables to a positive and a negative uncertainty shock increase when price rigidity weaker. The result implies that lower price rigidity increases the asymmetric responses of key macro variables in sticky price settings.

Figure 2.7 shows changes in the distance of key macro variables according to the changes in consumption habit. We assume that the household has external consumption habit persistence and the household maximizes lifetime utility by solving the following problem:

$$V_t = \max\left[a_t((C_t - h\overline{C}_{t-1})^{\eta}(1-N_t)^{1-\eta})^{(1-1/\psi)} + \beta(\mathbb{E}_t V_{t+1}{}^{1-\sigma})^{(1-1/\psi)/(1-\sigma)} \right]^{1/(1-1/\psi)}.$$

The result shows that the first distance absolute value is largest when assuming no habit persistence except investment responses distance. The distance due to habit persistence get closer over periods. However, there are no significant difference among different habit persistence in investment distance case.

Figure 2.8 shows changes in the distance of key macro variables according to the changes in a risk aversion parameter. In risk neutral case, there are no difference between the responses to a positive and negative uncertainty shocks at the first period. If the household is risk averse, the first period response distance increases as the risk aversion parameter increases. However, the absolute distance of asymmetric responses is larger when the risk aversion parameter is higher in all periods except the investment case.

Figure 2.9 shows the distance of key macro variables estimated from the extreme case model and the baseline model. For comparison with the baseline model, we estimate the extreme case model by setting the value of price rigidity parameter to 50, the value of habit persistency parameter to 0 and the value of risk aversion parameter to 200. In the first period, the absolute value of distance estimated by the extreme case is at least twice as higher as that estimated by the baseline model. The result show that the asymmetry of responses is larger in the extreme model than in the baseline model over all periods except the consumption and investment. In consumption case, distances of the baseline model are larger than those of the extreme model after the first period. However, in investment case, distances of the baseline model are larger than those of the extreme model after the fifth period, but the distances of the baseline model are larger than of the extreme model in the third and fourth period.

2.6. Conclusion

We argue that uncertainty aversion makes economic agent act differently against the increasing uncertainty and the decreasing uncertainty shocks. The uncertainty aversion is a motive to sensitively response to increasing uncertainty shock. Thus, economic agents have large precautionary acts against the increasing uncertainty shock, and it is not change to normal acts even there are the decreasing uncertainty shock.

Asymmetric uncertainty shocks have two features. First, the magnitude of the increasing and decreasing shocks is different. Uncertainty is an ambiguous concept, so it is inherently difficult to measure the probability distribution of uncertainty. Many studies measure 'economic' uncertainty with several measures but these measures do not fully represent the economic agent's uncertainty. Thus, uncertainty measures do not represent the size of economic agent's uncertainty but can divide an event into increasing uncertainty and decreasing uncertainty. When people have an uncertainty aversion, people averse the uncertain situations. Therefore, people get more shock to an increasing uncertainty than to a decreasing uncertainty. Furthermore, in economic situations, positive uncertainty shocks often increase significantly due to large events such as economic crisis or COVID-19. However, negative uncertainty shocks often occur when responses to uncertain situations such as fiscal policy or vaccine development. Thus, the negative uncertainty shock has smaller size and longer lasting than a positive uncertainty shock. In VXO data, the average value of increasing VXO changes is bigger than that of decreasing VXO changes [12], implying there are asymmetric size of uncertainty shocks. Second, the recovery speed of the increasing and decreasing shocks is different. The increasing uncertainty shock recovery faster than the decreasing uncertainty shock. In our empirical results, the uncertainty measure, VXO, have faster recovery of response to a positive shock than to a negative shock. Furthermore, in estimation results of DSGE model parameters, preference uncertainty process also has higher persistence in a negative shock than in a positive shock. The impact of

[12] Appendix table C

increasing uncertainty is usually large but, temporary. However, shocks with decreasing uncertainty are often small but persistent as a response to increasing uncertainty shocks.

As a result, asymmetric responses of economic agents to the uncertainty shock cause the asymmetric response of macro variables to the uncertainty shock. Past studies suggest that uncertainty shock cause precautionary saving motives and decrease aggregate demand. In asymmetric sense, the size of increasing uncertainty shock is bigger but have lower persistence, than that of decreasing uncertainty shock. Thus, precautionary saving motives are bigger in increasing uncertainty shock, but rapidly decreases. These motives lead the asymmetric response of macro variables to uncertainty shock.

Moreover, this study suggests that the asymmetry of responses to uncertainty shocks changes due to economy price rigidity, consumption habit and risk aversion changes. In our model, the asymmetry of the response occurs mainly due to the asymmetry of the uncertainty shock, but this asymmetry can also change due to some parameters. The asymmetry of responses increases when price rigidity is present, but rigidity is weaker, no consumption habit, and risk aversion is high.

This study contributes how modelling the asymmetry of the uncertainty process in a DSGE model. Our findings suggest asymmetric uncertainty of economic agents using an observable economic uncertainty measure. The study of the asymmetric response of economic agents can be a substantial issue when economic uncertainty increases. In particular, study has important implications for monetary and fiscal policy in response to the economic crisis.

Chapter 3. Dynamic relationships between stocks and treasury bonds with spillover effects: Evidence from US financial markets

3.1. Introduction

When an unexpected economic shock occurs, investors coordinate their portfolios for risk diversification, which causes severe fluctuation in financial markets. For instance, the treasury bond yield and stock market index severely fluctuated due to uncertain economic situations (e.g., COVID-19 pandemic and 2007–2009 financial crisis) as shown in Figure 3.1.[13] With the development of technology, investors can easily access and invest in a variety of financial markets. Thus, portfolio investments have increased and have become easy to coordinate portfolio selections as changing market conditions. Consequently, when an unexpected shock occurs in one market, whole financial markets share risks and severely fluctuate.

Asset reallocation is the main channel that the stock and bond markets influence each other. Investors usually treat treasury bond as safety heaven and stock as risky asset. One of the most common ways of risk diversification is investing in treasury bonds and stocks. Risky assets have high returns, hence the expression "high risk, high return." Thus, portfolio investors mainly choose the stock for their portfolio and only coordinate their portfolios when financial markets are in trouble.[14]

[13] Figure 1 shows Standard & Poor's 500 index and the one-year maturity bond (i.e., T-bills) excess yield from 2006 to 2020. The left axis and right axis indicate the bond yield and stock index, respectively. Gray bars are recession periods, which are 2007–2009 financial crisis and COVID-19 pandemic. During the recessions, the stock index and bond yield sharply declined and gradually recovered.

[14] In Flavin et al. (2014), the one-year maturity treasury bond is a good hedge against common risks, but 10-year maturity bond performs better in a risk hedging when the stock

Although it is a common ways of risk diversification, the degree of risk diversification varies depending on the type of treasury bonds.

In crisis periods, spillovers can be major problems and sensitive issues in portfolio investments. When one market is in trouble, investors change their investment plans and portfolios. This behavior of investors causes one market to influence another. Moreover, changes in portfolios cause the time varying changes in correlations among financial markets. Volatility and correlation are main variables in portfolio investments, and volatility refers to risk measurement in financial markets. Thus, estimation of precise relations among financial markets is important for portfolio investors who want to risk diversification and for the policy makers who want to stabilize the financial market when a market is in trouble. Without considering the spillover effect, dynamic conditional volatilities and correlations are underestimated or overestimated. Given the spillover effect in financial markets, portfolio investments become increasingly complex and require more considerations. Therefore, finding the relations among financial markets with spillover effects, especially about two big financial markets, the stock and treasury bond markets, is crucial for portfolio investors and policy makers.

This study investigates the relationship between the stock and treasury bond markets. Exponential general autoregressive conditional heteroskedastic (EGARCH) models are used to measure the conditional volatility of the stock and bond markets. For time-varying conditional correlations, I use multivariate EGARCH models. To find spillover effects in the stock and bond markets, I add each market's moving average (MA) terms of the conditional volatility (i.e. ARCH terms) in other markets'

market experiences large fluctuations. Perras et al. (2020) propose two dynamic asset re-allocation phenomena, which are called "flight-to-quality" and "fear-of-missing-out." The former, which is the most popular concept in finance, is about dynamic asset re-allocation from stocks to bonds, and the latter is about re-allocations to risky assets owing to the fear of missing higher return. Baur and Lucey (2010) present empirical evidence of "flight-to-quality" and "flight-from-quality," which is a similar concept to "fear-of-missing-out," in eight countries' stock and bond markets.

conditional variance equations. I also add stock market volume changes in conditional variance equations to find financial information spillover effects. The empirical results show the dynamic nonlinear relations between volatilities and returns of bond and stock markets with spillover effects.

This paper is organized as follows. Section 2 reviews the relevant literature. Section 3 presents the data and variables used in empirical works. Section 4 presents empirical linear and nonlinear models, estimation results and the further analysis. Section 5 concludes the paper.

3.2. Literature Review

In the last decades, many studies have analyzed relations between the stock and bond markets in various ways. Fleming et al. (1998), Scruggs and Glabadanidis (2003), Connolly et al. (2005), Guidolin and Temmermann (2006), and Steeley (2006) study returns and volatility relations in stock–bond relations. Fleming et al. (1998) show the volatility linkage in stocks, bonds, and money markets by using the future index of each market to measure the information movement and volatility linkages among financial markets. Their result shows that linkages among US financial markets have become stronger since the 1987 stock market crash. Steeley (2006) presents empirical evidence on the volatility relation and spillover effects of stocks and bonds in the UK. Scruggs and Glabadanidis (2003) and Connolly et al. (2005) demonstrate that financial market volatility has a negative impact on their returns. Connolly et al. (2005) find that bond returns tend to be highly relative to stock returns when the stock-implied volatility increases. Their result also supports the important role of stock market uncertainty in cross-market pricing and stock–bond diversification. Scruggs and Glabadanidis (2003) show that not only does volatility affect returns, but covariance among financial markets also affects returns as risk premiums. Guidolin and Temmermann (2006), unlike the previous works, divide the market conditions in several states and show that the stock market has low returns when it is in crash, and that the bond market has low returns when it is in crash or bullish.

Recent studies focus on the co-movement between a stock market and a bond market. (e.g., De Goeji and Marquering, 2004; Cappiello et al., 2006; Kim et al., 2006; Baur and Lucey, 2009; Yang et al., 2009; Baele et al., 2010; Flavin et al., 2014; Asgharian et al., 2016; Li et al., 2016). Many studies estimate dynamic conditional correlations by using GARCH style models (e.g., De Goeji and Marquering, 2004; Kim et al., 2006; Yang et al., 2009; Asgharian et al., 2016), whereas others estimate conditional correlations or covariances by using dynamic factor model or state-dependent model. A number of studies argue that decline in conditional correlations between stocks and bonds when markets are in trouble may represent the “flight-to-quality” phenomenon. The “flight-to-quality” phenomenon and changes in correlations occur not only when financial markets are unstable but also when the macroeconomy is in an uncertain situation, such as unexpected inflation shocks (Baele et al., 2010; Asgharian et al., 2016). De Goeji and Marquering (2004) and Baur and Lucey (2009) document asymmetries in stock–bond co-movements. Flavin et al. (2014) find that one-year maturity bond is a good hedging asset for financial asset investors against common shocks, whereas 10-year maturity bond becomes a better hedging asset when stock markets are severely volatile. The “flight-to-quality” phenomenon is not only observed in US financial markets but also in international financial markets (e.g., Cappiello et al., 2006; Kim et al., 2006; Steeley, 2006; Baur and Lucey, 2009).

Liquidities and information also have a significant role in analyzing the relations between stocks and bonds. Underwood (2009) shows that the treasury bond order imbalance is strongly related to intraday stock returns, and it is most pronounced when the stock market is in high uncertainty. Furthermore, Underwood (2009) documents strong correlation between the order flow and return and suggests that trading activities are correlated with unobserved factors, such as “private information,” in US financial markets. Fleming et al. (1998) argue about the significant role of financial information in stock–bond relations. In the stock market literature, many works show the information transmission in international stock markets on the basis of two theories namely, mixture of distribution hypothesis (MDH) and sequential information arrival hypothesis (SIAH) (e.g., Clark, 1973; Coopeland, 1976; Epps and Epps, 1976; Harris, 1987; Jennings et al., 1987). The two theories suggest that financial information affects the stock market and changes the market structure, especially volatility structure. Some studies use the GARCH model to test MDH and SIAH in developed countries and emerging markets and present empirical evidence of volume effects in stock return structures (e.g., Lamoureux and Lastrapes, 1990; Darrat et al., 2003; Wang and Huang, 2012).

Most past studies only focus on finding returns and volatility relations between the stock and bond markets but inadequately analyze the spillover effects. Fleming et al. (1998) suggest the importance of financial information in stock–bond relations but explain financial information spillover indirectly by using conditional correlations. Steeley (2006) investigates volatility spillovers in stock–bond relations but only considers the volatility spillover but not financial information spillover. Underwood (2009) shows the important role of order flow in determining the stock and bond returns. However, Underwood (2009) only focuses on finding return relations between the stock and bonds but does not consider volatility and correlations.

In this paper, I find non-linear relations between stock and treasury bonds, specifically first moments, returns, second moments, volatilities, and correlations. Unlike past studies, this study uses all types of bond market data (e.g., T-bonds, T-notes, and T-bills) with long period of high frequency data. Lastly, I utilize the EGARCH model while considering risk spillover effects of unexpected shocks in the stock and bond returns, and information spillover effects, which are measured by stock volume changes. With the estimated non-linear model, I calculate the conditional volatility and correlation between stock and treasury bonds. Furthermore, I compare the conditional risk of stock-bond portfolios to investigate the most hedging strategies to the stock.

3.3. Data

I use the S&P 500 daily index for the stock index and three different types of US treasury bonds, which are treasury bills (T-bills), treasury notes (T-notes), and treasury bonds (T-bonds) for bond data. Thirty-year, ten-year, and one-year maturity bonds represent T-bonds, T-notes, and T-bills, respectively. All data consist of daily closing prices and constant maturity rates from the Federal Reserve Economic Database over the period of February 15, 1977 to October 27, 2020. The log difference of S&P 500 index is used for the stock market return, and the difference between bond yields and federal fund rates is used for the bond market excess yield.[15] Furthermore, I define the bond return as follows:

$$R_{B,t} = \ln[(1+i_{t-1})/(1+i_t)],$$

where $R_{B,t}$ and i_t represent the bond returns and the bond market excess yield at time t, respectively.[16] To measure the financial information, I use

[15] To control the policy effects in bond yield changes, I use the difference between FFR and bond yields as bond excess yields data.

[16] To calculate the bond return, I compare the current bond value. In day-to-day trading,

the stock volume changes, which is the log difference of S&P 500 daily volumes.

Tables 3.1 shows the summary of data used in this paper. I test the autocorrelation and stationarity of whole time series and test the heteroscedasticity except the stock volume changes. To test autocorrelation and stationarity, I use the Ljung–Box Q test and the augmented Dickey–Fuller (ADF) test. I test the heteroscedasticity of the stock and bond returns by using the ARCH LM test and putting lag 20. All values of sample means are nonzero and positive, but the t-statistic results show that only the stock return has statistically nonzero mean in sample periods. Moreover, the stock return and volume changes are negatively skewed and bond returns are positively skewed. All variables have leptokurtic with non-normal distributions. The results of the Ljung–Box Q and ADF tests support that all series are autocorrelated and stationary. However, heteroskedasticity tests are only performed for the stock and bond returns, and the results show that the stock and bond returns have heteroskedasticity.

The results presented in Table 3.1 support that the stock and bond returns are stationary series with heteroskedasticity and autocorrelations.

3.4. Methodology and Results

3.4.1. Univariate EGARCH (1,1)-M models

Heteroskedasticity is one of the important issues in an analysis of financial market movements. Many previous works have captured heteroscedasticity with time-varying conditional volatility models.

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bonds in day t and t+1 have similar conditions for the maturity and annual coupon payment. Thus, I only consider the bond excess yield for current bond value and calculate the bond return as follows:

$$R_{B,t} = \ln\left\{\left[1/(1+i_t)\right]/\left[1/(1+i_{t-1})\right]\right\} = \ln[(1+i_{t-1})/(1+i_t)].$$

GARCH style models are one of the powerful tools to analyze the nonlinear relations among financial markets with heteroscedasticity. For the univariate model, I estimate the univariate EGARCH model (Nelson, 1991) to measure the conditional volatility of the stock and bond markets. To estimate the lagged effects and risk premiums, I adopt the EGARCH (1,1)-M model, which has the lagged return and conditional volatility in a mean equation. This mean equation is similar to the EGARCH (1,1)-M model used by Hafner and Kyriakopoulou (2019). Moreover, I consider the asymmetric shock effect in conditional variance. The mean equation and conditional variance equation are follows:

$$
\begin{aligned}
&R_t = c_0 + \alpha R_{t-1} + \beta V_t + \varepsilon_t, \\
&\ln V_t = c_1 + a\left|h_{t-1}\right| + dh_{t-1} + b\ln h_{t-1}, \\
&h_t = \varepsilon_t \big/ \sqrt{V_t},
\end{aligned}
$$

where R_t and V_t represent returns and conditional volatilities of the stock and bond markets, respectively. ε_t is a heteroskedastic residual that is normally distributed with mean zero and variance as V_t.

Table 3.2 shows the estimation results of the EGARCH (1,1)-M model. Panel A and B represent estimation results of the mean and variance equations, respectively. In panel A, all financial markets have positive constants except the stock and one-year bond markets. Lagged returns significantly decrease the current returns in the bond markets, but not in the stock market. Volatility coefficients are statistically significant in mean equations. The stock volatility significantly increases the stock return while the bond volatility significantly decreases the bond return. In panel B, coefficients A and B represents ARCH terms and GARCH terms coefficients, respectively. All coefficients A and B terms are positively significant, implying that all financial markets have ARCH effects and GARCH effects in conditional variances. In addition, GARCH coefficients are close to unity, indicating that conditional variances have strong persistence over time. Coefficient D represents the asymmetry effects, and the results support that all financial markets have asymmetry effects. The stock and one-year bond markets have statistically negative asymmetry coefficients, whereas thirty-year bond and ten-year bond markets have statistically positive asymmetry ones. Estimation results suggest that negative shocks in the stock and one-year bond markets have greater impact on conditional variances than positive shocks, whereas positives shocks have more impact on conditional variances in case of other bond markets.

The estimation result of the univariate EGARCH (1,1)-M model indicates that the stock return has the risk premium, whereas the bond returns do not. Lagged bond returns and conditional volatility significantly decrease the bond returns. Furthermore, conditional volatilities have strong persistence and asymmetry effects in all markets.

3.4.2. Multivariate EGARCH (1,1)-M models

In this section, I estimate three types of multivariate EGARCH models to find the nonlinear relation between the stock and bonds markets. Although financial markets are sensitive to financial information, studies about the role of financial information in stock–bond relations are scant. Thus, I measure financial information on the basis of stock volume changes and add it in the conditional volatility equation. Moreover, cross-ARCH terms are added in the stock and bond conditional volatility equations to check unexpected shock spillover effects. The stock and bond markets are closely related financial markets, and investments in both assets are common for risk diversification. Thus, the stock and bond market share financial information and a risk. Estimated coefficients of volume changes and cross-ARCH terms illustrate financial information and risk spillover effects in the stock–bond relations.

To estimate lagged effects, the baseline EGARCH (1,1) model have lag terms of the stock and bond returns in their own mean equations as in the univariate case. Furthermore, conditional volatilities of the stock and bond markets are added in the mean equations to investigate the stock and bond volatility premiums in returns like in the univariate EGARCH-M model. In univariate EGARCH results, all financial markets have an asymmetry effect; hence, asymmetry terms are also added in variance equations. Mean equations and conditional variance equations are follows:

$$StockR_t = \alpha_0 + \alpha_1 StockR_{t-1} + \alpha_2 BondR_{t-1} + \alpha_3 StockV_t + \alpha_4 BondV_t + \varepsilon_t \,,$$

$$BondR_t = \alpha'_0 + \alpha'_1 StockR_{t-1} + \alpha'_2 BondR_{t-1} + \alpha'_3 StockV_t + \alpha'_4 BondV_t + \varepsilon'_t \,,$$

$$\ln StockV_t = c + a\left|h_{t-1}\right| + dh_{t-1} + b \ln StockV_{t-1} \,,$$

$$\ln BondV_t = c' + a'\left|h'_{t-1}\right| + d'h'_{t-1} + b' \ln BondV_{t-1} \,,$$

$$h_t = \varepsilon_t \Big/ \sqrt{StockV_t} \,, h'_t = \varepsilon'_t \Big/ \sqrt{BondV_t} \,,$$

where $BondR_t$, $StockR_t$, $BondV_t$, and $StockV_t$ represent bond returns, stock returns, bond market conditional volatility, and stock market conditional volatility, respectively. ε_t and ε'_t are heteroskedastic residuals that are normally distributed with mean zero and variance as $StockV_t$ and $BondV_t$, respectively.

In the second model, I add the volume change term in conditional variance equations to capture the financial information effect. According to SIAH and MDH, financial information affects and changes the financial market return structure especially in the second moment. In addition, a financial information effect in the second moment is confirmed by many studies (e.g., Lamoureux and Lastrapes, 1990; Darrat et al., 2003; Wang and Huang, 2012). Hence, I add the stock volume changes in a stock conditional variance equation to measure financial information effect and in bond conditional variance equations to measure financial information spillover effect. Mean equations and conditional variance equations are follows:

$$StockR_t = \alpha_0 + \alpha_1 StockR_{t-1} + \alpha_2 BondR_{t-1} + \alpha_3 StockV_t + \alpha_4 BondV_t + \varepsilon_t \ ,$$

$$BondR_t = \alpha'_0 + \alpha'_1 StockR_{t-1} + \alpha'_2 BondR_{t-1} + \alpha'_3 StockV_t + \alpha'_4 BondV_t + \varepsilon'_t \ ,$$

$$\ln StockV_t = c + a\left|h_{t-1}\right| + dh_{t-1} + b\ln StockV_{t-1} + \beta VC_t \ ,$$

$$\ln BondV_t = c' + a'\left|h'_{t-1}\right| + d'h'_{t-1} + b'\ln BondV_{t-1} + \beta VC'_t \ ,$$

$$h_t = \varepsilon_t \Big/ \sqrt{StockV_t} \ , h'_t = \varepsilon'_t \Big/ \sqrt{BondV_t} \ ,$$

where $BondR_t$, $StockR_t$, $BondV_t$, $StockV_t$ and VC_t represent bond returns, stock returns, bond market conditional volatility, stock market conditional volatility, and stock volume changes, respectively. ε_t and ε'_t are heteroskedastic residuals that are normally distributed with mean zero and variance as $StockV_t$ and $BondV_t$, respectively.

In the last model, I add the stock and bond conditional variance ARCH term in each market's conditional variance equation to investigate the spillover effect (Koutmos, 1996). Mean equations and conditional variance equations are follows:

$$StockR_t = \alpha_0 + \alpha_1 StockR_{t-1} + \alpha_2 BondR_{t-1} + \alpha_3 StockV_t + \alpha_4 BondV_t + \varepsilon_t \,,$$

$$BondR_t = \alpha'_0 + \alpha'_1 StockR_{t-1} + \alpha'_2 BondR_{t-1} + \alpha'_3 StockV_t + \alpha'_4 BondV_t + \varepsilon'_t \,,$$

$$\ln StockV_t = c + a_1\left(\left|h_{t-1}\right| + dh_{t-1}\right) + a_2\left(\left|h'_{t-1}\right| + d'h'_{t-1}\right) + b\ln StockV_{t-1} + \beta VC_t \,,$$

$$\ln BondV_t = c' + a'_1\left(\left|h_{t-1}\right| + dh_{t-1}\right) + a'_2\left(\left|h'_{t-1}\right| + d'h'_{t-1}\right) + b'\ln BondV_{t-1} + \beta' VC_t \,,$$

$$h_t = \varepsilon_t \big/ \sqrt{StockV_t} \,, h'_t = \varepsilon'_t \big/ \sqrt{BondV_t} \,,$$

where $BondR_t$, $StockR_t$, $BondV_t$, $StockV_t$ and VC_t represent bond returns, stock returns, bond market conditional volatility, stock market conditional volatility, and stock volume changes, respectively. ε_t and ε'_t are heteroskedastic residuals that are normally distributed with mean zero and variance as $StockV_t$ and $BondV_t$, respectively. a_2 and a'_1 capture risk spillover effects, which are from bond markets to the stock market and from the stock market to bond markets, respectively.

Finally, I estimate dynamic conditional correlations (DCCs) between the stock and bond markets in all EGARCH models. A DCC suggested by Engle (2002) allows the time-varying condition in calculating correlations as follows:

$$DCC_t = q_t \big/ \sqrt{StockV_t \cdot BondV_t} \,,$$

$$q_t = (1 - a_{DCC} - b_{DCC})\bar{q} + a_{DCC}(\varepsilon_{t-1}\varepsilon'_{t-1}) + b_{DCC} q_{t-1} \,,$$

where $\bar{q}$ is the unconditional covariance between ε_{t-1} and ε'_{t-1}. q_t is not a covariance but is only used to provide the dynamic correlation series.

I then estimate models by maximizing the quasi log-likelihood function by using Broyden–Fletcher–Goldfarb–Shanno algorithms.[17]

Estimation results

Table 3.3 presents the estimation results for the baseline multivariate EGARCH-M model. Panels A and B show the estimation results of mean equations and variance equations, respectively. In Panel A, stock and bond volatility coefficients are statistically significant in both markets, but directions are opposite. Stock and bond volatilities significantly increase stock returns but significantly decrease bond returns. Thus, the results support that volatilities have premiums on stock returns but have negative impacts on bond returns.[18] Lagged returns have negatively significant coefficients in estimation results. Lagged bond returns significantly decrease the stock and bond returns, whereas lagged stock returns are statistically significant in bond equations but not in stock equations. In panel B, coefficients A, B, and D represent ARCH, GARCH, and asymmetric coefficients, respectively. The results of multivariate model cases are similar to those of the univariate model case. In multivariate model cases, the stock and T-bills have negative asymmetry effects, but T-bonds and T-notes have positive asymmetry effects. Furthermore, the estimation results support that the volatility has ARCH effects and strong persistency in all cases. In the estimated results of covariance equations, the lag coefficient of DCC is close to unity in all cases. This result implies that DCCs between the stock and bonds have strong persistency in all bond markets.

Table 3.4 presents the estimation results for multivariate EGARCH-M models with stock volume changes in conditional variance equations. Panels A and B show the estimation results of mean equations

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[17] I use the RATS program (version 10.0) to estimate the whole models.

[18] In the research of Scruggs and Glabadanidis (2003), the market volatility has positive effects on stock returns and negative effects on bond returns. However, unexpected stock shocks increase the bond return in the empirical results of Connolly et al. (2005).

and variance equations, respectively. Most estimation results are like the baseline EGARCH-M model results, but bond market coefficients are not statistically significant in stock mean equations. In panel A, lagged stock returns significantly decrease stock and bond returns, whereas lagged bond returns significantly decrease bond returns. Stock volatilities significantly increase stock returns, but significantly decrease bond returns. Unlike the previous result, bond volatility coefficients are not statistically significant in stock mean equations, but statistically and negatively significant in bond mean equations. In panel B, the estimated ARCH term and GARCH term coefficients are statistically significant at 1% level like in previous results. The financial information measured by stock volume change coefficients is statistically positive in variance equations of all financial markets. This finding implies that financial information affects the financial market and changes the financial market volatility. The estimation results support the MDH, SIAH, and financial information spillovers.[19] Like previous results of DCC equations, the lag coefficient of DCC is close to unity in all cases, and DCCs between the stock and bonds have strong persistency in all bond markets.

Table 3.5 presents the estimation results for multivariate EGARCH-M models with spillover effects in conditional variance equations. Panels A and B show the estimation results of mean equations and variance equations, respectively. In panel A, estimation coefficients are statistically significant in the same levels and directions, similar to previous results in Table 3.4. Lagged stock returns have negative impacts on stock and bond mean equations, but lagged bond returns are not statistically significant in stock mean equations. However, stock and bond volatility coefficients are smaller than in the result of Table 3.4, indicating

[19] Fleming et al. (1998) and Lamoureux and Lastrapes (1990) show that information affects volatility relations between stock and bond markets. Chordia et al. (2005) and Bale et al. (2010) also present empirical evidence of the high volatility when market liquidity is up.

that stock risk premium decreases when considering the risk spillovers. In panel B, all estimated coefficients are statistically significant. As in previous results, volatilities of US financial markets have ARCH effects, strong persistency, and asymmetry effects. Stock variance ARCH terms in bond variance equations and bond variance ARCH terms in the stock variance equation are statistically and positively significant, implying risk spillover effects in financial markets, like in previous studies (e.g., Chordia et al., 2005; Kim et al., 2006; Steeley, 2006). The result shows that an uncertain stock return shock significantly increases the bond return variance, and vice versa. However, the absolute values of estimated asymmetry coefficients are bigger than the results in Table 3.4. Estimation results suggest that the asymmetric effects have bigger sizes when considering the risk spillover effects. Furthermore, financial information effects are positively significant in variance equations. Volume change coefficients are statistically significant in both volatility equations, implying that MDH and SIAH still hold in this model and that a spillover effect occurs. In the estimation results of DCC coefficients, the lag coefficient of DCC is close to unity in all cases, and DCCs between the stock and the bond have strong persistency in all bond markets as in previous results.

Table 3.6 and 3.7 present the estimation results for multivariate EGARCH-M models with spillover effects during the crisis periods and non-crisis periods, respectively. The crisis periods are during the US recessions and financial crisis in other countries[20]. The sample periods of crisis and non-crisis are not fully continuous; hence, I estimate the constant correlation (CC) for correlations between stocks and bonds instead of DCCs. When comparing Tables 3.6 and 3.7, lagged bond returns coefficients are statistically significant during the crisis but not

[20] The Asian and Latin American financial crisis, European sovereign debt crisis, Japanese asset price bubbles and Black Monday, and Mexico economic crisis are included in a crisis sample.

during the non-crisis. However, the stock volatility premium is not statistically significant in divided samples except in the case of T-bonds. In conditional volatility equations, estimations results are similar to those in Table 3.5, except the spillover effects and asymmetry effects. During the crisis, estimated own markets ARCH effects are bigger than the non-crisis case, whereas cross-ARCH terms are smaller or statistically not significant. Furthermore, the risk spillover effect weakens when the market is in a crisis except in the case of T-bills. In such case, the value of stock risk spillover effect coefficient is 0.0343 during the crisis and much bigger in non-crisis periods. Furthermore, volume change coefficients are smaller in the stock equations and bigger in the bond equations during the crisis periods, indicating that financial information spillover effects become stronger in the bond markets and weaker in the stock market during the crisis. Estimated asymmetry coefficients are similar to those in Table 3.5, but statistically not significant in a T-bills case and a T-notes case during the crisis periods and non-crisis periods, respectively.

Table 3.8 presents the correlation coefficient between the stock and bonds for different sample periods. Panels A, B, and C present for the full sample period, crisis periods, and non-crisis periods, respectively. The table shows the unconditional correlation coefficient and DCC coefficients between the stock and bond returns for three different types of bonds. Unlike the unconditional correlation, DCCs are calculated by models, and they are time-varying conditional series. Thus, I perform the T-test for the mean values in which the null hypothesis is 0. The table presents the mean values of DCCs, and "*" indicates the significance level of the T-test for mean in which the null hypothesis is 0. DCC, DCC (with V.C.), and DCC (with S.O.) represent the estimated DCC from the baseline multivariate EGARCH-M model, the multivariate EGARCH-M model with volume changes, and the multivariate EGARCH-M model with spillover effects, respectively. Unconditional correlation coefficients are −0.0297, −0.0337, and −0.0232 for T-bonds, T-notes, and T-bills, respectively, and they are close to 0. However, the absolute mean values of DCCs for all bond market cases are bigger than unconditional correlation coefficients. The highest values of DCCs are 0.48, 0.40, and 0.09 in T-bonds, T-notes, and T-bills cases, respectively. The lowest values are −0.74, −0.67, and −0.38 in T-bonds, T-notes, and T-bills cases, respectively. In crisis periods, correlations increase more than twice as non-crisis periods. The mean values of DCCs during the crisis are −0.1570, −0.1612, and −0.0699 in T-bonds, T-notes, and T-bills cases, respectively. During non-crisis periods, the mean values of DCCs are −0.0468, −0.0627, and −0.0310 in T-bonds, T-notes, and T-bills cases, respectively. Furthermore, DCCs are different in models in the whole sample period. The mean values of DCCs increase when considering the spillover effects in a T-bills case, whereas they decrease in a T-notes case. However, in a T-bonds case, DCCs decrease when considering only the financial information spillover effect, but they increase when considering financial information and risk spillover effects. In non-crisis periods, the changes in DCCs have the same directions with the result of the whole sample period. However, during the crisis, DCCs increase when considering the spillover effects in a T-notes case, whereas they decrease in a T-bonds case. Most of these changes are statistically significant. Table 3.9 presents the T-test result in which the null hypothesis shows no difference among DCCs estimated from different models. Test results support that estimated DCCs are statistically different except the T-bonds case in crisis periods. During the crisis, DCCs are not different between the baseline model and the model with spillover effects in the T-bonds case.

Figure 3.2 to Figure 3.5 show time-varying DCCs in sample periods. Parts with lighter shade represent the recessions and the financial crisis period in the US. Parts with darker shade represent other countries’ financial crisis periods.[21] The first graph shows the DCCs between the stock and T-bonds returns. A black line, a blue dotted line, and a red dashed dot line represent the DCCs that are estimated by the baseline EGARCH-M model, the EGARCH-M model with volume changes, and the EGARCH-M model with spillover effects, respectively. In the T-bonds case, three DCC series have similar values and movements. However, DCCs estimated by the baseline model have more volatility movement than other models[22]. The second and third graphs show the DCCs of T-notes and T-bills cases, respectively. Unlike the graph of the T-bonds case, DCCs in T-notes and T-bills cases become different when considering the spillover effect in models. The last graph shows DCCs estimated by EGARCH-M models with spillover effects in all bond cases. A black line, a blue dotted line, and a red dashed dot line represent the DCCs of the T-bonds case, T-notes case, and T-bills case, respectively. The DCCs of the T-bonds case have most volatile movements, whereas the DCCs of T-bills case have the least volatility movements. In Figure 3.5, prior to 2000, the DCCs of T-bills are smaller in non-crisis periods and bigger in crisis periods than other cases. However, after 2000, the DCCs of T-bills are bigger than other cases in all periods. Therefore, for risk diversification, long-term bonds are a better choice than T-bills recently when considering the conditional correlation coefficients.

In addition, I calculate stock-bond portfolio risk with estimated models to compare the bond hedging ability for the stock. A common hedging strategy is to build a portfolio with 60% bonds and 40% stocks. However, many investors recommend investing 80% of assets in stocks when stock market going well. Table 3.10 reports the estimated results of

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[21] Parts with darker shade indicate Japanese asset price bubbles and Black Monday, Mexico economic crisis, Asian and Latin American financial crisis, and European sovereign debt crisis in order.

[22] In the T-bonds case, the standard deviation values of DCCs estimated from each model (the baseline model, the model with V.C., and the model with S.O.) are 0.221, 0.191, and 0.199, respectively.

portfolio conditional risks. I compare four types of portfolios. Panels A, B, C and D represent the mean value of estimated conditional risks of the 100% stock portfolio, the 80% stock portfolio, the 60% stock portfolio and the 100% bond portfolio, respectively. Conditional risks are estimated by the baseline M-GARCH model and the M-GARCH with spillover effects model. Last rows in each panel represent difference between estimated conditional risks from two models. * indicates the significance level of the T-test for a mean whose null hypothesis is zero. In all cases, estimated conditional risks in two models are statistically different at the 1% significance level. Conditional risks of portfolios with stocks are overestimated in the baseline model but conditional risks of the bond are underestimated in the baseline model. In panel B and C, the empirical results show that T-bills is the best hedging asset to the stock in the estimated result of the baseline model. However, when considering spillover effects, T-notes is the best hedging asset to the stock in the case of the 60% stocks portfolio. Additionally, I divide the sample periods into the crisis periods and the non-crisis periods. Table 3.11 and 3.12 reports estimated conditional risks during the crisis periods and the non-crisis periods, respectively. During the crisis periods, portfolios conditional risks estimated by two models are statistically different except portfolios with stocks and T-notes. Unlike the results in table 3.10, conditional risks are underestimated in the baseline model for all cases. However, portfolios conditional risks estimated by two models are statistically different except bonds conditional risks during the non-crisis periods. Furthermore, conditional risks are overestimated in the baseline model except bonds conditional risks. More importantly, T-bills is the best hedging asset to the stock in all cases during the non-crisis periods while T-notes is the best hedging asset to the stock in the case of the 60% stocks portfolio during the crisis periods.

To summarize, stock market returns have significant and negative coefficients in bond market mean equations, implying that the increase in stock returns decreases bond returns. This effect can be explained by the portfolio investor behavior of decreasing their bond portions when stock markets are going well. By contrast, bond return coefficients are not significant in stock returns mean equations when considering the spillover effects[23]. Additionally, financial market volatilities affect financial markets' first moments. Stock market volatility coefficients are significant in both markets' mean equations, whereas bond market volatility coefficients are significant only in bond market mean equations. Stock market volatilities significantly increase the stock return, whereas stock and bond market volatilities significantly decrease the bond returns. The results support that the current financial markets' risk has the premium in the stock market and a negative effect in bond markets.

More importantly, the empirical results show that financial markets have spillover effects in volatility relations. Financial markets are influenced by changes in financial information measured by stock volume changes. Volume change coefficients are positively significant in all financial market volatility equations. The changes in financial information not only affect the stock market but also the bond market. Empirical results illustrate the financial information spillover effect in financial market relations. Furthermore, unexpected shocks in financial markets have a spillover effect in variance relations. Cross MA terms in variance equations are positively significant in all financial markets, implying that the stock and bond markets' unexpected shocks have bi-directional

[23] Further research is required to explain this empirical result. Nevertheless, I suggest explaining it as a behavior of rebalancing stocks and bonds on the basis of financial information. The stock market is more sensitive to financial information than treasury bond markets. Moreover, the stock is main asset in portfolio investments for high returns. Consequently, the stock market has a dominant role in the stock–bond relation, and the bond effects in the stock market decrease when considering financial information.

spillover effects. The results support that the risk of one market spreads to other financial markets. Moreover, asymmetry coefficients are statistically significant in a univariate case and all multivariate models. Results shows that financial markets have asymmetry effects for unexpected shocks and risk spillover effects. Stocks and T-bills have bigger negative shocks than positive shocks, whereas other bonds have bigger positive shocks than negative shocks. Spillover effects also affect conditional correlations. DCCs increase or decrease when considering spillover effects, and they are statistically different among DCCs that are estimated by the baseline model and by models with spillover effects. In addition, DCCs vary depending on market conditions. DCCs have smaller values in the crisis than in non-crisis periods. Furthermore, risk spillover coefficients decrease during the crisis in T-bonds and T-notes cases, whereas they increase during a crisis in a T-bills case. Thus, bonds are good hedging assets against stock, and long-term bonds are especially a better choice to avoid the risk spillover than short-term bonds during crises. Moreover, during a crisis, financial information spillover effects decrease in the stock market, whereas they increase in bond markets. The finding indicates that the increase in financial information effects in bond markets is due to the “flight-to-quality” phenomenon during crises. More importantly, in further analysis for portfolios conditional risks, empirical results suggest that conditional risks are changing when considering spillover effects. In a common hedging strategy, which investing 60% assets in stocks and 40% in bonds, T-notes is the best hedging asset to the stock during the crisis periods as mentioned in Flavin et al (2014). However, in other hedging strategies, empirical results support that T-bills is the best hedging asset to the stock in all periods. Consequently, financial information and risk spillover effects have significant roles in dynamic relations between the stock market and bonds market, and both spillover effects vary according to market conditions.

3.5. Conclusions

When financial markets severely fluctuate, changes in returns, volatilities, and correlations in financial markets become substantial issues for portfolio investors. Given that stocks are a risky financial asset and treasury bonds are treated as a safety heaven, the changes in the relations of the two assets have become substantial issues for portfolio investors. Portfolio selection on the basis of market conditions like “flight-to-quality” and “flight-from-quality,” leads to changes in stock–bond relations. When assembling assets, correlation coefficients and volatilities are important considerations for determining returns and risk, implying the importance of the latest conditional correlation coefficients and volatilities. This study analyzes the nonlinear relations considering spillover effects between the US stock market and treasury bond markets.

The results show three major findings in US financial markets.

First, the stock market return and volatility decrease the bond market return, whereas the bond market return and volatility have no effects on the stock return when considering the spillover effects. The stock market return and conditional volatility have negative coefficients in bonds return equations. This study shows the empirical evidence of “flight-to-quality” and “fear-of-missing-out” in which finance investors actively change their portfolio decision when the stock market becomes a bull market or volatile. However, bond returns and volatilities are not statistically significant in the stock market equation.

Second, spillover effects are noted in US financial markets. Financial markets’ new information, which is measured by stock volume changes, affects the stock and bond markets. Specifically, changes in stock volume increase the stock and bond market volatility. The finding shows the financial information spillovers between the stock and bond markets. Furthermore, unexpected shocks in stock and bond markets affect their own volatility and have a cross effect on each volatility. One market’s risks do not affect only that market but also affect other financial markets, implying risk spillover effects in US financial markets. Additionally, spillover effects vary depending on market conditions. In crisis periods, risk spillover effects are weakened, whereas own risk effects become stronger, except the risk spillover effect from stocks to T-bills. Moreover, financial information spillover effects become stronger in bonds markets and weaker in the stock market during crises.

Third, spillovers affect the conditional second moments relations between the stock and bond markets. Spillover effects significantly affect the conditional correlations. Although the direction of changes depends on the maturity of bonds and market conditions, spillovers have statistically significant impacts on DCCs. The absolute value of correlations between the stock and bond markets during crises increase to more than twice of the absolute value of correlations in non-crises periods when considering spillover effects. The results suggest bonds are good hedging assets against stocks and are consistent with those of previous studies. Furthermore, spillover effects significantly change the conditional risk of portfolios. In a common hedging strategy, T-notes is the best hedging asset to the stock in the crisis periods. However, in other hedging strategies, T-bills is the best hedging asset to the stock in all periods.

This study demonstrates spillover effects that one market’s changes, such as becoming volatile or increasing returns, can affect other markets’ structures in financial markets. Spillover effects affect the financial market relation and can vary depending on the economic status. Spillover effects have important implication for risk diversification of investors in US financial markets. Risk premiums, conditional volatility and correlations are changing due to spillover effects. Thus, the finding can improve investor's calculation of expected portfolio returns and measuring the risk. Moreover, the finding can help policy makers put forward policies for stabilizing the financial market when unexpected economic or financial shocks occur. The finding suggests the importance of spillover effects. Furthermore, spillovers can improve the development on the linkage structure among financial markets and can guide the effectiveness of a policy in preventing unexpected shocks.

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Tables

[Table 1.1] Summary Statistics

This table shows summary statistics of all variables. LR, CR, BM, CPI and IP represents lending rates, call rates, the measure for bond market development, consumer price index and industrial production, respectively. Δ indicates changes from the previous period.

	Obs	Mean	Std.Dev	Median	Min	Max
LR	7533	6.159	4.815	5.208	0.250	78.140
CR	7533	3.358	4.466	2.326	-0.500	69.480
BM	3232	4.055	2.180	3.877	0.216	11.441
ΔCPI	7284	0.222	0.553	0.182	-2.938	6.648
ΔIP	7284	1.924	60.528	0.186	-97.024	3528.811
ΔLR	7284	-0.015	0.537	0.000	-9.310	17.900
ΔCR	7284	-0.015	0.585	0.000	-10.150	14.690

[Table 1.2] Summary Statistics of the Measure of Bond Market Development

	Period	Obs	Mean	Std.Dev	Min	Max
Argentina	1995Q1~2019Q1	97	1.556	0.850	0.668	4.059
Australia	1988Q2~2019Q2	125	4.312	0.908	2.885	6.327
Austria	1995Q1~2019Q2	98	5.031	1.047	2.999	7.001
Belgium	1989Q4~2019Q2	119	5.525	0.657	4.114	6.933
Bulgaria	2006Q4~2019Q2	51	0.736	0.247	0.446	1.204
Canada	1987Q1~2019Q2	130	4.936	1.136	3.689	8.049
Chile	2002Q4~2019Q2	67	2.609	0.564	1.724	3.871
China	2000Q4~2019Q2	75	1.959	0.894	0.683	3.936
Croatia	2006Q4~2019Q2	51	1.845	0.561	0.951	2.557
Estonia	2007Q4~2019Q2	47	0.330	0.083	0.216	0.550
Finland	2000Q4~2019Q2	119	3.539	0.698	2.260	5.418
France	1989Q4~2019Q2	119	4.764	1.430	2.280	6.859
Germany	1989Q4~2019Q2	119	4.027	1.026	1.771	5.809
Greece	1989Q4~2019Q2	98	3.457	1.202	1.728	7.077
Hongkong	1995Q1~2019Q2	90	2.903	1.406	1.221	5.707
Hungary	1997Q4~2019Q2	87	2.925	0.506	2.127	3.962
Israel	1995Q1~2019Q2	98	2.577	0.549	1.628	3.400
Italy	1989Q4~2019Q2	119	5.487	1.052	4.027	7.585
Japan	1997Q4~2019Q2	87	8.300	1.583	4.928	10.247
Latvia	2010Q4~2019Q2	35	1.022	0.308	0.464	1.462
Lithuania	2013Q4~2019Q2	27	1.299	0.066	1.182	1.459
Malaysia	2005Q1~2019Q2	58	4.174	0.322	3.408	4.779
Netherlands	1989Q4~2019Q2	119	7.341	3.054	2.449	11.441
Norway	1995Q4~2019Q2	95	3.276	0.890	2.146	5.019
Peru	2007Q4~2019Q2	47	0.887	0.220	0.611	1.282
Philippines	2015Q1~2019Q2	18	1.760	0.074	1.667	1.885
Poland	2003Q4~2019Q2	63	2.139	0.285	1.611	2.657
Portugal	1989Q4~2019Q2	119	3.996	1.579	2.130	7.411
Singapore	2000Q1~2019Q2	78	3.679	0.696	1.828	5.084
Slovenia	1998Q4~2019Q2	83	1.824	0.787	0.954	3.306
Spain	1989Q4~2019Q2	119	4.016	1.756	2.193	7.337
Sweden	2001Q4~2019Q2	71	5.046	0.803	3.410	6.248
Thailand	2005Q1~2019Q2	58	2.769	0.420	1.648	3.309
Turkey	2004Q4~2019Q2	59	1.366	0.149	1.164	1.832
UK	1987Q1~2019Q2	130	5.130	2.487	1.887	9.134
US	1987Q1~2019Q2	130	6.263	1.287	4.132	8.074

[Table 1.3] Correlation Matrix

This table shows correlations of all variables. LR, CR, BM, CPI and IP represent lending rates, call rates, bond market measures, CPI and industrial production, respectively. Δ indicates changes from the previous period.

	ΔLR	ΔCR	BM	ΔCPI	ΔIP
ΔLR	1.000	-	-	-	-
ΔCR	0.758	1.000	-	-	-
BM	-0.009	-0.008	1.000	-	-
ΔCPI	0.147	0.122	-0.161	1.000	-
ΔIP	-0.007	0.002	-0.003	0.001	1.000

[Table 1.4] Results of Baseline Model 1 (Random vs. Individual Fixed Effects)

This table reports results of the baseline panel regression model with random effects and with individual fixed effects as follows:

$$\Delta LR_{it} = \alpha_i + \beta \Delta CR_{it} + e_{it}$$

where ΔLR and ΔCR represent changes in lending rates and call rates, respectively. The results of Hausman test is also reported in the last row.

	ΔLR	
	Random effects	Ind Fixed effects
ΔCR	0.696***	0.692***
	(99.167)	(98.185)
Constant	-0.005	
	(-1.128)	
Hausman test	25.970***	

Notes: Numbers in parentheses show t-statistics. '***','**' and '*' represent the significance level of 1%, 5%, and 10%, respectively.

[Table 1.5] Results of Baseline Model 1(Individual Fixed Effects vs. Individual and Time Fixed Effects)

This table reports results of the baseline panel regression models with individual fixed effects and with individual and time fixed effects as follows:

$$\Delta LR_{it} = \alpha_i + \delta_t + \beta \Delta CR_{it} + e_{it}$$

where ΔLR and ΔCR represent changes in lending rates and call rates, respectively. The results of the F-test for time fixed effect is reported in the last row.

	ΔLR	
	Ind. Fixed Effects	Both Fixed Effects
ΔCR	0.692*** (98.185)	0.692*** (94.642)
F(390,6892)	1.108*	

Notes: Numbers in parentheses show t-statistics. '***','**' and '*' represent the significance level of 1%, 5%, and 10%, respectively.

[Table 1.6] Results of Baseline Model 2 (Random vs. Individual Fixed Effects)

This table reports results of the baseline panel regression model with random effects and with individual fixed effects as follows:

$$\Delta LR_{it} = \alpha_i + \beta \Delta CR_{it} + \gamma BM_{it} \Delta CR_{it} + e_{it}$$

where ΔLR, ΔCR and BM represent changes in lending rates, call rates and the measure for bond market development (bond/GDP), respectively. The results of Hausman test is also reported in the last row.

	ΔLR	
	Random effects	Ind. Fixed effects
ΔCR	0.633***	0.630***
	(50.171)	(49.746)
BMΔCR	0.034***	0.034***
	(5.938)	(5.945)
Constant	-0.003	
	(-0.778)	
Hausman test	26.292***	

Notes: Numbers in parentheses show t-statistics. '***','**' and '*' represent the significance level of 1%, 5%, and 10%, respectively.

[Table 1.7] Results of Baseline Model 2 (Individual Fixed Effects vs. Individual and Time Fixed Effects)

This table reports results of the baseline panel regression models with individual fixed effects and with individual and time fixed effects as follows:

$$\Delta LR_{it} = \alpha_i + \delta_t + \beta \Delta CR_{it} + \gamma BM_{it} \Delta CR_{it} + e_{it}$$

where ΔLR, ΔCR and BM represent changes in lending rates, call rates and the measure for bond market development (bond/GDP), respectively. The results of the F-test for time fixed effect is reported in the last row.

	ΔLR	
	Ind. Fixed Effects	Both Fixed Effects
ΔCR	0.630*** (49.746)	0.621*** (47.281)
BMΔCR	0.034*** (5.945)	0.040*** (6.514)
F (390,6891)	1.133**	

Notes: Numbers in parentheses show t-statistics. '***','**' and '*' represent the significance level of 1%, 5%, and 10%, respectively.

[Table 1.8] Results of Model with Macro Variables 1

This table reports results of the baseline panel regression models with individual fixed effects and with individual and time fixed effects as follows:

$$\Delta LR_{it} = \alpha_i + \delta_t + \beta \Delta CR_{it} + \gamma BM_{it} \Delta CR_{it} + \theta \Delta CPI_{it} + \mu \Delta IP_{it} + e_{it}$$

where ΔLR, ΔCR, BM, ΔIP, and ΔCPI represent changes in lending rates, call rates, the measure for bond market development (bond/GDP), CPI inflation rate, and IP growth rate, respectively. The results of the F-test for time fixed effect is reported in the last row.

	ΔLR	
	Ind. Fixed Effects	Both Fixed Effects
ΔCR	0.628***	0.618***
	(49.731)	(47.151)
BMΔCR	0.032***	0.040***
	(5.698)	(6.434)
ΔCPI	0.048***	0.048***
	(5.955)	(5.351)
ΔIP	-0.000	-0.000
	(-1.072)	(-0.904)
F(390,6878)	1.118*	

Notes: Numbers in parentheses show t-statistics. '***','**' and '*' represent the significance level of 1%, 5%, and 10%, respectively.

[Table 1.9] Results of Model with Macro Variables 2

This table reports results of the baseline panel regression models with individual fixed effects and with individual and time fixed effects as follows:

$$\Delta LR_{it} = \alpha_i + \delta_t + \beta \Delta CR_{it} + \gamma BM_{it} \Delta CR_{it} + \theta \Delta\Delta CPI_{it} + \mu \Delta\Delta IP_{it} + e_{it}$$

where Δ LR, Δ CR, BM, ΔΔ IP, and ΔΔ CPI represent changes in lending rates, call rates, the measure for bond market development (bond/GDP), changes in CPI inflation rate, and changes in IP growth rate, respectively. The results of the F-test for time fixed effect is reported in the last row.

	Δ LR	
	Ind. Fixed Effects	Both fixed effects
Δ CR	0.630***	0.621***
	(49.743)	(47.271)
BM Δ CR	0.034***	0.040***
	(5.933)	(6.491)
ΔΔ CPI	0.005	0.006
	(0.798)	(0.938)
ΔΔ IP	-0.000	-0.000
	(-1.106)	(-1.441)
F(390,6876)	1.130**	

Notes: Numbers in parentheses show t-statistics. '***','**' and '*' represent the significance level of 1%, 5%, and 10%, respectively.

[Table 1.10] Results of the model with the financial corporate bond market index

This table reports results of the baseline panel regression models with individual fixed effects and with individual and time fixed effects as follows:

$$\Delta LR_{it} = \alpha_i + \delta_t + \beta \Delta CR_{it} + \gamma BM_{it}^{F} \Delta CR_{it} + e_{it}$$

where ΔLR, ΔCR and BM^F represent changes in lending rates, call rates and the measure for the financial corporate bond market development (financial corporate bond/GDP), respectively. Results of the F-test for time fixed effect is reported in the last row.

	ΔLR	
	Ind. Fixed Effects	Both fixed effects
ΔCR	0.758***	0.770***
	(85.071)	(84.930)
BMΔCR (Financial)	-0.253***	-0.290***
	(-26.155)	(-28.005)
F(390,6891)	1.531***	

Notes: Parentheses are T-statistics. '***','**' and '*' represent the significance level of 1%, 5% and 10%, respectively.

[Table 1.11] Results of the model with the non-financial corporate bond market index.

This table reports results of the baseline panel regression models with individual fixed effects and with individual and time fixed effects as follows:

$$\Delta LR_{it} = \alpha_i + \delta_t + \beta \Delta CR_{it} + \gamma BM_{it}^{NF} \Delta CR_{it} + e_{it}$$

where ΔLR, ΔCR and BM^{NF} represent changes in lending rates, call rates and the measure for the nonfinancial corporate bond market development (nonfinancial corporate bond/GDP), respectively. Results of the F-test for time fixed effect is reported in the last row.

	ΔLR	
	Ind. Fixed Effects	Both fixed effects
ΔCR	0.5292***	0.5362***
	(44.819)	(44.327)
BMΔCR (Nonfinancial)	0.242***	0.2242***
	(8.027)	(7.205)
F(390,6891)	1.165**	

Notes: Parentheses are T-statistics. '***','**' and '*' represent the significance level of 1%, 5% and 10%, respectively.

[Table 1.12] Results of the model with subgroup countries (Financial bond)

This table reports results of the baseline panel regression models with individual fixed effects and with individual and time fixed effects using subgroup countries data as follows:

$$\Delta LR_{it} = \alpha_i + \delta_t + \beta \Delta CR_{it} + \gamma BM_{it}^F \Delta CR_{it} + e_{it}$$

where ΔLR, ΔCR and BM^F represent changes in lending rates, call rates and the measure for the financial bond market development (financial bond/GDP), respectively. Panel A and B report estimation results of market-based countries and bank-based countries, respectively. Results of the F-test for time fixed effect is reported in the last row of each panels.

	ΔLR	
	Ind. Fixed Effects	Both fixed effects
Panel A. Market-based countries		
ΔCR	-0.236***	-0.159***
	(-6.107)	(-3.443)
BMΔCR (Financial)	0.274***	0.203***
	(8.996)	(5.622)
F(390,918)	0.989	
Panel B. Bank-based countries		
ΔCR	0.787***	0.796***
	(86.690)	(85.324)
BMΔCR (Financial)	-0.195***	-0.224***
	(-18.290)	(-18.917)
F(390,5581)	1.310***	

Notes: Parentheses are T-statistics. '***','**' and '*' represent the significance level of 1%, 5% and 10%, respectively.

[Table 1.13] Results of the model with subgroup countries (Nonfinancial bond)

This table reports results of the baseline panel regression models with individual fixed effects and with individual and time fixed effects using subgroup countries data as follows:

$$\Delta LR_{it} = \alpha_i + \delta_t + \beta \Delta CR_{it} + \gamma BM_{it}^{NF} \Delta CR_{it} + e_{it}$$

where ΔLR, ΔCR and BM^{NF} represent changes in lending rates, call rates and the measure for the nonfinancial bond market development (nonfinancial bond/GDP), respectively. Panel A and B report estimation results of market-based countries and bank-based countries, respectively. Results of the F-test for time fixed effect is reported in the last row of each panels.

	ΔLR	
	Ind. Fixed Effects	Both fixed effects
Panel A. Market-based countries		
ΔCR	-0.030**	-0.007
	(-1.965)	(-0.334)
BMΔCR (Nonfinancial)	0.502***	0.353***
	(12.683)	(6.851)
F(390,918)	0.858	
Panel B. Bank-based countries		
ΔCR	0.679***	0.679***
	(50.242)	(49.210)
BMΔCR (Nonfinancial)	0.028	0.044
	(0.824)	(1.249)
F(390,5581)	1.194***	

Notes: Parentheses are T-statistics. '***','**' and '*' represent the significance level of 1%, 5% and 10%, respectively.

[Table 1.14] Results of the Model with Lagged Effects

This table reports results of the panel regression model with individual fixed effect, time fixed effects and Arellano-Bond method which are estimated from:

$$\Delta LR_{it} = \alpha_i + \delta_t + \omega \Delta LR_{it-1} + \beta \Delta CR_{it} + \gamma BM_{it} \Delta CR_{it} + \theta \Delta CR_{it-1} + \mu BM_{it-1} \Delta CR_{it-1} + e_{it}$$

where ΔLR, ΔCR and BM represent changes in lending rates, call rates and the measure for bond market development (bond/GDP), respectively. The results of the F-test for time fixed effect is reported in the last row.

	ΔLR		
	Fixed effects	Time fixed effects	Arellano-Bond
ΔLR(-1)	-0.050***	-0.051***	-0.088***
	(-4.269)	(-4.215)	(-7.241)
ΔCR	0.643***	0.624***	0.593***
	(50.415)	(47.077)	(40.062)
BMΔCR	0.029***	0.044***	0.060***
	(4.919)	(6.940)	(8.389)
ΔCR(-1)	-0.004	-0.010	-0.011
	(-0.247)	(-0.636)	(0.691)
BM(-1)ΔCR(-1)	0.059***	0.061***	0.074***
	(10.148)	(9.710)	(11.298)
F(389,6831)	1.093		

Notes: Parentheses are T-statistics. '***','**' and '*' represent the significance level of 1%, 5% and 10%, respectively.

[Table 1.15] Results of the model with bank characteristic measurements

This table reports results of the baseline panel regression models with individual fixed effects and with individual and time fixed effects as follows:

$$\Delta LR_{it} = \alpha_i + \delta_t + \beta \Delta CR_{it} + \gamma BM_{it} \Delta CR_{it} + \theta \Delta CPI_{it} + \mu Con_{it} \Delta CR_{it} + \rho Com_{it} \Delta CR_{it} + e_{it}$$

where ΔLR, ΔCR, BM and ΔCPI represent changes in lending rates, call rates, the measure for the bond market development (bonds/GDP) and CPI inflation rates, respectively. ΔCon and ΔCom represent bank characteristic which are 3 bank asset concentrations and competition indexes (i.e. Lerner index), respectively. Results of the F-test for time fixed effect is reported in the last row.

	ΔLR	
	Ind. Fixed Effects	Both fixed effects
ΔCR	0.144***	0.223***
	(2.959)	(4.474)
BMΔCR	0.071***	0.051***
	(10.815)	(7.225)
ΔCPI	0.038***	0.024**
	(4.386)	(2.500)
ΔCon	-0.004***	-0.005***
	(-5.556)	(-6.828)
ΔCom	0.893***	0.888***
	(9.779)	(9.669)
F(226,4671)	1.867***	

Notes: Parentheses are T-statistics. '***','**' and '*' represent the significance level of 1%, 5% and 10%, respectively.

[Table 2.1] Testing the asymmetry of the response

The table reports asymmetry test results of the response. The null hypothesis is that no difference between impulse responses to positive and negative VXO shocks. Chi-squared test are performed, and the degree of freedom depends on the length of response. H represents the length of the response. Parentheses indicate the P-value of the test. ***, **, and * represent the significance level of 1%, 5%, and 10%, respectively.

H	VXO	Output	Consumption	Investments	Working hours	Inflation	Policy rate
4	6.47	13.43***	47.67***	7.25	5.13	6.55	2.00
	(0.17)	(0.01)	(0.00)	(0.12)	(0.27)	(0.16)	(0.74)
8	11.91	82.67***	90.16***	11.24	10.57	11.59	3.49
	(0.16)	(0.00)	(0.00)	(0.19)	(0.23)	(0.17)	(0.90)
12	26.82***	123.79***	303.16***	19.18*	35.72***	18.82*	6.00
	(0.01)	(0.00)	(0.00)	(0.08)	(0.00)	(0.09)	(0.92)
16	36.14***	367.77***	781.15***	58.02***	122.56***	21.05	10.30
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.18)	(0.85)
20	47.87***	504.39***	1324.99***	111.77***	167.78***	27.69	12.40
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.12)	(0.90)

[Table 2.2] Testing the asymmetry of the response (Multipliers)

The table reports mean values of multipliers. H represents the length of the response.

H	Shock	Output	Consumption	Investment	Working hour	Inflation	Policy rate
4	Positive	-0.06	-0.04	-0.38	-0.02	-5.82	-2.91
	Negative	-0.04	-0.03	-0.22	-0.01	-0.13	-1.25
8	Positive	-0.03	-0.02	-0.22	-0.01	-5.28	-1.21
	Negative	-0.14	-0.13	-0.72	-0.04	5.06	-4.37
12	Positive	-0.04	-0.03	-0.21	-0.01	-5.25	-0.51
	Negative	-0.10	-0.09	-0.51	-0.03	-2.56	-2.30
16	Positive	-0.05	-0.04	-0.30	-0.02	-4.42	-0.57
	Negative	-0.11	-0.09	-0.57	-0.03	-6.19	-0.82
20	Positive	-0.04	-0.03	-0.35	-0.02	-3.69	-0.48
	Negative	-0.06	-0.03	-0.53	-0.02	-6.58	1.55

[Table 2.3] Parameter values

The table reports the calibrated and estimated parameters in the DSGE model.

Parameter	Interpretation	Value
Panel A. Household		
β	Discount factor	0.994
σ	Risk aversion	80
ψ	Intertemporal elasticity of substitution	0.95
η	Share of consumption in Cobb-Douglas aggregator	0.35
h	Habit persistence	0.6
Panel B. Firm		
α	Labor share	0.333
δ	Capital depreciation rate	0.025
ϕ_I	Investment adjustment cost parameter	1.58
ϕ_P	Price adjustment cost parameter	100
θ_μ	Demand elasticity	6
ν	Share of bonds in capital	0.9
Panel C. Monetary Policy		
Π	Steady state inflation rate	1.005
ρ_π	Coefficient of inflation target in monetary policy	1.5
ρ_y	Coefficient of output growth target in monetary policy	0.2
Panel D. Shocks		
ρ_a	Persistence of preference shock	0.938
a	Steady state of preference	1
σ^a	Steady state volatility of preference shock	0.0004
ρ_{σ^a}	Persistence of uncertainty shock	0.625
$\rho^+_{\sigma^a}$	Asymmetry coefficient of uncertainty shock persistence	-0.086
σ_{σ^a}	Volatility of uncertainty shock	0.008
$\sigma^+_{\sigma^a}$	Asymmetry coefficient of uncertainty shock volatility	0.002
ρ_Z	Persistence of labor productivity shock	0.840
Z	Steady state of labor productivity shock	1
σ^Z	Volatility of labor productivity shock	0.006

[Table 2.4] Empirical and model-implied volatility

The table reports the second moment of macro variables from data and model implied. Statistics of the data are calculated by HP-filtered sample data. Model implied statistics are calculated from the simulated data which have same length of the sample data.

	Percent		**Relative to Output**	
Standard deviation	**Data**	**Model**	**Data**	**Model**
Output	1.33	1.35	1	1
Consumption	1.28	1.28	0.96	0.95
Investment	0.88	0.90	0.66	0.67
Hours Worked	5.53	5.38	4.16	3.99

[Table 3.1] Summary Statistics

The table reports the summary statistics of stock and bond markets in the US. I use Ljung–Box Q test for autocorrelation and ARCH LM test for heteroscedasticity. I perform augmented Dickey–Fuller (ADF) test for unit root test. ***, **, and * represent the significance level of 1%, 5%, and 10%, respectively.

	Stock Returns	**Stock Volume Changes**	**Bond 30Yr Returns**	**Bond 10Yr Returns**	**Bond 1Yr Returns**
Observations	10910	10910	10910	10910	10910
Sample Mean	0.029	0.238	1.26E-04	1.67E-04	5.30E-05
Standard Error	1.111**	19.609	0.330***	0.330***	0.327***
t-Statistic (Mean=0)	2.764***	1.267	0.04	0.053	0.017
Skewness	−1.251***	−0.093***	0.305***	0.267***	0.308***
Kurtosis (excess)	26.234***	19.906***	93.564***	93.703***	100.52***
Jarque–Bera Statistics	3.16E+05***	1.80E+05***	3.98E+06***	3.99E+05***	4.59E+06***
Autocorrelation Test					
Ljung–Box Q Test (20)	83.908***	1.46E+03***	946.703***	943.819***	999.843***
Heteroscedasticity Test					
ARCH LM Test (20)	67.271***	-	148.138***	148.486***	157.884***
Unit Root Test					
ADF Test	−110.153***	−107.038***	−95.982***	−96.232***	−98.669***

[Table 3.2] EGARCH (1,1)-M Model Estimation Results

The table reports the estimation results of EGARCH (1,1)-M models. Panel A shows the estimation result of mean equations. Panel B shows the estimation result of variance equations. The first column represents the estimation results of stock market return, and remaining columns represent those of bonds, which are thirty-year treasury bond (i.e., T-bonds) returns, ten-year treasury excess bond (i.e., T-notes) returns, and one-year treasury bond (i.e., T-bills) returns, respectively. Parentheses indicate the T-statistics. ***, **, and * represent the significance level of 1%, 5%, and 10%, respectively.

	Stock	**Bond 30Yr**	**Bond 10Yr**	**Bond 1Yr**
Panel A. Mean Equations				
Constant	0.011	0.004***	0.004***	0.001
	(1.063)	(5.032)	(4.954)	(1.348)
Returns {1}	0.008	−0.1687***	−0.1731***	−0.231***
	(0.790)	(−16.678)	(−19.448)	(−23.904)
Volatility	0.0245**	−0.0308***	−0.0339***	−0.0014***
	(2.028)	(−17.315)	(−3.462)	(−24.168)
Panel B. Variance equations				
Constant	−0.1263***	−0.2083***	−0.2168***	−0.2175***
	(−20.010)	(−27.234)	(−26.752)	(−29.317)
A	0.1597***	0.2828***	0.295***	0.3027***
	(19.822)	(30.189)	(31.998)	(32.880)
B	0.9728***	0.9941***	0.9944***	0.9941***
	(410.961)	(1170.444)	(984.188)	(1527.394)
D	−0.0994***	0.0286***	0.0154***	−0.0151**
	(−19.994)	(5.146)	(5.887)	(−2.562)

[Table 3.3] Multivariate EGARCH (1,1)-M Model Estimation Results

The table reports the estimation results of multivariate EGARCH (1,1)-M models as mean equations and variance equations are follows:

$$StockR_t = \alpha_0 + \alpha_1 StockR_{t-1} + \alpha_2 BondR_{t-1} + \alpha_3 StockV_t + \alpha_4 BondV_t + \varepsilon_t$$

$$BondR_t = \alpha'_0 + \alpha'_1 StockR_{t-1} + \alpha'_2 BondR_{t-1} + \alpha'_3 StockV_t + \alpha'_4 BondV_t + \varepsilon'_t$$

$$\ln StockV_t = c + a\left|h_{t-1}\right| + dh_{t-1} + b \ln StockV_{t-1}$$

$$\ln BondV_t = c' + a'\left|h'_{t-1}\right| + d'h'_{t-1} + b' \ln BondV_{t-1}$$

$$h_t = \varepsilon_t \Big/ \sqrt{StockV_t}\ ,\ h'_t = \varepsilon'_t \Big/ \sqrt{BondV_t}$$

where $BondR_t$, $StockR_t$, $BondV_t$, and $StockV_t$ represent bond returns, stock returns, bond market conditional volatility, and stock market conditional volatility, respectively. In variance equations, c, a, b, and d represent the constant term, the ARCH term, the GARCH term, and the asymmetric effects term, respectively. DCC(A) and DCC(B) show the coefficients of DCC equations. Parentheses indicate the T-statistics. ***, **, and * represent the significance level of 1%, 5%, and 10%, respectively.

	Stock	**Bond 30Yr**	**Stock**	**Bond 10Yr**	**Stock**	**Bond 1Yr**
Panel A. Mean Equations						
Constant	0.0044	0.0065***	0.0046	0.0063***	0.0071	0.0013***
	(0.42)	(7.46)	(0.63)	(17.56)	(1.05)	(5.54)
Stock Returns {1}	0.0001	−0.0021***	0.0009	−0.0027***	0.0049	−0.0005**
	(0.01)	(−2.58)	(0.11)	(−7.22)	(0.53)	(−2.57)
Bond Returns {1}	−0.0427*	−0.1658***	−0.0391*	−0.1712***	−0.0363*	−0.23***
	(−1.90)	(−18.00)	(−1.73)	(−30.27)	(−1.67)	(−25.94)
Stock Volatility	0.0227**	−0.0024***	0.0208**	−0.0016***	0.0235***	−0.0008***
	(1.97)	(−6.45)	(2.01)	(−2.83)	(3.23)	(−25.44)
Bond Volatility	0.0325**	−0.0303***	0.0332**	−0.0328***	0.0336***	−0.0279***
	(2.18)	(−10.66)	(2.26)	(−2.82)	(3.23)	(−35.77)
Panel B. Volatility Equations						
Constant	−0.1279***	−0.2114***	−0.1251***	−0.2171***	−0.126***	−0.2175***
	(−20.63)	(−27.49)	(−25.45)	(−59.13)	(−30.86)	(−57.92)
A	0.165***	0.2896***	0.1611***	0.2979***	0.1595***	0.3042***
	(20.64)	(31.04)	(25.80)	(63.55)	(31.91)	(64.40)
B	0.972***	0.9943***	0.9726***	0.9948***	0.9726***	0.9943***
	(400.02)	(1.13E+03)	(479.36)	(2.16E+03)	(483.34)	(2.18E+03)
D	−0.1016***	0.0206***	−0.1002***	0.0091**	−0.0996***	−0.0204***
	(−17.44)	(3.85)	(−21.94)	(2.13)	(−20.54)	(−4.93)
DCC(A)	0.0249***		0.0171***		0.0024***	
	(531.55)		(581.62)		(68.48)	
DCC(B)	0.9751***		0.9829***		0.9976***	
	(7.56E+04)		(3.24E+07)		(1.11E+07)	

[Table 3.4] Multivariate EGARCH (1,1)-M Model with Stock Volume Changes Estimation Results

The table reports the estimation results of multivariate EGARCH (1,1)-M models with volume changes as mean equations and variance equations are follows:

$$StockR_t = \alpha_0 + \alpha_1 StockR_{t-1} + \alpha_2 BondR_{t-1} + \alpha_3 StockV_t + \alpha_4 BondV_t + \varepsilon_t$$

$$BondR_t = \alpha'_0 + \alpha'_1 StockR_{t-1} + \alpha'_2 BondR_{t-1} + \alpha'_3 StockV_t + \alpha'_4 BondV_t + \varepsilon'_t$$

$$\ln StockV_t = c + a\left|h_{t-1}\right| + dh_{t-1} + b \ln StockV_{t-1} + \beta VC_t$$

$$\ln BondV_t = c' + a'\left|h'_{t-1}\right| + d'h'_{t-1} + b' \ln BondV_{t-1} + \beta' VC_t$$

$$h_t = \varepsilon_t \Big/ \sqrt{StockV_t}\ , h'_t = \varepsilon'_t \Big/ \sqrt{BondV_t}$$

where $BondR_t$, $StockR_t$, $BondV_t$, $StockV_t$ and VC_t represent bond returns, stock returns, bond market conditional volatility, stock market conditional volatility, and stock volume changes, respectively. In variance equations, c, a, b, and d represent the constant term, the ARCH term, the GARCH term, and the asymmetric effect term, respectively. DCC(A) and DCC(B) show the coefficients of DCC equations. Parentheses indicate the T-statistics. ***, **, and * represent the significance level of 1%, 5%, and 10%, respectively.

	Stock	**Bond 30Yr**	**Stock**	**Bond 10Yr**	**Stock**	**Bond 1Yr**
Panel A. Mean Equations						
Constant	0.0017	0.0068***	0.0040	0.0062***	0.0050	0.0011***
	(0.24)	(10.14)	(0.56)	(9.77)	(0.76)	(3.37)
Stock Returns {1}	−0.0207**	−0.0026***	−0.0203**	−0.0027***	−0.0182**	−0.0005**
	(−2.48)	(−3.62)	(−2.27)	(−4.01)	(−2.41)	(−2.29)
Bond Returns {1}	−0.0249	−0.167***	−0.0229	−0.1709***	−0.0229	−0.2322***
	(−1.25)	(−22.86)	(−1.24)	(−41.37)	(−1.13)	(−24.12)
Stock Volatility	0.0298***	−0.003***	0.0254***	−0.0018***	0.0308***	−0.0006**
	(3.27)	(−6.72)	(3.35)	(−2.64)	(4.12)	(−2.54)
Bond Volatility	0.0139	−0.0223***	0.0142	−0.0327***	0.0127	−0.0238***
	(1.07)	(−10.88)	(1.18)	(−26.44)	(0.98)	(−11.34)
Panel B. Volatility Equations						
Constant	−0.1272***	−0.2295***	−0.1261***	−0.2387***	−0.1254***	−0.2334***
	(−28.17)	(−113.10)	(−114.62)	(−52.55)	(−19.47)	(−43.00)
A	0.1534***	0.3042***	0.1519***	0.3162***	0.1498***	0.3188***
	(27.28)	(68.10)	(96.92)	(59.08)	(17.80)	(43.57)
B	0.9757***	0.9931***	0.9762***	0.9932***	0.9772***	0.9932***
	(636.54)	(1.72E+03)	(618.33)	(2.84E+03)	(588.50)	(2.28E+03)
D	−0.0858***	0.0217***	−0.0851***	0.0093***	−0.0836***	−0.0200***
	(−22.33)	(7.08)	(−16.15)	(3.35)	(−16.15)	(−5.73)
Volume Changes	0.0147***	0.0078***	0.0147***	0.0074***	0.0147***	0.0059***
	(39.91)	(28.21)	(51.81)	(26.09)	(45.70)	(13.57)
DCC(A)	0.0092***		0.0057***		0.0026***	
	(2.14E+03)		(655.34)		(26.21)	
DCC(B)	0.9908***		0.9943***		0.9973***	
	(4.19E+07)		(2.07E+07)		(1.13E+07)	

[Table 3.5] Multivariate EGARCH (1,1)-M with Spillovers Model Estimation Results

The table reports the estimation results of multivariate EGARCH (1,1)-M models with spillover effects as mean equations and variance equations are follows:

$$StockR_t = \alpha_0 + \alpha_1 StockR_{t-1} + \alpha_2 BondR_{t-1} + \alpha_3 StockV_t + \alpha_4 BondV_t + \varepsilon_t$$

$$BondR_t = \alpha'_0 + \alpha'_1 StockR_{t-1} + \alpha'_2 BondR_{t-1} + \alpha'_3 StockV_t + \alpha'_4 BondV_t + \varepsilon'_t$$

$$\ln StockV_t = c + a_1\left(\left|h_{t-1}\right| + dh_{t-1}\right) + a_2\left(\left|h'_{t-1}\right| + d'h'_{t-1}\right) + b \ln StockV_{t-1} + \beta VC_t$$

$$\ln BondV_t = c' + a'_1\left(\left|h_{t-1}\right| + dh_{t-1}\right) + a'_2\left(\left|h'_{t-1}\right| + d'h'_{t-1}\right) + b' \ln BondV_{t-1} + \beta' VC_t$$

$$h_t = \varepsilon_t \big/ \sqrt{StockV_t}\,,\ h'_t = \varepsilon'_t \big/ \sqrt{BondV_t}$$

where $BondR_t$, $StockR_t$, $BondV_t$, $StockV_t$ and VC_t represent bond returns, stock returns, bond market conditional volatility, stock market conditional volatility, and stock volume changes, respectively. In variance equations, c, a, b, and d represent the constant term, the ARCH term, the GARCH term, and the asymmetric effect term, respectively. DCC(A) and DCC(B) show the coefficients of DCC equations. Parentheses indicate the T-statistics. ***, **, and * represent the significance level of 1%, 5%, and 10%, respectively.

	Stock	Bond 30Yr	Stock	Bond 10Yr	Stock	Bond 1Yr
Panel A. Mean Equations						
Constant	0.0183***	0.0065***	0.0139**	0.0062***	0.0145**	0.0011***
	(3.47)	(8.33)	(2.39)	(10.37)	(2.09)	(4.87)
Stock Returns {1}	−0.0205**	−0.0031***	−0.0208**	−0.0027***	−0.0181***	−0.0005***
	(−2.32)	(−4.16)	(−2.43)	(−8.68)	(−2.70)	(−2.62)
Bond Returns {1}	−0.0151	−0.1683***	−0.0136	−0.1709***	−0.0179	−0.2327***
	(−1.16)	(−21.93)	(−1.21)	(−42.43)	(−0.92)	(−25.35)
Stock Volatility	0.0126**	−0.0023***	0.0159**	−0.0017**	0.0207**	−0.0006***
	(2.02)	(−4.82)	(2.04)	(−2.47)	(2.49)	(−10.26)
Bond Volatility	−0.0167	−0.0245***	−0.0069	−0.0335***	0.0008	−0.0252***
	(−0.97)	(−4.36)	(−0.44)	(−25.36)	(0.05)	(−2.79)
Panel B. Volatility Equations						
Constant	−0.1595***	−0.2692***	−0.1528***	−0.2579***	−0.1412***	−0.2476***
	(−67.60)	(−223.78)	(−69.37)	(−40.83)	(−26.31)	(−290.25)
Stock MA	0.1532***	0.0517***	0.1514***	0.0309***	0.1503***	0.0192***
	(93.21)	(23.44)	(50.41)	(7.68)	(29.14)	(9.64)
Bond MA	0.0514***	0.3073***	0.0418***	0.3134***	0.0253***	0.3187***
	(12.47)	(207.38)	(9.57)	(47.70)	(5.84)	(68.46)
B	0.9816***	0.9936***	0.9795***	0.9939***	0.9800***	0.9933***
	(870.16)	(2.43E+03)	(740.41)	(1.50E+03)	(1.13E+03)	(3.80E+03)
D	−0.5252***	0.0626***	−0.5358***	0.0274*	−0.5361***	−0.0649***
	(−27.18)	(6.41)	(−20.23)	(1.74)	(−17.57)	(−5.54)
Volume Changes	0.0151***	0.0075***	0.0150***	0.0073***	0.0148***	0.0059***
	(46.23)	(20.49)	(48.47)	(23.57)	(92.02)	(10.63)
DCC(A)	0.0152***		0.0067***		0.0021***	
	(458.97)		(531.89)		(33.86)	
DCC(B)	0.9848***		0.9933***		0.9978***	
	(2.91E+05)		(6.02E+07)		(1.01E+07)	

[Table 3.6] Multivariate EGARCH-M Spillover Model Estimation Results (Crisis periods)

The table reports the estimation results of multivariate EGARCH (1,1)-M models with spillover effects during the crisis periods. The mean and variance equations are follows:

$$StockR_t = \alpha_0 + \alpha_1 StockR_{t-1} + \alpha_2 BondR_{t-1} + \alpha_3 StockV_t + \alpha_4 BondV_t + \varepsilon_t$$

$$BondR_t = \alpha'_0 + \alpha'_1 StockR_{t-1} + \alpha'_2 BondR_{t-1} + \alpha'_3 StockV_t + \alpha'_4 BondV_t + \varepsilon'_t$$

$$\ln StockV_t = c + a_1\left(\left|h_{t-1}\right| + dh_{t-1}\right) + a_2\left(\left|h'_{t-1}\right| + d'h'_{t-1}\right) + b \ln StockV_{t-1} + \beta VC_t$$

$$\ln BondV_t = c' + a'_1\left(\left|h_{t-1}\right| + dh_{t-1}\right) + a'_2\left(\left|h'_{t-1}\right| + d'h'_{t-1}\right) + b' \ln BondV_{t-1} + \beta' VC_t$$

$$h_t = \varepsilon_t \big/ \sqrt{StockV_t}\,,\; h'_t = \varepsilon'_t \big/ \sqrt{BondV_t}$$

where $BondR_t$, $StockR_t$, $BondV_t$, $StockV_t$ and VC_t represent bond returns, stock returns, bond market conditional volatility, stock market conditional volatility, and stock volume changes, respectively. In variance equations, c, a, b, and d represent the constant term, the ARCH term, the GARCH term, and the asymmetric effect term, respectively. CC shows the constant correlation with the result of non-zero null tests. Parentheses indicate the T-statistics. ***, **, and * represent the significance level of 1%, 5%, and 10%, respectively.

	Stock	**Bond 30Yr**	**Stock**	**Bond 10Yr**	**Stock**	**Bond 1Yr**
Panel A. Mean Equations						
Constant	0.0060	0.0033***	0.0050	0.0029**	0.0162	−0.0006***
	(0.52)	(7.85)	(0.28)	(2.43)	(1.54)	(−4.49)
Stock Returns {1}	−0.0259**	−0.0011**	−0.0239	−0.0002	−0.025***	−0.0003
	(−2.07)	(−2.04)	(−1.56)	(−0.28)	(−2.88)	(−0.93)
Bond Returns {1}	−0.0861**	−0.1081***	−0.0787**	−0.1393***	−0.0656**	−0.2143***
	(−2.50)	(−19.14)	(−1.98)	(−7.64)	(−2.18)	(−59.24)
Stock Volatility	0.0210***	−0.0029***	0.0214	−0.0009***	0.0127	−0.0001
	(6.66)	(−37.63)	(1.45)	(−3.03)	(1.00)	(−1.36)
Bond Volatility	0.0202	−0.0151***	0.0230*	−0.0162***	0.0201*	−0.0161***
	(1.42)	(−39.81)	(1.67)	(−14.84)	(1.84)	(−23.82)
Panel B. Volatility Equations						
Constant	−0.1603***	−0.3247***	−0.1526***	−0.3080***	−0.1551***	−0.3287***
	(−56.80)	(−206.68)	(−14.18)	(−17.06)	(−14.88)	(−23.15)
Stock MA	0.1889***	0.0151***	0.1889***	−0.0024	0.1885***	0.0345***
	(95.54)	(6.96)	(17.36)	(−0.24)	(18.23)	(4.97)
Bond MA	0.0238***	0.4012***	0.0121	0.3999***	0.0162	0.4208***
	(5.57)	(192.95)	(0.85)	(24.94)	(1.56)	(29.24)
B	0.9651***	0.9883***	0.9659***	0.9898***	0.9692***	0.9953***
	(449.99)	(1712.19)	(276.53)	(511.64)	(276.43)	(921.98)
D	−0.5828***	0.0866***	−0.5651***	0.0564***	−0.5673***	0.0072
	(−34.20)	(4.07)	(−10.12)	(2.65)	(−15.32)	(0.60)
Volume Changes	0.0127***	0.0099***	0.0127***	0.0090***	0.0126***	0.0060***
	(36.56)	(30.82)	(15.88)	(10.94)	(34.07)	(10.09)
CC	−0.1313***		−0.1393***		−0.0508***	
	(−8.99)		(−9.76)		(−3.27)	

[Table 3.7] Multivariate EGARCH-M Spillover Model Estimation Results (Non-crisis periods)

The table reports the estimation results of multivariate EGARCH (1,1)-M models with spillover effects during the non-crisis periods. The mean and variance equations are follows:

$$StockR_t = \alpha_0 + \alpha_1 StockR_{t-1} + \alpha_2 BondR_{t-1} + \alpha_3 StockV_t + \alpha_4 BondV_t + \varepsilon_t$$

$$BondR_t = \alpha'_0 + \alpha'_1 StockR_{t-1} + \alpha'_2 BondR_{t-1} + \alpha'_3 StockV_t + \alpha'_4 BondV_t + \varepsilon'_t$$

$$\ln StockV_t = c + a_1\left(\left|h_{t-1}\right| + dh_{t-1}\right) + a_2\left(\left|h'_{t-1}\right| + d'h'_{t-1}\right) + b\ln StockV_{t-1} + \beta VC_t$$

$$\ln BondV_t = c' + a'_1\left(\left|h_{t-1}\right| + dh_{t-1}\right) + a'_2\left(\left|h'_{t-1}\right| + d'h'_{t-1}\right) + b'\ln BondV_{t-1} + \beta' VC_t$$

$$h_t = \varepsilon_t \Big/ \sqrt{StockV_t}\,,\; h'_t = \varepsilon'_t \Big/ \sqrt{BondV_t}$$

where $BondR_t$, $StockR_t$, $BondV_t$, $StockV_t$ and VC_t represent bond returns, stock returns, bond market conditional volatility, stock market conditional volatility, and stock volume changes, respectively. In variance equations, c, a, b, and d represent the constant term, the ARCH term, the GARCH term, and the asymmetric effect term, respectively. CC shows the constant correlation with the result of non-zero null tests. Parentheses indicate the T-statistics. ***, **, and * represent the significance level of 1%, 5%, and 10%, respectively.

	Stock	Bond 30Yr	Stock	Bond 10Yr	Stock	Bond 1Yr
Panel A. Mean Equations						
Constant	0.0532***	0.0066***	0.0481***	0.0059***	0.0443***	0.0016***
	(5.24)	(12.12)	(3.88)	(4.86)	(4.58)	(3.55)
Stock Returns {1}	−0.0104	−0.0032***	−0.0104	−0.0032***	−0.0115	−0.0008***
	(−1.18)	(−4.64)	(−1.11)	(−2.64)	(−1.00)	(−8.10)
Bond Returns {1}	0.0123	−0.1992***	0.0082	−0.1959***	0.0188	−0.2521***
	(0.69)	(−52.09)	(0.49)	(−18.11)	(0.72)	(−54.39)
Stock Volatility	−0.0246*	−0.0015**	−0.0169	0.0001	−0.0101	−0.0010***
	(−1.94)	(−2.10)	(−0.84)	(0.08)	(−0.82)	(−6.71)
Bond Volatility	−0.0394***	−0.0345***	−0.0375	−0.0385*	−0.039	−0.0461***
	(−3.00)	(−15.79)	(−1.53)	(−1.81)	(−1.62)	(−9.32)
Panel B. Volatility Equations						
Constant	−0.1599***	−0.2207***	−0.1560***	−0.2230***	−0.1452***	−0.2145***
	(−20.21)	(−52.43)	(−14.86)	(−17.79)	(−14.87)	(−25.83)
Stock MA	0.1378***	0.0570***	0.1343***	0.0487***	0.1329***	0.0329***
	(17.29)	(13.50)	(14.33)	(5.10)	(14.89)	(3.67)
Bond MA	0.0609***	0.2453***	0.0577***	0.2559***	0.0445***	0.2574***
	(8.45)	(27.03)	(6.38)	(21.43)	(5.77)	(82.66)
B	0.9842***	0.9969***	0.9826***	0.9965***	0.9813***	0.9939***
	(382.16)	(1.15E+03)	(334.62)	(1.02E+03)	(335.82)	(1.63E+03)
D	−0.5555***	0.0615**	−0.5749***	0.0380	−0.5845***	−0.1374***
	(−10.93)	(2.22)	(−8.52)	(1.31)	(−10.07)	(−8.40)
Volume Changes	0.0164***	0.0062***	0.0163***	0.0063***	0.0162***	0.0058***
	(34.49)	(11.89)	(31.73)	(7.81)	(32.90)	(7.61)
CC	−0.0253**		−0.0378***		−0.0084	
	(−2.14)		(−3.16)		(−0.70)	

[Table 3.8] Correlations between the Stock Market and Bond Markets

The table reports the unconditional correlation and DCCs between the stock and bond returns. Each panel presents the different sample periods and estimated DCCs from different models. Panels A, B, and C represent the whole sample period, crisis periods, and non-crisis periods. DCC represents the estimated DCC from baseline multivariate EGARCH-M model. V.C. and S.O. indicate the model that considers volume changes and the model that considers all spillover effects, respectively. * indicates the significance level of the T-test for a mean whose null hypothesis is zero. ***, **, and * represent the significance level of 1%, 5%, and 10%, respectively.

	Bond 30Yr	**Bond 10Yr**	**Bond 1Yr**
Panel A. All periods			
Unconditional Correlations	−0.0297	−0.0337	−0.0232
DCC	−0.0873***	−0.0989***	−0.0453***
DCC (with V.C.)	−0.0903***	−0.1027***	−0.0393***
DCC (with S.O.)	−0.0858***	−0.1001***	−0.0418***
Panel B. Crisis periods			
Unconditional Correlations	−0.0624	−0.0658	−0.0487
DCC	−0.1570***	−0.1612***	−0.0699***
DCC (with V.C.)	−0.1592***	−0.1530***	−0.0642***
DCC (with S.O.)	−0.1573***	−0.1548***	−0.0656***
Panel C. Non-crisis periods			
Unconditional Correlations	0.0069	0.0022	0.0049
DCC	−0.0468***	−0.0627***	−0.0310***
DCC (with V.C.)	−0.0502***	−0.0735***	−0.0249***
DCC (with S.O.)	−0.0443***	−0.0683***	−0.0280***

[Table 3.9] Difference among DCCs

The table reports T-test results for the difference among DCCs of different sample periods. Panels A, B, and C represent the whole sample period, crisis periods, and non-crisis periods, respectively. DCC represents the estimated DCC from the baseline multivariate EGARCH-M model. V.C. and S.O. indicate the model that considers volume changes and the model that considers all spillover effects, respectively. The null hypothesis is that no difference exists among DCCs estimated from different models. ***, **, and * represent the significance level of 1%, 5%, and 10%, respectively.

	Bond 30Yr	Bond 10Yr	Bond 1Yr
Panel A. All periods			
H_0: DCC = DCC(V.C.)	4.2142***	5.1476***	57.9445***
H_0: DCC = DCC(S.O.)	3.6638***	1.8485*	39.2053***
H_0: DCC(V.C.) = DCC(S.O.)	13.3577***	23.0020***	36.8359***
Panel B. Crisis periods			
H_0: DCC = DCC(V.C.)	1.8997**	6.1455***	30.5307***
H_0: DCC = DCC(S.O.)	0.5414	5.5912***	31.2094***
H_0: DCC(V.C.) = DCC(S.O.)	3.0839***	8.5209***	10.5579***
Panel C. Non-crisis periods			
H_0: DCC = DCC(V.C.)	4.2142***	5.1476***	57.9445***
H_0: DCC = DCC(S.O.)	3.6638***	1.8485*	39.2053***
H_0: DCC(V.C.) = DCC(S.O.)	13.3577***	23.0020***	36.8359***

[Table 3.10] Portfolios Conditional Risk

The table reports the portfolios conditional risk and T-test results for the difference among portfolios conditional risks. Each panel presents different stock-bond portfolios conditional risks. Panels A, B, C and D represent the 100% stock portfolio, the 80% stock portfolio, the 60% stock portfolio and the 100% bond portfolio, respectively. M-GARCH and M-GARCH with S.O. indicate the baseline model and the model that considers all spillover effects, respectively. * indicates the significance level of the T-test for a mean whose null hypothesis is zero. ***, **, and * represent the significance level of 1%, 5%, and 10%, respectively.

	Bond 30Yr	**Bond 10Yr**	**Bond 1Yr**
Panel A. Stocks (100%)			
Volatility (M-GARCH)	1.1803	1.1717	1.1519
Volatility (M-GARCH with S.O.)	1.1485	1.1298	1.1235
Difference	0.0318***	0.0420***	0.0284***
Panel B. Stocks (80%)			
Volatility (M-GARCH)	0.7561	0.7503	0.7397
Volatility (M-GARCH with S.O.)	0.7357	0.7237	0.7217
Difference	0.0204***	0.0266***	0.0180***
Panel C. Stocks (60%)			
Volatility (M-GARCH)	0.4380	0.4344	0.4304
Volatility (M-GARCH with S.O.)	0.4269	0.4202	0.4209
Difference	0.0111***	0.0142***	0.0095***
Panel D. Stocks (0%)			
Volatility (M-GARCH)	0.1201	0.1204	0.1204
Volatility (M-GARCH with S.O.)	0.1245	0.1251	0.1251
Difference	-0.0044***	-0.0047***	-0.0047***

[Table 3.11] Portfolios Conditional Risk (Crisis periods)

The table reports the portfolios conditional risk and T-test results for the difference among portfolios conditional risks during the crisis periods. Each panel presents different stock-bond portfolios conditional risks. Panels A, B, C and D represent the 100% stock portfolio, the 80% stock portfolio, the 60% stock portfolio and the 100% bond portfolio, respectively. M-GARCH and M-GARCH with S.O. indicate the baseline model and the model that considers all spillover effects, respectively. * indicates the significance level of the T-test for a mean whose null hypothesis is zero. ***, **, and * represent the significance level of 1%, 5%, and 10%, respectively.

	Bond 30Yr	Bond 10Yr	Bond 1Yr
Panel A. Stocks (100%)			
Volatility (M-GARCH)	1.6618	1.6493	1.6217
Volatility (M-GARCH with S.O.)	1.7008	1.6609	1.6525
Difference	-0.0389**	-0.0116	-0.0308*
Panel B. Stocks (80%)			
Volatility (M-GARCH)	1.0594	1.0513	1.0393
Volatility (M-GARCH with S.O.)	1.0839	1.0597	1.0593
Difference	-0.0245**	-0.0084	-0.0200*
Panel C. Stocks (60%)			
Volatility (M-GARCH)	0.6084	0.6038	0.6023
Volatility (M-GARCH with S.O.)	0.6230	0.6106	0.6149
Difference	-0.0146**	-0.0068	-0.0126**
Panel D. Stocks (0%)			
Volatility (M-GARCH)	0.1644	0.1648	0.1630
Volatility (M-GARCH with S.O.)	0.1754	0.1761	0.1738
Difference	-0.0110***	-0.0113***	-0.0109***

[Table 3.12] Portfolios Conditional Risk (Non-crisis periods)

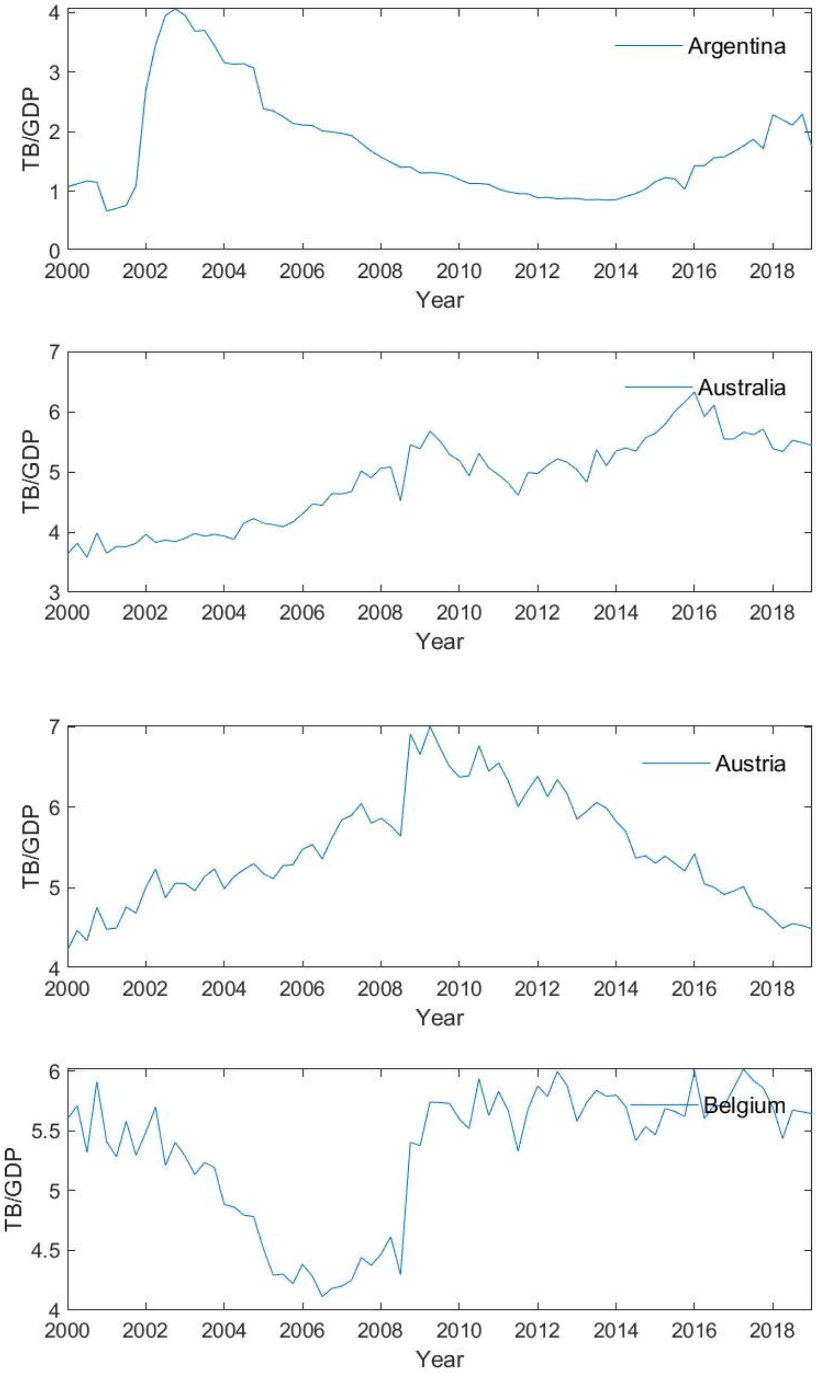
The table reports the portfolios conditional risk and T-test results for the difference among portfolios conditional risks during the non-crisis periods. Each panel presents different stock-bond portfolios conditional risks. Panels A, B, C and D represent the 100% stock portfolio, the 80% stock portfolio, the 60% stock portfolio and the 100% bond portfolio, respectively. M-GARCH and M-GARCH with S.O. indicate the baseline model and the model that considers all spillover effects, respectively. * indicates the significance level of the T-test for a mean whose null hypothesis is zero. ***, **, and * represent the significance level of 1%, 5%, and 10%, respectively.

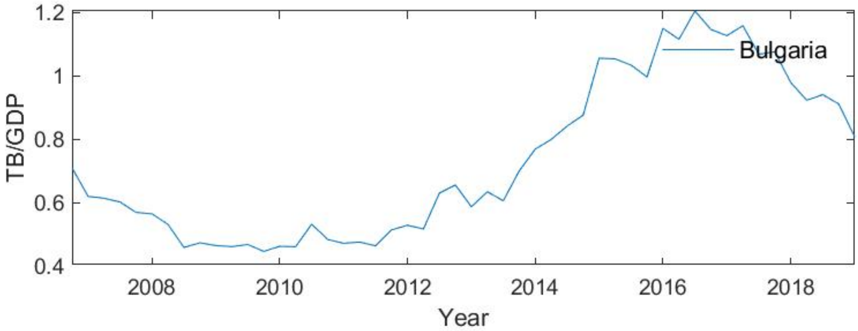
	Bond 30Yr	**Bond 10Yr**	**Bond 1Yr**
Panel A. Stocks (100%)			
Volatility (M-GARCH)	0.9004	0.8940	0.8788
Volatility (M-GARCH with S.O.)	0.8274	0.8210	0.8160
Difference	0.0729***	0.0730***	0.0628***
Panel B. Stocks (80%)			
Volatility (M-GARCH)	0.5798	0.5752	0.5655
Volatility (M-GARCH with S.O.)	0.5333	0.5284	0.5254
Difference	0.0466***	0.0469***	0.0401***
Panel C. Stocks (60%)			
Volatility (M-GARCH)	0.3390	0.3359	0.3305
Volatility (M-GARCH with S.O.)	0.3130	0.3095	0.3082
Difference	0.0260***	0.0264***	0.0223***
Panel D. Stocks (0%)			
Volatility (M-GARCH)	0.0943	0.0946	0.0957
Volatility (M-GARCH with S.O.)	0.0950	0.0955	0.0968
Difference	-0.0006	-0.0009	-0.0011*

Figures

[Figure 1.1] Bond Market Development

(Ratio of Outstanding Bonds to GDP)

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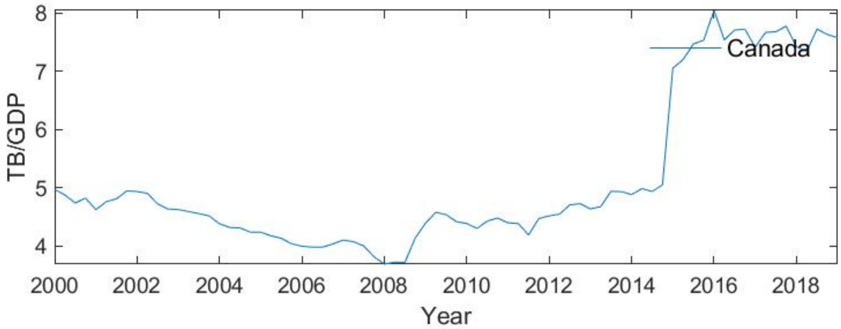
TB/GDP
Year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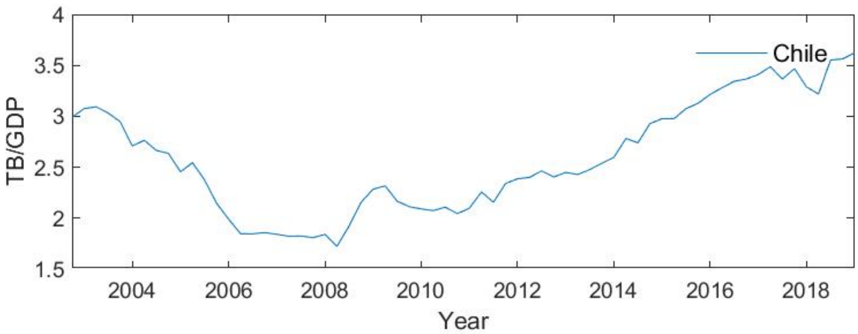
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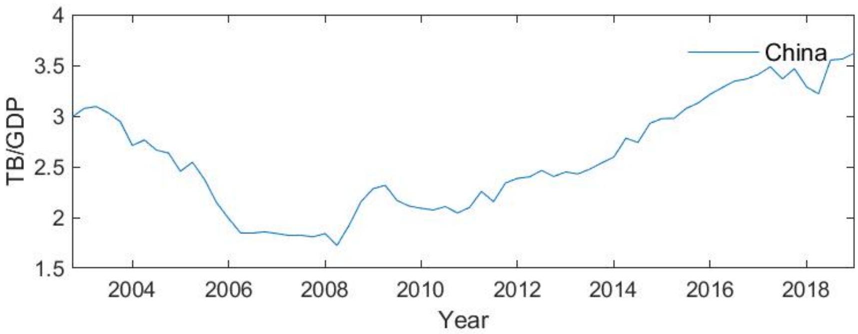
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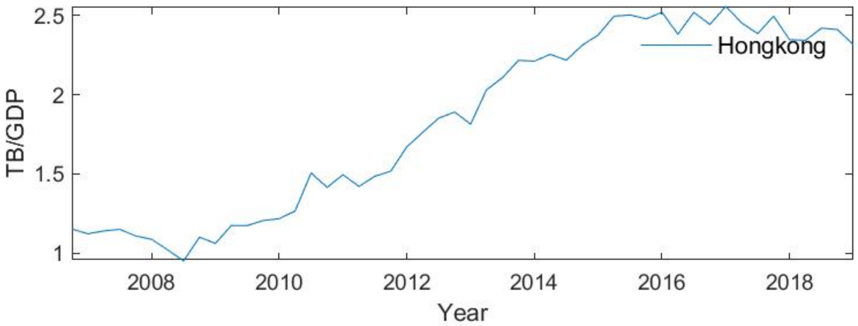
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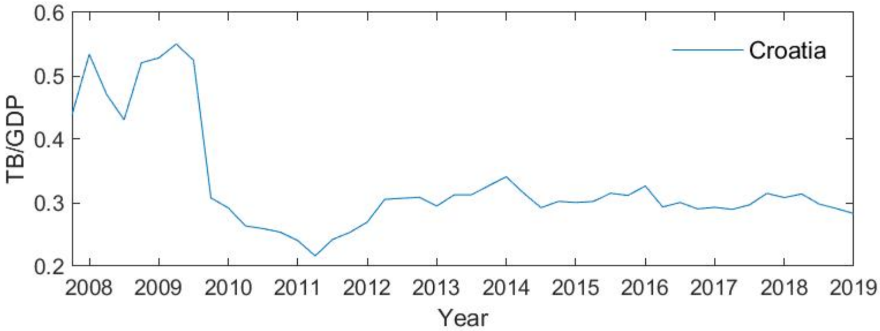
2018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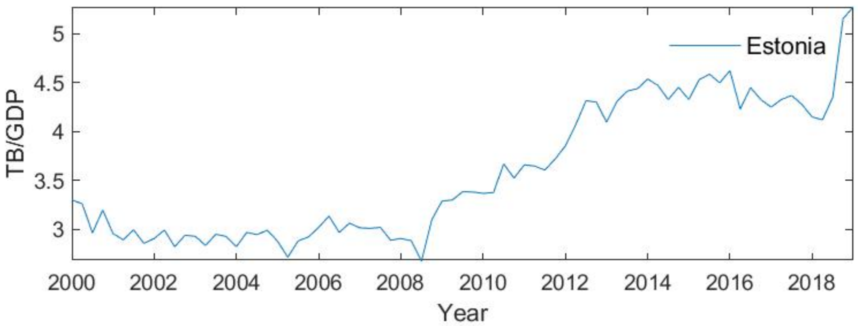
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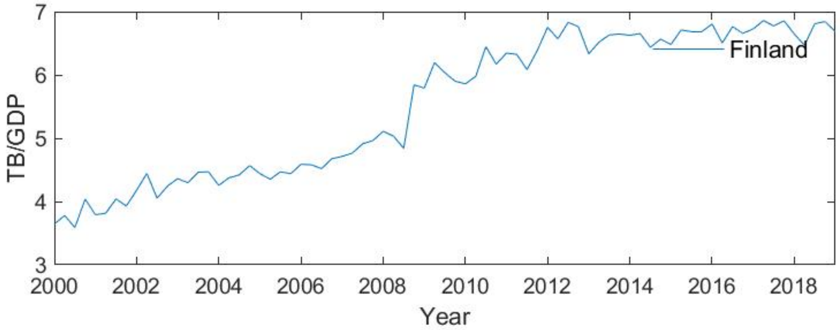
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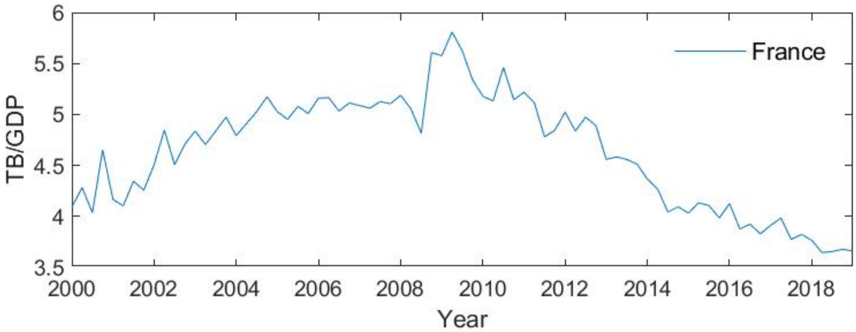
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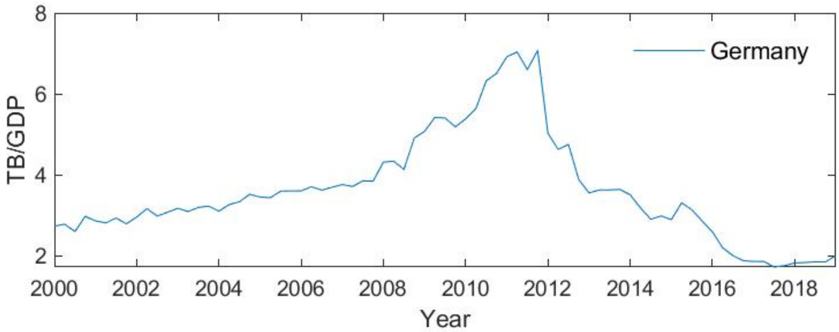
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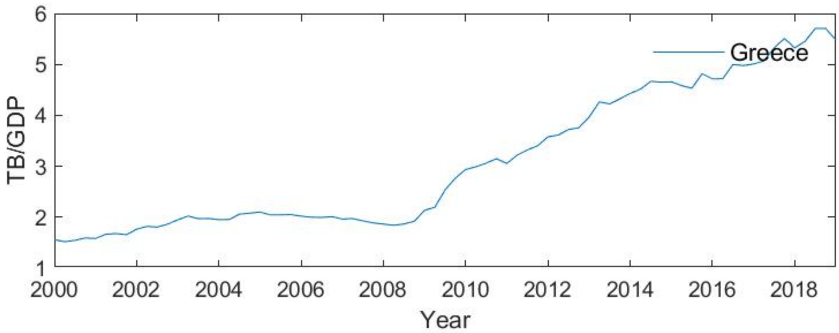
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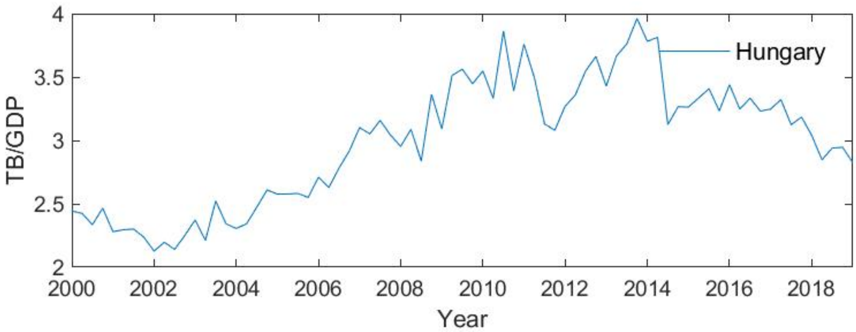
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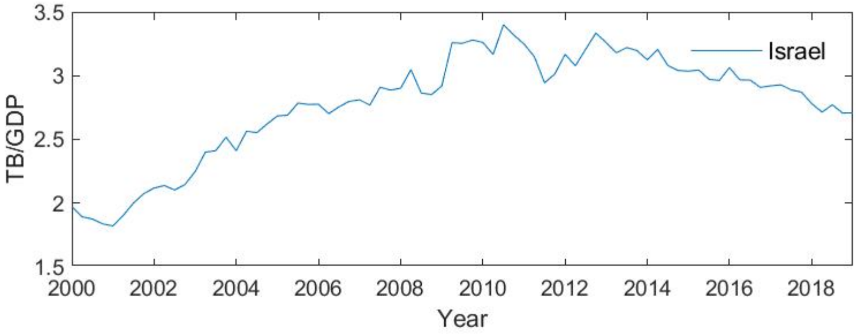
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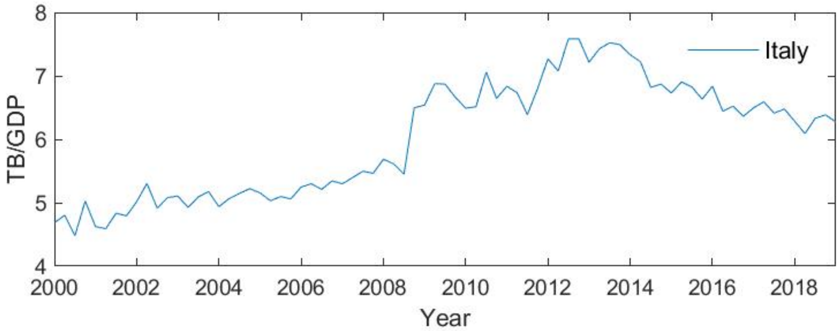
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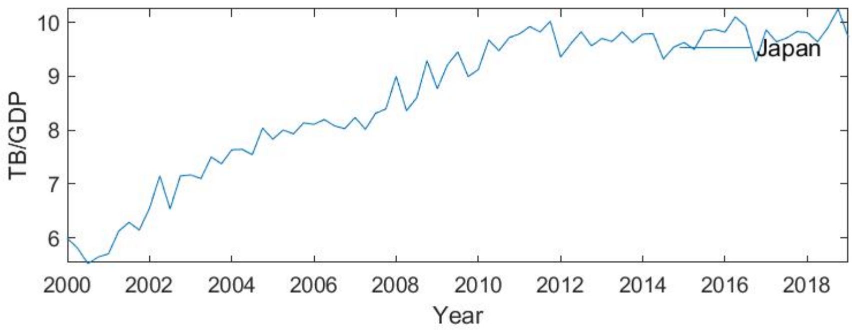
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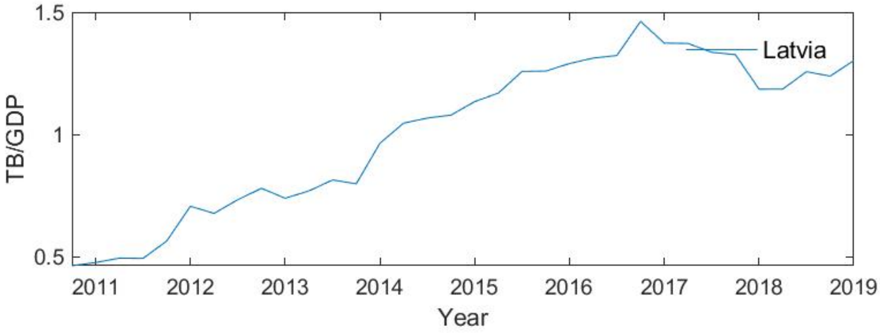
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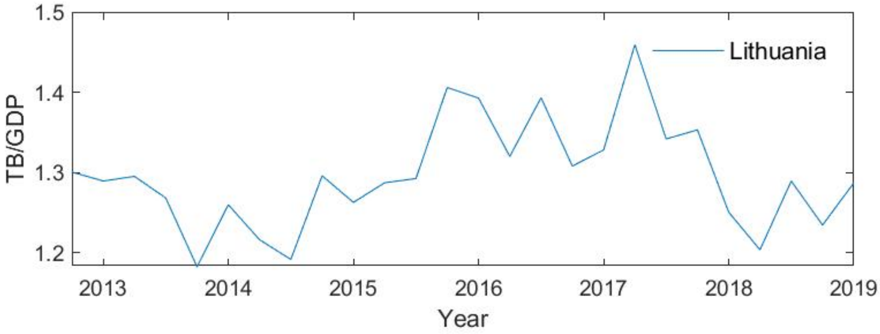
Year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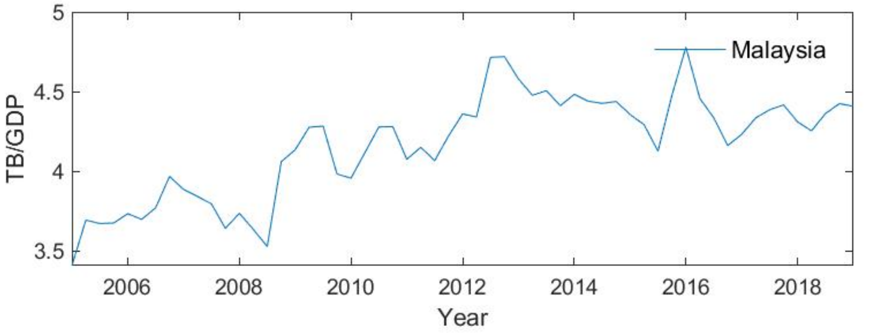
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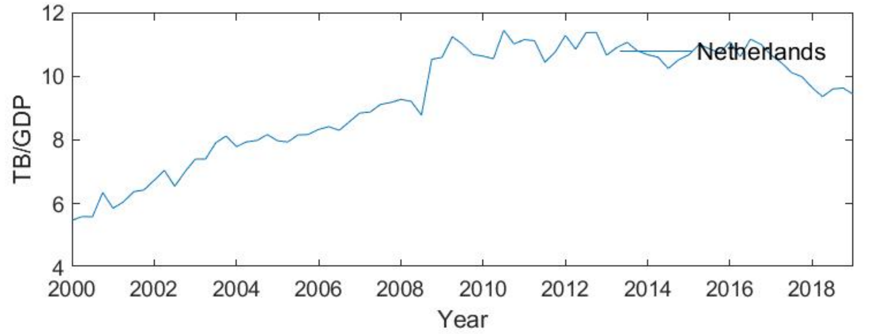
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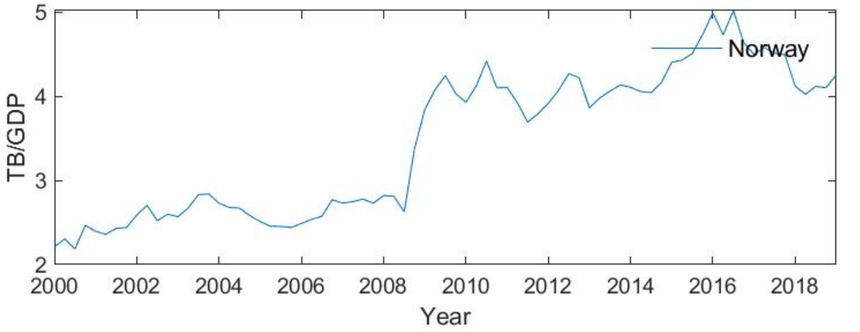
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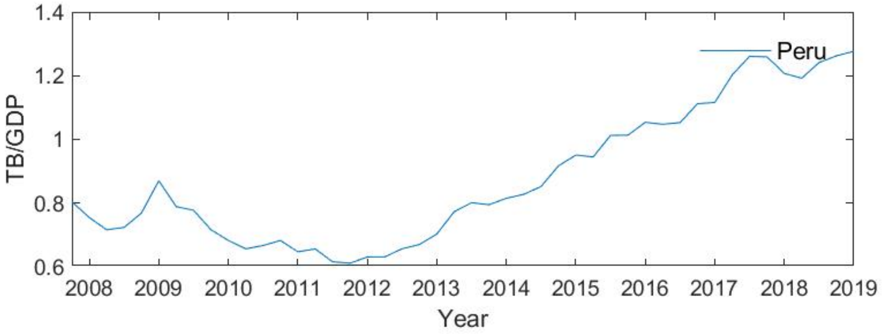
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TB/GDP
Year
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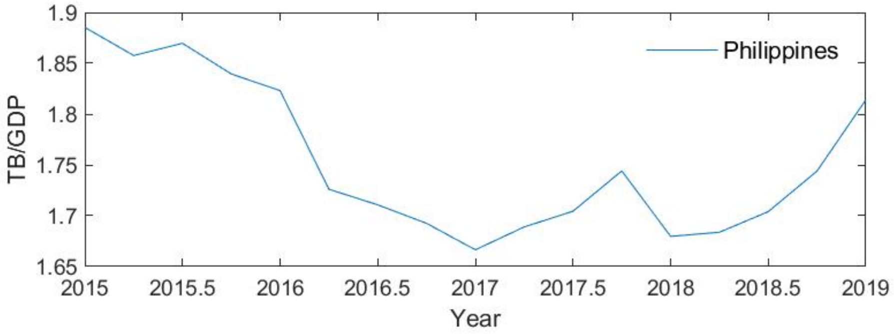
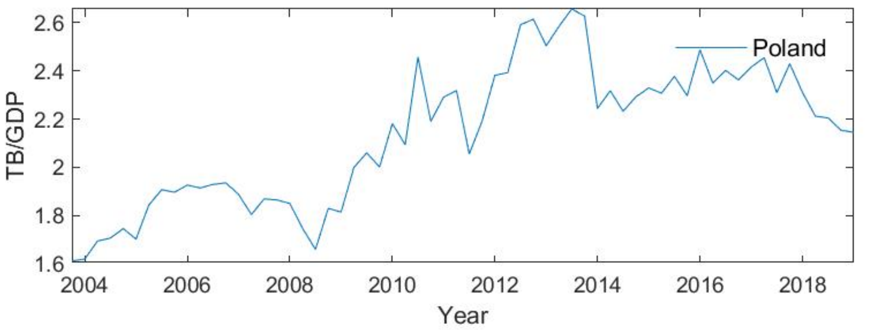
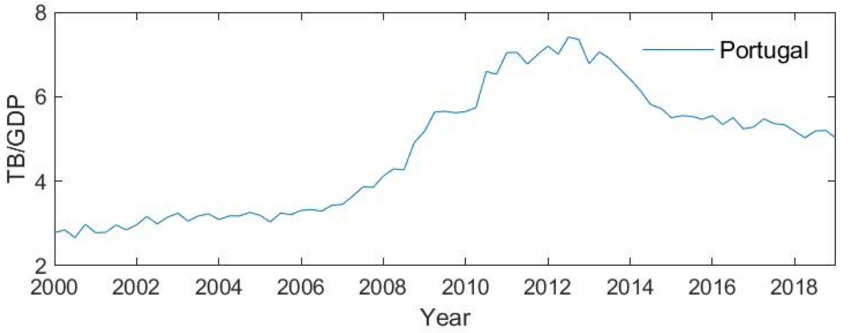
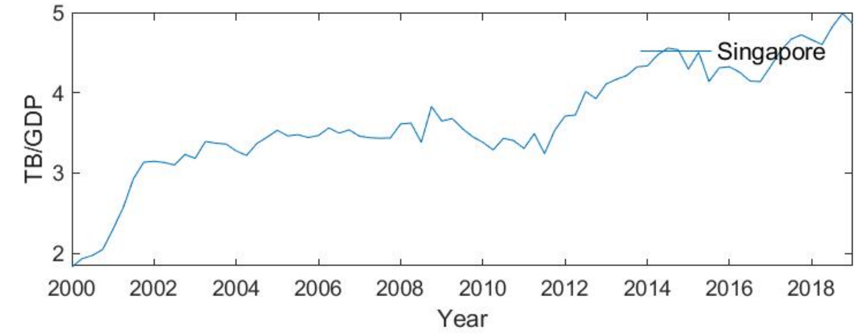
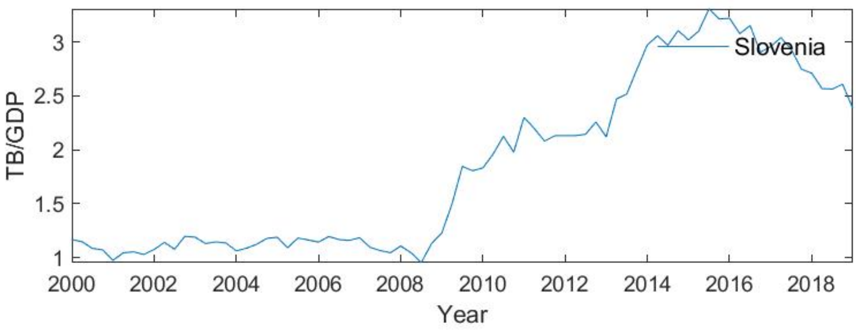
2018
2019

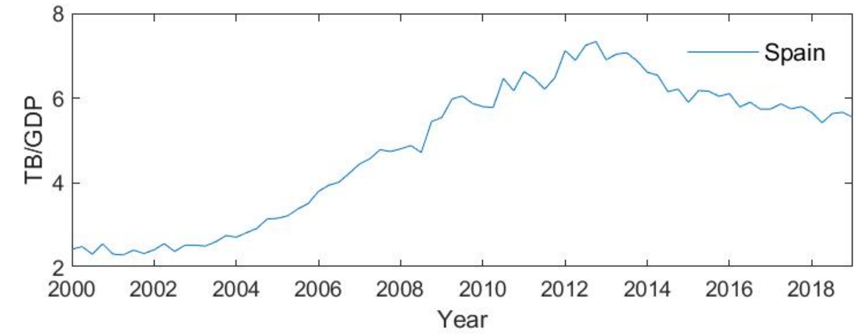

Philippines
TB/GDP
Year
1.9
1.85
1.8
1.75
1.7
1.65
2015
2015.5
2016
2016.5
2017
2017.5
2018
2018.5
2019

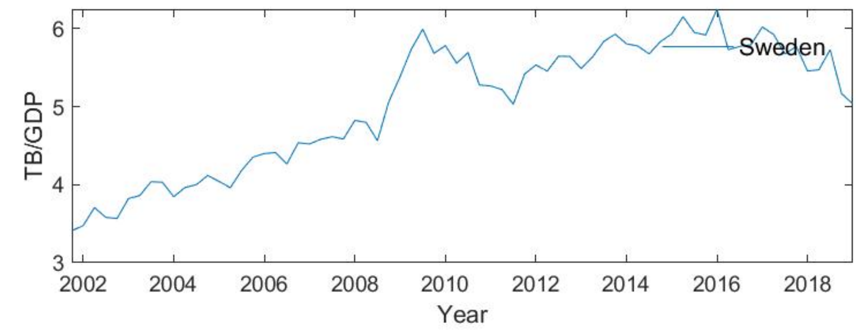

Poland
TB/GDP
Year
2.6
2.4
2.2
2
1.8
1.6
2004
2006
2008
2010
2012
2014
2016
2018

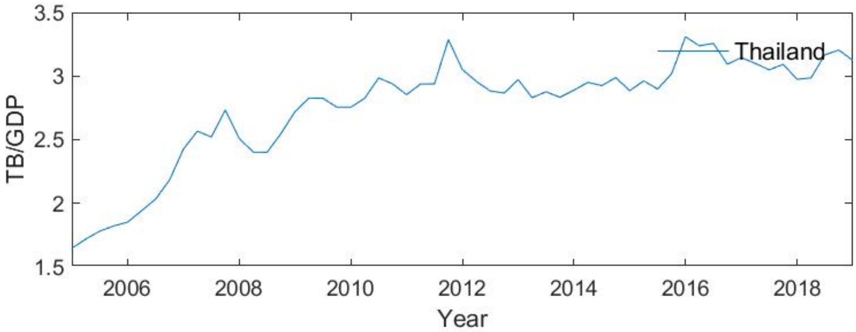

Portugal
TB/GDP
Year
8
6
4
2
2000
2002
2004
2006
2008
2010
2012
2014
2016
2018

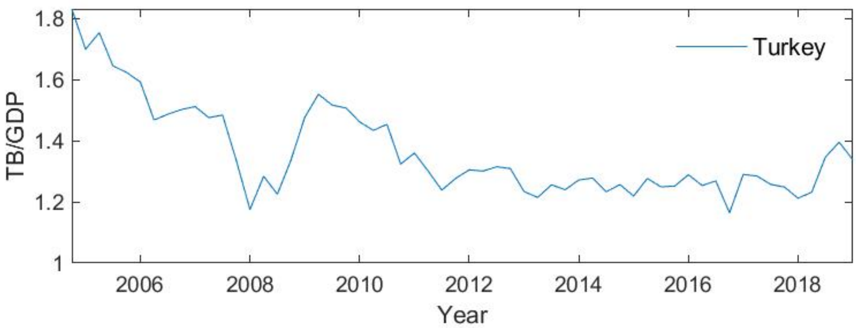

Singapore
TB/GDP
5
4
3
2
2000
2002
2004
2006
2008
2010
2012
2014
2016
2018
Year

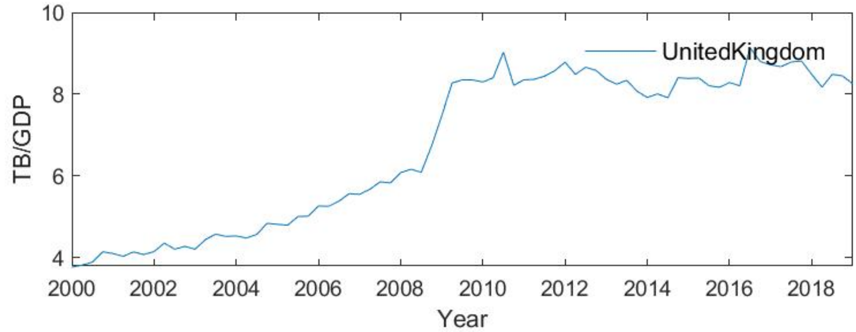

Slovenia
TB/GDP
3
2.5
2
1.5
1
2000
2002
2004
2006
2008
2010
2012
2014
2016
2018
Year

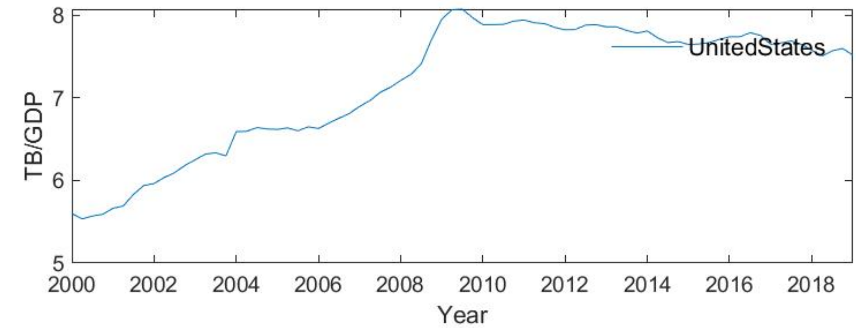

Spain
TB/GDP
8
6
4
2
2000
2002
2004
2006
2008
2010
2012
2014
2016
2018
Year


Sweden
TB/GDP
6
5
4
3
2002
2004
2006
2008
2010
2012
2014
2016
2018
Year

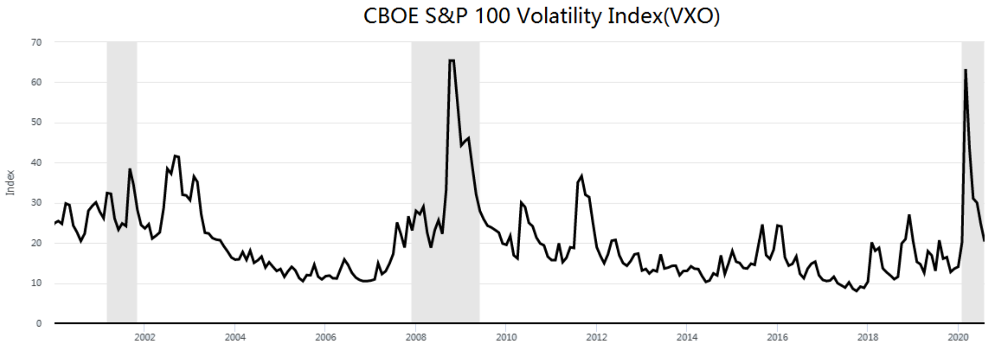

Thailand
TB/GDP
Year


Turkey
TB/GDP
Year


UnitedKingdom
TB/GDP
Year

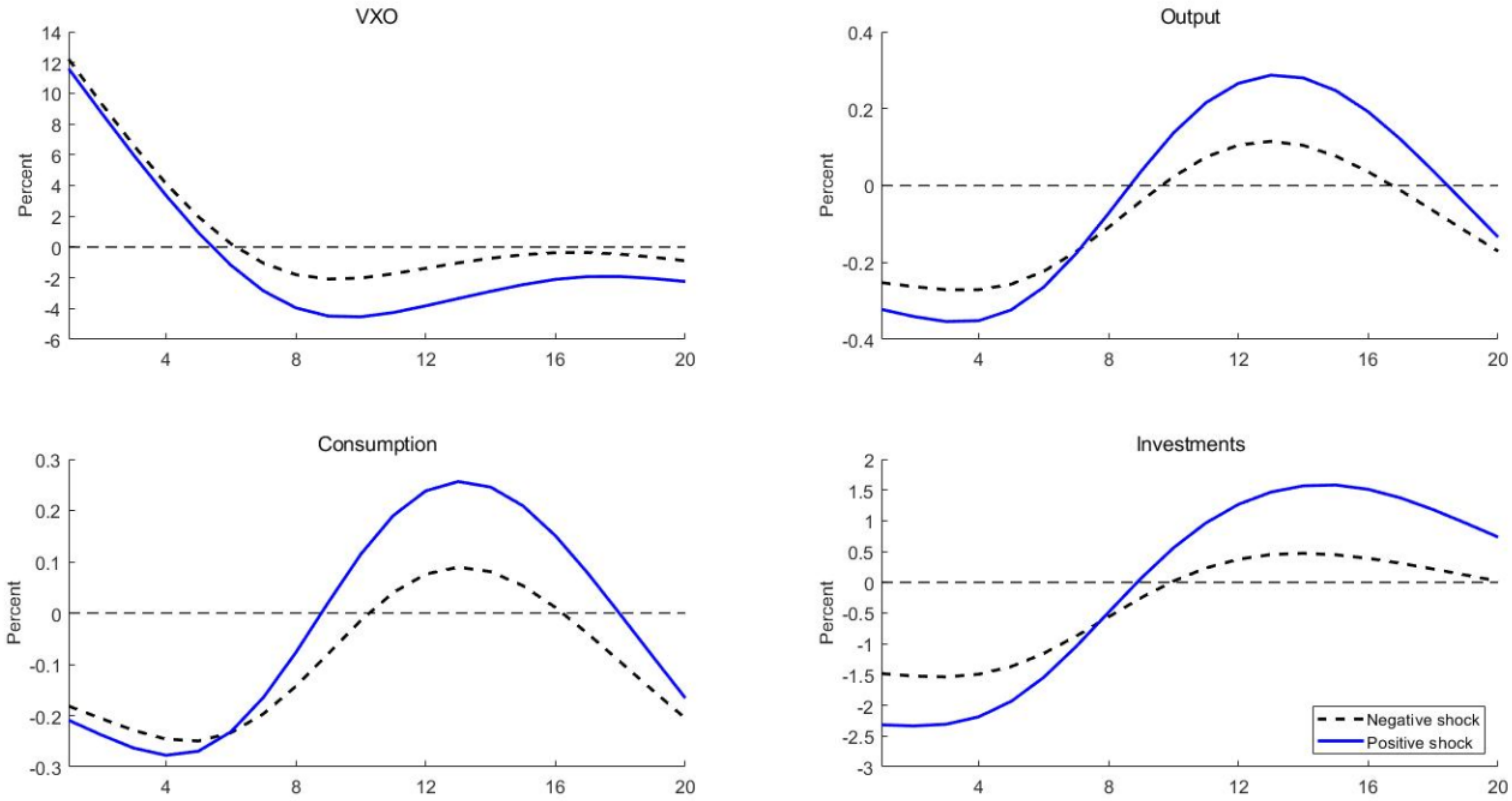

UnitedStates
TB/GDP
Year

[Figure 2.1] Chicago Board Options Exchange (CBOE) Standard & Poor's 100 volatility index (VXO)



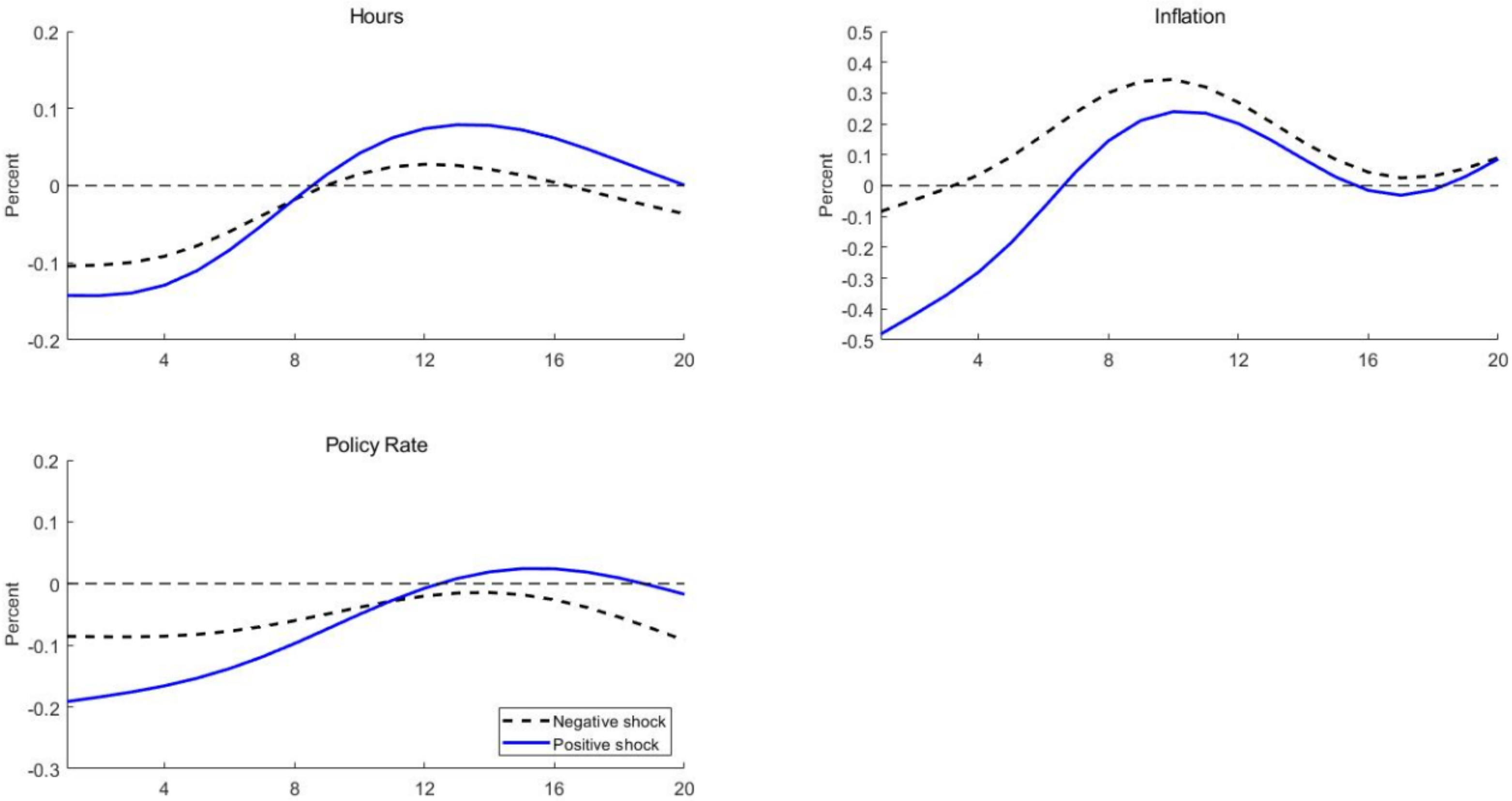
Notes: Figure 1 shows the VXO index of 30-day implied volatility on the Standard & Poor's 100 stock market index. It is estimated by values of options on the Standard & Poor's 100 index and represents the expectation of volatility over the next 30 days. Gray bars are recession periods.

[Figure 2.2.1] Empirical impulse response to VXO shocks



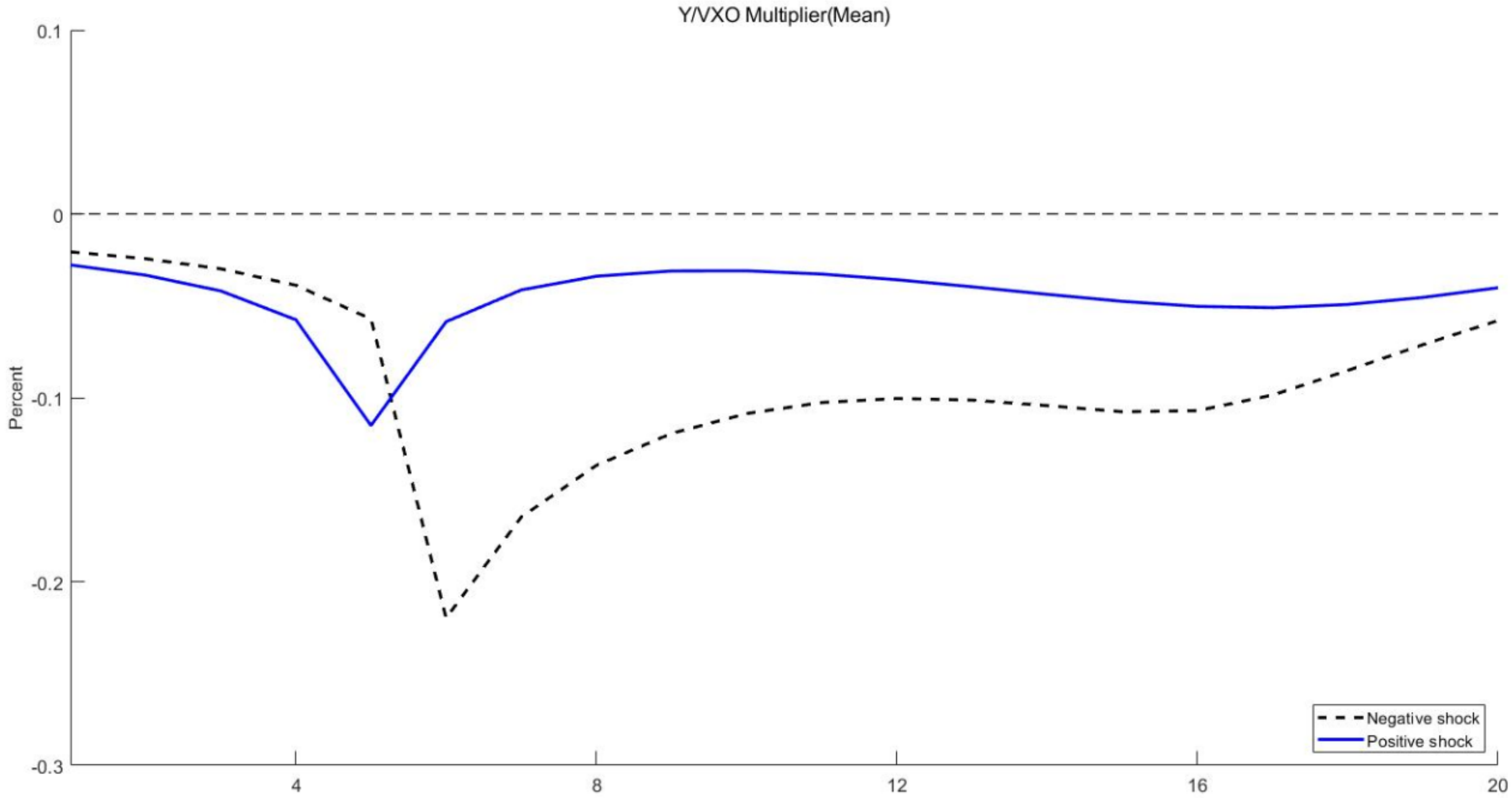
Note: The figure shows the estimated responses to VXO shocks. The blue solid line and black dashed line represent the impulse response to a positive and a negative shock, respectively. The response to negative shock is represented by the mirror image.

[Figure 2.2.2] Empirical impulse response to VXO shock



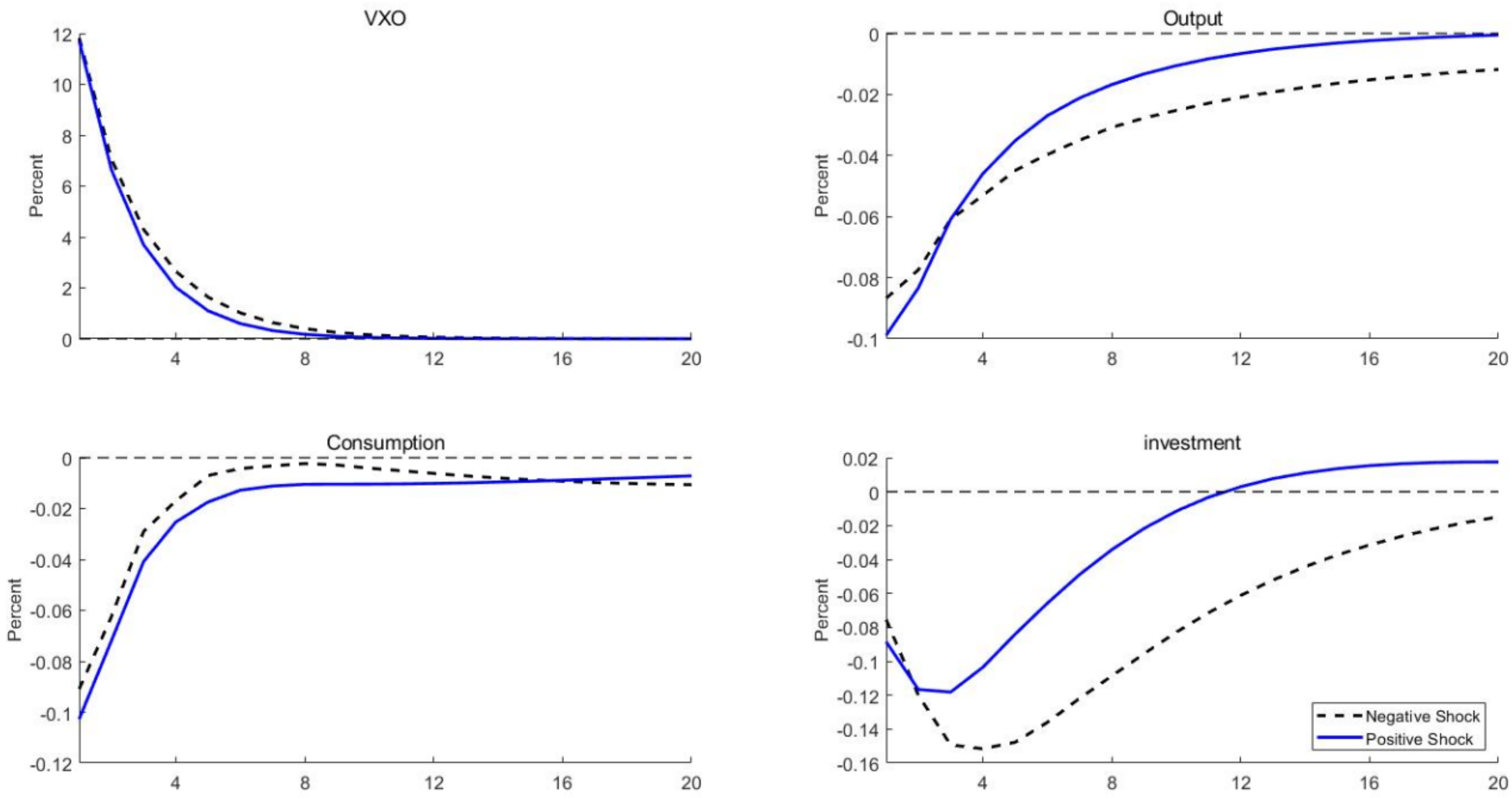
Note: The figure shows the estimated responses to VXO shocks. The blue solid line and black dashed line represent the impulse response to a positive and a negative shock, respectively. The response to negative shock is represented by the mirror image.

[Figure 2.3] The mean value of the output multipliers



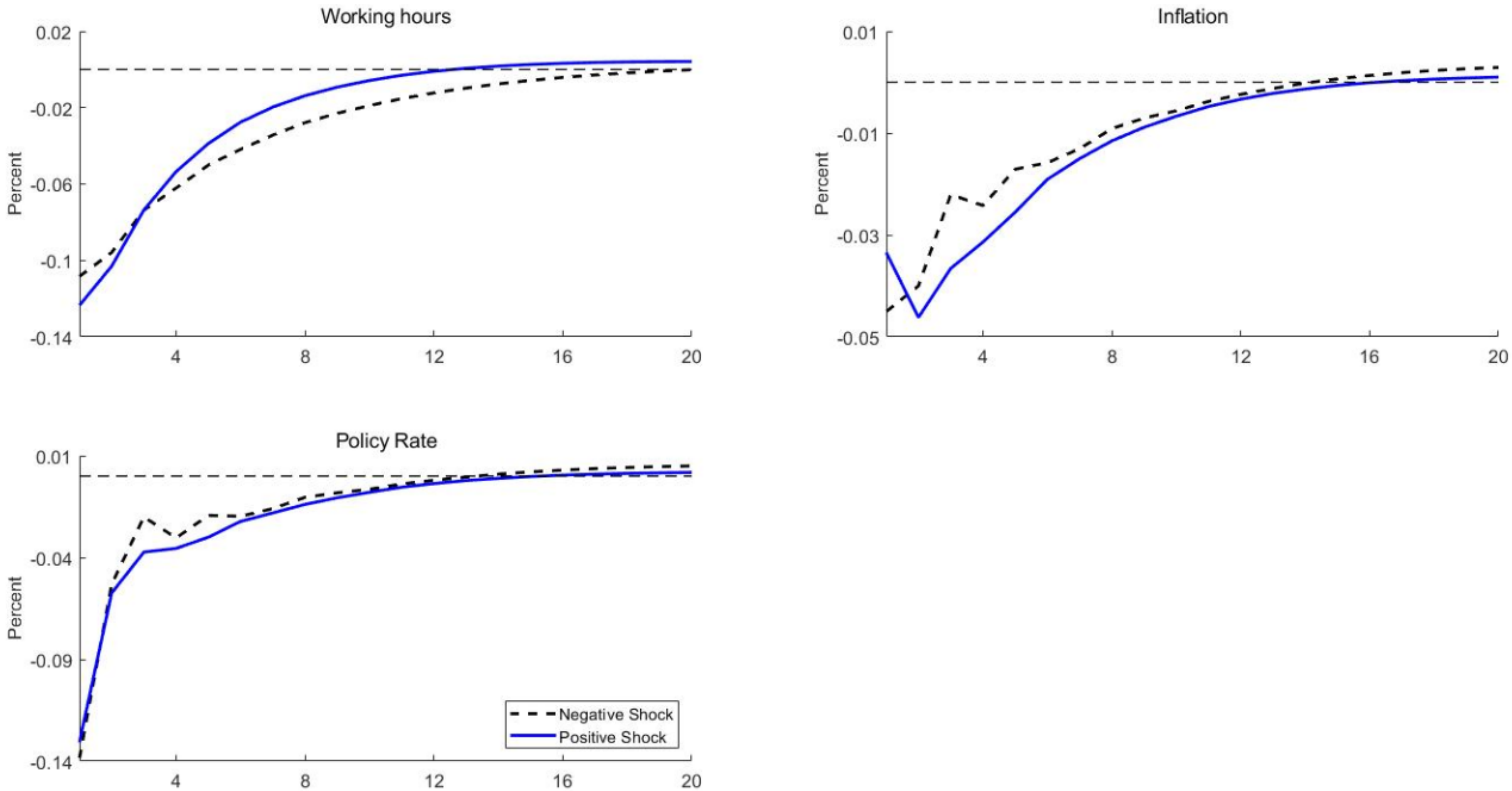
Note: The figure shows changes in the mean value of the output multipliers. The blue solid line and black dashed line represent the mean value of the multipliers to a positive and a negative shock, respectively. The multipliers to negative shock is represented by the mirror image.

[Figure 2.4.1] Model implied responses to uncertainty shocks



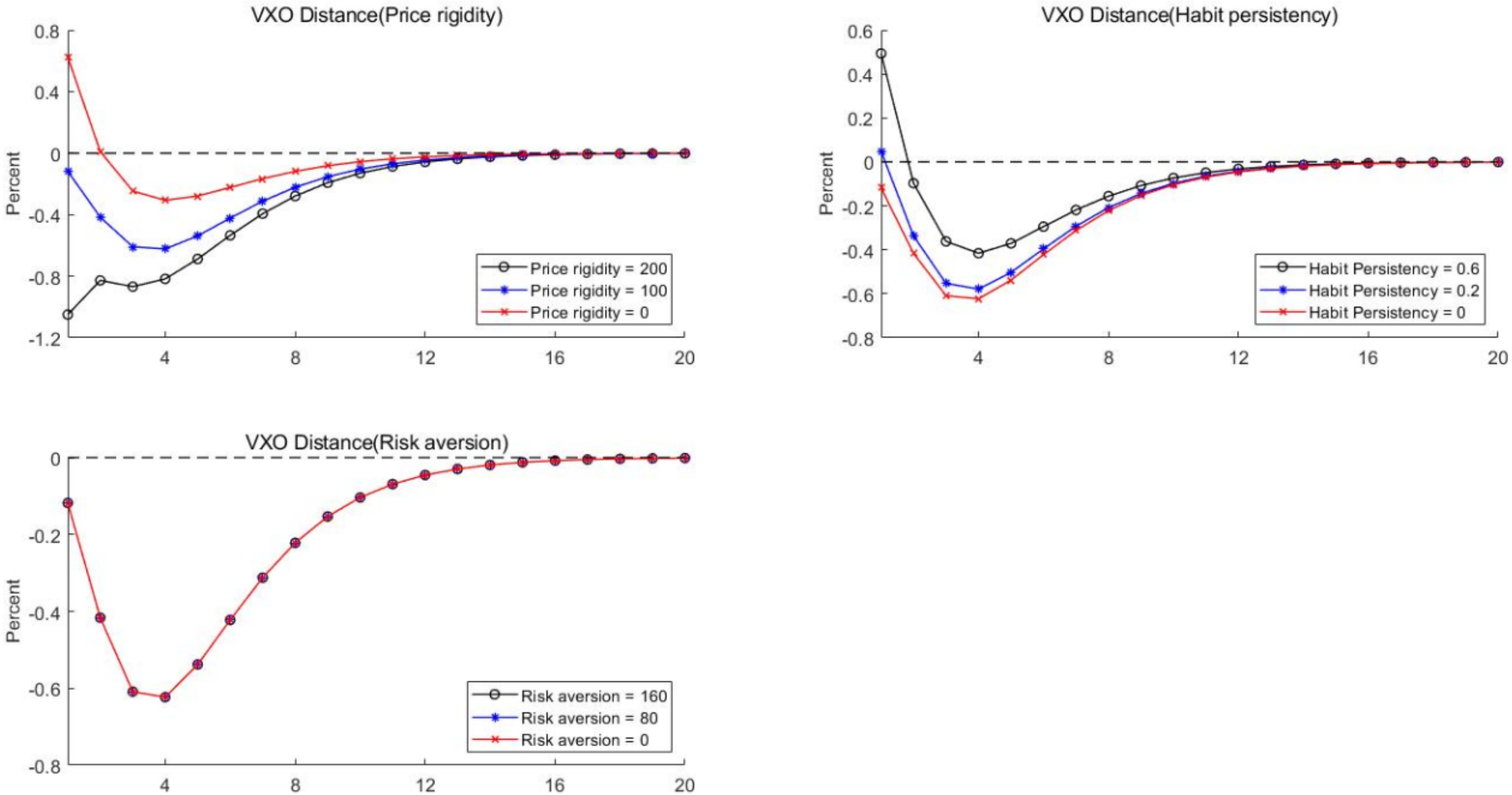
Note: The figures show the model implied responses to uncertainty shocks. The blue solid line and black dashed line represent the impulse response to a positive and a negative shock, respectively. The response to negative shock is represented by the mirror image.

[Figure 2.4.2] Model implied responses to uncertainty shocks



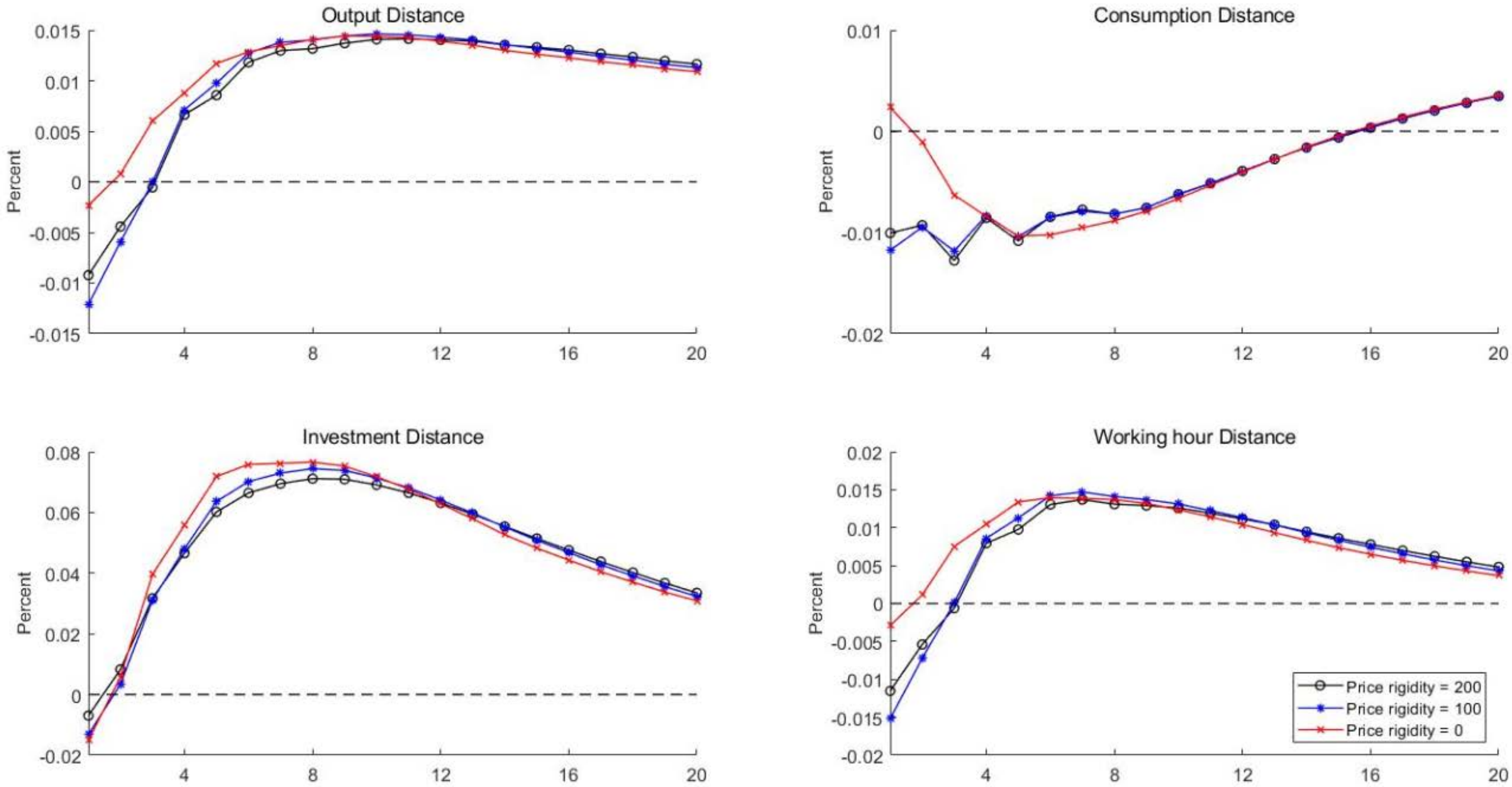
Note: The figures show the model implied responses to uncertainty shocks. The blue solid line and black dashed line represent the impulse response to a positive and a negative shock, respectively. The response to negative shock is represented by the mirror image.

[Figure 2.5] Distance of VXO between responses to asymmetry shocks



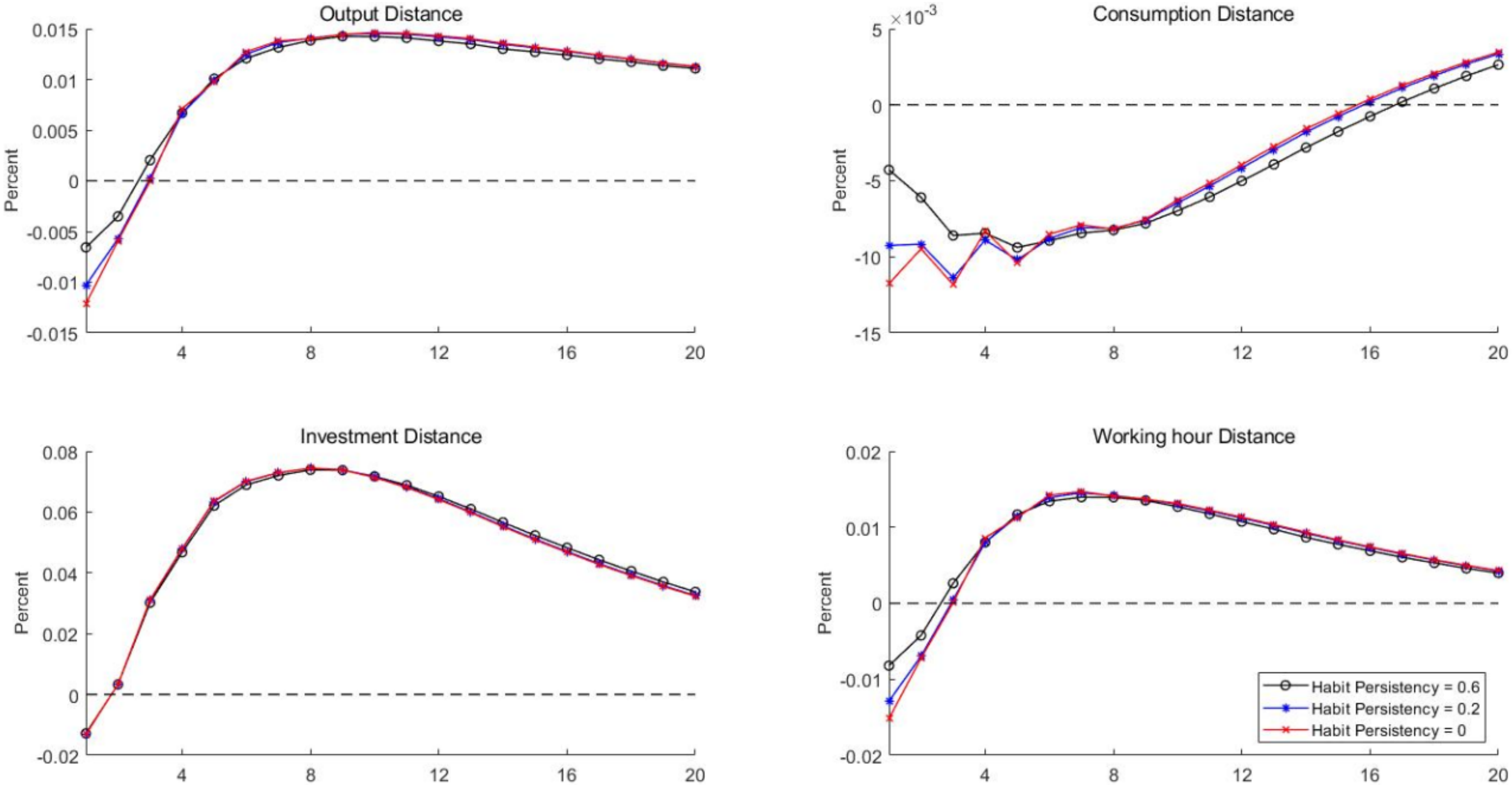
Note: The figures show the distance of asymmetric VXO responses to an increasing uncertainty shock and a decreasing uncertainty shock. Each graph plots changes in the distance according to either price rigidity, habit persistence or risk aversion.

[Figure 2.6] Distance of key macro variables between responses to asymmetry shocks (Price rigidity)



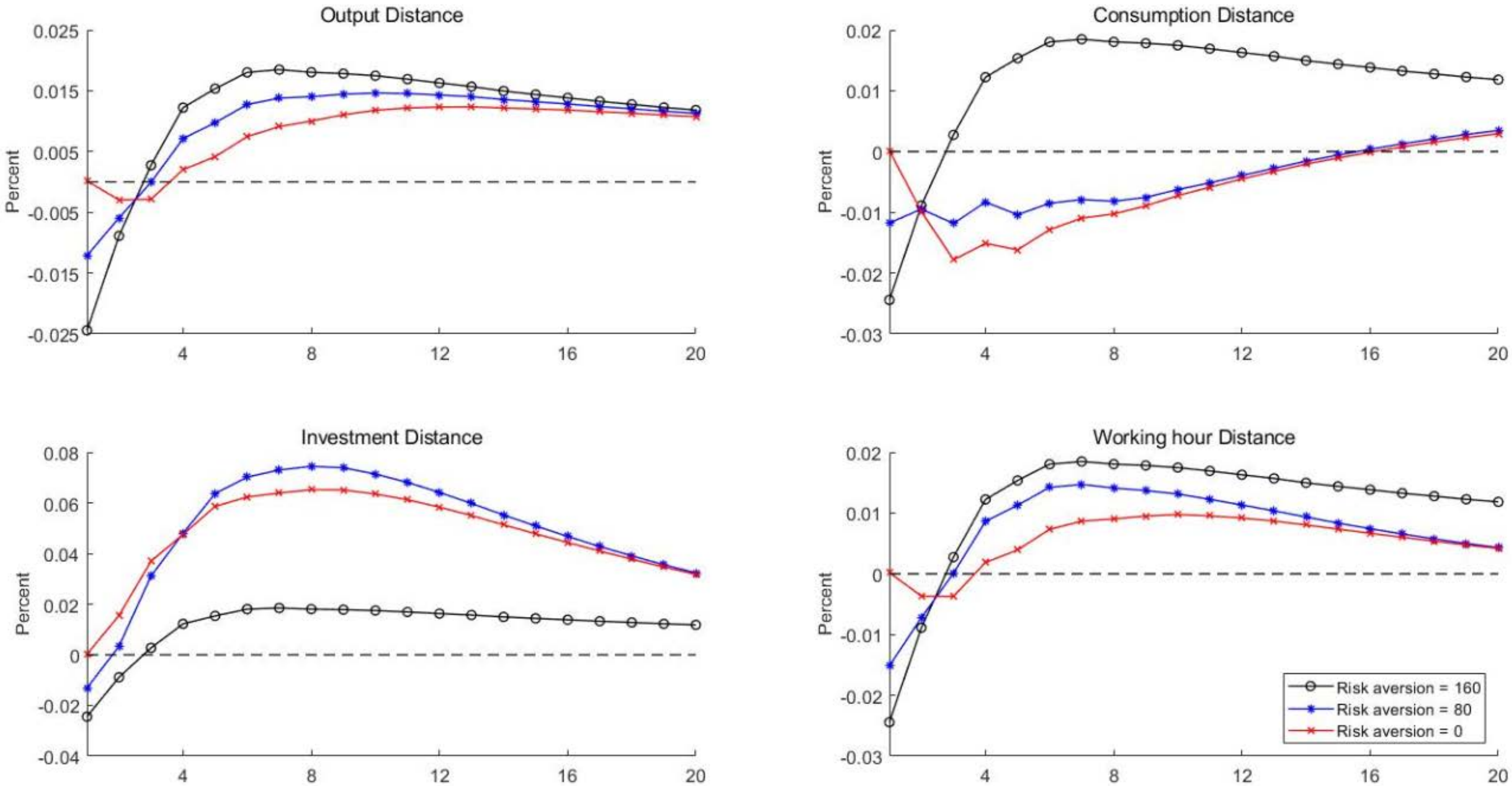
Note: The figures show the distance changes of asymmetric macro variables responses to an increasing uncertainty shock and a decreasing uncertainty shock according to price rigidity.

[Figure 2.7] Distance of key macro variables between responses to asymmetry shocks (Habit persistence)



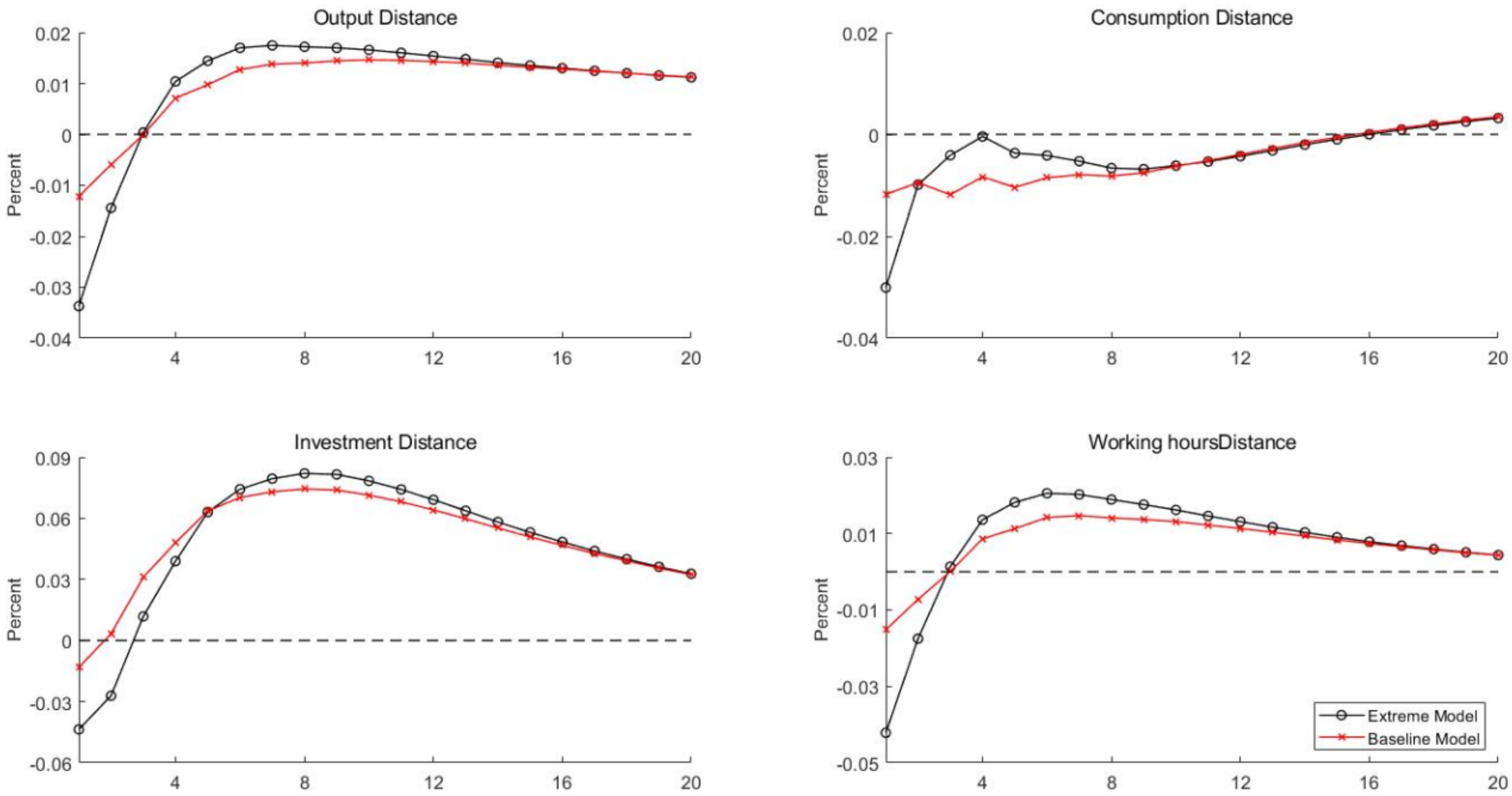
Note: The figures show the distance changes of asymmetric macro variables responses to an increasing uncertainty shock and a decreasing uncertainty shock according to habit persistence.

[Figure 2.8] Distance of key macro variables between responses to asymmetry shocks (Risk aversion)



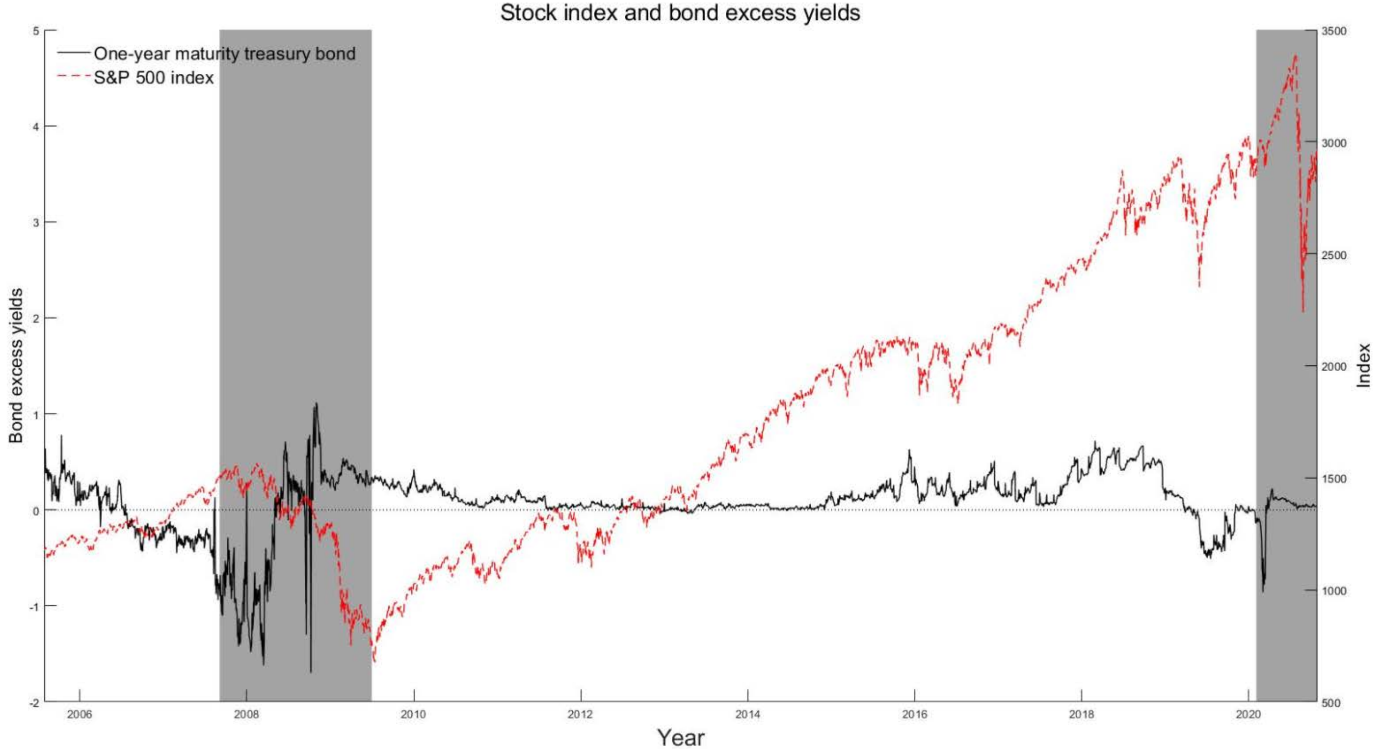
Note: The figures show the distance changes of asymmetric macro variables responses to an increasing uncertainty shock and a decreasing uncertainty shock according to risk aversion.

[Figure 2.9] Distance of key macro variables between responses to asymmetry shocks (Extreme model vs Baseline model)



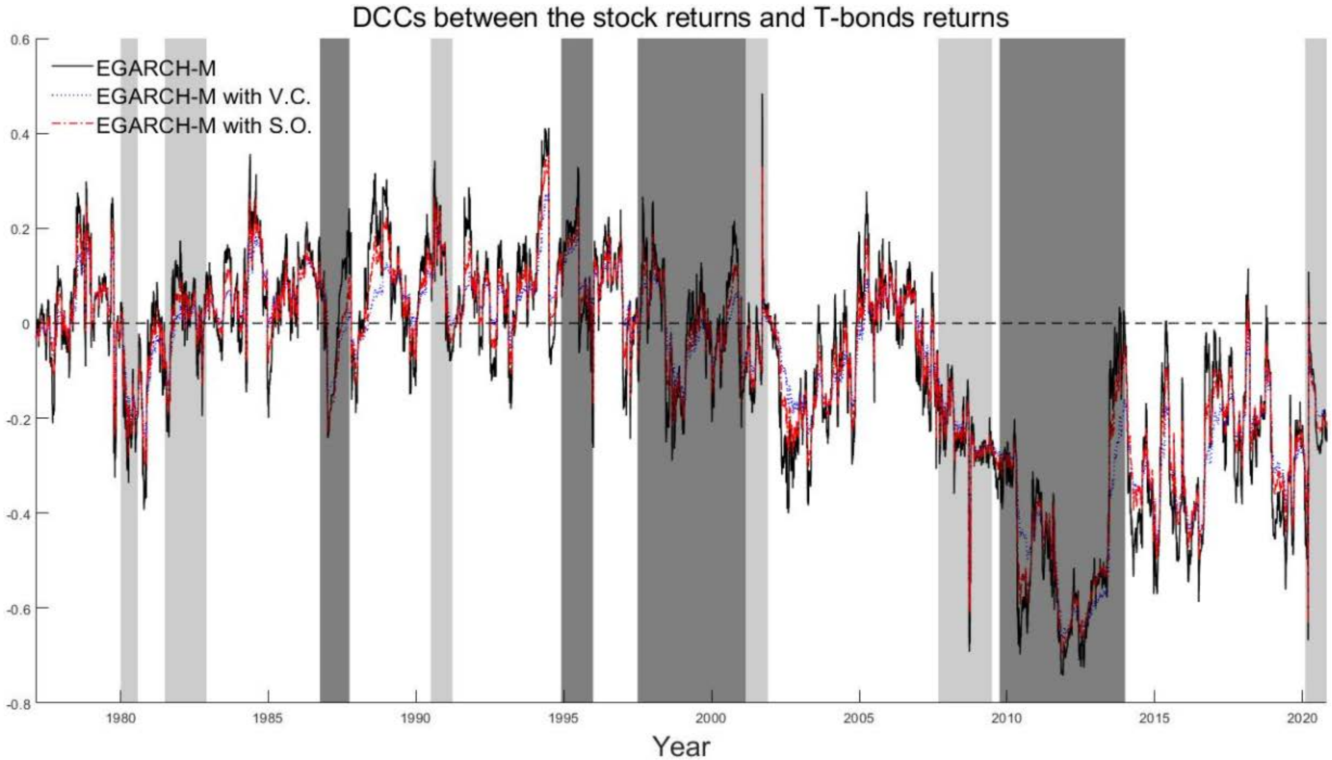
Note: The figures show the distance changes of asymmetric macro variables responses to an increasing uncertainty shock and a decreasing uncertainty shock. The black 'o' marked line and red 'x' marked line represent the distance changes estimated from an extreme case model and baseline model, respectively.

[Figure 3.1] Stock index and bond excess yields



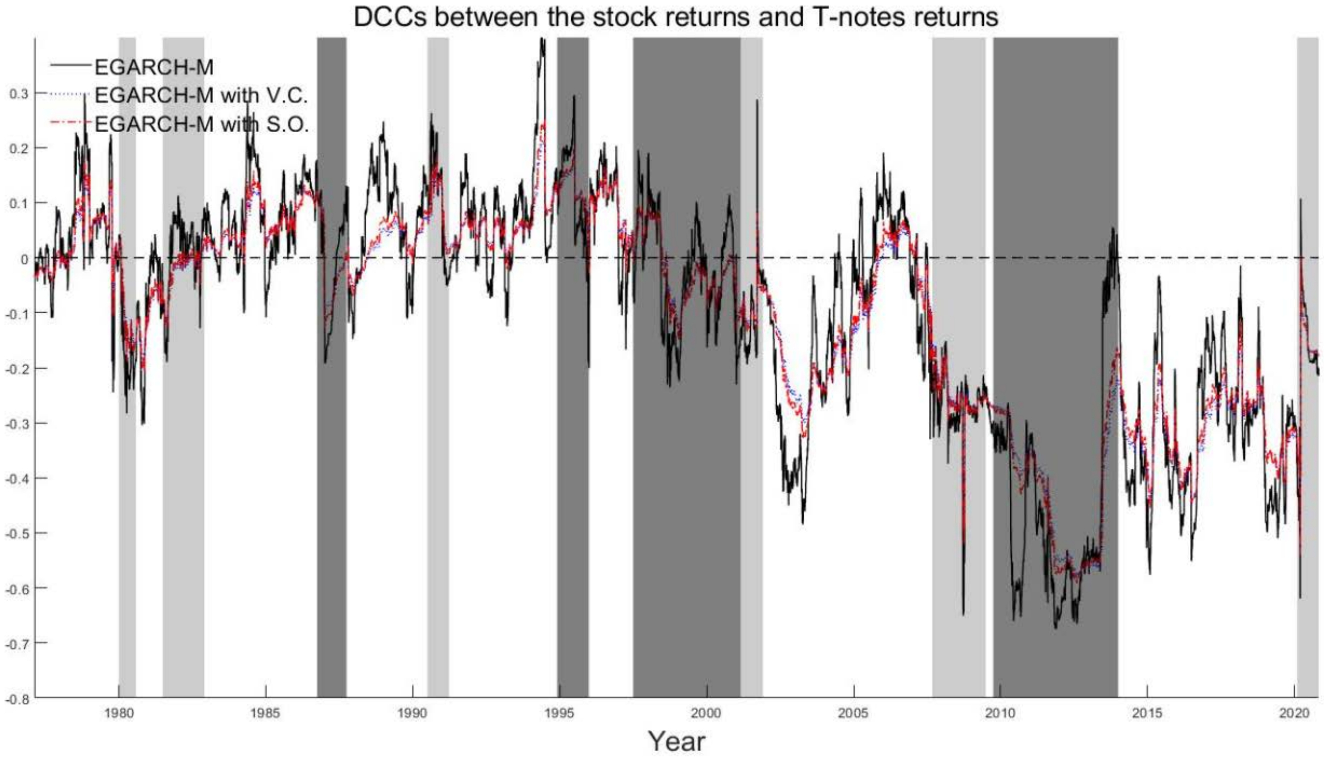
Notes: The figure shows Standard & Poor's 500 index and the one-year treasury bond (i.e., T-bills) excess yields from 2006 to 2020. The left and right axes indicate the bond yield and the stock index, respectively. Shaded bars are recession periods, which are the 2007–2009 financial crisis and COVID-19 pandemic.

[Figure 3.2] Correlations between the stock and thirty-year bond markets



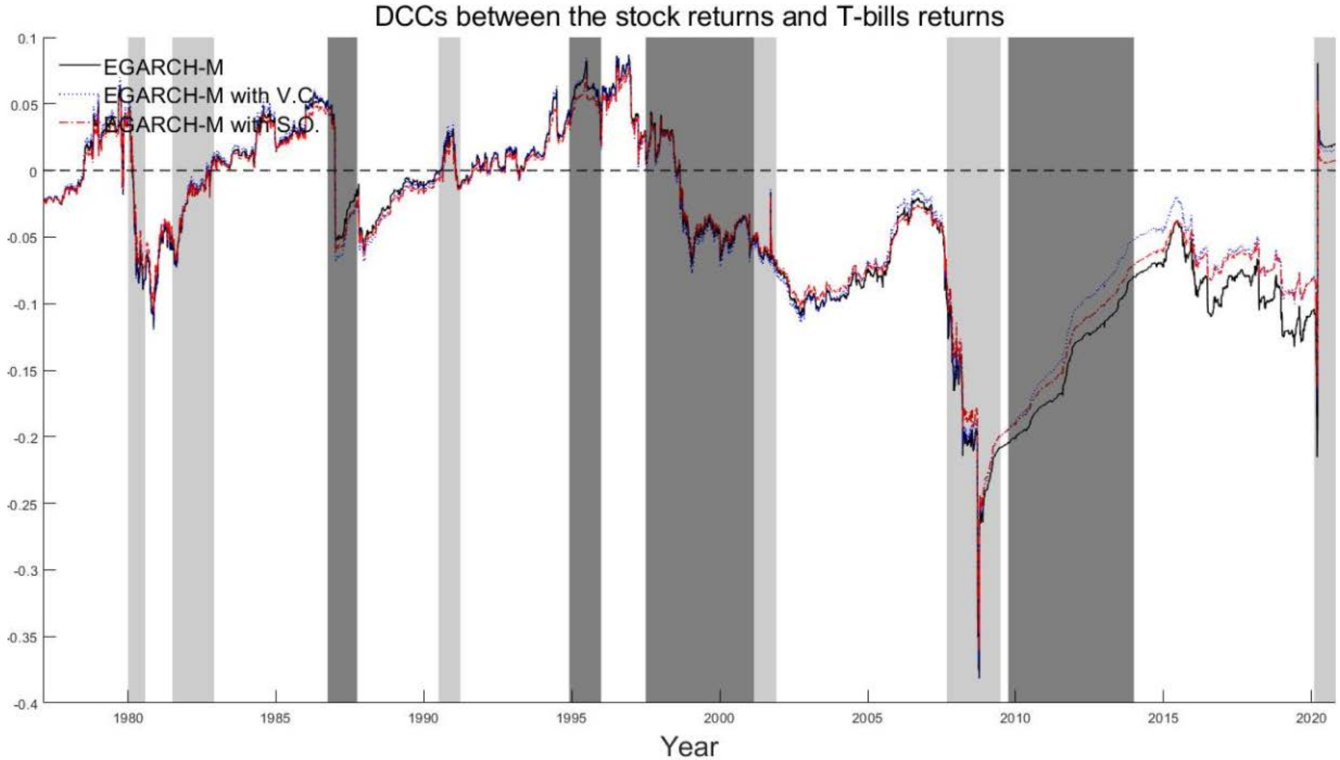
Notes: The figure shows dynamic conditional correlations (DCCs) between the stock returns and thirty-year treasury bond (i.e., T-bonds) returns, which are estimated by using EGARCH-M models. Shaded bars are recession periods. Lighter shades refer to US recession periods. Darker shades are other countries' financial crisis periods, namely, the Japanese asset price bubbles and Black Monday, Mexico economics crisis, Asian and Latin American financial crisis, and European sovereign debt crisis in order.

[Figure 3.3] Correlations between the stock and ten-year bond markets



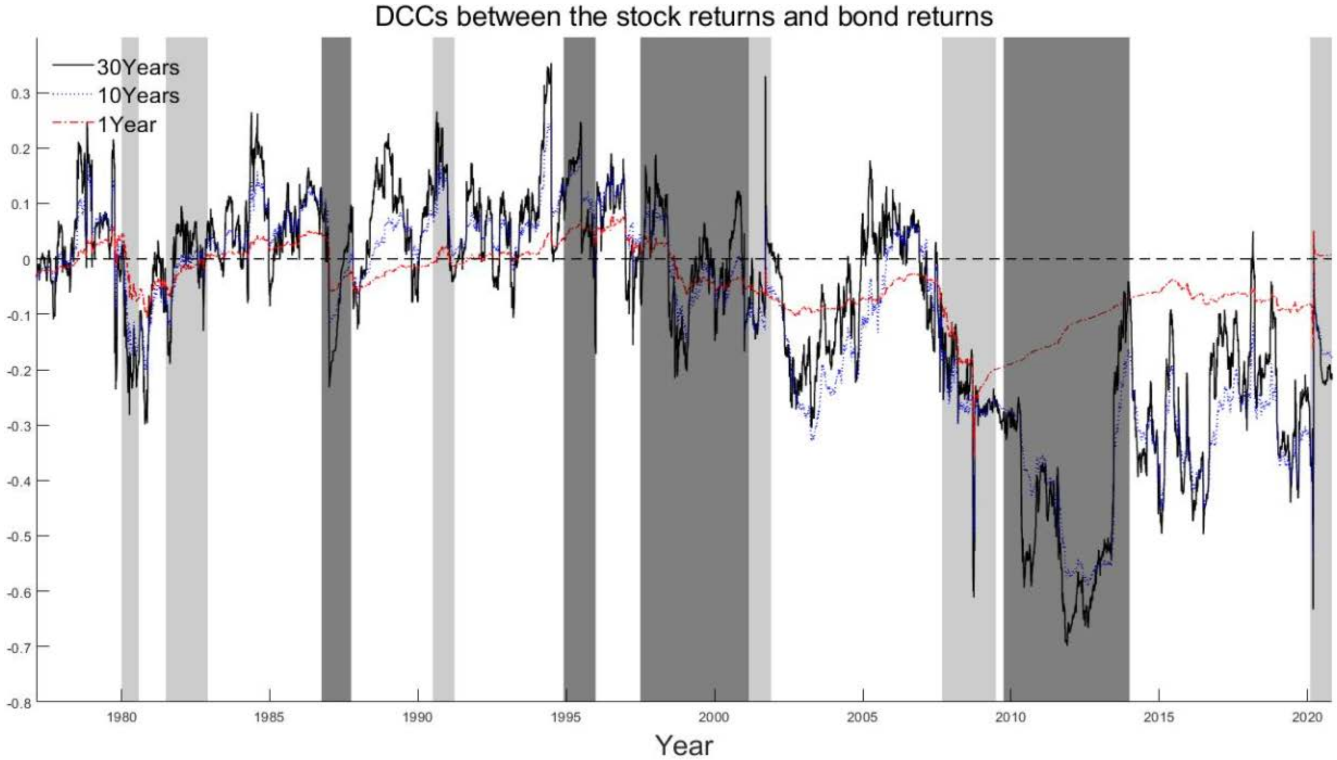
Notes: The figure shows DCCs between the stock and ten-year treasury bond (i.e., T-notes) returns, which are estimated by using EGARCH-M models. Shade bars are recession periods. Lighter shades refer to US recession periods. Darker shades are other countries' financial crisis periods, namely, Japanese asset price bubbles and Black Monday, Mexico economics crisis, Asian and Latin American financial crisis, and European sovereign debt crisis, in this order.

[Figure 3.4] Correlations between the stock and one-year bond markets



Notes: The figure shows DCCs between the stock and one-year treasury bond (i.e., T-bills) returns, which are estimated by using EGARCH-M models. Shaded bars are recession periods. Lighter shades refer to US recession periods. Darker shades are other countries' financial crisis periods, namely, Japanese asset price bubbles and Black Monday, Mexico economics crisis, Asian and Latin American financial crisis, and European sovereign debt crisis, in this order.

[Figure 3.5] Correlations between the stock and bond markets



Notes: The figure shows DCCs among the stock and all types of treasury bond returns, which are estimated by EGARCH-M with spillover models. Shaded bars are recession periods. Lighter shades refer to US recession periods. Darker shades are other countries' financial crisis periods, namely, Japanese asset price bubbles and Black Monday, Mexico economics crisis, Asian and Latin American financial crisis, and European sovereign debt crisis, in this order.

Appendix

A. Data

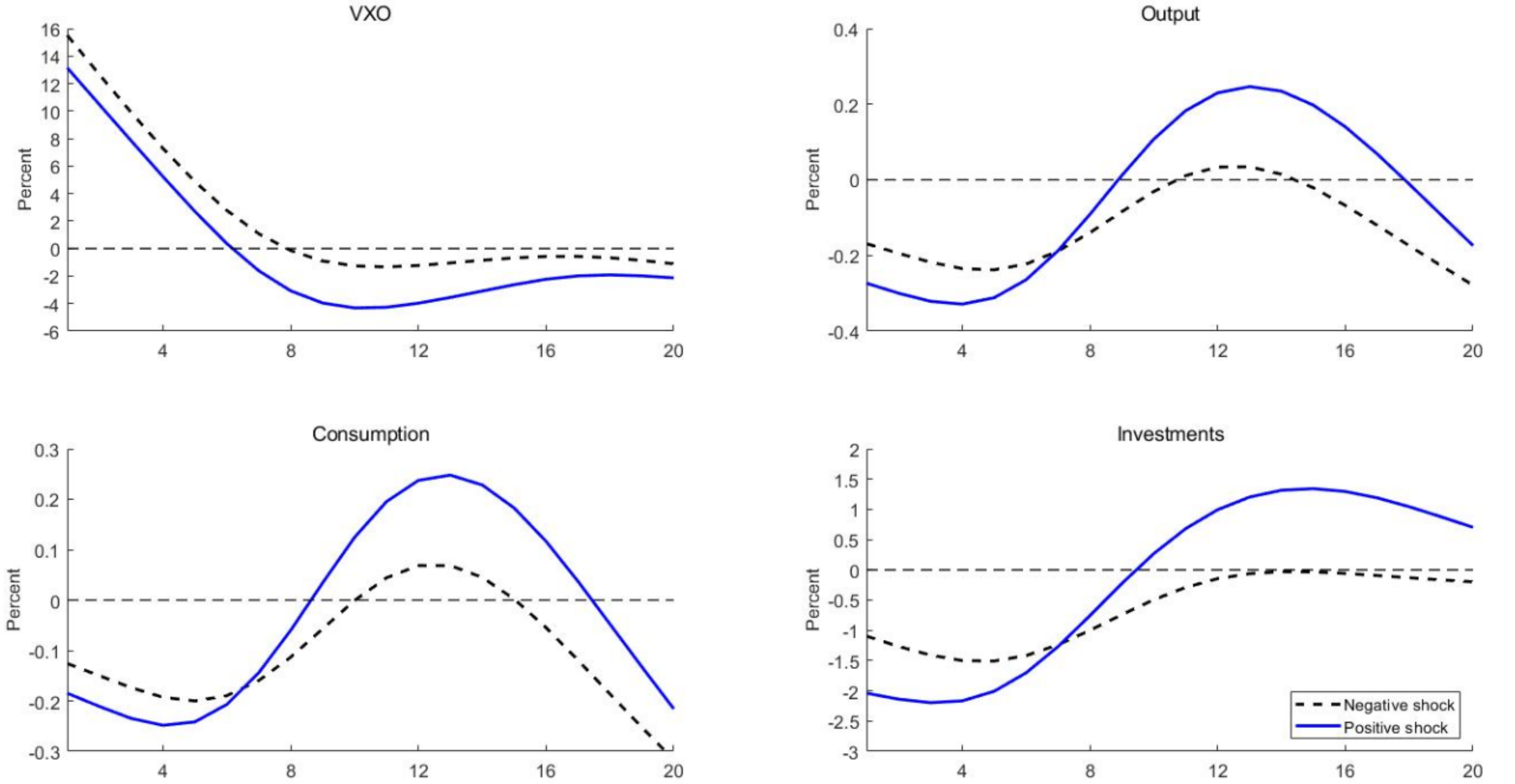
Data appendix

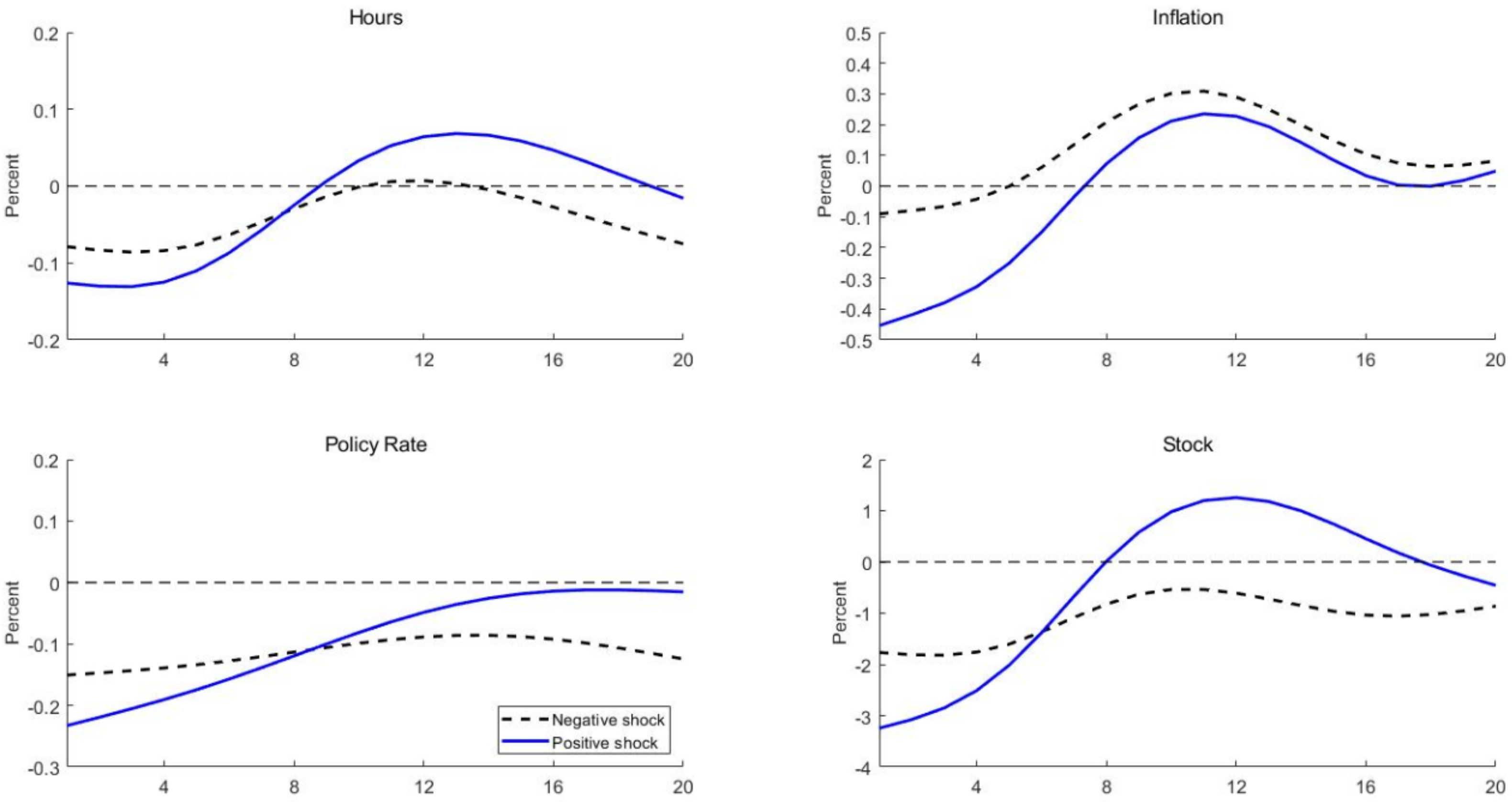
The table reports the details of data used in IRF estimations. Units of GDP, Consumptions and Investment are billions of chained 2012 dollars. SAAR and SA represent seasonally adjusted annual rate and seasonally adjusted, respectively.

Variables	Description	Units	Frequency	Source	Period
VXO	CBOE S&P 100 Volatility Index	Index (Average)	Quarterly	FRED database	1986Q1~2020Q4
GDP	Real Gross Domestic Product	Billions SAAR	Quarterly	FRED database	1986Q1~2020Q4
Consumptions	Real Personal Consumption Expenditures	Billions SAAR	Quarterly	FRED database	1986Q1~2020Q4
Investment	Real Gross Private Domestic Investment	Billions SAAR	Quarterly	FRED database	1986Q1~2020Q4
Working hour	Weekly Hours Worked (Nonfarm Business Sector, 2012=100)	Hours SA	Quarterly	FRED database	1986Q1~2020Q4
Inflation	CPI based Inflation	Percentage (Average)	Quarterly	FRED database	1986Q1~2020Q4
Policy rate	Wu-Xia Shadow Rate	Percentage (Average)	Quarterly	FRB of Atlanta	1986Q1~2020Q4
M2	Money Stock: M2	Billions SA	Quarterly	FRED database	1986Q1~2020Q4

Stock	Standard & Poor's 500 Stock Price Index	Index (Average)	Quarterly	FRED database	1986Q1~2020Q4

B. Empirical impulse response to VXO shock (The baseline model with stock price)




Hours
Inflation
Policy Rate
Stock
Percent
Negative shock
Positive shock
0.2
0.1
0
-0.1
-0.2
0.5
0.4
0.3
-0.3
-0.4
-0.5
2
1
-1
-2
-3
-4
4
8
12
16
20

C. Equilibrium conditions of the DSGE model

Households

$$M_{t+1} = \left(\beta \frac{a_{t+1}}{a_t}\right)\left(\frac{C_{t+1}{}^{\eta}(1-N_{t+1})^{1-\eta}}{C_t^{\eta}(1-N_t)^{1-\eta}}\right)^{1-\sigma/\theta_v}\left(\frac{C_t}{C_{t+1}}\right)\left(\frac{V_{t+1}^{1-\sigma}}{\mathbb{E}_t\left[V_{t+1}{}^{1-\sigma}\right]}\right)^{1-1/\theta_V} \qquad \textbf{(C. 1)}$$

$$\frac{1-\eta}{\eta}\frac{C_t}{1-N_t} = \frac{W_t}{P_t} \qquad \text{(C. 2)}$$

$$\frac{P_t^{Equity}}{P_t} = \mathbb{E}_t\left\{M_{t+1}\left(\frac{D_t^{Equity}}{P_t} + \frac{P_t^{Equity}}{P_t}\right)\right\} \qquad \text{(C. 3)}$$

$$1 = R_t^R \mathbb{E}_t\left\{M_{t+1}\right\} \qquad \text{(C. 4)}$$

Firm

$$Y_t = K_t^{\alpha}(Z_t N_t)^{1-\alpha} - \Phi \qquad \textbf{(C. 5)}$$

$$\frac{W_t}{P_t}N_t = (1-\alpha)mc_t(Y_t + \Phi) \qquad \text{(C. 6)}$$

$$\frac{R_t^K}{P_t}K_t = \alpha \cdot mc_t(Y_t + \Phi) \qquad \text{(C. 7)}$$

$$K_{t+1} = (1-\delta)K_t + \left(1 - \frac{\phi_I}{2}\left(\frac{I_t}{I_{t-1}} - 1\right)^2\right)I_t \qquad \text{(C. 8)}$$

$$1 = q_t\left(1 - \phi_I\left(\frac{I_t}{I_{t-1}} - 1\right)\frac{I_t}{I_{t-1}} - \frac{\phi_I}{2}\left(\frac{I_t}{I_{t-1}} - 1\right)^2\right) + \mathbb{E}_t M_{t+1} q_{t+1}\phi_I\left(\frac{I_t}{I_{t-1}} - 1\right)\left(\frac{I_t}{I_{t-1}}\right)^2 \qquad \text{(C. 9)}$$

$$q_t = \mathbb{E}_t M_{t+1}(R_t^K + q_{t+1}(1-\delta)) \qquad \text{(C. 10)}$$

$$\phi_P\left(\frac{\pi_t}{\Pi} - 1\right)\left(\frac{\pi_t}{\Pi}\right) = (1-\theta_\mu) + \theta_\mu mc_t + \phi_P\mathbb{E}_t\left\{M_{t+1}\left(\frac{\pi_t}{\Pi} - 1\right)\left(\frac{\pi_t}{\Pi}\right)\frac{Y_{t+1}}{Y_t}\right\} \qquad \text{(C. 11)}$$

$$\frac{D_t(i)}{P_t} = \frac{D_t^{Equity}(i)}{P_t} + \nu\left(K_t(i) - \frac{1}{R_t^R}K_{t+1}(i)\right) \qquad \text{(C. 12)}$$

Monetary policy and market equilibrium

$$\ln(R_t) = r + \rho_\pi(\ln(\pi_t) - \ln(\Pi)) + \rho_y(\ln(Y_t) - \ln(Y_{t-1})) \qquad \textbf{(C. 13)}$$

$$1 = R_t \mathbb{E}_t \left\{ \frac{M_{t+1}}{\pi_{t+1}} \right\} \qquad \text{(C. 14)}$$

$$Y_t = C_t + I_t - \frac{\phi_P}{2} \left[\frac{P_t}{\Pi P_{t-1}} - 1 \right]^2 Y_t \qquad \text{(C. 15)}$$

Shock processes

$$a_t = (1-\rho_a)a + \rho_a a_{t-1} + \sigma_{t-1}^a \varepsilon_t^a \qquad \textbf{(C. 16)}$$

$$\sigma_t^a = (1-\rho_{\sigma^a} - \rho_{\sigma^a}^+)\sigma^a + (\rho_{\sigma^a} + \rho_{\sigma^a}^+)\sigma_{t-1}^a + (\sigma_{\sigma^a} + \sigma_{\sigma^a}^+)\varepsilon_t^{\sigma^a} \qquad \text{(C. 17)}$$

$$Z_t = (1-\rho_Z)Z + \rho_Z Z_{t-1} + \sigma^Z \varepsilon_t^Z \qquad \text{(C. 18)}$$

Habit persistence in household consumption

$$M_{t+1} = \left(\beta \frac{a_{t+1}}{a_t} \right) \left(\frac{(C_{t+1} - h\overline{C}_t)^\eta (1-N_{t+1})^{1-\eta}}{(C_t - h\overline{C}_{t-1})^\eta (1-N_t)^{1-\eta}} \right)^{1-\sigma/\theta_v} \left(\frac{C_t - h\overline{C}_{t-1}}{C_{t+1} - h\overline{C}_t} \right) \left(\frac{V_{t+1}^{1-\sigma}}{\mathbb{E}_t \left[V_{t+1}{}^{1-\sigma} \right]} \right)^{1-1/\theta_V} \qquad \textbf{(C. 19)}$$

$$\frac{1-\eta}{\eta} \frac{C_t - h\overline{C}_{t-1}}{1-N_t} = \frac{W_t}{P_t} \qquad \text{(C. 20)}$$

Monetary policy with persistence

$$\ln(R_t) = \rho_r \ln(R_{t-1}) + (1-\rho_r)\Big(r + \rho_\pi (\ln(\pi_t) - \ln(\Pi)) + \rho_y (\ln(Y_t) - \ln(Y_{t-1}))\Big) \qquad \textbf{(C. 21)}$$

D. VXO statistics

[Table D] VXO statistics

The table reports statistics of VXO data. The average and standard deviation values of VXO changes over three different frequency are reported according to the increase or decrease.

	Increasing changes		**Decreasing changes**	
Frequency	**Mean**	**Volatility**	**Mean**	**Volatility**
Quarterly	4.09	6.39	-3.13	3.48
Monthly	2.96	5.17	-2.39	2.55
Daily	1.16	2.44	-1.05	1.71

Abstract in Korean

금융 경제에 관한 연구

금융 경제는 여러 기술의 발전과 함께 빠르게 성장하고 있다. 이러한 기술의 발전은 많은 사람들이 금융자산에 접근하기 쉽게 만들었고 이는 금융 경제가 실물 경제에 미치는 영향을 증가시키고 있다. 그러므로 금융 경제의 보다 정확한 영향을 분석하기 위해서는 많은 연구가 필요한 상황이다. 본 학위 논문은 금융 경제에 관한 세 개의 다른 주제로 금융 경제를 분석하는 것을 목적으로 한다.

첫 번째 주제는 채권시장의 개발이 통화 정책의 pass-through에 미치는 영향을 분석한 연구이다. 채권 시장의 발전 지표로 채권의 발행양을 GDP로 나누어 사용하였으며 연구의 결과에서 대출 금리에 대한 통화 금리의 pass-through가 채권 시장의 발전 정도에 따라 크게 영향을 받음을 확인할 수 있었다.

두 번째 주제는 불확실성 충격에 대한 주요 거시 변수들의 비대칭 반응을 연구한 내용으로서 Smooth local project (SLP) 방법을 이용하여 주요 거시변수들의 비대칭 반응을 실증 분석하고 실증 분석의 결과를 토대로 DSGE 모형에 불확실성 충격의 비대칭성을 calibration하였다. 모델 추정 결과 양의 불확실성 충격이 음의 불확실성 충격보다 지속성이 낮고 변동성이 높다는 사실을 확인하였다. 또한 가격 경직성과 위험 회피성은 이러한 불확실한 충경의 비대칭성에 영향을 주는 것으로 확인되었다.

세 번째 주제는 금융시장의 유출 효과를 고려한 경우 주식과 국고채 간의 동적 관계를 분석한 연구이다. 금융 시장의 유출 효과로서 위험 유출 효과와 금융 정보 유출 효과를 정의하고 이러

한 유출 효과가 있는 경우 미국의 주식과 국고채 간의 관계를 실증 분석하였다. 연구의 결과를 통해 이러한 유출 효과가 두 시장의 관계에 유의미한 효과를 주는 것을 확인하였고 조건부 변동성과 상관 계수에 영향을 주는 것을 확인하였다. 이러한 발견은 금융 프토폴리오 투자자와 정부 정책 입안자에게 중요한 의미를 제공한다고 볼 수 있다.

주요어: 금융 경제, 통화 정책 pass-through, 불확실성, Smooth local projection (SLP), DSGE 모형, 주식-채권 관계
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