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The Impact of Uncertainty and Risk Measures

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

in

Economics

by

Soojin Jo

Committee in charge:

Professor James D. Hamilton, Chair
Professor Davide Debortoli
Professor Marjorie Flavin
Professor Dimitris Politis
Professor Rossen Valkanov

2012

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The dissertation of Soojin Jo is approved, and it is acceptable in quality and form for publication on microfilm and electronically:

Chair

University of California, San Diego

2012

DEDICATION

To Hayne, Ki Woon and my parents

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VITA

- 2005 B. A. in German Language and Literature *summa cum laude*,
Ewha Women's University, Seoul, Korea
- 2005 M. A. in Economics, Ewha Women's University, Seoul, Korea
- 2008-2012 Graduate Teaching Assistant, University of California, San
Diego
- 2012 Ph. D. in Economics, University of California, San Diego

PUBLICATIONS

Soojin Jo, "The Consumption Behavior of Korean Households: Habit Formation vs. Durability", with Eun Young Chah, *Korean Economic Studies*, 2008.

ABSTRACT OF THE DISSERTATION

The Impact of Uncertainty and Risk Measures

by

Soojin Jo

Doctor of Philosophy in Economics

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Professor James D. Hamilton, Chair

This dissertation seeks to better understand how uncertainty impacts a variety of economic activities and how to measure systemic risk.

In the first chapter, “The effects of oil price uncertainty on the macroeconomy” focuses on oil price uncertainty, and how it affects the global economic growth. In particular, I define oil price uncertainty as the time-varying standard deviation of one-quarter ahead forecasting error that follows stochastic volatility. Then I use a quarterly VAR with stochastic volatility in mean to examine the effect of oil price uncertainty. Stochastic volatility allows for the separation of effects of the oil price uncertainty from the level, and thus enables the examination of an oil price uncertainty shock in a flexible yet tractable way. One important contribution of this chapter is that it makes significant improvements in recovering an more

accurate historical uncertainty series by incorporating a realized volatility series from daily oil price data to the main VAR as an additional oil price uncertainty indicator. The estimation result suggests that apart from the changes in oil price level, an oil price uncertainty shock alone has negative effects on both global and advanced economies' industrial production growth.

Next I move on to the propagation of uncertainty in the financial sector of the economy in the second chapter, "Bank lending and loan securitization under uncertainty". This chapter analyzes how US commercial banks adjust lending activities in response to macroeconomic uncertainty with a focus on asset securitization. During 2001Q2-2009Q3, macroeconomic uncertainty has been negatively related to the loan growth rate. In addition, comparing banking institutions with and without asset securitization, I find that loan growth rate of asset-securitizing banks was not particularly protected from the increase in uncertainty, which implies that securitization did not effectively help transfer aggregate risk from the banking sector to investors. I postulate factors that may have contributed to the ineffective risk transfer of securitization; one important reason is due to the banks' credit exposure through explicit/implicit recourse and/or seller-provided credit enhancements which also fluctuate with the changes in the macroeconomic uncertainty level.

My final dissertation chapter surveys the recent literature on the systemic risk measures in the purpose of better understanding the concept of systemic risk in relation with financial stability. In "Financial stability and systemic risk: a survey of systemic risk measure", I start from "model-free" measure of *CoVaR*, an extension of Value-at-Risk to quantify the contribution of an individual entity to systemic risk, that can be used and applied to practice very easily and flexibly. Then, I introduce GARCH-based measure, SRISK, whose main goal is to quantify the expected capital shortfall of a firm given that the financial sector is in distress. Next, I look at the measures rooted in the CDS pricing model, one of which attempts to capture systemic risk among sovereigns. Finally, I review the recent development that brings in the rare event, i.e., systemic risk crisis, into the DSGE framework with the intermediary sector.

Chapter 1

The Effects of Oil Price Uncertainty on the Macroeconomy

Abstract

This chapter examines the effect of oil price uncertainty on global real macroeconomic activity using a quarterly VAR with stochastic volatility-in-mean model. Stochastic volatility allows for the separation of effects of the oil price uncertainty from the level, and thus enables the examination of an oil price uncertainty shock in a flexible yet tractable way. The estimation results suggest that apart from the changes in oil price level, an oil price uncertainty shock alone has negative effects on world industrial production. This paper also improves the recovery of an accurate historical uncertainty series substantially by incorporating an additional oil price uncertainty indicator, i.e., a realized volatility series obtained from daily oil price data, into the main VAR.

1.1 Introduction

The effects of an unanticipated oil price changes on real macroeconomic activity have long been studied since the seminal paper of Hamilton (1983)[37], which is one of the first papers indicating crude oil price shocks as a contributing factor to economic recessions. A large body of subsequent literature has confirmed this view and argued that an unforeseen oil price increase can slow down macroeconomic activity. One common empirical approach in this literature is to regress a variable that represents the growth of macroeconomic activity on oil price changes, which are defined using several different oil price series. This usually yields coefficient estimates below zero, which is evidence of an inverse relationship between the two. Implicit in this approach is the assumption that the relationship is linear and symmetric: a sudden oil price spike drags down economic growth while an unexpected oil price drop can generate economic expansion of the same magnitude. However, when the sudden oil price drop in mid-1980 failed to generate the expected economic expansion, many researchers started to look at the relationship from a different angle. For example, Mork (1989)[58] finds that price declines show smaller and insignificant correlations compared to price surges, and hence supports an asymmetry in the responses.

To explain this, one strand of literature emphasizes the role played by the higher moments of the oil price series in addition to the changes in levels. The second moment, which determines the distribution of the price series, has gained special attention because this controls the size of a possible price variation in a certain period. In other words, it is harder to predict the actual price realization with a larger conditional variance, and there is a higher chance of an extreme oil price change hitting the economy. This implies oil price uncertainty can be well approximated by conditional time-varying volatilities of the series, which in turn enables examination of a more integrated version of the oil-economy relationship still in a computationally tractable way.

One other reason that this paper focuses on oil price uncertainty lies in the theoretical background that reports negative effects of various types of uncertainty on real economic activities. For instance, Bernanke(1983)[17] points out that firms

may postpone irreversible investment decisions, resulting in cyclical fluctuation in the economy under high inflation uncertainty. More recently Bertola, Guiso and Pistaferri (2005) [18] find that uncertainty of income flows affect the size of the inaction band that determines the frequency of durable goods adjustment. Finally, Bloom, Fluetotto, Jaimovich, Saporta-Eksten, and Terry (2011)[23] recently find that an uncertainty shock, defined as an unexpected change in the conditional second moment of a productivity innovation process, can result in a sharp and rapid economic recession even though the first moment remains unchanged. In sum, the above mentioned papers suggest high economic uncertainty can induce economic fluctuations by providing a “real option” as economic agents prefer to wait for uncertainty to resolve before making any irreversible decision. Further, it is reasonable to hypothesize that changes in oil price uncertainty, in addition to the oil price movement itself, will have effects on economic fluctuations, as oil is a salient factor for both households’ consumption and firms’ production decisions.

To see how oil price uncertainty has moved over time, Figure ??figure1 plots different measures of the crude oil price volatility series. The upper panel plots the quarterly standard deviation of real average crude oil prices from 1957Q1 to 2010Q1 computed from three-month price data in the corresponding quarter ¹. The lower panel shows global crude oil price uncertainty from 1958Q2 to 2008Q3 recovered from the statistical model used in this paper. Note that the oil price volatility series in both cases are increasing in level and become more volatile over time. What induces the increasing trend in oil price uncertainty? One possible factor pointed out by Hamilton (2009)[39] and Baumeister and Peersman (2010)[14] is that both the oil supply and demand curves have become more inelastic. This inelasticity means that even a small shock can bring more sensitive responses in the oil market than in the past, leading to unstable oil prices. Another possible factor that contributes to more volatile oil prices is increasing participation in the oil related financial market as mentioned, for example, in Hamilton (2009). All

¹The monthly average crude oil price series measured in US dollars per barrel is taken from International Financial Statistics of International Monetary Fund and deflated by the US CPI (CPIAUCSL: monthly seasonally adjusted consumer price index for all urban consumers: all items, index 1982-1984=100) obtained from the FRED database.

in all, the increasing trend of oil price uncertainty will continue in the market for some time in the near future. In addition, as more and more people perceive and fear the possibility of oil depletion in the near future, oil price uncertainty will increasingly contribute to real economic activity. Therefore, it is important to pay closer attention to the relationship between oil price uncertainty and economic activity since Figure 1 suggests that its influence matters more and more to the macroeconomy, if, in particular, oil price uncertainty has any direct effect on the real economy at all.

In this study, I investigate how oil price uncertainty, defined as the time-varying standard deviation of the one-quarter ahead forecast error, affects global real economic activity.² In particular, I quantify the effects of oil price uncertainty directly by including the time-varying volatility in the mean equations of a three-variable vector autoregression (VAR).

This paper makes a number of contributions. First, it recovers historical oil price uncertainty series spanning a long period of 1958Q2 - 2008Q3 with substantial improvement in precision by modeling it originally as stochastic volatility and later incorporating realized volatility as an additional uncertainty indicator, based on Dobrev and Szerszen (2010) [29].³ That is to say, I define oil price uncertainty to follow stochastic volatility, which is a very flexible yet parsimonious way of modeling the time-varying volatility. More importantly, this modeling strategy has an advantage in incorporating an additional uncertainty indicator, realized volatility, constructed by the jump-robust median realized volatility estimator that is in principle similar to an average of squared daily oil price changes. The inclusion of observed realized volatility series shows striking improvements in precision, and as a result, the paper provides a reliable measure of oil price uncertainty time series.

Another advantage of having a stochastic volatility process is that it permits an independent source of innovations to the time-varying uncertainty process,

²Thus, I use the term *oil price uncertainty* and *oil price volatility* interchangeably henceforth.

³As discussed in detail in the later section, Dobrev and Szerszen (2010) incorporate the information summarized in realized volatility of high-frequency data when estimating volatility series which is modeled as stochastic volatility, achieving a high efficiency gain.

regardless of the shocks to the first moment. Therefore, the paper provides an effective method to quantify the responses to an unanticipated oil price uncertainty shock independent of price changes. This framework can also be easily modified for the cases where the oil price shock and the oil price uncertainty shock are correlated to each other. The impulse response result of this paper indicates that the oil price uncertainty shocks have immediate and persistent negative effects on global industrial production growth.

This paper also contributes to the literature on uncertainty by providing an empirical evidence of its destructive impact on real economic activities. I find oil price uncertainty deters global real economic activity growth, which further suggests a steady price movement will have a less substantial impact on the economy – regardless of their direction – than does a sudden and unexpected price shock. In addition, while the focus of previous literature lies more on measuring the impact of price uncertainty at the national level, I use the global economy’s industrial production series to extend the analysis to a broader context. With the world industrial production index series, I draw a more general conclusion regardless of a country’s position in the oil market, i.e., whether it is an oil importer or an exporter.⁴ This result is robust to the changes of oil price series, sub-periods of the sample, and also holds for advanced economies. Together, the finding emphasizes the importance of tracking the oil price uncertainty series since it can distort the effect of a policy that assumes the linearity in the oil price-economic activity relationship.

The rest of the paper is organized as follows: Section 2 reviews the literature, with a particular focus on the non-linear relationship between oil prices and the macroeconomy; Section 3 introduces a statistical model for the empirical analysis; Section 4 presents empirical results along with impulse responses; and Section 5 concludes.

⁴Oil price uncertainty refers to the dispersion of possible price change to either direction, i.e., increase or decrease. However, some studies, e.g., Kilian and Vigfusson (2010)[50], argue that only one side of the price distribution would matter at the national level, depending a country’s position in the oil market. Although the theoretical uncertainty literature shows that uncertainty itself, regardless of the direction of the first moment change, is the factor that affects the economy, looking at the global level data may provide evidence robust to such argument.

1.2 Review of Literature

Broadly speaking, this paper belongs to the literature that looks at changes in price uncertainty and their effect. In terms of oil prices, numerous papers have studied empirically the relationship between oil price changes and real economic activity, and many of them demonstrate non-linearity. This section reviews the literature that focuses on non-linearity, and further the ones analyzing price volatility explicitly.

Hamilton (2003)[38] finds strong evidence supporting non-linearity. More specifically, a price increase after a long stable period has a more prominent effect than one after a more volatile period, which would be interpreted as a normal price adjustment. He further defines a new oil price variable, net oil price increase, as the amount by which the oil price in a certain quarter exceeds the previous 12-month peak, and finds that this nonlinear transformation of the oil price movements performs well in forecasting the GDP growth level.

Cogni and Manera (2009)[27] experiment oil-economy relationship with different types of Markov-switching regime autoregressive models. They find that positive oil price changes, net oil price increases and oil price volatility are the three oil shock definitions that best describe the impact of oil prices on output growth rate in G-7 countries among seven other variants of oil shock proxies. Not only does this finding confirm non-linearity in the oil-economy relationship, but it also supports the argument that oil price uncertainty measured by its volatility is an important factor in forecasting real economic activity.

There are some papers that attempt to explore the possible effect of oil price uncertainty more straightforwardly, and the empirical results have been in support of the significance of uncertainty in various perspectives. First, Lee, Ni and Ratti (1995)[55] construct a new variable reflecting both the unexpected level change and the time-varying conditional variance of price change. They find that this normalized oil price shock variable is highly significant and matches the US data to a much higher degree than the usual price changes across different sample periods. More importantly, this result implies that the oil price shocks would have a less severe impact on economy when oil price movements are erratic since a price

variation is possibly regarded as another transitory event.

Kellogg (2010) [48] takes a more direct approach to find the empirical evidence to the real option theory by testing the responsiveness of firms' investment decisions to changes in uncertainty using Texas oil well drilling data and expectations of future oil price volatility from the NYMEX futures options market. The result points to the support of the real option as firms reduce their drilling activity in the magnitude that is consistent with the optimal response prescribed by theory when expected volatility rises.

Elder and Serletis (2010)[32] and Bredin, Elder and Fountas (2010) [24], which are most closely related to this paper, are among the first papers that measure the impact of oil price uncertainty directly in the two-variable GARCH-in-Mean VAR using US and G-7 economies data. From the empirical analysis of the US, they obtain robust results that an increase in oil price uncertainty deters various types of real economic activities, such as output production, investment, and consumption. Furthermore, they document that economic activities are negatively affected by oil price uncertainty in four of G-7 countries. Based on the results, they suggest that the reason the 2003-2008 oil price surge did not lead to an economic recession is because the price increase has been steady and continuous, resulting in the oil price uncertainty kept at a very low level, so the overall change in oil price had smaller effects on the economy.

It is worth noting that the main objective of the above papers by Elder et al. and Bredin et al. is to gauge the oil price uncertainty-economy relationship using data sets of specific countries. While this analysis has advantages in answering a more specialized question, it is difficult to generalize the result to other countries as the effect may differ depending on a country's position in the oil trade. This paper attempts to extend the analysis beyond the country level by making use of global and advanced economies' data. In addition, by modeling the oil price uncertainty process with stochastic volatility, which allows a free driving variable in the volatility generating process, it is possible to investigate the dynamic impact of an unanticipated oil price uncertainty shock on economic activities, independent of any other changes in the endogenous variables. Furthermore, I make use of three

variables in the VAR, oil production quantity as well as oil price and economic activity, to better reflect the underlying structure of oil markets.

Baumeister and Peersman (2008, 2010) [14] [15] approach the problem of possible non-linearity in a much more flexible way; they generalize the presumed linear relationship by letting the coefficients in a VAR be time-varying in every period. The time-varying coefficients are then adaptable to the possible nonlinearities or structural changes between the variables in the VAR, and hence, can closely capture the dynamic interaction between oil price changes and economic growth that could be left out in a standard linear specification. In addition, they also allow time-variation to the elements of the variance covariance matrix, upon which the measurement of oil price uncertainty in this paper is based. Inspired by this variance covariance matrix modeling strategy, I measure uncertainties of variables harnessing the time-varying volatility of innovation and include it in the mean equations of a VAR to investigate the impact of oil price uncertainty directly.

The statistical model in this paper also bears some similarity to that of Berument, Yalcin and Yildirim (2009) [19] in that their model exploits a Stochastic Volatility in Mean model⁵ which investigates the effect of the inflation uncertainty innovation on inflation. However, their model is a univariate VAR and is not directly applicable for our purpose where stochastic volatility of an endogenous variable is assumed to have effects on the dynamics of another variable.

1.3 Model and Estimation

1.3.1 Model

In order to measure the effect of oil price uncertainty on the economy, I first exploit a modified version of the VAR with the time-varying stochastic volatilities by Primiceri (2005) [60] and Baumeister and Peersman (2008, 2010). I add an additional term $\Lambda\sigma_t$ which captures the effect of time-varying oil price uncertainty on the dynamics of economic activity. Another difference of the model lies in the

⁵See Koopman and Uspensky (2002)[52] for the detailed explanation of the application of this model.

time-invariance of VAR coefficients while the correlation and variance parameters' time-dependence is preserved. This is partly because of the fact that this paper focuses on a more specific form of non-linearity, namely, the effect of the conditional second moment of oil price series.⁶ Hence, the VAR can be written as,

$$y_t = B_0 + B_1 y_{t-1} + \dots + B_p y_{t-p} + \Lambda \sigma_t + u_t, \quad (1.1)$$

where y_t is a 3×1 vector consisting of quarterly global crude oil production, crude oil price and real economic activity. The real economic activity is measured by the industrial production index series of the global economy, as explained in detail in the Data section. All variables are in first differenced logs multiplied by 100 to represent the quarterly growth rate. The 3×1 vector B_0 is an intercept, B_i for $i = 1, \dots, p$ are 3×3 coefficient matrices with number of lags p set at 4 to allow for the dynamics of the system. The reduced form innovation vector u_t is defined to have conditional mean zero and conditional time-varying variance-covariance matrix given by Ω_t such that $\Omega_t = A_t^{-1} \Sigma_t \Sigma_t' (A_t^{-1})'$ where

$$A_t = \begin{bmatrix} 1 & 0 & 0 \\ a_{21,t} & 1 & 0 \\ a_{31,t} & a_{32,t} & 1 \end{bmatrix}, \quad \Sigma_t = \begin{bmatrix} h_{1,t} & 0 & 0 \\ 0 & h_{2,t} & 0 \\ 0 & 0 & h_{3,t} \end{bmatrix}. \quad (1.2)$$

By letting the lower triangular elements of A_t and the diagonals of Σ_t be time-varying, any change in the correlations between variables will be captured, and at the same time the possible structural changes in the oil market will be reflected.

In the main VAR, $\sigma_t = [\log \sigma_{1,t} \log \sigma_{2,t} \log \sigma_{3,t}]'$ is a 3×1 vector of uncertainties given by logarithms of the diagonal elements of $A_t^{-1} \Sigma_t$. The time-varying standard deviation series captures variability of the unforecasted part of the series, which would be an appropriate way of modeling uncertainty.

⁶Moreover, not much variation over time is observed for the coefficient of interest (λ) when I let the coefficients be time-varying, and hence, time-invariant coefficients seem to capture the intended relationship sufficiently well in a more parsimonious way with lower computational burden.

The structure of Λ is restricted to be,

$$\Lambda = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & \lambda & 0 \end{bmatrix}, \quad (1.3)$$

so that it can specifically capture the effect of oil price uncertainty on the real economy – the main interest of this paper. While it is possible to have all other elements of Λ unrestricted and to let the data determine them, the timing of the variable may complicate the drawing from the posterior distribution. Put differently, as the model specifies that the volatility in one period affects variables in the same period, an approximation method, e.g., second-order Taylor approximation, needs to be applied in such cases, which comes at a cost of intensive computation due to the non-linearity and high-dimensionality in the prior error distributions. For the purpose of this paper, implementing the restriction on the elements of Λ is sufficient and makes computation much faster.

Let $\alpha_t \equiv [a_{21,t} a_{31,t} a_{32,t}]'$. Then the dynamics of the volatilities are modeled as follows:

$$a_t = a_{t-1} + e_t, \quad (1.4)$$

$$\log h_t = \mu + \rho \log h_{t-1} + \eta_t, \quad (1.5)$$

where $e_t \sim N(0, S)$ and $\eta_t \sim N(0, W)$. This specification implies that a_t evolves as a random walk process, and logarithms of h_t , a first-order autoregressive process, which falls into the category of the stochastic volatility model. Here, ρ is a diagonal matrix with AR(1) coefficients in the diagonal and μ is a 3×1 vector of intercepts. Instead of defining $\log h_t$ as a unit root process *a priori*, I let the AR(1) coefficients be determined by data.

Then, in the matrix form, the main VAR can be rewritten as,

$$\begin{aligned} y_t &= B_0 + B_1 y_{t-1} + \dots + B_p y_{t-p} + \Lambda \log h_t + u_t \\ &= [X_t \log h_t]' [\beta \ \lambda] + A_t^{-1} \Sigma_t \epsilon_t. \end{aligned}$$

Some comments about stochastic volatility will be in order. Having the error term follow stochastic volatility is one common and flexible way of modeling

time-varying volatilities. One popular alternative is to employ the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model developed by Engle (1982)[35], as in Elder and Serletis (2010). Two models differ crucially in that the former has a free driving variable in the volatility data generating process and the latter does not. Thus, in the GARCH model, the shock that changes the oil price level is the same shock that increases volatility, whereas in the stochastic volatility framework, in principle, the volatility can have a shock independent from any changes in the level. As a result, stochastic volatility enables investigating the dynamic impact of an exogenous oil price uncertainty shock, which is hard to achieve in a model where the data generating process of the volatility is defined to be rather deterministic. In sum, the stochastic volatility model attains flexibility, and yet it keeps the structure fairly parsimonious, so that the computation is not very burdensome. More importantly, an additional oil price uncertainty indicator obtained from the high-frequency oil price data can be easily incorporated into the stochastic volatility model, which allows for better inference of unobservable volatility components with higher precision, as explained next.

The idea of using an extra indicator for oil price uncertainty in addition to the unforecasted price changes from the main VAR follows Dobrev and Szerszen (2010), which belongs to the literature that links realized volatility to stochastic volatility. Using intra-day stock return data, they show there is a substantial efficiency gain when the information content of the realized volatility series is added to a model of time-varying stochastic volatility. To be more specific, the efficiency gain is the result of having an additional measurement equation in the state-space model, where the additional measurement equation is obtained from the asymptotic distribution of a realized volatility estimator.

In the context of my paper, where the main VAR models quarterly dynamics, high-frequency data may refer to daily oil price changes. Dobrev and Szerszen design this framework originally for the case when the sample period is relatively short and both low and high frequency data are attainable for the full sample period. Yet the daily price data are not available for the earlier sample period analyzed in this paper, as the petroleum industry was heavily regulated and oil was

not traded as often to begin with. For example, the daily West Texas Intermediate (WTI) price series begins in 1983, and Brent oil in 1987. Hence, I extend Dobrev and Szerszen's framework using a time-varying Kalman filter so that as soon as the high frequency data become available, the new information contained in the daily price series is employed through a new measurement equation. In particular, I construct the following state-space model of three measurement and one state equations, when the oil price uncertainty is estimated in the algorithm:

$$y_{2,t}^{**} = 2 \times \log(h_{2,t}) + \zeta_{2,t}, \quad (1.6)$$

$$\tilde{y}_{3,t} = \lambda \log(h_{2,t}) + h_{3,t}\epsilon_t, \quad (1.7)$$

$$\log(\widehat{RV}_{t,M}) = 2 \times \log(h_{2,t}) + \sqrt{\frac{\nu}{M} \frac{\widehat{IQ}_{t,M}}{\widehat{RV}_{t,M}^2}} \xi_t, \quad (1.8)$$

$$\log h_{2,t} = \mu_2 + \rho_2 \log h_{2,t-1} + \eta_{2,t}, \quad (1.9)$$

where $y_{2,t}^{**}$ is the second element of the vector $\log(\{A_t(y_t - X_t'\beta - \underline{\sigma}'\lambda)\}^2 + c)$ with a small offset constant c^7 added to avoid the case that $A_t(y_t - X_t'\beta - \underline{\sigma}'\lambda)$ is too small and thus a logarithm is not well-defined, and, $\zeta_{2,t}$ is $\log(\epsilon_t)^2$. This is the result of the transformation that squares both sides of $A_t(y_t - X_t'\beta - \underline{\sigma}'\lambda) = \Sigma_t\epsilon_t$ and takes logarithms. It is a part of a step in the Gibbs sampling algorithm for volatility, where mixture Normal treatment of Kim, Shephard and Chib (1998)[51] is applied to solve the problem of non-Normality of the state space model. In addition, $\tilde{y}_{3,t}$ denotes a value after subtracting the level effect of lags of endogenous variables from $y_{3,t}$.

The key feature due to the incorporation of the realized volatility series is the appearance of new measurement equation (1.8) in the original state-space model consisting of the measurement equations (1.6), (1.7) and the state equation (1.9). That is, for the earlier period during which daily data are not available, the state-space model consists of equations (1.6), (1.7), and (1.9), and from 1983, the model expands to have three observation equations with equation (1.8) added.

This observation equation (1.8) is obtained from the asymptotic distribution

⁷I set c to be 0.001.

of a general class of realized volatility estimators, i.e.,

$$\sqrt{M}(\widehat{RV}_{t,M} - h_{2,t}^2) \rightarrow^D N(0, \nu \cdot IQ_t),$$

which is explained in detail in Appendix. Applying the Delta method to the above distribution yields,

$$\sqrt{M} \frac{\log(\widehat{RV}_{t,M}) - \log(h_{2,t}^2)}{\sqrt{\nu \frac{\widehat{IQ}_{t,M}}{\widehat{RV}_{t,M}^2}}} \rightarrow^D N(0, 1).$$

Approximating the above distribution results in the equation (1.8). Here, $\log(\widehat{RV}_{t,M})$ denotes the logarithm of the realized volatility estimated by the jump-robust median realized volatility estimator, M is the number of days in each quarter, ν is a known asymptotic variance factor and $\widehat{IQ}_{t,M}/\widehat{RV}_{t,M}^2$ is the asymptotic variance of the realized volatility estimator.⁸ In short, the observed realized volatility is considered as a function of the unobserved stochastic volatility, and provides additional information that otherwise would not have been available, thus the efficiency improves.

To show the improvements in efficiency more clearly, I estimate the main VAR with and without the additional indicator of the price volatility and present both results in the later section for comparison; even though the additional price volatility indicator is used only during the half of the sample period, the coefficients in the VAR, as well as oil price volatility, exhibit much higher precision. Together with realized price volatility, the statistical model of this paper constructs a reliable world oil price uncertainty series of extended time periods starting from 1958Q2.

In sum, conditional error terms of the whole system ϵ_t, e_t, η_t are assumed to follow a Normal distribution and to be uncorrelated to each other given the history up to $t - 1$, i.e.,:

$$\begin{pmatrix} \epsilon_t \\ e_t \\ \eta_t \end{pmatrix} \sim N \left(0, \begin{pmatrix} I_3 & 0 & 0 \\ 0 & S & 0 \\ 0 & 0 & W \end{pmatrix} \right). \quad (1.10)$$

⁸More detailed explanations about the Kalman filter setup are provided in Appendix along with notes on the estimation algorithm of the model.

In addition, W is assumed to be a diagonal matrix with each error term being independent of each other, and S is a block diagonal as,

$$S \equiv Var(e_t) = \begin{bmatrix} S_1 & 0 \\ 0 & S_2 \end{bmatrix}, \quad (1.11)$$

where $S_1 \equiv Var(e_{21,t})$ and $S_2 \equiv Var([e_{31,t} e_{32,t}]')$. As noted by Primiceri (2005), this structure can be easily generalized to the non-block diagonal matrix case.

1.3.2 Bayesian estimation strategy and priors

The VAR model in the previous section is estimated using Bayesian methods to assess the joint posterior distributions of parameters of interest, unobserved states and hyperparameters. Bayesian estimation is a natural choice for this model as it has several state variables appearing non-linearly in the measurement equation. As pointed out by Primiceri (2005, pp.826), classical likelihood methods may not be the optimal choice when high dimensionality and nonlinearity exist in the model because of the danger of having multiple local peaks in the likelihood function. Bayesian methods, on the other hand, deal with this type of problem particularly well by separating the parameter space into several blocks which simplifies the estimation process to a great extent. Thus the Markov Chain Monte Carlo (MCMC) algorithm, particularly the Gibbs sampling procedure, is applied to draw from a series of conditional posterior distributions of parameter blocks. Furthermore, this algorithm can be expedited by imposing conjugate prior distributions. Each step of the Gibbs sampler is explained in detail in Appendix.

In order to obtain parameter values that define the prior distributions, the first 40 observations are used as a training period, i.e., 1947Q2 - 1958Q1. In particular, an OLS regression is run assuming a time-invariant error structure, and the obtained point estimates are then used to construct prior distributions. When running the OLS regression, I use the logarithms of 5-quarter rolling standard deviation as a proxy for uncertainty for the training period for the prior distribution of λ , since it will cause a multicollinearity if a constant term and a time-invariant volatility are included at the same time in the left hand side of the VAR. The

priors for the VAR coefficients, time-varying covariance and log standard deviations are assumed to follow Normal distributions, independent of each other and of hyperparameters. Table ??table:prior summarizes all of the prior distributions used in the estimation.

The mean of $[\beta \ \lambda]$ prior comes from the OLS estimates and the variance-covariance matrix of the prior is obtained by multiplying a constant, 4, to the variance of OLS coefficient estimates, following the specification of Baumeister and Peersman (2008). With respect to the prior of α and $\log h$, I follow the previous literature (i.e., Primiceri (2005), Benati and Mumtaz (2007)[16], and Baumeister and Peersman (2008)) by applying the Cholesky decomposition to the variance-covariance matrix and using the diagonal and the lower triangular elements after standardization.

Hyperparameters S and W , which govern the variability of α and $\log h$, respectively, are presumed to follow the Inverse Wishart distribution and Inverse Gamma. The prior distributions of μ and ρ reflect the belief that the log of volatility series are so persistent that the process is close to random walks, which would be one way of reflecting the modeling conventions of the previous literature but still giving a chance to data to determine the posterior distributions. Later, I multiply a constant p to $\sqrt{\frac{\nu}{M} \frac{\widehat{IQ}_{t,M}}{\widehat{RV}_{t,M}^2}}$ in equation (1.8) for a sensitivity check to determine how large the measurement error of the realized volatility is relative to what is predicted by the theory. When doing so, I impose the inverse-Gamma(2,2) prior to have the prior average of 1, since p should be arbitrarily close to 1 if the theory applies well.

1.3.3 Data

It is important to choose an appropriate oil price series that can be representative of the global price series, as the key analysis of this paper is subject to the world economy. Many candidates can be considered as a “world oil price” series; however, for the baseline VAR estimation I use the imported refiner acquisition cost (IRAC) for both global and advanced economies, as in Baumeister and Peersman (2010). This series is a volume-weighted average price of all crude oils

imported into the United States over a specified period. Since the United States imports more types of crude oil than any other countries, this series is often regarded as the “true” world crude oil price. One problem arising from using IRAC is that the series is available only from January 1974, and thus I use the backdated series starting from 1947 that was generously provided by Christiane Baumeister. Another caveat of this series is that it is provided at a monthly frequency at most. This means that the same series cannot be used when constructing the realized volatility series that requires at least daily frequency. Thus, daily West Texas Intermediate (WTI) is used to estimate the realized volatility of each quarter starting 1983.⁹ To test the sensitivity of the results, I vary the combination of data sets by using WTI for both the main VAR and realized volatility. The IRAC is originally taken from the Department of Energy and used after being deflated by the US CPI, WTI series is retrieved from Global Financial Database after adjusting for inflation.

With respect to world economic activity, I use the world index of industrial production series spanning from 1947Q1 to 2008Q3¹⁰. This index covers global industrial activities in mining and quarrying, manufacturing and electricity, gas and water supply. Later in the paper, the sensitivity of the result is checked by using the advanced economies’ industrial production index series taken from International Financial Statistics (IFS) of International Monetary Funds (IMF).¹¹ I apply the X-12-ARIMA of the U.S Census to adjust for the seasonality of the series. The quarterly data series span from 1957Q1 to 2010Q1. The list of “advanced countries” are : Australia, Austria, Belgium, Canada, Cyprus, Czech Republic, Denmark, Finland, France, Germany, Greece, Hong Kong SAR, Iceland,

⁹Crude oil futures started to be traded on the New York Mercantile Exchange (NYMEX) since 1983.

¹⁰This data series is also provided by Christiane Baumeister and is an updated version of the one used in Baumeister and Peersman (2010)[15]. In particular, the original source of world index of industrial production is the United Nations Monthly Bulletin of Statistics, from which a coherent series is constructed by Baumeister by re-weighting and seasonally adjusting the raw data. The series can be obtained by contacting Baumeister at CBaumeister@bank-banque-canada.ca. For more detailed explanation on each series, see Baumeister and Peersman (2010), Appendix A.

¹¹The coverage of this index also similar to that of world industrial production index, i.e., the index comprises mining and quarrying, manufacturing and electricity, and gas and water, according to the UN international Standard Industrial Classification (ISIC) and is compiled using the Laspeyres formula.

Ireland, Israel, Italy, Japan, Luxembourg, Malta, Netherlands, New Zealand, Norway, Portugal, Singapore, Slovak Republic, Slovenia, South Korea, Spain, Sweden, Switzerland, Taiwan Province of China, United Kingdom and the United States.

The world oil production data provided by Baumeister are originally obtained from the DoE starting January 1973, from Oil & Gas Journal for the period April 1953 to December 1972, and the earlier series from January 1947 is interpolated from the yearly oil production data.¹² In addition, I add quarterly observations during the period October 2008 to March 2010 from the DoE for advanced economies. Quarterly data are averages of monthly observations.

1.4 Results

In this section, I present the empirical results along with impulse responses to the oil price uncertainty shock. First a closer look is given to the estimated posterior distribution of the coefficient λ for the global economy followed by the dynamic analysis on the effect of an oil price uncertainty shock, and then I perform various types of sensitivity checks.

1.4.1 The estimated effect of oil price uncertainty

The column (1) of Table ??result1 reports the summary statistics of posterior distribution for λ of the global economy analysis. Oil price uncertainty is inferred to have a significantly negative effect on the global economic activity; from the posterior sample draws, the mean of the coefficient λ is -0.1136 , the standard deviation is 0.0514 , and 98.89% of λ draws is below zero. Figure ??figure2 displays the posterior distribution of the λ constructed from 15,000 sample draws. The high probability of negative λ suggests that oil price uncertainty alone can work as a deterrent to economic growth of the global economy when increased to a higher level. This result further confirms that not only oil price movements but

¹²As noted by Baumeister and Peersman (2008), the use of interpolated data in the earlier periods is of minor importance, as this part of the data set is mostly used in training sample to construct priors that is dominated fairly quickly in the algorithm.

also changes in the oil price uncertainty matter, supporting the non-linearity in the oil price - macroeconomy relationship.

To better understand what the value of λ means, let's take 1986Q1 for illustration. The mid-1980s is recorded as the first period when the non-linear relationship between oil prices and real economic activity has been observed. At that time, the world oil consumption declined in response to the oil crises in 70's with improved energy use efficiency. On the other hand, there was additional production particularly from Iran and Iraq to finance their lingering war. As an effort to keep the prices from falling further, Saudi Arabia had cut back its production in the meantime; however, in 1986, Saudi Arabia reversed its decision and started pumping up oil production. As a result, the over-production and the reduced demand for oil resulted in a huge drop in the price; the real price of oil in 1986Q1 was \$17.4, compared to \$24.5 in the previous quarter.¹³ This sudden and huge decline in oil prices resulted in an oil price uncertainty jump to 31.79% points according to the median of the posterior draws of oil price volatility. This is an increase from the much lower level of 14.11% points in 1985Q4, doubling oil price uncertainty.

While the mid 1980s price plummet has partly been a positive factor for oil consumers and thus, for output, the global economy in general did not go through the anticipated expansion. Based on the empirical analysis of this paper, one can postulate part of the reason we went through the modest growth was due to the unusually rapid and severe increase of oil price uncertainty. The oil price uncertainty had almost doubled, and if we multiply the differences in uncertainties in logs (i.e., $\log 32.79 - \log 14.11 = 0.8123$) by the posterior median of λ (-0.1131), the result suggests the quarterly global industrial production growth rate would have been 0.9348% on average instead of its predicted rate of 0.8443%.¹⁴ Figure ??figure33 is the histogram of the possible realizations of the industrial growth rate in 1986Q1 obtained using the posterior distribution of λ , assuming that the oil price uncertainty had remained at the same level as the previous quarter. The

¹³For more detailed history of 1980's, see Downey (2009)[30](pp.19) and Hamilton (2011)[41](pp.17-18).

¹⁴The actual growth rate of global industrial production is realized at 0.7788%

dotted line shows the predicted industrial production growth rate (0.8443%). The 95% interval of the counterfactual distribution is [0.6641, 1.1990], and there is 76.43% chance that the industrial growth rate would have been higher than its predicted level. In sum, oil price uncertainty played a significant role in reducing real economic activity in the mid-1980s even though the price level stayed quite low.

With the baseline result in mind, I next estimate the main VAR, omitting equation (1.8) from the state-space model to compare the effect of having the additional uncertainty indicator, the realized volatility series, on the estimation result. In other words, the Gibbs sampling algorithm is run based on the same model but the extra information content from the realized oil price volatility indicator is discarded. The result is shown in column (2) of Table ??result1. The point estimate is -0.1995 , which implies a negative impact of oil price uncertainty, consistent with the baseline result, although the mean is larger in size (in absolute value). However, this is estimated with less precision, i.e., standard deviation is 0.0709, compared to the baseline case, which shows one contribution of the additional information content from the high frequency data.

To see if there is any other impact of including the additional price uncertainty indicator, I plot the time series of the oil price uncertainties from the baseline (with realized volatility indicator) and the current (without realized volatility indicator) VAR estimations with 95% error bands, in Figure ??figure4. Here the difference is more visible and striking. In the upper panel where I use the two oil price uncertainty indicators, the error band become much narrower from 1983 onwards when additional information content becomes available. In addition, one can observe the improvement in precision even in the period earlier than 1983 when the realized volatility series is not available. On the contrary, the lower panel exhibits a larger error band for the whole sample period, though the median (solid line) does not differ very much. Therefore, appending the supplementary price volatility indicator substantially improves the inference of the posterior distribution of the oil price uncertainty, also resulting in a more reliable and precise inference of posterior distribution of λ . Hence, this demonstrates the benefit of using an extra

volatility indicator from the high-frequency data.

In Figure ??figure45, I plot oil price uncertainty recovered from the baseline model along with the global industrial production index, oil production, and oil price growth rates. As seen in the above illustration, uncertainty is at its peak in 1986Q1, accompanied by the modest growth rate in industrial production. Furthermore, the last two quarters in 1991 exhibit highest oil price uncertainty, which coincide with the First Persian Gulf War. Oil price volatility retains a relatively high level in 90's and 2000's, and the the stochastic volatility model captures the periods in mid-1998 and the first half of 2003 as the time with particularly high oil price volatility. Specifically, the first half of 2003 that lies in between the two red vertical lines corresponds to the strike in Venezuela and the Second Persian Gulf War. Although both the oil production and oil price were affected only modestly for a relatively short period of time compared to the previous unrests, the stochastic volatility measure of my paper picks the periods with doubling of oil price uncertainty (2002Q4 : 12.18% point \rightarrow 2003Q1 : 25.36% point). This period can be a good example of the uncertainty measure moving idiosyncratically from the oil price level, which can be easily modeled using the stochastic volatility, showing the advantage of the framework of this paper. At this time, the global industrial index exhibits a short-lived dip (2003Q2) for which oil price uncertainty may have played a role. With respect to this point, I further investigate impulse responses to the oil price uncertainty shock in the next section.

1.4.2 Dynamic impacts of an oil price uncertainty shock

Suppose oil price uncertainty increases unexpectedly and substantially without affecting the actual price series, because, for example, it is not resulted from the structural changes of oil market. This is surely feasible when, for example, economic agents fear a much higher future oil demand that has not yet led into any “meaningful” change in the actual oil market, and thus there is no obvious variation in the first moment even if the underlying price distribution of oil price series has become more dispersed, and hence, more uncertain. The “uncertainty shock” of this paper may be comparable to the *oil-specific demand shock* defined

in Kilian (2009)[49] in a sense that it does not necessarily reflect any visible fundamental changes of oil supply and/or demand. However, the uncertainty shock here presumes more exogenous change since I do not require this shock to imply any changes in the price growth rate level. In addition, it can also reflect some changes in the market which is not strong enough to lead any severe results on oil supply and/or demand as in the first half of 2003. In sum, the uncertainty shock mainly describes higher possibility of facing an extreme change in oil price, but it does not imply anything about increase, decrease or no change in the price growth rate.

This type of impulse responses to the uncertainty shock has not been explored so far in the related literature, mainly because the statistical models implemented in the previous papers are based on the ARCH/GARCH framework. It is not feasible to have a sudden change in the uncertainty alone in such a framework without making specific changes in innovations to the level of oil price, as ARCH/GARCH models, by definition, do not allow any free driving variable in the volatility generating process and thus, volatility is completely deterministic according to past changes in the first moment. That is, the shock that raises or drops the oil prices is the same shock that increases uncertainty.

By contrast, the stochastic volatility model of this paper enables us to look at the impact of such an unanticipated oil price uncertainty increase on economic activities, independent of any other changes in the endogenous variables included in the VAR. This is due to the volatility generating process which has its own free parameter (η_t in equation (1.5)) that permits exogenous innovations to uncertainty. Thus, in principle, it is possible to have independent increase in oil price uncertainty.

The specifics of this exercise are as follows: I generate a one-time oil price uncertainty increase of 100-percent. Since we have the logarithm of oil price uncertainty in the mean equation of VAR, this is equivalent to have the log oil price uncertainty increase by *a unit*. As an illustration, the 100-percent uncertainty surge is comparable to what has happened during the first oil shock in 1973 and 1986Q1, according to the statistical model of this paper. This shock will be highly

persistent over time, as reflected in the posterior distribution of ρ_2 ,¹⁵ and as a result, the uncertainty series comes back to its normal path very slowly.¹⁶ It is worth to note again that it is unnecessary to look at any possible subsequent changes in oil price level as the uncertainty shock does not imply anything about the first moment.

Figure ??figure5 shows the median impulse responses of the real price of oil, the world oil production, and the global industrial production growth to a 100-percent increase of oil price uncertainty over a 12-quarter horizon after the impact period. As oil price uncertainty is negatively correlated with economic activities, a shock which increases the oil price uncertainty unexpectedly would result in a drop in industrial production growth rate. Confirming this view, a doubling of oil price uncertainty yields an immediate drop of approximately -0.11 percentage point in global industrial production growth rate in the same quarter. In other words, the exogenous shock doubling oil price uncertainty solely can deter real economic activity growth almost by 0.4%-point annually. This negative response remains very persistent over the 12-quarter horizon due to the close-to-unit root characteristics of the oil price volatility process, although oil price responds little. Finally, oil production quantity decreases slightly along with the drop in industrial production through the oil price uncertainty channel.

Next I look at the impulse responses to a temporary uncertainty shock. That is, the oil price uncertainty doubles at the impact period, but in the next period, it comes down to steady-state level by, say, a negative uncertainty shock that reverts the previous increase, capturing the case that uncertainty resolves quickly by a counter shock. Hence, oil price uncertainty shock propagates only by the dynamics of endogenous variables, ignoring close-to-unit root feature of the volatility process. Industrial production drops immediately as before, but recovers

¹⁵The point estimate of the oil price volatility AR(1) coefficient, ρ_2 , is 0.9590, and the standard deviation is 0.0221, confirming the prior belief that oil price volatility follows a process close to unit root. In case of oil production volatility, the posterior distribution of ρ_1 is much less persistent with mean 0.5287 and the standard deviation 0.1670. In addition, the point estimate of the industrial production index volatility AR(1) coefficient is 0.2807 and the standard deviation is 0.0988.

¹⁶Given the persistence of oil price uncertainty process, it can be interpreted as a permanent shock to the oil price uncertainty in practice.

the normal growth rate in about a year, and the same is true for oil production. Thus, the size of initial response of industrial production is similar, but the negative impact last for much shorter period.

1.4.3 Sensitivity Check

In this section, I check the robustness of the result in various ways. First, I look at whether the oil market structural break detected in mid-80's changes the way that oil price uncertainty affects real economic activity. The structural change in the oil market is noted by a number of recent studies, e.g., Blanchard and Gali (2007)[21], although there is no consensus on the existence of the break (e.g., Ramey and Vine (2010)[61]). In order to control for the possible changes in the oil market, I first add an indicator variable for 1984Q1 on the right hand side of the main VAR, which is the quarter set for the break in Blanchard et al. Next, I split the sample period into two, one until 1983Q4, the other from 1984Q1, and repeat the VAR estimation for different sample periods.¹⁷

Table ??1984d and Table ??split reports the summary statistics of the posterior λ draws from the above variations. All three posterior distributions of λ appear to mostly locate in the negative range, and furthermore, the means are in line with the baseline result. Although standard deviations, particularly in the first subsample period, are generally larger due to the fewer number of observations, it is apparent that the negative impact of oil price uncertainty has not been affected by the potential structural change in 1980's, and remained very consistent.

Second, I use the industrial production index of the *advanced economies* with more recent but shorter sample periods (1957Q1-2010Q1). The first column of Table ??result2 reports the summary statistics of the posterior λ draws. The point estimate, -0.1154 , is very similar to that of the global economy, and the posterior distribution is in the similar range with a very high chance of λ being negative (95.09%). This result is in line with the fact that the world GDP distribution is

¹⁷For this exercise, the main VAR is run without including equation (1.8) of realized volatility. The exclusion of realized volatility is because the realized volatility series starts only from 1983Q1, and thus there is only four observation available for the first subsample period. Hence, to treat two subsample period as equal as possible, I exclude equation (1.8) for both periods.

highly skewed to advanced economies. It also confirms and extends the results in Elder and Serletis (2010) and Bredin, Elder and Fountas (2010) obtained using the U.S and G-7 countries' various real economic activities data, since all of the countries examined in their papers are the members of advanced economies.

In second column of Table ??result2, I present the result from VAR with stochastic volatility without incorporating realized oil price volatility data, which is comparable to the result in column (2) in Table ??result1. The point estimate of λ shows weaker association, but well within the range. More importantly, consistent with the global economy's case, the posterior distribution appears to be more dispersed with lower precision. This highlights the efficiency gain achieved by the additional oil price uncertainty indicator. Moreover, the realized volatility estimator also helps estimate more reliable historical oil price uncertainty series as it does for global economy, though the posterior distribution is not presented here.

Then I rerun the estimation procedure using different oil price series. The third and the fourth columns of Table ??result1 and Table ??result2 report the estimation result obtained from using WTI as a world oil price series. Affirming the baseline result with IRAC and WTI, oil price uncertainty works destructively both in the global and advanced economies in all estimations, and the point estimates are consistently statistically significant across the different combinations. One can find that the previous improvements in precision through realized volatility are also shown here; the posterior distributions of λ are more centered in all cases when the additional price uncertainty indicator is included and thus show higher chances of λ to be significantly negative. This again evidences the efficiency gain due to the extra information content obtained from daily oil price series.

Finally, as briefly mentioned in the previous section, I re-estimate the VAR , multiplying a constant p to the term representing the measurement error ($\sqrt{\frac{\nu}{M} \frac{\widehat{IQ}_{t,M}}{\widehat{RV}_{t,M}^2}}$) in equation (1.8) and let the data determine that of the realized volatility relative to what is predicted by the theory. That is, equation (1.8) is substituted by

$$\log(\widehat{RV}_{t,M}) = 2 \times \log(h_{2,t}) + p \times \sqrt{\frac{\nu}{M} \frac{\widehat{IQ}_{t,M}}{\widehat{RV}_{t,M}^2}} \xi_t.$$

As explained in detail in Appendix, the generic asymptotic result predicts p to be arbitrarily close to one as the data sampling frequency becomes infinitesimally small. Table ??rs presents the summary statistics of the parameter p , and one can see that the 95% interval does include *one*, although it might have been affected by the relatively strong prior.

In sum, the baseline empirical result of this paper, that increase in oil price uncertainty is detrimental, remains when the potential structural change in the oil market is considered. Moreover, it is also applicable to the advanced economies' case, and is insensitive to the different combination of oil price time series data. Furthermore, the statistical improvement achieved by having realized volatility conforms to the baseline result, consistently shown across different data sets. In addition, the improvement does not seem to be forcefully driven by the small measurement error predicted by the asymptotic distribution of the realized volatility.

1.5 Conclusion

This paper investigates the effect of oil price uncertainty on real economic activity during 1958Q2 - 2008Q3, by estimating a VAR model with time-varying volatility by Bayesian estimation methods. In line with Elder and Serletis (2010) and Bredin, Elder and Fountas (2010), this paper shows that oil price uncertainty has significantly negative effects on global economy's real economic activities measured by industrial production index. This result implies when uncertainty, i.e., the possibility of an extreme oil price to be realized, increases, it can work as a deterrent for the industrial production growth, regardless of the actual price level change. For example, the case study of 1986Q1 shows high oil price uncertainty in the economy may dampen economic growth even though oil price is low. The result also applies to advanced economies, as reported in the sensitivity check section.

The main contribution of this paper is achieved by incorporating realized volatility series of oil price as an extra uncertainty indicator in addition to the stochastic volatility. In particular, the asymptotic distribution of realized volatil-

ity indicator provides the extended version of state-space model with an additional measurement equation. As a result, the historical oil price uncertainty series is estimated with much higher precision for the entire sample period with this indicator at hand, and the overall statistical inference becomes more significant. Thus, a reliable oil price uncertainty time series for a extended period is successfully recovered. Furthermore, this improvement is observed consistently in case of advanced economies, and robust to the changes of oil price series.

The empirical results of this paper add to the literature on the propagation of uncertainty shocks, e.g., by Bernanke (1983) and more recently by Bloom et al. (2011), which suggest that an uncertainty shock alone can bring a sizable negative impact on the real side of an economy. However, the impulse responses to the oil price uncertainty shock reports a persistent effect on real economic activity, as opposed to a relatively brief recession followed by an overshooting period due to pent up demand in Bloom et al (2011) . This result mainly arises from the high persistence of oil price uncertainty series. In that sense, the dynamic response result of this paper bears more similarity to that of Bachmann, Elstener and Sims (2010) [10], in which they document protracted negative effects of an unanticipated increase in uncertainty. More generally, this paper contributes to the literature that emphasizes the importance of modeling time-varying volatility correctly (e.g., Hamilton (2010)[40]), as the volatility can directly have an effect on the conditional first moment.

1.6 Appendix

Realized Volatility

As shown in Dobrev and Szerszen (2010), there is a high efficiency gain when the information content from high-frequency data is additionally used in estimating oil price volatility state. In the context of my paper, high-frequency data refers to daily oil price changes as opposed to the quarterly price series used in the main VAR. The daily series is not available for the entire sample period analyzed in this paper; however, I estimate the realized volatility of each quarter

by using jump-robust median realized volatility estimator (MedRV) of Andersen, Dobrev, and Schaumburg (2009) [6] for the period when the daily price variation is observable:

$$\begin{aligned}\widehat{RV}_{t,M} &= \text{Med}RV_{t,M} \\ &= \frac{\pi}{6 - 4\sqrt{3} + \pi} \left(\frac{M}{M-2} \right) \sum_{i=2}^{M-1} \text{med}(|\Delta OP_{i-1}|, |\Delta OP_i|, |\Delta OP_{i+1}|)^2.\end{aligned}$$

Here, M is the number of days oil is traded in each quarter and ΔOP_i denotes the observed daily change of logarithmic oil price in quarter t with $i = 1, 2, \dots, M$. MedRV is a consistent estimator of $IV_t = \int_{t-1}^t \zeta_s^2 ds$ if the log oil price evolves in continuous time as:

$$dOP_t = \mu_t dt + \zeta_t dB_t + dJ_t$$

where μ_t is the drift, ζ_t is the volatility, B_t is a standard Brownian motion, and J is a finite jump process (see Huang and Tauchen (2005) [43]; Dobrev and Szerszen (2010)). IV_t is equivalent to $h_{2,t}^2$ in our context and hence, MedRV will provide further information for oil price uncertainty as an additional indicator.¹⁸

Then the central limit theorem implies the following generic asymptotic results:

$$\sqrt{M}(\widehat{RV}_{t,M} - h_{2,t}^2) \rightarrow^D N(0, \nu \cdot IQ_t)$$

where ν is a known asymptotic variance factor-i.e., 2.96 for MedRV-and $IQ_t = \int_{t-1}^t \zeta_s^4 ds$ is the integrated quarticity controlling the precision of realized volatility estimators.

By applying the Delta method with a consistent jump-robust estimator $\widehat{IQ}_{t,M}$ of IQ_t , we get

$$\sqrt{M} \frac{\log(\widehat{RV}_{t,M}) - \log(h_{2,t}^2)}{\sqrt{\nu \frac{\widehat{IQ}_{t,M}}{\widehat{RV}_{t,M}^2}}} \rightarrow^D N(0, 1).$$

¹⁸I use MedRV and MedRQ estimators by Andersen, Dobrev, and Schaumburg (2009), but the result is robust to the use of different realized volatility estimators.

Here, I estimate IQ_t by the median realized quarticity estimator MedRQ such that

$$MedRQ_{t,M} = \frac{3\pi M}{9\pi + 72 - 52\sqrt{3}} \left(\frac{M}{M-2} \right) \sum_{i=2}^{M-1} med(|\Delta OP_{i-1}|, |\Delta OP_i|, |\Delta OP_{i+1}|)^4.$$

for each quarter t . When obtaining the above asymptotic results, the log transformation is conducted which becomes very handy to incorporate the additional information to the stochastic volatility setup of this paper. With this result, I write a new measurement equation which will be added into the step in the Gibbs sampler algorithm to estimate oil price uncertainty as follows:

$$\log(\widehat{RV}_{t,M}) = \log(h_{2,t})^2 + \sqrt{\frac{\nu}{M} \frac{\widehat{IQ}_{t,M}}{\widehat{RV}_{t,M}^2}} \xi_t$$

where ξ_t follows the standard Normal distribution and is independent of the underlying process. Note that $\log(\widehat{RV}_{t,M})$ and $\sqrt{\frac{\nu}{M} \frac{\widehat{IQ}_{t,M}}{\widehat{RV}_{t,M}^2}}$ can be readily estimated provided a high frequency data series. Therefore, in addition to the measurement equation (6), I use the above measurement equation (equation (7)) for the period that daily oil price data are observable. That is, a time-varying state-space model is constructed to generate smoothed draws of volatility states. More accurate description on how to obtain draws from the posterior distribution of $\{h_{2,t}\}_{t=1}^T$ inside the Gibbs sampler algorithm is provided in the next section.

Gibbs sampler algorithm

When it is not feasible to analytically derive the joint posterior distribution due to the model's high dimensionality and non-linearity, the Gibbs sampler algorithm provides a computationally tractable way of simulating the posterior distributions. It is because the Gibbs sampler algorithm repeatedly draws from a sequence of conditional posterior distributions after separating the parameters into several blocks whose conditional posterior distributions are known. After iterating the chains for long enough times, the draws will be equivalent to those from the joint posterior distribution. Starting from the initial values for each block, the first 30,000 "burn-in" draws are discarded in order to eliminate the possible impact of

initial values and to ensure the chain mixes well. Then following 15,000 draws are collected, and thus, 45,000 iterations in total are conducted for each analysis.

Before getting into the algorithm, I rewrite the main VAR in a simpler matrix form for convenient estimation such that

$$\begin{aligned} y_t &= X_t' \beta + \underline{\sigma}_t' \underline{\lambda} + u_t \\ &= X_t' \beta + \underline{\sigma}_t' \underline{\lambda} + A_t^{-1} \Sigma_t \epsilon_t. \end{aligned}$$

Here, X_t denotes $I_3 \otimes x_t$ where x_t is a vector containing one and all four lags of y_t and $\underline{\sigma}_t$ is $I_3 \otimes \sigma_t$. Furthermore, β and $\underline{\lambda}$ denote the vectors of parameters with $3 \times (3p+1)$ and 3×3 elements obtained by stacking each row of the coefficient matrices into vectors.

Step 1: Drawing coefficients of lags (β) and of uncertainty (λ)

Given α^T, h^T, y^T and other hyperparameters, this step is equivalent to regressing y_t on $X_t^{*'} where X_t^* is a (40×3) matrix whose elements are the lags of y_t and the log of oil price uncertainty. We can expedite this step with the independent conjugate Normal priors, whose parameters are based on the homoskedastic OLS regression result of the training period. The error term is heteroskedastic; however, given all the values of α^T and h^T , the error covariance and variance matrices are completely known in this step as they consist Ω^T .$

Step 2: Drawing covariance states (α) and hyperparameter S

Conditional on β, λ, h^T, Y^T and other hyperparameters, the following equation simplifies the sampling procedure of covariance states α^T and becomes the measurement equations in this step with the observable homoskedastic reduced form innovation u_t :

$$A_t(y_t - X_t' \beta - \underline{\sigma}_t' \underline{\lambda}) = A_t u_t = \Sigma_t \epsilon_t$$

This transforms the problem to a standard linear Gaussian state space model with the state equation (4). Now, the elements of α^T are divided into two sub-groups,

$\{a_{21,t}\}_{t=1}^T$ and $\{a_{31,t}, a_{32,t}\}_{t=1}^T$ and drawn in turn. More specifically, we have the following two state-space models:

$$\begin{aligned} a_{21,t} &= a_{21,t-1} + e_{21,t} & e_{21,t} &\sim N(0, S_1) \\ u_{2,t} &= -u_{1,t}a_{21,t} + \epsilon_{2,t} & \epsilon_{2,t} &\sim N(0, h_{2,t}^2) \end{aligned}$$

and

$$\begin{aligned} \begin{pmatrix} a_{31,t} \\ a_{32,t} \end{pmatrix} &= \begin{pmatrix} a_{31,t-1} \\ a_{32,t-1} \end{pmatrix} + \begin{pmatrix} e_{31,t} \\ e_{32,t} \end{pmatrix} & \begin{pmatrix} e_{31,t} \\ e_{32,t} \end{pmatrix} &\sim N(0, S_2) \\ u_{3,t} &= -u_{1,t}a_{31,t} - u_{2,t}a_{32,t} + \epsilon_{3,t} & \epsilon_{3,t} &\sim N(0, h_{3,t}^2). \end{aligned}$$

More specifically, one can obtain the conditional mean $a_{i,t|t-1}$ and variance $P_{i,t|t-1}$ from a forward Kalman filter for each sub-group i of α . Note that the last state of the forward Kalman filter yields $a_{i,T|T}$ and $P_{i,T|T}$ of the posterior distribution of $a_{i,T}$. Using this state value, one can draw from $N(a_{i,T|T}, P_{i,T|T})$, then feed this sample back into the backward recursion to get $a_{i,T-1|T}$ and $P_{i,T-1|T}$. This is repeated until the beginning period by updating as following¹⁹ :

$$\begin{aligned} a_{i,t|t+1} &= a_{i,t|t} + P_{i,t|t}P_{i,t+1|t}^{-1}(a_{i,t+1} - a_{i,t}) \\ P_{i,t|t+1} &= P_{i,t|t} - P_{i,t|t}P_{i,t+1|t}^{-1}P_{i,t|t}. \end{aligned}$$

After drawing α^T , the elements of hyperparameter S are sampled from the inverse-Wishart posterior distributions by updating the observable innovations given the new α^T draws.

Step 3: Drawing volatility states (h) and hyperparameter W

With other parameter values given, drawing the volatility state h^T becomes a non-linear and non-Gaussian state-space problem. This is because h_t is modeled to follow a log Normal distribution and thus it is not possible to use the standard linear state-space model applied in the previous step. Moreover, $h_{2,t}$ appearing in the third mean equation of the main VAR multiplied by λ further complicates

¹⁹See Carter and Kohn (1994) [26] for more details on the use of Gibbs sampler for a state space model.

this stage. Therefore, I apply log transformation to linearize the system and then apply use the mixture Normal treatment by Kim, Shephard and Chib (1998)[51]. In particular, the entire history of each element of the vector $\{h_i\}^T$ is drawn one after one starting from $\{h_1\}^T$. After $\{h_1\}^T$ is sampled, sampling $\{h_2\}^T$ is in order, which requires the use of time-varying Kalman filter and smoother, depending the data availability of high-frequency oil price series. Finally, $\{h_3\}^T$ can be drawn harnessing the updated value of $\{h_2\}^T$. This procedure requires the variance covariance matrix, W , to be diagonal since we implicitly disregard the possible effect of correlation by drawing one $\{h_i\}^T$ at a time.

The procedure common for $\{h_1\}^T$ and $\{h_2\}^T$ starts by obtaining the first two elements of the orthogonalized innovation, i.e., $A_t(y_t - X_t'\beta - \underline{\sigma}'_t\lambda) = \Sigma_t\epsilon_t$. Conditional on α^T from the previous step and all other values, these are observable. To linearize the equations, I take logarithms after squaring both sides and adding an offset constant c to the left hand sides.²⁰ Then, the following state-space models are obtained for $\{h_1\}^T$ and $\{h_2\}^T$, respectively:

$$\begin{aligned}\log h_{1,t+1} &= \mu_1 + \rho_1 \log h_{1,t} + \eta_{1,t+1} \\ y_{1,t}^{**} &= 2 \log h_{1,t} + \zeta_{1,t}\end{aligned}$$

$$\begin{aligned}\log h_{2,t+1} &= \mu_2 + \rho_2 \log h_{2,t} + \eta_{2,t+1} \\ y_{2,t}^{**} &= 2 \log h_{2,t} + \zeta_{2,t} \\ \tilde{y}_{3,t} &= \lambda \log(h_{2,t}) + h_{3,t}\epsilon_{3,t}\end{aligned}$$

where $y_{i,t}^{**}$ is the first two elements of the vector $\log(\{A_t(y_t - X_t'\beta - \underline{\sigma}'_t\lambda)\}^2 + c)$ after the transformations, $\zeta_{i,t}$ comes from $\log(\epsilon_t)^2$, and $\tilde{y}_{3,t}$ denotes a value obtained after subtracting the effect of lags of endogenous variables from $y_{3,t}$. One should note that at least two measurement equations are available for oil price volatility, $h_{2,t}$ for all time periods since it appears in the mean equation of $y_{3,t}$, multiplied by the coefficient λ . The number of measurement equation increases to three, including the equation (8), during the period when daily oil price series exists as described

²⁰An offset constant is added since squared value of the right hand side can be infinitesimal. Following the previous literature, I set c to 0.001.

s	$q_j = Pr(s = j)$	m_j	v_j^2
1	0.00730	-10.12999	5.79596
2	0.10556	-3.97281	2.61369
3	0.00002	-8.56686	5.17950
4	0.04395	2.77785	0.16735
5	0.34001	0.61942	0.64009
6	0.24566	1.79518	0.34023
7	0.25750	-1.08819	1.26261

in detail in Section 3 and Appendix.

The above linear system is still non-Gaussian as the distribution of $\zeta_{i,t}$ follows $\log \chi^2(1)$, and thus, it is approximated by mixing seven different Normal distributions as Kim et al. (1998) and Primiceri (2005). In doing so, an indicator variable $s_{i,t}$ is assigned for each time period t , which determines the particular Normal distribution by which the distribution of $\zeta_{i,t}$ is approximated.²¹ In particular, by independently sampling each $s_{i,t}$, is independently sampled from the discrete density function defined as

$$Pr(s_{i,t} = j | y_{i,t}^{**}, h_{i,t}) \propto q_j f_N(y_{i,t}^{**} | 2h_{i,t} + m_j - 1.2704, v_j^2), \quad j = 1, \dots, 7, i = 1, 2.$$

where the mean, $m_j - 1.2704$, and the variance, v_j^2 , of the seven Normal distributions are given in Table 1.

One can now apply the same forward and backward Kalman filter algorithm as in Step 2 to obtain the volatility series of $\{h_1\}^T$ and $\{h_2\}^T$. Lastly, this stage is completed by sampling a new set of the indicator variable $s_{i,t}$ conditional on the updated $\{h_1\}^T$ and $\{h_2\}^T$ draws (see Kim, Shephard and Chib (1998) and Appendix in Primiceri (2005)).

With the updated value of $\{h_2\}^T$, we are ready to draw the series of $\{h_3\}^T$ as the third element of the orthogonalized innovation vector, $A_t(y_t - X_t'\beta - \underline{\sigma}'_t\lambda)$, is observable. Denote this element as $y_{3,t}^*$. Then, the state-space model is the

²¹To start the Gibbs sampling algorithm, one can randomly assign any number to $s_{i,t}$ for all i and t for the initial iteration.

following:

$$\begin{aligned}\log h_{3,t} &= \mu_3 + \rho_3 \log h_{3,t-1} + \eta_{3,t} \\ y_{3,t}^{**} &= 2 \log h_{3,t} + \zeta_{3,t}.\end{aligned}$$

where $y_{3,t}^{**} = \log((y_{3,t}^*)^2 + c)$ and $\zeta_{3,t}$ denotes $\log(\epsilon_{3,t})^2$. With this arrangement, the mixture Normal approximation method can be applied again to obtain the time series of industrial production volatility using the forward and backward Kalman recursions. This step is also completed by sampling the new values of $s_{3,t}$ according to (12), which will be used in approximating the distribution of $\zeta_{3,t}$ in the next iteration.

Finally the diagonal elements of the hyperparameter W are drawn one at a time by updating the differences of newly sampled $\{h\}^T$, as each element of the matrix is considered to be distributed following the inverse Gamma distribution. This step is fairly simple because conditional on the new set of $\{h\}^T$ draws, the innovation is perfectly observable and the inverse Gamma distribution belongs to the conjugate prior family.

Table 1.1: Prior distributions

$[\beta \ \lambda]$	$N([\hat{\beta}_{OLS}, [\hat{\lambda}_{OLS}], 4 \cdot V([\hat{\beta}_{OLS}, \hat{\lambda}_{OLS}]])$
α	$N(\hat{\alpha}_{OLS}, 10 \cdot V(\hat{\alpha}_{OLS}))$
$\log h_0$	$N(\log \hat{h}_{OLS}, \log \hat{h}_{OLS} / \hat{h}_{OLS}^2)$
$[\mu_i \ \rho_i]$	$N([0 \ 1], 0.05 \cdot I_2)$
S_1	$IW(V(\hat{\alpha}_{1,OLS}), 2)$
S_2	$IW(V(\hat{\alpha}_{2,OLS}), 3)$
w	$IG((0.01)^2/2, 1/2)$
s	$IG(2, 2)$

This table shows the conditional prior distributions of the VAR coefficients $[\beta \ \lambda]$, the elements of the time-varying variance covariance matrix α and h , autoregressive parameters for volatilities $[\mu_i \ \rho_i]$, and finally, hyperparameters S_1 , S_2 and w .

Table 1.2: Summary statistics of posterior λ draws - Global economy

	(1)	(2)	(3)	(4)
Main OP series	IRAC	IRAC	WTI	WTI
RV series	WTI	n/a	WTI	n/a
mean	-0.1136	-0.1995	-0.1087	-0.1887
std. dev.	0.0514	0.0709	0.0644	0.0742
95% interval	[-.216, -.014]	[-.341, -.064]	[-.238, .011]	[-.316, -.018]
$P(\lambda < 0)$	98.89%	99.99%	96.27%	98.81%

This table shows the summary statistics of the 30,000 posterior λ draws. Column (1) is the result from the baseline model that makes use of the additional measurement equation (1.8) obtained using the realized volatility series. Column (2) is the result from the same model but excluding equation (1.8). Column (3) and (4) repeat the exercise of (1) and (2) using WTI series as the world oil price in the main VAR.

Table 1.3: Robustness check - 1984Q1 dummy

λ	
mean	-0.1495
std. dev.	0.0763
95% interval	[-0.3191, -0.0202]
$P(\lambda < 0)$	99.15%

This table reports the summary statistics of the posterior λ draws when the dummy variable for 1984Q1 is included in the right hand side of the main VAR. The inclusion of 1984 dummy variable is to see whether the effect of uncertainty remains when considering the structural change in 1984 as noted in Blanchard and Gali (2007).

Table 1.4: Robustness check - split sample VAR

λ	$\sim 1983Q4$	$1984Q1 \sim$
mean	-0.1115	-0.1310
std. dev.	0.1508	0.1036
$P(\lambda < 0)$	78.8%	89.6%

This table reports the summary statistics of the posterior λ draws for two subsample periods. The subsample periods is split before- and after- 1984Q1 and the main VAR is run without including equation (1.8) of realized volatility. The exclusion of realized volatility is because the realized volatility series starts only from 1983Q1, and thus there is only four observation available for the first subsample period. Hence, to treat two subsample period as equal as possible, I exclude equation (1.8) for both periods. Again, this exercise is to see whether the effect of uncertainty differs when the structural change in 1984 noted in Blanchard and Gali (2007) is considered.

Table 1.5: Robustness check - Advanced economies

Main OP series	IRAC	IRAC	WTI	WTI
RV series	WTI	n/a	WTI	n/a
mean	-0.1154	-0.0768	-0.1711	-0.1903
std. dev.	0.0963	0.0838	0.0734	0.0758
$P(\lambda < 0)$	95.09%	81.38%	99.17%	99.35%

This table reports the summary statistics of the 30,000 posterior λ draws of the advanced economy. As in the global economy's case, Column (1) is the result from the baseline model that makes use of the additional measurement equation (1.8) obtained from the realized volatility series. Column (2) is the result from the same model but excluding equation (1.8). Column (3) and (4) repeat the exercise of (1) and (2) using WTI series in the main VAR.

Table 1.6: Robustness check - multiplication of the parameter p

p	
mean	1.1807
std. dev.	0.5932
95% interval	[0.4004 2.6825]

This table reports the summary statistics of posterior p draws, that is the parameter multiplied to the measurement error of equation (1.8).

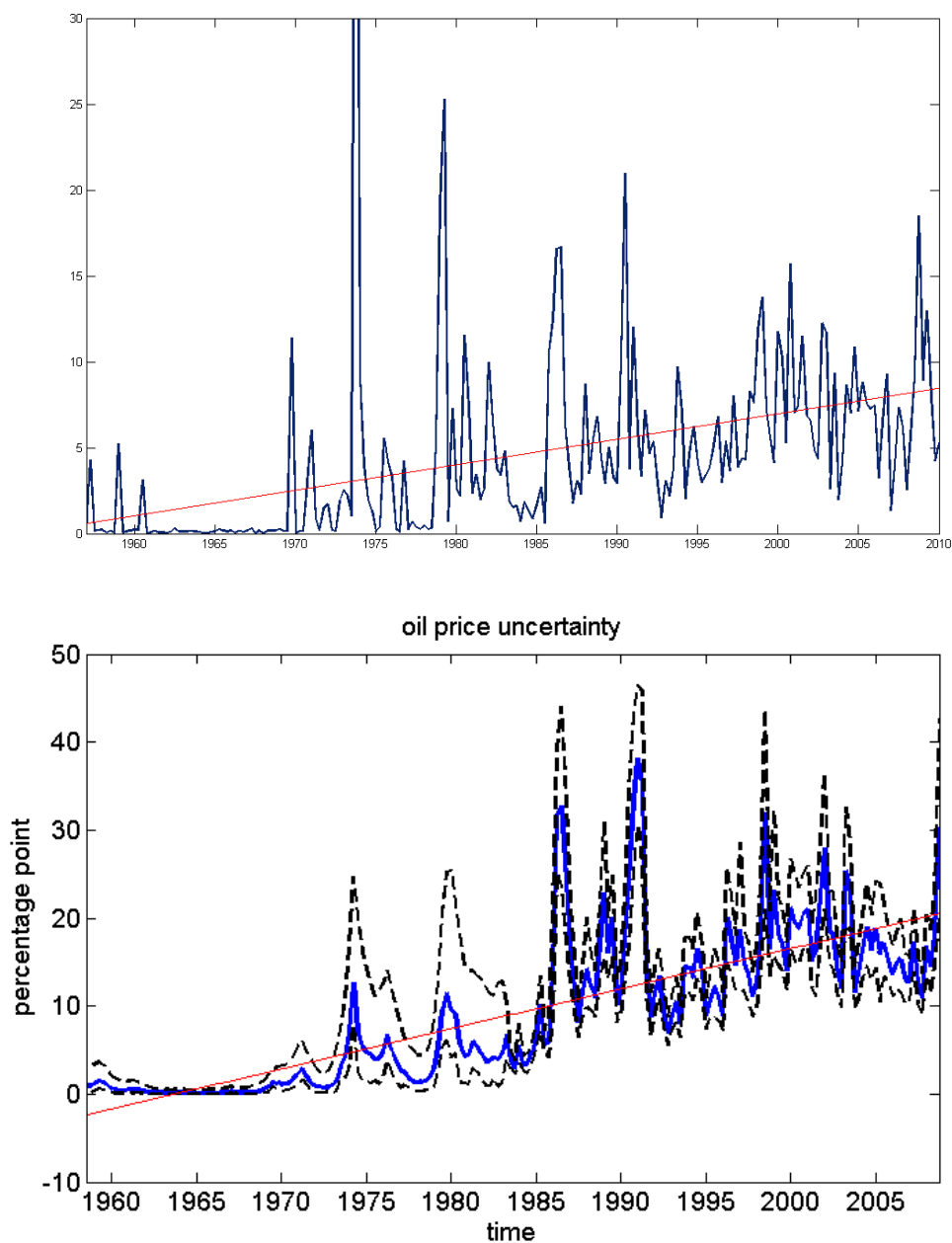


Figure 1.1: Oil price volatility

Upper panel : Quarterly standard deviation of the 3-month crude oil prices from 1957Q1 to 2010Q1.

Lower panel : Mean of the nominal refiner acquisition cost of imported crude oil price uncertainty with 2.5th and 97.5th percentiles of posterior distribution. The dotted red lines represent the series trends over time.

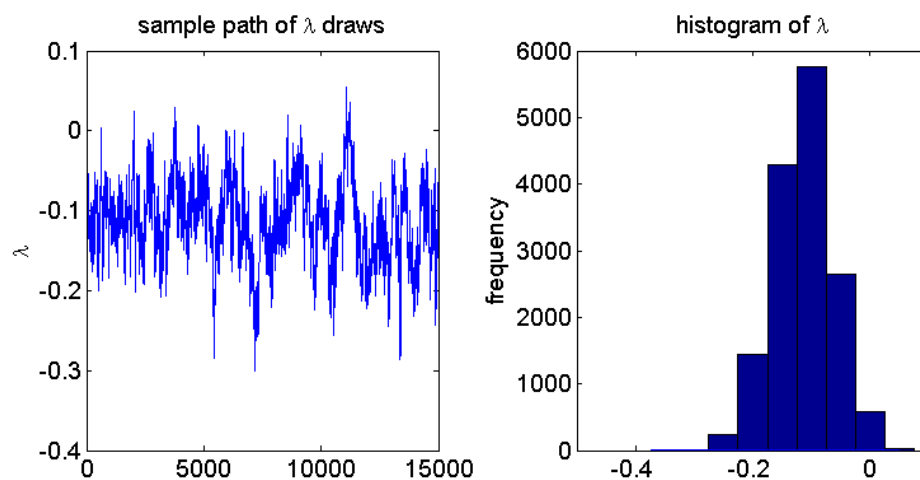


Figure 1.2: Posterior distribution of λ

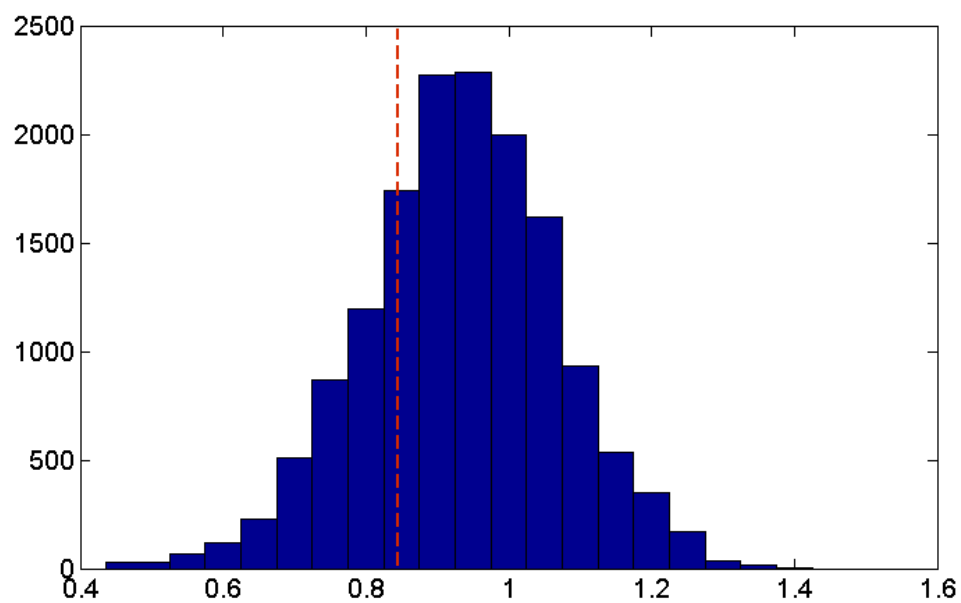


Figure 1.3: 1986Q1 illustration

This panel is a histogram of possible realization of the global industrial production growth rate in 1986Q1 if oil price uncertainty had not increased at that time. The dotted red line represents the predicted industrial production growth rate, 0.8423%.

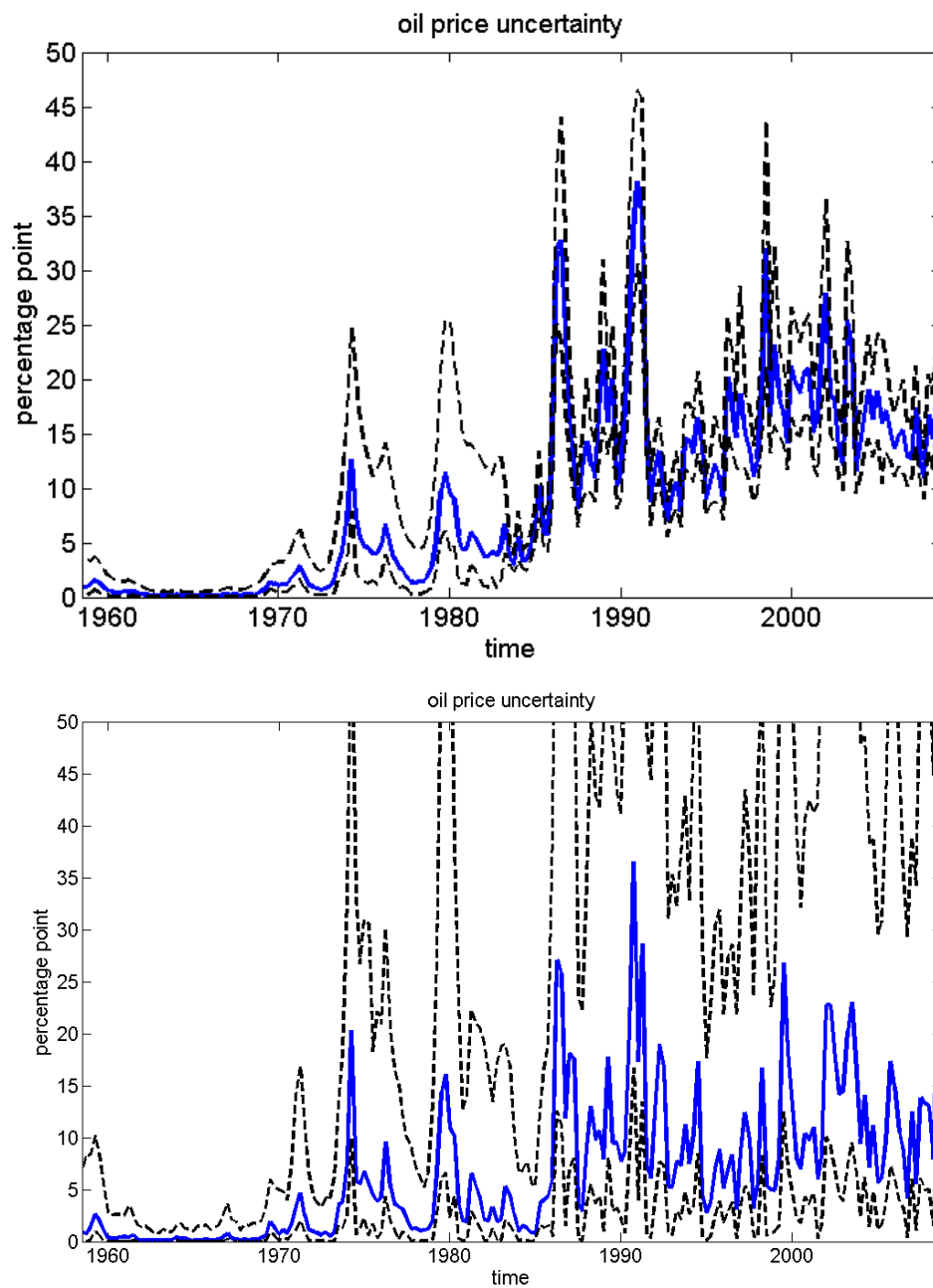


Figure 1.4: Oil price uncertainty with and without realized volatility

The posterior distributions of oil price uncertainty from the statistical model of this paper. The upper panel plots the distribution obtained when the information content of high-frequency data is incorporated to the main VAR. The lower panel illustrates oil price uncertainty from the main VAR without using the additional price volatility indicator.

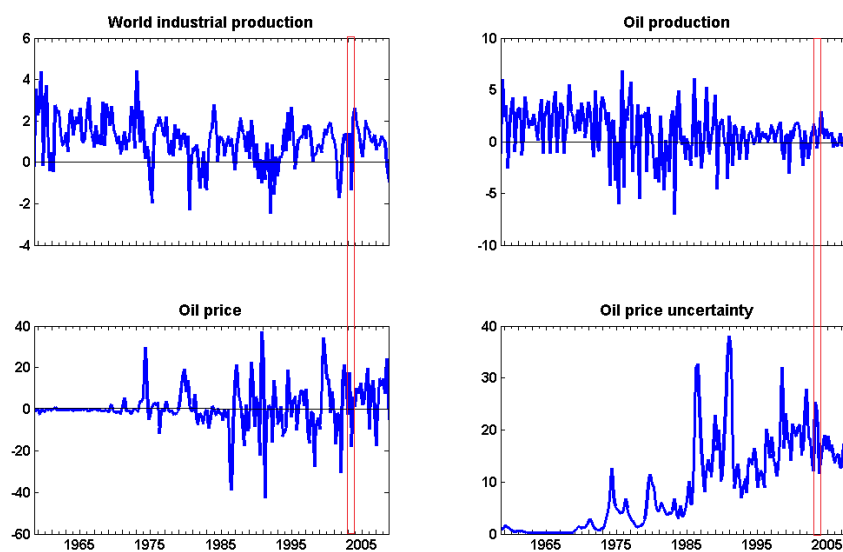


Figure 1.5: Industrial production, oil production, oil price and oil price volatility

This table plots the data series used in the main VAR along with the median oil price uncertainty from the posterior draws recovered from the model. The red vertical box denotes 2003Q1 and 2003Q2.

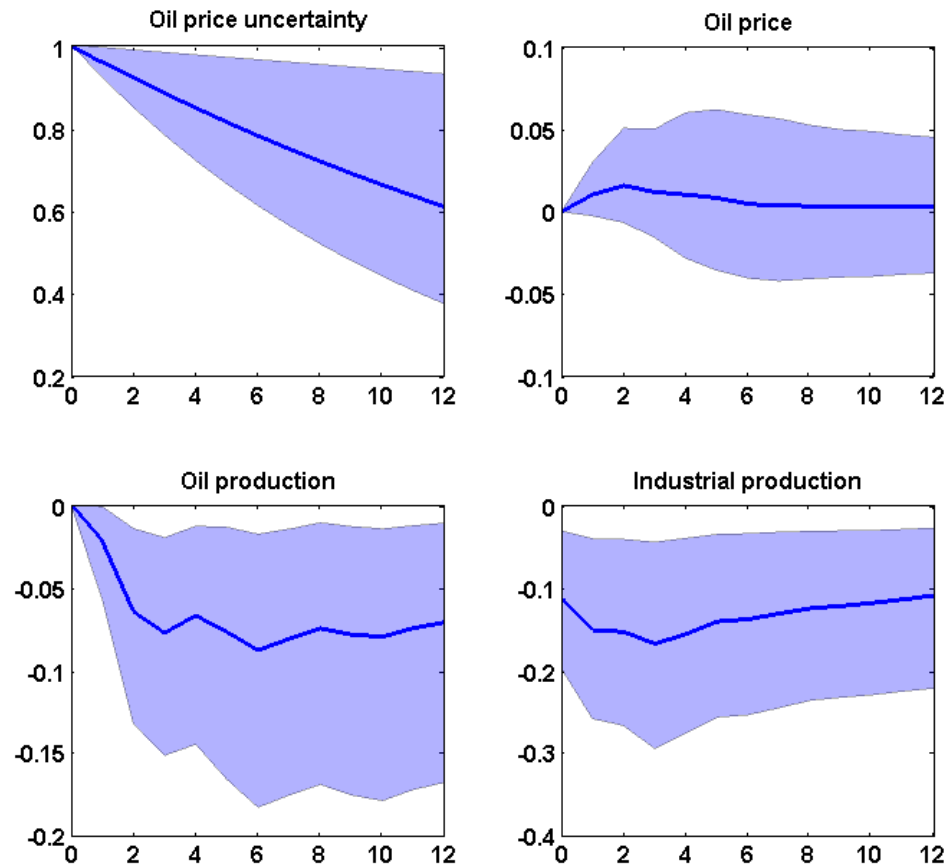


Figure 1.6: Impulse responses to a 100 % uncertainty shock

Impulse responses to the shock that doubles the level of oil price uncertainty. Since we have the logarithm of oil price uncertainty in the mean equation of VAR, this means that the log oil price uncertainty increases by a unit. Thus, the left top panel shows the dynamics of log of oil price uncertainty.

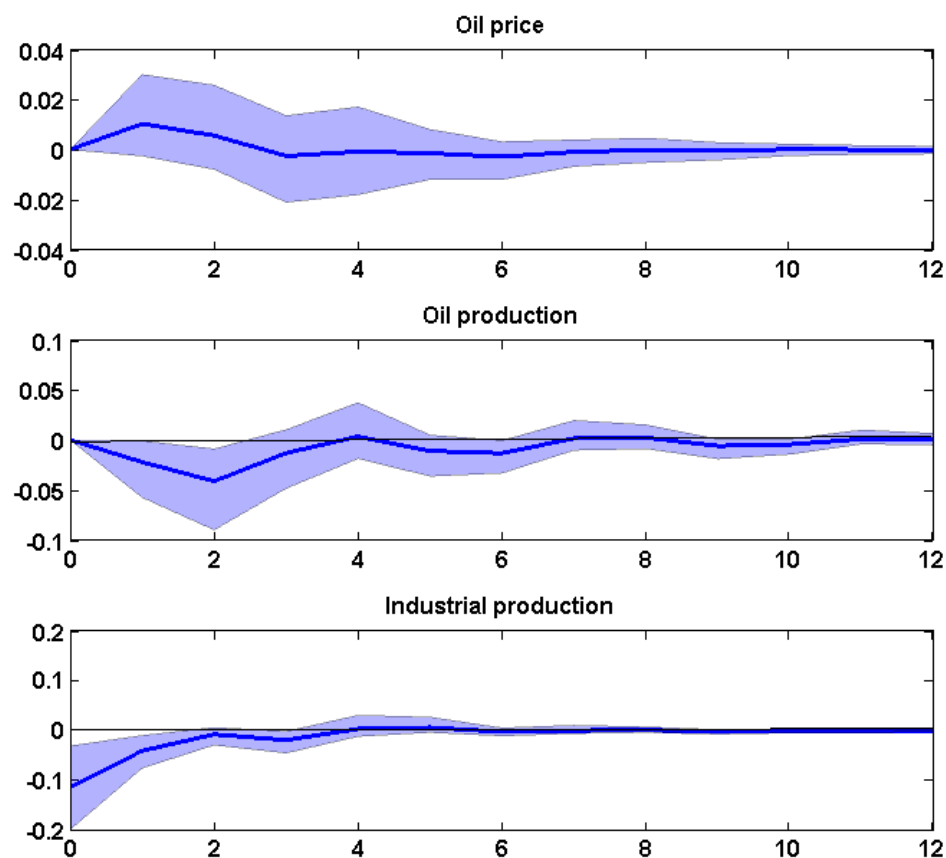


Figure 1.7: Impulse responses to a temporary 100% uncertainty shock

A temporary uncertainty shock implies that the oil price uncertainty doubles at the impact period, but in the next period, it comes down to steady-state level by, for instance, a negative uncertainty shock that reverts the previous increase. That is, oil price uncertainty shock propagates only by the dynamics of endogenous variables.

Chapter 2

Bank lending and loan securitization under uncertainty

Abstract

This chapter studies how US commercial banks adjust lending activities in response to macroeconomic uncertainty with a focus on asset securitization. During 2001Q2-2009Q3, macroeconomic uncertainty has been negatively related to the loan growth rate. In addition, comparing banking institutions with and without asset securitization, I find that loan growth rate of asset-securitizing banks was not particularly protected from the increase in uncertainty, which suggests that securitization did not effectively help transfer aggregate risk from the banking sector to investors. I postulate factors that may have contributed to the ineffective risk transfer of securitization; one important reason is due to the banks' credit exposure through explicit/implicit recourse and/or seller-provided credit enhancements which also fluctuate with the changes in the macroeconomic uncertainty level.

2.1 Introduction

This paper studies how US commercial banks adjust their lending activities in response to macroeconomic uncertainty and whether the loan securitization activity has played a role in the mechanism. If macroeconomic uncertainty surges, banks face an increase in the probabilities of default across all the potential projects they consider funding since the distributions become more dispersed, even when all other things do not change. As a result, it is likely that banks reduce loan supply as there are higher chances of default. However, loan securitization, which has been at the center of many discussions during and after the Great Recession, may have affected the way that commercial banks respond to the macroeconomic uncertainty, as it provides the banking institutions with a tool to sell out the due risk to investors, to remove loans from the balance sheets, and also to free up extra liquidity with which banks can extend to new borrowers. In other words, one might expect loan securitization to function as an extra layer of protection, making loan growth less susceptible to the increase in aggregate uncertainty.

Contrary to this expectation, this paper finds that in practice, securitization did not particularly work in such way; I fail to find a significant difference between banks with and without loan securitization in terms of loan response to macroeconomic uncertainty changes. Macroeconomic uncertainty has a significant negative relationship with the growth of loans across all commercial banks, but the magnitude does not seem to be changed much due to securitization. It should be noted that the analysis of this paper is limited to the case where loans are sold and securitized in a Special Purpose Vehicle (SPV) owned by the reporting bank. Hence, loans that are sold to government-sponsored agencies, i.e., the Federal National Mortgage Association (Fannie Mae) and the Federal Home Loan Mortgage Corporation (Freddie Mac), or sold to and then securitized in other private SPV's are not included.¹

The failure to find differences is potentially due to the exposure of securitiz-

¹This is due to the limitation in data: in the Call Report data from which the securitization variable is extracted, loans that are sold to and securitized by an entity outside of the reporting bank is reported together with assets sold under the asset sales item, and hence it is not possible to parse out how much of the sold asset is securitized in the end.

ing banks to having to buy back the part of the loans securitized (explicit and/or implicit recourse) and from any necessary credit enhancements. I find evidence that securities-originating banks face increased credit exposure due to the various types of credit enhancements in response to increases in uncertainty, thereby retaining more risk themselves rather than removing it. Moreover, I also find some evidence that the quality of newly extended loans of securitizing banks is more likely to be worse. In other words, the indirect effect of securitization in generating more loans may not have been positive in terms of coping with uncertainty. As a consequence, loan-securitizing banks have not effectively transferred the risk from the banks to investors, and hence, securitization did not protect the banks from fluctuations in macroeconomic uncertainty substantially.

This paper is related to the line of recent literature investigating the effects of the uncertainty shocks of various kinds on real economic activities. For example, Bloom (2009)[22], Bloom, Fluetotto, Jaimovich, Saporta-Eksten, and Terry (2011)[23] discuss general effects of uncertainty shocks. Gilchrist, Sims and Zakrajšek (2010) [36] study the amplification of uncertainty shocks through financial frictions. Baker, Bloom, and Davis (2011) [11] explain the effects of policy uncertainty, Elder and Serletis (2010) [32] and Jo (2011) [45] look at oil price uncertainty, and Baum, Caglayan, and Ozkan (2012) [13], and Valencia (2010) [63] explain the effect of the uncertainty shocks on the banking sectors. In particular, Baum et al. (2012) find financial uncertainty has an important and significant role in the monetary policy transmission mechanism, but the actual size and the direction of the effect of financial uncertainty differ across bank categories, balance sheet strength, and the type of loans. This paper differs from Baum et al. (2012) in that it focuses more on macroeconomic uncertainty in conjunction with securitization, and abstracts from the policy transmission mechanism. In addition, the results of this paper are based on pooled sample with no distinction made for different characteristics of banks except whether a bank participates in loan securitization or not.

This paper is also related to a number of previous studies that have looked at the relationship between securitization and bank lending. Many of them find loan

securitization strengthens banks' capacity to generate loan supply using liquidity slacks obtained from securitization.

Some studies focus more on how securitization would affect the transmission mechanism of monetary policy shocks; see for example Altunbas, Gambacorta, Marques-Ibanez (2009)[4], and Aysun and Hepp (2011)[9] who reach different conclusions. Altunbas et al. (2009) analyze European bank data and show that loan securitization has stimulated lending activities and that securitizing banks are affected less by the monetary transmission mechanism. By contrast, Aysun et al. (2011) find that loan securitizing banks become more sensitive to the balance sheet channels of borrowers, and hence become more affected by monetary policy changes.

A number of papers also examine the role securitization has played in enhancing financial stability or distributing credit risk. This is particularly because subprime mortgage loan securitization has been in the center of discussions looking for the cause of the Great Recession. For example, Shin (2009)[62], and Acharya, Schnabl, and Suarez (2010)[2] show that actual transfer of risk to third party investors was little observed among the banks that securitize. In particular, Shin (2009) shows that bad loans are more likely to be on the balance sheet of the asset-securitizing banks or in SPVs, since lowering loan standards may have been unavoidable in order to make use of the slack resulted from securitization. Hence, Shin argues securitization may not have been helpful in enhancing financial stability. The findings of this paper are closely related to this line of literature and provide empirical evidence that the U.S commercial banks that securitize loans are by no means more resilient to changes in aggregate uncertainty in practice.

The remainder of this paper proceeds as follows. Section 2 briefly reviews the background and key related literature. Section 3 describes the econometric model and the data set used in the paper. Results are reported in Section 4, followed by Section 5 which looks for explanations of these results. Section 6 concludes.

2.2 Uncertainty and Securitization

Why would macroeconomic uncertainty matter for lending activity? To answer this question, one can think about a random variable that determines the loan repayment process, such as in a single-factor Vasicek model. This random variable is often modeled as a sum of aggregate and idiosyncratic factors. To the extent that the loan repayment probability is dependent upon the aggregate level economic factor, macroeconomic uncertainty will matter as it affects the distribution, especially dispersion of the aggregate factor. As a consequence, lending activity is likely to be negatively affected by the increase in macroeconomic uncertainty. Moreover, Valencia (2010) shows that banks also have a precautionary savings motive, so that they are hesitant to extend loans under higher uncertainty in order to maintain a specific capital level that can be used as a buffer.

Baum et al. (2012) empirically examine how commercial banks' lending activity responds to monetary policy and financial sector uncertainty using the U.S. bank level data from 1986 to 2000. The key regression in their paper is:

$$\begin{aligned}
\Delta \log Loan_{j,t} = & \sum_{k=1}^4 \beta_{1k} \Delta \log Loan_{j,t-k} + \sum_{k=0}^4 \beta_{2k} \Delta GDP_{t-k} + \sum_{k=0}^4 \beta_{3k} \Delta M_{t-k} \\
& + \sum_{k=0}^4 \beta_{4k} \sigma(M)_{t-k} \Delta GDP_{t-k} + \sum_{k=0}^4 \beta_{5k} \sigma(M)_{t-k} \Delta M_{t-k} \\
& + \sum_{k=0}^4 \beta_{6k} \sigma(M)_{t-k} + B_{j,t-1} (\beta_7 + \beta_8 Y_t + \sum_{k=0}^4 \beta_{9k} \Delta GDP_{t-k}) \\
& + \sum_{k=0}^4 \beta_{10k} \Delta M_{t-k} + \sum_{k=0}^4 \beta_{11k} \sigma(M)_{t-k} + \sum_{k=1}^{12} \beta_{12k} FRB_{j,k} + \beta_{13} Y_t \\
& + \sum_{k=1}^3 \beta_{14k} Q_{k,t} + \Gamma X_{j,t} + \epsilon_{j,t}
\end{aligned}$$

where the dependent variable $\Delta \log Loan_{j,t}$ is loan growth rate, ΔGDP_t is the nominal GDP change, ΔM_t is a change in a monetary policy indicator, $\sigma(M)_t$ denotes financial sector uncertainty, $B_{j,t}$ is a balance sheet strength measure²,

²The measure is defined as the ratio of securities plus federal funds sold total assets.

FRB is a geographic proximity to Federal Reserve banks, Y and Q represent year and quarter dummies, and finally, $X_{j,t}$ denotes a vector of bank-specific variables.

The above equation attempts to measure the direct ($\beta_{6,0}, \dots, \beta_{6,4}$) and the indirect ($\beta_{4,0}, \dots, \beta_{4,4}, \beta_{5,0}, \dots, \beta_{5,4}$, and $\beta_{11,0}, \dots, \beta_{11,4}$) effects of financial uncertainty. The empirical findings of Baum et al. (2012) regarding the effects of uncertainty vary across different groups of bank. However, in general banks with lower liquidity increase lending activities when uncertainty is high, whereas banks with higher liquidity tend to reduce the loan growth, possibly due to the different risk appetite already reflected in the level of liquidity held. They also find that larger banks are more likely to increase lending under higher uncertainty, as they are more likely to have more sophisticated risk management skills.

In my analysis, I will use a similar specification to that in Baum et al. (2012), controlling for GDP and monetary policy. However, I do not include indirect effects arising from interaction terms with uncertainty, as the main purpose of this paper is to examine the role of securitization played in managing uncertainty.

Securitization has been used in the U.S. from the early 70s, and became extremely popular during the last two decades. In order to securitize an asset, originating banks first sell the loans to an organization called Special Purpose Vehicle (SPV) that specializes in issuing securities. Then SPV pools different loans, splits the resulting liquidity flow into different tranches so as to generate assets with different risk characteristics, and finally makes them available to investors. Thus, on the investors' end, it provides assets of various classes that they can invest. With respect to banking institutions, banks are able to obtain a new flow of liquidity coming from the selling of loans and from the processing fees, which can be used to extend new loans that generate more profits. Securitization also helps banks that are bound by capital regulations, as it can remove loans from the balance sheet, and thus, frees up some of the capital required. In addition, securitization itself creates extra profit by regularly collecting fees. It is this perspective that gives securitization a potential chance to mitigate the negative impacts of uncertainty on the loan growth. Banks have a means to extend loans even during the periods of high uncertainty through securitization, and therefore, securitizing banks can

be, in theory, less sensitive to changes in uncertainty.

A number of studies analyze how securitization affects the monetary policy transmission mechanism. The specification of the second model in this paper is similar to that in Aysun et al. (2011), which is:

$$\begin{aligned} \Delta \log Loan_{ijt} = & \beta_0 + \sum_{k=1}^4 \beta_{1k} \Delta \log Loan_{ijt-k} + \sum_{k=0}^8 \beta_{2k} M_{t-k} + \sum_{k=1}^4 \beta_{3k} B_{ijt-k} \\ & + \sum_{m=1}^4 \sum_{k=m}^{m+7} \beta_{4km} B_{ijt-k} M_{t-k} + \sum_{k=1}^4 \beta_{5k} X_{ijt-k} + \epsilon_{ijt} \end{aligned}$$

where most variables are defined as the deviation of the bank i from the average of all other banks affiliated to the same Bank Holding Company j .³ They estimate the above model for two different groups: one that has securitized loans and the other that has not.

Aysun et al. (2011) find that securitizing banks are more sensitive to monetary policy changes even after controlling for both internal capital markets of BHC affiliates and other bank-specific variables. Specifically, a 100-basis-point increase in the long term bond spread would result in 2.38 percent lower loan growth rate of asset securitizing banks in two years, which is much larger than the estimated effect of 0.16 percent decrease for non-securitizing banks. Based on a similar method of comparison, I divide the sample into two groups and compare the size of uncertainty coefficients in the second specification of this paper.

In sum, the model of this paper combines the two lines of literature on the relationship of uncertainty and lending activity and on the effect of securitization. Using Condition and Income Report data (Call Report data) from 2001Q2 to 2009Q3 of the U.S. commercial banks, I investigate whether asset securitization affects the way loan growth responds to macroeconomic uncertainty.

In the next section, I present the details of the data and the models.

³Here, B again denotes the borrower's balance sheet strength, but measured as the difference of income gap of state where bank i is located from the average income gap of all states where the i 's BHC has affiliates.

2.3 Model and Data

2.3.1 Data

Bank Level Data

In this paper, I use Reports of Condition and Income data (FFIEC 031, more commonly known as the Call Report) for commercial banks collected every quarter by the Federal Reserve Board. The sample period is determined to be 2001Q2-2009Q3 due to the availability of securitized loan data, despite the fact that longer time series data are available for other variables. Securitization data for different categories of loans were first collected in 2001Q2. Then, there has been a major change in accounting standard since 2010Q1 due to the implementation of FAS 166,167 accounting rules, which mainly puts the securitized assets back on the balance sheet. However, the actual change in data can be already observed from 2009Q4 particularly in the 1-4 Family Residential loans, and hence, I restrict the sample period to stop in 2009Q3.

To minimize the potential problem coming from the sample selection, I ensure every commercial bank (i.e., RSSD9331=01) in the sample has nonnegative equity capital and positive asset and total outstanding loans. In addition, I use the ones that are insured (RSSD9424 = 1,2 or 6) and located within the fifty states and DC area ($0 < \text{RSSD9210} < 57$), following Haan, Summer, and Yamashiro (2002) [28]. I do not control for the exit and the entering of banks, but exclude mergers, i.e., entities with loan growth rate more than five standard deviation away from the group mean in each quarter. The final sample has 359 securitizing banks, and 7,406 non-securitizing commercial banks.

Securitization

Starting in 2001Q2, all commercial banks report the level of securitized loans of different types; 1-4 Family residential loans, home equity lines, credit card receivables, auto loans, other consumer loans, commercial and industrial loans, and all other loans and all leases. Thus in addition to the on-balance sheet items, banks file outstanding principal balance of assets sold and securitized by the reporting

institution with recourse or other seller-provided credit enhancements (RCFDB705 - RCFDB711). However, one should note that these items exclude the outstanding balance of assets, particularly that in case of 1-4 family residential mortgages, that the reporting institution has sold to the Federal National Mortgage Association (Fannie Mae) or the Federal Home Loan Mortgage Corporation (Freddie Mac) and the government-sponsored agencies securitize, which have taken huge part of securitization activity before the financial crisis. This also excludes the loans sold to private entities outside of the reporting bank, e.g., to investment bank SPVs such as Goldman Sachs. Thus, the main analysis is limited to the loans sold and securitized by the reporting bank.

A binary variable, *ISB*, is created to categorize commercial banks. Specifically, a bank that has engaged in securitization at least once is assigned *ISB*=1. Hence, banks that securitized any type of the loan minimum one quarter during the entire sample period are in group *ISB*=1. On the other hand, a bank is given *ISB*=0 if it has never securitized loans. Table ??Number reports the summary statistics calculated for two groups.

When looking at the data, only a small number of banks securitized their loans. As shown in Figure ??NBS, there are only about 100 commercial banks on average that securitize the loan in each quarter, which amounts to only around 1% of the total number of banks. Nevertheless, in terms of size, securitized banks' asset takes up more than 70%.(Figure ??CBA) This reflects the fact that loan securitization has been more popular among large banks, and it is more so considering that the securitization activity captured in the Call Report data is that conducted by the reporting banks only. It also shows up in Table ??Number as the higher mean of *SIZE*, log of total assets, of loan securitizing banks. Among the different types of loan that are securitized, family residential loan takes the largest part, followed by credit card loans, as shown in Figure ??LS.

Table ??SECsum reports summary statistics of loan securitization ratio to total asset. For example, for those banks in group *ISB*=1, banks securitized about 12 % of total assets. When we narrow down the focus to the banks that were involved in securitization in that quarter by eliminating *ISB*=1 banks with zero

securitization in every quarter, then more than 30% of assets are securitized on average.

Macroeconomic Uncertainty

Following Bassett, Chosak, Driscoll, and Zakrajšek (2011)[12], I construct an index that captures the macroeconomic uncertainty. In particular, this index measures changes in the degree of certainty about the economic outlook. This index is the first principal component of 10 series, which are VIX (a market-based measure of uncertainty in equity return), and the cross-sectional forecast dispersion of Survey of Professional Forecasters in the expectations of the year-ahead values for 9 different variables: level of unemployment, of change in real GDP, industrial production, housing starts, the GDP price index, corporate profits, personal consumption expenditures, nonresidential fixed investment, and residential fixed investment. As the macroeconomic outlook becomes less certain, the repayment probability distributions will become more dispersed, and thus, the dispersion will imply higher probability of default given no change in the threshold.

The Survey of Professional Forecasters is the quarterly survey of macroeconomic forecasts in the United States, currently conducted by the Federal Reserve Bank of Philadelphia. The measure of dispersion is the interquartile range of the forecasts. VIX is also included to reflect the changes in the market's expectation of stock market volatility. Figure ??Basis plots the 10 original underlying series from 2001Q2-2009Q4. All of the series show increased uncertainty during the Great Recession, and most of the series began at a relatively high level reflecting increased level of uncertainty during 2001 recession. However, these two recessions are not the only source that generates dynamics in the 10 underlying series; most of the series exhibit a fair amount of variation throughout the sample periods except the dispersion of housing starts, and interestingly enough, the dispersion of corporate profit reaches to the maximum level not during the recessions but in 2004Q1.

With the 10 series total, I extract the first principal component to account for the greatest possible common variance component in the series. In doing so, figure ??Basis shows that the uncertainty index constructed as the first principal

component would not be driven solely by a few underlying series, as most of the series show reasonable time series variation.

Figure ??UN plots the uncertainty index from 2001Q2 to 2009Q3. From Figure ??UN , the uncertainty index appears to increase during economic recessions, and especially surged during the Great Recession. Thus, when 2007Q4-2009Q3 period is included, the standard deviation jumps up to 2.67, whereas during the “normal” period, it is much lower at 1.20.

2.3.2 Dynamic Panel Model

In the spirit of Kashyap and Stein (1995)[46], the first econometric model is designed to see how banks adjust lending activities in response to changes in macroeconomic uncertainty:

$$\begin{aligned}
\Delta \log Loan_{j,t} = & \sum_{k=1}^4 \beta_{1k} \Delta \log Loan_{j,t-k} + \sum_{k=0}^4 \beta_{2k} \log NGDP_{t-k} + \sum_{k=0}^4 \beta_{3k} FFR_{t-k} \\
& + \sum_{k=1}^4 \beta_{4k} LIQ_{j,t-k} + \sum_{k=1}^4 \beta_{5k} CAP_{j,t-k} + \sum_{k=1}^4 \beta_{6k} SIZE_{j,t-k} \\
& + \sum_{k=0}^4 \beta_{7k} U_{t-k} + \sum_{k=0}^4 \beta_{8k} ISB \times U_{t-k} + \beta_{9k} I_R + \epsilon_{j,t}
\end{aligned} \tag{2.1}$$

with $j = 1, \dots, N$ and $t = 1, \dots, T$, where N is the number of banks and T is 30.

Here, the dependent variable $\Delta \log Loan_{j,t}$ is the growth rate of total loans outstanding at bank j in quarter t . Unlike the general literature on bank lending activities, I define the loan growth rate considering the level of securitization altogether in the spirit of Altunbas et al. (2009). That is, for the banks that securitize loans, I define the total loan to be the sum of on-balance sheet total loan (RCFD2122) and the level of securitization (RCFDB705+...+RCFDB711), and use the change in the logs of the sum as loan growth. This is to measure the loan growth more accurately including the newly extended loans that may be uncovered if on-balance sheet loans are considered only. When a bank securitizes x dollars of loans, then they will disappear from the balance sheet. And if the bank lends out the exact same amount x to the new borrowers, then it will appear as if the bank has made no change in loans. Therefore, to measure the lending activity that can

be hidden by securitization, I define the total loan as the sum of the on-balance sheet loan and securitization, and later check whether the result is sensitive by using conventionally defined loan growth rate as the dependent variable.

Among the explanatory variables, three are aggregate variables, $NGDP$, FFR , and U , and their lags. First, the log of nominal GDP ($NGDP$) is included to control for the changes in the demand side of financial market. Second, effective Fed Funds Rate (FFR) controls for the variations in loan growth due to changes in monetary policy stance. In addition, inclusion of $NGDP$ and FFR reflects the intention to control for the first moment (level) changes in aggregate variables, as the main focus of this paper is on the macroeconomic uncertainty, U , that is the dispersion of forecast, or the second moment.

In addition to the aggregate variables, the model includes bank-specific variables, such as the lags of liquidity (LIQ : the ratio of sum of cash and easily liquidatable assets to total assets), size($SIZE$: log of total assets), and capital to asset ratio(CAP : the ratio total equity capital to total assets), and finally, four lags of quarterly loan growth rate.⁴ Finally, I_R is an indicator variable taking the value one during the Great Recession referencing NBER recession dates, i.e., 2007Q3–2009Q2.

To see the effect of macroeconomic uncertainty and how securitization plays a role in the uncertainty propagation mechanism, I include the variables which are the interactions between the securitization activity indicator (ISB) and the dynamics of uncertainty. Hence, $\beta_{7,0}, \dots, \beta_{7,4}$ will capture the size of the relationship of loan growth with uncertainty common to both groups, and $\beta_{8,0}, \dots, \beta_{8,4}$ can quantify how much the lending activity of the asset-securitizing banks is differently related to uncertainty than that of the non-securitizing bank.

Next, as a second test, I estimate the following model for each group, ISB=1

⁴See Appendix for more detailed description of the bank-specific variables.

and $ISB=0$,

$$\begin{aligned}
\Delta \log Loan_{j,t} = & \sum_{k=1}^4 \beta_{1k} \Delta \log Loan_{j,t-k} + \sum_{k=0}^4 \beta_{2k} \log NGDP_{t-k} + \sum_{k=0}^4 \beta_{3k} FFR_{t-k} \\
& + \sum_{k=1}^4 \beta_{4k} LIQ_{j,t-k} + \sum_{k=1}^4 \beta_{5k} CAP_{j,t-k} + \sum_{k=1}^4 \beta_{6k} SIZE_{j,t-k} \\
& + \sum_{k=0}^4 \beta_{7k} U_{t-k} + \beta_{9k} I_R + \epsilon_{j,t}. \tag{2.2}
\end{aligned}$$

Then, I look for the difference in the mechanism by comparing coefficient estimates of the two groups. Therefore, the main purpose of the second model is to look at the coefficient estimates of the contemporaneous level of uncertainty, and its four lags, i.e., $\beta_{7,0}, \dots, \beta_{7,4}$. This model is less restrictive than the first model, since it allows the variation in the coefficients of other variables in addition to those of uncertainty. Hence, equation (2.2) is to see whether the estimation result of (2.1) is mainly driven by having all other coefficients but those of uncertainty pooled across two groups.

Since the above models have lags of dependent variable on the right hand side, they will give rise to autocorrelation, and the usual fixed effect panel regression is likely to yield biased estimates. Thus, I estimate the model with Arellano and Bond (1991)[8] difference GMM estimation method. This method uses the lags of dependent variables as instrument variables, and thus, provides consistent estimates, simultaneously taking care of unobserved time-invariant bank-specific fixed effects by taking first differences.

2.4 Results

Table ??modell1 shows the estimation result for equation (2.1). First, the sum of uncertainty coefficients ($\sum_{k=0}^4 \beta_{7,k}$) is negative: the point estimate is around -0.004 and significant at the 1% level. In addition, most of the individual coefficients are estimated to be significantly negative, except the one for the first lag ($\beta_{7,1}$), which is positive. Thus, macroeconomic uncertainty is negatively related to bank lending activities especially during the same quarter. Although the loan

growth bounces back to some extent in the next quarter, it again decreases later. This result suggests that when macroeconomic uncertainty increases, a bank perceives higher chance of default for loans in general, and thus, decreases lending. This is in line with the previous literature that points out the negative effect of uncertainty. In particular, the result indicates that when uncertainty increases by one standard deviation (2.67), the loan growth rate (which includes the change in the level of securitization for securitizing banks) is first reduced by around 0.8 percentage point in that quarter, and this is common for both groups. Considering the fact that the sample means of loan growth are 2.3% and 2.6 % quarterly for ISB=0 and ISB=1 banks, respectively, this is quite a huge change.

More importantly, examining the β_8 estimates, the lending activity of asset-securitizing banks does not seem to be particularly protected from the effect of uncertainty. Rather, securitizing banks appear to be exposed more to the macroeconomic uncertainty; for example, in response to a one-standard deviation increase in uncertainty, banks in ISB=1 group decrease the lending activity by 1.3% during the contemporaneous quarter, 0.5% point more than non-securitizing banks, as $\beta_{8,0}$ is significantly negative. The result shows that the second and fourth lags of uncertainty also affect securitizing banks significantly differently, although the directions may differ. All in all, one can conclude asset securitization did not help protecting the lending activity of commercial banks to macroeconomic uncertainty, and sometimes it instead seems to have made the banks more vulnerable.

Next, Table ??bresult shows the estimation result for equation (2.2) when allowing all coefficients to be varying across two groups. The first column of Table ??bresult shows the result of securitizing banks (ISB=1), and the second column is that of non-securitizing bank (ISB=0). Again, uncertainty is negatively related to the lending activity overall for both groups except a temporary bounce-back shown in the first lag coefficient ($\beta_{7,1}$), and the point estimate of the sum of the uncertainty coefficients (i.e., $\sum_{k=0}^4 \beta_{7k}$) are almost similar at $-0.003 \sim -0.004$, despite the sum for ISB=1 being statistically insignificant. From the second lag, the uncertainty coefficients become insignificant for asset-securitizing banks; however, the relationship is much stronger for the contemporaneous uncertainty for them,

resulting in the totaling effect to be similar. Again, securitization does not seem to be protecting banks from uncertainty, which contradicts our prior expectation that uncertainty would affect loan-securitizing banks less, as the banks in theory, sell out risks to investors and gain the ability to generate new loans.

In addition to the relationship with uncertainty, it is possible to assess the relationships of loan growth and other variables through the result in Table ??bresult. Consistent with the previous literature, nominal GDP (NGDP) is positively related to loan growth for both groups, reflecting that when the economy is in a good state and GDP growth is higher, the demand of loan increases since more projects are expected to be profitable with higher net present values, as noted by Kashyap, Stein and Wilcox (1993)[47]. The magnitude of the effect is larger for the securitizing banks, as it can generate more loans through securitization when economic conditions are better. The effects of monetary policy (FFR) appear to be negative for both groups as expected; it should be noted that the size of monetary policy effects is larger for the banks that securitize loans. This is consistent with the empirical findings of Aysun et al. (2011) using the same data set as this paper that monetary policy has a greater impact on lending activities of securitizing banks since they are more sensitive to borrowers' balance sheet channel. They do not particularly consider the effect of economic condition (e.g., nominal GDP), but higher sensitivity of ISB=1 banks to borrowers' balance sheet can also explain larger coefficients of GDP.

With respect to the bank specific variables, liquidity (LIQ) and capital-to-asset ratio (CAP) of ISB=0 group are positively related to lending. This means that banks with higher capital holding and more liquid portfolio can generate more loans. As for asset-securitizing banks, liquidity still matters in a positive way, whereas the coefficients of capital-to-asset ratio lose their overall significance. On the other hand, the coefficients on SIZE have significant negative values in both groups, implying that larger banks tend to expand the loan supply less. This result is consistent to the result of Altunbas et al. (2009) and Ehrmann, Gambarcorta, Martinez-Pagez, Sevestre and Worms (2001)[31], and implies that the size is not a particularly useful indicator of informational asymmetries.

Table ??result reports the second model estimation result (i.e., equation (2.2)) for ISB=1 when the conventional definition of loan growth rate that excludes the changes in securitization is used, along with the baseline result of asset securitizing banks to check the robustness.⁵ The uncertainty coefficients has very similar point estimate as the previous case, which further supports that the similarity between the two groups is robust. Hence, this again implies that asset-securitizing banks are not different in terms of protecting loan growth from macroeconomic uncertainty, and moreover, securitization has not effectively dispersed the risk from the banking sector.

In sum, macroeconomic uncertainty is negatively correlated with the lending activities of commercial banks. Furthermore, loan securitization does not seem to decrease the magnitude of the negative effects, indicating that securitization did not play the role of risk transfer from the banking institutions to investors.

2.5 Ineffective Transfer of Risk through Securitization

The above results imply that securitization has not helped insulate lending activity from uncertainty. In this section, I look for the potential factors that might account for this result: (1) the seller provided credit enhancements that accompanied asset securitization, (2) lower quality of newly generated loans, and lastly (3) macroeconomic uncertainty as a common risk factor.

2.5.1 Recourse and Credit Enhancement of Securitized Assets

When securitizing assets, it has been very common for a bank to provide some sort of credit enhancement. Credit enhancement can be implemented in a variety of forms; the originating bank may purchase subordinate securities so

⁵Note that the results for the ISB=0 group by definition are unaffected by this choice, and thus not reported.

that it absorbs the loss first in case of underlying assets' default; the bank can hold interest spread with which it can make up for some defaults, and thus retain constant cash flow for investors; haircut or cash collateral is another widely-used option.

More importantly, it may have been a factor that retains the amount of risk corresponding to the size of enhancement to the originator of securities. For example, Kothari (2006)[53] notes on page 16 of his book that:

It is quite common for the originator to retain or re-acquire the first loss risk, that is, to the extent the total loss in the portfolio does not exceed the first loss limit, and the hit will be taken by the originator. This is done by one of the several methods of **credit enhancements** provided by the originator.

In the reporting form for the Call Report, asset securitizing banks are asked to report the credit exposure arising from the particular forms of credit enhancements in addition to the level of securitization: credit-enhancing interest-only strips, subordinated securities and other residual interests, standby letters of credit and other enhancements. Using this data, I construct a variable, CE , which is the ratio of total credit exposure to the total level of securitization.⁶ Then I estimate a forecasting regression that predicts the credit exposure ratio. The regression model follows,

$$\begin{aligned} \Delta CE_{j,t} = & \sum_{k=1}^4 \beta_{0k} \Delta CE_{j,t-k} + \sum_{k=1}^4 \beta_{1k} \log NGDP_{t-k} + \sum_{k=1}^4 \beta_{2k} FFR_{t-k} + \sum_{k=1}^4 \beta_{3k} U_{t-k} \\ & + \sum_{k=1}^4 \beta_{5k} LIQ_{j,t-k} + \sum_{k=1}^4 \beta_{6k} CAP_{j,t-k} + \sum_{k=1}^4 \beta_{7k} SIZE_{j,t-k} \\ & + \sum_{k=1}^4 \beta_{8k} sec_{j,t-k} + \beta_9 I_R + \epsilon_{j,t}. \end{aligned} \quad (2.3)$$

where sec is the outstanding securitization level.

The first column of Table ??CE reports the estimates of uncertainty coefficients. The second and the fourth lags are significant at the 1% and 5% levels,

⁶That is, $CE = (RCFDB712 + RCFDB713 + \dots + RCFDB724 + RCFDB725) / (RCFDB705 + RCFDB706 + \dots + RCFDB710 + RCFDB711)$.

respectively, and the point estimate of the sum($\sum_{k=1}^4 \beta_{3k}$) is also significantly positive. Therefore, it strongly supports the idea that asset-securitizing banks will increase the credit exposure ratio as uncertainty increases. In line with the uncertainty coefficients, I also find that the recession indicator, which becomes 1 during the time when the uncertainty index jumped, is highly statistically significant and the size is also economically very significant. To illustrate, if uncertainty has increased by one standard deviation during the Great Recession, it will result in 8.01-dollar increase in the credit exposure for every 100-dollar loan a bank securitizes in next two quarters. If the one-standard deviation uncertainty increase has happened during the normal times, than cumulatively it is related to 2.14-dollar increase in credit enhancement for every 100 dollars. Hence, as noted above, the credit enhancement provided by banks implies that banks are still connected to the off-balance sheet assets, and moreover, higher CE during the more uncertain times will leave the banks more exposed to higher risks.

The last remark to make is that this result may be due to the higher chance of securitization activity reported on the Call Report to be of a worse quality. That is, the securitized assets captured in the Call Report are the ones that are securitized by the reporting bank, which are not qualified to be sold and further securitized by government-sponsored agencies or investment banks, or to be sold separately. To make up for the lower quality, banks have to provide more credit enhancements during uncertain times. This argument is consistent since uncertainty is no longer significantly related to credit enhancement change, when equation (2.3) is estimated for asset sales with credit enhancement, or the sum of asset securitization and sales, although the results are not reported here. Hence, it is not just the business-cycle factor that brings about the significance of uncertainty coefficients for credit enhancement of securitization. Rather, what is found here is the feature which makes the reported securitization distinct from other asset sales activity.

In sum, securitization in practice does not completely remove risk from the originating banks. Moreover, the size of risk retained in the bank is positively related to macroeconomic uncertainty, resulting in the banks' larger exposure to

the risk during the periods with high level of uncertainty. As a consequence, asset-securitizing banks are not significantly protected from uncertainty than non-securitizing banks.

2.5.2 Quality of New Loans

If asset-securitizing banks attempt to extend loans with the extra flow of liquidity obtained from securitization, they might have to reach to the borrowers whose credit ratings are lower. However, it is not easy to empirically test the difference in the quality of loans using the balance sheet data, since the data only contain information about the outstanding level of loans, and thus, it is difficult to infer anything regarding the quality of the individual loan. Nevertheless, the Call Report data includes provision for loan and lease losses, which is a widely used ex-post accounting measure of credit risk. Although this analysis would be limited to on-balance sheet loans and leases, we can gauge whether the asset-securitizing banks adjust allowance for loan and lease losses more than non-securitizing banks in times of high uncertainty, as this will imply such banks extend loans to borrowers whose repayment decisions are later assessed to be more correlated with aggregate risk, and thus, of lower quality.

I construct two new variables; first, $PVS1$, as the ratio of loan and lease loss provision to total loans and leases (i.e., $(RIAD4230/RCFD2122) \times 100$), and next, $PVS2$, as the ratio of loan and lease loss provision to total assets (i.e., $(RIAD4230/RCFD2170) \times 100$).⁷ Table ??sumPVS reports the means and the standard deviations of these variables for different groups. The sample means are very distinct, and the t-tests reject the hypothesis that the sample means of $PVS1$ and $PVS2$ are the same across two groups at 1% significance level. Moreover, both means are much larger in size for asset-securitizing banks, indicating that on average, banks in ISB=1 group tend to set larger amount aside for bad loans relative to the on-balance sheet loans and relative to their size, and thus are

⁷Note that RIAD variable are reported on a calendar year-to-date basis, and thus one has to convert the value to capture quarterly levels. In this paper, such conversion is necessary for RIAD4230, provision for loan lease losses, and RIAD4301, income before taxes and other adjustment.

likely to hold riskier loans compared to banks that do not securitize.

To see whether this is the case in detail, I run the following forecasting regression and whether there exist differences in the relationship between $PVS1$ and uncertainty across asset-securitizing and non-securitizing commercial banks:

$$\begin{aligned}
PVS1_{j,t} = & \sum_{k=1}^4 \beta_{0k} PVS1_{j,t-k} + \sum_{k=1}^4 \beta_{1k} \log NGDP_{t-k} + \sum_{k=1}^4 \beta_{2k} FFR_{t-k} \\
& + \sum_{k=1}^4 \beta_{3k} U_{t-k} + \sum_{k=1}^4 \beta_{4k} ISB \times U_{t-k} \\
& + \sum_{k=1}^4 \beta_{5k} LTA_{j,t-k} + \sum_{k=1}^4 \beta_{6k} INC_{j,t-k} + \sum_{k=1}^4 \beta_{7k} CAP_{j,t-k} \\
& + \sum_{k=1}^4 \beta_{8k} SIZE_{j,t-k} + \beta_9 I_R + \epsilon_{j,t}.
\end{aligned} \tag{2.4}$$

where LTA is the ratio of total loans to assets (i.e., RCFD2122/RCFD2170), and INC is the ratio of income to assets (i.e., RIAD4301/RCFD2170) included to capture income-smoothing purpose of banks. If the loans extended by asset securitizing banks are riskier in the sense that they are more closely correlated with macroeconomic uncertainty, this can show up as $\beta_{41}, \dots, \beta_{44}$ being positive, and moreover, larger for $ISB=1$ group than for $ISB=0$.

Table ??PVS provides the estimation results. First, the coefficients of uncertainty, i.e., β_{3k} 's, are all significantly positive at 1% level, implying banks in both groups commonly increase loan and lease loss provision when uncertainty is high. Now, as for the interaction coefficients, β_{42} is significantly positive, and the size of the point estimate is almost the same as that of β_{32} . This means asset-securitizing banks are expected to increase the loan loss provision twice as much as non-securitizing banks. However, the fourth lag of uncertainty would revert this tendency back to the pooled mean level with β_{44} being significantly negative. Hence, the higher sensitivity of asset-securitizing banks' to uncertainty appears to be only short-living and is not very clear. Therefore, it is difficult to conclude the estimation result strongly supports the idea of asset-securitizing banks' reaching out to lower-quality borrowers, despite the fact that sample means of $PVS1$ and $PVS2$ are significantly higher for that group.

Related to this analysis, Shin (2009)[62] claims that bad loans are more likely to be on the balance sheet of the asset securitizing banks or in SPVs, since lowering loan standards may have been unavoidable in order to make use of the funds freed by securitization. He also points out that the bad loans were not passed to investors as evidenced by 2007 - 2008 financial crisis. From this perspective, it may have been the case that riskier loans are quickly moved to SPVs and securitized in less than a year, so that the estimation result of equation (2.4) shows increase in PVS and then decrease later. In sum, I find some evidence that asset-securitizing banks use the new liquidity flow to finance riskier loans thereby still exposing themselves to aggregate uncertainty, but the evidence is not very strong.

2.5.3 Uncertainty as a Common Risk Factor

Finally, if all loans are equally exposed to aggregate level common risk, it is not easy for banking institutions to diversify macroeconomic uncertainty. Then loan securitization cannot help banks hedge against common risk factors in principle. This argument may be true to the extent that macroeconomic uncertainty is the common factor for every loan. Nevertheless, unless one believes the correlation coefficients of all loans' idiosyncratic factors with the aggregate factor are exactly identical, it is reasonable to think that this type of uncertainty accompanying the loans can also be dispersed through balance sheet adjustment, loan sales, and securitization. Moreover, in the previous section, we found evidence though weak that securitizing banks are lending to the borrowers whose individual risk factors are likely to co-move more closely with the common factor, which also shows loans are of different quality. Thus, this claim may be valid only in a limited sense.

2.6 Conclusion

This paper investigates how macroeconomic uncertainty affects the lending activity of U.S. commercial banks. The estimation result shows that uncertainty is negatively related to loan growth rates, and more specifically, a one standard-deviation increase of uncertainty can drag down loan growth up to around 0.8

percentage-point in the same quarter.

Moreover, it focuses on the role of asset securitization in protecting banks from uncertainty increases and in transferring risks to investors. Comparing commercial banks with and without asset securitization, I find banks are still exposed to macroeconomic uncertainty even after securitization. That is, loan growth of asset-securitizing banks is not particularly protected from the increase in uncertainty, which implies that securitization did not effectively help transfer aggregate risk from the banking sector to investors.

Searching for the factors that have resulted in such ineffective risk transfer of securitization, I find that the credit exposure of a securitizing bank may have played a significant role. Asset-securitizing banks usually securitize loans with seller provided credit enhancements and recourse, and more importantly, the size of credit enhancements is expected to increase during the times of high uncertainty. This is likely to have made the risk transference role of securitization impotent, and left loan-securitizing banks still vulnerable to macroeconomic uncertainty. Second, the analysis on provision in loan and lease losses provides some evidence that securitizing banks may have financed lower quality loans and hence, still exposed themselves to changes in uncertainty. Finally, since macroeconomic uncertainty is a common risk factor to all assets, one may argue it cannot be dispersed even with asset securitization, although this can be valid only in a limited sense.

2.7 Appendix

Call Report Data

Table ??TABLECR shows the items of the Call Report Data used for the main analysis of this paper and their brief descriptions. More detailed descriptions on the variables can be found in the Federal Reserve Board’s Micro Data Reference Manual.⁸

Table 2.1: The Call Report Items

	Item	Description
Loan	RCFD2122	Total loans and leases (net of unearned income)
Liquidity	RCFD0010	Cash and balances due from depository institutions
	RCFD1754	Total securities held to maturity
	RCFD3545	Trading assets
	RCFD1773	Total available-for-sale securities
Capital	RCFD3210	Total equity capital
Size	RCFD2170	Total assets (sum of all asset items; equal total liabilities, limited-life preferred stock, equity capital)
Securitization	RCFDB705	1-4 Family residential loans
	RCFDB706	Home equity lines
	RCFDB707	Credit card receivables
	RCFDB708	Auto loans
	RCFDB709	Other consumer loans
	RCFDB710	Commercial and industrial loans
	RCFDB711	All other loans

⁸<http://www.federalreserve.gov/reportforms/mdrm/DataDictionary/search.cfm>

Table 2.1 continued

	Item	Description
Recourse & Credit Enhancement	RCFDB712 - -RCFDB717 RCFDB718 - - RCFDB724	Credit-enhancing interest-only strips Subordinated securities and other residual interest + Standby letters of credit and other enhancement
Loan loss allowance	RCFD3123 RIAD4230	Allowance for loan and lease losses Provision for loan lease losses
ID Date State Primary Insurer	RSSD9001 RSSD9999 RSSD9210 RSSD9424	Primary identifier Report date Two-digit code assigned to a state of the US or a US territory The highest level of deposit-related insur- ance of the entity

Next, Table ??TABLEVAR summarizes how the variables used in the paper are defined from the items in the Call Report.

Table 2.2: Variable Definitions

Variable	Definition
$\Delta Loan_t$	$\log(RCFD2122_t + sec_t) - \log(RCFD2122_{t-1} + sec_{t-1})$
<i>LIQ</i>	$(RCFD0010 + RCFD1773 + RCFD1754 + RCFD3545) / RCFD2170$
<i>CAP</i>	$RCFD3210 / RCFD2170$
<i>SIZE</i>	$\log(RCFD2170)$
<i>sn</i>	$(RCFDB705 + RCFDB706 + \dots + RCFDB710 + RCFDB711)$
<i>SEC</i>	$sn / RCFD2170$
<i>sec</i>	$sn \times 10^{-7}$
<i>CE</i>	$(RCFDB712 + RCFDB713 + \dots + RCFDB724 + RCFDB725) / sn$
<i>PVS1</i>	$(RIAD4230 \times 100) / RCFD2122$
<i>PVS2</i>	$(RIAD4230 \times 100) / RCFD2170$
<i>INC</i>	$RIAD4301 / RCFD2170$
<i>LTA</i>	$RCFD2122 / RCFD2170$

Subscripts j and t are abstracted in the table unless necessary. RIAD4230 and RIAD4301 are adjusted to denote quarterly level, which are originally reported as calendar year-to-date values.

Table 2.3: Summary Statistics

	Mean	Std. Dev.	Min	Max
ISB=1				
Loan growth	0.023	0.081	-1.235	1.166
<i>LIQ</i>	0.175	0.117	0.001	0.718
<i>CAP</i>	0.102	0.045	0.010	0.729
<i>SIZE</i>	13.350	2.306	8.397	21.293
ISB=0				
Loan growth	0.021	0.070	-0.825	1.114
<i>LIQ</i>	0.240	0.143	0	1.391
<i>CAP</i>	0.108	0.026	0.000	1
<i>SIZE</i>	11.663	1.185	7.082	18.889

This table reports the pooled summary statistics for the bank-specific variables in ISB=1 and ISB=0 groups from 2001Q2 to 2009Q3.

Table 2.4: Summary Statistics of Securitization (SEC_t)

	No. of banks	No. of observations	Mean	Std. Dev.
ISB=1	425	11,359	0.089	0.372
SB=1	425	3,628	0.248	0.624

This tables reports the pooled summary statistics of securitized loan ratio of different groups. SEC is defined as the ratio of total securitization to total asset, i.e., $(RCFDB705 + \dots + RCFDB711)/RCFD2170$. “The number of banks” denotes the number of the group in each quarter. “ISB=1” indicates the group of banks that securitized loans at least once during the whole sample period, whereas “SB=1” only includes the observations of banks with positive securitization in a quarter. That is, among the banks included in “ISB=1” group, we obtain “SB=1” group by excluding the observations with zero securitization.

Table 2.5: Baseline Estimation Results I

$\beta_{7,0}$	-0.003*** (0.0002)	$\beta_{8,0}$	-0.002** (0.001)
$\beta_{7,1}$	0.002*** (0.0001)	$\beta_{8,1}$	-0.008 (0.001)
$\beta_{7,2}$	-0.0003 (0.0002)	$\beta_{8,2}$	-0.002** (0.001)
$\beta_{7,3}$	-0.001*** (0.0002)	$\beta_{8,3}$	0.0002 (0.001)
$\beta_{7,4}$	-0.002*** (0.0002)	$\beta_{8,4}$	0.002*** (0.001)
$U(\sum_{k=0}^4 \beta_{7k})$	-0.004*** (0.001)	$ISB \times U(\sum_{k=0}^4 \beta_{8k})$	-0.004*** (0.001)
$Loan(\sum_{k=1}^4 \beta_{1k})$	-0.431*** (0.030)	$NGDP(\sum_{k=0}^4 \beta_{2k})$	0.619*** (0.020)
$FFR(\sum_{k=0}^4 \beta_{3k})$	-0.007*** (0.001)	$LIQ(\sum_{k=1}^4 \beta_{4k})$	0.821*** (0.017)
$CAP(\sum_{k=1}^4 \beta_{5k})$	0.488*** (0.089)	$SIZE(\sum_{k=1}^4 \beta_{6k})$	-0.393*** (0.012)
$I_R(\beta_{9k})$	-0.004*** (0.001)		
	No. of banks	7,765	
	No. of observations	187,703	

This table reports the regression result of equation (2.1). The number in parentheses are robust standard errors. The symbols ** and *** represent significance levels of 5%, and 1%, respectively.

Table 2.6: Baseline Estimation Results II

	ISB=1	ISB=0
$\beta_{7,0}$	-0.005*** (0.001)	-0.003*** (0.0002)
$\beta_{7,1}$	0.002** (0.001)	0.002*** (0.0002)
$\beta_{7,2}$	-0.001 (0.001)	-0.0003 (0.0002)
$\beta_{7,3}$	0.001 (0.002)	-0.001*** (0.0003)
$\beta_{7,4}$	-0.0001 (0.001)	-0.002*** (0.0002)
$U(\sum_{k=0}^4 \beta_{7k})$	-0.003 (0.004)	-0.004*** (0.001)
Loan($\sum_{k=1}^4 \beta_{1k}$)	-0.207** (0.087)	-0.441*** (0.030)
NGDP($\sum_{k=0}^4 \beta_{2k}$)	0.909*** (0.108)	0.598*** (0.021)
FFR($\sum_{k=0}^4 \beta_{3k}$)	-0.011*** (0.002)	-0.007*** (0.001)
LIQ($\sum_{k=1}^4 \beta_{4k}$)	0.612*** (0.086)	0.827*** (0.017)
CAP($\sum_{k=1}^4 \beta_{5k}$)	0.079 (0.265)	0.536*** (0.090)
SIZE($\sum_{k=1}^4 \beta_{6k}$)	-0.436*** (0.051)	-0.384*** (0.012)
$I_R(\beta_{8k})$	0.0002 (0.005)	-0.004*** (0.001)
No. of banks	359	7,406
No. of observations	8,848	178,855

This table reports the regression results of equation (2.2). The number in parentheses are robust standard errors. The symbols ** and *** represent significance levels of 5%, and 1%, respectively.

Table 2.7: Results - Robustness Check

ISB=1	Baseline	Conventional Loan Growth
$\beta_{7,0}$	-0.005*** (0.001)	-0.004*** (0.001)
$\beta_{7,1}$	0.002** (0.001)	0.002** (0.001)
$\beta_{7,2}$	-0.001 (0.001)	-0.001 (0.001)
$\beta_{7,3}$	0.001 (0.002)	0.001 (0.001)
$\beta_{7,4}$	-0.0001 (0.001)	-0.0001 (0.001)
$U(\sum_{k=0}^4 \beta_{7k})$	-0.003 (0.004)	-0.003 (0.003)
Loan($\sum_{k=1}^4 \beta_{1k}$)	-0.207** (0.087)	-0.338*** (0.111)
NGDP($\sum_{k=0}^4 \beta_{2k}$)	0.909*** (0.108)	0.905*** (0.096)
FFR($\sum_{k=0}^4 \beta_{3k}$)	-0.011*** (0.002)	-0.010*** (0.002)
LIQ($\sum_{k=1}^4 \beta_{4k}$)	0.612*** (0.086)	0.673*** (0.077)
CAP($\sum_{k=1}^4 \beta_{5k}$)	0.079 (0.265)	0.410 (0.290)
SIZE($\sum_{k=1}^4 \beta_{6k}$)	-0.436*** (0.051)	-0.465*** (0.048)
$I_R(\beta_{8k})$	0.0002 (0.005)	0.001 (0.004)
No. of banks		359
No. of observations		8,848

The first column is the baseline estimation result of ISB=1 group, and the second column is that of the same group using conventional definition of loan growth rate. The number in parentheses are robust standard errors. The symbols ** and *** represent significance levels of 5%, and 1%, respectively.

Table 2.8: Credit Exposure and Uncertainty

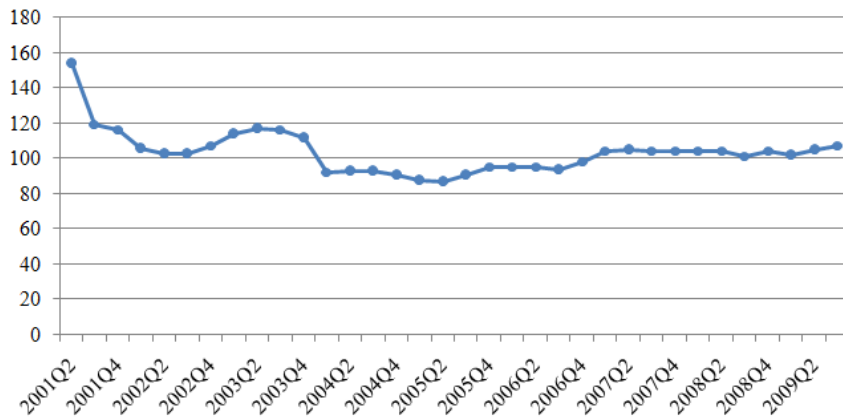
β_{31}	0.0003 (0.002)
β_{32}	0.003*** (0.001)
β_{33}	0.001 (0.002)
β_{34}	0.004** (0.002)
$\sum_{k=1}^4 \beta_{3k}$	0.008** (0.003)
$I_R(\beta_{8k})$	0.027*** (0.008)
NGDP($\sum_{k=0}^4 \beta_{2k}$)	-0.104* (0.058)
FFR($\sum_{k=0}^4 \beta_{3k}$)	0.008*** (0.003)
LIQ($\sum_{k=1}^4 \beta_{4k}$)	0.030 (0.074)
CAP($\sum_{k=1}^4 \beta_{5k}$)	0.055 (0.125)
SIZE($\sum_{k=1}^4 \beta_{6k}$)	0.009 (0.018)
sec($\sum_{k=1}^4 \beta_{1k}$)	$1.2 \times \exp(-5)^*$ ($7.48e^{-6}$)

This table reports the coefficient estimate of uncertainty effect's on credit exposure due to recourse and/or seller-provided credit enhancements in securitization. The numbers in parenthesis are standard errors. The dependent variable of the first column is the ratio of the credit exposure to outstanding securitization level. The symbols *, ** and *** represent significance levels of 10%, 5% and 1%, respectively.

Table 2.9: Summary Statistics of Loan Loss Allowance Provision

		Mean	Std. Dev
<i>PVS1</i>	ISB=1	0.419	1.098
	ISB=0	0.257	0.707
<i>PVS2</i>	ISB=1	0.128	0.326
	ISB=0	0.082	0.271

This table reports the sample means and standard deviations of *PVS1*, defined as the ratio of loan loss allowance provision to total loans, and *PVS2*, the ratio of loan loss allowance provision to total assets across different groups of commercial banks. The t-test results reject sample means of the two groups are the same at 1% significance level for both variables.

**Figure 2.1:** Number of Banks That Securitized Loans

This figure plots the number of banks that reported securitization activity in the Call Report from 2001Q2 to 2009Q2. A bank is considered to have participated in securitization if any asset among 7 different categories (i.e., any item among RCFDB705–RCFDB711) is reported to be non-zero.

Table 2.10: Changes of Loan Loss Allowance Provision

U	$\beta_{3,1}$	0.030*** (0.002)	ISB \times U	$\beta_{4,1}$	0.005 (0.007)
	$\beta_{3,2}$	0.018*** (0.002)		$\beta_{4,2}$	0.018** (0.007)
	$\beta_{3,3}$	0.021*** (0.002)		$\beta_{4,3}$	0.008 (0.007)
	$\beta_{3,4}$	0.025*** (0.003)		$\beta_{4,4}$	-0.016** (0.008)
	$\sum_{k=1}^4 \beta_{3k}$	0.094*** (0.005)		$\sum_{k=1}^4 \beta_{4k}$	0.015 (0.013)
PVS1($\sum_{k=1}^4 \beta_{0k}$)	-0.477*** (0.115)	NGDP($\sum_{k=1}^4 \beta_{1k}$)	-0.494*** (0.152)		
FFR($\sum_{k=1}^4 \beta_{2k}$)	0.033*** (0.004)	LTA($\sum_{k=1}^4 \beta_{5k}$)	0.924*** (0.140)		
INC($\sum_{k=1}^4 \beta_{6k}$)	-0.588*** (0.186)	CAP($\sum_{k=1}^4 \beta_{7k}$)	0.483 (0.424)		
SIZE($\sum_{k=1}^4 \beta_{8k}$)	0.291*** (0.044)	$I_R(\beta_{9k})$	0.132*** (0.013)		
No. of banks	7,767				
No. of observations	187,791				

This table shows the selected coefficient estimates of equation (2.4). The symbols ** and *** represent significance levels of 5% and 1%, respectively.

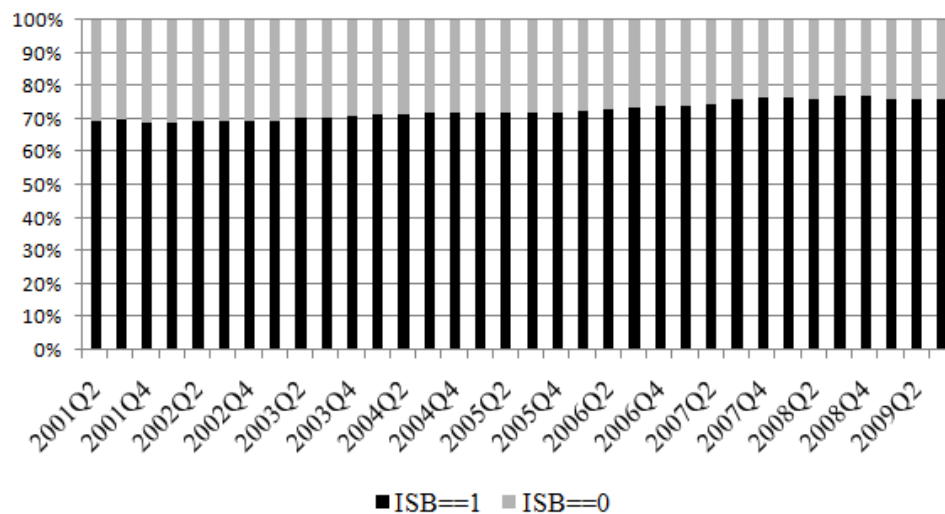


Figure 2.2: Commercial Bank Assets

This figure shows the proportion of assets of each group in commercial banks. The percentage is calculated from the sum of total assets of individual commercial banks in the sample.

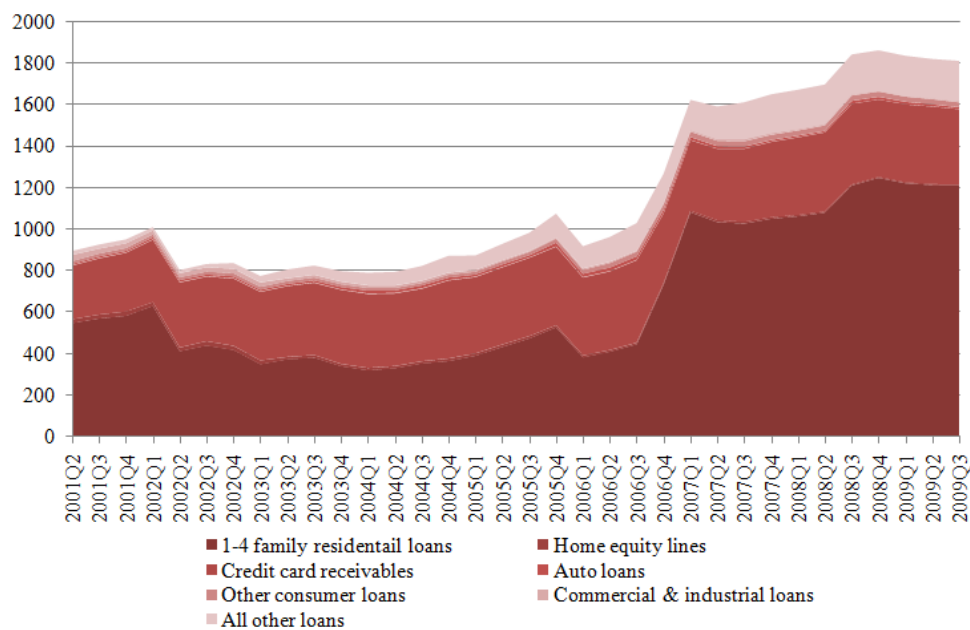


Figure 2.3: Loan Securitization Trend (in billions of dollars)

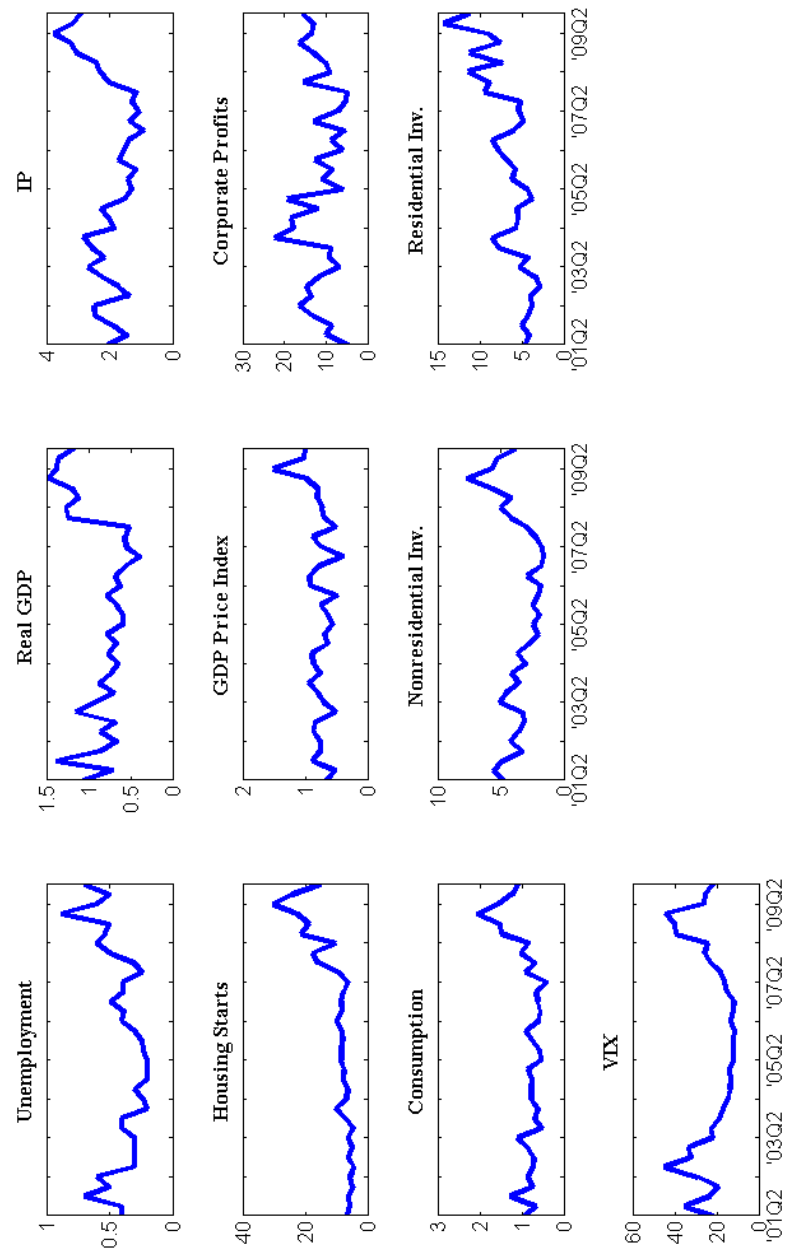


Figure 2.4: Uncertainty Index Basis Data

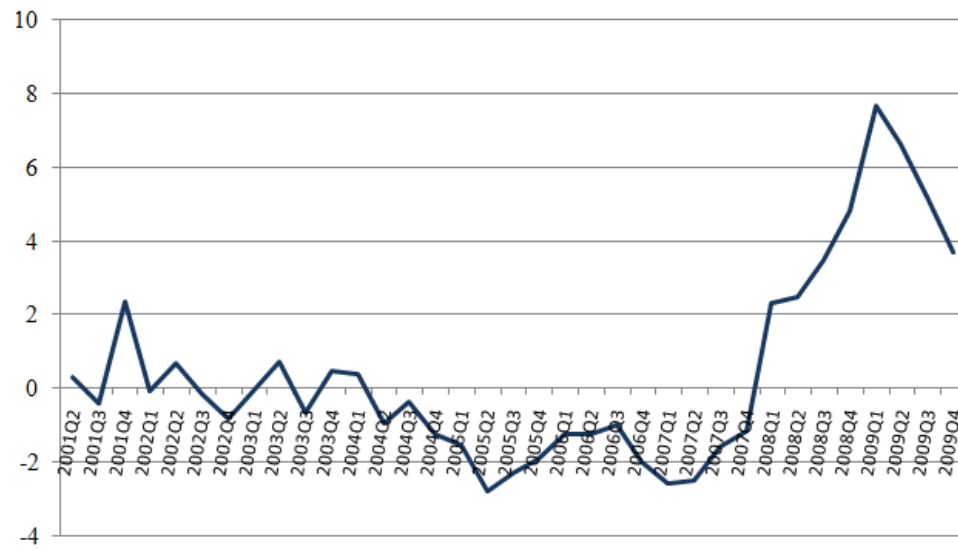


Figure 2.5: The Measure of Uncertainty

This figure plots the time series of uncertainty index created as the first principle component of ten underlying series which are forecast dispersion and VIX.

Chapter 3

Financial Stability and Systemic Risk: A Survey of Systemic Risk Measures

Abstract

Since the 2007-2009 financial crisis, a number of papers have tried to develop a suitable method to measure systemic risk. This is a very critical problem especially for a regulatory purpose to monitor the level of systemic risk properly and, to implement a new set of regulations for the financial sector. Therefore, this chapter surveys the recent literature on systemic risk measurement. I describe five recent studies, starting with a review of the model-free and flexible measure, *CoVaR*, and continuing on to the GARCH-based metric, SRISK. Then, the measures using credit derivative data are surveyed including a measure that quantifies systemic sovereign credit risk. Finally, an approach that uses a macroeconomic model to characterize systemic crisis state is introduced. By looking at a variety of metrics along with advantages and disadvantages of each measure, this chapter also seeks to better understand the concept of systemic risk.

3.1 Introduction

Systemic risk generally refers to the possibility of the whole financial market being in a distress state that adversely affects not only the financial market but also the real economy. Since the onset of the Great Recession in 2007-2009, there has been great interest in systemic risk, as the financial market went through the serial breakdown of major investment banks and other banking institutions with heightened uncertainty and liquidity stress, which caused the real economic growth to plunge as well. However, only little has been understood regarding the nature of systemic risk. What is systemic risk? What makes it systemic? Is there any way the regulators would have been able to prevent the financial crisis from happening? What is the chance of another occurrence of financial crisis in the future? These are some of the many fundamental questions that are being very actively studied at this moment.

Among the efforts to answer the above questions, Federal Reserve Chairman, Ben Bernanke once said in a letter to Senator Bob Corker in October 2009 that “Systemic risks are developments that threaten the stability of the financial system as a whole and consequently the broader economy, not just that of one or two institutions.” This broad definition reflects the perspective that systemic risk can destabilize the whole market, and further, the real economy. In addition, the speech by Governor Daniel K. Tarullo, at the 2011 Credit Markets Symposium, shows four ways that the systemic risk state can be triggered. Among those are a *fire-sale effect* that is caused by the asset sales of a distressed firm can further reduce the market prices by creating excess supply, and also a *contagion effect* that is due to market participants’ suspicion that firms with similar assets to the distress firms are also at risk.¹

In sum, distress of an individual firm during financially less-stable times imposes a negative externality through the above-mentioned effects, threatening the system even more. Then, with the heightened systemic risk, more firms are exposed to financial system’s distress, and this negative self-feeding loop may even-

¹For full version of the speech,
<http://www.federalreserve.gov/newsevents/speech/tarullo20110331a.htm>.

tually affect real economy side as well. Here, both externality and self-feeding loop make it difficult to understand the nature of systemic risk.

Another very critical question that is a subject of many current studies is how one should measure systemic risk. Especially for entities that regulate the financial sector, it is necessary to find a suitable method that can measure, and thus monitor systemic risk, for example, before implementing a new set of regulations. Hence, this paper aims to survey the important developments in the systemic risk measures, which regulators might use as a starting point to select the most appropriate measure in practice. Among the many new papers on this topic, I select five representative papers accommodating different approaches. I start with reviewing the model-free and flexible measure, *CoVaR*, by Adrian and Brunnermeier (2011) [3]. Next, I continue on to the GARCH-based metric, *SRISK*, by Brownlees and Engle (2011) [25]. Then, I look at the measure using credit derivative data by Bhansali, Gingrich and Longstaff (2008) [20], which extracts information from the indexed credit derivatives' prices. Next, I move on to the extension of this measure to quantify systemic sovereign credit risk by examining the recent work by Ang and Longstaff (2011) [7]. Finally, He and Krishnamurthy (2012) [42]'s macroeconomic model in which systemic crisis state is characterized. The metrics are slightly different in defining risk they measure as well as the specific methodology, and thus, this paper is also intended to better understand the concept of systemic risk by looking at a variety of metrics. I also highlight advantages and disadvantages briefly after introducing the key estimation method/concept of each measure.

Although it is not reviewed in detail here, the paper by Andersen, Bollerslev, Christoffersen and Diebold (2012) [5] provides an extensive survey of literature related to risk measurements at various levels, which also include a section on systemic risk.

3.2 CoVaR

Adrian and Brunnermeier (2012) proposes a systemic risk measure that is an extension of widely-used Value-at-Risk (VaR), and hence, model-free in nature. Contrary to VaR which quantifies risk at an individual institution level, the new measure, $CoVaR$, is constructed to capture VaR of the whole financial system given an individual institution is at a certain value. More formally, VaR_q^i of an institution i is defined as the q quantile :

$$Pr(X^i \leq VaR_q^i) = q,$$

where the authors use market-valued total financial assets for X^i . Analogous to this definition, $CoVaR^{system|i}$ of the system is defined as the q quantile, i.e.,

$$Pr(X^{system} \leq CoVaR_q^{system|C(X^i)} | C(X^i)) = q,$$

where $C(X^i)$ is the set of some events of institution i on which $CoVaR$ is conditioned.

In particular, the authors focus on the difference of $CoVaRs$, i.e., $\Delta CoVaR$, that is the difference between the value of the system at q quantile conditional on a firm i being at risk and the system's q quantile value when i is at its median state, and considers it as the *contribution* of the firm i to the systemic risk. Thus, $\Delta CoVaR$ of the system is defined as:

$$\Delta CoVaR_q^{system|i} = CoVaR_q^{system|X^i=VaR_q^i} - CoVaR_q^{system|X^i=Median^i}.$$

The idea behind $\Delta CoVaR_q^{system|i}$ is to capture the contribution of institution i , which will differ institution by institution. Hence, from a regulation perspective, the standard required to those entities with large absolute value of $\Delta CoVaR_q^{system|i}$ should differ from those with $\Delta CoVaR_q^{system|i} = 0$, as the latter imply that those institutions add little to the systemic risk. Therefore, one direct advantage of $CoVaR$ is it makes it possible to apply different level of regulation depending on the degree of contribution to systemic risk of an individual institution.

Next, by replacing *system* with another individual financial institution, j , i.e., $\Delta CoVaR_q^{j|i}$ enables measuring the spillover effects of i 's distress to other individual institutions easily. Thus, another merit is that it can be easily generalized to use in various situations. As noted by the authors, it is also feasible to compute $\Delta CoVaR_q^{i|system}$ to capture the institution i 's increase in value-at-risk when there is a financial crisis, which can be called "exposure *CoVaR*."²

It is worthwhile to note some of the characteristics of $\Delta CoVaR$. As mentioned above, $\Delta CoVaR_q^{system|i}$ is different from $\Delta CoVaR_q^{i|system}$, showing the directionality of the measure. However, it does not imply any causality or exogeneity of the conditioning institution i . That is to say, it is not feasible to distinguish whether the institution i causes the financial system to be at risk or the changes in systemic risk level is due to a shift in a common factor just by looking at $\Delta CoVaR$ value. Related to that, the measure only quantifies the changes in the equilibrium, which is the value after all the dynamics in the financial network are considered. The lack of causality and exogeneity can be advantageous in case one is interested in having a more integrated, still simple measure, as $\Delta CoVaR$ summarizes direct and indirect contributions of an individual institution through the financial network in a single number.

Computation of *CoVaR* depends on whether one considers information available up to time t or one is interested in the unconditional value. Here, I briefly introduce the estimation of time-varying, conditional *CoVaR*, which is more useful and relevant in many settings. First, one serially runs the following quantile regressions of the institution i 's and the financial system's values using the weekly data:

$$\min_{\{\alpha^i, \gamma^i\}} \sum (\rho_q(X_t^i - (\alpha^i + \gamma^i M_{t-1}))),$$

and

$$\min_{\{\alpha^{system|i}, \beta^{system|i}, \gamma^{system|i}\}} \sum (\rho_q(X_t^{system} - (\alpha^{system|i} + \beta^{system|i} X_t^i + \gamma^{system|i} M_{t-1}))),$$

where the vector of lagged state variables M_{t-1} is included to reflect the overall changes in mean and the conditional volatility of the economy. Note that $\rho_q(\cdot)$ is

²This measure is related to Huang, Zhou, and Zhu (2010) [44] and Acharya, Pedersen, Philippon, and Richardson (2010) [1].

a loss function, e.g., the tilted absolute value function that yields the q th sample quantile as its solution. The specific variables included in M_{t-1} are VIX , the change in the three-month Treasury bill rate, and so on. Although these variables are included as common factors that shift conditional distributions, one should note that the coefficient attached can differ across institutions so that it is possible to capture different risk-loadings.

Then, using the coefficients estimates from the quantile regression, the values of $VaR_t^i(q)$ and $CoVaR_t^{system|i}(q)$ can be predicted in a straightforward manner as:

$$\begin{aligned} VaR_t^i(q) &= \hat{\alpha}_q^i + \hat{\gamma}_q^i M_{t-1}, \\ CoVaR_t^{system|i}(q) &= \hat{\alpha}_q^{system|i} + \hat{\beta}^{system|i} VaR_t^i(q) + \hat{\gamma}_q^{system|i} M_{t-1}. \end{aligned}$$

Finally, $\Delta CoVaR$ is computed as the following:

$$\begin{aligned} \Delta CoVaR_t^{system|i}(q) &= CoVaR_t^{system|i}(q) - CoVaR_t^{system|i}(50\%) \\ &= \hat{\beta}^{system|i} (VaR_t^i(q) - VaR_t^i(50\%)). \end{aligned}$$

Later, the authors move on to an extension of $CoVaR$, which they call *forward- $\Delta CoVaR$* that calculates forward looking systemic risk at a quarterly frequency, by incorporating information from institution-specific variables, e.g., leverage ratio, size, and such. This is intended to measure how much a firm i is expected to contribute to the systemic risk in the future. Thus, *forward- $\Delta CoVaR$* is an extremely useful measure for monitoring financial stability, and more importantly, has a purpose of alleviating the problems of systemic risk regulations in practice so far: measurement error and procyclicality.

In particular, *forward- $\Delta CoVaR$* is constructed by first fitting a panel regression of previously predicted $\Delta CoVaR$ values on an expanded set of explanatory variables that include lagged institution-specific characteristics in addition to M_{t-1} . The lags of firm characteristics correspond to the forecasting horizon, e.g., one-quarter, one-year, and two-year. The variables added by the authors are: leverage ratio, maturity mismatch of liabilities, market-to-book value of total equity, size, equity return volatility, and finally, equity market beta. Then,

forward- $\Delta CoVaR$ is the fitted value from the panel regression. The firm-specific variables at quarterly frequency are not only easily observable, but also more robust compared to the weekly data used in the original setup. Hence, adding these variables is likely to result in more reliable inferences. In case of financial institutions like Bank Holding Companies, there are even more variables available, such as loans and loan-loss allowances, from the balance sheet data. Moreover, as *forward- $\Delta CoVaR$* aims to predict future contribution of institution i , it may alleviate part of the procyclicality problem of financial regulations caused when using a contemporaneous risk measure. This is mainly due to the idea that by implementing a measure of future risk, it may give a chance to regulators to act in advance before any real distress happens.

Out-of-sample exercise of *forward- $\Delta CoVaR$* shows that it moves quite differently from the contemporaneous $\Delta CoVaR$; there is a negative correlation between the two, which supports the idea that regulations based on *forward- $\Delta CoVaR$* are likely to be countercyclical. Moreover, *forward- $\Delta CoVaR$* predicted at the end of 2006 was able to explain more than 50% of the realized cross sectional covariance during the crisis regardless of the variation in forecasting horizon.

Overall, $\Delta CoVaR$ can be a powerful and parsimonious measure that contains a lot of information content. In addition, it can be easily calculated from many statistical packages due to the use of quantile regression. Another advantage of $\Delta CoVaR$ is that it opens up the possibility of developing a countercyclical regulation which can be particularly helpful given the procyclicality in regulation policies, which have been pointed out to have aggravated the financial crisis.

However, as pointed out by the authors, one should note that $\Delta CoVaR$ is not based on a structural model, and hence, it is not possible to parse out the contribution of a firm i in a causal sense. This may be an advantage in that $\Delta CoVaR$ value represents total effect of a firm being at distress. Nevertheless, this can be a disadvantage in implementing a more fine-tuned regulatory policy. For example, if the contribution of the firm i is due to the changes in common factor, the regulation policy required will be different from the case which it is the firm i that is expected to cause financial system distress. One will not be able to

distinguish the two cases just by monitoring $\Delta CoVaR$ only.

3.3 A Measure Based on GARCH Process

Brownlees and Engle (2011) propose a methodology to measure systemic risk. Compared to $CoVaR$, the proposed measure, SRISK, has more structure, and thus, incorporate more assumptions about return distributions and data generating processes. However, it is flexible enough to embrace time-varying volatility and correlation of returns, and moreover, it provides additional estimates of some important and interesting time series while generating the risk index series.

Before looking at the details of the measure, it is important to note that the specific concept of systemic risk on which SRISK is based that is in line with that of Acharya et al. (2010) : it is the failure of a firm when the financial sector is already in distress, so that the capital shortfall of the firm cannot be accommodated within the market as it would have during the normal times. Furthermore, it has significant negative effects on the financial system and the real economy. Hence, the key idea is to quantify the expected capital shortfall of a firm given that the financial sector is in distress, i.e., market return is under a threshold value. If a firm's capital shortfall under the constrained financial market is expected to be large, than one can say the firm is systemically risky. Therefore, the concept of risk that SRISK measures is different from, and in opposite to that of $CoVaR$, in the sense that the former measures individual firm's exposure to system's risk, but the latter captures the contribution of an individual firm to the system's risk.

With this idea, the authors intend to capture the capital shortage of different firms, which is likely to depend on the leverage ratio and the expected equity loss conditional on a financial crisis. One thing to note is that the expected equity loss of a firm is something that has to be estimated while the leverage ratio is observable. More specifically, the capital shortage of the firm i ($CS_{i,t}$) is defined

as,

$$\begin{aligned}
CS_{i,t} &= E_t(k(F_{i,t+1} + G_{i,t+1} + W_{i,t+1}) - W_{i,t+1} | Crisis) \\
&= k(F_{i,t+1} + G_{i,t+1}) - (1 - k)E_t(W_{i,t+1} | R_{m,t+1} < C) \\
&= k(F_{i,t+1} + G_{i,t+1}) - (1 - k)W_{i,t}E_t(R_{i,t+1} | R_{m,t+1} < C) \\
&= k(F_{i,t+1} + G_{i,t+1}) - (1 - k)W_{i,t}MES_{i,t}.
\end{aligned}$$

where k is the prudential ratio of asset value to equity, $F_{i,t+1}$ is the face-value of risky debt the firm i has to repay at $t + 1$ and $G_{i,t+1}$ that of guaranteed debt both of which are known at t , and $W_{i,t+1}$ the firm's equity capital. Financial crisis is defined as the time when market return, $R_{m,t}$, plummets under a threshold value C . The equity capital's return is denoted as $R_{i,t+1}$. Finally, $MES_{i,t}$ is Marginal Expected Shortfall which is the tail expectation of the firm return given market's failure. Hence, we see that the first term on the right can be observed whereas the MES of the second term should be estimated.

Then, the systemic risk index of i ($SRISK_{i,t}$) and its percentage version ($SRISK\%_{i,t}$) are:

$$\begin{aligned}
SRISK_{i,t} &= \min(0, CS_{i,t}), \\
SRISK\%_{i,t} &= \frac{SRISK_{i,t}}{\sum_i SRISK_{i,t}}.
\end{aligned}$$

The estimation of $MES_{i,t}$ requires knowledge of the market and firm returns according to the definition. The focus of the paper is to develop an appropriate time series technique to have $MES_{i,t}$, which is flexible yet easily applicable. In particular, the authors use a bivariate conditionally heteroskedastic model to describe the dynamics of the daily market and firm log returns, $r_{i,t}$ and $r_{m,t}$, respectively. That is,

$$\begin{aligned}
r_{m,t} &= \sigma_{m,t}\epsilon_{m,t}, \\
r_{i,t} &= \sigma_{i,t}\rho_{i,t}\epsilon_{m,t} + \sigma_{i,t}\sqrt{1 - \rho_{i,t}^2}\xi_{i,t} \\
(\epsilon_{m,t}, \xi_{i,t}) &\sim F.
\end{aligned}$$

where $\sigma_{m,t}$ and $\sigma_{i,t}$ are the conditional time-varying standard deviations of market and the firm i , and $\rho_{i,t}$ captures the conditional time-varying correlation of

the returns. Hence, the model is general enough to allow time variations in both standard deviations and the correlation coefficient. The errors $(\epsilon_{m,t}, \xi_{i,t})$ are independent and identically distributed following an unspecified distribution F with zero mean and unit variance.

In order to estimate this model, the paper proceeds by defining processes of volatilities and correlation, and finally the computation of the market and firm returns' tail expectations. First, the volatilities are defined to follow TARCh (Threshold GARCH) process, which allows asymmetry in GARCH data generating process to reflect the leverage effect³, i.e.,

$$\begin{aligned}\sigma_{m,t}^2 &= \omega_m + \alpha_m r_{m,t-1}^2 + \gamma_m r_{m,t-1}^2 I\{r_{m,t-1} < 0\} + \beta_m \sigma_{m,t-1}^2, \\ \sigma_{i,t}^2 &= \omega_i + \alpha_i r_{i,t-1}^2 + \gamma_i r_{i,t-1}^2 I\{r_{i,t-1} < 0\} + \beta_m \sigma_{m,t-1}^2.\end{aligned}$$

Then, the correlation coefficient is modeled based on the Dynamic Conditional Correlation (DCC) approach of Engle (2002, 2009) [33] [34] that models the pseudo correlation matrix instead of covariance matrix of $(r_{m,t}, r_{i,t})$. In DCC formulation, the pseudo correlation matrix is defined to follow ARMA(1,1) using the rescaled standardised (degarched) returns given the volatility estimates. That is, the matrix is an exponentially weighted average of outer products of the rescaled standardised returns and the lagged pseudo correlation matrix, which then is mapped to the original correlation matrix.

Now, the final step of estimating tail expectations differs depending on whether the main interest lies on estimating Short Term MES (one-day ahead) or Long Term MES (six-month ahead). In case of Short Term MES, the task boils down to compute $E(\epsilon_{m,t} | \epsilon_{m,t} < C/\sigma_{m,t})$ and $E(\xi_{i,t} | \epsilon_{m,t} < C/\sigma_{m,t})$ given the time

³As long as γ is positive, we see that this process is able to capture the widely-observed financial market behavior which is the negative return generates higher volatility than the positive return, i.e., the "leverage effect".

series of $(\sigma_{m,t}, \sigma_{i,t})$ and ρ_t ,⁴ since

$$\begin{aligned} MES_{i,t-1}^1(C) &= E_{t-1}(r_{i,t}|r_{m,t} < C) \\ &= \sigma_{i,t}E_{t-1}(\rho_{i,t}\epsilon_{m,t} + \sqrt{1 - \rho_{i,t}^2}\xi_{i,t}|\epsilon_{m,t} < C/\sigma_{m,t}) \\ &= \sigma_{i,t}\rho_{i,t}E_{t-1}(\epsilon_{m,t}|\epsilon_{m,t} < C/\sigma_{m,t}) \\ &\quad + \sigma_{i,t}\sqrt{1 - \rho_{i,t}^2}E_{t-1}(\xi_{i,t}|\epsilon_{m,t} < C/\sigma_{m,t}). \end{aligned}$$

With respect to the Long Term MES which does not have a closed form solution, the paper proposes the use of empirical cumulative density function of the estimated residuals, \hat{F} , from which the innovation samples are drawn with replacement. Then, the Long Term MES with h -period ahead can be forecast by simulating the return paths up to horizon h for S times and averaging over the simulated paths, i.e.,

$$MES_{i,t-1}^h(C) = \frac{\sum_{s=1}^S R_{i,t:t+h-1}^s I\{R_{m,t:t+h-1}^s < C\}}{\sum_{s=1}^S I\{R_{m,t:t+h-1}^s < C\}},$$

where $R_{i,t:t+h-1}^s$ is the cumulative return in the s th simulation from period t to $t + h - 1$.

In estimating MES, one can also obtain the estimates of the time-varying conditional probability of a systemic event, i.e., $C\%$ loss in the market:

$$PoS_t^h(C) = \begin{cases} P_{t-1}(r_{m,t} < C) & \text{when } h = 1 \\ P_{t-1}(R_{m,t:t+h-1} < C) & \text{when } h > 1. \end{cases}$$

In sum, SRISK is a well-defined measure that provides many interesting statistics along the estimation procedure. In addition, the TARARCH/DCC time series structure imposed for the estimation of MES is very general in that it could accommodate time-varying volatility and correlation structure, which is highly advantageous considering the characteristics of financial market. Another huge merit of the setup is that it is not limited to the particular TARARCH/DCC process, but one can replace it by the wide class of GARCH-type models and even expand to some other volatility and correlation models.

⁴In other words, one can simply look at the average of the residuals $(\hat{\epsilon}_{m,t}, \hat{\xi}_{i,t})$ of the cases when $\hat{\epsilon}_{m,t}$ is under threshold. However, the authors also suggest a nonparametric kernel estimation method to improve efficiency.

One should note, however, that estimation of a bivariate conditionally heteroskedastic model with non-linear residual dependence for a large number of firms may not be easy, as the authors point out, especially when the length of an asset return time series is short. However, one can choose the parameters to be less frequently updated, e.g., weekly or monthly, and produce daily short term and long term MES, SRISK, and PoS, as it is currently done in the Volatility Laboratory (V-Lab).⁵ In this way, the computational burden would be reduced, but still real time risk measurement can be provided. Furthermore, SRISK gives a chance to produce aggregate-level time series such as the time-varying probability forecast of a $C\%$ loss in the market. Especially, one can also have the time series of the expected capital shortage of the whole system by summing up all the positive capital shortfalls of all firms, which can be a particularly useful number to consider when empirically analyzing the linkage between the financial sector and the real economy.

3.4 Measures Using Credit Derivatives

Next, we look at the metrics based on the credit derivative pricing model, which can be easily generalized to capture systemic risk of different groups. First, Bhansali, Gingrich and Longstaff (2008) use the prices of indexed credit derivatives and its tranches to get the information about the market's expectation on different types of financial risk. In particular, the model of the paper is the linearized version of Longstaff and Rajan (2008) [57]'s three-jump Collateralized Debt Obligation (CDO) pricing model. The important idea of Longstaff and Rajan is that the credit spreads (price) of CDO are composed of multiple credit risk components. Based on this idea, Bhansali et al. (2008) look at the linearized version of the model, i.e., the index spread is the sum of company-specific default spread, sector-specific spread, and finally, systemic risk spread which reflects an economy-wide financial disaster.

The authors begin by defining L , the total portfolio losses realized on the

⁵<http://vlab.stern.nyu.edu/>

index portfolio per \$1 notional amount, as

$$L = \gamma_1 N_1 + \gamma_2 N_2 + \gamma_3 N_3$$

where γ_i are jump size parameters, and N_i are independent Poisson counters which models the number of jumps. Then, with λ_i that is time-invariant parameter of intensity, P_{ij} , the probability of j times jumps for the i th Poisson process can be written as

$$P_{ij} = \frac{e^{-\lambda_i T} (\lambda_i T)^j}{j!}.$$

As the indexed CDO is based on Credit Default Swap (CDS), an investor of this index receives a flow of C as a premium for the underlying bonds that do not default, and pays out the face value of a bond in case it defaults. Thus, equating expected profit (premium leg, left hand side) to expected loss (protection leg, right hand side) for a risk-neutral investor, we get the coupon rate C :

$$C \int_0^T D(t) \{1 - E[L(t)]\} dt = \int_0^T D(t) E[dL],$$

where $D(t)$ is the riskless discount factor. From the previous equations, this becomes

$$C \int_0^T D(t) (1 - \gamma_1 \lambda_1 t - \gamma_2 \lambda_2 t - \gamma_3 \lambda_3 t) dt = \int_0^T D(t) (\gamma_1 \lambda_1 + \gamma_2 \lambda_2 + \gamma_3 \lambda_3) dt.$$

In other words, for every dollar put in the portfolio, the investor expects to receive the coupon C for the proportion that did not default until time t , i.e., $(1 - \gamma_1 \lambda_1 t - \gamma_2 \lambda_2 t - \gamma_3 \lambda_3 t)$, under the contract to compensate for the loss of the defaulted bonds.

Rearranging the terms we get,

$$\lambda_1 = \frac{[C/(1 + AC)] - \gamma_2 \lambda_2 - \gamma_3 \lambda_3}{\gamma_1}, \quad (3.1)$$

where $A = \frac{\int_0^T D(t) dt}{\int_0^T D(t) dt}$ is the duration of an annuity. Now, we are ready to estimate the parameters, λ_i 's and γ_i 's, using the index spreads and spreads on standardized tranches data. In particular, the authors use Markit CDX for the U.S. and Markit iTraxx for the European markets, and associated tranches.

Now, one starts the numerical estimation process by assuming that jump size γ_i parameters are given, and then, uses the tranche data with attachment point a and detachment point b .⁶ Here, note that the spread (coupon) of this tranche, $C_{a,b}$, is again determined by equating the premium leg and the protection leg:

$$C_{a,b} \int_0^T D(t) \{1 - E[L_{a,b}(t)]\} dt = \int_0^T D(t) E[dL_{a,b}].$$

Conditional on a given set of γ_i 's, the model-implied coupon value is estimated by allowing a sufficiently large number of jumps and computing the corresponding Poisson probabilities, $P_{i,j}$. In doing so, the authors allow for up to 50 jumps for the first Poisson process, up to 10 jumps for the second Poisson process, and up to 3 jumps for the third Poisson process.

Next, by minimizing the root-mean-squared percentage pricing error between the model-implied and the observed market tranche prices for each day, λ_2 and λ_3 are first identified among other parameters. Then, λ_1 is determined from equation (3.1), using the observed market index spread as C . Finally, this numerical optimization loop is closed by iterating over the different set of γ_1, γ_2 and γ_3 until the global minimum root-mean-squared percentage error is achieved.

Initially, the specification of the portfolio loss process L as a sum of three factors is not based on a structural model; it is rather following the test result of Longstaff and Rajan (2008) on the number of factors that the three factor model can fit the data very closely. In fact, the γ_i estimates across eight index credit derivatives provided in the paper show that the jump size estimated γ_i 's are very different for the three Poisson processes, and the difference is consistently observed in all eight index credit derivative data; γ_1 is the smallest whereas γ_3 is the largest, and γ_3 is on average 60 times larger than γ_1 . More importantly, this estimation result is conformable to the interpretation that when a jump occurs for the first Poisson process, then one firm defaults idiosyncratically, a jump for the second process is sector-specific default, and finally, the a jump that causes about 60 cents loss per one dollar would be economy-wide systemic crisis.

⁶Simply put, the tranche of attachment point a and detachment point b starts to have loss when $a\%$ of underlying portfolio default, and absorbs the loss increasingly until the size of the total losses reaches $b\%$. For more detailed description of Indexed CDOs and its tranches, see Longstaff and Rajan (2008).

Hence, with the estimated λ 's and γ 's values at hand, the full index spread can be finally decomposed into three different spreads, and one can interpret this decomposition to be:

$$\begin{aligned} \text{Idiosyncratic spread} &\equiv S_1 = \frac{\gamma_1 \lambda_1}{1 - (\gamma_1 \lambda_1 + \gamma_2 \lambda_2 + \gamma_3 \lambda_3)A}, \\ \text{Sector-wide spread} &\equiv S_2 = \frac{\gamma_2 \lambda_2}{1 - (\gamma_1 \lambda_1 + \gamma_2 \lambda_2 + \gamma_3 \lambda_3)A}, \\ \text{Economy-wide spread} &\equiv S_3 = \frac{\gamma_3 \lambda_3}{1 - (\gamma_1 \lambda_1 + \gamma_2 \lambda_2 + \gamma_3 \lambda_3)A}, \end{aligned}$$

where $C = S_1 + S_2 + S_3$. It should be noted that this decomposition is done under risk-neutral setting, thus, one can think of this as capturing both risk premium and risk without distinction.

All in all, the proposed metric is based on the simple and intuitive idea of decomposing the observed spread into three risk factors. Hence, it can be particularly useful when the intention is to look at the dynamics of aggregate level risk. Nevertheless, this measure is general enough to accommodate different attachment and detachment points of tranches. The advantage of this measure is that it can integrate the co-movements of risk factors across multiple tranches thereby resulting in a more accurate systemic risk measure. This is because the recovered time series of each component may be different across tranches or depending on the attachment and detachment points, therefore, the relative size of components may also differ. Thus, contrary to the copula-based measure based on the presumed distribution that focuses more on correlation, this measure quantifies the risk factors at a more integrated sense, as the authors point out.

In addition, as the underlying portfolio is the indexed credit derivatives, the measure is likely to be more forward-looking and reflective of market's expectation. Also, the linear structure makes it possible to quantify more aggregate level risk easily, e.g., systemic risk of the whole European Union, by increasing the number of factors in portfolio loss function.

Another thing to note is the setting behind the spread decomposition assumes risk-neutrality without distinguishing risk premium from actual risk. Thus, one should be careful about the interpretation of the spread series. Nonetheless,

this might be a particularly useful measure in estimating the distress level of the credit market that the market participants actually feel.

However, one important caveat is that it does not explicitly consider the externality of an individual firm's decision which is a critical component of systemic risk; all the firms included in the index is treated as the same ignoring their differences in the size of potential adverse effects on the financial system and the real economy. As a result, in the regulatory point of view, this measure may not provide enough information to implement a firm-specific regulations. The time-invariant parameter setup of the model may also show some rigidity, compared to other time-varying or conditional measures.

Next, I look at a systemic *sovereign* credit risk measure by Ang and Longstaff (2011), that is rooted from a very similar model of CDS spread pricing. As pointed out above, the flexibility of the systemic risk measure based on the credit derivative pricing model allows having layered structure of different types of risk, thereby making it possible to quantify systemic risk from cross-country data. Thus, given the on-going financial risk contagion among the members of European Union, this method provides a widely-applicable metric as it enables to monitor the time series of systemic risk, and/or the sensitivity of sovereigns to systemic distress, etc., which is a great advantage compared to the other methods based on a single factor (i.e., sovereign-specific risk factor in this context) model. In addition, it can be also applied, as the authors show, to the countries like the U.S., where individual state has sovereignty but is highly likely to be exposed to a common systemic risk factor.

The specifics of this approach is an extended version of Pan and Singleton (2008)[59] and Longstaff, Pan, Pedersen, and Singleton (2011) [56]. That is, a sovereign may default by the realization of the sovereign-specific risk factor or the systemic factor that triggers a series of default across sovereigns. Hence, the authors model the two independent credit risk factors to follow the Poisson process, whose intensity parameters are determined as:

$$\begin{aligned} d\xi &= (a - b\xi)dt + c\sqrt{\xi}dZ, \\ d\lambda &= (\alpha - \beta\lambda)dt + \sigma\sqrt{\lambda}dZ_\lambda. \end{aligned}$$

Here, ξ and λ are the parameters of the intensity of the sovereign-specific process and systemic shock process, respectively. In addition, a, b, c and α, β, σ are constants, and dZ and dZ_λ are Brownian motions uncorrelated to each other. However, no specific restriction is implemented about the correlation of Z across sovereigns, so it is possible to capture some co-movement across different entities in this framework. Also, note that the above structure allows for mean reversion and conditional heteroskedasticity in ξ process and guarantees ξ and λ to be nonnegative.

The key idea here is that a sovereign will default when the first jump of a sovereign-specific Poisson process arrives, or when a systemic shock occurs. However, important distinctions between the two processes are that the probability of a sovereign default conditional on the arrival of systemic process jump (denoted as γ) differs across sovereigns⁷, and that it is thus possible for a country to survive through a systemic distress with probability $1 - \gamma$. Hence, a sovereign will default with probability 1, when the sovereign-specific jump occurs, or it will default with probability γ when the systemic jump arrives given that the sovereign-specific jump has not occurred. Or, it may survive the first systemic shock and default by the second systemic jump arrival with probability $(1 - \gamma) \times \gamma$. Further, it can default when the third systemic jump comes in with probability $(1 - \gamma)^2 \times \gamma$, and so on.

Based on this idea, one can write the probability that a default does not occur by time t conditional on the realized paths of the intensity processes ϵ_t and λ_t as,

$$\begin{aligned} P(\text{no default}|\lambda, \xi) &= \exp\left(-\int_0^t \xi_s ds\right) \left[\sum_{i=0}^{\infty} \frac{1}{i!} \exp\left(-\int_0^t \lambda_s ds\right) \left((1 - \gamma) \int_0^t \lambda_s ds\right)^i\right] \\ &= \exp\left(-\int_0^t \xi_s ds\right) \exp\left(-\int_0^t \lambda_s ds\right) \exp\left((1 - \gamma) \int_0^t \lambda_s ds\right) \\ &= \exp\left(-\int_0^t \gamma \lambda_s + \xi_s ds\right). \end{aligned}$$

Hence, the instantaneous probability of default will be proportional to $\gamma \lambda_s + \xi$.

⁷Note that γ can thus be used as a parameter measuring the sensitivity of a sovereign to systemic risk.

Now, the authors assume that a bondholder would recover a fraction $1 - w$ of the par value when the bond defaults following Lando (1998)[54]. Then, as in Bhansali et al. (2012), one can calculate the spread (coupon) rate s , by equating the premium (spread) leg to the protection leg of a sovereign CDS:

$$\begin{aligned} & E[s \int_0^T D(t) \exp(-\int_0^t \gamma \lambda_s + \xi ds) dt] \\ &= E[w \int_0^T D(t)(\gamma \lambda_t + \xi_t) \exp(-\int_0^t \gamma \lambda_s + \xi ds) dt], \end{aligned}$$

where $D(T)$ is the value of a riskless zero-coupon bond with maturity T given the riskless rate r_t , i.e.,

$$D(T) = E[\exp(-\int_0^T r_t dt)].$$

Solving the pricing equation for s yields,

$$s = \frac{w E[\int_0^T \{D(t)(\gamma \lambda_t + \xi_t) \exp(-\int_0^t \gamma \lambda_s + \xi) ds\} dt]}{E[\int_0^T D(t) \exp(-\int_0^t \gamma \lambda_s + \xi ds) dt]}$$

This can be rewritten as a closed-form solution, since the intensity processes follow the square-root dynamics, and the specific form and the terms are introduced in Appendix.

With the closed-form solution, one can now start empirical analysis. In particular, the authors use one-, two-, three-, four-, and five-year CDS spreads of ten U.S. state bonds, U.S. Treasury, and ten EMU countries.

The specific estimation process⁸ is as following: let s_{ijt} denotes the market spread in time t for the i -th issuer for a CDS contract that matures in j years, and \hat{s}_{ijt} is the corresponding spread implied by the model after substituting in the estimated values of the systemic intensity parameter λ , the sovereign-specific intensity parameter ξ , and the other estimated parameter θ . Then, one minimizes

⁸The authors make two identifying restrictions for the estimation. First, they restrict the coefficient γ for the U.S. Treasury is normalized to be one in order to scale the result more conveniently and to emphasize the interpretation of γ as a sensitivity parameter. Second, a Treasury default can only occur with the arrival of the systemic shock, as it is difficult to imagine the case that the Treasury defaults idiosyncratically without having any affects on states. For EMU members, they restrict Germany to be subject to the above identification conditions.

the following:

$$\min_{\lambda, \xi_N, \theta} \sum_i \sum_j \sum_t [s_{ijt} - \hat{s}_{ijt}]^2,$$

in order to estimate the parameter vector and the time series of the intensity processes.

The advantage of the above model is it provides a stepping stone for measuring systemic risk at a more aggregated level, which can be very useful and practical given the current extremely integrated financial market. Especially, this measure is effective in quantifying how much a sovereign is exposed to systemic risk. In addition, it is flexible enough to reflect the different degree of exposure to systemic risk across sovereigns, and/or to consider dependency between sovereigns through the correlation of sovereign-specific factor.

However, as Bhansali et al. (2008)'s measure, it is silent about a more fundamental question; what makes systemic risk systemic? In line with this reasoning, the measure would not be very appropriate to consider the contagion effect or the size of contribution when a systemic distress state is triggered by a default of one sovereign and the risk spreads to other entities. In sum, it will be a nice measure to look at the degree of exposure of an individual sovereign to systemic credit risk, but the contribution of an entity's distress to systemic risk increase may not be captured as well as other metric such as *CoVaR*.

3.5 Systemic Risk in Macroeconomic Model

Relatively few papers are devoted on developing systemic risk measure in a full-blown macroeconomic model setup. Very recent work by He and Krishnamurthy (2012) is one of the few studies that attempt to develop a macroeconomic model in which systemic risk can be quantified by having a financial intermediary sector. The key feature of the economy which their model can capture is the non-linearity that real economic variables may respond very differently to shocks of the same size, depending whether the current state of economy is normal, distress, or systemic risk periods. This is done by modeling the financial intermediary sector

having an equity capital constraint that binds only in a few states that correspond to systemic risk states. With this feature, the model can accommodate the nonlinearity in distress, non-distress and systemic crisis periods as it produces a stochastic steady state distribution. Thus, the important advantages of the model are 1) one can look at the transition dynamics from the normal state to the systemic risk state, and 2) the impact of systemic risk state on the real economic variables can be well captured, although the current version of the model does not have a very explicit measure of systemic risk itself. Here, I describe the important features of the model in the purpose of understanding how the occasionally binding equity capital constraint works to capture nonlinearity, but abstain from going into details of the model solution and simulation.

The model consists of bankers and two types of households: the equity households which invest their wealth to the equity of the bank, and the debt households which instead purchase the bank-issued bonds. There are two types of capital: productive capital K_t , and housing capital H that is normalized to 1.

Starting from the intermediary sector, there is a continuum of competitive intermediaries owned by households but ran by bankers with managerial skills and corresponding reputation, ϵ_t . The variable ϵ_t that depends on a banker's performance is very important since the banker can raise equity capital only up to ϵ_t from equity households, and thus, has to make up for the remainder by short-term debt financing. A banker's objective is to choose the intermediary's investment in order to maximize their cumulative reputation,

$$\max E\left[\int_0^\infty \exp(-\eta t) \log \epsilon_t dt\right],$$

where η is a Poisson rate of a banker's death on any date. With the assumption that the reputation of the banker evolves as

$$\frac{d\epsilon_t}{\epsilon_t} = m d\tilde{R}_t,$$

with $d\tilde{R}_t$ denoting the realized profit-rate on the investment from t to $t + dt$, net of debt repayment, i.e., return on equity, and a positive constant m . Then, the banker's objective function becomes,

$$\max E_t[d\tilde{R}_t] - \frac{m}{2} \text{Var}_t[d\tilde{R}_t].$$

Hence, a banker maximizes the mean excess return on equity minus the variability with the parameter m that can be interpreted as the degree of risk aversion.

At the aggregated level, the dynamic of the maximum aggregated equity capital, \mathcal{E} , is defined as,

$$\frac{d\mathcal{E}_t}{\mathcal{E}_t} = m\tilde{R}_t - \eta dt + d\psi_t,$$

where $d\psi_t$ which is non-negative is the entry of new bankers, contrary to the exit of bankers due to death, ηdt .⁹ Intuitively, the maximum level of aggregated equity (or, aggregate reputation stock) evolves with the equity return, $m\tilde{R}_t$, of the intermediary that is identical to each other, and is also affected by the exit and the entry.

Now, let's look at the working capital more closely. It is used to produce consumption goods, where the production technology is as follow:

$$Y_t = AK_t$$

with a positive constant A . The fundamental shock arises to the capital evolution process as,

$$\frac{dK_t}{K_t} = i_t dt - \delta dt + \sigma dZ_t$$

where i_t is investment per capital, δ is a constant depreciation rate, and Z_t is standard Brownian motion. Thus, K_t can be understood as the efficiency of capital, and Z_t is a capital quality shock which is the only source of uncertainty in the model.

Making investment i_t to the working capital K is dependent upon the decision of the producers (owned by households), and occurs some cost (in consumption good unit),

$$\Phi(i_t, K_t) = i_t K_t + \frac{\kappa}{2}(i_t - \delta)^2 K_t,$$

where κ is a positive constant. That is, installing $i_t K_t$ unit of new capital incurs costs that is a quadratic function of net investment. After making the investment,

⁹The exit is to make the model stationary by removing strictly positive drift. In addition, the entry is assumed to happen only when the aggregate intermediary sector has low capital level, as it will increase the incentives to enter.

the producers are assumed to sell the capital to the intermediaries at price q_t . Hence, the investment decision is made given q_t to maximize,

$$\max_{i_t} q_t i_t K_t - \Phi(i_t, K_t),$$

that yields the first order condition for the optimal investment rate:

$$i_t = \delta + \frac{q_t - 1}{\kappa}.$$

The economic interpretation between this producers (owned by household)-intermediary relationship is that a household either starts a business or purchases car, needs to raise q_t from banks, and is thus affected by the intermediary sector's lending decision.

Next, for the households, the utility function of the aggregate households can be written as,

$$E\left[\int_0^\infty e^{-\rho t} ((1 - \phi) \log c_t^y + \phi \log c_t^h) dt\right],$$

with c_t^y and c_t^h are consumption of output and housing service, respectively, from which the first order condition is driven as

$$\frac{c_t^y}{c_t^h} = \frac{1 - \phi}{\phi} D_t,$$

where D_t is the rental rate on housing.

In addition, it is assumed that there is a unit measure of identical households that enters time t with financial wealth W_t . The λ fraction is allocated to the “debt household” who can only purchase the intermediary bond. Then, the remaining $(1 - \lambda)W_t$ is assigned to the “equity household” that, in turn, decides whether to invest in the intermediary capital equity or to purchase the intermediary bond. The financial decision is subject to the above-mentioned equity capital constraint, i.e., maximum amount of equity the equity household would invest will be the sum of reputations at most. Hence, when $\mathcal{E}_t > (1 - \lambda)W_t$ than the economy has a sufficiently high level of reputation for the equity household. Or, in case when $\mathcal{E}_t < (1 - \lambda)W_t$, than the equity household will only place \mathcal{E}_t and buy the riskless bond with the rest.

Coming back to the intermediary sector, a bank makes a portfolio decision of owning housing and working capital given the debt and equity financing. The return on housing capital purchase is,

$$dR_t^h = \frac{dP_t + D_t dt}{P_t},$$

where P_t is the housing capital price. In addition, the return on working capital is,

$$dR_t^k = \frac{dq_t + A dt}{q_t} - \delta dt + \sigma dZ_t + \left[\frac{dq_t}{q_t}, \sigma dZ_t\right].$$

Given the above return equations, the net return on bank equity is,

$$d\tilde{R}_t = \alpha_t^k dR_t^k + \alpha_t^h dR_t^h - (1 - \alpha_t^k - \alpha_t^h)r_t.$$

where r_t is the riskless rate of return on the debt of the banking sector.¹⁰

Then, a Markov equilibrium can be derived after defining a new variable e_t where $e_t \equiv \mathcal{E}_t/K_t$ and setting up a system of ODEs for asset price functions $p(e_t)$ and $q(e_t)$ where $p(e_t) = P_t/K_t$ and $q(e_t) = Q_t$.

The ODE system is solved with the boundary conditions of e . As for the upper bound with $e \rightarrow \infty$, the aggregate equity capital will not bind, i.e., $\mathcal{E}_t > (1 - \lambda)W_t$, thus the economy is essentially frictionless and one can solve for $p(\infty)$ and $q(\infty)$. Next, on lower bound, as e approaches zero, the Sharpe ratio (i.e., intermediaries' portfolio volatility) increases, and the incentive to enter the intermediary sector rises. The authors assume an entry requires physical capital, but it will also increase the aggregate level reputation \mathcal{E} at the conversion rate of β . Then, there is an entry point \underline{e} determined to be the point at which Sharpe ratio equals γ exists that reflects a barrier to the intermediary sector. At this point, the price of capital should not change during the entry although capital conversion to reputation would affect the level of capital since q is measured as per unit of K . However, as for housing capital, decline in K would lower equilibrium consumption and housing rent, thereby lower P as well. That is,

$$\begin{aligned} q'(\underline{e}) &= 0, \\ p'(\underline{e}) &= \frac{p(\underline{e})\beta}{1 + \underline{e}\beta} > 0. \end{aligned}$$

¹⁰Note that α_t^k and α_t^h do not necessarily add up to one.

Next, one can calibrate the model and compare the simulation results to aggregate consumption, investment, intermediary equity, land prices, and expected excess return on corporate bond investment. The simulation of the model shows it can capture the nonlinearity both qualitatively and quantitatively. Thus, by analyzing the policy functions of variables over and under the systemic risk point (entry point), one can compare how the economy behaves differently across normal, distress and extreme systemic risk periods.

To analyze the features of systemic crisis state more closely, the authors impose a sequence of negative quarterly shocks from 2007Q2 to 2009Q4, with which the intermediary equity values of the model match the data during the crisis period. Other key endogenous variables such as land prices, investment, and the Sharpe ratio simulated after imposing this sequence of shocks seem to resemble the observed series, supporting the mechanism through intermediary equity. Furthermore, it is also possible to calculate the probability of a systemic crisis, i.e., the probability that the equity capital constraint binds in next T years. That is, one can fix an initial condition, for example, that the economy is near the distress boundary, and then simulate the model for T years. Then, one can calculate the probability that the economy moves to the distress region, or the probability that the capital constraint would bind. He et al. find the probability has been very low even in early 2007, implying that it would have been not easy to predict the arrival of the financial crisis early on.

Overall, this model suggests one way of how systemic crisis state can be characterized into a stochastic macroeconomic model by making use of a constraint that binds only occasionally. More importantly, the model foreshadows a way of incorporating the linkage between systemic risk and the real economic activities, and provides means to gauge the transition dynamics between different states of the economy. Consequently, it may also be able to answer some of the important policy questions, if the current model is expanded to embody some other features such as labor market and to elaborate production sides.

3.6 Conclusion

After the 2007-2009 financial crisis, great efforts have been made in economics literature to understand what systemic risk is and how it can be measured. However, some key features of systemic risk, e.g., the externality of a firm's decision to the whole system, the co-movement among a number of firms, the self-feeding loop that is contagious, and the adverse effect on the real economy, are difficulties researchers face in achieving an agreed definition of systemic risk, or in developing an effective measure. Still, there are important developments on this line of literature that can help understand the subject and inspire future research in this line.

This paper surveys the recent literature on the systemic risk measure. I start from “model-free” measure of *CoVaR*, extension of Value-at-Risk to quantify the contribution of an individual entity to systemic risk, that can be used and applied to practice very easily and flexibly. Then, I introduce GARCH-based measure, *SRISK*, whose main goal is to quantify the expected capital shortfall of a firm given that the financial sector is in distress. Next, I look at the measures rooted from the CDS pricing model, one of which attempts to capture systemic risk among sovereigns. Finally, I review the recent development that brings in the rare event, i.e., systemic risk crisis, into the DSGE framework with the intermediary sector.

3.7 Appendix

The closed-form solution of Ang and Longstaff (2011)

As mentioned above, the CDS spread can have a closed-form solution where s will be written as following with the current (or time-zeros) values ξ and λ :

$$s = \frac{wE[\int_0^T D(t)(A(\lambda, t)C(\xi, t) + \gamma B(\xi, t)F(\lambda, t))dt]}{E[\int_0^T D(t)A(\lambda, t)B(\xi, t)dt]},$$

where

$$\begin{aligned}
A(\lambda, t) &= A_1(t) \exp(A_2(t)\lambda), \\
B(\xi, t) &= B_1(t) \exp(B_2(t)\xi), \\
C(\xi, t) &= (C_1(t) + C_2(t)\xi) \exp(B_2(t)\xi), \\
F(\xi, t) &= (F_1(t) + F_2(t)\lambda) \exp(B_2(t)\lambda),
\end{aligned}$$

with

$$\begin{aligned}
A_1(t) &= \exp\left(\frac{\alpha(\beta + \psi)t}{\sigma^2}\right) \left(\frac{1 - \nu}{1 - \nu \exp(\psi t)}\right)^{2\alpha/\sigma^2}, \\
A_2(t) &= \frac{\beta - \psi}{\sigma^2} + \frac{2\psi}{\sigma^2(1 - \nu \exp(\psi t))}, \\
B_1(t) &= \exp\left(\frac{a(b + \phi)t}{c^2}\right) \left(\frac{1 - \theta}{1 - \theta \exp(\phi t)}\right)^{2a/c^2}, \\
B_2(t) &= \frac{b - \phi}{c^2} + \frac{2\phi}{c^2(1 - \theta \exp(\phi t))}, \\
C_1(t) &= \frac{a}{\phi} (\exp(\phi t) - 1) \exp\left(\frac{a(b + \phi)t}{c^2}\right) \left(\frac{1 - \theta}{1 - \theta \exp(\phi t)}\right)^{2a/c^2+1}, \\
C_2(t) &= \exp\left(\frac{a(b + \phi)t}{c^2} + \phi t\right) \left(\frac{1 - \theta}{1 - \theta \exp(\phi t)}\right)^{2a/c^2+2}, \\
F_1(t) &= \frac{\alpha}{\psi} (\exp(\psi t) - 1) \exp\left(\frac{\alpha(\beta + \psi)t}{\sigma^2}\right) \left(\frac{1 - \nu}{1 - \nu \exp(\psi t)}\right)^{2\alpha/\sigma^2+1}, \\
F_2(t) &= \exp\left(\frac{\alpha(\beta + \psi)t}{\sigma^2} + \psi t\right) \left(\frac{1 - \nu}{1 - \nu \exp(\psi t)}\right)^{2\alpha/\sigma^2+2},
\end{aligned}$$

and

$$\begin{aligned}
\psi &= \sqrt{\beta^2 + 2\gamma\sigma^2}, \\
\nu &= (\beta + \psi)/(\beta - \psi), \\
\phi &= \sqrt{b^2 + 2c^2}, \\
\theta &= (b + \phi)/(b - \phi).
\end{aligned}$$

See Appendix in Ang and Longstaff (2011) for more details.

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