

## Article

# The Impact of Uncertainty Shocks to Consumption under Different Confidence Regimes Based on a Stochastic Uncertainty-in-Mean TVAR Model

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**Abstract:** Exogenous uncertainty shocks may have different effects on domestic and foreign consumption under different consumer confidence regimes. In this paper, we specify a threshold vector autoregressive (TVAR) model with different consumer confidence regimes to study the response of endogenous macroeconomic variables to exogenous shocks. The evidence shows that in China, compared to high consumer confidence, low consumer confidence dampens consumption both at home and abroad. However, low consumer confidence benefits exports, the source of foreign consumption. A forecast error variance decomposition analysis further confirms the difference in the effects under different consumer confidence regimes. A comparative analysis shows that consumer confidence is much more influential in the US than in China. Our findings differ from those of earlier works, as we introduce stochastic uncertainty to both the mean and heteroscedasticity and apply counterfactual analysis to show the hazard of ignoring stochastic uncertainty in the traditional threshold vector autoregression. Finally, from the ex ante and ex post perspectives, we provide managerial implications for the authorities to tackle economic issues based on different consumer confidence regimes.

**Keywords:** TVAR; uncertainty; consumption; consumer confidence regimes



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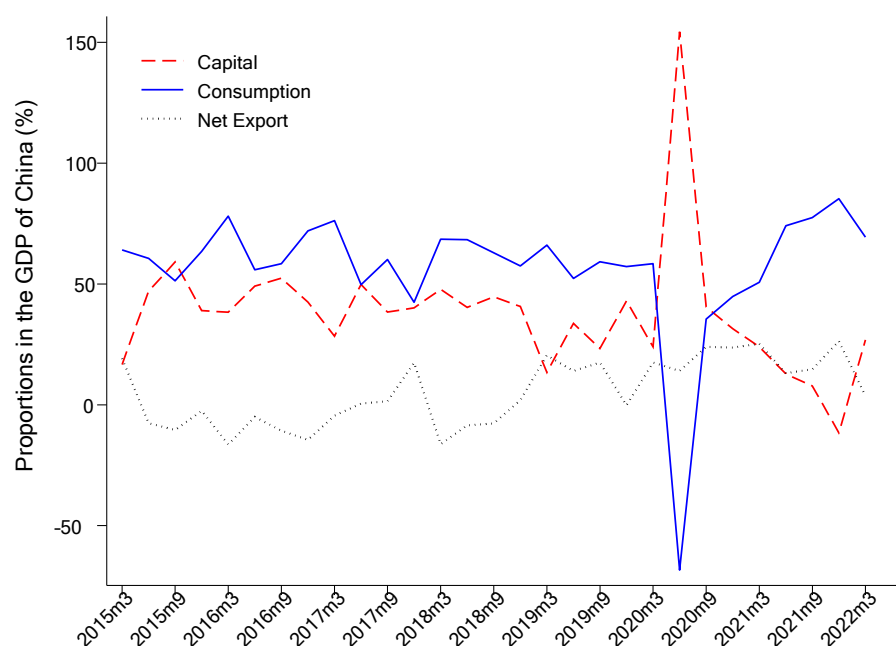


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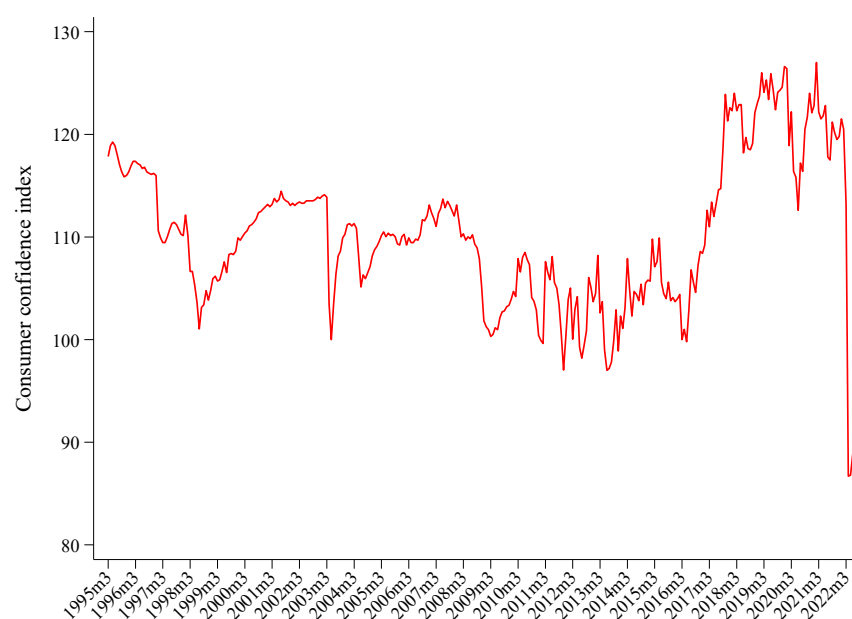
## 1. Introduction

Among the three main “drivers” of the economy, consumption has been the primary engine of economic development in China since 2015 (see Figure 1), except in 2020, when the shock of the pandemic occurred and consumption in China plummeted dramatically. According to “Mainland China Consumer Confidence Index Report” released by Capital University of Economics and Business and Central University of Finance and Economics, the overall confidence of mainland consumers was severely insufficient during early 2020 due to the pandemic shock (available online: <https://www.ccn.com.cn/Content/2020/07-29/1547428331.html> (accessed on 28 December 2022)). However, consumption recovered quickly in early 2021 and once again contributes the most to economic growth among the three main drivers, showing that sustainable consumption plays a very important role in promoting economic sustainability. One of the important reasons for the rapid recovery of consumption may be the rebound of Chinese consumer confidence.

Figure 2 shows that Chinese consumer confidence has displayed dramatic fluctuations since 1995. The extant literature has shown that shifts in consumer sentiment, such as positive shocks to consumer confidence pertaining to output or output growth in the future, can be “self-fulfilling”, showing a positive relationship between consumer confidence and economic activity [1]. In particular, consumption and consumer confidence responding to uncertainty shocks are simultaneously related. This provides the motivation of our study. The specific question that this paper seeks to answer is whether there are differences in the effects of shocks to China’s economic uncertainty on consumption and other macroeconomic variables under different levels of consumer confidence.



**Figure 1.** Proportions of domestic consumption, net export and capital in the GDP of China.



**Figure 2.** Consumer confidence index.

In fact, different consumer confidence regimes may have heterogeneous effects on macroeconomic variables, especially on consumption. For example, some studies find robust evidence that shifts in sentiment affect spending intention [2]. From a historical point of view, the decline in consumption foreshadowed in consumer sentiment was an important contributor to the 1990–1991 recession in the United States [3,4]. However, the exact way in which consumer confidence affects the macroeconomic variables is still vague.

To answer the above question, we establish a stochastic uncertainty-in-mean threshold vector autoregressive (SU-M-TVAR) model and focus on the impact of uncertainty shocks on China's domestic consumption and foreign consumption (i.e., international trade) using Chinese monthly data from March 1995 to December 2021. Compared with the methods used in most empirical studies, the method in our paper has two notable characteristics. First, similar to the settings of current studies [1–3], we allow stochastic uncertainty to

affect not only the endogenous variables directly by introducing it into the mean equation but also the covariance matrix of the disturbance term in the mean equation. Such a setting can incorporate the first- and second-order moments of the endogenous variables into a unified framework, making our model distinctive from the models in previous studies [4]. Second, we use the consumer confidence index (CCI) to describe consumer confidence and define regimes based on whether the CCI falls below an endogenous threshold. The parameters in our model are specified differently under the different regimes, meaning that our model dynamically depends on the different CCI regimes.

The SU-M-TVAR model specification in our paper is flexible because it allows the macroeconomic variables to respond to uncertainty shocks differently under different CCI regimes and thus avoids inconsistent parameter estimation and subsequent inappropriate inference. We find that the macroeconomic effects of uncertainty shocks significantly differ under different CCI regimes. Under the low-CCI regime, uncertainty shocks reduce consumption gradually but decrease imports and increase exports immediately. However, under the high-CCI regime, uncertainty shocks decrease consumption and exports in the short run but increase imports immediately, in contrast to the scenario under the low-CCI regime.

To a certain extent, our allowance for differences in the effects of uncertainty on consumption under different CCI regimes compensates for the defects in the linear structural vector autoregressive (SVAR) model, which ignores the heterogeneity between the two CCI regimes. Doing so makes it difficult to identify the true impact of uncertainty shocks on consumption.

Through counterfactual analysis, we confirm the necessity of using the SU-M-TVAR specification instead of a TVAR specification. We also find that the uncertainty shock can explain a considerable proportion of the fluctuations in consumption and that the proportion explained is higher under the low-confidence regime than under the high-confidence regime through the forecast error variance decomposition analysis. This finding justifies the importance of uncertainty shocks in explaining historical fluctuations and deserves more attention from macroeconomic authorities.

An interesting exercise is to compare the effects of exogenous shocks on the macroeconomy of the two largest economies: the US and China. We find that relative to the outcomes under high consumer confidence, low consumer confidence deteriorates the US economy after an uncertainty shock. In contrast, in China, an uncertainty shock benefits exports and outputs in both the short term and the long term but has different impacts on consumption and imports in the different periods under the low-confidence regime relative to the effects under the high-confidence regime. This finding shows that the US economy is more likely to be influenced by consumer sentiment.

Based on the findings of our paper, the following conclusions can be drawn. First, consumer confidence deserves more attention from the authorities because the consumption effects of China's uncertainty shocks are significantly different under different consumer confidence levels. Second, uncertainty shocks are an important source of consumption volatility in China, especially under the low-confidence regime. Third, the Chinese government usually acts in a timely manner to stabilize the economy to some extent when consumer confidence is low so that the Chinese economy is less influenced by consumer confidence. In contrast, in the US, since there are fewer regulations, the economy is more susceptible to consumer sentiment. Our findings provide new empirical evidence to support our understanding of the impact of the interaction between uncertainty shocks and consumer confidence on China's consumption, and they offer some insights for the authorities.

Consumption matters in economic sustainability. In the model specification of this paper, consumption and other endogenous macroeconomic variables are assumed to be dependent on the uncertainty shocks and the regimes of consumer confidence. The study is linked to the economic sustainability. The contributions of our paper are as follows. First, unlike most of the current literature, our paper directly adds the stochastic uncertainty in logarithmic form subject to an AR (1) process and its lagged versions to the TVAR

model as regressors in the mean equations. At the same time, it allows uncertainty to indirectly affect the endogenous variables in their disturbance terms by driving their variances to change over time. This setting can make the empirical model similar to a theoretical dynamic stochastic general equilibrium (DSGE) model. Notably, although this model is close to the reduced form of a DSGE model with stochastic volatility, there are two main differences between them: (1) our focus is on the average volatility of shocks rather than the volatility of a specific structural shock; (2) the threshold structure neglects some of the interactions that arise naturally in high-order solutions to a nonlinear DSGE model. Second, we introduce the threshold effect of endogenous consumer confidence to capture the impact of uncertainty shocks on macroeconomic variables under different consumer confidence regimes. Third, based on our estimation of the SU-M-TVAR model, we quantify and compare the importance of uncertainty shocks to China's macroeconomic fluctuations under different consumer confidence regimes through forecast error variance analysis. Overall, this paper takes a new step in examining the impact of the interaction of uncertainty shocks and consumer confidence on China's macroeconomy, thus expanding the scope of this research area. Our study has realistic implications for the Chinese economy, especially in the face of numerous instabilities around the world.

## 2. Literature Review

The literature related to our study can be divided into three parts: (1) studies on the impact of uncertainty on consumption; (2) studies on the relationships between consumer confidence and aggregate economic fluctuations; and (3) studies related to methodology.

Although there is no unified definition of economic uncertainty, most scholars connect uncertainty to macroeconomic effects. For example, some scholars define macroeconomic uncertainty as the impact of unanticipated changes in the macroeconomic system, especially on households [5]. In contrast, others define economic uncertainty as “people's uncertainty about possible future conditions” and believe that economic uncertainty can cause economic recessions [6,7]. Economic uncertainty shocks are generally of two types: shocks from pure macroeconomic uncertainty [8]; and shocks from economic policy uncertainty (EPU) [9–11]. These two types of shocks are categorized by the extent of their exogeneity. Macroeconomic uncertainty is usually measured based on an economic survey in which survey participants are provided with probabilistic assessments of future events. For example, macroeconomic news and survey forecasts have been used to construct an ex post realized measure of uncertainty about the state of the economy. EPU shocks, measures of which typically rely on newspapers and other text sources [9,10], can easily be exacerbated by geopolitical uncertainty shocks, which have gradually come to be highlighted by the governments of many countries [12]. Although their definitions are slightly different, these two types of shocks can cause non-negligible impacts on the economy.

However, there are also many discrepancies in research on the influence of economic uncertainty. Some studies have stated that “pure uncertainty” from policy fluctuations is unlikely to play a significant role in economic cycle fluctuations [13]. However, most studies agree that policy uncertainty negatively affects the macroeconomic environment [10]. Higher economic uncertainties foreshadow lower investment and employment and are associated with a higher disaster probability and larger downside risks [12]. An uncertainty shock identified in the data can cause significant declines in output, consumption, investment, and hours worked [14], and even prevent the economy from recovering from a recession [9]. The underlying reasons are that uncertainty induces borrowing costs to climb significantly [15–19], causing households to delay their consumption [19–21]. In addition, uncertainty can affect the overall economy differently in different periods. Short- and medium-term economic uncertainties have negative impacts on economic growth, and the negative impact is stronger in periods of higher economic uncertainty [22]. However, the impact of long-term economic uncertainty is weaker, mainly running through changes in aggregate demand. However, these papers either consider overall uncertainties, neglecting the heterogeneity, or distinguish between different uncertainties based on economic uncer-

tainties or policy uncertainties. Compared to these papers, we try to divide the influences of uncertainties from the perspective of consumer confidence, which can provide us with a unique basis for understanding the relationship between uncertainty and the economy.

Another branch of the literature pertaining to our topic concerns consumer confidence. There are close relationships between consumer confidence and aggregate economic fluctuations. Moreover, there are many explanations for this link in the literature: business cycles [23], sunspot fluctuations [24,25], and changes in expectations due to news and noise in economic fundamentals [26].

However, there are two contrasting approaches to examining whether this relationship is causal. The first relies on the theory of “animal spirits” and posits autonomous fluctuations in beliefs that, in turn, have causal effects on economic activity [27,28]. This approach portrays exogenous movements in consumption as a cause of business cycles and argues that the cause of a recession is a powerful, long-lasting negative consumption shock associated with an exogenous shift in pessimism that had a causal effect on overall aggregate demand.

The second approach to confidence is the “information” or “news” view, which suggests that a relationship between innovations in consumer confidence and subsequent macroeconomic activity arises because confidence contains fundamental information about the current and future states of the economy. For example, sentiment is bullish following good news and bearish following bad news [29]. Consumption supplies a proxy for news that consumers receive about future productivity that otherwise does not appear in the information sets of econometricians [30]. The news view of confidence supposes that confidence innovations might contain similar information. In this view, the impact of confidence on the macroeconomy should be the same under different regimes.

These two opposite approaches show that it is necessary to examine the role played by consumer confidence in the transmission of the influences of uncertainty shocks on the real macroeconomy. However, the econometric methods used in the current literature cannot capture this relationship.

Methodologically, the cross-sectional information in state data from the University of Michigan’s (2016) Surveys of Consumers has been used to examine the relationship between consumer confidence and economic activity [31]. The research team at the University of Michigan utilizes a predicted relationship between political partisanship and economic confidence concerning national economic prospects as an instrumental variable to eliminate endogeneity.

To investigate whether innovations to consumer sentiment have a causal effect on consumption, some scholars use the variation in consumer sentiment associated with political preferences [32]. They match individual consumers’ expectations of future economic conditions from a consumer sentiment survey to these consumers’ spending intentions. These scholars find that consumers who have a better economic outlook report higher positive spending intention.

Current studies often use a structural VAR setup with restrictions at various frequencies to identify sentiment shocks [23,33]. They find that while accounting for a large share of confidence, confidence shocks explain little of output and inflation in the short run. Scholars also estimate stochastic processes with time-varying volatilities for US government tax and spending policies and then feed the estimated processes into a calibrated standard new Keynesian model [22]. Their main finding is that “fiscal volatility shocks can have a sizable adverse effect on economic activity”. In terms of the macroeconomic effects of US EPU, some scholars construct an SVAR model in which the volatility of structural shocks can exert a direct impact on the endogenous variables [1]. They find that monetary policy uncertainty and fiscal policy uncertainty have important effects on the volatility of key economic variables of the United States. Other scholars estimate a bivariate VAR model with the news-based trade policy uncertainty (TPU) index and real business fixed investment per capita and find that prolonged periods of uncertainty reduce investment [12].

Additionally, Bayesian time-varying parameter structural VAR models with stochastic volatility, identified using mixed identification, are often used to explore the effects of policy uncertainty shocks within the context of the Great Recession [34,35]. Recently, some scholars have proposed a new model for measuring uncertainty and its effects on the economy based on a large VAR model with stochastic volatility driven by common factors in macroeconomic and financial uncertainty [36].

Compared to the traditional econometric methods used in the abovementioned literature, our novel model overcomes two disadvantages. First, we capture the heterogeneity in consumer confidence, which is neglected in the above literature. Second, we succeed in embedding uncertainty into agents' (in)ability to form predictions on the fundamentals of the economy. Therefore, by specifying a SU-M-TVAR model, we manage to study the effect of uncertainty shocks on consumption both at home and abroad under different confidence regimes in China.

### 3. SU-M-TVAR Model

As noted above, the macroeconomy, especially consumption, may behave differently under different consumer confidence regimes. To study the effect of the interaction of uncertainty shocks and consumer confidence on China's macroeconomic variables, we divide the economy into two regimes based on the CCI and nest them into a SU-M-TVAR model.

#### 3.1. Model Specification

There are three types of variables in our model specification: (i) five endogenous variables: the CCI, consumption, exports, imports, and output; and (ii) the stochastic uncertainty variable  $\lambda_t$ , which is obtained based on the following AR (1) process [36]:

$$\ln \lambda_t = \alpha + F \ln \lambda_{t-1} + \eta_t \quad (1)$$

where  $\alpha$  and  $F$  are unknown constants and  $\eta_t$  is i.i.d innovations with a 0 mean and variance  $Q$  denoting the uncertainty shock; and (iii) the CCI regime variable  $\tilde{S}_t = 1\{CCI_{t-d} \leq CCI^*\}$ , which depends on the unknown  $d$ -order lag of the CCI and an unknown threshold parameter  $CCI^*$ ; that is, when the CCI is lower than the critical value  $CCI^*$ ,  $\tilde{S}_t = 1$ , which means that the economy is in the "low-CCI regime"; conversely, when the CCI is higher than the critical value  $CCI^*$ ,  $\tilde{S}_t = 0$ , which means that the economy is in the "high-CCI regime". Therefore, the CCI determines the regimes of the economy.

Referring to the VAR model framework introduced by current studies [2,37], we specify the following SU-M-TVAR model with the two consumer confidence regimes:

$$Z_t = \left( c_1 + \sum_{j=1}^M \beta_{1j} Z_{t-j} + \sum_{j=0}^J \gamma_{1j} \ln \lambda_{t-j} + \Omega_{1t}^{1/2} e_t \right) \tilde{S}_t + \left( c_2 + \sum_{j=1}^M \beta_{2j} Z_{t-j} + \sum_{j=0}^J \gamma_{2j} \ln \lambda_{t-j} + \Omega_{2t}^{1/2} e_t \right) (1 - \tilde{S}_t) \quad (2)$$

where  $Z_t = (CCI_t, Consumption_t, Export_t, Import_t, Output_t)'$  is a vector composed of the five endogenous macroeconomic variables,  $M$  is the lagged order of the endogenous variables, and the economic uncertainty variable  $\lambda_t$  (defined by Equation (1)) and its  $J$ -order lag directly affect the endogenous variables. The model allows structural differences between the two regimes of the economy: in addition to the differences in the structural coefficients,  $c_i$ ,  $\beta_{ij}$ , and  $\gamma_{ij}$ , the two random disturbance terms  $\Omega_{1t}^{1/2} e_t$  and  $\Omega_{2t}^{1/2} e_t$  have different variance structures, where  $e_t$  is an i.i.d random vector with a 0 mean and unit variance matrix that is uncorrelated with the uncertainty shock  $\eta_t$ , and the variance covariance matrices  $\Omega_{1t}$  and  $\Omega_{2t}$  are time-varying:

$$\Omega_{1t} = A_1^{-1} H_t A_1^{-1'} \quad (3)$$



$$\Omega_{2t} = A_2^{-1} H_t A_2^{-1'} \quad (4)$$

where  $A_1$  and  $A_2$  are lower triangular matrices obtained through diagonal decomposition and  $H_t$  is a diagonal matrix that is affected by the uncertainty variable  $\lambda_t$  through the following equation:

$$H_t = \lambda_t S \quad (5)$$

$$S = \text{diag}(s_1, s_2, s_3, s_4, s_5) \quad (6)$$

Here,  $\{Z^*, \alpha, F, d, c_i, \beta_{ij}, \gamma_{ij}, A_i, s_1, s_2, s_3, s_4, s_5, i = 1, 2\}$  are unknown coefficients or matrices.

From Equations (2)–(6), the economic uncertainty variable  $\lambda_t$  and its lags directly affect the endogenous variables (the systematic part of the model) and simultaneously influence the covariance matrix of the model disturbance terms by driving  $H_t$  to change over time. This means that a positive uncertainty shock ( $\eta_t > 0$ ) increases uncertainty in the economy, making the eigenvalues of the covariance matrix of the disturbance terms increase, which in turn leads to a sudden deterioration in the accuracy with which agents can forecast  $Z_{t+k}$ . Simultaneously, by letting  $\lambda_t$  enter Equation (2), our framework allows output, consumption, imports and exports to adjust endogenously to the newer, riskier (and less predictable) state of the economy. Unlike the specification in extant research [4], the stochastic uncertainty-in-mean specification examines the first- and second-order moments of the economic variables in a unified, internally consistent framework. The occurrence of regime shifts associated with periods of consumer confidence fluctuation captures the time-varying nature of the underlying transmission mechanisms: the two sets of parameters  $\{c_i, \beta_{ij}, \gamma_{ij}, \Omega_{it}\}_{i=1,2}$  can capture the behaviors of the economy in periods of “high” and “low” confidence determined by the CCI. We empirically examine whether consumer confidence has an amplifying effect on the macroeconomic effects of uncertainty shocks by comparing the responses of macroeconomic endogenous variables to the impulses from uncertainty shocks  $\eta_t$  under the two regimes.

### 3.2. Model Estimation Procedure

Note that given the uncertainty process  $\{\lambda_t\}$ , model (2) degenerates into a threshold VAR model with a known heteroscedasticity form, which can be transformed into a standard TVAR model through generalized least squares (GLS) transformation [38]. Based on this idea, the estimation of model (2) is predicated on the following steps:

Step 1: Set the initial uncertainty state variable  $\ln \lambda_t = 0$ . Assume that the conditional posterior distribution of the lag term coefficient of model (2) is a multiple normal distribution. The threshold parameter is obtained by sampling from the nonstandard posterior distribution through the Metropolis step [39], which divides the observation sample into two regimes. We then sample from the normal distribution to obtain the autoregressive coefficients in the VAR model, thereby calculating the residual vector of the VAR model (2) under the two regimes;

Step 2: Given the residual sequence obtained in the first step, the posterior distribution of matrices  $A_1$  and  $A_2$  is acquired through the method in [40]. The variance  $S$  is obtained by sampling from an inverse gamma distribution. Given these parameters, a new state variable  $\lambda_t$  is sampled using the Metropolis algorithm [41];

Step 3: Given  $\lambda_t$  sampled in the second step, repeat the above two steps until the estimated  $\lambda_t$  converges, and obtain the parameter estimation of the model.

After estimating model (2), we apply the generalized impulse response method [42] to perform impulse response analysis of uncertainty shocks. Specifically, after estimating the posterior distribution of all parameters, we obtain the conditional expectations of the endogenous variables in the two cases by simulating the model with and without shocks and calculate the difference between the two conditional expectations to obtain the impulse response. Given a regime ( $s = \tilde{s}_t$ , i.e.,  $s = 0, 1$ ) and a specific historical path ( $Y_{t-1}^s$ ), the generalized impulse response is calculated as  $IRF_t^s = E(Y_{t+k} | \Psi_t, Y_{t-1}^s, \mu) - E(Y_{t+k} | \Psi_t, Y_{t-1}^s)$ , where  $\Psi_t$  represents all the parameters and hyperparameters of the model,

$k$  is the horizon under consideration, and  $\mu$  denotes the shock of interest (in our case, an increase in uncertainty).

The model above has two characteristics. On the one hand, the switch among regimes is treated as endogenous in our calculation, and the economy can freely move from low confidence to high confidence and vice versa over the considered horizon, depending on the sign and size of the shock. This allows us to take the dynamics of both the endogenous variables  $Y_t$  and the parameters  $\Psi_t$  into account. On the other hand, even within a given initial regime  $s$ , the responses depend on the specific history of the system prior to the shock ( $Y_{t-1}^s$ ). Intuitively, the economy will respond differently when the CCI is at its historical minimum and when it is just below its critical threshold, even though both scenarios denote low-confidence regimes. Therefore, we focus on the average responses of the endogenous variables in each regime. The low-confidence (high-confidence) response is thus calculated as the average response to the shock of interest across all histories that belong to regime  $s = 1$  ( $s = 0$ ). By averaging over histories, we aim to obtain a representative picture of the dynamics associated with each regime.

### 3.3. Advantages of the Model Specification

Most existing studies regard uncertainty as an endogenous macroeconomic variable and form a VAR model following a two-step estimation method [12]. An uncertainty variable, for example, the TPU index, is first constructed and then plugged into the SVAR model as one of its endogenous variables. This method separates uncertainty from the fundamentals of the economy and does not reflect reality. In contrast, in our specification, a model-based measure of uncertainty is directly linked to agents' (in)ability to form predictions on economic fundamentals, which avoids any possible bias from using a proxy variable usually weakly related to macroeconomic predictability. The stochastic uncertainty-in-mean specification employed in this paper has the advantage of modelling the economy's first and second moments in a unified framework.

In our model, agents form expectations  $E_t Z_{t+h}$  based on the following steps: they estimate  $\lambda_t$ , project it forward based on its persistence ( $F$ ), and determine its influence with the economy ( $\gamma_{ij} \neq 0$ ) within both regimes. These expectations are then integrated into the impulse response analysis. Such integration cannot be realized in a two-step procedure where uncertainty is first estimated using a forecasting model and then linked to macroeconomic fundamentals through a separate set of regressions.

## 4. Data and Regression Analysis

### 4.1. Data

We use Chinese monthly data from March 1995 to June 2021 and study five endogenous variables, i.e., the CCI, consumption growth rate, export growth rate, import growth rate, and output growth rate. The CCI is acquired from the National Bureau of Statistics, and its range is from January 1990 to February 2022. We gather the rest of the data from the CEInet Statistics Database. We take the current year-on-year growth rate (the year-on-year growth rate of the monthly data is calculated as the rate of change in the current month expressed over the corresponding month of the previous year) of industrial added value as a proxy for the output growth rate, the year-on-year growth rate of total retail sales of consumer goods as a proxy for the consumption growth rate, and the year-on-year growth rates of the value of exports and imports as a proxy for the export and import growth rates, respectively.

We conduct unit root tests on each of the five endogenous variables and find that they are all stationary (see Table A1 in the Appendix A). Furthermore, combining the available data ranges of these variables, we take their intersection as our final data range: March 1995 to December 2021.

The descriptive statistics of the five variables are listed in Table 1. The table shows that the growth rate of exports on average is the largest over the 26 years, whereas the variable with the largest variance is imports. In terms of the coefficient of variation, the fluctuation in consumer confidence is relatively small compared to that in other variables



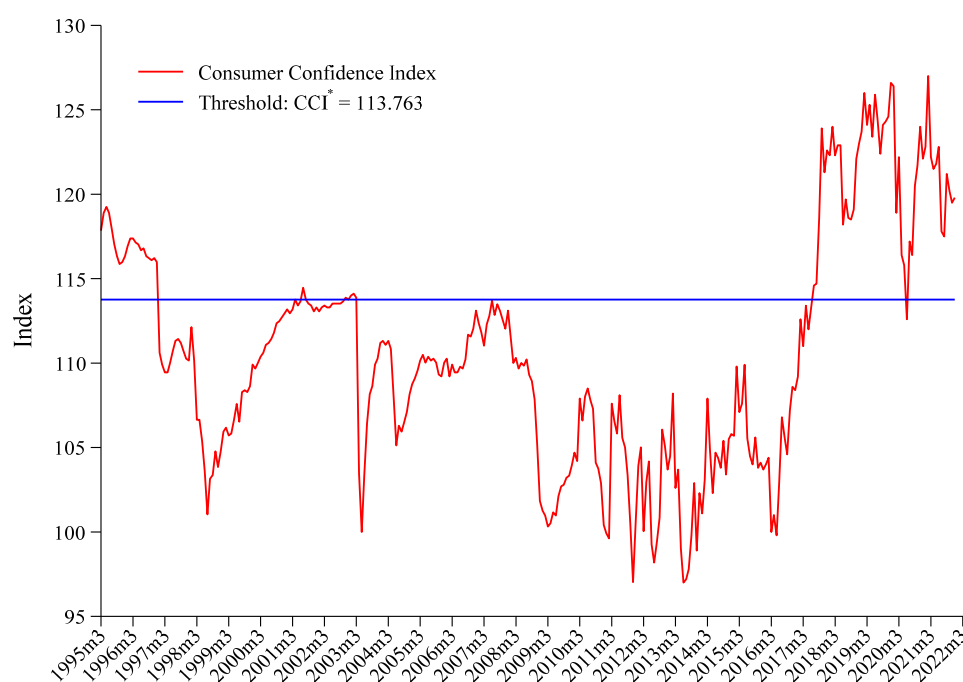
such as output and consumption. The largest fluctuation is in imports or exports, which is consistent with the reality in China. This finding implies that using the CCI as the regime variable to define a two-regime model may be more suitable for studying the relationship among the five endogenous variables.

**Table 1.** Descriptive Statistics.

Variable	Obs	Mean	Std Dev	Coefficient of Variation (%)	Min	Max
CCI	322	110.53	6.768	6.12	97	127
output	322	11.017	4.475	40.62	−1.1	23.2
consumption	322	12.494	5.895	47.18	−15.8	34.2
exports	322	14.458	18.501	127.96	−40.6	154.6
imports	322	14.034	19.02	135.53	−43.1	85.5

#### 4.2. Initial Study on the Model Specification

We first show that the TVAR model without stochastic uncertainty in the mean and the variance (i.e.,  $\lambda_t = 1$ ,  $\ln \lambda_{t-j} = 0$  for  $j = 0, 1, 2, \dots, J$ ) in model (2) is inadequate to illustrate the relationships among the five endogenous variables. For the monthly data, we choose maximum lags equal to 12 and estimate the different models (here, we apply R package tsDyn to estimate the TVAR model. For brevity, the details of the estimated parameters are not reported here but are available upon request) with  $M = 1, 2, \dots, 12$ . By applying the Akaike information criterion (AIC) and Bayesian information criterion (BIC), as well as the log-likelihood values (see Tables A2–A4 in the Appendix A), we ultimately choose  $M = 12$  for the lag order of the endogenous variables and  $d = 2$  for the lag order of the threshold variable. The estimated threshold value is  $CCI^* = 113.763$ , which is displayed in the horizontal line of Figure 3. The two periods (from January 2001 to January 2003 and from June 2006 to January 2008) with high CCI levels are not marked in the high-CCI regime. Hence, the specification without stochastic uncertainty may not be sufficient to illustrate the case.

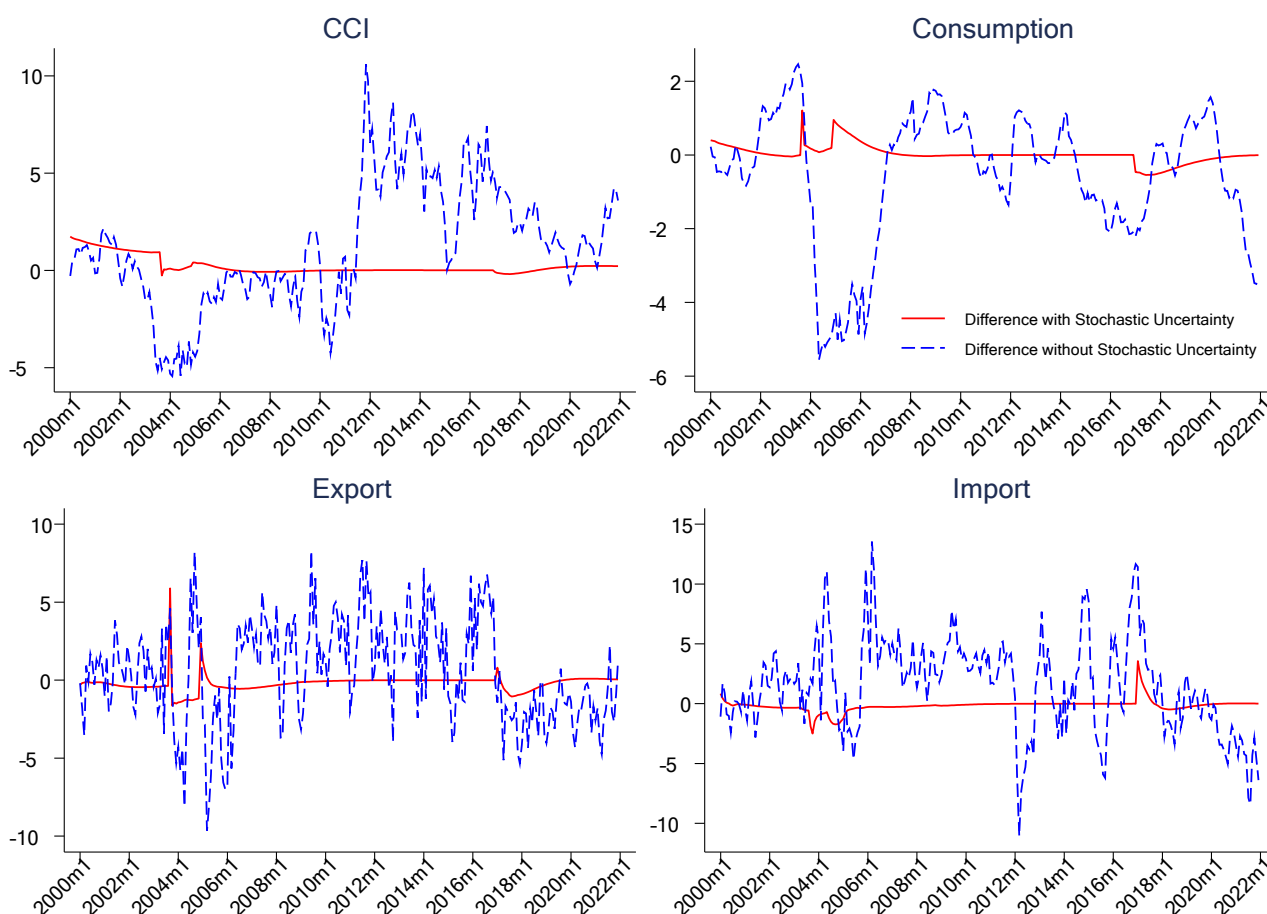


**Figure 3.** Results of the TVAR model without stochastic uncertainty in the mean.

We further use counterfactual analysis to show that the TVAR model without stochastic uncertainty is inadequate. The volatilities of all levels of shock in the counterfactual world

are set to be constant at their sample means. This “constant uncertainty” world is simulated using the estimated TVAR model. We first simulate the data under the counterfactual scenario and then calculate the difference between the actual and simulated monthly series as a measure of the importance of uncertainty shocks. This difference is a direct gauge of the role played by uncertainty shocks.

The dotted curves in Figure 4 are the differences between the actual data of the endogenous variables and their model-fitted data from the counterfactual specification without stochastic uncertainty. The dotted curve for CCI shows that the differences between the CCI and its simulated counterpart after 2012 are positive, indicating that ignoring uncertainty shocks causes an underestimation of the CCI. This finding means that the TVAR specification not specifying stochastic uncertainty has quite a large bias in illustrating the dynamics of the CCI. Similarly, the dotted curves for exports, consumption and imports, also in Figure 4, show that ignoring uncertainty shocks also induces large biases, with especially serious overestimates in these variables for the period during the global pandemic after 2020. Ignoring uncertainty shocks leads to a biased picture of the contribution of uncertainty shocks to consumption both at home in China and abroad.



**Figure 4.** Differences between actual data and the fitted data of the four endogenous variables.

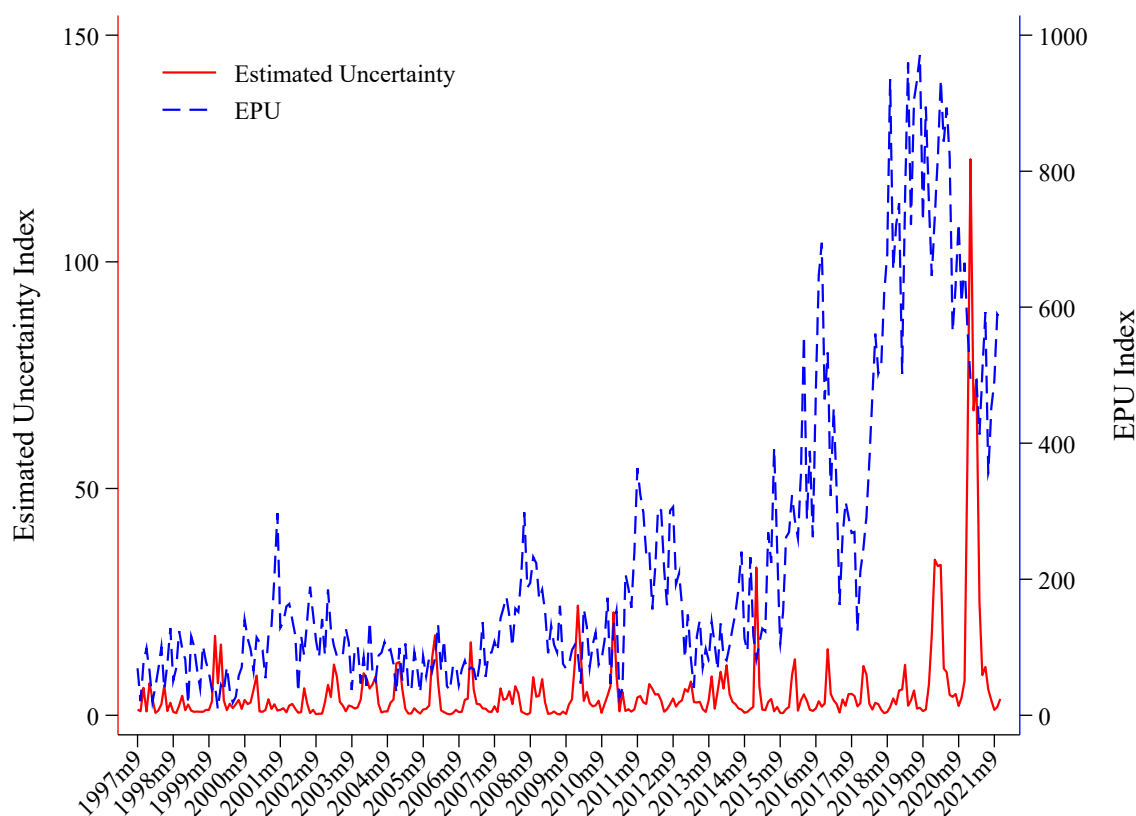
#### 4.3. SU-M-TVAR

We now add uncertainty shocks to the threshold VAR model and estimate the SU-M-TVAR model. We focus mainly on the uncertainty variable  $\lambda_t$  and the threshold value  $CCI^*$  and examine the necessity of using the specification.

First, to see whether our estimated uncertainty ( $\lambda_t$ ) can reflect the actual world, we calculate its correlation with the EPU index [9], which captures uncertainty from news, policy, market, and economic indicators, is publicly available and easily replicated, and it can be expanded for longer periods [9], is more comprehensive than previous indices,

and is usually regarded as a reference index for a country's economic policy uncertainty. The correlation is 0.2266 and is significant at the 0.01% level, showing that the estimated uncertainty can capture uncertainty in the macroeconomy.

Figure 5 shows that the estimated uncertainty follows the economy more closely than EPU, especially during extremely uncertain periods such as the COVID-19 pandemic, a period for which EPU begins to slide down but our estimated uncertainty spikes to an abnormally high point. This finding arose partly because we take different regimes of the economy into account.



**Figure 5.** Estimated uncertainty and EPU.

Second, the estimated threshold value is 110.36, which is similar to the abovementioned TVAR result. To see whether the estimate can reflect the actual world, we present the CCI and the estimated threshold in Figure 6, where the shaded regions are marked when the CCI is lower than the threshold. As defined in model (2), consumers are reluctant to spend money when the CCI is lower than the threshold value; conversely, they are willing to increase their expenditure when the CCI is higher than the threshold. Figure 6 shows that the CCI was below the critical value during the Asian financial crisis and the global financial crisis. However, after the outbreak of COVID-19, although the CCI dropped to a relatively low level, it did not reach the threshold value. Two possible factors could account for this phenomenon: first, the government took timely actions to stimulate consumption during the pandemic (for example, on 28 February 2020, the National Development and Reform Commission (NDRC) issued the “Implementation Opinions on Promoting the Expansion of and Quality Improvement in Consumption and Accelerating the Formation of a Strong Domestic Market”, enhancing the consumption environment and boosting the level of consumption; under the guidance of this opinion, provincial governments actively took actions including the implementation of a consumer voucher policy and measures to improve consumption levels, given their own economic conditions); second, the CCI had already levelled off above the threshold to a large extent before the COVID-19

outbreak. However, if we check the CCI growth rate over time, we find that this decline is still relatively moderate compared to previous decreases, which means that the second factor is an implausible explanation for the phenomenon.

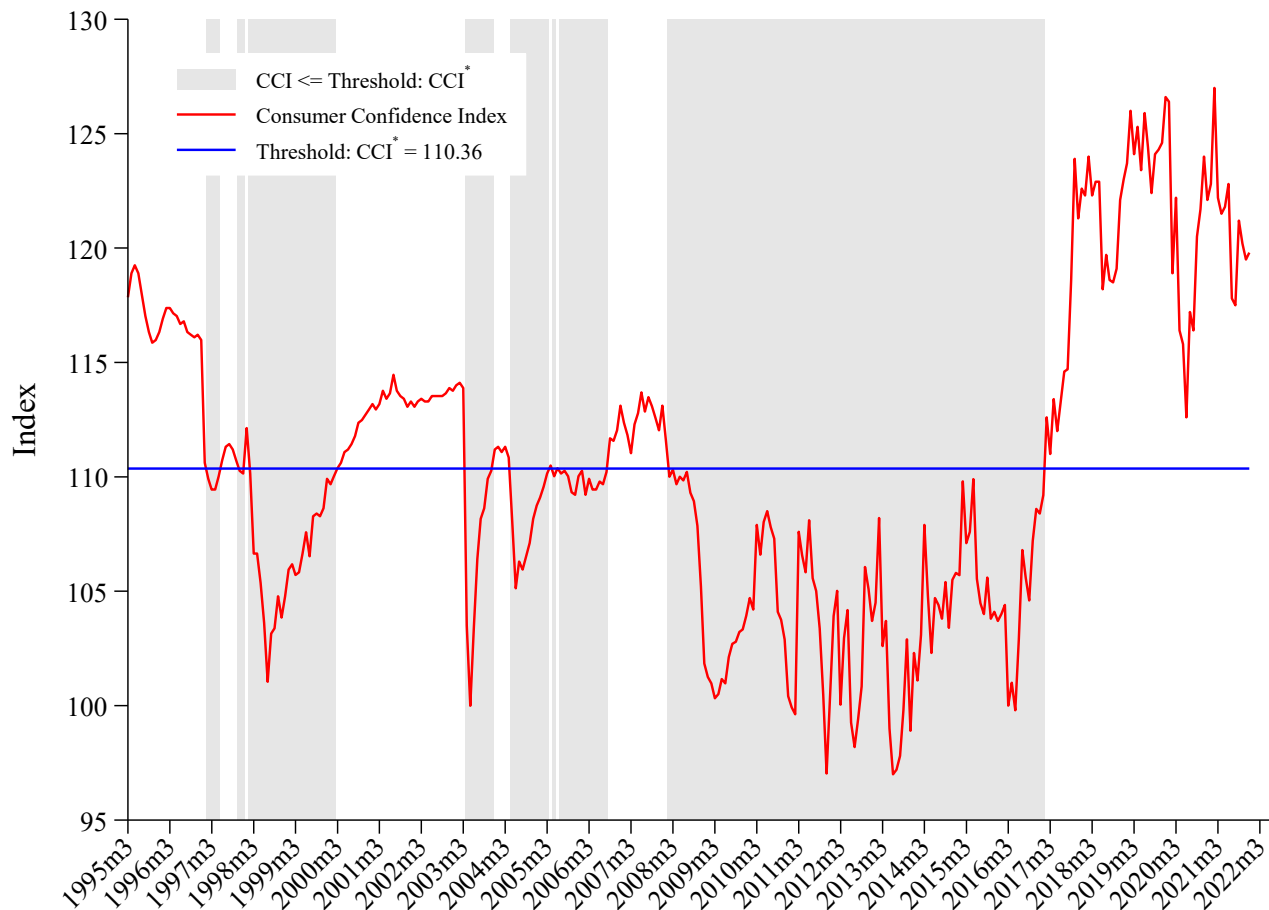


Figure 6. CCI and the estimated threshold.

Compared with the estimated threshold in the case of specifying no stochastic uncertainty (Figure 3), Figure 6 shows that the two periods with high CCI levels (from January 2001 to January 2003 and from June 2006 to January 2008) are now successfully marked in the high-CCI regime. Hence, this specification with stochastic uncertainty can illustrate the actual world better than the previous specification without stochastic uncertainty.

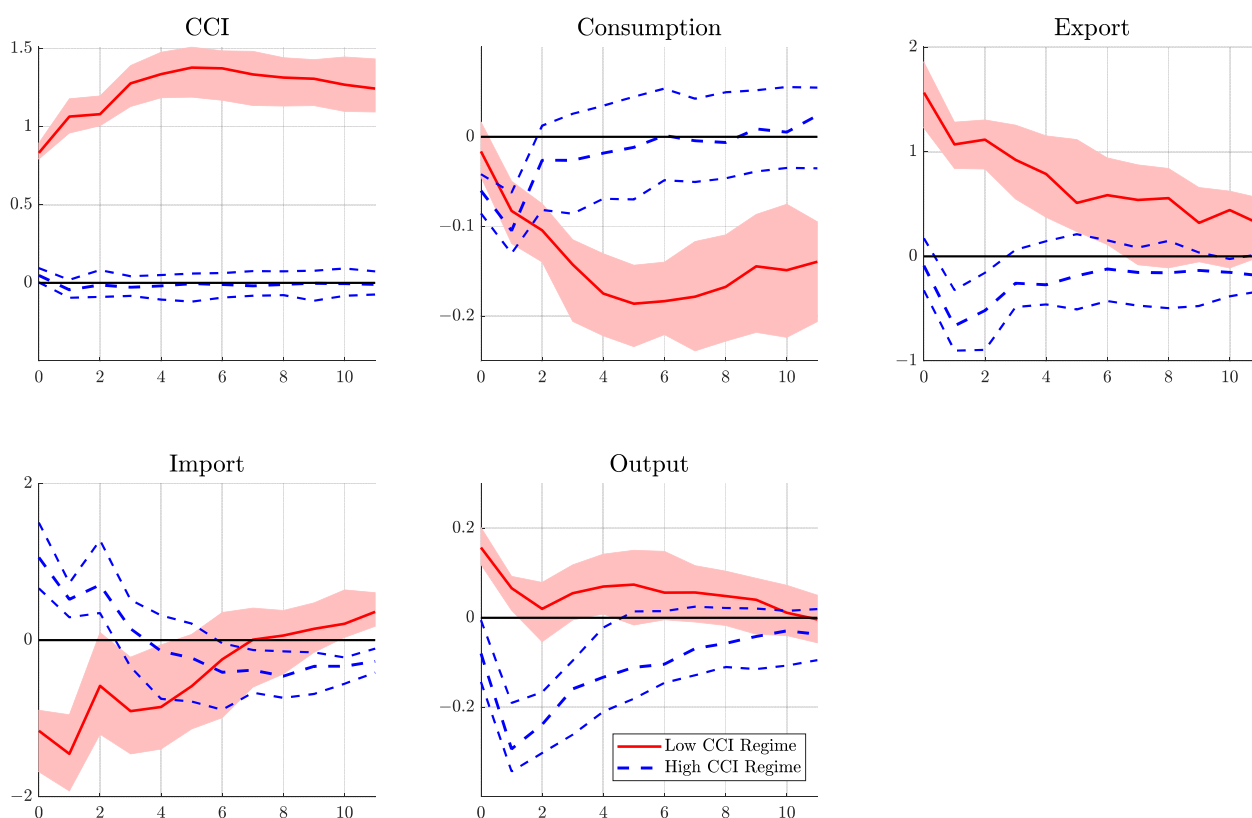
Moreover, the SU-M-TVAR estimation can capture macroeconomic variables more precisely than the previous TVAR estimation without specifying stochastic uncertainty. We calculate the differences between actual data and the model-fitted data from the estimated model in the specification with stochastic uncertainty, which is depicted by the solid lines in Figure 4. The difference for each endogenous variable is close to zero, showing that the actual and fitted data are basically identical for most periods across the four variables. Even if there are a few periods with some abnormal differences between the volatilities simulated by the SU-M-TVAR model, the magnitudes of the differences are still even smaller than those simulated by the TVAR model without uncertainty. This result further justifies the necessity of specifying the SU-M-TVAR model in our study.

## 5. Impulse Response and Variance Decomposition

Our model specification in Section 4 has been proven to be more suitable for illustrating endogenous macroeconomic variables than its counterpart without stochastic uncertainty. Now, we apply it for the impulse response and variance decomposition analysis.

### 5.1. ImpulseR

We first conduct the analysis on the impulse response of the uncertainty shock in the model. Figure 7 plots the median generalized impulse responses of the endogenous variables with respect to a one-standard-deviation increase in the exogenous shock  $\eta_t$ . Here, the red solid line represents the impulse response of the low-CCI regime (i.e., the regime in which the CCI is lower than the estimated threshold), and the shaded area around the solid line is the 68% confidence interval (plus or minus one standard deviation). The solid blue line represents the impulse response for the high-CCI regime (i.e., that in which the CCI is higher than or equal to the estimated threshold), and the area between the two blue dashed lines is the 68% confidence interval.



**Figure 7.** Macroeconomic effects under different CCI regimes.

Figure 7 shows that the responses of all five endogenous variables are different under different regimes. A positive exogenous shock triggers an abrupt jump in consumer confidence under a low-CCI regime, while it has little effect on consumer confidence under a high-CCI regime. Under the low-CCI regime, consumption falls and slows down for a relatively long period after a one-unit exogenous uncertainty shock. However, under the high-CCI regime, consumption is negatively affected in the short run, although this negative impact disappears very quickly.

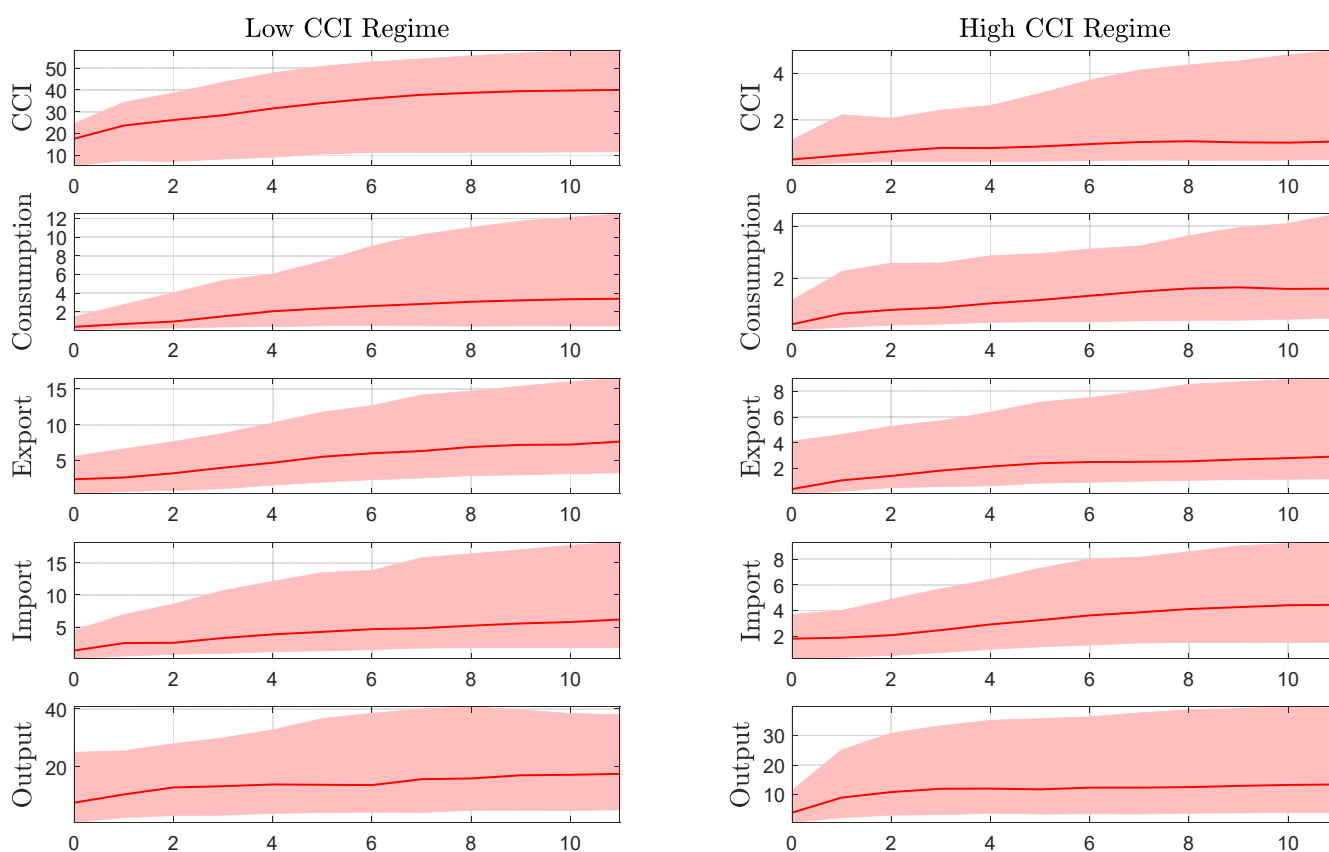
In terms of imports, under the low-CCI regime, the exogenous shock decreases imports immediately, but they gradually recover afterwards, although this impact is insignificant. Under the high-CCI regime, the impact is almost the opposite. The exogenous shock boosts imports immediately, and this positive impact decays over time. In contrast, the impacts on exports under the two regimes are quite the opposite of the impacts on imports under the corresponding regimes. This finding means that when people do not have sufficient confidence to consume, they reduce their purchases from abroad and sell more overseas if they face an uncertainty shock. However, when people have sufficient confidence to consume, the uncertainty shock induces them to buy more from abroad and sell less overseas.



With respect to output, under the low-CCI regime, the overall response of output to the uncertainty shock decreases but is always positive and gradually disappears over time in the long run. In contrast, under the high-CCI regime, the overall response effect is always negative, decreasing in the short run, then gradually increasing and eventually converging to zero. This finding means that under a high-CCI regime, the response of output to the exogenous shock is negative in the short run but eventually decays to zero in the long run. Overall, the positive exogenous shock of  $\eta_t$  may cause more serious repercussions in the high-CCI regime than in the low-CCI regime.

### 5.2. The Importance of Uncertainty Shocks

Based on the above impulse response analysis, we further examine the importance of uncertainty shocks to China's macroeconomic fluctuations through forecast error variance decomposition. Figure 8 shows the forecast error variance decomposition of each endogenous variable under the two regimes by the uncertainty shock, where the solid line represents the explained proportion (%) of the forecast error variance and the shadow is the 68% confidence interval estimation.



**Figure 8.** Forecast error variance decomposition of macro variables.

First, it is obvious that the forecast error variance in consumer confidence can be explained to a much larger extent in the low-CCI regime (40%) than in the high-CCI regime (less than 2%).

Second, 18% of the forecast error variance in output under the low-CCI regime can be explained under the low-CCI regime, whereas this figure drops to 14% under the high-CCI regime.

For consumption, under the low-CCI regime, exogenous uncertainty shocks can explain approximately 4% of the forecast error variance in consumption; under the high-CCI regime, this figure is less than 2%.

For exports and imports, we see that uncertainty shocks can explain a very similar percentage of their forecast error variance, approximately 8% and 6%, under the low-CCI regime, respectively. However, under the high-CCI regime, uncertainty shocks can explain only 3% of the variance in exports and 4% of the variance in imports.

The above forecast variance decomposition analysis in Figure 8 further confirms that it is necessary to specify different regimes to study the Chinese macroeconomic effects of uncertainty shocks. The comprehensive results show that uncertainty shocks can explain a higher proportion of the fluctuations in each endogenous variable under the low-CCI regime than under the high-CCI regime. The effect of uncertainty shocks on the economy in the low-CCI regime is greater than that in the high-CCI regime. This finding implies that consumer confidence plays a more important role when it is at a lower level than when it is at a higher level. The construction of consumer confidence is quite important in economic development. The authorities should thus take it into account when making related policies.

## 6. Comparison to the US

For comparison, we collect US data with the same time range and variables as our Chinese data. However, since the year-on-year growth rate of industrial added value and total retail sales of consumer goods in the US are quarterly data, we interpolate them into monthly data. The Dickey–Fuller test with drift shows that the five variables (CCI, consumption, exports, imports, output) are all stationary (see Table A5 in the Appendix A).

We then use the same method to calculate the impulse response function of the CCI, consumption, exports, imports, and output (see Figure 9). First, let us look at US consumer confidence. Unlike confidence in China, consumer confidence plummets to approximately  $-450$  under both regimes and then gradually recovers. The difference in the responses of the CCI to an exogenous shock under the low-CCI regime and high-CCI regime is not conspicuous, which means that consumer sentiment is much more susceptible to exogenous shocks in the US than to exogenous shocks in China. This finding is in line with the extant results in [31], who also show that consumer confidence in the US is easily swayed by exogenous volatility.

For consumption, uncertainty influences consumption in the US under the low-CCI regime in a manner that is quite similar to how it influences consumption in China. In contrast, under the high-CCI regime, the effect is quite different in that uncertainty shocks have a persistent negative effect on consumption in the US.

For exports, exogenous shocks decrease the exports of the US in the short run and then increase them under the low-CCI regime, while exogenous shocks almost always increase US exports under the high-CCI regime. US exports recover more quickly than Chinese exports, although they still drop slightly in a short period. Comparing the response dynamics of Chinese exports (Figure 7) and US exports (Figure 8), we find that the most obvious difference is that the response of US exports to a one-standard-deviation positive shock under the high-CCI regime is larger than that under the low-CCI regime. In contrast, the response of Chinese exports under the high-CCI regime is lower than that under the low-CCI regime. China's exports always decrease under the low-CCI regime, while US exports increase under both the low- and high-CCI regimes. It seems that the CCI regimes are not very important in the response dynamics of US exports.

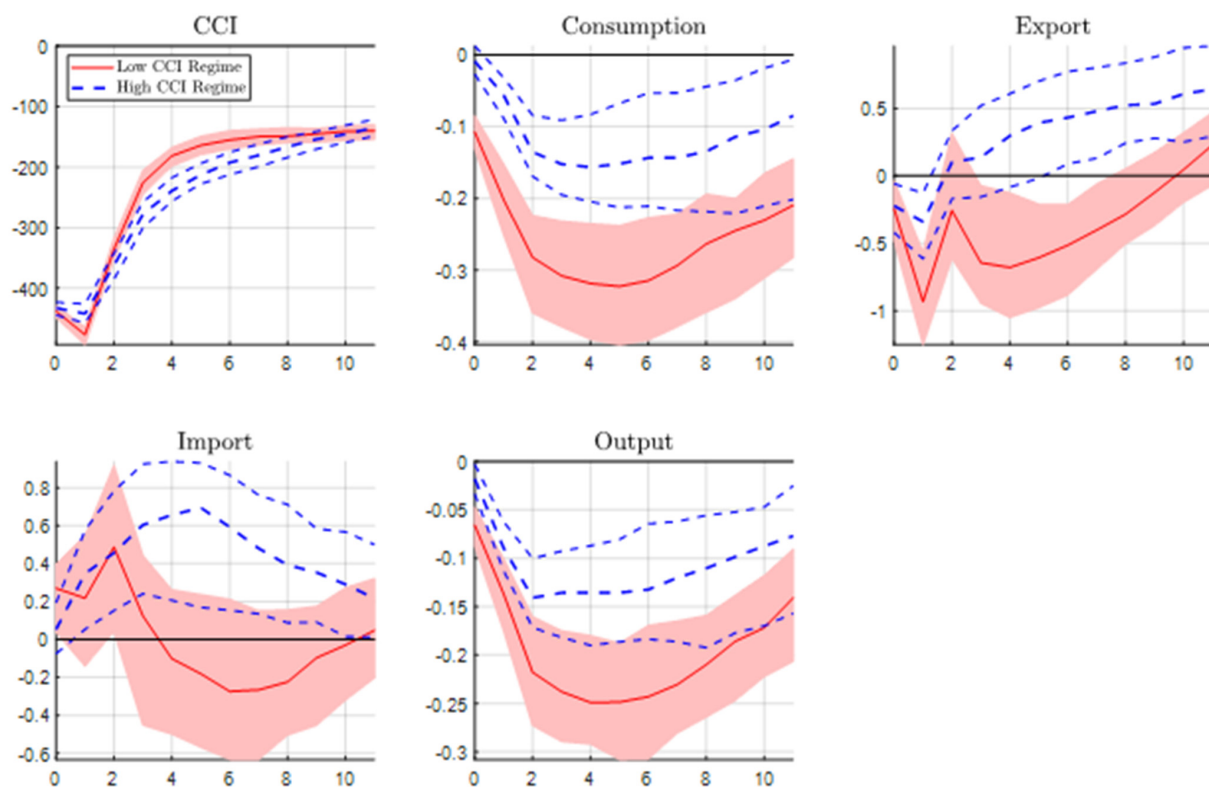


Figure 9. Macroeconomic effects in the US under different CCI regimes.

For US imports, under the low-CCI regime, exogenous shocks initially increase imports over a long period; then, the effect decreases. However, under the high-CCI regime, uncertainty shocks increase imports in a short period and then decrease them afterwards. This finding is also different from the case of China, where the effect always decreases under the low-CCI regime and increases under the high-CCI regime.

Finally, the response of US output to uncertainty shocks under the high-CCI regime behaves similarly to the response of Chinese output. However, shocks reduce rather than increase the output of the US under the low-CCI regime. Similar to the case of exports, the largest difference is that the response of US output to a one-standard-deviation positive shock under the high-CCI regime is larger than that under the low-CCI regime, while the response of Chinese output behaves in the opposite way under the low-CCI regime.

In summary, the impact of uncertainty on US consumer confidence, consumption, exports, imports, and output shows that compared to high confidence, low confidence deteriorates the economy of the US. This finding indicates that consumer confidence is more important in the US economy in both the short term and the long term. However, in China, compared to the high confidence regime, when consumers have low confidence, uncertainty shocks benefit exports and output in both the short term and the long term but have different impacts on consumption and imports in different periods. This finding shows that in China, consumer confidence is not a decisive factor that can influence the economy. In other words, the correlation of the CCI with the Chinese economy is not as large as that of the CCI with the US economy. The reason might be that in the US economy, there is not much regulation, which allows consumer sentiment to sway the economy a great deal. In contrast, the Chinese government takes more actions to stabilize the economy, making consumer confidence less crucial for economic performance.

## 7. Conclusions

This paper studies the impact of uncertainty shocks on China's macroeconomic variables and the role of the CCI in the transmission of uncertainty shocks. We extend academic

research on the interaction of consumer confidence and uncertainty on the macroeconomic effects of uncertainty shocks.

In contrast to the setting of traditional VAR models, which often take uncertainty proxy indicators as endogenous variables, we assume that economic uncertainty follows an AR (1) process that is exogenous to changes in endogenous economic variables. We also classify the economy based on endogenous consumer confidence and nest the interaction between uncertainty and consumer confidence into the TVAR model, forming a SU-M-TVAR model. Therefore, this setting closely resembles the reduced form of a DSGE model and is consistent with Chinese economic development.

Using Chinese monthly data from March 1995 to December 2021 to estimate the SU-M-TVAR model, we find that the sustainability of consumption is dependent on the uncertainty shocks and the two regimes of consumer confidence. Under both regimes, uncertainty shocks lead to a decline in consumption. However, the impact under the low-CCI regime lags behind that under the high-CCI regime. Under the low-CCI regime, imports decrease immediately and recover afterwards, while under the high-CCI regime, imports increase immediately and drop afterwards. The scenario for exports is exactly the opposite of that for imports. Overall, under the low-CCI regime, exogenous uncertainty shocks can impede domestic consumption in the long term but affect international trade only in the short term. However, under the high-CCI regime, uncertainty shocks have barely any effect on consumption and have an opposite impact on international trade to that under the low-CCI regime.

The evidence from the SU-M-TVAR model confirms the importance of consumer confidence in the economy. The economy behaves differently under different confidence regimes. We find that uncertainty shocks can explain more of the forecast error variance in the endogenous variables under the low-CCI regime than under the high-CCI regime. By comparing China and the US, we find that consumer confidence in the US is more susceptible to exogenous shocks and has a greater influence on the US economy.

Through counterfactual analysis, we substantiate the hazard of neglecting uncertainty in a TVAR model. The analysis shows that without the specification of stochastic uncertainty, the TVAR model fails to capture shocks from black swan events. Moreover, the estimated uncertainty from the SU-M-TVAR model is positively correlated with the extant EPU index [9]. Furthermore, since we take different regimes into account, we can capture the uncertainty shock more precisely under extreme events than can Baker et al.'s EPU index.

Based on these conclusions, the following policy suggestions are made. From an ex ante perspective, the authorities should make policies more transparent and mitigate uncertainty in their policies to calm the economy to a certain extent. From an ex post perspective, even if the government has done its best to reduce policy uncertainty, there might still be other uncertainties that cannot be controlled, especially in the current world. The authorities should enact different policies based on different consumer confidence regimes.

Finally, it is worth noting that there are still some further directions we may consider in the future. On the one hand, although our intention is to focus more on Chinese consumption, including domestic consumption and foreign consumption, i.e., exports, the choice of only four endogenous variables (consumption, exports, imports, and output) may be biased. We may add more endogenous variables (e.g., variables reflecting fiscal policy and monetary policy) to the study in the future. On the other hand, there are still some limitations in the current method in spite of its flexibility. For example, the model in our current paper focuses only on exogenous shocks that are the same in different economies. In future research, we may take the heterogeneity of exogenous shocks into account. Further, our model only reflects the average responses of endogenous macroeconomic variables to the shocks in the two confidence regimes. As we said earlier, responses of endogenous variables to the shocks may be different at different parts in the low-confidence regime, for instance, where CCI is at its historical minimum and where CCI is just below its critical threshold. In a future study, we can take the heterogeneity of the extent to which the endogenous variables respond into consideration.

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## Appendix A

**Table A1.** Dickey-Fuller test with drift for the five endogenous variables.

	CCI	Output	Consumption	Exports	Imports
Z statistic	−2.584	−9.253	−6.774	−9.516	−8.844
p-Value	0.0051	0.0000	0.0000	0.0000	0.0000

**Table A2.** AIC.

Lag	1	2	3	4	5	6	7	8	9	10	11	12
1	4618.47											
2	4400.96	4370.81										
3	4375.24	4346.88	4343.92									
4	4397.76	4370.19	4351.02	4401.69								
5	4384.88	4322.00	4300.79	4337.92	4381.54							
6	4406.50	4341.69	4297.39	4302.66	4394.34	4477.80						
7	4408.47	4350.32	4312.12	4301.26	4395.03	4456.04	4430.36					
8	4380.31	4370.20	4348.95	4339.24	4427.65	4472.72	4501.79	4612.05				
9	4403.48	4487.41	4482.93	4470.89	4411.17	4489.11	4481.63	4662.66	4556.18			
10	4422.23	4492.95	4480.67	4468.19	4421.90	4464.62	4470.22	4658.78	4556.67	4509.25		
11	4381.13	4390.66	4396.65	4383.27	4394.25	4378.19	4473.11	4575.65	4550.97	4500.68	4442.86	
12	4233.23	4188.40 *	4239.44	4240.03	4241.59	4271.70	4406.76	4392.34	4380.01	4283.23	4318.34	4302.78

Note: \* represents the lag chosen based on the AIC.

**Table A3.** BIC.

Lag	1	2	3	4	5	6	7	8	9	10	11	12
1	4848.52											
2	4819.24	4789.09 *										
3	4981.43	4953.08	4950.12									
4	5191.55	5163.98	5144.81	5195.48								
5	5365.95	5303.07	5281.87	5318.99	5362.62							
6	5574.54	5509.73	5465.43	5470.70	5562.37	5645.84						
7	5763.14	5705.00	5666.79	5655.94	5749.71	5810.72	5785.04					
8	5921.31	5911.20	5889.95	5880.24	5968.65	6013.72	6042.79	6153.05				
9	6130.48	6214.41	6209.93	6197.89	6138.17	6216.11	6208.63	6389.66	6283.18			
10	6334.91	6405.63	6393.34	6380.86	6334.57	6377.29	6382.90	6571.46	6469.35	6421.92		
11	6479.15	6488.68	6494.67	6481.29	6492.27	6476.21	6571.14	6673.67	6649.00	6598.70	6540.88	
12	6516.27	6471.44	6522.49	6523.07	6524.64	6554.74	6689.80	6675.39	6663.06	6566.28	6601.39	6585.83

Note: \* represents the lag chosen according to the BIC.



**Table A4.** Log-likelihood criterion.

Lag	1	2	3	4	5	6	7	8	9	10	11	12
1	−4525.63											
2	−4359.78	−4344.71										
3	−4289.82	−4275.65	−4274.17									
4	−4243.99	−4230.21	−4220.62	−4245.96								
5	−4180.46	−4149.02	−4138.41	−4156.98	−4178.79							
6	−4134.18	−4101.77	−4079.62	−4082.25	−4128.09	−4169.82						
7	−4078.06	−4048.99	−4029.89	−4024.46	−4071.34	−4101.85	−4089.01					
8	−4006.89	−4001.83	−3991.21	−3986.35	−4030.56	−4053.09	−4067.63	−4122.76				
9	−3961.38	−4003.35	−4001.10	−3995.09	−3965.22	−4004.19	−4000.45	−4090.97	−4037.73			
10	−3913.66	−3949.02	−3942.88	−3936.64	−3913.49	−3934.85	−3937.65	−4031.93	−3980.88	−3957.17		
11	−3836.01	−3840.78	−3843.77	−3837.08	−3842.57	−3834.54	−3882.01	−3933.27	−3920.94	−3895.79	−3866.88	
12	−3704.97	−3682.55 *	−3708.08	−3708.37	−3709.15	−3724.20	−3791.73	−3784.53	−3778.36	−3729.97	−3747.53	−3739.75

Note: \* represents the lag chosen based on the log-likelihood criterion.

**Table A5.** Dickey-Fuller test with drift for the five endogenous variables for the US.

	Exports	Imports	CCI	Consumption	Output
Z statistic	−3.430	−3.037	−2.749	−2.473	−2.461
p-Value	0.0003	0.0013	0.0032	0.0070	0.0072

## References

- Mumtaz, H.; Surico, P. Policy uncertainty and aggregate fluctuations. *J. Appl. Econ.* **2018**, *33*, 319–331. [\[CrossRef\]](#)
- Mumtaz, H.; Theodoridis, K. The International Transmission of Volatility Shocks: An Empirical Analysis. *J. Eur. Econ. Assoc.* **2015**, *13*, 512–533. [\[CrossRef\]](#)
- Mumtaz, H.; Zanetti, F. The Impact of the Volatility of Monetary Policy Shocks. *J. Money Credit. Bank.* **2013**, *45*, 535–558. [\[CrossRef\]](#)
- Jurado, K.; Ludvigson, S.C.; Ng, S. Measuring Uncertainty. *Am. Econ. Rev.* **2015**, *105*, 1177–1216. [\[CrossRef\]](#)
- Abel, A.B. Optimal Investment Under Uncertainty. *Am. Econ. Rev.* **1983**, *73*, 228–233.
- Bloom, N. Fluctuations in Uncertainty. *J. Econ. Perspect.* **2014**, *28*, 153–176. [\[CrossRef\]](#)
- Stock, J.H.; Watson, M.W. Disentangling the Channels of the 2007–2009 Recession. *Brookings Pap. Econ. Act.* **2012**, *2012*, 81–135. [\[CrossRef\]](#)
- Scotti, C. Surprise and uncertainty indexes: Real-time aggregation of real-activity macro-surprises. *J. Monetary Econ.* **2016**, *82*, 1–19. [\[CrossRef\]](#)
- Baker, S.R.; Bloom, N.; Davis, S.J. Measuring Economic Policy Uncertainty\*. *Q. J. Econ.* **2016**, *131*, 1593–1636. [\[CrossRef\]](#)
- Hassan, A.T.; Hollander, S.; van Lent, L.; Tahoun, A. Firm-Level Political Risk: Measurement and Effects\*. *Q. J. Econ.* **2019**, *134*, 2135–2202. [\[CrossRef\]](#)
- Handley, K.; Li, J.F.; Chen, C.; Davis, S.; Fitzgerald, D.; Furceri, D.; Hassan, T.; Kim, E.H.; Lu, Y.; Mitra, I.; et al. *Measuring the Effects of Firm Uncertainty on Economic Activity: New Evidence from One Million Documents*; NBER: Cambridge, MA, USA, 2020.
- Caldara, D.; Iacoviell, M. Measuring Geopolitical Risk. *Am. Econ. Rev.* **2022**, *112*, 1194–1225. [\[CrossRef\]](#)
- Born, B.; Pfeifer, J. Risk Matters: The Real Effects of Volatility Shocks: Comment. *Am. Econ. Rev.* **2014**, *104*, 4231–4239. [\[CrossRef\]](#)
- Basu, S.; Bundick, B. Uncertainty Shocks in a Model of Effective Demand. *Econometrica* **2017**, *85*, 937–958. [\[CrossRef\]](#)
- Jens, C.E. Political uncertainty and investment: Causal evidence from U.S. gubernatorial elections. *J. Financ. Econ.* **2017**, *124*, 563–579. [\[CrossRef\]](#)
- Kelly, B.; Pástor, L.; Veronesi, P. The Price of Political Uncertainty: Theory and Evidence from the Option Market. *J. Finance* **2016**, *71*, 2417–2480. [\[CrossRef\]](#)
- Pástor, L.; Veronesi, P. Political uncertainty and risk premia. *J. Financ. Econ.* **2013**, *110*, 520–545. [\[CrossRef\]](#)
- Bernanke, B.S. Irreversibility, Uncertainty, and Cyclical Investment. *Q. J. Econ.* **1983**, *98*, 85–106. [\[CrossRef\]](#)
- Pástor, L.; Veronesi, P. Uncertainty about Government Policy and Stock Prices. *J. Finance* **2012**, *67*, 1219–1264. [\[CrossRef\]](#)
- Bloom, N. The Impact of Uncertainty Shocks. *Econometrica* **2009**, *77*, 623–685. [\[CrossRef\]](#)
- Bach, L.; Calvet, L.E.; Sodini, P. Rich Pickings? Risk, Return, and Skill in Household Wealth. *Am. Econ. Rev.* **2020**, *110*, 2703–2747. [\[CrossRef\]](#)
- Fernández-Villaverde, J.; Guerrón-Quintana, P.; Kuester, K.; Rubio-Ramírez, J. Fiscal Volatility Shocks and Economic Activity. *Am. Econ. Assoc.* **2015**, *105*, 3352–3384. [\[CrossRef\]](#)
- Angeletos, G.-M.; Collard, F.; Dellas, H. Quantifying Confidence. *Econometrica* **2018**, *86*, 1689–1726. [\[CrossRef\]](#)
- Angeletos, G.-M.; La’O, J. Sentiments. *Econometrica* **2013**, *81*, 739–779.
- Benhabib, J.; Wang, P.; Wen, Y. Sentiments and Aggregate Demand Fluctuations. *Econometrica* **2015**, *83*, 549–585. [\[CrossRef\]](#)
- Lorenzoni, G. A Theory of Demand Shocks. *Am. Econ. Rev.* **2009**, *99*, 2050–2084. [\[CrossRef\]](#)
- Hall, R.E. Macro Theory and the Recession of 1990–1991. *Am. Econ. Rev.* **1993**, *83*, 275–279.
- Blanchard, O. Consumption and the Recession of 1990–1991. *Am. Econ. Rev.* **1993**, *83*, 270–274.

29. Martin, I.W.R.; Papadimitriou, D. Sentiment and Speculation in a Market with Heterogeneous Beliefs. *Am. Econ. Rev.* **2022**, *112*, 2465–2517. [[CrossRef](#)]
30. Cochrane, J.H. Shocks. *Carnegie-Rochester Conf. Ser. Public Policy* **1994**, *41*, 295–364. [[CrossRef](#)]
31. Benhabib, J.; Spiegel, M.M. Sentiments and Economic Activity: Evidence from US States. *Econ. J.* **2019**, *129*, 715–733. [[CrossRef](#)]
32. Gillitzer, C.; Prasad, N. The Effect of Consumer Sentiment on Consumption: Cross-Sectional Evidence from Elections. *Am. Econ. J. Macroecon.* **2018**, *10*, 234–269. [[CrossRef](#)]
33. Fève, P.; Guay, A. Sentiments in SVARS. *Econ. J.* **2019**, *129*, 877–896. [[CrossRef](#)]
34. Benati, L. *Economic Policy Uncertainty and the Great Recession*; University of Bern: Bern, Switzerland, 2013; Available online: [http://www.policyuncertainty.com/media/Uncertainty\\_Benati.pdf](http://www.policyuncertainty.com/media/Uncertainty_Benati.pdf) (accessed on 6 June 2022).
35. Uhlig, H. Do Technology Shocks Lead to a Fall in Total Hours Worked? *J. Eur. Econ. Assoc.* **2004**, *2*, 361–371. [[CrossRef](#)]
36. Carriero, A.; Clark, T.E.; Marcellino, M. Measuring Uncertainty and Its Impact on the Economy. *Rev. Econ. Stat.* **2018**, *100*, 799–815. [[CrossRef](#)]
37. Alessandri, P.; Mumtaz, H. Financial regimes and uncertainty shocks. *J. Monetary Econ.* **2019**, *101*, 31–46. [[CrossRef](#)]
38. Alessandri, P.; Mumtaz, H. Financial conditions and density forecasts for US output and inflation. *Rev. Econ. Dyn.* **2017**, *24*, 66–78. [[CrossRef](#)]
39. Chen, C.W.S.; Lee, J.C. Bayesian Inference of Threshold Autoregressive Models. *J. Time Ser. Anal.* **1995**, *16*, 483–492. [[CrossRef](#)]
40. Cogley, T.; Sargent, T.J. Drifts and volatilities: Monetary policies and outcomes in the post WWII US. *Rev. Econ. Dyn.* **2005**, *8*, 262–302. [[CrossRef](#)]
41. Jacquier, E.; Polson, N.G.; Ross, P.E. Bayesian Analysis of Stochastic Volatility Models. *J. Bus. Econ. Stat.* **1994**, *12*, 69–87.
42. Koop, G.; Pesaran, M.; Potter, S.M. Impulse response analysis in nonlinear multivariate models. *J. Econ.* **1996**, *74*, 119–147. [[CrossRef](#)]

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