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The Impact of Policy Uncertainty on China's Macroeconomy

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RÉSUMÉ

Depuis la crise financière mondiale de 2008, plusieurs chercheurs et commentateurs ont avancé que le niveau élevé d'incertitude relié aux politiques économiques représentait un frein à la reprise macroéconomique et la stabilité financière. Toutefois, peu se sont penchés sur l'impact macroéconomique de ce type d'incertitude pour la Chine. Afin de palier à cette carence, cette étude s'attaque donc à cette question à l'aide de données chinoises à fréquence mensuelle et de modèles de projection locale (Jordà, 2005) pour la période 1992 à 2021. Afin d'étudier le rôle potentiel joué par la forte croissance de la dette résidentielle en Chine durant cette période, un ratio d'endettement est employé comme variable de transition d'état entre divers régimes de dette liée au marché immobilier. Les résultats démontrent qu'en général, l'incertitude concernant les politiques économiques a un impact négatif et persistant sur l'économie chinoise. En outre, il est documenté que l'incertitude accrue réduit davantage la consommation et les exportations nettes lorsque les ratios d'endettement sont faibles, et que le rebond des exportations nettes est moins prononcé sous un tel régime. En revanche, des ratios d'endettement élevés amplifient l'effet négatif de l'incertitude sur le niveau des prix à la consommation. Finalement, il ne semble y avoir de repli marqué des investissements étrangers à court terme, ni d'effets significatifs à plus long terme.

Mots clés: Incertitude de la politique économique; Projection locale; Ratio d'endettement des ménages

ABSTRACT

Since the global financial crisis in 2008, economic uncertainty has become an important topic and potential source of macroeconomic fluctuations. However, there is still a lack of relevant literature focusing on China, and this thesis seeks to fill this gap by studying the impact of uncertainty on China's macroeconomy. This paper investigates the macroeconomic impact of Economic Policy Uncertainty (EPU) by using monthly data and a Local Projection (LP) model (Jordà, 2005) for the period 1992 to 2021. Considering the possible macroeconomic consequences of China's highly growing residential debt, the author uses the residential debt ratio as a state-transition variable to compare the differences in macroeconomic exposure to shocks under different debt ratios. The findings demonstrate that, in general, higher economic policy uncertainty has a persistent negative macroeconomic impact on China. In addition, increased uncertainty reduces more China's consumption and net exports under low debt ratios, and net exports have more difficulty rebounding under low debt ratios. High debt ratios amplify the negative effects to price levels. In contrast, there is no short-term panic withdrawal of foreign investment in the face of uncertainty and no significant negative response in the long run.

Keywords: Economic Policy Uncertainty; Local Projection; Household debt ratio

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Finally, may the epidemic end soon; may we hold on to our love and run to the mountains and the sea without forgetting the beginning.

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LIST OF ABBREVIATIONS

AIC	Akaike Info Criterion
CEPU	Chinese Economic Policy Uncertainty
CPI	Consumer Price Index
DSGE	Dynamic Stochastic General Equilibrium Model
EPU	Economic Policy Uncertainty
FAVAR	Factor-Augmented Vector Autoregressive Model
FDI	Foreign Direct Investment
FPE	Final Prediction Error
GARCH	Generalized AutoRegressive Conditional Heteroskedasticity
GDP	Gross Domestic Product
HQ	Hannan-Quinn Criterion
IFO BCS	German IFO Business Climate Survey
LP	Local Projection
M2	Board Money Supply
MSE	Mean Squared Error Predictor
NBS	Chinese National Bureau of Statistics
NFPs	Non-Farm Payrolls
OLS	Ordinary Least Squares
PPI	Producer Price Index
SC	Schwarz Criterion
SPF	The Survey of Professional Forecaster
SVAR	Structual Vector Autoregressive Model
TFP	Total Factor Productivity
VAR	Vector Autoregressive Model
VIX	CBOE Volatility Index

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Chapter 1

Introduction

After the global international financial crisis broke out in 2008, governments of various countries successively introduced expansionary economic policies to boost their economies. However, at the same time, increases in policy uncertainty became an important factor hindering economic recovery, and the imperfection of financial markets amplified the negative impact of uncertainty on economic growth. The issue of uncertainty became a hot topic of concern among scholars. Since 2020, the Covid-19 pandemic has spread rapidly worldwide, causing a substantial negative impact on the global economy. Major developed countries, led by the Federal Reserve, have successively implemented quantitative easing policies, and economic policy uncertainty again has risen significantly.

Although most studies of uncertainty have arisen in the last 15 years, as early as 1921, the American economist Frank Knight already distinguished between risk and uncertainty in his article *Risk, Uncertainty, and Profit*. Using measurability as the difference between risk and uncertainty, Knight argued that risk is a probability distribution that can be known as certainty. However, uncertainty is entirely unknown or unforecastable to people about the possible outcomes of events and, therefore, cannot be foreseen or quantitatively analyzed by existing theory or experience. (Knight, 1921)

Since it is more challenging to directly measure macro uncertainty quantitatively, economists often look for proxy variables based on the characteristics and effects of uncertainty. Some of the more common proxy variables are the option implied volatility of the S&P 500 index and the economic policy uncertainty (EPU) indicator. The former is a panic index widely used to measure market risk and investor panic, while the latter is an index constructed by Baker et al. (2016) using textual analysis based on the monthly count of newspaper articles containing economic, policy, and uncertainty keywords. In this paper, we use China's EPU as the specified variable to measure exogenous uncertainty in China. Other metrics and methods will be specified in the literature review section.

In recent years, many papers have focused on the impact of uncertainty on the economy at the macroeconomic level. However, most of these papers focus on developed countries such as the U.S. and Western Europe, and the number of studies is minimal for developing countries, including China. Jin et al. (2014) were the first to develop a Factor-Augmented Vector Autoregressive Model (FAVAR) model to analyze the impact of policy uncertainty on China's macroeconomy. Using a VAR and Dynamic Stochastic General Equilibrium Model (DSGE), Xu and Wang (2019) conclude that policy uncertainty significantly increases output and price level volatility by about 10% and 15%, respectively.

These previous papers used linear models to analyze the impact of uncertainty. However, a spike in the residential debt ratio can affect the effectiveness of economic policy implementation by limiting residents' ability to consume and changing their investment behavior (Wang and Li, 2020). Therefore, this paper hypothesizes that the effect of uncertainty on China's macroeconomy could differ under regimes of high and low resident indebtedness. To test this notion, a nonlinear model is utilized.

According to data provided by the National Balance Sheet Research Center, from 1993Q4 to 2021Q4, the leverage ratio of China's residential sector grew from 8.31% to 62.2%, an increase of nearly eight times. In particular, after the financial crisis in 2008, the compound annual growth rate of China's residential leverage ratio exceeded 10%. But from 1993Q4-2008Q4, the compound annual growth rate of the debt ratio was only 5.25%. Ruan et al. (2020) argues that skyrocketing house prices are the main reason for the rise in China's residential debt ratio.

This paper investigates how and to what extent uncertainty shocks affect China's macroeconomy under different resident debt ratios. By building a Local Projection (LP) (Jordà, 2005) model and introducing the resident debt ratio as a state transition variable, this paper investigates the impact of uncertainty shocks on aggregate output, the price level, consumption, and investment. In addition, to make the conclusions more robust, this paper considers an alternative proxy variable for uncertainty, the CEPU measure (Huang and Luk, 2020), and adds two variables, net exports and foreign direct investment, as explanatory variables.

The paper draws the following main conclusions. 1. Economic Policy Uncertainty has a persistent negative impact on China's macroeconomy. 2. Increased uncertainty reduces more China's consumption and net exports under low debt ratios, and net exports take longer to rebound under low debt ratios. 3. High debt ratios amplify the adverse effects to the price level. 4. There is no short-term panic withdrawal of foreign investment in response to uncertainty shocks and no significant decline in the long run.

This paper differs from the literature slightly in its focus and implementation of the estimation. Firstly, based on Chinese macro data, the LP method is used to test the immediate and long-term effects of EPU on China's macroeconomic conditions under different resident debt states. Secondly, this paper selects monthly rather than quarterly or annual macroeconomic data, which increases the sample size and makes the conclusions more accurate. Thirdly, this paper is the first to use a nonlinear LP model, which complements the research gap of economic policy uncertainty for China.

The overall structure of the study takes the form of five chapters, including this introductory chapter. The rest of the paper is organized as follows: chapter 2 is the literature review; chapter 3 gives the empirical model; chapter 4 describes the data; chapter 5 shows the empirical results. Chapter 6 concludes.

Chapter 2

Literature Review

2.1 Definition of Economic Policy Uncertainty

Various definitions of economic uncertainty and its relation to economic policy exist in the literature. Bloom et al. (2014) defined economic uncertainty as "an environment in which people have little or no knowledge of future economic conditions." They further pointed out that there are many sources of economic uncertainty, including changes in monetary and fiscal policies; divergence in economic growth prospects among households, enterprises, and government departments; changes in economic indicators such as GDP, the inflation rate, and productivity; and non-economic events, such as war, terrorism, climate change, and natural disasters.

Rossi and Sekhposyan (2015) defined economic uncertainty as a state where a "rational man cannot be completely rational and clear about the distribution of future economic states." Further, even if one can describe the distribution of future output, one cannot assign the correct probability to future outcomes. This standpoint continues the idea of Jurado et al. (2015) that economic uncertainty is primarily a situation used to describe the degree of uncertainty of rational people about current or future economic conditions.

More recently, Gulen and Ion (2015) argued that economic uncertainty refers to the uncertainty created by whether and when economic policies will be introduced and the strength of policy implementation. This paper's definition of economic uncertainty is consistent with Gulen and Ion (2015).

2.2 Statistical Measurements

Since the uncertainty metric is not a directly observable variable, but rather a latent variable that needs to be derived from other variables, estimating economic uncertainty reasonably, appropriately, and accurately quantitatively has been a challenging research problem. According to different measurement philosophies, the uncertainty metrics used in current research can be classified into three categories.

2.2.1 *Measuring economic policy uncertainty with the volatility of proxy variables*

Several past studies measured economic uncertainty based on the volatility of proxy variables. However, if one wishes to measure economic policy uncertainty, these measures risk confounding genuine policy uncertainty with other factors.

Romer (1990) used the implied or historical stock market volatility as a proxy for macroeconomic uncertainty, such as the CBOE Volatility Index (VIX).[1] However, VIX movements may be related to investor risk aversion or stock market sentiment, not economic policy uncertainty, so it may not fully match economic uncertainty (Bekaert et al., 2013).

After that, Bloom (2009) measured economic uncertainty indicators based on the dispersion of micro-level data, such as the standard deviation of stock returns of listed companies and the standard deviation of corporate profit growth rates. Bachmann et al. (2013) used the spread between U.S. corporate Baa bond index and the 30-year Treasury bond as a proxy variable for economic uncertainty. Subsequent researchers used a GARCH (1, 1) model to measure the conditional heteroskedasticity of macroeconomic indicators such as real GDP, Non-Farm Payrolls (NFPs), and Total Factor Productivity (TFP) growth rate to describe economic uncertainty (Bloom et al., 2018). However, since macroeconomic indicators are highly correlated, the measurement is prone to bias.

Some measures of economic policy uncertainty are based on changes in local govern-

[1] CBOE Volatility Index: 30-day implied volatility of the S&P500 index

ment officials (Jia et al., 2013; Julio and Yook, 2012). However, local government official turnover can only reflect local policy uncertainty and is not national in scope, so the indicator has some limitations.

2.2.2 *Measuring economic uncertainty with differences in expectations*

Bomberger (1996) was the first to characterize economic uncertainty based on analysts' current subjective perceptions and forecast bias of inflation indicators. Using data from the German IFO Business Climate Survey (IFO BCS), Bachmann et al. (2013) quantified entrepreneurs' qualitative forecasts of future output.[2] They then compared them with actual results, finding that economic uncertainty is more a consequence than a cause of the recession. Rossi and Sekhposyan (2015) found that if the current forecast deviation of macroeconomic variables (e.g., real GDP growth rate) is in the tail of the historical distribution of forecast deviations, the predictability will be poor and economic uncertainty will be high. Scotti (2016) used the difference between the actual and Bloomberg expected macroeconomic variables (e.g., real GDP, inflation rate, productivity) as the expected deviation (unexpected news) and then constructed an economic uncertainty index by weighting the expected deviations.

Bloom (2009) used GDP growth rate as the core variable and the standard deviation of the The Survey of Professional Forecaster (SPF) experts' forecasts as the difference of opinion to measure uncertainty.[3] After that, Gulen and Ion (2015) used the difference between the upper and lower quartiles of experts' forecasts of economic indicators in the SPF as a proxy variable for economic policy uncertainty.

The methods mentioned above have not become mainstream measures due to some limitations. First, experts' predictions and expectations are intensively subjective, and the metric lacks objectivity and fairness. Second, there may be asymmetries in the information available to the experts, leading to significant differences in the final prediction

[2] The qualitative forecasts include growth, no change, or a decline.

[3] The Survey of Professional Forecasters (SPF), published by the Federal Reserve Bank of Philadelphia, contains statistics on experts' output forecasts and other data since 1968.

results.

2.2.3 *Measuring economic uncertainty from the news media*

Alexopoulos and Cohen (2009) argued that most economic policy uncertainty shocks are news shocks, and the main channel for the public to obtain information about financial markets and economic dynamics is the news media. Using textual analysis methods, they constructed an economic uncertainty index based on the number of monthly articles containing the terms economic and uncertainty in the *New York Times*.

Based on this, Baker et al. (2016) selected the ten most influential newspapers in the United States and counted the frequency of keywords containing economic, policy, and uncertainty categories. Then, they subsequently standardized the data to construct the Economic Policy Uncertainty Indices and applied this index construction method for 22 countries and two GDP-weighted indices of Global EPU.

Baker et al. (2016) constructed Newspaper-Based Uncertainty Indices for China by choosing the South China Morning Post, Hong Kong's leading English-language newspaper, as the premier newspaper source. However, as a regional newspaper, South China Morning Post is hard to reflect on the actual economic situation in China. To reflect China's economic policy uncertainty more accurately, Huang and Luk (2020) constructed a new China Economic Policy Uncertainty Index (CEPU) based on ten representative Chinese newspapers.[4]

This article will simultaneously use the EPU index in China (Baker et al., 2016) and the CEPU index (Huang and Luk, 2020), as each index has its own merits. The EPU index in China has more extended time coverage (from 1949 up to now), which can better reflect the economic policy uncertainty in China since the founding of the country. By contrast, the CEPU index starts only in January 2000. However, it is based on 10 Mandarin-language newspapers with influence and wide readership in mainland China, and may

[4] The ten representative Chinese newspapers are *Beijing Youth Daily*, *Guangzhou Daily*, *Jiefang Daily*, *People's Daily Overseas Edition*, *Shanghai Morning Post*, *Southern Metropolis Daily*, *The Beijing News*, *Today Evening Post*, *Wen-Hui Daily*, and *Yangcheng Evening News*.

measure China uncertainty more accurately.

2.3 The macroeconomic impact of Economic Policy Uncertainty

Past research has shown that economic uncertainty has several different effects on the macroeconomy of different countries.

After the financial crisis in 2008, Bloom (2009) first began to study the impact of economic policy uncertainty on macroeconomic performance and found that firms under high uncertainty would adopt a "wait and see" attitude. Namely, suspending or reducing investment and hiring, which in turn directly affects aggregate output, investment, and labor market activity.

Guvenen et al. (2014) studied U.S. Social Security data and found that increased economic uncertainty increased income uncertainty, reducing consumer spending. This effect is more pronounced for low-income populations, causing an increase in income disparity and laying a hidden danger for social equity.

In addition, uncertainty can also impact international trade. Uncertainty can hinder international trade, and reducing uncertainty in economic policies can significantly contribute to trade and cross-border investment (Handley and Limao, 2015). Novy and Taylor (2020) supported this view, finding firms collectively and selectively cut import orders following uncertainty shocks due to cost and risk considerations, leading to a contraction in international trade activity in 2008-2009.

Currently, most studies have focused more on the impact of uncertainty on the economies of developed countries, notably the U.S. Bloom (2014) found the sudden rise in uncertainty exacerbated the economic recession and caused the global financial crisis in 2008 with an over 30% drop in GDP. After that, Baker et al. (2016) found that an increase in the EPU index caused a 3.2% decline in U.S. real GDP, a 16% decline in private investment, and a 2.3 million job loss from the years 2006 to 2011. Similarly, this view was supported by the study of Gulen and Ion (2015), where a 1% rise in economic uncertainty lead to a decline in quarterly investment of about 6.3%. In contrast, Born and Pfeifer (2014) argued that the impact of economic uncertainty is strongly overestimated. Their study found that even a two-standard deviation shock on economic uncertainty only caused a 0.065% decline in GDP.

Related studies have reached similar conclusions in other developed countries as in the U.S. Bachmann and Bayer (2014) used a VAR model to find that uncertainty from forecasters' opinion differences reduces the industrial output and employment rate in the U.S. and Germany. However, economic uncertainty has a more significant and permanent impact on the U.S. economy. Colombo (2013) found that, compared to European policy uncertainty, policy uncertainty in the US has a more significant impact on the European economy. Afterward, this view was supported by the study by Cheng (2017), who found that foreign economic policy uncertainty has a more significant impact on output than domestic policy uncertainty in Korea. In particular, a 1% standard deviation shock of the U.S. EPU index leads to a 0.2% decline in output in Korea, which is twice as large as a shock of the Korean EPU index.

Compared to the typical developed economy, developing and emerging markets do not dominate in global resource allocation and pricing power. Hence, uncertainty can have more severe macroeconomic consequences. Carrière-Swallow and Céspedes (2013) found that policy uncertainty shocks in the U.S. have a more significant impact on consumption and investment in developing countries than in other developed countries.

For China, the large population base and its particular market system led to a more critical role in the economic operation and resource allocation. Jin et al. (2014) used the FAVAR model approach to analyze the impact of EPU shocks on China's macroeconomy. They found that as EPU increases, the pessimism level of economic agents' macroeconomic expectations increases, and the public confidence index decreases. This harms the real economy, leading to a decline in GDP, investment, consumption, and exports. At the same time, it has a negative impact on prices, leading to a depreciation of the real effective exchange rate and prompting a decline in stock prices and real estate prices.

Xu and Wang (2019) introduced the EPU index into a New Keynesian DSGE model for quantitative analysis and found that higher EPU significantly increases the volatility of output and prices, with the degree of volatility reaching about 10% and 15%, respectively. Moreover, public policy expectations significantly enhance the impact of uncertainty shocks on economic volatility.

In summary, the existing literature has not used nonlinear models to study the macroeconomic consequences of uncertainty in China. Previous studies focused more on the direct effects caused by higher uncertainty. In contrast, this paper will build on the existing literature and discuss the differences in the macroeconomic responses caused by EPU shocks for different resident indebtedness ratios, by introducing the household debt ratio as a state-transition variable.

Chapter 3

Methodology

In this chapter, the methodology used to measure the impact of China's economic policy uncertainty on China's macroeconomy is described. The Local Projection method (Jordà, 2005) is used to estimate the impulse responses. Using the household debt ratio as a regime-switching variable and data from January 1992 to March 2021, this paper investigates the impact of economic uncertainty on output, the price level, consumption, investment, and net exports under different thresholds of the household debt ratio.

Past studies have mainly used a reduced form VAR model, Structual Vector Autoregressive Model, or FAVAR model with linear data to measure the effects of policy uncertainty shocks on macroeconomic variables (Huang and Luk, 2020; Jin et al., 2014; Xu and Wang, 2019). However, these methods have many drawbacks. On the one hand, a VAR model requires a sufficiently large data sample to obtain consistent and valid estimation results. On the other hand, a VAR requires assigning values or constraints to some parameters of the estimated coefficient matrix, which can be subjective. In addition, a VAR is essentially a linear model, and it is more challenging to deal with nonlinear or structurally transformed equations.

To overcome these shortcomings, Jordà (2005) created a local projection model to estimate the impulse response function. The local projection method can be easily estimated by simple regression techniques with standard regression packages. Also, it can easily accommodate experimentation with highly nonlinear and flexible specifications.

3.1 Estimating impulse response functions using local projections

According to Hamilton and Susmel (1994); Koop et al. (1996), the impulse response is strictly defined as the difference between two time forecasts. Based on the status X_t with and without relevant experimental shocks d_i, Equation 3.1 can be written as:

$$IR\left(t,h,d_i\right)=E\left(y_{t+h}\mid v_t=d_i;X_t\right)-E\left(y_{t+h}\mid v_t=0;X_t\right)\qquad h=0,1,2,\ldots,h \tag{3.1}$$

where IR represents the impulse response, the operator $E(\cdot\mid\cdot)$ denotes the Mean Squared Error Predictor (MSE), $\mathrm{MSE}\left(E\left(y_{t+h}\right)\mid X_t\right)=E\left(u_{t+h}^h\right);X_t\equiv\left(y_{t-1},y_{t-2},\ldots,y_{t-p}\right)'$; d_i represents the structural shock to the i^{th} element in y_t (which specifies the endogenous variables), and u_{t+h}^h denotes the moving average of the forecast errors from time t to $t+h$.

Projecting y_{t+h} onto the linear space, the Ordinary Least Squares (OLS) regressions for each forecast horizon are calculated. Equation 3.2 below is termed the local projection by Jordà (2005):

$$y_{t+h}=\alpha^h+B_1^{h+1}y_{t-1}+B_2^{h+1}y_{t-2}+\cdots+B_p^{h+1}y_{t-p}+u_{t+h}^h\qquad h=0,1,2,\ldots,h \tag{3.2}$$

where α^h is a vector of regression constants; B_i^{h+1} are coefficient matrices for each lag and horizon, and u_{t+h}^h denotes the moving average of the forecast errors from time t to $t+h$.

Based on the definition of the impulse response in Equation 3.1, the impulse responses under the local projection method can be expressed as:

$$\widehat{IR}\left(t,h,d_i\right)=\widehat{B_1^h}d_i\qquad h=0,1,2,\ldots,h \tag{3.3}$$

The purpose of the local projection model is to establish consistency and estimate the coefficients of impulse responses $\widehat{B_1^h}$.

3.2 Local Projection Model

Jordà's local projection method (2005) can be summarized by a series of linear regressions for each variable at each horizon h, and the linear model can be written as:

$$Y_{t+h} = [\alpha_h + \Pi_h(L)Z_{t-1} + \beta_h shock_t] + \varepsilon_{t+h} \tag{3.4}$$

where Y_{t+h} is the variable of interest; Z_{t-1} is a vector of control variables; $\Pi_h(L)$ is a polynomial in the lag operator, and $shock_t$ is the identified shock.

Nonlinearity can be easily applied to the local projection model by using binary or regime-switching variables. Compared to other approaches to account for a nonlinear framework, the local projection method performs more robustly to error specification (Calmès and Théoret, 2020). However, using a dummy variable to separate data into two regimes will lower the degrees of freedom. Auerbach and Gorodnichenko (2012) propose an alternative approach computing the state probability with a logistic function for estimation with the LP model to alleviate this problem. Alternatively, using the dummy approach, Ramey and Zubairy (2018) estimate the impulse responses via:

$$\begin{aligned} Y_{i,t+h} = {} & I_{i,t-1}\left[\alpha_{i,h}^A + \Pi_h^A(L)Z_{i,t-1} + \beta_h^A shock_{i,t}\right] \\ & + (1 - I_{i,t-1})\left[\alpha_{i,h}^B + \Pi_h^B(L)Z_{i,t-1} + \beta_h^B shock_{i,t}\right] + \varepsilon_{i,t+h} \end{aligned} \tag{3.5}$$

where $I_{i,t-1}$ denotes a binary variable with values 0 or 1. When $I_{i,t-1} = 1$, it represents estimation in Regime 1, and when $I_{i,t-1} = 0$, it represents estimation in Regime 2. $Y_{i,t+h}$ denotes the endogenous variables; $\Pi_h(L)$ denotes the lagging factor, where the lagging number is determined by the information determination criterion; $Z_{i,t-1}$ indicates control variables; $\varepsilon_{i,t+h}$ indicates a residual term; $shock_{i,t}$ denotes identified shocks; h denotes the number of periods of the impulse response function, $h = 0, 1, 2, \ldots h$.

Further, in this paper, since the switching variable is a continuous variable, the state probability with a logistic function is more appropriate. In this case, the LP model is expressed as Equation 3.6:

$$
\begin{aligned}
Y_{i,t+h} = {} & f\left(D_{i,t-1}\right)\left[\alpha_{i,h}^{A} + \Pi_{h}^{A}(L) Z_{i,t-1} + \beta_{h}^{A} shock_{i,t}\right] \\
& + \left(1 - f\left(D_{i,t-1}\right)\right)\left[\alpha_{i,h}^{B} + \Pi_{h}^{B}(L) Z_{i,t-1} + \beta_{h}^{B} shock_{i,t}\right] + \varepsilon_{i,t+h}
\end{aligned}
\tag{3.6}
$$

where $D_{i,t-1}$ denotes the continuous switching variable, $f\left(D_{i,t-1}\right) = \frac{e^{-\gamma D_{i,t-1}}}{1+e^{-\gamma D_{i,t-1}}}$ denotes the switching function, and γ denotes the modulation factor of the transition curve. According to Adämmer (2019), a higher value for γ determines a faster regime-switch. Referring to Wang and Li (2020)'s parameters set in their literature, this paper sets γ to 10.

In this paper, the logarithm of output, the price level, consumption, net export, and investment are the endogenous variables. EPU is assumed to be an exogenous measure of an uncertainty, and the switching variable is the household debt ratio, which separates the data into two states, namely high household debt and low household debt. The control variables include the money supply, deposit bank rate, and government spending. Since the endogenous variables are nonstationary, linear and quadratic trend terms are included as additional controls.

Due to the inconsistent time horizon over which the data are available, different endogenous variables will be selected depending on uncertainty proxy variables (EPU & CEPU). When the shock is determined from EPU, real GDP, Consumer Price Index (CPI), consumption, and investment are considered as endogenous variables. When the uncertainty proxy is measured from CEPU, net exports is added to the group of endogenous variables. In addition, to further study the impact of uncertainty on foreign investment, FDI replaces investment as one of the endogenous variables.

To isolate the cyclical components from the original time series, the HP filter is used to detrend the switching-variable. As for the HP filters parameter setting, Ravn and Uhlig (2002) suggest that the penalty term should be 129600 for monthly data, and this study uses this value.

Figure 3.1 shows the evolution of switching variables (household debt ratio) in China between 1992 and 2021. Specifically, the high value of the transition variable refers to a low household debt ratio, which corresponds to Regime 2.

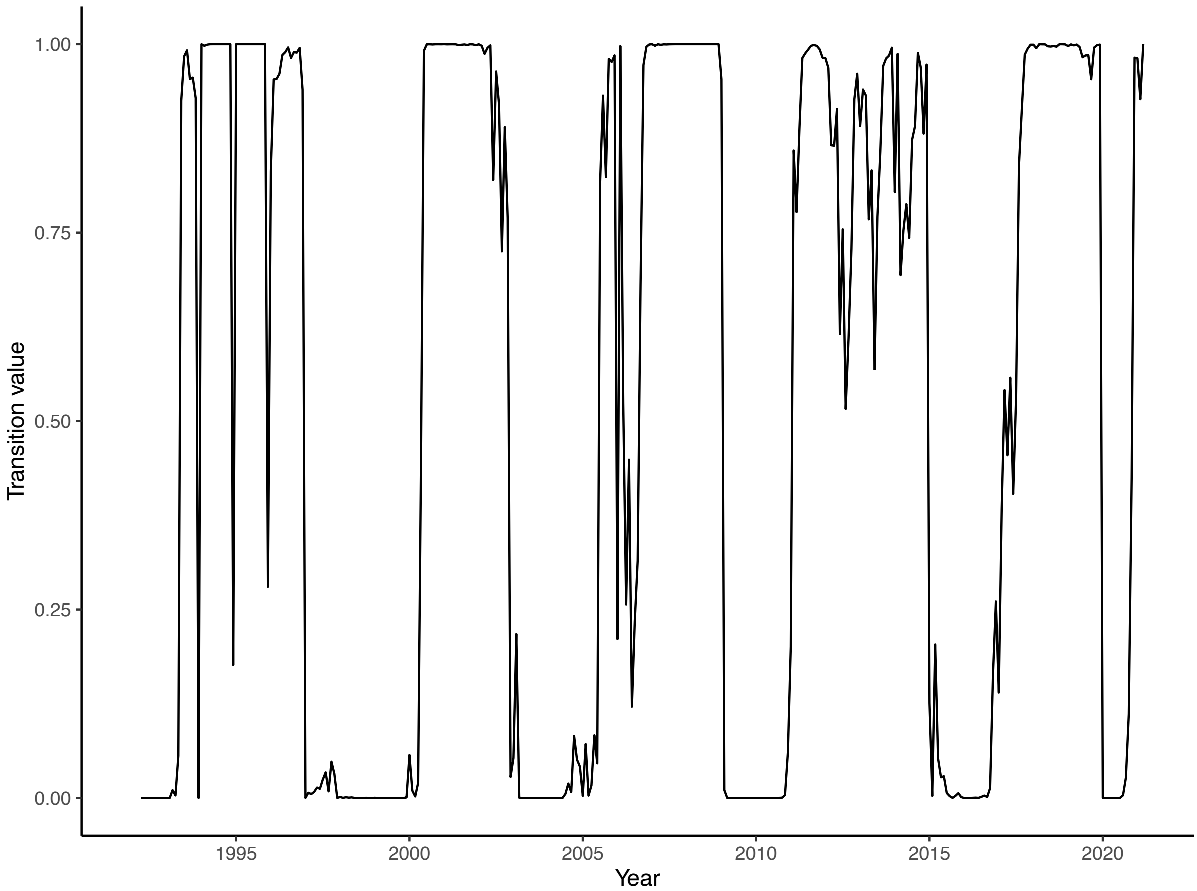


Figure 3.1: The evolution of the transition variable $f(D_{i,t-1})$

The following section gives a more detailed description of the variables.

Chapter 4

Data

This chapter includes the data sources used in the LP model and the descriptive statistics of the data. A set of monthly time series for China from January 1992 to March 2021 is constructed for the analysis. This paper estimates the model using monthly data rather than quarterly or annual, since the financial institutions are sensitive to uncertainty and react quickly to its news. In particular, the main variables selected for this paper are the EPU index in China (Baker et al., 2016), the CEPU (Huang and Luk, 2020), real gross domestic production, consumer price index, foreign direct investment, and household debt ratio.

In the early years of the People's Republic of China, the Chinese National Bureau of Statistics (NBS) was negligent in data statistics. This led to the absence of a large amount of official economic data, including GDP, the inflation rate, and the unemployment rate. This problem was gradually alleviated after the reform and opening-up in 1979, when Chinese macro databases began to be established and the statistical caliber was brought into line with international standards. However, the database did not progress well due to the lack of experience in the early reform period, when China faced political corruption, a rapidly widening gap between rich and poor, and severe inflation.

It was not until 1992, when Deng Xiaoping (retired Paramount leader of China, former Chairman of the Central Military Commission of China) delivered his Southern Tour speech, that the progress of China's reform and opening-up was brought back to speed and economic development became China's top priority again. At the same time, China's macroeconomic database gradually improved. Therefore, the starting time of the data in this paper is determined as the year 1992.

4.1 Data Source

Following Baker et al.'s (2016) newspaper-based method of measuring uncertainty, Davis et al. (2019) created a monthly EPU index for China, covering October 1949 to the present. In contrast to Baker's EPU index, they used two mainland Chinese newspapers to perform the text searches instead of using information from a Hong Kong-based English newspaper.[5] This variable measures the EPU index based on the frequency of articles that contain at least one keyword in each of the three criteria, namely *Economy*, *Uncertainty*, and *Policy*, in each month. In this paper, the data for the period January 1992 to March 2021 are used as a proxy variable for uncertainty shocks. The underlying assumption is that each period's index value represents an exogenous change to policy uncertainty. Figure 4.1 shows the monthly EPU index from January 1992 to March 2021, with significant events affecting uncertainty.

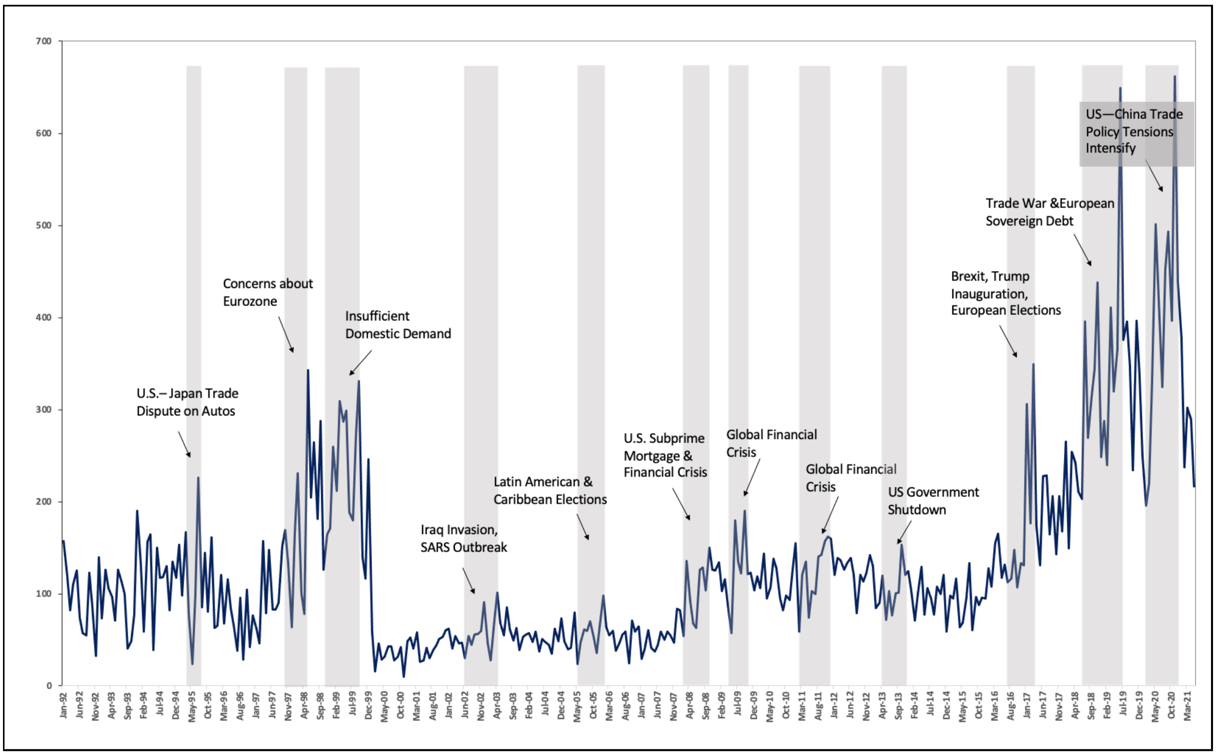


Figure 4.1: Evolution of the EPU index in China Mainland between 1992 and 2021

[5]The two mainland Chinese newspapers are the *Renmin Daily* and the *Guangming Daily*, respectively.

Using the same methodology, Huang and Luk (2020) enhanced the China EPU indicator using information from multiple mainland Chinese newspapers and selecting different keywords. The quality of the improved China EPU index is not significantly affected by the included newspapers (Huang and Luk, 2020). However, since this measure starts in 2000, the sample size is limited, and it is used for robustness tests in this paper. Figure 4.2 shows the monthly CEPU index in Mainland China from January 2000 to March 2021, with significant events affecting uncertainty.

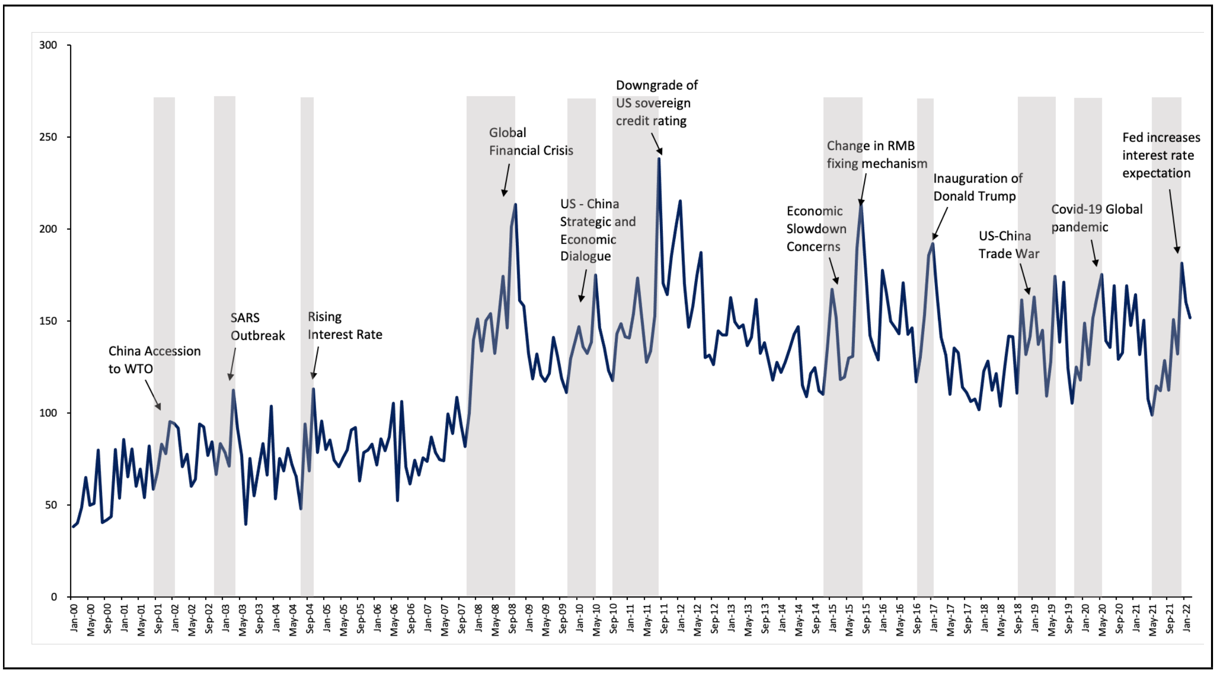


Figure 4.2: Evolution of the CEPU index in China Mainland between 2000 and 2021

Based on Figure 4.1 and 4.2, from the years 2000 to 2021, the two indicators captured some of the same events, such as the SARS outbreak, the global financial crisis, and inauguration of Donald Trump. However, the two indicators tracked different events as well. The EPU index in Figure 4.1 is more inclined to track international events affecting China's uncertainty, such as the U.S. government shutdown and the European sovereign debt crisis. In contrast, the CEPU index in Figure 4.2 is better at capturing uncertainties in China, such as rising interest rates and changing the RMB fixing mechanism. The correlation coefficient between EPU and CEPU is 0.482, indicating a weak correlation.

The variables real GDP, consumer price index, real consumption, real investment, net exports, and money supply (M2) are obtained from Chang et al. (2015). Since there are plenty of problems and shortcomings in Chinese macroeconomic data, Chang et al. (2015) used rigorous statistical techniques to improve the primitive macroeconomic data published by the Chinese National Bureau of Statistics and provide monthly data for the relevant variables. The data used in this paper are publicly available on the official website of the Federal Reserve of Atlanta.

More specifically, monthly real GDP is calculated by dividing nominal GDP by the GDP deflator.[6] [7] CPI was obtained by seasonally adjusting the monthly consumer price index using the X-12 ARIMA method considering the Chinese New Year effect. The chosen proxy variable for real consumption is calculated by dividing the seasonally adjusted nominal retail sales of consumer goods by the GDP deflator. For the investment series, the X-11 ARIMA method is used to eliminate seasonal residuals, and "capital + innovation + fixed asset investment" is summed to obtain nominal investment, after which it is divided by the GDP deflator to obtain real investment. Net exports is calculated by "nominal export – nominal import" with the X-12 ARIMA method to eliminate the Chinese New Year effect.

To address the problem of abrupt changes in the statistical range for specific periods in the sample, Chang et al. (2015) derived the M2 level series from the level series from 2015M7 to 2016M6 and the year-over-year growth rates published by the People's Bank of China for all other months. The series above have been available since 1992M1.

In addition, the series of real government spending, foreign direct investment, and the one-year benchmark deposit rates are officially provided. Government spending represents the current monthly value of the national public budget expenditure, including the current value of the central and local public budget expenditure. The National Bureau of Statistics has continuously updated the monthly government spending data since 1990M1.

[6] Chang et al. (2015) calculated the monthly nominal GDP by interpolating the seasonally adjusted quarterly nominal GDP value-added with seasonally adjusted monthly nominal retail sales of consumer goods, nominal exports, nominal imports, and the nominal value added of industries.

[7] Using the same method, they calculated the GDP deflator by interpolating the seasonally adjusted quarterly GDP deflator with the seasonally adjusted monthly series of the Producer Price Index (PPI), retail price index, CPI and M2.

According to the Ministry of Commerce of the People's Republic of China, monthly foreign direct investment (in 100 million US Dollars) has been recorded since January 1999. Furthermore, the People's Bank of China has offered the one-year benchmark deposit rate since 1988M9.

The regime-switching variable is the household debt ratio. Since there is no official monthly household debt ratio data in China, I refer to Wang and Li (2020)'s measurement method, where the household debt ratio is measured by the Loans Balance of Financial Institutions as a share of nominal GDP. Table 4.1 summarizes the variables, their time periods of availability, and sources.[8]

Table 4.1: Summary of variables

Variables	Source	Period
EPU (Index)	Baker et al. (2016)	1992M1–2021M3
CEPU (Index)	Federal Reserve of Atlanta, Chang et al. (2015)	2000M1–2021M3
GDP (Billion RMB)	Federal Reserve of Atlanta, Chang et al. (2015)	1992M1–2021M3
CPI (Index)	Federal Reserve of Atlanta, Chang et al. (2015)	1992M1–2021M3
Con (Billion RMB)	Federal Reserve of Atlanta, Chang et al. (2015)	1992M1–2021M3
Inv (Billion RMB)	Federal Reserve of Atlanta, Chang et al. (2015)	1992M1–2021M3
XN (%)	Federal Reserve of Atlanta, Chang et al. (2015)	1994M1–2021M3
M2 (Billion RMB)	Federal Reserve of Atlanta, Chang et al. (2015)	1992M1–2021M3
Gov (Billion RMB)	National Bureau of Statistics	1992M1–2021M3
Bank Rate (%)	People's Bank of China	1992M1–2021M3
FDI (100 million USD)	Ministry of Commerce of the People's Republic of China	1999M1–2021M3
HDR (%)	People's Bank of China/Federal Reserve	1992M1–2021M3

4.2 Data Description

The final time series are obtained by taking the logarithm to the original data. Considering the specificity of the variable net exports (XN), we divide the nominal net exports by the nominal GDP and multiply by 100.

Four information criteria are used to select the optimal lag order. According to the results in Appendix Table A.1, the Schwarz Criterion (SC) indecates the optimal lag

[8]The data source of the Loans Balance of Financial Institutions is the People's Bank of China, from 1978M12 to the present, in 100 million yuan.

number is 3, however, Hannan-Quinn Criterion (HQ), Akaike Info Criterion (AIC), and Final Prediction Error (FPE) favor 12 lags. Since the horizon of the time series in this paper is not very long, the lower lag order of 3 is preferred. To maintain consistency with the subsequent LP estimates, 3 lags is used for all empirical specifications. Table 4.2 shows the summary statistics for the variables with their description and statistics.

Table 4.2: The descriptive statistics

Variables	Description	Mean	S.D.	Min	Max
EPU	The logarithmic form of monthly EPU index in China	4.612	0.696	2.314	6.495
CEPU	The logarithmic form of monthly CEPU index	4.706	0.375	3.643	5.474
GDP	The logarithmic form of monthly real GDP	0.007	0.014	-0.141	0.158
CPI	The logarithmic form of monthly CPI	4.651	0.25	3.903	5.009
Con	The logarithmic form of monthly real retail sales of consumer goods	6.641	0.832	5.230	7.931
Inv	The logarithmic form of monthly real investment	6.753	1.190	4.726	8.571
XN	The nominal net exports divided by nominal GDP and multiplied by 100	3.376	12.160	-3.476	13.12
M2	The logarithmic form of Broad Money Supply	10.39	1.322	7.669	12.33
Gov	The logarithmic form of Government Spending	8.039	1.395	5.019	10.54
Bank Rate	The one-year benchmark deposit rate set by the People's Bank of China	-0.000	0.0025	-0.018	0.018
FDI	The logarithmic form of Foreign Direct Investment	4.250	0.487	2.908	5.236
HDR	The switching variable	12.68	2.9	7.347	22.14

Chapter 5

Empirical Results

We now turn to our empirical results. This chapter describes the results of the study based on the previous methodology. We first show the results of uncertainty shocks caused by EPU and CEPU without regime-switching variables, which we consider as a baseline. Then, we analyze the impact on macroeconomic variables when debt is included as a threshold variable.

5.1 Responses without regime-switching (baseline)

Figure 5.1 illustrates the estimated impulse responses of real GDP, CPI, consumption, and investment to an EPU shock, along with the 95% confidence intervals. Overall, a change in the EPU index causes adverse responses of these four macro variables, albeit to varying degrees. Specifically, the EPU index has a negative long-term effect on consumption and investment, while for GDP and CPI, the negative effects last about a year. In addition, the negative shock of EPU is statistically significant for consumption, but not significant for other variables. The small sample may be the reason for this result.

Although the immediate response of GDP is not negative, it is minimal and declines quickly. It is not until period 13 that there is a shift in the adverse effects, and GDP starts to recover gradually. This is in line with Xu and Wang's (2019) conclusion. For the price level, the negative effect lasts about one year.

Further, the EPU shock to consumption is statistically significant. Consumption suffers a decline in all 20 periods, with the lowest point occurring in the 9^{th} period with a change of about -0.013%. Uncertainty shocks are detrimental to residential consumption. Increased policy uncertainty may increase precautionary savings at the macroeconomic level and, therefore, discourage consumer spending (Bayer et al., 2019).

Although the shock to investment improves briefly after period 10, there is still a more pronounced negative effect in the long run. The negative impact of the change in EPU on investment might be explained by the irreversibility effect of real options and the adjustment cost of the firm. When uncertainty strikes, the marginal profit of the firm's investment fluctuates, so the firm prefers to "wait and see" rather than blindly continue to invest in bearing the risk and cost of uncertainty. In addition, adjustment costs associated with uncertainty may force firms to reduce investment and employment (Bloom et al., 2014).

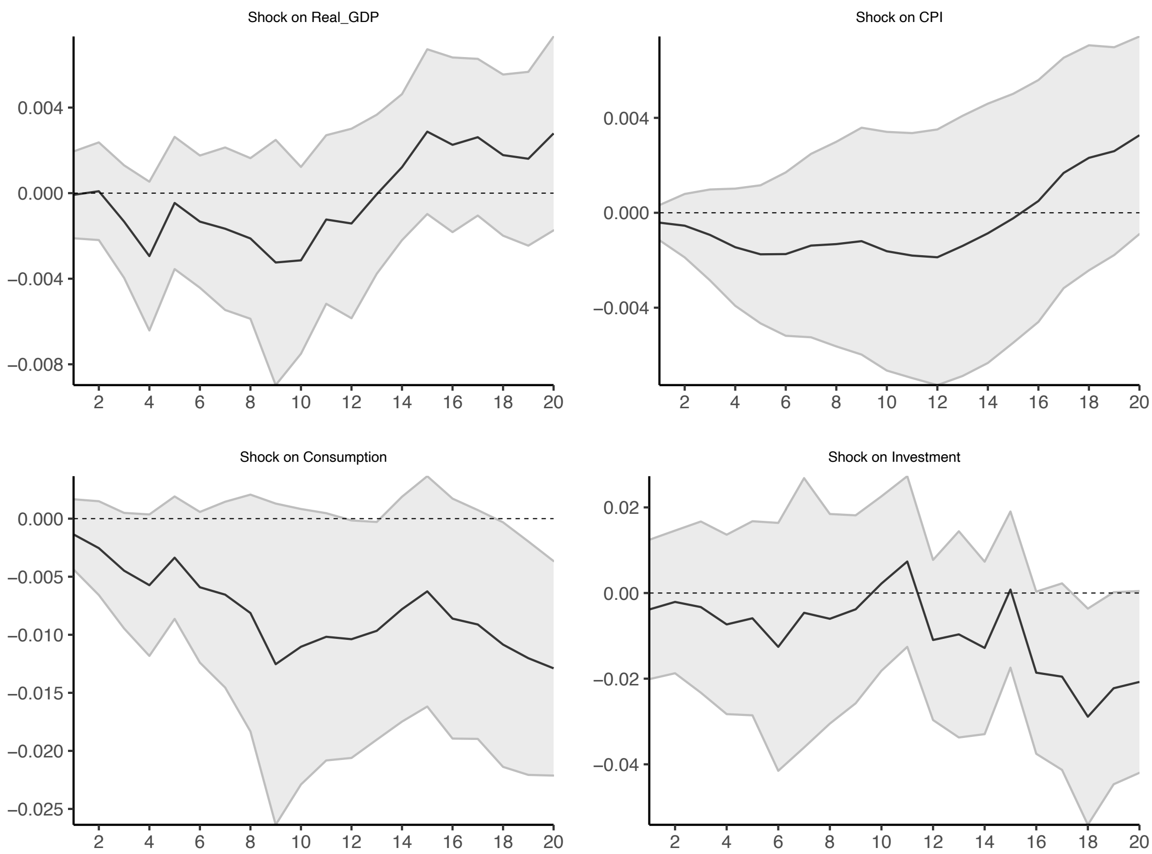


Figure 5.1: The impulse response of the macroeconomics variables to an EPU shock

After changing the proxy variable for the shock to the values of the CEPU index, Figure 5.2 shows the impulse responses of real GDP, CPI, consumption, net exports, and foreign direct investment, along with the 95% confidence intervals. Similar to the previous findings, the changes in the CEPU index also have a negative macroeconomic impact. More specifically, GDP, CPI, consumption and net exports decline, and the negative effects to CPI and net exports are statistically significant.

Both GDP and CPI show a sustained decline in response to the shock. However, unlike the EPU shock, this downward trend does not stop after 12 months. The short-term impact on consumption, although small and positive, declines rapidly and consistently after period 5, with the lowest point occurring in period 16 at about -0.02%. Net exports show a significant deterioration in response to the CEPU shock, with a decrease of more than 2% for every 1% increase in the CEPU index. One explanation for the decrease in net exports is that uncertainty creates a real option to wait for access to foreign markets, and increased transaction costs tend to discourage firms from exporting. In addition, uncertainty may reduce firms' desire to reinvest and discourage them from exporting (Jin et al., 2014).

However, contrary to Zhang's (2016) findings, FDI does not show a persistent decline following a CEPU index and even shows a short-term increase of almost 0.1%. This result is consistent with Zhu and Zhang (2019), who find that economic policy uncertainty positively impacts FDI in the long run. Foreign investment may be more stable because it is a long-term investment involving fixed assets such as production equipment and plant construction. Since China acceded to the WTO, the Chinese government has attracted a large amount of foreign investment through tax rebates and rent reductions, so many policies are generally favorable for foreign investment to enter the Chinese market.

To conclude, the above results are consistent with the conclusions of Jin et al. (2014); Xu and Wang (2019). There studies note that uncertainty has a significant negative effect on output, the price level, consumption, and investment.

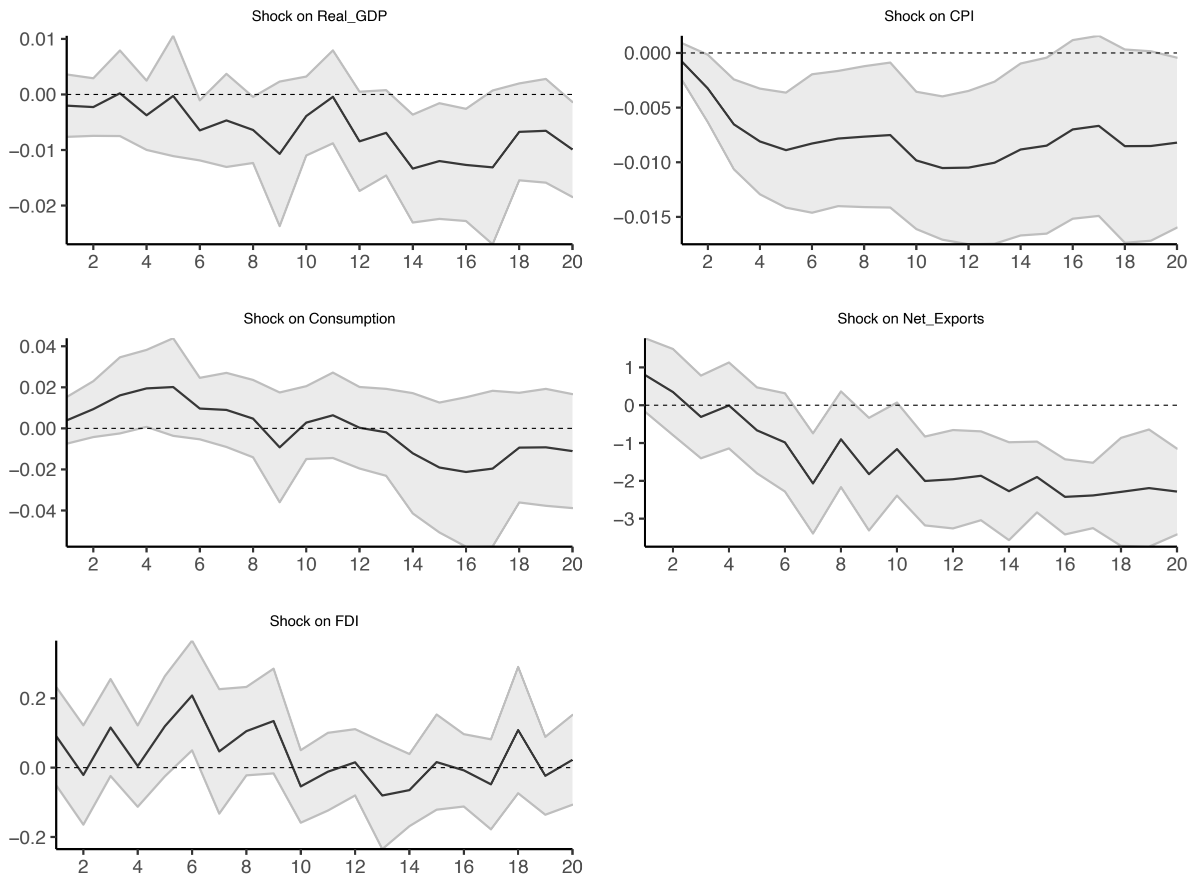


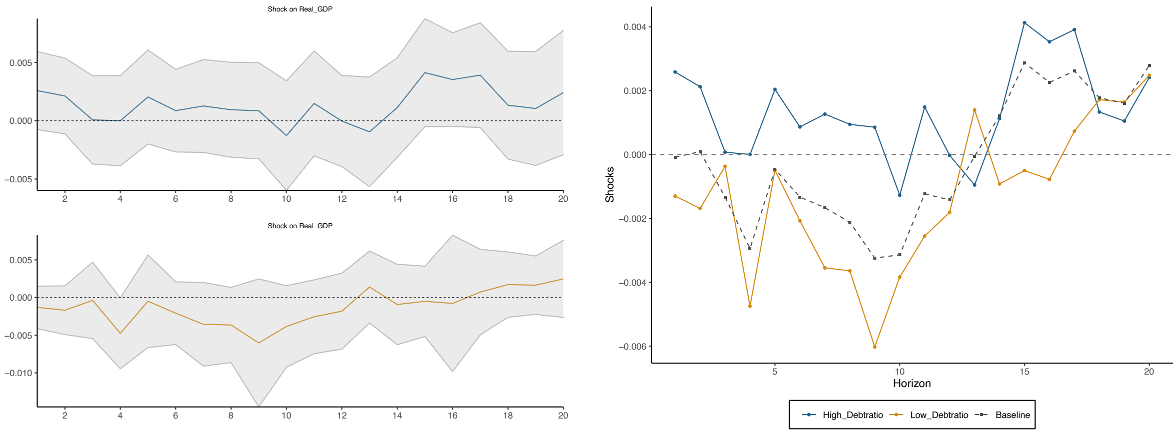
Figure 5.2: The impulse response of the macroeconomics variables to a CEPU shock

5.2 Regime-switching model with EPU uncertainty

We now turn to the effect that the state of household debt can have following uncertainty shocks. Figure 5.3(a) presents the impulse responses of real GDP to an EPU shock in the high household debt ratio (top) and low household debt ratio (bottom), with the 95% confidence band (grey shaded part). Figure 5.3(b)) shows the comparison of the mean value of the impulse responses in the high debt ratio, low debt ratios, and baseline scenarios. Based on Figure 5.3, the shock immediately reduces output by about 0.002% in the low debt ratio state and reaches its lowest point in the ninth period, with -0.006%. By contrast, the shock in the high debt ratio state leads to a long-lived increase.

The impact of EPU on GDP is very different in the two debt regimes, and this finding may be explained by the fact that a high debt ratio is a consequence of EPU growth.

For example, when the uncertainty index increases, the Chinese central bank tends to implement an accommodative monetary policy to boost the economy. With lower lending rates, household debt ratios may rise, stimulating consumption and investment and thus increasing GDP.



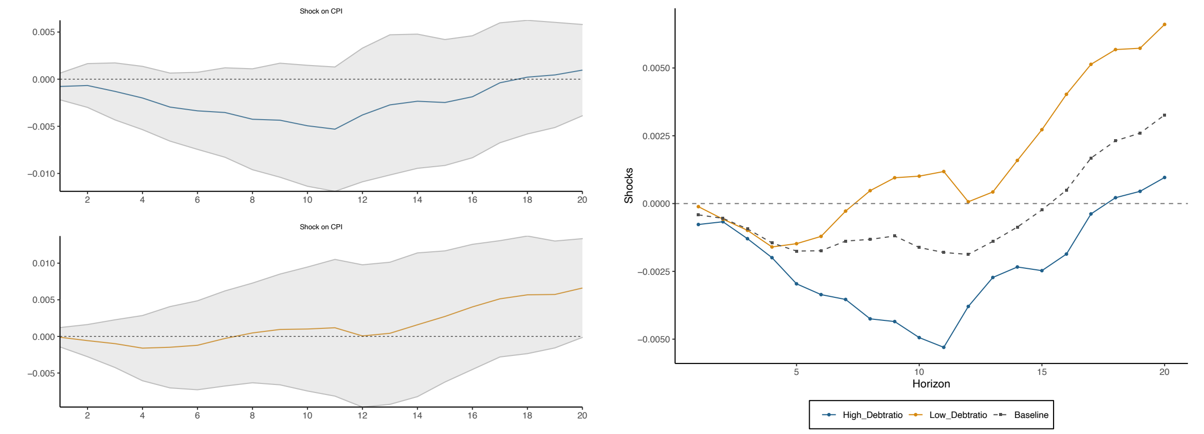
(a) Shocks plot with 95% confidence interval (grey shaded part), in the high household debt ratio state (top) and low household debt ratio state (bottom)

(b) The comparison of the mean values of the impulse responses in the high debt ratio state, low debt ratio state, and baseline.

Figure 5.3: The impulse response of GDP to an EPU shock

As shown in Figure 5.4, under the uncertainty shock, the price level exhibits a continuous decline in the high debt state, with the lowest point occurring in the 11^{th} period with a change of about -0.005%. However, in the low debt state, the effect is initially significantly smaller than in the high debt period.

In short, with low debt ratios, price levels are subject to smaller changes than with high debt and recover more quickly. One potential reason is that, under low indebtedness, the residential sector's willingness to consume is less affected. In addition, after an EPU shock, the less indebted residential sector may regain its willingness to consume or retaliate with consumption at a faster pace due to its smaller debt burden, and strong demand helps prices rebound.

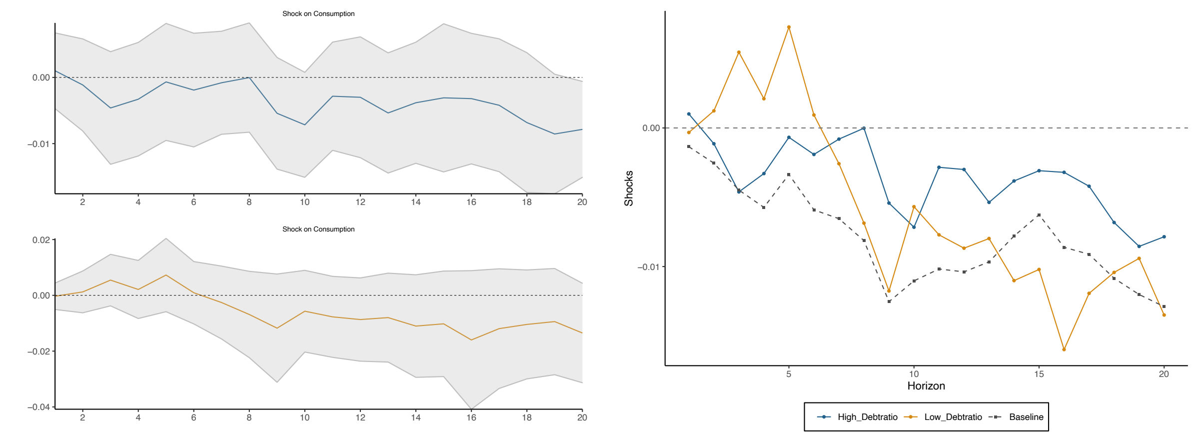


(a) Shocks plot with 95% confidence interval (grey shaded part), in the high household debt ratio (top) and low household debt ratio state (bottom

(b) The comparison of the mean values of the impulse responses in the high debt ratio state, low debt ratio state, and baseline.

Figure 5.4: The impulse response of the CPI to an EPU shock

From Figure 5.5, consumption decreases in the high debt state in almost all periods. In contrast, consumption initially increases in the low debt regime, peaking at 0.065% after 5 periods. Then, it sharply decreases. These findings also confirm the reasons for the faster recovery of prices under the low debt ratio state. The willingness to consume will recover more quickly with low debt ratios.



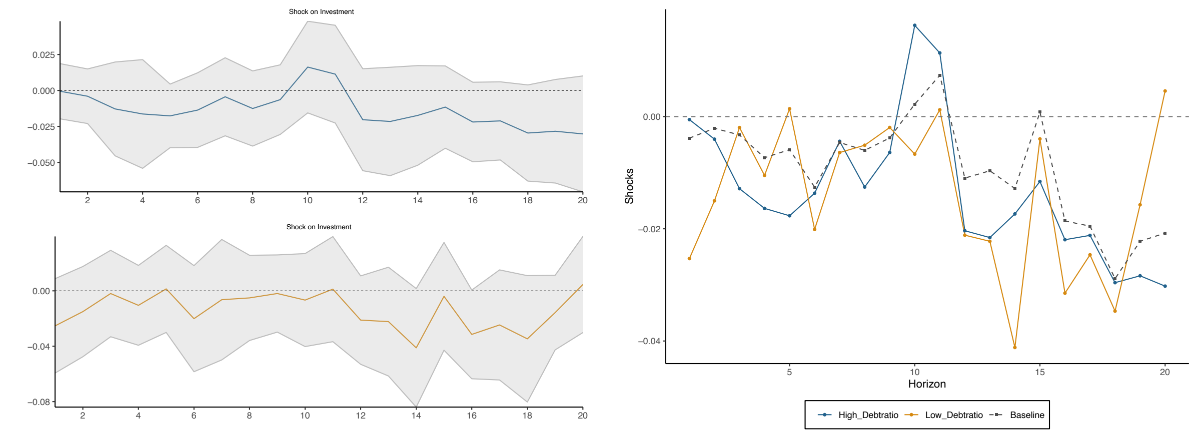
(a) Shocks plot with 95% confidence interval (grey shaded part), in the high household debt ratio (top) and low household debt ratio state (bottom

(b) The comparison of the mean values of the impulse responses in the high debt ratio, low debt ratio state, and baseline.

Figure 5.5: The impulse response of consumption to an EPU shock

Figure Figure 5.6 shows that the sudden negative impact of the uncertainty shock on investment is highly significant in the low debt regime, exceeding -0.02%. In contrast, the impulse response function with the high debt ratio has a "hump" shape, peaking in the 10^{th} period and then starting to decline.

The resident's debt ratio does not significantly influence investment. One possible reason for this is that the residential sector is not the one that significantly affects the investment performance in China, and thus different residential indebtedness ratios do not have a significant impact on investment. Currently, the sectors that have a more significant impact on investment in China remain government-led funds and state-owned enterprises.



(a) Shocks plot with 95% confidence interval (grey shaded part), in the high household debt ratio (top) and low household debt ratio state (bottom

(b) The comparison of the mean values of the impulse responses in the high debt ratio, low debt ratio state, and baseline.

Figure 5.6: The impulse response of investment to an EPU shock

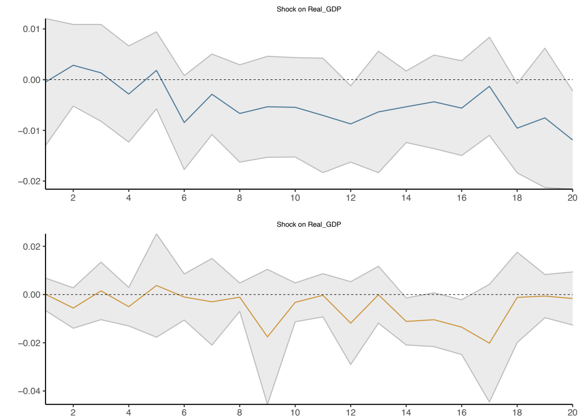
To summarize, with the low household debt ratio, an EPU shock exhibits adverse short-term effects to the macroeconomy. In particular, it causes a decline of about -0.002% and -0.025% for output and investment, respectively. In addition, with a high household debt ratio, although the effect of EPU shocks to macroeconomic variables is not significantly negative in the short run, each macro variable shows a significant decline over time.

Comparing the performance of macroeconomic variables under the different regimes, it can be found that EPU shocks have a significant amplifying effect on the price level and consumption under a high debt ratio.

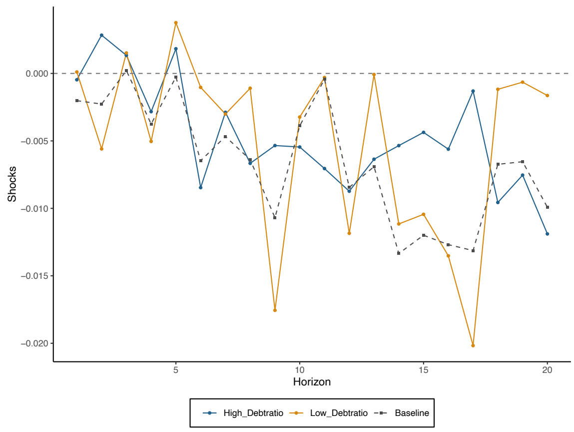
In the long run, the adverse effect of uncertainty generally eases by period 10. Nevertheless, the EPU shock has a damaging longer-term persistent effect to the price level and consumption under the high debt ratio state.

5.3 Regime-switching model with CEPU uncertainty

Figure 5.7 shows the results obtained from the impulse response function of real GDP to a unitary CEPU shock, along with the 95% confidence band. As can be seen from the figure, the response of GDP to CEPU shocks is negative in the long run for both high and low residential debt ratio states, and does not differ significantly.



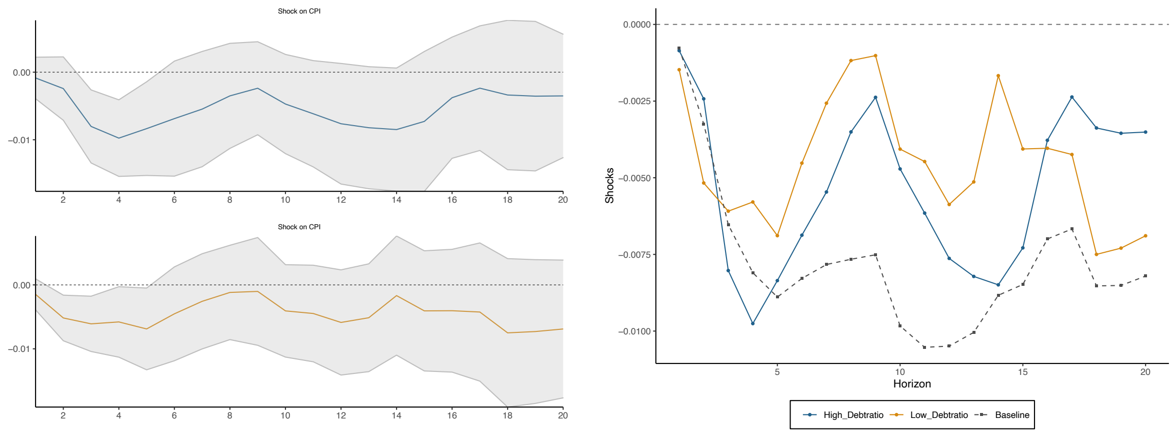
(a) Shocks plot with 95% confidence interval (grey shaded part), in the high household debt ratio state (top) and low household debt ratio state (bottom)



(b) The comparison of the mean value of the impulse responses in the high debt ratio, low debt ratio state, and baseline.

Figure 5.7: The impulse response of GDP to a CEPU shock

Figure 5.8 presents a persistent negative impact of CEPU on the price level. The negative effects are more dramatic with high debt ratios than low debt ratios until the 16^{th} period. At the same time, this supports the conclusion in the previous section that shocks to the price level are moderated at low debt ratios.

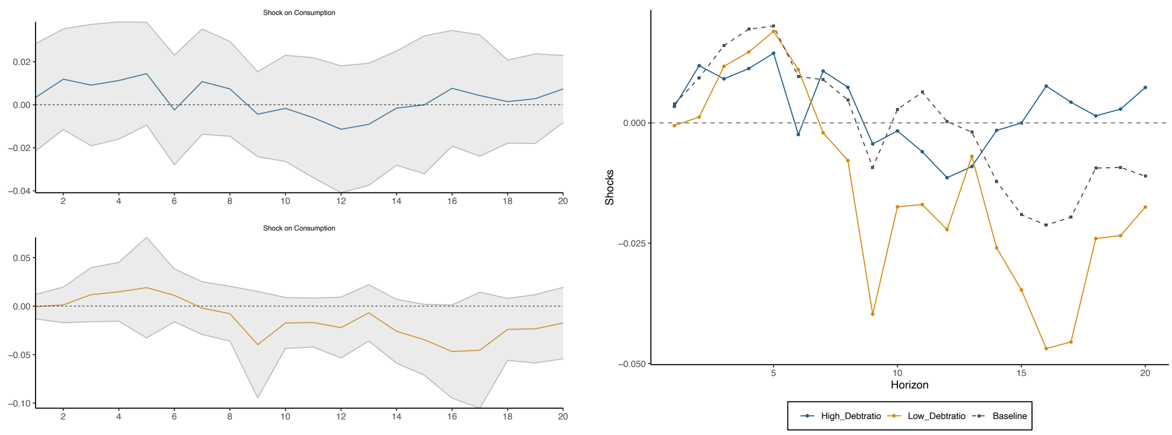


(a) Shocks plot with 95% confidence interval (grey shaded part), in the high household debt ratio (top) and low household debt ratio state (bottom)

(b) The comparison of the mean values of the impulse responses in the high debt ratio, low debt ratio state, and baseline.

Figure 5.8: The impulse response of the CPI to a CEPU shock

Figure 5.9 demonstrates that there is no immediate and significant negative effect to consumption for either high or low debt states. In the long run, however, the negative effect of a CEPU shock to consumption is more pronounced at low debt ratios.



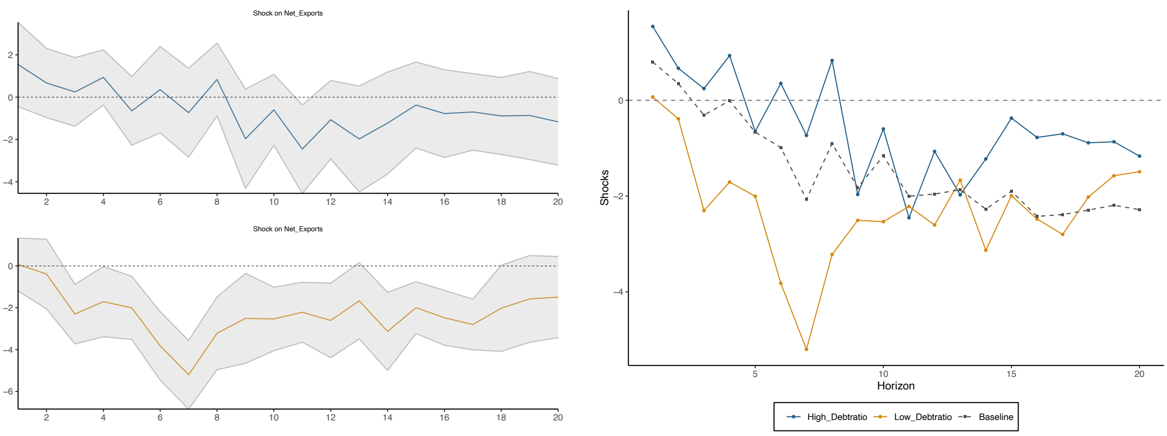
(a) Shocks plot with 95% confidence interval (grey shaded part), in the high household debt ratio (top) and low household debt ratio state (bottom)

(b) The comparison of the mean values of the impulse responses in the high debt ratio, low debt ratio state, and baseline.

Figure 5.9: The impulse response of consumption to a CEPU shock

Based on Figure 5.10, it can be concluded that, in the case of low household debt, net exports drop sharply, and this tends to be statistically significant in the long run. In contrast, the negative effect under the high debt state starts after 6 months and is not significant. A possible economic explanation is that China has many individual entrepreneurs (e.g., the Yiwu International Trade City in China, mainly engaged in exporting small commodities) who receive more export orders and take loans from banks for production in high indebtedness of the population. Even in the case of an uncertainty shock, the orders in hand can guarantee short-term exports so that net exports will be hit later. A high debt ratio state may mean that the market is favored by more capital and has more orders to withstand shocks.

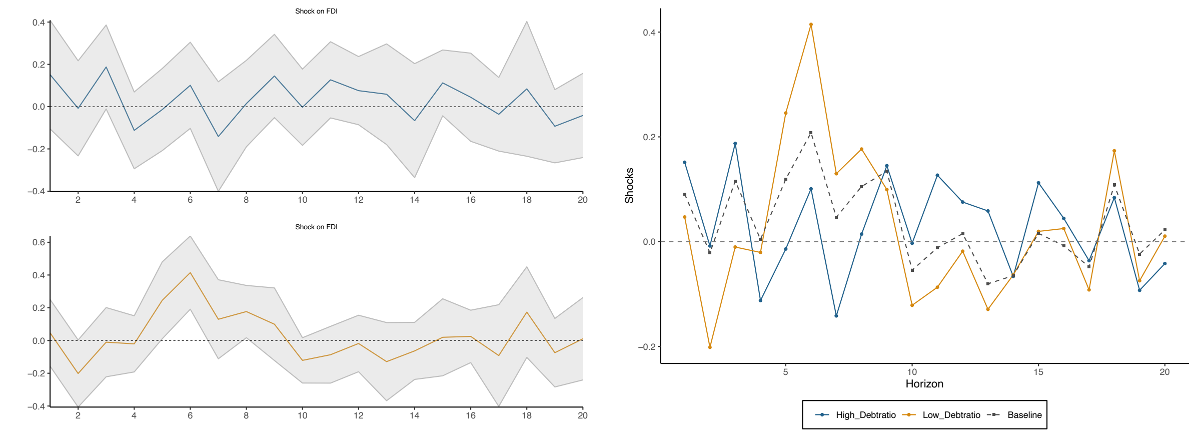
Based on the information in Figure 5.11, it is somewhat surprising that there are no long-run unfavorable fluctuations in FDI under uncertainty shocks. Moreover, there is no significant difference in FDI across different resident indebtedness ratios.



(a) Shocks plot with 95% confidence interval (grey shaded part), in the high household debt ratio (top) and low household debt ratio state (bottom)

(b) The comparison of the mean value of the impulse responses in the high debt ratio, low debt ratio state, and baseline.

Figure 5.10: The impulse response of net exports to a CEPU shock



(a) Shocks plot with 95% confidence interval (grey shaded part), in high household debt ratio state (top) and low household debt ratio state (bottom)

(b) The comparison of the mean values of the impulse responses in the high debt ratio, low debt ratio state, and baseline.

Figure 5.11: The impulse response of FDI to a CEPU shock

To conclude, with low debt ratios, CEPU has negative effects on output, the price level, consumption, and net exports. In addition, there exists statistically significant negative effects to consumption and net exports in the long run. With high household debt, the CEPU has negative effects to these macro variables in the long run, but effects are significantly smaller than in periods of low household debt. Moreover, the uncertainty is not a significant shock to foreign investment, nor does its effect on foreign investment depend on residential indebtedness.

5.4 Findings and Discussions

Based on the previous results, it can be concluded that a significant immediate negative response exists in the low debt ratio regime, and the negative effect is persistent. Although GDP increses in the first period in response to the CEPU shock, it is not significant nor persistent. Thus, overall, the uncertainty shocks harm aggregate output.

As for the effects to the price level, the two uncertainty proxy variables draw similar conclusions. The shock would lead to a long-term sustained decline in the price level, regardless of the household debt ratio. In other words, shocks lead to long-lasting damage to price levels. In addition, the price level under the high household debt regime is subject to a more severe decline and takes longer to recover and rebound.

The results suggest that consumption rebounds faster with low household debt ratios but still shows persistent negative effects in the long run. One possible reason is that high household debt ratios limit some non-essential consumption demand, while a low debt status does not limit the household sector's purchasing power in the short run.

When EPU is the uncertainty variable, short-term investment is severely negatively impacted in the low debt ratio state. This may be because China has many individual business owners (who invest in the real economy) and individual stock market investors (who invest in financial assets), who are not committed long-term investors. When uncertainty increases, they may prefer to reduce their leverage and leave the market quickly, resulting in lower debt ratios.

When the uncertainty variable is measured as CEPU, foreign investment shows positive effects in the short run regardless of the debt ratio, and there is no long-term negative effect.

This finding is unexpected following uncertainty studies: net exports decline more quickly at low debt ratios. Perhaps this is due to the fact that overseas import and export orders have the property of forward contracts, and even if policies targeting exports are implemented immediately, orders signed earlier will remain in effect until the contract expires, so the effect has a lag.

Overall, the economic policy uncertainty has a persistent negative effect on China's macroeconomy. Under the low household debt state, consumption and net exports suffer larger declines.

For policy makers, efforts should be made to reduce the frequency of uncertainty events in the economic policy making process, in order to attenuate the negative impact of uncertainty. In addition, the different effects from uncertainty under different resident debt ratios should also be of concern to policy makers.

Chapter 6

Conclusion

Past studies have mainly used models such as VAR or SVAR to study the impact of uncertainty on developed countries such as the U.S. or Western Europe. For developing countries, including China, the number of such studies is minimal, and the few studies are limited to linear models such as a VAR.

With the transformation of China's economy, economic growth has shifted more to be more resident consumption-driven, and therefore the impact of changes in residential debt status on the macroeconomy is increasingly essential. This paper investigates the impact of economic policy uncertainty on China's macroeconomy using a nonlinear local projection model using the resident debt ratio as a state transition variable. Using monthly data instead of quarterly data dramatically improves the sample size and accuracy.

This paper finds a persistent negative impact of economic policy uncertainty on macroeconomic variables in China. In particular, the increase in uncertainty reduces GDP, the price level, consumption, investment, and net exports. But foreign investment is affected by uncertainty to a minimal extent. In addition, the high household debt state has an amplifying effect for the CPI index, but consumption and net exports have a greater negative effect under the low debt regime.

The results suggest that policymakers should pay more attention to macroeconomic deterioration brought about by higher policy uncertainty. Especially with low resident indebtedness, consumption and net exports will suffer more, and these two variables are essential components of GDP.

At the same time, there are some limitations of this paper. First, there are some biases in the proxy variables of uncertainty. Specifically, the EPU/CEPU indices only represent the frequency of relevant keywords in selected newspapers, while the mentioned keywords are not necessarily reporting economic uncertainty but may only objectively describe the macroeconomic situation. In addition, the selection of variables and the available time horizon limit the sample size because of the late construction of the Chinese macroeconomic database.

Finally, measuring uncertainty by the frequency of keywords from newspapers might capture endogenous policy responses to fundamental uncertainty, or uncertainty from the rest of the world or from domestic sources. It would be useful for future studies to try to separate these differences and measure their respective impacts.

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APPENDICES

A Information Criteria

Table A.1: The results of optimal lags criteria

Lags	AIC	HQ	SC	FPE
1	34.71	35.04	35.53	1.19×10^{15}
2	33.63	34.24	35.16	4.01×10^{14}
3	32.66	33.56	34.92	1.53×10^{14}
4	32.38	33.56	35.36	1.16×10^{14}
5	32.23	33.70	35.93	1.00×10^{14}
6	32.16	33.93	36.59	9.44×10^{13}
7	32.12	34.17	37.27	9.17×10^{13}
8	32.06	34.40	37.93	8.70×10^{13}
9	31.86	34.49	38.45	7.26×10^{13}
10	31.26	34.17	38.57	4.05×10^{13}
11	30.74	33.94	38.78	2.48×10^{13}
12	29.25	32.74	38.01	5.77×10^{12}