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Auteurs

Yifei Cai, Jamel Saadaoui, Yanrui Wu

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www.beta-economics.fr

@beta_economics

Contact :
jaoulgrammare@beta-cnrs.unistra.fr

The Political Relation and Trade - The Case of US, China and Australia*

Yifei Cai †
Macau University of Science and Technology

Jamel Saadaoui ‡
University of Strasbourg

Yanrui Wu §
University of Western Australia

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Abstract

This paper employs structural vector autoregression and local projection methods to examine the impacts of the deterioration in US-China political rela-tions on Australia-China bilateral trade. By imposing a recursive identifi-cation scheme with different assumptions, the empirical results illustrate that worsening US-China political relations have a negative impact on Australian exports to and imports from China. Under a time-varying structural vector autoregression model, it is found that the deterioration in US-China political rela-tions augments the negative impacts on Australia-China bilateral trade during the Trump's administration. The empirical findings provide insightful policy suggestions to both Australian and Chinese governments.

Keywords: Structural vector autoregression, Local projection, Impulse response; US-China political relation; Australia-China trade

Journal of Economic Literature Codes: C32, F14, F51

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†School of Business, Macau University of Science and Technology, Macao, China. Email: yfcai@must.edu.mo.

‡University of Strasbourg, University of Lorraine, BETA, CNRS, 67000, Strasbourg, France. Email: saadaoui@unistra.fr.

§Corresponding author. Business School, University of Western Australia, Perth, Australia. Email: yanrui.wu@uwa.edu.au.

1 Introduction

The link between political relations and trade has been widely investigated. Earlier studies show that bilateral trade declines as a result of military conflicts (Morrow et al., 1998; Long, 2008; Hegre et al., 2010), disputes over territories (Simmons, 2005), and conflicting political objectives (Pollins, 1989a,b). Although many studies discussed the negative impacts of worsening political relations on trade between two countries, very few investigated the spillovers of a worsening relationship on third-country trade. After the World War II, the US became a leading economy, military superpower and technological innovator. However, China is a rising power with rapid economic growth, especially after joining the World Trade Organization in 2001. Due to the differences in their economic structure, political system and common values, there are many ongoing disputes between US and China.

In recent decades, the political relations between US and China began with the so-called "secret trip" by Henry Kissinger in 1971 which broke the political ice and paved the road for diplomatic relations. Thereafter, some key events put a sharp end to the d´etente, including the Tiananmen Square Event in 1989 and the US bombing of the Chinese embassy in Belgrade in 1999. The following years witnessed ups and downs in the Sino-US relations. Since former president Donald Trump came to power in 2017, the US and China have been experiencing the worst diplomatic relations in recent decades. In March 2018, Trump announced sweeping tariffs on Chinese imports such as clothing, shoes, and electronics, which is commonly viewed as the start of a US-China trade war. In addition to these, there are confrontations in other fields such as human rights, technology and intellectual property, China being labeled a currency manipulator by the US and China's new national security law on Hong Kong's judicial independence. Existing studies such as Du et al. (2017) examined the impacts of political relations on trade between China and its counterparts. However, there is no related literature emphasizing the spillover effects of deteriorating political relations.

Since US and China are two leading economies in the world, their political relationship could affect the relation between a third country and China. Although China's influence is rising, the US still dominates international affairs and is supported by strong alliances. This paper focuses on the trade of Australia and China for several reasons. First, US and China are both important trade partners of Australia. Facing the confrontation between US and China, the diplomatic position of Canberra would matter to China's relations with Australia as the latter has a longstanding alliance with the US. Second, Australian politicians publicly made remarks on China's new national security law on Hong Kong's judicial independence and treatment of the Uighurs, which are viewed as interference in Beijing's sovereignty. Furthermore, the Australian government banned the Chinese telecommunications company Huawei from entering the market while the Chinese government reduced the imports of barley, wine, red meat, cotton, timber, lobster, coal and so on from Australia. Third, Australia is one of the few developed nations that exports more to China than it imports from China. In other words, trading with China would be beneficial to Australia's domestic economy. Therefore, it would be interesting to determine whether the political tensions between China and the US have an impact on trade between China and Australia. The economic implications provided are meaningful to other countries which are struggling in US and China's confrontation.

To identify macroeconomic shocks, the widely used method is structural vector autoregression (SVAR). The empirical specification and identification strategy is essential to impulse responses. To avoid reverse causality problems, we consider three different assumptions related to political outcomes such as "America First", "China Threat Theory", and "US Labels China a Currency Manipulator". Under different assumptions, the variable order is changed accordingly. To solve the misspecification problem, we utilize a local projection (LP) method proposed by Jordà (2005). Besides, we also provide time-varying impulse responses by using a forward expanding method. Last, we carry out a series of robustness checks to validate the main conclusions.

The empirical findings could be summarized as follows. First, deteriorating US-China relations could provide a negative shock to Sino-Australian relations with significant spillover effects. Second, Australian exports to and imports from China would decrease as US-China political relations worsen. Third, by excluding the period of Trump's administration, Australian exports to and imports from China do not react to political tensions. Last, within a time-varying analytical framework, the bilateral trade is strongly affected by the degradation of political relationships during Trump's presidency.

The remainder of this paper is organized as follows. Section 2 presents some discussion about the political relation index. Section 3 briefly introduces SVAR and LP methods. Section 4 describes the source of dataset and empirical strategy. Section 6 shows empirical results. The last section provides concluding remarks and policy implications.

2 Quantifying Political Relations

Measuring political relations is not an easy task. Fortunately, Yan and Qi (2009) and Yan et al. (2010) first propose political relation index (so-called PRI hereafter) to quantify China's political relations with its counterparts (including US, Japan, Russia, UK, France, India, Germany, South Korea, Vietnam, Australia, Indonesia, and Brazil). The PRI is built upon the reports of bilateral political events from "The People's Daily" and official website of Ministry of Foreign Affairs of the People's Republic of China.[1] Moreover, they also take into account some key political events which are not covered in "The People's Daily", such as the "secret trip" by Henry Kissinger in 1971.

The PRI index is a quantitative measurement using scores which provide a general idea about the relationship between China and its counterparts. Yan and his colleagues divided the political relation into six categories, such as rival (-9 to -6), tense (-6 to -3), disharmonious (-3 to 0), ordinary (0 to 3), good (3 to 6), and friendly (6 to 9). The minimum unit of measure is 0.1 to reflect slight changes in bilateral relations. To calculate the influential score of a given political event, Yan and his colleagues propose the following function,

$$\mathcal{IS} = \begin{cases} \frac{N-P_0}{N}\mathcal{IS}_0 & \text{while} \quad \mathcal{IS}_0 \geq 0 \\ \frac{N+P_0}{N}\mathcal{IS}_0 & \text{while} \quad \mathcal{IS}_0 < 0 \end{cases}$$

where $\mathcal{IS}$ denotes the influential score of an event when the bilateral relation is located at P_0, N denotes the absolute range of bilateral relation, P_0 represents the initial score when the political event occurs, and $\mathcal{IS}_0$ is the unadjusted influential

[1] "The People's Daily" is an official newspaper of the Central Committee of the Chinese Communist Party (CPC).

score which is listed in the event score table. They set the maximum value of N as 9, and $\mathcal{IS}$ moves over the range of $[-9, 9]$. The PRI index calculated by using the above function has the following features. First, when $\mathcal{IS}_0 > 0$, the positive effects of a given political event decrease as the initial position P_0 moves from confrontation to friendship. While P_0 is 9 denoting a friendly relation, the positive effects will vanish. For example, Nixon's visit to China in 1971 which establishes the diplomatic relation is more important than Reagan's visit in 1978 because the US and China were enemies during the Vietnam War. When $\mathcal{IS}_0 < 0$, the negative effects of a political event will increase as the original bilateral relation P_0 turns from confrontation to friendship. Another point that should be highlighted is that military conflict is not equal to confrontation. During the period from the second half of 1953 to earlier 1954, US-China political relations suffered from confrontation, though there are no military conflicts.

Figure 1 plots PRI indices of US-China and Australia-China covering the period from January 1950 to June 2020. According to the evolution of PRI indices, we find the US-China PRI increases from 1971 when Henry Kissinger visited China. After that, US-China PRI sharply drops due to the Tiananmen Square Event in 1989 and the US bombing of the Chinese embassy in Belgrade in 1999. After that, US-China PRI slowly climbs until Donald Trump took office in 2017. The US-China PRI suddenly plunges during Trump's presidency. In comparison with US-China PRI, Australia-China PRI is relatively stable over time. After Kissinger's "secret trip" in 1971, Australia established diplomatic relations with China in 1972. In the following several decades, Australia-China political relations continued to improve till the end of 2016 though we also observe a set-back during the Tiananmen Square Event in 1989. After 2016, Australia-China PRI also experienced a sharp drop.

Figure 1 is here

According to the evolution of US-China PRI and Australia-China PRI, we can observe some synchronous changes immediately after the Tiananmen Square Event in 1989, the US bombing of the Chinese embassy in Belgrade in 1999 and Trump's trade war started in 2018. Therefore, we intuitively suspect lead-lag effects between them. We utilize the Granger non-Causality test to investigate the causality between US-China PRI and Australia-China PRI. Consider a bivariate VAR model,

$$y_{1t} = c_{10} + \sum_{i=1}^{p} \alpha_{1i} y_{1t-i} + \sum_{i=1}^{p} \beta_{1i} y_{2t-i} + \varepsilon_{1t}$$
$$y_{2t} = c_{20} + \sum_{i=1}^{p} \alpha_{2i} y_{1t-i} + \sum_{i=1}^{p} \beta_{2i} y_{2t-i} + \varepsilon_{2t}$$

where y_{1t} and y_{2t} are stationary processes. c denotes constant term, and p is the maximum lags added to the VAR model. Under the null hypothesis of non-Granger causality from y_{2t} to y_{1t}, that is $y_{2t} \xrightarrow{\mathcal{NG}} y_{1t}$, we could test

$$\mathbf{H}_0 : \beta_{11} = \beta_{12} = \cdots = \beta_{1p} = 0.$$

The above equations mean that the predictions of y_{1t} conditional on its own history cannot be improved by incorporating the past p lags of y_{2t} in the model. Since the PRI is a monthly dataset, we determine p as 12 and use first difference on US-China PRI (pri_t^{US-CH}) and Australia-China PRI (pri_t^{AUS-CH}) to ensure the variables are stationary, respectively. The Wald test statistic under the null hypothesis that Δpri_t^{AUS-CH} does not Granger cause Δpri_t^{US-CH} is 0.944 which is insignificant. In contrast, the null hypothesis that Δpri_t^{US-CH} does not Granger cause Δpri_t^{AUS-CH} is rejected at 5% significance level with the Wald test statistic 2.127. That is, the changes of US-China political relations Granger cause variations in Australia's political relations with China.

Table 1 is here

3 SVAR and LP Methods

A vector autoregression (VAR) is widely used by empirical scholars with different applications. By imposing a restriction matrix, the model is supposed to represent the structure of an economy. Consider a structural VAR(p) model,

$$\mathbf{A}_0 y_t = c + \mathbf{B}_1 y_{t-1} + \mathbf{B}_2 y_{t-2} + \cdots + \mathbf{B}_p y_{t-p} + \varepsilon_t \tag{1}$$

where $y_t = (y_{1t}, y_{2t}, \cdots, y_{kt})'$, c is a constant term, and $A_0, A_1, A_2, \cdots, B$ are coefficient matrices. The vector ε_t is presumed to be white noise processes, which includes k structural shocks $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t}, \cdots, \varepsilon_{kt})' \sim \mathbf{N}(0, \mathbf{I}_k)$. We then could rewrite (1) as a reduced form,

$$y_t = \boldsymbol{\alpha} + \boldsymbol{\Phi}_1 y_{t-1} + \boldsymbol{\Phi}_2 y_{t-2} + \cdots + \boldsymbol{\Phi}_p y_{t-p} + \mathbf{e}_t \tag{2}$$

where $\boldsymbol{\alpha} = \mathbf{A}_0^{-1} c$, $\boldsymbol{\Phi}_i = \mathbf{A}_0^{-1} \mathbf{B}_i y_{t-i}$ for $i = 1, 2, \cdots, p$ and $\mathbf{e}_t = \mathbf{A}_0^{-1} \varepsilon_t$. Here, we normalize the variance-covariance matrix of the structural residuals as $\mathbf{E}(\varepsilon_t' \varepsilon_t) = \sum_\varepsilon = \mathbf{I}_k$. In addition, the variance-covariance matrix of the reduced-form could be presented as $\mathbf{E}(\mathbf{e}_t' \mathbf{e}_t) = \sum_{\mathbf{e}} = \mathbf{A}_0^{-1} \mathbf{A}_0^{-1'}$. To establish the relationship between SVAR and the reduced-form VAR, we should pre-know $\mathbf{A}_0$ which represents contemporaneous impacts of the model variables or of its inverse. In this study, we use a recursive identification strategy and assume a lower-triangular $k \times k$ matrix $\mathbf{Q}$ with a positive main diagonal, which satisfies $\sum_{\mathbf{e}} = \mathbf{A}_0^{-1} \mathbf{A}_0^{-1'} = \mathbf{Q}\mathbf{Q}'$, and such that $\mathbf{A}_0^{-1} = \mathbf{Q}$. To recover $\mathbf{A}_0$, we utilize a typical Cholesky decomposition method.

Jordà (2005) suggests that the misspecification problem in a typical SVAR model leads to inaccurate impulse response estimates. He proposes a so-called "local projections" method by using a horizon-specific regression rather than the iterated regression method used in the traditional model. Ramey and Vine (2006) and Plagborg-Møller and Wolf (2021) point out that the local projections sometimes provide erratic impulse responses, Jordà (2005), Ramey (2016) and Montiel-Olea and Plagborg-Møller (2021) confirm that the local projection method is considerably robust against empirical specifications compared to a typical SVAR model.

The LP method is expressed as follows,

$$y_{k,t+h} = \alpha_{k,h} \cdot \varepsilon_{k,t} + \mathbf{controls} + \eta_{h,t}, \quad h = 0, 1, 2, \cdots$$

where $\alpha_{k,h}$ is the estimate of the impulse response of a variable $y_{k,t+h}$ at horizon h to a shock on $\varepsilon_{k,t}$. The control variables include deterministic trends such as constant term, lags of the $y_{k,t+h}$ and other variables that are necessary. Here, we utilize the method of Newey and West (1987) to correct potential serial correlation in $\eta_{h,t}$. In addition, the LP impulse response still relies upon the identification of $\varepsilon_{k,t}$ in a typical SVAR model. Plagborg-Møller and Wolf (2021) present that SVAR and local projections provide closely tied patterns in the shorter horizons. However, in the longer horizons, the specification with a small lag will generate observable gaps between SVAR and LP methods.

Other empirical specification strategies can be summarized as follows. First, we determine the optimal lags as 4 thanks to the Akaike Information Criteria corrected (AICc) proposed by Hurvich and Tsai (1993) in both SVAR and LP. Second, we use the wild bootstrap method to generate error bands for the typical SVARs and Newey-West standard errors to generate confidence level error bands for LP estimates.

4 Data and Empirical Specifications

4.1 Data

The PRI of US-China and Australia-China can be found on the official website of Institute of International Relations of Tsinghua University: http://www.imir.tsinghua.edu.cn/. The dataset of Australian exports to and imports from China is available at the Direction of Trade Statistics operated by International Monetary Fund (IMF). In addition, we also include gross domestic production (GDP) and real effective exchange rate (REER) into the baseline model. The GDP and REER are drawn from the International Financial Statistics database of the IMF. To deflate GDP and trade statistics, we utilize the consumer price index at constant prices (CPI), which is also available at the IFS database. Although Yan and Qi (2009) and Yan et al. (2010) measure the PRI at a monthly frequency, we convert it into a quarterly frequency due to unavailability of macroeconomic indicators of China and Australia at a monthly frequency. All data used in this study are seasonally adjusted and cover the period from 1992Q1 to 2020Q2. We choose the following notations for the involved variables: pri_t^{US-CH}, pri_t^{AUS-CH}, gdp_t^{CH}, gdp_t^{AUS}, $reer_t^{CH}$, $reer_t^{AUS}$, ex_t and im_t denote the political relation index between US and China, the political relation index between Australia and China, the real GDP of China, the real GDP of Australia, the real effective exchange rate of China, the real effective exchange rate of Australia, the Australian exports to

China and the Australian imports from China, respectively. Due to the negative values in PRI, we utilize the following use $pri + \sqrt{1 + pri^2}$ to replace the original PRI series.

4.2 Identification

The empirical specifications are crucial to impulse response analyses of the SVAR model. Since the contemporaneous relation matrix $\mathbf{A}_0$ in equation (1) relates to identifying the structural shocks, we implement a recursive identification scheme and recover $\mathbf{A}_0$ by using the Cholesky decomposition.[2] Therefore, variable orders should be carefully determined. The eight variables that we have considered can be divided into 4 groups which are pri_t^{US-CH}, Chinese variables, pri_t^{AUS-CH} and Australian variables. According to the Australian Bureau of Statistics 20XX, Australian total exports of goods to China were 150,488 million dollars, however its total imports from China were only 80,876 million dollars. Australia enjoyed a large surplus with China. Thus, the Australian economy could be influenced by both the sluggish Chinese demand and the deterioration of bilateral political relations. Therefore, we locate pri_t^{AUS-CH} after Chinese variables (gdp_t^{CH} and $reer_t^{CH}$) and before Australian economic indicators (gdp_t^{AUS}, $reer_t^{AUS}$, ex_t and im_t). We aim to identify the impacts pri_t^{US-CH} shock, thus the variables which we want to locate before pri_t^{US-CH} significantly matter to the empirical results. We consider three scenarios for the ordering of pri_t^{US-CH}.

Scenario I. Sino-American political relations are determined by the US.

Although China is a rising power with a rapid economic growth, its political influences are still non-dominant in US-China political relations. The unresolved concerns between Washington and Beijing are mainly about the role of democracy and human rights in China. In addition, the "America First" movement also affects the US politics and diplomatic policies. "America First" refers to a policy in the US that focuses on nationalism and non-interventionism. "America First" policies are inspired by Thomas Jefferson who promoted the Embargo Act of 1807

[2] Jordà (2005) presents that model misspecification could lead to inaccurate impulse response estimates and further proposes a Local Projection method. Although Jordà (2005) proposes an LP method which could solve the problem of model misspecification by choosing lags, it also relies upon the identification scheme in the SVAR model.

which aims to resist the impressment of Americans to serve on foreign warships. After that, this slogan has been used by both Democrats and Republicans. During World War II, the America First Committee opposed US's entry into the war with the exacerbation of American nationalism and unilateralism. Donald Trump revived this slogan during his election campaign and presidency, though with considerable differences. Some critics even describe Trump's "America First" as "America Alone". In other words, Trump's "America First" endows more isolationism and nativism. It is assumed that the government policies of US are influenced by this slogan and focused on domestic economic benefits. In this case, US-China political relations are exogenous and not instantaneously affected by other countries. Therefore, the model is specified as follows,

$$y_t = \left[pri_t^{US-CH} \quad gdp_t^{CH} \quad reer_t^{CH} \quad pri_t^{AUS-CH} \quad gdp_t^{AUS} \quad reer_t^{AUS} \quad ex_t \quad im_t \right]'. \tag{3}$$

The order of variables in equation (3) implies that shocks contemporaneously influence US-China political relations, Chinese GDP and exchange rate, Australia-China political relations, Australian GDP and exchange rate and finally Australian exports to and imports from China.[3]

Scenario II. Sino-American political relations are affected by both US and China.

China's rise not only creates development opportunities, but also poses challenges to international structure. The "China threat theory" emerged as a response to China's rapid economic growth. Concerns have previously been expressed about a strong China, which may threaten East Asian security. The "China threat theory" has gained wider attention since 2003 after China enters the WTO. In fact, joining the WTO probably contributed to accelerate China's growth. Although the 9/11 terrorist attacks temporarily diverted the US government's attention to terrorism, many scholars focused on the "China threat" issue. Since Donald Trump came to power, the "China threat theory" revived and quickly spread across western countries. Another problem that affects the US-China political relationship is the exchange rate of the Chinese currency (RMB).

[3]Since nominal GDP is priced by domestic currencies, we use domestic CPI to deflate nominal level variables. However, exports and imports are priced by US dollars, which are deflated by the US CPI index. We also make seasonal adjustments of the original datasets.

At the beginning of Trump's presidency, the US treasury officially labels China as a currency manipulator.

Although we implement a series of pairwise Granger non-causality tests under the null hypothesis, it is still necessary to assume that pri_t^{US-CH} is contemporaneously influenced by China's economic situation. To complement **Scenario I**, we locate pri_t^{US-CH} at the third position in the SVAR model. That is shocks of gdp_t^{CH} and $reer_t^{CH}$ have instantaneous impacts on pri_t^{US-CH}. Thus, we have the following variable order in equation (4),

$$y_t = \begin{bmatrix} gdp_t^{CH} & reer_t^{CH} & pri_t^{US-CH} & pri_t^{AUS-CH} & gdp_t^{AUS} & reer_t^{AUS} & ex_t & im_t \end{bmatrix}'. \tag{4}$$

The variables of Australia are located after pri_t^{US-CH}. Therefore, the identified pri_t^{US-CH} shocks could have contemporaneous influences on pri_t^{AUS-CH}, gdp_t^{AUS}, $reer_t^{AUS}$, ex_t and im_t, but the reverse impacts take time. This ordering implies that Australia-China political relations have no instantaneous impacts on US-China political relations. This scenario is more realistic because the global influence of Australia is not comparable to that of the US and China. In Section 2, we found unidirectional causality running from pri_t^{US-CH} to pri_t^{AUS-CH}, which supports this ordering.

Assumption III. Sino-American political relations are determined by another ally.

The Australia, New Zealand, United States Security Treaty (ANZUS) is a collective security non-binding agreement to cooperate on military matters in the Pacific Ocean region. The ANZUS is a military alliance that aims to provide military supports when one of the allies is attacked by other countries. The original treaty is a three-way defense pact, that is, Australia-New Zealand, Australia-US and New Zealand-US. Due to the disputes between New Zealand and the US over visiting rights for ships and submarines capable of carrying nuclear arms in 1984, the treaty exists only between Australia-US and Australia-New Zealand. Although the treaty is split in 1984, the Australia-US alliance remains intact[4].

In addition to military cooperation, Australia and the US also maintain strong economic links. The Australia - United States Free Trade Agreement (AUSFTA)

[4]As shown by the recent AUKUS partnership (with the US and the UK) and the turnaround about the deal on nuclear submarine negotiated between Australia and France.

came into force in January 2005 and widely met a mixed reception. The agreement is strongly supported by the former Howard government and is commonly viewed as a continuation of the Australia-US alliance. However, the outcomes of this agreement in the following year are declining Australian exports to the US, but increasing US exports to Australia. The worsening Australian trade deficit and the improving US trade deficit with Australia could not solely be attributed to the free trade agreement because of the lagged effects of the appreciation of the Australian dollar over the period from 2000 to 2003. One could suspect that both Australia and US would keep a watchful eye on each other's national interests. In the meantime, China is the largest trade partner of Australia. As the leading economy in the world, the US is careful to both its strategic competitor and ally. Therefore, we specify the model as follows in equation (5),

$$y_t = \begin{bmatrix} gdp_t^{CH} & reer_t^{CH} & pri_t^{AUS-CH} & gdp_t^{AUS} & reer_t^{AUS} & ex_t & im_t & pri_t^{US-CH} \end{bmatrix}'. \quad (5)$$

We put the pri_t^{US-CH} variable at last in the SVAR model. That means that the shocks caused by other variables could contemporaneously affect US-China political relations. However, the reverse effects take lags.

4.3 Granger non-causality tests

Ramey (2016) shows that the structural shocks should be exogenous with respect to other current and lagged variables in the model, and thus the ordering of variables is easily challenged. The US government policies not only affect their domestic affairs, but also the development and political affairs of foreign countries. To verify this point, we carry out a battery of pairwise Granger causality tests spanning from fiscal and economic variables to political relation index between US and China. The lags are set at 4 which is adequate to capture potential dynamics. The large p-values in Table 1 show that the non-causality hypothesis cannot be rejected.

Table 1 is here

Other practical issues are summarized as follows. First, some previous studies impose unit root and cointegrated relations to pretest the variables, however

Elliott et al. (1996) suggests that this procedure could lead to size distortions. Another key issue is the selection of lag length.[5] Ramey (2016) suggests that although LP avoids the misspecification problem, it suffers from less precise estimates due to fewer restrictions are imposed. Recent studies such as Plagborg-Møller and Wolf (2021) and Montiel-Olea and Plagborg-Møller (2021) suggest that SVAR and LP could give the same estimates in shorter and medium horizons. But in longer horizons, the impulse response estimates of SVARs and LP disagree substantially. Plagborg-Møller and Wolf (2021) also pose a series of warnings about the use of SVAR and LP. To balance the so called "bias-variance" trade-off presented by Plagborg-Møller and Wolf (2021), we fix the lags at 4 in the baseline estimates and check the robustness by using other lags such as 2 and 6. In addition, impulse response horizons are determined as 20.[6] Second, we use wild bootstrap procedure to generate confidence interval for SVAR model and utilize Newey-West standard errors to generate confidence level error bands in LP. Finally, the baseline estimates are built upon a quarterly dataset due to unavailability of monthly data for some macroeconomic variables of China and Australia.

5 Empirical Results

In this section, we show empirical specifications, including identification scheme and choice of lags. Next, we present empirical results of SVAR and LP. Last, we implement a battery of robustness checks.

[5]Although Jordà (2005) suggests using AICc proposed by Hurvich and Tsai (1993) to determine the optimal lags used in local projections, recent studies by Plagborg-Møller and Wolf (2021) and Montiel-Olea and Plagborg-Møller (2021) present that typical SVAR and local projections should deliver consistent impulse response estimates especially in the short and medium run. Based on their findings, the choice of lags should satisfy their conditions. The robustness checks are implemented by incorporating shorter and longer lags.

[6]Prior to determining the lags as 4, we put other lags into the model, such as 2 and 6 lags. We find significant gaps between SVAR and LP in short- and medium-run when we use shorter lags. As the recent study by Plagborg-Møller and Wolf (2021) shown, SVAR and LP should estimate the similar impulse response, especially in short and medium horizons. When we add the lags to 6, the impulse responses of SVAR and LP methods are similar.

5.1 Preliminary analysis

We first provide the plots of identified US-China PRI shocks over time-variation under the three different scenarios in Figure 2. The shocks are normalized by their mean and standard deviation.

Figure 2 is here

Obviously, the evolution of identified shocks under the three different scenarios is consistent over time. This is interesting since we consider different variable orders in the SVAR model. From the technical perspective, the typical SVAR model cannot deliver the causal impacts of the identified shocks because the reduced-form innovations likely represent a mixture of exogenous US-China political relation shocks and endogenous responses to other shocks in the economy, such as Australia and China's demand and exchange rate shocks.

5.2 Baseline results

Figure 3 plots the IRFs of pri_t^{US-CH}, pri_t^{AUS-CH}, $exports_t$ and $imports_t$ given 1% unexpected decrease in pri_t^{US-CH}. Such a shock represents the deterioration of US-China political relations. By ordering pri_t^{US-CH} at different positions, we find the IRFs patterns are highly consistent. Our results are explained by using one standard error band (around 68% confidence level).

Given an immediate decrease of pri_t^{US-CH}, the IRFs of pri_t^{AUS-CH} in the short-run (the first 6 quarters) is not significant, but the decrease persists in the medium and long run. The deterioration of US-China political relations causes significant spillovers to Australia-China political relation in the medium and long run. The reason for the insignificant results in the short run can be attributed to political motivation, such as "wait and see". For example, in the earlier stage of the US-China trade war, the conflicts are maintained at the diplomatic level. The countries, such as Australia, are not aware of the underlying motivations, meaning that the deterioration of US-China political relations cannot cause a significant decrease in the PRI of Australia-China. Another interesting point is that the IRFs of pri_t^{AUS-CH} under the two other scenarios are very similar.

Turning to the IRFs of exports and imports, the shocks have significant and negative impacts on Australian exports to China, with the maximum impacts of 0.1% being reached at the eighth quarter (two years). Such negative effects are long-lasting and still appear after 5 years. In other words, political tensions between China and the US decrease Australian exports to China. With respect to Australian imports from China, the median impulse response is significant, negative and persistent. The maximum impact occurs at the seventh quarter after an immediate decrease in pri_t^{US-CH}. These results suggest that deteriorating US-China political relations decrease bilateral trade between Australia and China. Under the other scenario (by allocating pri_t^{US-CH} from the front to the back), the IRFs patterns do not change significantly.

We also plot the results of the forecast error variance decomposition (FEVD) in Figure 4 which shows that the FEVD is sensitive to the ordering of the variables. In other words, the FEVD results are becoming smaller as we move the pri_t^{US-CH} variable from the first position to the last position. Under scenario 1, the contribution of pri_t^{US-CH} shocks to pri_t^{AUS-CH} variations increase as horizons expand. In addition, the shock could contribute roughly 5% to the fluctuations of exports after 2 years and around 10% to the variations of imports after the second quarter. Under scenarios 2 and 3, the pri_t^{US-CH} shocks account for a smaller proportion of variations in Australian exports to and imports from China.

Figures 3 and 4 are here

Jordà (2005) argues that the misspecification significantly affects the estimates of the SVAR model. The typical SVAR uses an iterated method to forecast errors, rather than a direct forecasting method used by Jordà (2005). Thereafter, we implement the LP method which provides the empirical results in Figure 5. The SVAR and LP methods present the same impulse response in the short and medium horizons, however the patterns in the long-run differ substantially. Our findings reconfirm the conclusions of Plagborg-Møller and Wolf (2021). In addition, a slight difference exists in the pattern of imports between SVAR and LP. That is the median impulse response based on SVAR is significant, however, the LP impulse response of imports is insignificant in the long term.[7] As for the results of FEVD shown in Figure 6, we find the paths are highly consistent

[7] Ramey (2016) suggests implementing the LP method as robustness checks against the typical SVAR model. In fact, there are no clear explanations as to why SVARs and LP are inconsistent in the longer horizons.

under the different scenarios. Specifically, the pri_t^{US-CH} shocks could roughly contribute, at the peak to 18% variations in pri_t^{AUS-CH}, 18% variations in ex_t and 10% of variations in im_t.

Figures 5 and 6 are here

We report the IRFs of the remaining variables in Figure A.5 in the appendix. Given the pri_t^{US-CH} shocks, the median responses of gdp_t^{CH} and $reer_t^{CH}$ drop. This indicates that worsening US-China political relations could decrease gdp_t^{CH} and depreciate RMB. In addition, the median response of gdp_t^{AUS} is not significant. The IRF of $reer_t^{AUS}$ goes down when pri_t^{US-CH} decreases.

To capture the impacts of pri_t^{US-CH} shocks on total trade between Australia and China, we repeat the exercises for the different scenarios. The results are available at Figure 8. According to the IRFs results of SVAR model, the pri_t^{US-CH} shocks decrease Australian trade under all hypotheses. As for the IRFs of LP model, the pri_t^{US-CH} shocks make significant and negative impacts on trade in the short- and medium-run. However, the long-term estimates of SVAR and LP disagree substantially.

Figure 8 is here

5.3 The IRFs before Trump's administration

Since Donald Trump came to power in 2016, the political relations between the US and China was significantly worsened. During his presidency, the Treasury Department of the US labeled China a "currency manipulator". Trump also ratcheted up tariffs on Chinese goods and further launched the trade war against China. In addition, he also frequently criticized China's new national security law on Hong Kong's judicial independence and human rights problem. These moves have profound and negative impacts on US-China relation. Therefore, it is interesting to compare the impacts of US-China political relations on Australia-China trade before and after Trump's administration. For this purpose, we use the same specifications of the benchmark model by setting the lag-order as 4 and considering the different scenarios. For a better understanding, we only report the median responses of pri_t^{US-CH}, pri_t^{AUS-CH}, ex_t and im_t in Figure 7.

Given one percentage decrease in the pri_t^{US-CH} index, the median response of the pri_t^{AUS-CH} index briefly moves up and drops persistently afterwards. This pattern is similar to the benchmark results. That is, even prior to Trump's administration, a deterioration in US-China political relations could affect the relations between Australia and China. AS for the IRFs of exports, the median responses under different assumptions increase over horizons and are not significant at the 68% significance level. These results are inconsistent with the benchmark estimates. The median response is a short drop followed by a slow increase in imports, before approaching zero. Likewise, the IRFs of imports are not significant at the 68% level.

Figure 7 is here

The above results imply that a worsening of US-China political relations does not significantly affect the bilateral trade between Australia and China when we exclude the period of Trump's administration. Contrary to these findings, the benchmark IRF show that the deterioration of Sino-American relations could decrease both Australian exports to and imports from China. In other words, worsening political relations between the US and China during Trump's administration plays a pivotal role in declining bilateral trade between Australia and China.

5.4 Augmented VAR model with the US variables

The benchmark model does not include the US economic variables. To complement this field, we augment the VAR model with the US real gross domestic production (gdp_t^{US}) and real effective exchange rate ($reer_t^{US}$). Only minor changes are made in the three scenarios. We order gdp_t^{US} and $reer_t^{US}$ to the first two positions. This ordering implies that the shocks of gdp_t^{US} and $reer_t^{US}$ could make contemporaneous impacts on other variables in the VAR system. The ordering of the rest of variables are the same as the benchmark model. In addition, the empirical specifications are unaltered.

By adding the gdp_t^{US} and $reer_t^{US}$ into the VAR system, the isolated pri_t^{US-CH} shocks exclude the components of gdp_t^{US} and $reer_t^{US}$ shocks. The results of SVAR and LP models are respectively available in Figures 9 and 10. We first look at the median response of a typical SVAR model which shows that Australian exports to China slightly increase in the short run and decrease after that. Furthermore, the median response of Australian imports from China also drops though there is a slow recover in the long term. According to the confidence intervals in SVAR model, the IRFs results are insignificant in most cases. However, the LP model presents that the pri_t^{US-CH} shocks could slightly increase exports in the short-run. After that, the median response drops persistently. In contrast, the median response of Australian imports from China is not significant in any of the three scenarios. In other words, there are visual changes in the IRFs pattern after we incorporate the US variables into the model.

Figure 9 and 10 is here

5.5 Sensitivity and robustness checks

The robustness checks are carried out with various factors affecting the baseline estimates, such as the selection of lag-order, data misreporting and SVAR model in first difference.

Selection of lag-order. Since the estimates of SVAR model are sensitive to the lag-order, we choose other lags such as 2 and 6 for robustness checks. The results are available in Figure A.2. The main conclusions using these lags are not changed according to the baseline findings. Slight differences are found in the median impulse response in longer horizons. Therefore, the results are robust against different lags.

Misreporting problem. Another concern is the misreporting of exports and imports between China and Australia. Because the baseline model uses exports and imports data provided by Australia, we further consider the dataset provided by China. In fact, the data on trade reported by both countries differ considerably. Other empirical specifications are the same as the ones used in the baseline model. Therefore, we check robustness against the misreporting problem of the trade dataset. The results are provided in Figure A.3. Specifically, the median responses of exports are similar when different datasets are utilized. As for the response of imports, we find a gap between the two median responses.

SVAR in first difference. The benchmark model is constructed by using log level dataset. Sims et al. (1990) illustrate that using log level specification could give consistent estimates when the variables have stochastic trends and are cointegrated. In spite of these, we re-estimate the VAR model in first difference. We report the IRFs results in Figure A.4. We find significant differences in the median responses between the log level specification and first difference specification. The IRFs of SVAR in first difference imply that tense US-China political relations improve political relations between Australia and China. This is unexpected. As one of the allies of the US, Canberra always keeps a close tie with Washington when it comes to international affairs. Elliott (1998) suggests that a log level specification is the safest approach because explicitly imposing the unit root and cointegration relationships could cause large distortions in the results.

6 Time-varying Impulse Response Functions

With political relations between US and China changing over time the transmission of pri^{US-CH} shocks to the economy could be time-varying. As we have previously stated, the pri^{US-CH} index sharply decreases during the Tiananmen Square event in 1989, the US bombing of the Chinese embassy in Belgrade in 1999 and Trade War in 2016. To provide time-varying impulse responses, we utilize forward-expanding and recursive-evolving methods. In terms of the forward-expanding method, the starting point $\mathcal{S}_1$ is fixed at the first observation (i.e., $\mathcal{S}_1 = 1$). We further expand the ending point $\mathcal{S}_2$ from the window size $\mathcal{S}_w$ to T. We set the window size $\mathcal{S}_w$ to 60 and the lag length as 4 which is consistent with the baseline model. Therefore, the impulse responses over the period from 2004Q1 to 2020Q2 are available.

Figures 11 delivers the overall evolution of impulse responses given the identified shocks over time. Figure 12 plots the horizontal IRFs (referred to as HIRFs hereafter) from 2004Q1 to 2020Q2. For the results of pri_t^{US-CH}, we could conclude some main features. First, there are some differences in the horizontal IRFs given different assumptions before 2009. Second, the HIRFs are consistent after 2009. Third, we find a significant drop in the transmission after 2017 in the HIRFs.

Figure 12 plots the HIRFs of pri_t^{AUS-CH} in different horizons. The results illustrate that the identified shocks have positive impacts on pri_t^{AUS-CH} in 4 quarters. From the perspective of a longer span, such shocks negatively affect the evolution of pri_t^{AUS-CH}. This could be owing to the Australian government using the wait-and-see tactics. Since the US and Australia are allies, they would adopt the same attitude in the long run. Therefore, the HIRFs of pri_t^{AUS-CH} in the 8, 12 and 20 quarters are below zero. Another interesting point worth stressing is that the HIRFs of different horizons drop significantly after 2017. In other words, the relatively stable transmission changes during Trump's administration.

As for the HIRFs of Australian exports to and imports from China, some characteristics could be summarized as follows. First, there are significant fluctuations over the period from 2004Q1 to 2009Q1. Especially in 2008Q3, there are sudden drops in the HIRFs of exports and imports under scenario 1, which could be attributed to the suppression effects of the of financial crisis. However, such decreases were quickly curbed and the HIRFs in the following years remained relatively stable till 2017. Since then, the HIRFs of exports and imports experience a downward trend during Trump's presidency and hit the bottom in 2019Q3. During Trump's administration, the political relations between the US and China got worse as the trade war intensified and this deterioration had spillovers to Australia-China bilateral trade. Obviously, the sharp decreases in HIRFs of exports and imports are transitory. However, the down turn after 2017 is persistent and intensifying. That is to say, Australia-China bilateral trade is significantly distorted by the deterioration of US-China political relations.

7 Conclusions

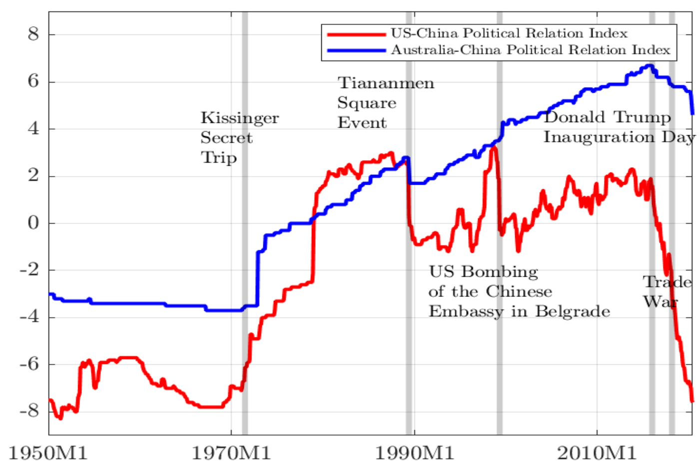
In this study, we utilize a recursive identification strategy to isolate US-China political relation shocks under several scenarios. The empirical results show that the sudden cooling of US-China political relations has persistent negative impacts on Australia-China political relations. Such political relation deterioration also decreases Australian exports to and imports from China. When we focus on the period prior to the Trump's administration, the IRFs of exports and imports are not significant. In addition, we employ a forward-expanding strategy to obtain time-varying IRFs and the empirical results demonstrate two sharp drops during the 2009 economic downturn and Trump's presidency. However, the first drop was quickly fixed, but the last sharp decrease is more persistent. In other words, the worsening political relations between the US and China during Trump's administration had persistent negative impacts on Australian exports to and imports from China.

Table 1: Pairwise Granger non-Causality tests

	Wald stat.	p. value
gdp_t^{CH}	0.65	0.65
gdp_t^{AUS}	0.52	0.72
ex_t	1.74	0.26
im_t	0.18	0.94
$reer_t^{CH}$	0.67	0.64
$reer_t^{AUS}$	1.25	0.38
pri_t^{AUS-CH}	0.23	0.91

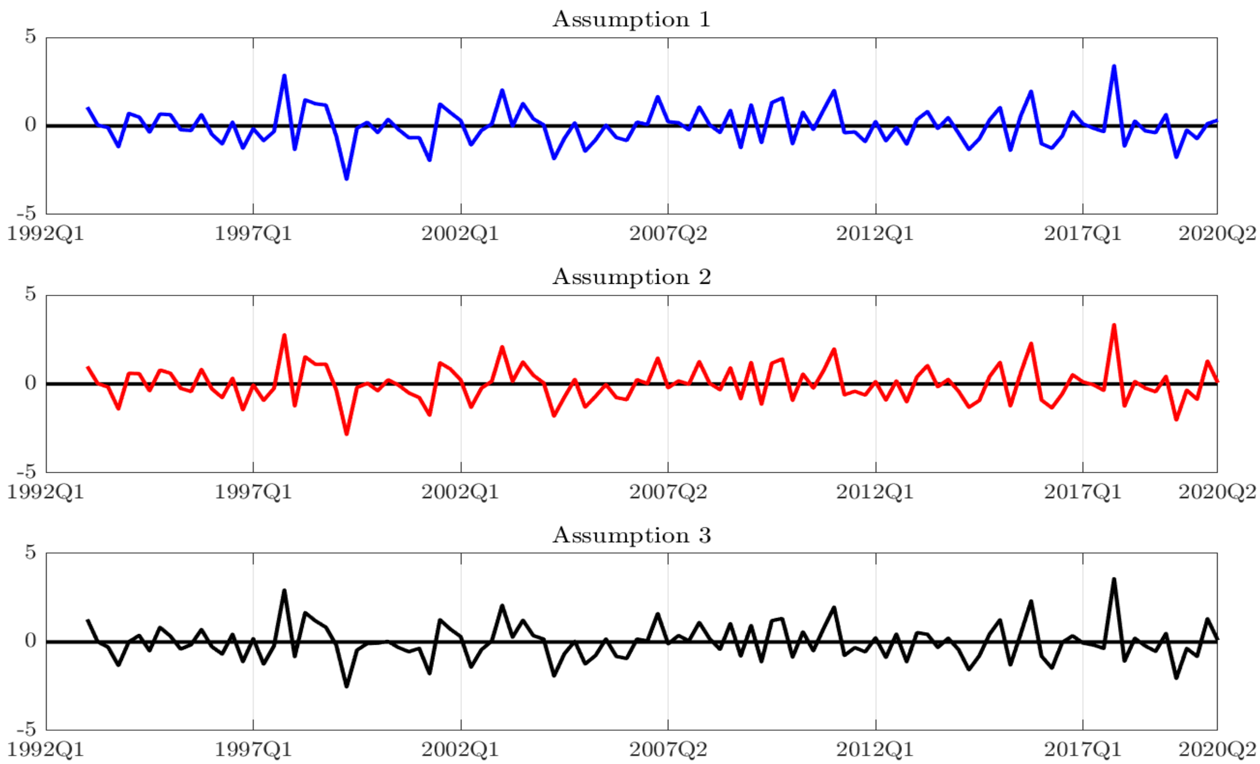
Note: Pairwise Granger causality tests are implemented with 4 lags. The null hypothesis is that there is no causality running from US-China PRI to target variables. The variables are taken difference where the indicators are unit root process to avoid spurious causality problems.

Figure 1: Political Relation Index



Note: The dataset is available on: http://www.imir.tsinghua.edu.cn/. The PRI index is monthly and covers the period from January 1950 to June 2020.

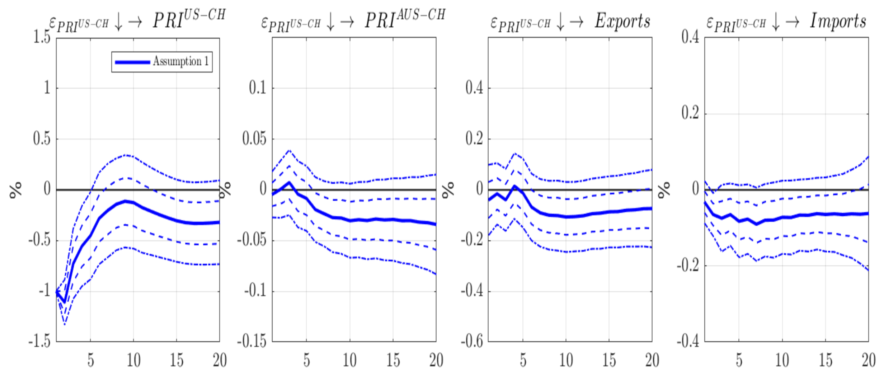
Figure 2: Identified US-China PRI shocks under different assumptions



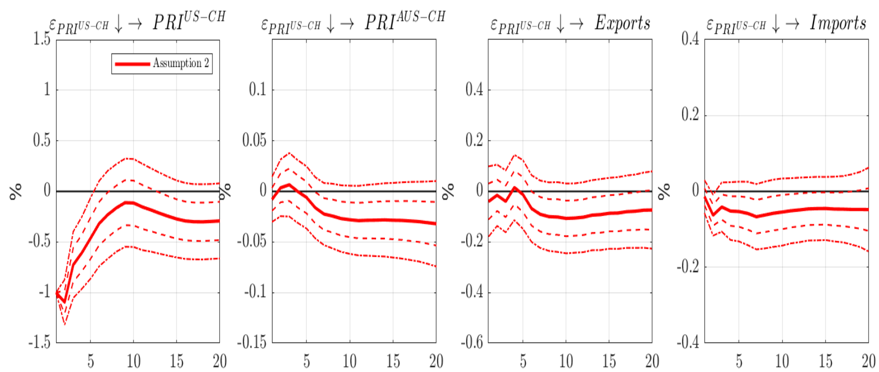
Note: the lags for the VAR system are determined as 4.

Figure 3: Impulse response functions of the typical SVAR model

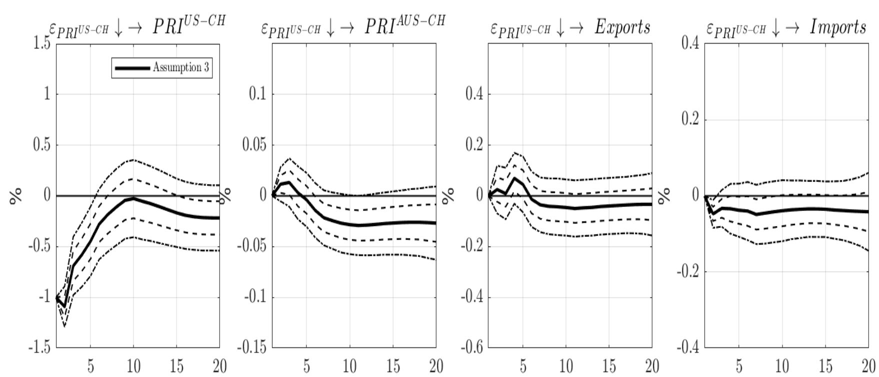
(a) Assumption 1



(b) Assumption 2



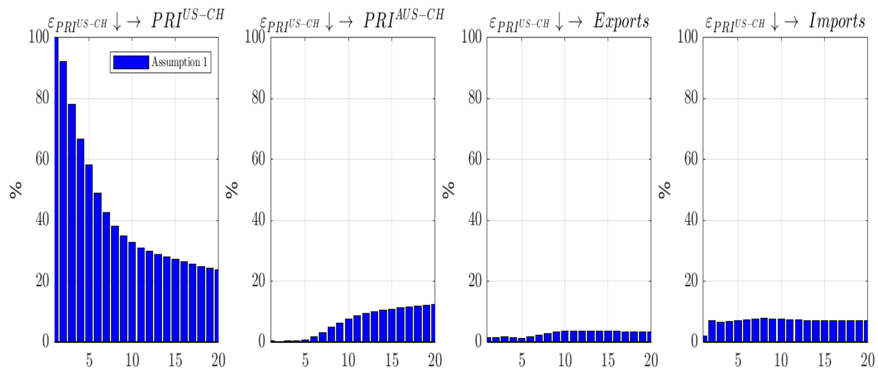
(c) Assumption 3



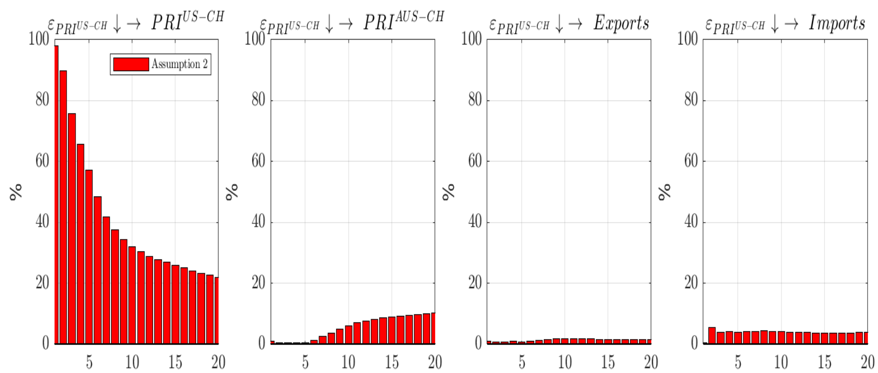
Note: the confidence intervals are constructed by using a wild bootstrapping method proposed by (Kilian, 2009) at 68% and 95% significance levels. The horizon is quarterly. The lags for the VAR system are determined as 4.

Figure 4: Forecast error variance decomposition of the typical SVAR

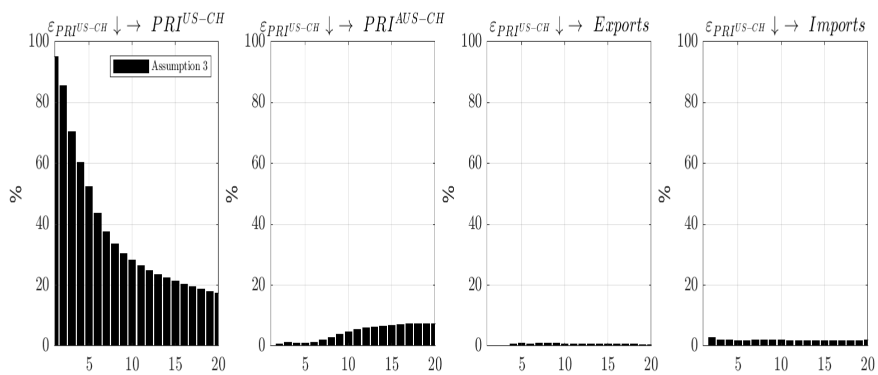
(a) Assumption 1



(b) Assumption 2



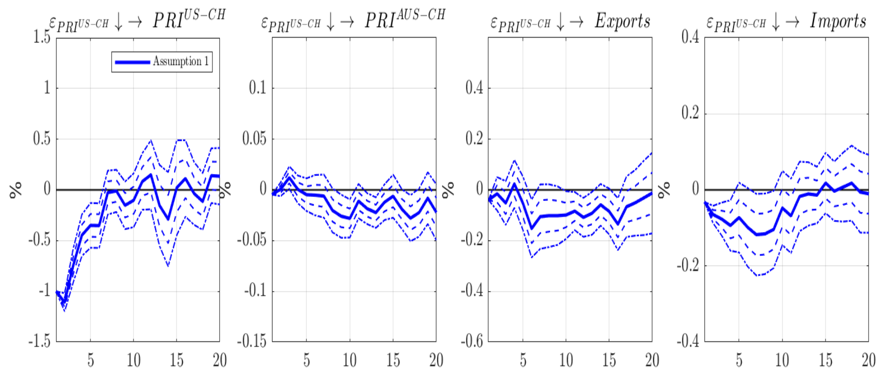
(c) Assumption 3



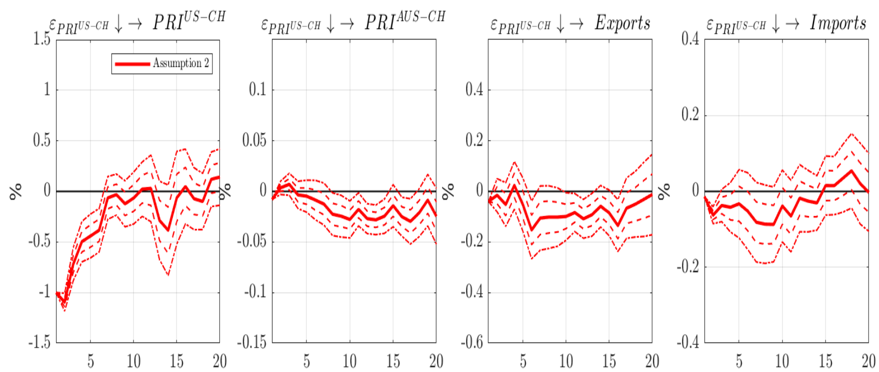
Note: the horizons are quarterly.

Figure 5: Impulse response functions of the local projections

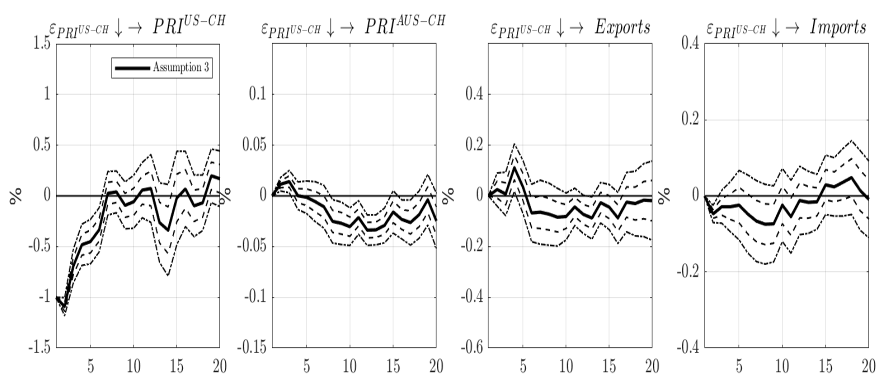
(a) Assumption 1



(b) Assumption 2



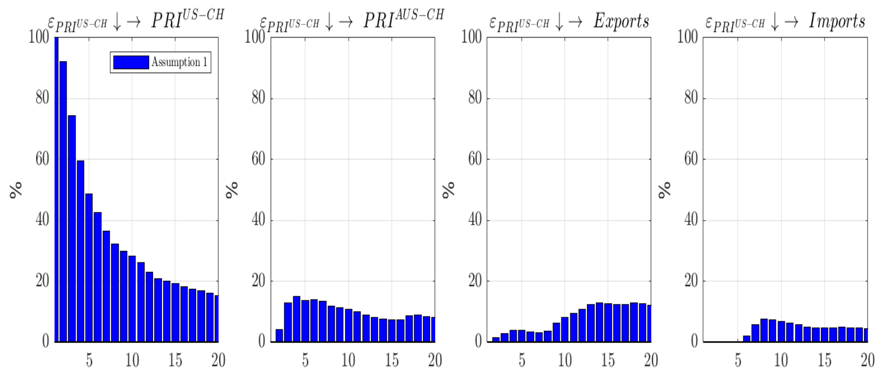
(c) Assumption 3



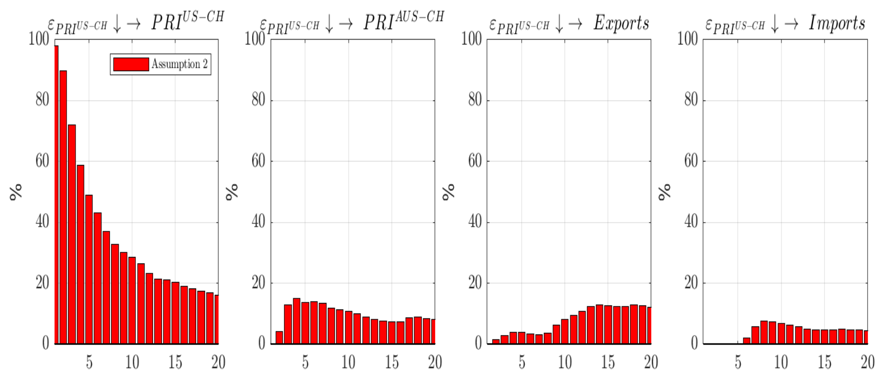
Note: the confidence intervals are constructed by using the error bands of Newey and West (1987) at 68% and 95% significance levels. The horizon is quarterly. The lags for the VAR system are determined as 4.

Figure 6: Forecast error variance decomposition of the local projections

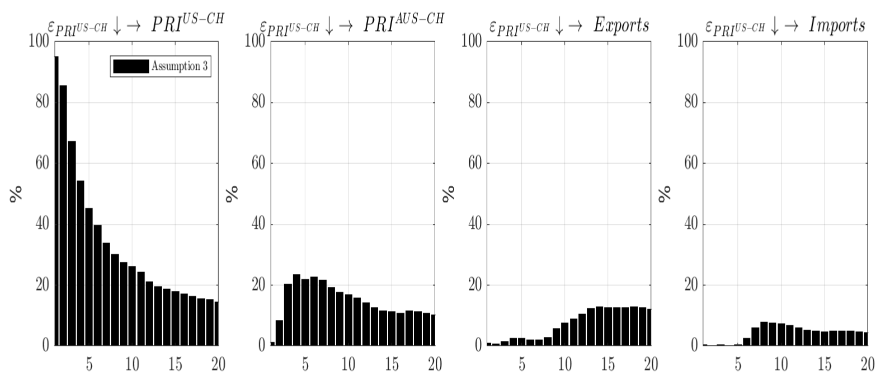
(a) Assumption 1



(b) Assumption 2



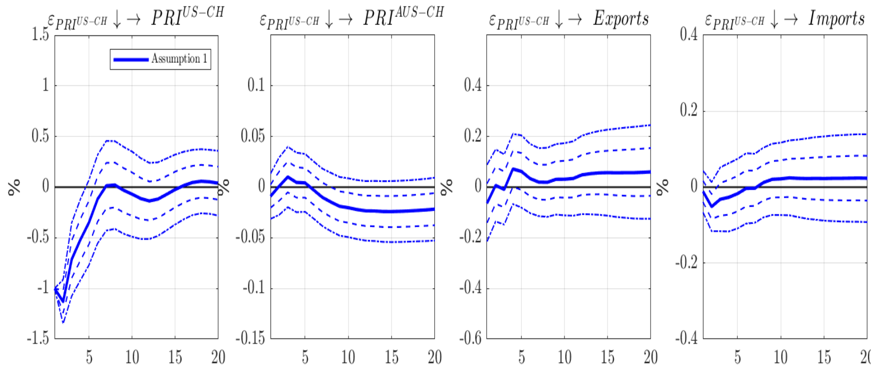
(c) Assumption 3



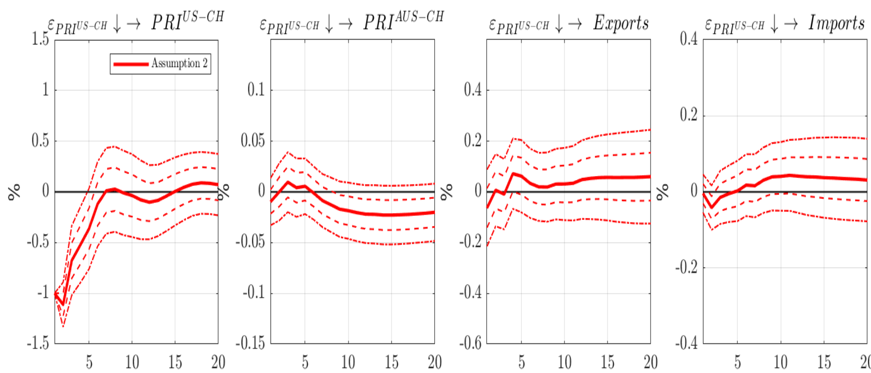
Note: the horizons are quarterly.

Figure 7: IRFs of the typical SVAR model (Prior to Trump's administration)

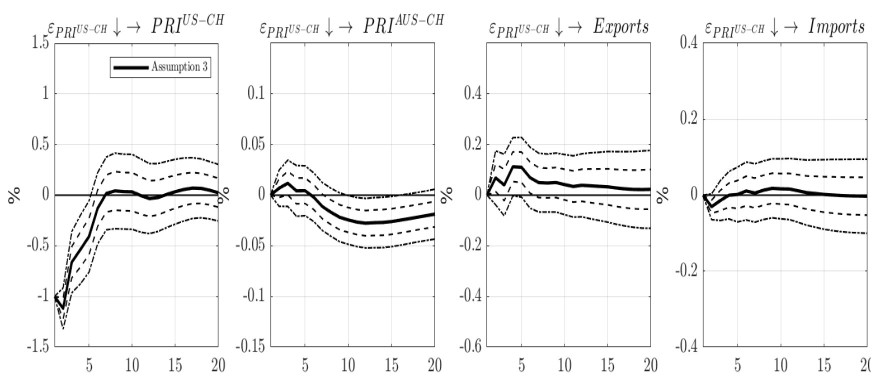
(a) Assumption 1



(b) Assumption 2



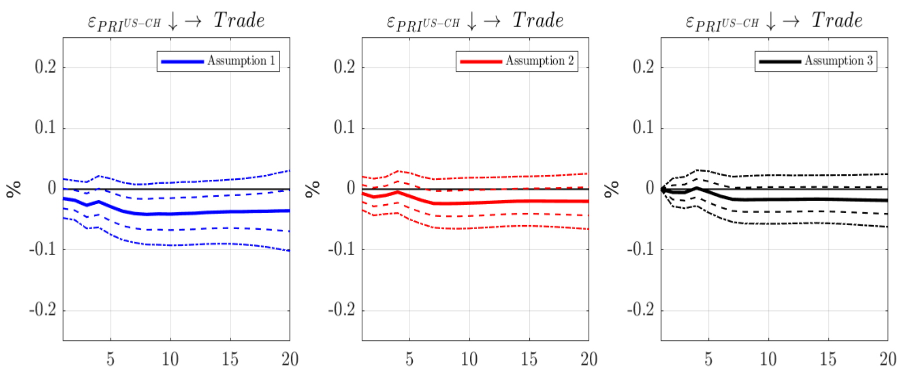
(c) Assumption 3



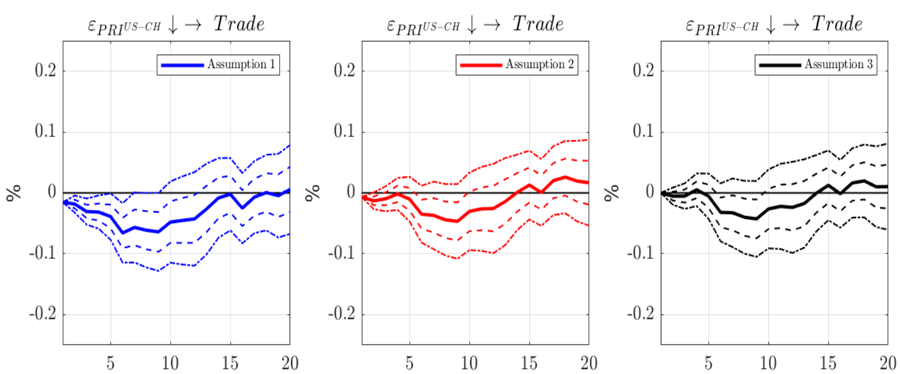
Note: the confidence intervals are constructed by using a wild bootstrapping method proposed by (Kilian, 2009) at 68% and 95% significance levels. The horizon is quarterly. The lags for the VAR system are determined as 4.

Figure 8: IRFs of trade by employing SVAR and LP methods

(a) SVAR model



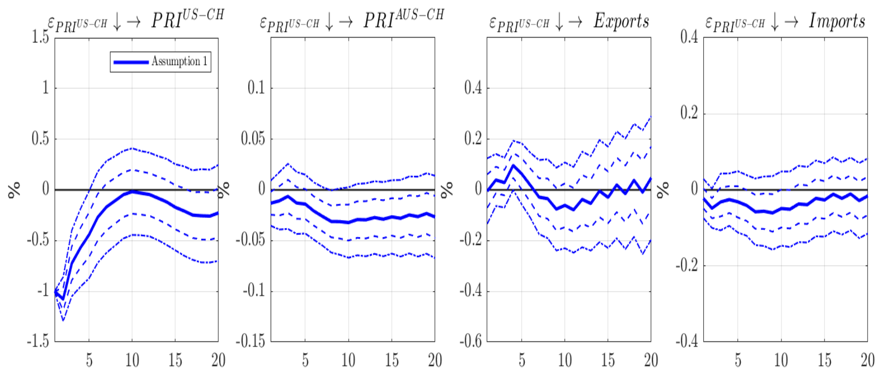
(b) LP model



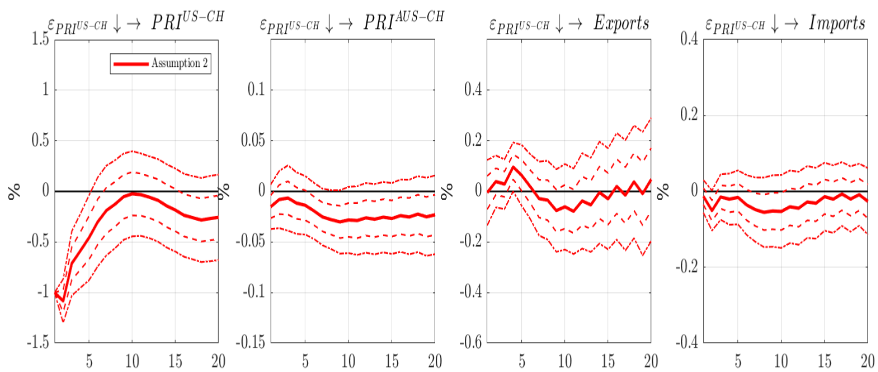
Note: the confidence intervals are constructed by using a wild bootstrapping method proposed by (Kilian, 2009) at 68% and 95% significance levels. The horizon is quarterly. The lags for the VAR system are determined as 4.

Figure 9: IRFs of an augmented SVAR model

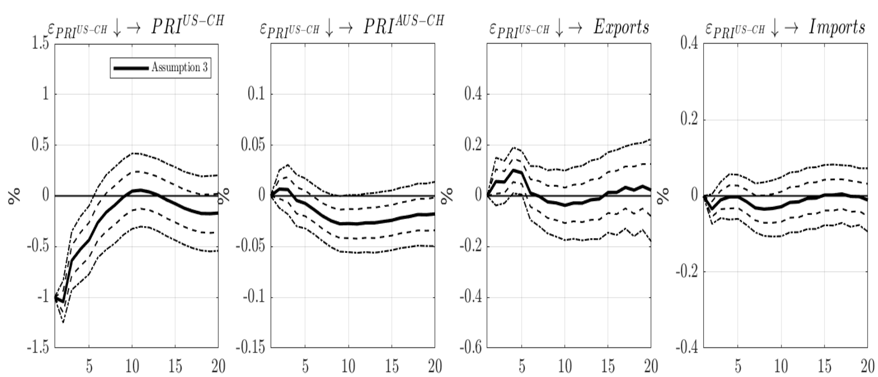
(a) Assumption 1



(b) Assumption 2



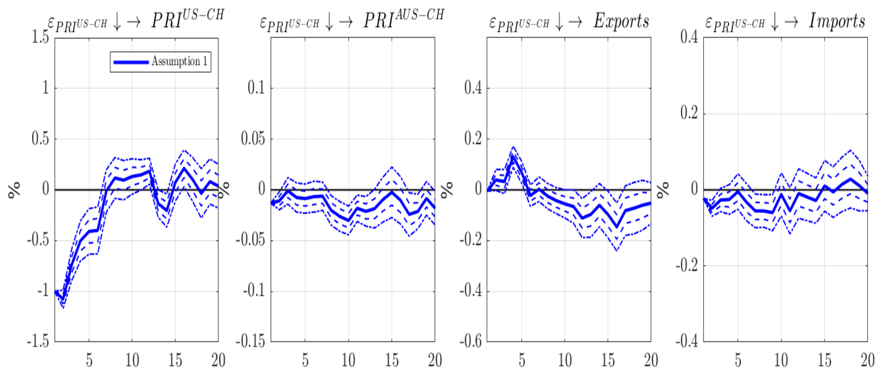
(c) Assumption 3



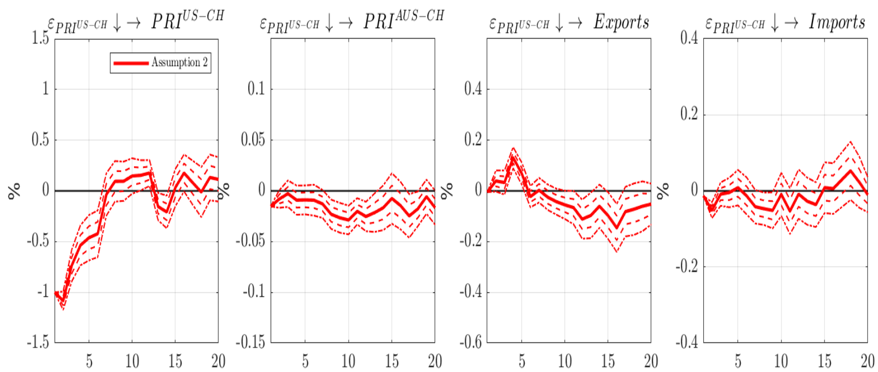
Note: the confidence intervals are constructed by using a wild bootstrapping method proposed by (Kilian, 2009) at 68% and 95% significance levels. The horizon is quarterly. The lags for the VAR system are determined as 4.

Figure 10: IRFs of an augmented LP model

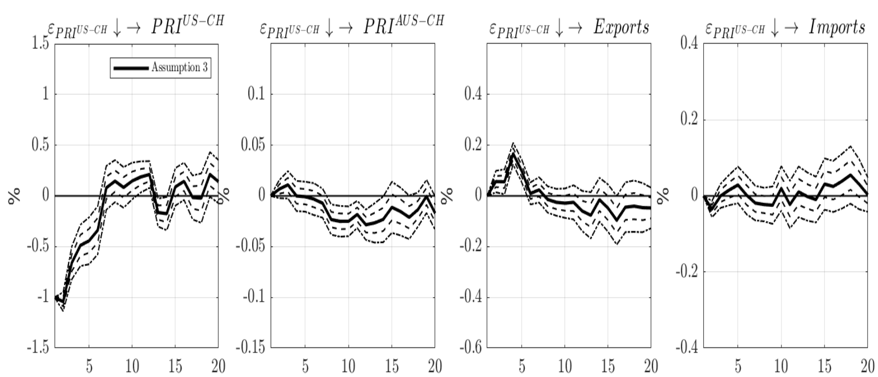
(a) Assumption 1



(b) Assumption 2



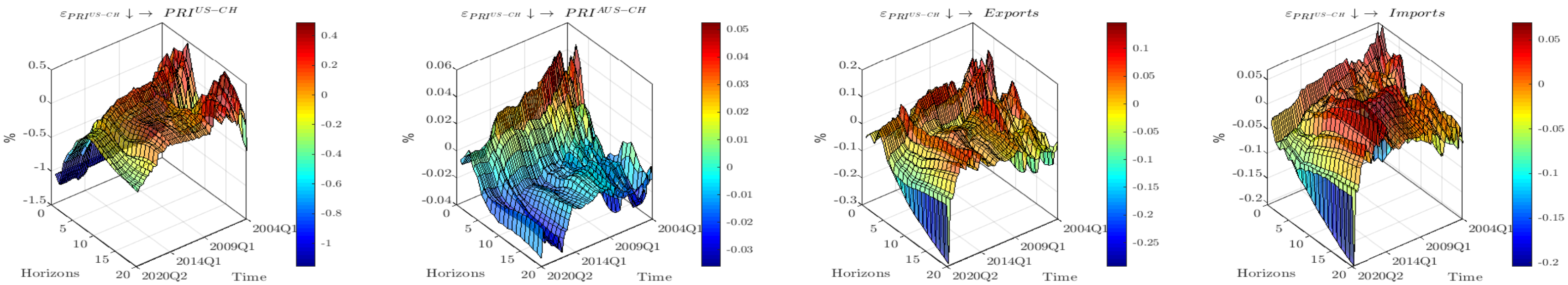
(c) Assumption 3



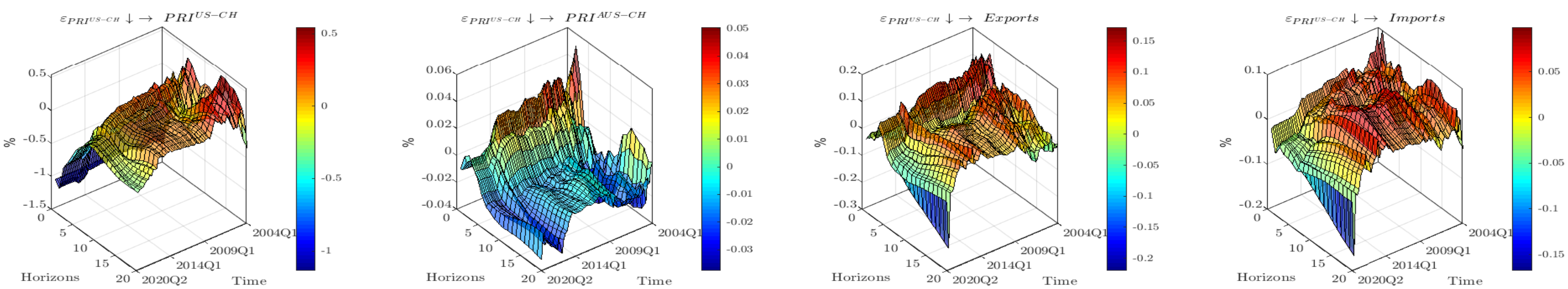
Note: the confidence intervals are constructed by using a wild bootstrapping method proposed by (Kilian, 2009) at 68% and 95% significance levels. The horizon is quarterly. The lags for the VAR system are determined as 4.

Figure 11: Time-varying IRFs of the typical SVAR model

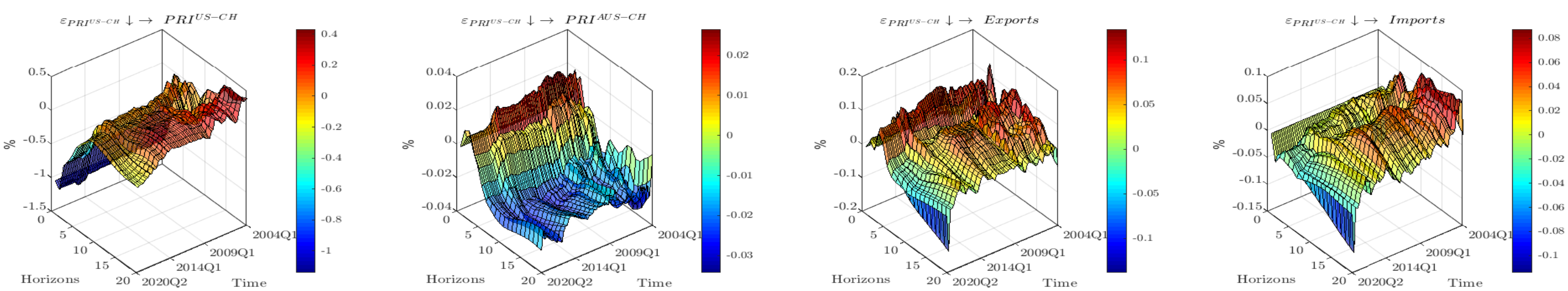
(a) Assumption 1



(b) Assumption 2



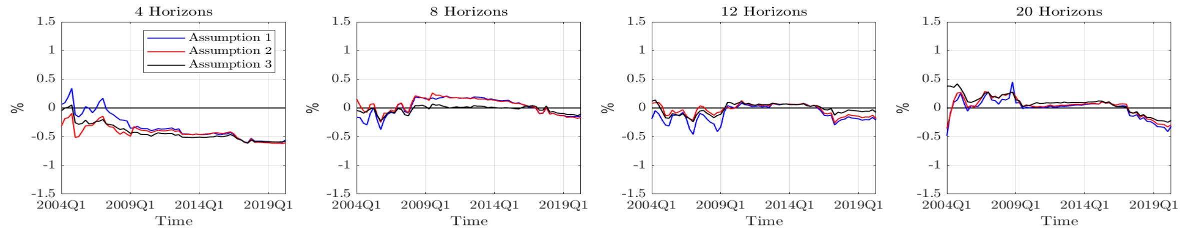
(c) Assumption 3



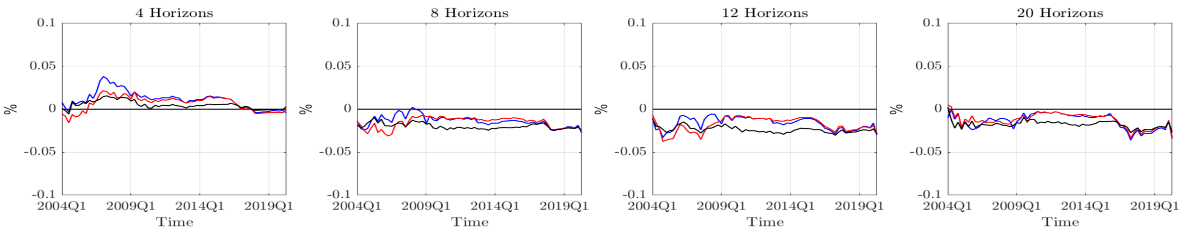
Note: the lags for the VAR system are determined as 4. To obtain time-varying impulse response functions, we use a forward-expanding method by setting the window size to 48. Therefore, the estimates start from 2004Q1 and end up with 2020Q2.

Figure 12: Time-varying IRFs of the typical SVAR model

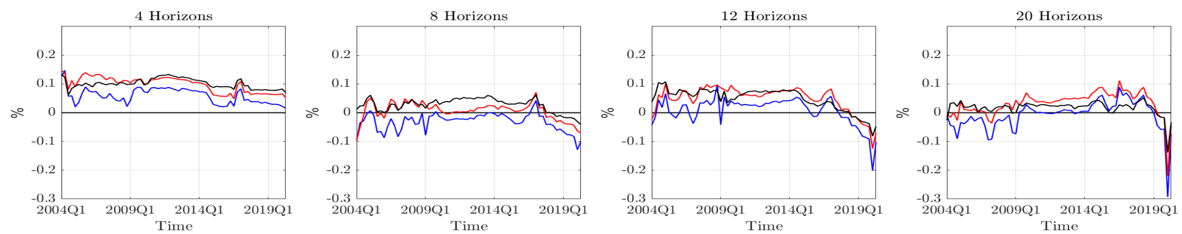
(a) $pri^{US-CH} \downarrow \rightarrow pri^{US-CH}$



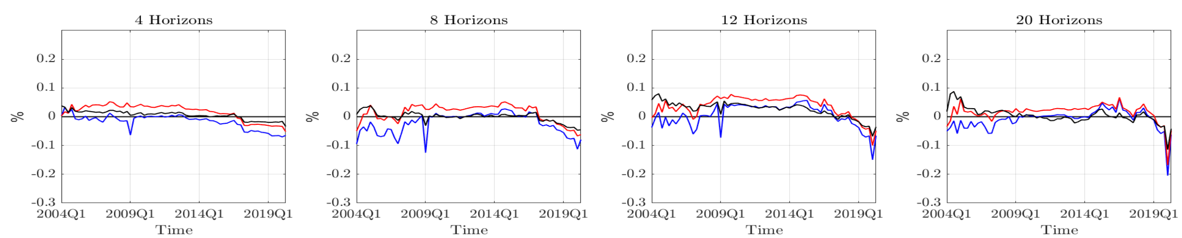
(b) $pri^{US-CH} \downarrow \rightarrow pri^{AUS-CH}$



(c) $pri^{US-CH} \downarrow \rightarrow Exports$



(d) $pri^{US-CH} \downarrow \rightarrow Imports$



Note: the lags for the VAR system are determined as 4. To obtain time-varying impulse response functions, we use a forward-expanding method by setting the window size to 48. Therefore, the estimates start from 2004Q1 and end up with 2020Q2.

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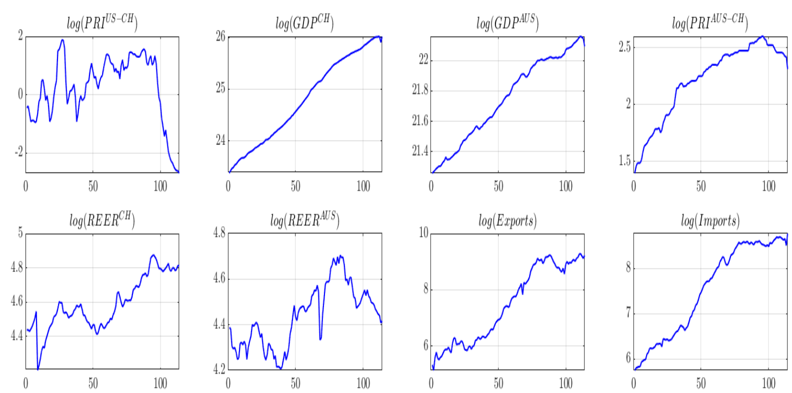
A Appendix. Supplementary Materials

In this section, we provide additional materials about the dataset, robustness checks and supplementary results.

A.1 Dataset

The PRI of US-China and Australia-China are drawn from the official website of the Institute of International Relations of Tsinghua University: http://www.imir.tsinghua.edu.cn/. The dataset of Australian exports to and imports from China can be found in the Direction of Trade Statistics operated by the International Monetary Fund (IMF). The nominal GDP and real effective exchange rate are available at International Financial Statistics dataset operated by IMF. To deflate the nominal dataset, we utilize the consumer production index at constant price which is also available in the IFS database. All variables are seasonally adjusted where necessary. Before implementing the SVAR model and local projections, we transform the data into logarithms. We plot all variables used in the benchmark model in Figure A.1. The sample covers the period from 1992Q1 to 2020Q2.

Figure A.1: Political Relation Index



A.2 Robustness checks

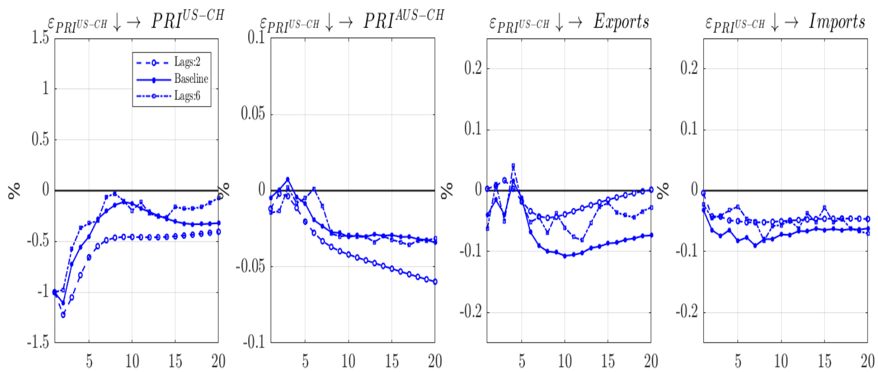
In this section, we first show the results of robustness checks by considering different empirical specifications, such as lag-order, data misreport and VAR in difference. In the benchmark model, the results are obtained by setting the lag-order to 4 quarters. In the robustness check, we incorporate fewer and more lags into the model, such as 2 and 6 lags. Other empirical specifications are the same as the baseline specifications. The robustness results of lag-order specifications under different assumptions are available in Figure A.2.

Due to different statistical standards in measuring trade between China and Australia, there is a misreport problem. In the benchmark model, we consider the datasets from Australia. However, in the robustness checks, we utilize the dataset reported by China. In other words, China's exports are viewed as Australian imports and the imports of China are Australian exports. The results are available at Figure A.3.

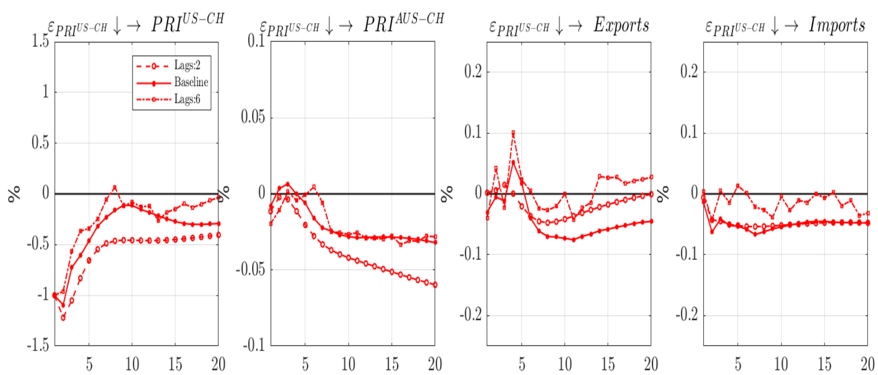
The benchmark model is estimated in log level specifications, Sims et al. (1990) suggest that the log level specifications can deliver consistent estimates when the variables in the VAR system have stochastic trends and are cointegrated. Furthermore, Elliott (1998) shows that imposing the unit root and cointegration relationships in the model could lead to large size distortions. Peersman (2018) estimates a food market model based on the log level specifications. In this sensitivity analysis, we provide results of the VAR estimated in difference in Figure A.4. In addition, we also implement Johansen cointegration tests which suggest 8 cointegration relations at the 5% level according to the Trace statistics.

Figure A.2: Robustness of lag-order

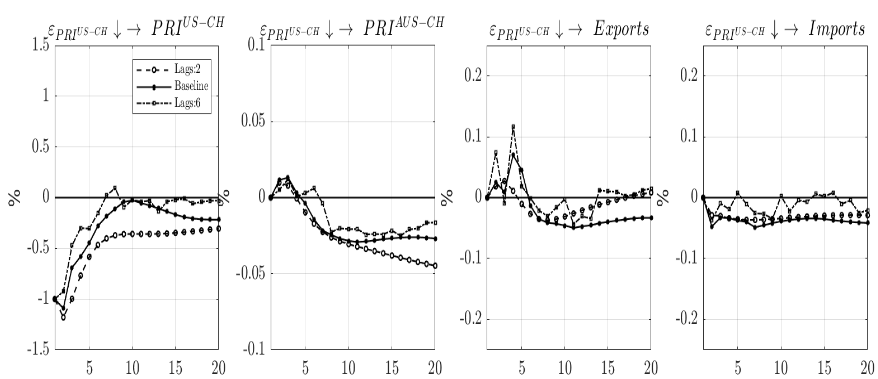
(a) Assumption 1



(b) Assumption 2



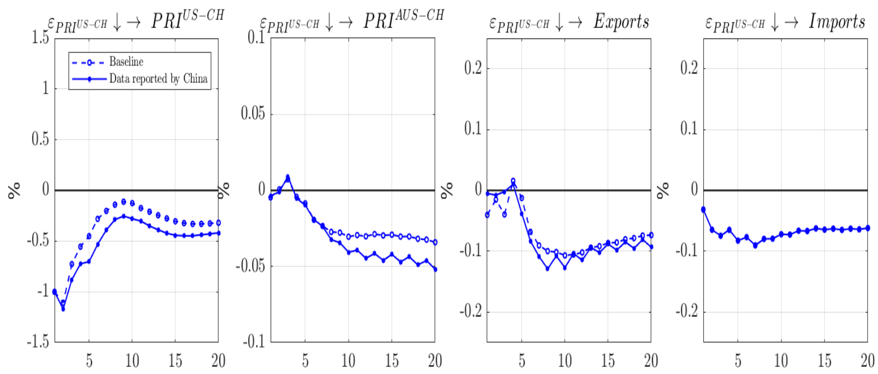
(c) Assumption 3



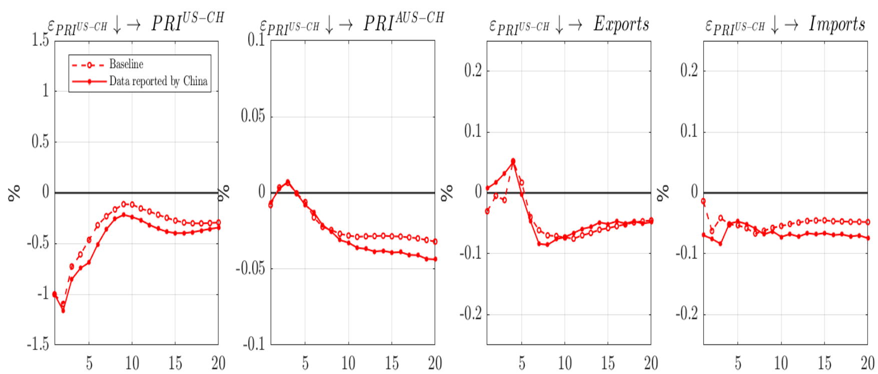
Note: the horizon is quarterly.

Figure A.3: Robustness of data misreport

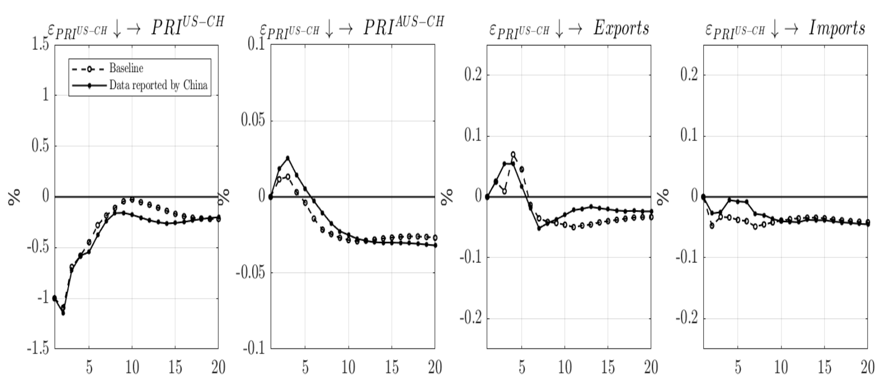
(a) Assumption 1



(b) Assumption 2



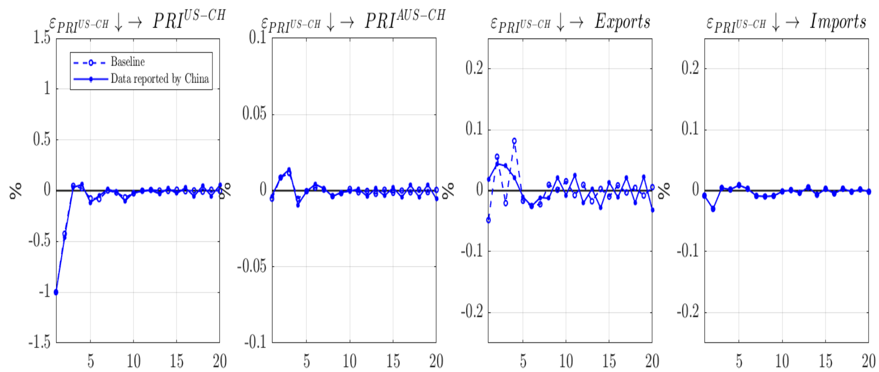
(c) Assumption 3



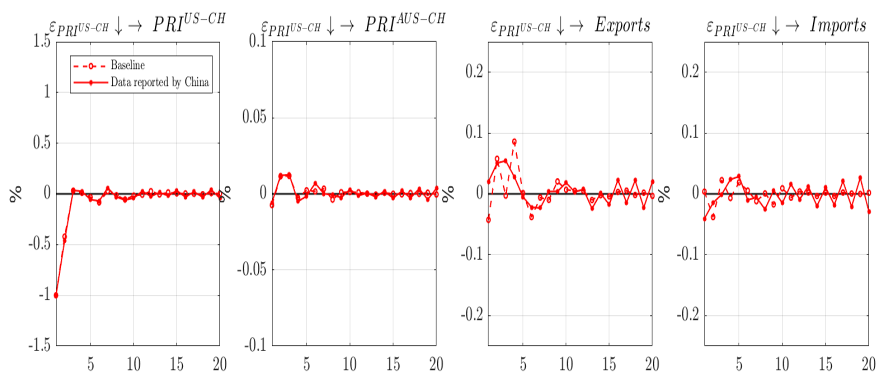
Note: the horizon is quarterly. The lags for the VAR system are determined as 4.

Figure A.4: Robustness of difference data

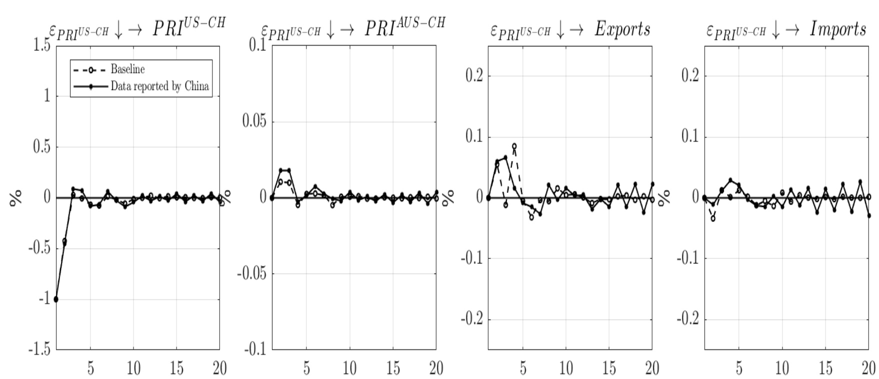
(a) Assumption 1



(b) Assumption 2



(c) Assumption 3



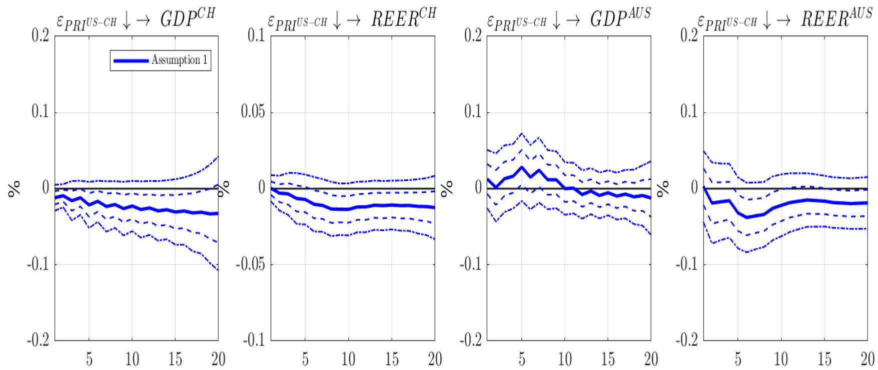
Note: the horizon is quarterly. The lags for the VAR system are determined as 4.

A.3 Additional IRFs results

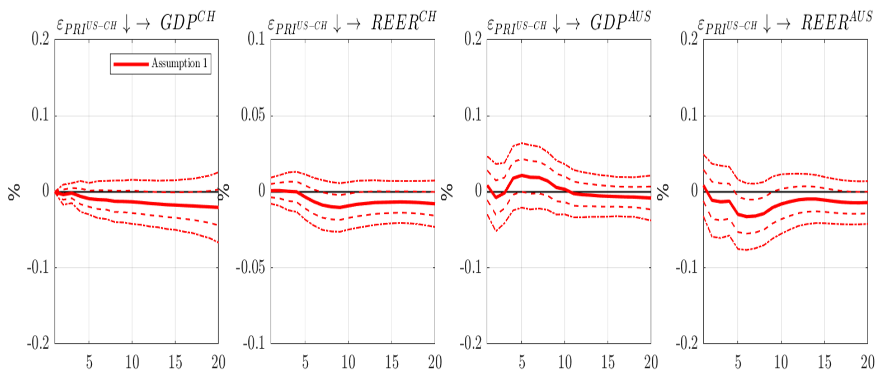
In this section, we provide additional IRFs of the rest of variables given oil supply shocks. The empirical specifications are the same as the ones shown in the benchmark model. The results based on a typical SVAR and LP methods are available in Figures A.5 and A.6.

Figure A.5: IRFs of the rest of variables in the typical SVAR

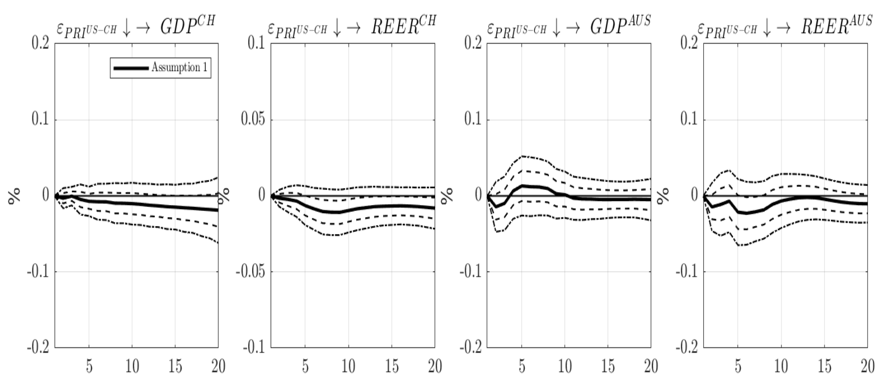
(a) Assumption 1



(b) Assumption 2



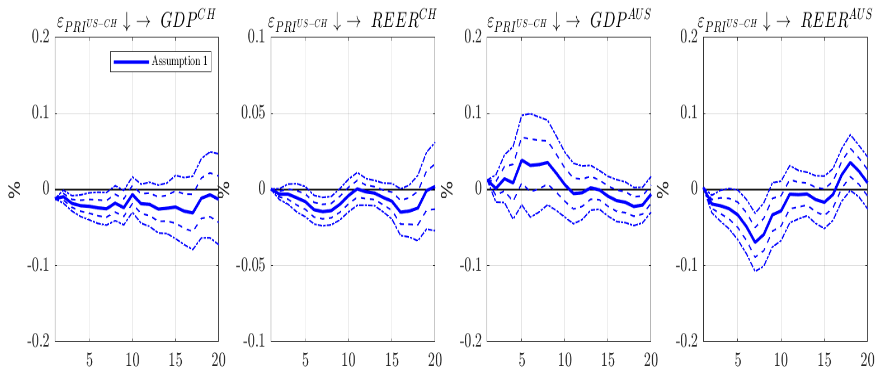
(c) Assumption 3



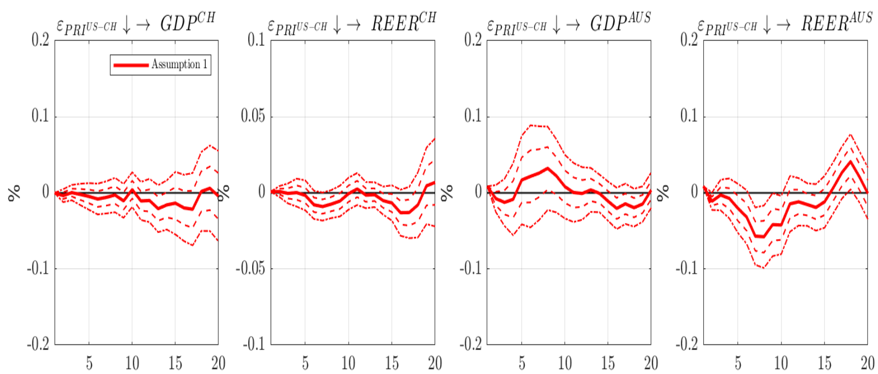
Note: the horizon is quarterly. The lags for the VAR system are determined as 4.

Figure A.6: IRFs of the rest of variables in the LP

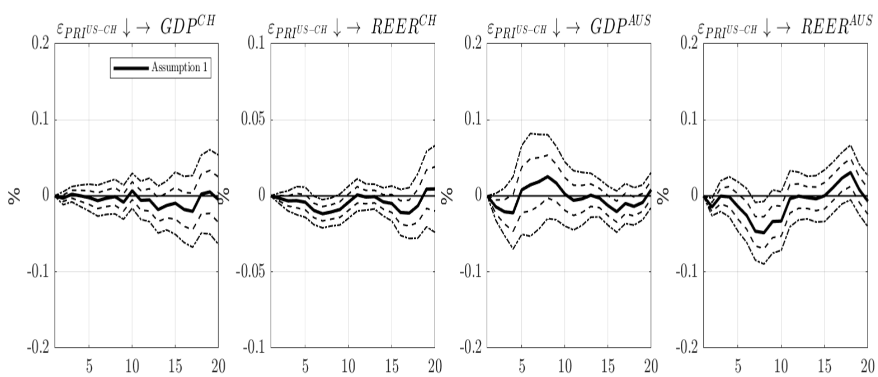
(a) Assumption 1



(b) Assumption 2



(c) Assumption 3



Note: the horizon is quarterly. The lags for the VAR system are determined as 4.