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The effects of external shocks on the business cycle in China: A structural change perspective

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The effects of external shocks on the business cycle in China: A structural change perspective

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Abstract
We study the effects of external shocks on the business cycle in China and its sectors (agriculture, industry, and services) in terms of real GDP growth using several small dimensional VAR models with Cholesky identification for the period 1996–2014. We show that China—in particular its industrial sector—is susceptible to shocks, which can be related to a trade channel, a financial channel, and a confidence channel of business cycle transmission from major trading partner countries to the Chinese economy. We extend the previous literature by explicitly focusing on response of the Chinese economy at the sectoral level and investigating the presence of confidence channels by analyzing the reaction in Chinese business and consumer confidence. If interpreted from the perspective of ongoing structural change and rebalancing in China, our findings can be interpreted as the result of a still very dominant industrial sector, and a previously export- and investment-driven growth model. Tertiarization in China could be one way of increasing the economy's future resilience to external shocks. However, the future structure of both the industrial and service sectors may be very decisive.

Keywords: International transmission channels, Transmission of shocks, Structural vector autoregression, Structural change

JEL classification: F43, F44, C32

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1. Introduction

China developed from being a low-income country toward a middle-income economy in terms of gross domestic product in a remarkably short period of time. China's process of development has been based on a traditional structural transformation process: workers were reallocated from the low-productivity agricultural sector, in eastern China, to newly developed industrial centers in western China. Furthermore, China profited from special terms, such as imports of technology and knowledge from Western companies via joint venture-restrained foreign direct investments.

After following an investment- and export-led growth model for an extended period of time, China entered a new phase of structural change. "Structural change" can be defined as the changing relative weight of the agricultural, industry and service sector, either measured as the relative sector shares in gross domestic product (GDP) or employment. After China's employment share in the service sector surpassed the employment share in the agricultural sector in 2011, China can now be characterized as being in a process of de-industrialization or tertiarization.

Rising negative economic, social and environmental side effects of rapid industrialization made China understand the urgency to transform its economy. This agenda has been acknowledged and supported by the Chinese government in its 12th and 13th Five Years Plans. This structural transformation is also part of a fundamental and necessary rebalancing process in China. This rebalancing further requires a shift from (net) exports toward domestic consumption, which is sometimes understood as the decoupling from the developments in industrial or advanced economies.

This characterizes China as an economy on the cusp of a new developmental path towards a more balanced economy. The remaining question is what consequences are associated with this structural change process. Theoretical arguments suggest that this rebalancing process will be associated with a reduction in economic growth, a decline in the current account surplus and thus in foreign reserves, and increasing inflation rates (Murach and Wagner, 2017).

In this paper, we investigate the effects of external shocks on real growth and confidence in China and its sectors (agriculture, industry, and services). We find convincing evidence for the existence of trade, financial, and confidence channels between China's major trading partner countries (the US, the Euro Area, the United Kingdom and Japan) and China, and especially China's industrial sector. First, we find a significant positive transmission of foreign real GDP growth shocks from major trading partner countries to China, especially its industrial sector. In contrast the agricultural and service sectors' real growth remains unaffected by these shocks. Hence, the trade channel seems to work through China's industrial sector. Second, financial shocks also especially affect growth in the industrial sector, but are also significant at an economy-wide level. Finally, we find support for the existence of a confidence channel. Our analysis is based on two measures of confidence in China: Business confidence and consumer confidence are clearly affected by trade and financial shocks, and could hence increase the impact of shocks working through trade and financial channels. In particular, a decrease in consumer confidence could be a way in which external shocks affecting the industrial sector could be transmitted into other subsectors of the Chinese economy and have negative effects on consumer spending. Our results are supported by the corresponding Granger-causality tests and variance decompositions.

To our knowledge, we are the first to investigate the effect of external shocks in China's trading partner countries at a sectoral level in China. We also extend previous research by analyzing potential confidence channels by accounting for the response of business and consumer confidence in China. Our empirical results provide insights in the dynamics of the Chinese economy during a major phase of its investment- and export-led growth strategy.

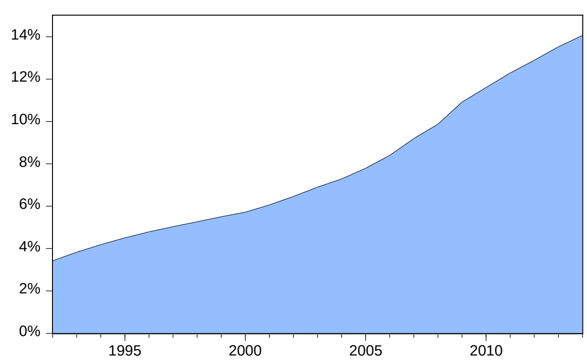
The rest of the paper is structured as follows. We first give a very brief overview of the rebalancing discussion, and the impact of structural change on economic growth and stability. We also review the literature on business cycle transmission and the main transmission channels. Our empirical analysis starts with a description of the data, and how we obtain our measure of aggregated real GDP growth and liquidity conditions in trading partner countries. We briefly present our econometric framework and explain the identification scheme. We then present the empirical evidence for each channel in turn. We close with a summary of our results and propose policy implications.

2. Literature review

Our study relates to different lines of literature. First, there is a connection to the discussion on rebalancing the Chinese economy. De-industrialization is from this perspective seen as a shift from an export-driven towards a consumption-driven business model in China. Our analysis shows that consumer confidence in China is currently also affected by developments outside China, which could also have implications for the prospects of a growth model that relies to a greater extent on domestic consumption. Second, structural change is part of a rebalancing process (see below) and thus there is a link to the structural change literature as we interpret our findings from the perspective of early de-industrialization in China. We show that industrialization and China's integration in world trade has probably increased the responsiveness of the Chinese industrial sector to external shocks. De-industrialization could, under certain conditions, reduce the responsiveness of the Chinese economy. Finally, our study extends the literature on empirical business cycle transmission. In particular, we systematically analyze different transmission channels for China and its three main sectors. In what follows, we briefly summarize the main arguments and findings in each strand of the literature, and show the connections with previous empirical literature.

2.1. Rebalancing the Chinese economy

The fast integration of China and the other BRIC countries in the world economy since the 1990s has been facilitated by favorable global economic circumstances: Strong foreign demand supported by trade liberalizations, such as for instance China's WTO entry in 2001, decreasing global interest rates and increases in commodity prices accounted for half of the increases in growth in the 2000s compared to the 1990s (Belke et al., 2018, Cubeddu et al., 2014). From the early 1990s until the financial crisis China's share in the world economy more than doubled (see Figure 1).

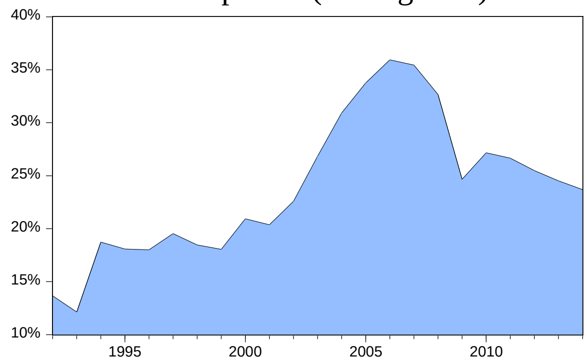


Source: Datastream, own calculations.

Fig. 1. Percentage Share of China in the World Economy, 1992–2014 (constant prices).

At the outbreak of the financial crisis, emerging market economies were severely hit by trade and financial shocks (Blanchard et al., 2010). In Russia, for instance, capital outflows played a dominant role. Countries with higher amounts of short-term foreign debt were affected more negatively in terms of GDP than less leveraged economies.

The immediate effects for China are also visible in the significant decline of the export share in Chinese GDP during the financial crisis period (see Figure 2).



Source: Datastream, own calculations.

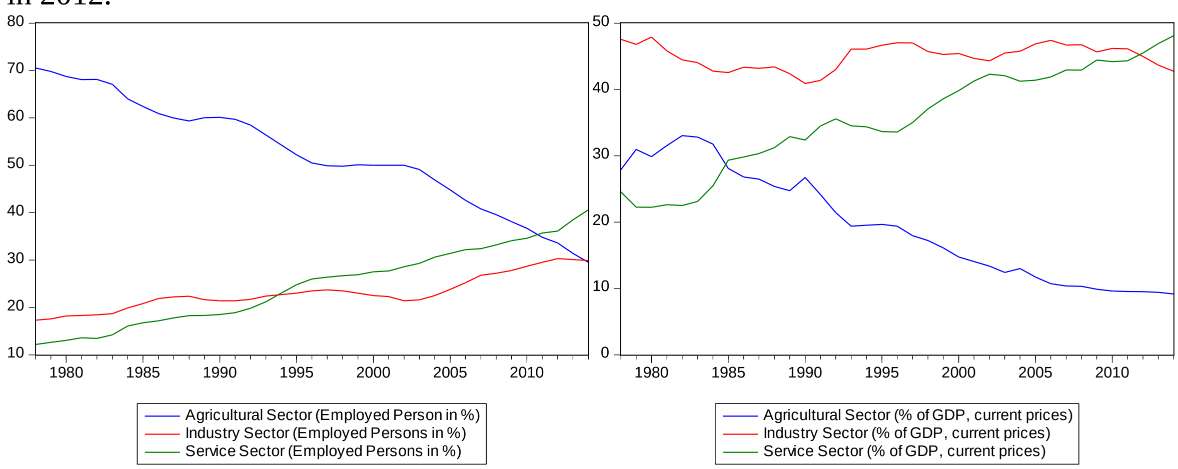
Fig. 2. Percentage Share of Exports in Goods & Services, 1992-2014 (% of GDP).

Based on a decomposition of forecast errors, Fayad and Perelli (2014) were able to show that decreasing demand from trading partners played a key role in explaining the slowdown. Moreover, risk aversion of international investor's contributed to the downturn.

The financial crisis pointed out the need for structural adjustments in China by promoting a rebalancing and structural change (see Section 1).

Wagner (2013) shows based on a comparison of the service sector in China with that in developed and developing countries from a historical perspective, that the service sector in China is too small compared to other countries when they were at the same stage of economic development. Hence China urgently needs to rebalance its economy in the light of the economic developments of the past years.

Fig. 3 displays the employment and value added shares of the agricultural, industrial, and service sectors in China from 1978 to 2014. In terms of employment share, the service sector started to dominate the industrial sector in 1994. In terms of value added, this was only the case in 2012.



Source: Datastream, own calculations.

Fig. 3. Sectoral employment and value-added shares in the Chinese economy (1978–2014).

Wagner (2015) points out that after an extended period of very high economic growth rates, China has reached the so-called middle-income range and has to implement fundamental structural reforms to avoid getting caught in the middle-income trap and to proceed to high-income status. Many others assume that the growth model pursued by China, together with measures taken to reduce the negative consequences of the financial and economic crisis, have increased imbalances in the Chinese economy.

The decline in GDP growth is associated with the end of extraordinary commodity and credit booms, and overinvestment (in the case of China) or underinvestment (in Brazil and Russia) (Aslund, 2013). The previously observed surge in growth rates is hence not sustainable, as structural factors are also important. Anand et al. (2014) argue that the slowdown in China and India is also due to a lower potential output growth, caused by a weaker development of TFP growth. A declining working age-population additionally puts reform pressure on China. Hence, China is wise to pursue structural reforms to ensure sustainable economic growth under challenging global conditions (Belke et al., 2018, Didier et al., 2015).

According to Blanchard and Giavazzi (2006), rebalancing in the case of China should include a decrease in savings, especially private savings and an increase in the supply of services, and an appreciation of the Renminbi. Albert et al. (2015) describe rebalancing as a reallocation from investment toward consumption, from manufacturing toward services, and altogether from an extensive toward an intensive growth model. Hence, tertiarization must be seen as an integrated element of China's rebalancing process.

2.2. Structural change and its impact on economic growth and stability

As result of tertiarization and rebalancing most previous research suggests that growth rates will most likely decrease: Baumol's cost disease implies that rising wages in the service sector are generally not accompanied by corresponding efficiency gains. As a consequence overall economic growth in an economy with an increasing service sector share will slow down (Wagner, 2013, 2015, Baumol and Bowen, 1965, 1966 and Baumol, 1967).

Recent research by Moro (2012, 2015) shows in the framework of a two-sector general equilibrium model calibrated for the US, that tertiarization reduces GDP growth and volatility. Hence, tertiarization generally has negative effects on economic growth, but positive effects on economic stability.

2.3. Previous studies

Besides the transmission of monetary policy shocks (see, for instance, Bernanke and Blinder, 1992, Sims,1992 or, more recently, Chen et al., 2015, for the transmission of unconventional US monetary policy), the transmission of business cycles has long been a subject of study in macroeconomics. In most studies, the focus is on the transmission of business cycles between regions, or from systemically relevant countries to other countries or regions (see Poirson and Weber, 2011 for a survey of these studies).[1]

The general finding of this stream of studies is that the US is the main source of growth spillovers (see Poison and Weber, 2011). Fewer studies have focused on the transmission channels, i.e., channels through which shocks are transmitted from one country or region to another. Using model-based simulation analyses, Helbling et al. (2007) find that most of the US spillover effects are trade related and the effects are relatively small. Interestingly, to obtain

[1] See Vasishtha and Maier (2013) for such a systematization of the literature.

larger effects, simulations need to be done with disturbances correlated around the world. These correlations of disturbances could, according to the authors, be connected to growing trade or financial integration and may be especially relevant in times of financial crisis. Larger spillover effects are, for instance, found by Arora and Vamvakidis (2006).The view that the trade channel may be the key transmission channel for economic developments in the US (see also Bagliano and Morana, 2012) is challenged by Bayoumi and Swiston (2009), who point out that most of the spillovers stem from financial rather than from trade variables. This view is supported by Galesi and Sgherri (2009), who also find support for the short-run importance of financial variables. Other macro variables are more important over a longer time horizon.

Two studies that are related to our analysis investigate the macroeconomic transmission of external shocks to the emerging economies of China, Emerging Asia and Latin America. Utlaut and van Roye (2010) find that an increase in real world GDP growth results in an increase in real GDP growth in both an average Emerging Asia country and China, while the response in Emerging Asia is more pronounced. They also find significant responses to a contractive interest rate shock and a worsening of financial conditions. Here, the resulting negative impact of global financial conditions on China is stronger than on Emerging Asia. The reactions of Emerging Asia and China to each other are far less pronounced. Hence, the authors conclude that economic activities in Emerging Asia can mostly be explained by world output and general financial conditions.

The research of Erten (2012) extends the analysis of Utlaut and van Roye (2010), although in contrast to the latter, it does not focus on global GDP, but takes a more differentiated perspective differing between shocks from US GDP, Eurozone GDP, and Latin American GDP. The authors find that in comparison, Chinese GDP is least affected by the respective shocks. Also, shocks to Eurozone GDP growth have a stronger impact on China than on the US. Looking at the variance decompositions, more than half of the variation in Latin America is explained by external shocks, while slightly less than half is explained by external shocks in the case of the US and China. Both studies use Bayesian vector autoregression (VAR) models for their analyses.

Poirson and Weber (2011) also discuss the different forms of VAR models in the analysis of cross-country growth spillovers. They distinguish between four different types of VAR models: Bayesian VARs, factor-augmented VARs, global VARs, and VARs based on regional groupings. The four approaches differ in the way the identification of the shocks is achieved.

Bayesian VARs use priors for cross-country correlations to achieve identification. In contrast factor-augmented VARs summarize the cross-country co-movements of several factors in one or more common factors. Global VARs (GVARs) reduce the individual countries' spillovers to a share in a weighted average for each variable of interest. The fourth and last approach consists of estimating a traditional structural VAR for a smaller set of countries to preserve degrees of freedom.

Our approach is related to the second stream of literature on business cycle transmission from systematically relevant countries to other countries. We do not explicitly account for monetary policy outside China. We consider economic developments in China's major trading partner countries as systematically relevant to a transmission of shocks to the Chinese economy. We use similar variables to those in Utlaut and van Roye (2010) and Erten (2012), but we extend the variable set by studying the response of Chinese confidence measures, and we clearly relate our choice of variables to the trade, financial, and confidence channels. In contrast to the approach in the two studies mentioned above, we focus solely on the effects of external shocks on China, while also extending the previous literature by an analysis of the three main sectors of the

Chinese economy—agriculture, industry, and services—and by explicitly considering a confidence channel for China.

As spillovers between China and its major trading partners could impact our results, we have to defend our approach against the use of multilateral models (e.g. global VARs (GVAR)). Georgiadis (2017) compares the performance of bilateral models which consider solely the spillover-sender and the spillover-recipient against multilateral model. The advantage of two country VAR models is their relatively easy implementation, but there are not able to capture higher order-spillovers that reach the recipient through third and further economies. Multilateral models can account for these higher order spillovers, but are technically more difficult. Generally, Georgiadis (2017) points out that bilateral models are subject to a larger bias and mean squared error in comparison with multilateral models. The asymptotic bias is however smaller if the spillover-recipient (in our case China) is less sensitive to developments in the rest of the world and when the direct bilateral spillovers from the spillover-sender account for a larger share of the recipient's overall sensitivity to developments in the rest of the world.

In our model we can assume that these conditions are given as we focus on China's largest trading partners in terms of their share in Chinese exports and which should improve the accuracy of our results. Moreover, we use established methods to concentrate the GDP growth dynamics of the trading partner countries in a single GDP measure and hence our approach is not restricted to the estimation of bilateral models (in the sense of two-country VAR models.) We are also confident that our estimations are able to mirror the underlying economic relationships as we are able to reproduce main features of related studies (see Utlaut and van Roye, 2010, Erten, 2012, and, Belke et al., 2018).

2.4. Channels of business cycle transmission

We distinguish between four potential channels of business cycle transmission.[2] First, there is the trade channel. Higher import demand in a relevant country will increase exports in the other country and lead to higher business cycle synchronization. Empirically this link can be regarded as well established (see Baxter and Kouparitsas, 2005; Clark and van Wincoop, 2001; Frankel and Rose, 1998). In this channel, productivity advances could be transmitted via vertical integration (Arkolakis and Ramanarayanan, 2009; Kose and Yi, 2001). These two effects could increase international business cycle transmission. However, inter-industrial specialization will lead to smaller effects of spillovers if industry-specific shocks occur (see, amongst others, Frankel and Rose, 1998).

These arguments could also be applied to China. In a first step, demand for Chinese intermediate products could have increased the effect of growth spillovers on the Chinese economy. The international division of labor and joint venture-induced spillovers of productivity may have additionally increased the business cycle transmission. As China's industry becomes more diversified over time and develops partly away from the fabrication of intermediate goods and toward more sophisticated production technologies and goods, for example the aircraft industry and the "Made in China 2025" initiative (see State Council of the People's Republic of China, 2015), the response to industry-specific shocks will probably decrease.

Second, we have an exchange rate channel of business cycle transmission. Here, the theoretical and empirical implications depend on the type of shocks and the frictions in the

[2] See also Eickmeier (2007).

economy. Generally, a shock that causes the domestic currency to depreciate will render domestic products more competitive and lead to rising exports.

Third, there is a financial channel. Rising financial integration allows investors to diversify their portfolios by investing in different markets. Also, arbitrage will lead to more synchronized financial prices. Johansson (2010) and Wang et al. (2014), for instance, find that China's financial market integration has indeed increased. Eickmeier (2007) points out that there may also be negative effects of financial integration. If capital is mobile, it will be reallocated to economies where it is used most productively, which could lead to a loosening of business cycle co-movements after industry-related shocks. Besides causing capital outflows, our measures could also imply an option value of waiting under uncertainty which has a negative effect on investments in China under increasing financial uncertainty. Firms will invest less and consumers may also postpone consumption and thus growth will decrease (Dixit and Pindyck, 1994, Leduc and Liu, 2016, Belke and Osowski, 2018).

Finally, there is a so-called confidence channel. If there is imperfect information concerning the development of foreign variables or the transmission of shocks to these variables to the domestic economy and there are costs in terms of forming expectations, domestic agents will make persistent expectation errors. These errors will add to the effects that would be transmitted via trade and financial markets, influencing domestic consumption and investments. Whether the confidence channel strengthens or weakens the effects of the other channels depends on whether agents under- or overestimate these spillovers.

3. Data and econometric framework

3.1.Data description

As previously in Utlaut and van Roye (2010) and Erten (2012), we focus on the short-run impact of external factors on China's growth at the economic level, but also shed light on transmission at a sectoral level. We focus on the financial channel, the trade channel, and the confidence channel. We thus do not cover all potential transmission channels in our analysis. Other possible channels which could be considered are an exchange rate channel and commodity price channel, as well as other measures of uncertainty such as economic policy uncertainty (see Belke et al, 2017, Belke and Osowski, 2018).

To analyze the trade channel, we calculate a common measure for GDP growth in China's major trading partner countries. For this purpose, we use quarterly time series from 1992Q1 to 2014Q4 for the US, the Euro Area, the United Kingdom (UK) and Japan. These countries can be identified as China's major trading partners, receiving the major share of Chinese exports. Hence, a slowdown in the economic growth of these countries (proxied by their quarter-on-quarter change in GDP growth) is also expected to affect Chinese GDP growth.

For the countries mentioned, we first collect data for nominal GDP. Based on data from the World Bank database, the selected countries represent at least over 60% of global GDP (in current US dollars) over the whole sample period. Moreover, the Euro Area and the UK encompass almost 90% of the economic activity in the European Union over the whole sample. Hence, we believe that a sufficiently large share of economic activity of relevant markets is covered in our analysis. In addition, we collect quarterly data for the implicit GDP deflator to calculate real GDP.

We include two measures related to global financial conditions to assess the financial channel of business cycle transmission. We use the Chicago Board of the Exchange Volatility Index (VIX) to measure general financial conditions and risk. Furthermore, we collect three-month interbank interest rates to mirror liquidity conditions in the banking sectors of major trading partner countries. These variables can be understood as proxies to account for the global risk appetite or aversion (VIX) and global liquidity conditions (I_TP), which impact capital flows (Belke et al., 2018). Alternatively economic policy uncertainty (Baker et al., 2015) as, for instance, used in Belke and Osowski (2018) could be considered. However, Baker et al. (2015) point out that their measure displays a strong relationship with other uncertainty measures, such as implied stock market volatility. As we are especially interested in liquidity and financial uncertainty, we do not further explicitly account for a policy uncertainty channel. For China, we collect quarterly data on nominal GDP as well as nominal GDP data for the three sectors. In addition, we collect an implicit GDP deflator for China to calculate real economic activity. Finally, we collect two measures of business and consumer confidence in China. We use the Business Climate Index for the industrial sector and future consumer income confidence. All data are taken from Datastream or the EABCN database.[3] All data except for the interest rates and the VIX are already seasonally adjusted or treated with the X12-ARIMA procedure.

To obtain a single measure for the trading partners' series, the first step consists of aggregating the country-specific time series to a single time series for all selected trading partners. The aggregation method we use has previously been applied by other authors: The methodological principles were first explained in Beyer et al. (2000, 2001), and more recently reconsidered by Beyer and Juselius (2010). Applications of this method can be found in Giese and Tuxen (2007), Belke et al. (2010), Belke et al. (2013), and Gattini et al. (2012). Hence, this method can be considered well-established in the economics literature.

For a detailed discussion of aggregation issues, we refer the reader to Beyer et al. (2000, 2001), and Beyer and Juselius (2010). In brief, Beyer et al. (2001) conclude that there are four possible aggregation methods, either aggregating levels or growth rates of the series with either constant or flexible (i.e., changing) weights, and with a fixed or variable exchange rates. Beyer et al. (2001) conclude that aggregation with growth rates and changing weights delivers the most reliable results. Moreover, Beyer and Juselius (2010) show that instead of real weights, which are recommended in Beyer et al. (2001), it may be better to use nominal weights. However, a critical point is the transformation with variable or fixed exchange rates if purchasing power parity is not fulfilled.

In a first step, we use nominal GDP weights to construct the aggregated series of nominal GDP Y_t and the GDP deflator P_t. Following the literature cited above, with nominal output as $Y_{i,t}$ and the implicit deflator as $P_{i,t}$, real output $X_{i,t}$ is defined as $X_{i,t} \equiv \frac{Y_{i,t}}{P_{i,t}}$ for countries $i = 1, \dots, n$ and $t = 1, \dots, T$. The corresponding growth rates are denoted by $\Delta y_{i,t}$, $\Delta x_{i,t}$, and $\Delta p_{i,t}$, where lower case letters denote the log of the corresponding capitals, so that, for instance, $\Delta y_{i,t} = y_{i,t} - y_{i,t-1} = \Delta log Y_{i,t}$. The weight of country i in period $t-1$ is given by:

$$w_{i,t-1} = \frac{E_{i.c,t-1} \cdot Y_{i,t-1}}{\sum_{i=1}^{n} (E_{i.c,t-1} \cdot Y_{i,t-1})},$$

where $E_{i.c,t}$ is the exchange rate of country i at time $t-1$ vis-à-vis a common currency, c, which in our case will be the US dollar in current prices.

In a second step, growth rates for every variable and country, measured in the domestic currency, are calculated and aggregated using the weights $w_{i,t-1}$, such that:

[3] For a detailed description of the data sources, we refer the interested reader to Table 29 in the Appendix.

$$\Delta y_t = \sum_{i=1}^{n}(\Delta y_{i,t} \cdot w_{i,t-1}), t = 1, \dots, T,$$

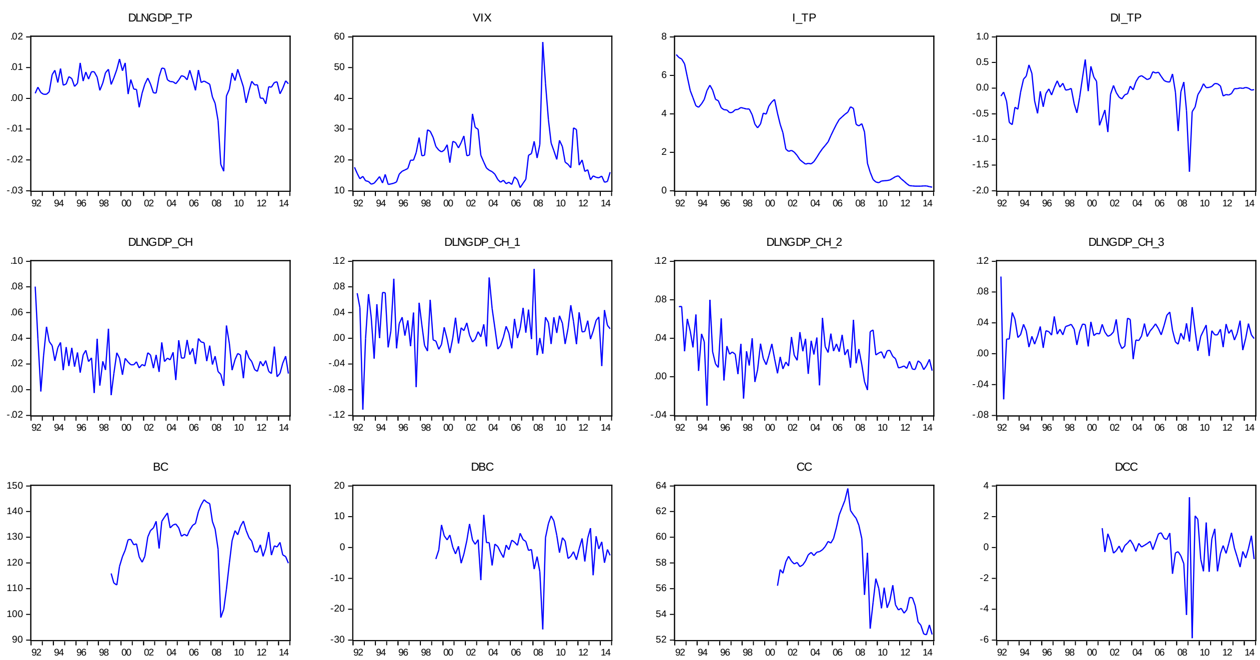
where $\Delta y_{i,t}$ are the individual countries' growth rates for the relevant variables (here nominal GDP), measured in national currencies. This procedure is followed for nominal GDP and the implicit GDP deflator with nominal GDP weights. For instance, in the case of nominal GDP, an index is calculated as:

$$Index_T = 100 \cdot \prod_{t=2}^{T}(1 + \Delta y_t)$$

with $Index_1 = 100$. As we use lagged weights, like Beyer et al. (2001), a weight for the initial period is missing. Therefore we set $w_{i,0} = w_{i,1}$, as in Beyer et al. (2001). We are able to calculate real GDP implicitly by calculating $X_t = \frac{Y_t}{P_t}$. The interest rates are aggregated using real GDP weights, but without calculating growth rates.

We calculate Chinese real GDP by means of the aforementioned Chinese implicit GDP deflator. Here, our results rely on the assumption that the GDP deflator reliably captures the development of prices in all sectors on average.

Fig.4 displays the economic developments in China's trading partner countries in terms of real GDP (difference of logs), short-term interest rates (in levels and first differences), VIX (in levels), and for the real GDP development in China (difference of logs), as well as disaggregated data for the agricultural, industry and service sector in China between the second quarter of 1992 and the fourth quarter of 2014. Confidence measures for business confidence (BC) and consumer confidence (CC) are displayed in levels and first differences depending on the availability of data.



Source: Datastream and EABCN, own calculations.

Fig. 4. First differences of logs of variables for aggregated trading partners and China over 1992Q2–2014Q4.

Real GDP growth in trading partner countries is relatively stable over the whole period, while there is a strong decline during the financial crisis. This strong decline in real growth rates corresponds to exceptionally high values of the volatility index, VIX. Our measure of short-term interest rates shows that liquidity conditions ease in trading partner countries for most of our sample. Furthermore, we see that lower levels of the volatility index generally correspond to more stable or higher growth rates in trading partner countries. Looking at China's growth rates at the level of the whole economy, we first observe higher volatility prior to and during the Asian crisis around 1997 and afterwards. During the financial crisis, we observe the most considerable slowdown in economic growth in China since its entry to the World Trade Organization (WTO) 2001, with a relatively fast rebound in China. The development in business confidence in the industry sector closely resembles real growth developments in trading partner countries and suggests a close relationship. The effect of the financial crisis is also clearly visible in the confidence measures. While consumer confidence in terms of future income expectations shows arising trend prior to the financial crisis, it does not recover fully afterwards and seems to have suffered considerably.

Based on the visual impression of developments in China and its sectors, these do not seem to be related particularly closely to the external developments described. However, the effect of the financial crisis is clearly visible. We also observe that after the financial crisis, growth in the industry sector slows down considerably, while service sector growth remains relatively stable.
When looking at the sector level in China, we have to bear in mind that the shares of the sectors in Chinese GDP are different (see Fig. 3). As the industry sector dominates China's economy for most of the sample, it is no surprise that the industry sector resembles China's overall real growth pattern the closest.

From this prima facie analysis, we can determine that the growth pattern of the industry sector seems to be most representative of the developments in China's growth as a whole. This is not a surprise as China has so far followed a growth model based on the production and export of intermediate industrial products. Generally, lower growth rates in China's industry sector seem to correspond to higher levels of perceived risk and lower growth rates in the trading partner countries. However, at this point of our analysis we would not overstress the importance of external shocks for China's growth from this descriptive analysis.

3.2. Econometric framework

The VAR methodology used in the econometric analysis can be regarded as a work horse in empirical economics as it became popular after the publication of Sims (1980). A major advantage of VAR models is that all variables can be taken as endogenous, which allows us to test different assumptions concerning causality without imposing a concrete model structure separating exogenous and endogenous variables. This, however, has also led to criticism of VAR models as atheoretical. Another disadvantage is that degrees of freedom quickly become scarce if the number of lags and variables is extended. For our model, it is thus advantageous to combine the developments in China's major trading partner countries in just two aggregated index time series and the VIX.
Hamilton (1994) points out three different approaches to empirical VAR modelling. Sims et al. (1990) show that Ordinary Least Squares estimates of VAR coefficients are consistent in many cases even if the variables are stationary. Hence, a first approach consists of is to ignore possible nonstationarities and merely estimate the VAR in levels. A second option is to routinely difference nonstationary variables before estimating the VAR. This approach especially improves the performance of estimates in small samples. A third approach is to investigate the nonstationarity of the variables under consideration and explicitly testing for possible

cointegration among the series. As a practical solution Hamilton (1994) suggests to employ parts of all three approaches. We hence provide assessments on the stationarity of the time series, cointegration tests and results for the VARs in levels and first differences.

[Insert Table 1 about here]

Table 1 displays the unit root tests for the time series considered. All time series can be regarded as stationary in first differences. VIX and BC are even stationary in levels. The results of our unit root tests for the global interest rate measure I_TP should be considered with caution. Although it is not reasonable that interest rates are non-stationary in the long run, the unit root tests clearly indicate non-stationarity. Hence, when using I_TP we should test the stability properties of the model.

The nonstationarity of LNGDP_CH, LNGDP_TP, I_TP makes it necessary to account for cointegration. Bivariate cointegration analysis indicates that if at all there could exist a cointegration relationship between LNGDP_TP and I_TP, i.e. variables outside China. However, testing the full set of variables indicates that there is no cointegration between the time series. Table 2 displays the Trace test for cointegration for the sample 1996:01-2014:04.

[Insert Table 2 about here]

We then proceed with estimating our VAR models both in levels and in first differences. As models yield similar results, we consider our assumption of no cointegration between the time series as valid. In absence of cointegration the small sample performance of a VAR in differences is better in comparison with a VAR in levels (Hamiliton, 1994). With T=76 (and T=64, for the VARs including our confidence measures) observations, we consider our samples as rather small and hence assume the estimations with first differences to be a better representation of the underlying relations among the time series.[4] The corresponding lag length is specified using information criteria. To reduce potential bias from historical events (especially financial crisis), we account for outliers with dummy variables were necessary. We base our decisions on the corresponding properties of the residuals of our estimated VAR models.

For illustrative purposes, we formulate the model with the trading partners' real GDP growth and real Chinese GDP growth. The corresponding vector is:

$$x'_t = (DLNGDP_{CH}\ DLNGDP_{TP})'.$$

The sample period is1996:01–2014:04. Our selection of this subsample period is based on our prior knowledge of relevant historical events. We choose 1996 as a starting point as this coincides with the strategic plan to develop infrastructure and other heavy industries in China (see Chang et al., 2015). 2014 is the end point of our sample as this is shortly after the point of tertiarization in China (see Fig. 3 in Section 2.1). The structural VAR representation with p lags is:

$$A_0 y_t = c + A_1 y_{t-1} + \cdots + A_p y_{t-p} + \varepsilon_t,$$

[4] However, we underline the robustness of our results with estimations of VARs in levels in Section 4.4.

where A_i is a 2×2 coefficient matrix and c is a 2×1 vector containing constant terms. $\varepsilon_t = (\varepsilon_{1,t}, \varepsilon_{2,t})'$ is a vector with the properties:

$$E(\varepsilon_t) = 0$$
$$E(\varepsilon_t, \varepsilon_\tau) = \begin{cases} \Omega \, for \; t = \tau \\ 0 \quad else \end{cases}.$$

Ω in this case is a 2×2 symmetric positive definite matrix. We can obtain consistent estimates of the coefficients of A_i by estimating each equation with ordinary least squares (OLS). We assume thatA_0^{-1} has a recursive structure and the reduced from errors e_t can be decomposed according toe_t=$A_0^{-1}\varepsilon_t$. This ordering implies that the variables ordered last affect the variables ordered before them.

$$e_t = \begin{bmatrix} e_t^{DLNGDP_{CH}} \\ e_t^{DLNGDP_{TP}} \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} \\ 0 & a_{22} \end{bmatrix} \cdot \begin{bmatrix} \varepsilon_t^{DLNGDP_{CH}} \\ \varepsilon_t^{DLNGDP_{TP}} \end{bmatrix}$$

In what follows, we replace $DLNGDP_{CH}$ with the corresponding sector variables or confidence measures and $DLNGDP_{TP}$ will be replaced with the respective external variables.

4. Results

4.1. The trade channel

We first explore the existence of a trade channel between China and its major trading partner countries. For this purpose, we estimate a bivariate VAR model with the vector:

$$x_t = (DLNGDP_{Ch} \; DLNGDP_{TP})'.$$

We order the trading partner variable last as we expect that shocks arise in the trading partner countries and then affect the Chinese economy. This view could, however, be challenged. As it can be observed in Figure 1 China's share in the world economy has increased strongly and hence its economic influence has increased considerably during our sample period. The effect of this development became very visible during and after the financial crisis. While large emerging economies recovered relatively quickly, their performance deteriorated again in the more recent years, despite the, at first very modest, recovery in advanced economies. This higher divergence of business cycles was linked to the Chinese economy. During and after the crisis fiscal stimulus measures prevented a more abrupt decline in GDP growth not only in China, but also in resource-rich economies. China plays by now a crucial role in determining global trade and oil prices (Belke et al., 2018). We will however show that the results obtained in the following also hold under alternate orderings of the variables (see Section 4.4. for these robustness checks).

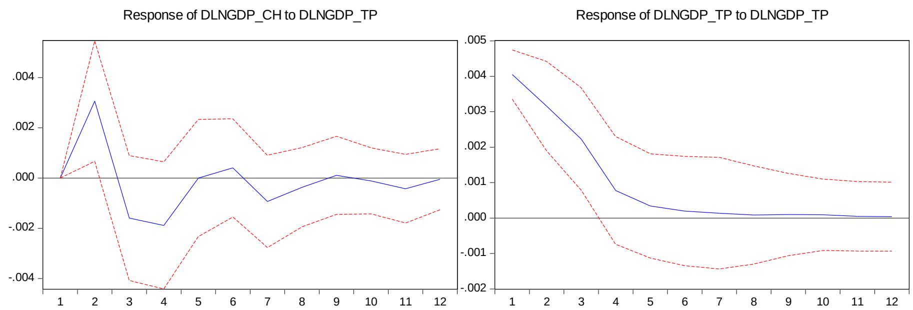
To choose the appropriate order of lags, we consider several information criteria such as the Akaike Information Criterion (AIC) and the Schwartz Information Criterion. Lag length criteria propose a lag order of between two and four lags, but mainly four lags. We hence chose a lag length of four. However, we detect a few outliers in the residuals, especially around the occurrence of the financial crisis, but as there is no indication of autocorrelation and heteroscedasticity in the residuals can be rejected, we decide against treating these outliers with dummy variables. The diagnostic tests for this model are displayed in Table 3.

[Insert Table 3 about here]

The chosen lag length is further supported by Granger causality tests, which indicate that $DLNGDP_{TP}$ significantly Granger causes $DLNGDP_{CH}$ at lags two and four (see Table 4). The possibility that Chinese real GDP growth Granger causes GDP growth in trading partner countries is however rejected (results for these tests not displayed).

[Insert Table 4 about here]

In Fig. 5, the impulse response functions also show that a positive shock to real GDP growth in trading partner countries positively affects real GDP growth in China. The response is relatively strong and cancels out after about two quarters.



Source: Own calculations.

Fig.5. Impulse responses of DLNGDP_CH to DLNGDP_TP.

Variance decompositions further support the interpretations based on the Granger causality tests and the impulse response functions. After 12 quarters, more than 14% of the variation in Chinese GDP can be explained by variations in the trading partner's real GDP developments. About 10% of the variation in the trading partners' GDP measure is explained by developments in China (see Table 5).

[Insert Table 5 about here]

In the next step, we strive to obtain a more detailed picture of the transmission of demand shocks via a trade channel to the Chinese economy. For this purpose, we now use the disaggregated sectoral real growth rates of the agricultural, industrial, and service sectors. The vector for the corresponding four variables VAR is now:

$$x_t = (DLNGDP_{Ch_1} DLNGDP_{Ch_3} DLNGDP_{Ch_2} DLNGDP_{TP})'.$$

Thus, we implicitly assume that demand shocks from trading partner countries are transmitted to the industrial sector, and are then further transmitted into the service sector and the agricultural sector. Although most services are non-tradable, we assume that the service sector supports the industry sector (industry-related services) to a certain degree. However, our results are generally robust to different orderings of the real sectoral growth rates (see Fig. A2 for the results for generalized impulse responses in the Appendix and Section 4.4) .

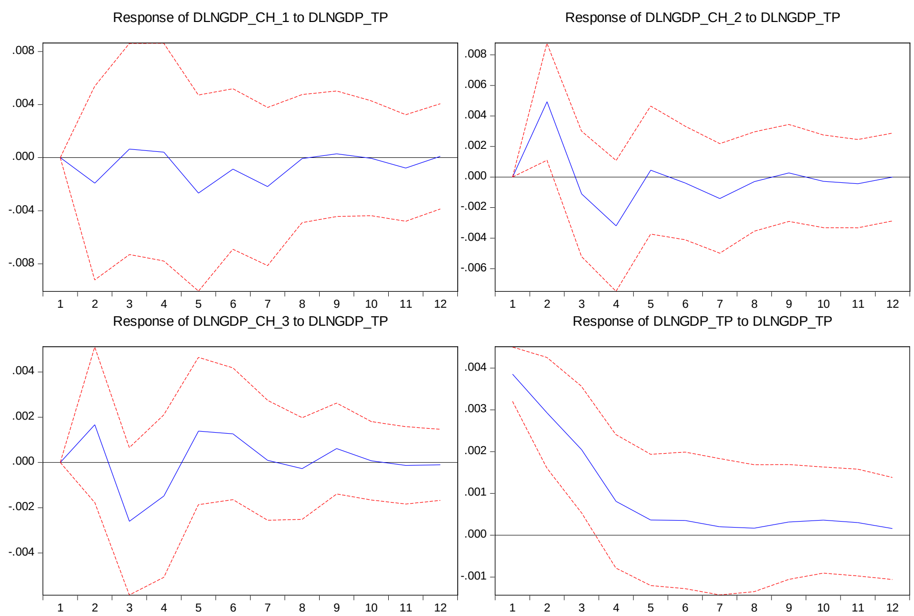
The lag length criteria recommend between one and four lags, where we achieve the best residual properties with four lags. The residual diagnostics are displayed in Table 6.

[Insert Table 6 about here]

Granger causality tests indicate that shocks in trading partner countries' GDP only affect the industry sector at the fourth lag. The agricultural and service sectors remain unaffected (see Table 7).

[Insert Table 7 about here]

This picture is also supported by the corresponding impulse response functions. We find a significant response only in the case of the industrial sector. The response is similar to that we obtained in the previous model, that is, the demand shock has a strong effect on real growth in the industrial sector for about two quarters. While the service sector shows a similar pattern in terms of the shape of the impulse response, there is no significant impact. The agricultural sector is clearly unaffected by external shocks (see Fig.6).



Source: Own calculations.
Fig. 6. Impulse response of DLNGDP_CH_1, DLNGDP_CH_2, and DLNGDP_CH_3 to DLNGDP_TP.

The variance decompositions also support the assumption that the industry sector especially is affected by the shocks considered. After 12 quarters, approximately 11.7% of the variation in the Chinese industrial sector can be explained by variations in the trading partners' GDP. For the service sector, the share is considerably smaller, with only around 7.6% explained and only around 1.8% of the variation in the agricultural sector explained by the corresponding variations (see Table 8).

[Insert Table 8 about here]

4.2. The financial channel

We turn now to the financial channel. The first bivariate VAR is estimated with the vector:

$$x_t = (DLNGDP_{Ch} VIX)'.$$

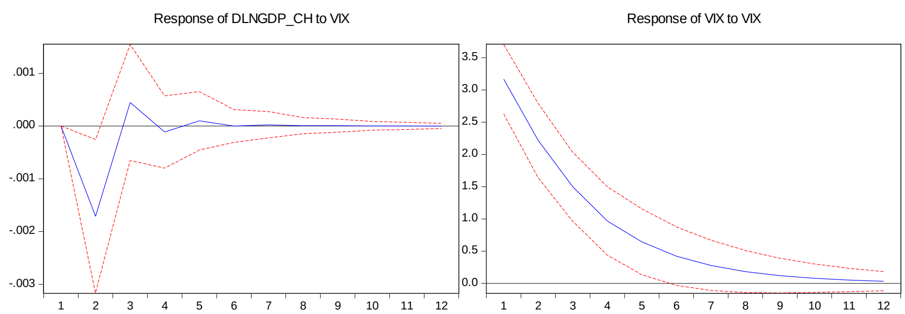
The lag length criteria again recommend between one and four lags. The volatility index, in particular, shows a couple of outliers (2003:02, 2008:04, 2011:03). We correct these values with dummy variables.[5] We achieve a fairly well specified model with a lag length of two lags. Table 9 shows that there is some indication of autocorrelation in the second lag, but not too much. Heteroscedasticity is rejected.

[Insert Table 9 about here]

Looking at the Granger causality tests (see Table 10), we see that there is some evidence that the VIX Granger causes real Chinese GDP growth at lags one to four. The evidence is strongest for the second lag.

[Insert Table 10 about here]

The relationship is also supported by the corresponding impulse response in Fig.7, in which we observe a negative response of real Chinese GDP growth for about two quarters.



Source: Own calculations.

Fig. 7. Impulse response of DLNGDP_CH to VIX.

The variance decompositions in Table 11 show that only around 2.8% of the variance in Chinese real GDP growth is explained by variations in the VIX. However, we have to bear in mind that we have removed extreme positive values from the VIX, such that the above value probably corresponds to more normal times in the absence of extreme financial turmoil.

[Insert Table 11 about here]

From the more disaggregated perspective, we estimate the VAR with four variables:

$$x_t = (DLNGDP_{Ch_1} DLNGDP_{Ch_3} DLNGDP_{Ch_2} VIX)'.$$

[5] See Table 30 in the Appendix for the dummies we use and for possible explanations.

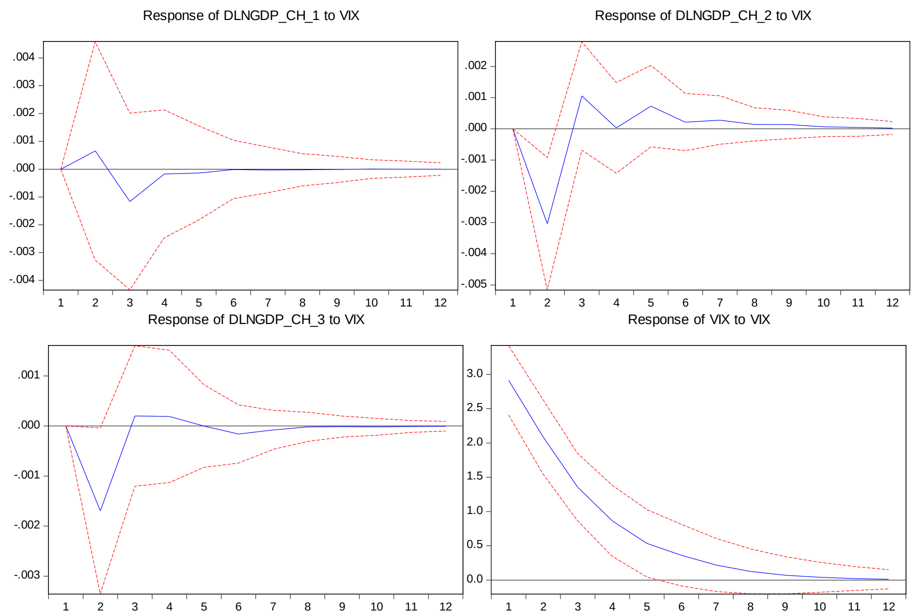
Again we correct outliers with dummy variables as in the previous model. At a lag length of two, we find practically no residual autocorrelation and heteroscedasticity. Table 12 displays the residual diagnostic tests.

[Insert Table 12 about here]

The Granger causality tests in Table 13 strongly support the view that the financial channel also works especially through the Chinese industrial sector. The VIX Granger causes real growth in the industrial sector at lags one to four. There is some evidence that the VIX could also affect the service sector.

[Insert Table 13 about here]

The impulse response functions in Fig.8 show the same picture. The response in the service sector resembles the response in the industrial sector, but the effect is only significant in the industrial sector. There is no significant response in the agricultural sector.



Source: Own calculations.
Fig. 8. Impulse response of DLNGDP_CH_1, DLNGDP_CH_2, and DLNGDP_CH_3 to VIX.

The variance decompositions in Table 14 show that the VIX does not significantly explain variations in agricultural sector growth. About 3.9% of the variation of the industrial sector is explained by variations in the VIX. Variations in the service sector are also not significantly explained.

[Insert Table 14 about here]

As a possible means of transmission, we assess the impact of liquidity conditions in trading partner countries on the Chinese variables. The corresponding vector for this model is:

$$x_t = (DLNGDP_{Ch}\ I\_TP)'.$$

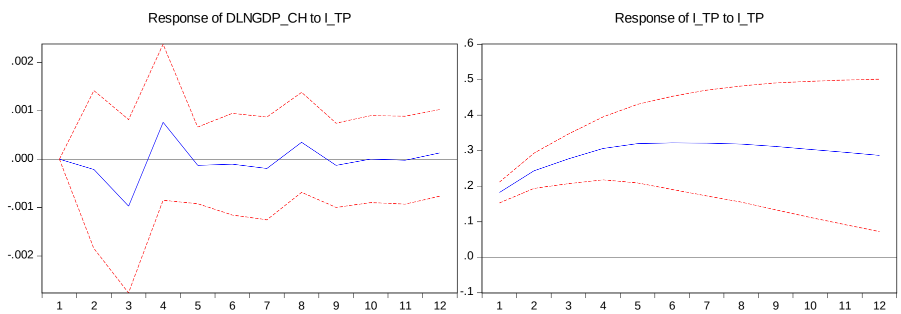
The necessary residual properties can be established with four lags and three dummies, which account for extreme interest rate movements in times of crisis. Table 15 displays the residual properties.

[Insert Table 15 about here]

The Granger causality tests displayed in Table 16 do not indicate that the liquidity conditions measure affects Chinese GDP growth.

[Insert Table 16 about here]

The same is valid for the impulse response functions shown in Fig.9 and the variance decompositions.



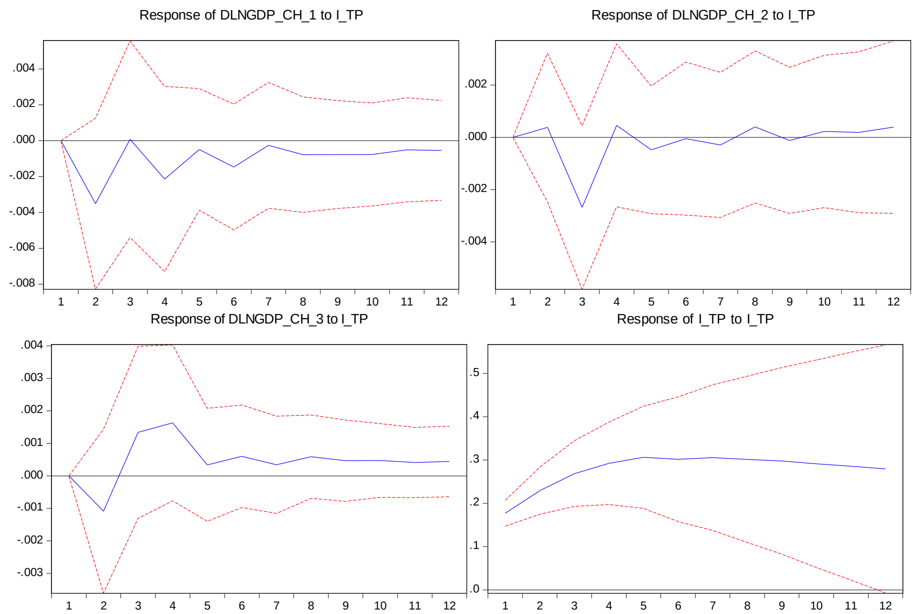
Source: Own calculations.
Fig. 9. Impulse response of DLNGDP_CH to I_TP.

Specifying a corresponding model with the vector for the disaggregated sectors (see Table 17 for the diagnostic tests) does not alter the impression that the measure of liquidity conditions does not affect growth in China, while there is very limited evidence from the Granger-causality tests (see Table 18) that the agricultural and the service sectors could be affected.

[Insert Table 17 about here]

[Insert Table 18 about here]

Fig.10 displays the corresponding impulse response function and Table 19 the variance decompositions.



Source: Own calculations.
Fig. 10. Impulse response of DLNGDP_CH_1, DLNGDP_CH_2, and DLNGDP_CH_3 to I_TP.

[Insert Table 19 about here]

4.3. The confidence channel

Finally, we turn to possible confidence channels. We first assess the impact of the external variables on business confidence in China's industrial sector. As the business confidence, BC, was already stationary in levels, we can estimate the bivariate VAR with the vector:

$$x_t = (BC\ DLNGDP\_TP)'.$$

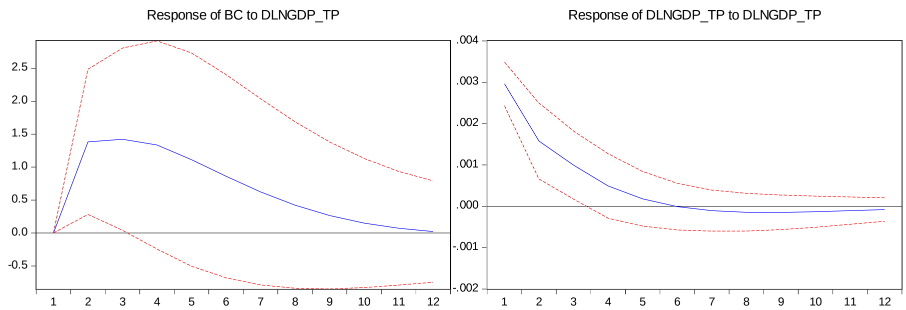
Due to the limited availability of data for business confidence, we are restricted to the investigation of the period from the first quarter of 1999 until the fourth quarter of 2014. With three dummies related to the financial crisis (2008:04, 2009:01, 2009:02) and a lag length of two lags, we can establish the necessary residual properties as shown in Table 20.

[Insert Table 20 about here]

The Granger-causality tests displayed in Table 21 show that real growth in trading partner countries clearly Granger-causes business confidence in China's industrial sector, but there is also some evidence of bi-directional Granger causality which might point toward sentiment spillovers from China to the trading partner countries.

[Insert Table 21 about here]

The picture that business confidence in China is influenced by GDP growth in trading partner countries is further supported by the corresponding impulse response function, which shows that the effect is significant for about three quarters before it cancels out (see Fig. 11).



Source: Own calculations.
Fig. 11. Impulse response of BC to DLNGDP_ TP.

The variance decompositions displayed in Table 22 show that almost one fifth of the variance in business confidence in the industrial sector can be explained by variations in trading partners' real growth.

[Insert Table 22 about here]

We also test the effect of the VIX on business confidence in China. While the impulse response shows that an increase in the VIX leads to an insignificant decrease in business confidence, neither the Granger causality tests nor variance decompositions indicate a strong impact on business confidence. Nor do we find significant evidence for an impact of the interest rate. Thus, we would tend to assume that business confidence is solely affected by GDP developments in trading partner countries.

We now look at the impact of the external shocks on consumer confidence. Here we only have data from the first quarter of 2001 onwards. Also, consumer confidence, CC, is found to be non-stationary so that we perform our estimation in first differences with dCC. The vector for the bivariate VAR is:

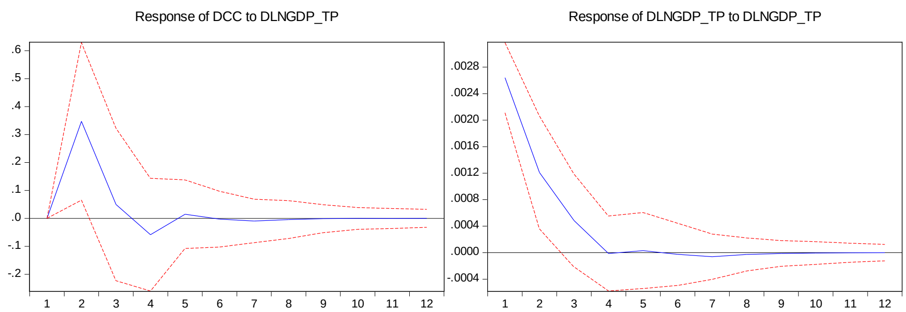
$$x_t = (DCC\ DLNGDP_{TP})'.$$

With three lags and two dummies (2008:04, 2009:01), we achieve the necessary residual properties as shown in Table 23.

[Insert Table 23 about here]

The Granger causality tests (see Table 24) support the hypothesis that a change in real GDP growth in the trading partner countries leads to a change in Chinese consumer confidence. We also find that consumer confidence in China Granger-causes the real GDP growth in trading partner countries (results not displayed). This can be taken as an indication that China has also become an important market for goods produced in its major trading partner countries. The impulse response function also shows a clear effect of growth in trading partner countries on consumer confidence in China. However, in this case the significance of the impulse response is somewhat susceptible to the choice of dummy variables. Fig.12 displays the corresponding impulse response.

[Insert Table 24 about here]



Source: Own calculations.
Fig. 12. Impulse response of dCC to DLNGDP_ TP.

Variance decompositions (see Table 25) show that about 11% of the variation in the change in Chinese consumer confidence can be explained by variations in real GDP in China's trading partner countries. As almost 25% of the variation of the change in the trading partner's GDP growth is explained by changes in the consumer confidence the assumption of bi-directional causalities is further supported.

[Insert Table 25 about here]

Finally, we investigate the effect of the VIX on consumer confidence in China. The corresponding vector is:

$$x_t = (DCC\ VIX)'.$$

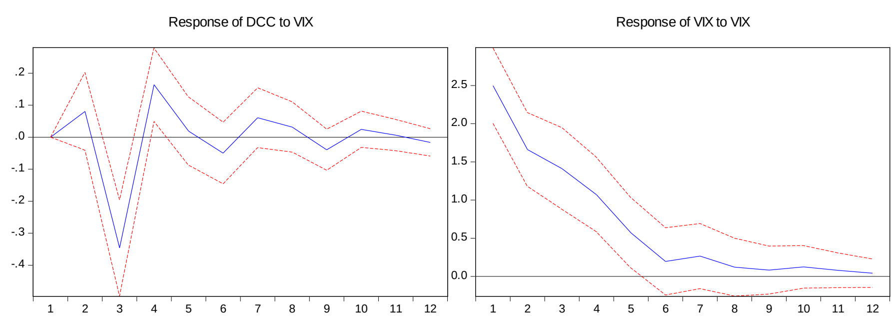
With three lags and three dummies (2002:03, 2008:04, 2011:03), we are again able to establish the necessary residual properties (see Table 26).

[Insert Table 26 about here]

The Granger causality tests indicate that the VIX Granger causes changes in China's consumer confidence at lag lengths of two to four (see Table 27).

[Insert Table 27 about here]

We observe a deterioration in consumer confidence after a period of around three quarters in response to an increase in risk perception as displayed in Figure 13.



Source: Own calculations.

Fig. 13. Impulse response of dCC to VIX.

The variance decompositions (see Table 28) show that the VIX accounts for about 10% of the variation in consumer confidence after 12 quarters.

[Insert Table 28 about here]

4.4. Robustness Checks

As we have only a rather small sample, it is difficult to perform a reliable subsample analysis. Also, the period under investigation could be characterized as fully belonging to the industrialization period, with perhaps slight signs of de-industrialization toward the end.

The general conclusions we draw are also valid for the full sample of 1992 to 2014. That is, demand and financial shocks significantly Granger-cause real Chinese GDP growth and the disaggregated perspective shows that this is mainly because the industry sector is affected.

Thus, we are generally able to reproduce our results from the baseline sample considering the impulse responses, the Granger-causality tests, and the variance decompositions. However, we observe that the results become slightly more significant if we exclude the earlier years of our sample. We interpret this as indicating that the impact of shocks has actually increased over time, which is in line with China becoming more integrated in the world economy. This is not surprising as we assume that the integration of China in the world economy took place during the 1990s and was promoted by specific strategic plans to develop infrastructure and other heavy industries in China (Chang et al., 2015). Fig. 1 and Fig. 2 also support the view that China's integration into international trade strongly increased after China joined the WTO in 2001.

In the following we comment on some selected alternate specifications to prove the robustness of our results from the previous sections. A first concern could be that we should rather estimate our models in levels instead of first differences (Hamilton, 1994, see above) and that we should include the variables in a larger-dimensional VAR model instead of estimating bivariate models. We hence estimate the model

$$x_t = (LNGDP_{CH}\ LNGDP_{TP}\ \ I_{TP}\ VIX)'$$

for our baseline sample period. It contains all variables in levels. Shock identification is obtained by Cholesky identification. The corresponding impulse responses are displayed in Figure A1 in the Appendix. The first row displays the impulse response for the effects on China. The results are in line with our previous findings. China's GDP is significantly affected by shocks via trade (response to LNGDP_TP) and financial channels (response to VIX).

Next we would like to show that the ordering of the sectoral level variables does not affect our results. We estimate the VAR

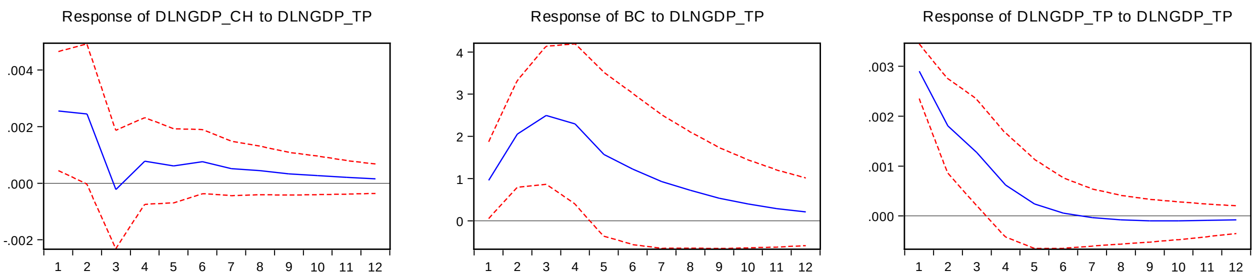
$$x_t = \left(DLNGDP_{CH\_1} DLNGDP_{CH\_2}\ DLNGDP_{CH\_3} DLNGDP\_TP\right)'$$

for the baseline sample period with generalized impulse responses. The corresponding results are displayed in Figure A2 in the Appendix. Figure A3 in the Appendix displays the corresponding generalized impulse responses for the VAR including the VIX.

Furthermore, we would like to test the robustness of our results for the confidence channels. We choose the sample to cover the period 2001:01 until 2014:04 and estimate the model

$$x_t = (DLNGDP_{CH}\ BC\ DLNGDP\_TP)'$$

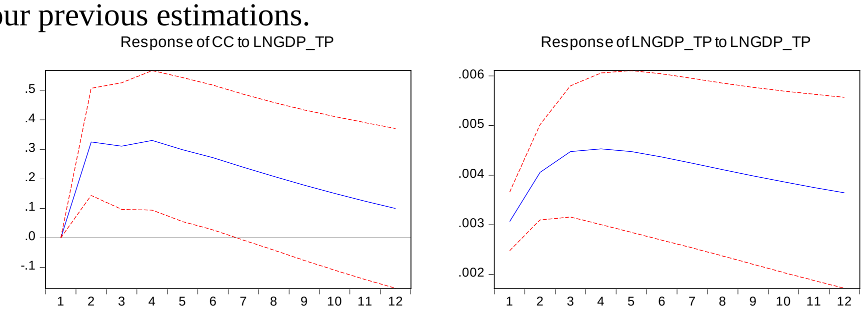
to get a better insight in the transmission of shocks via the confidence channel. Information criteria indicate a lag length of two and we use three intervention dummies to account for the financial crisis (2008:04, 2009:01, 2009:02). Figure 14 displays the corresponding results obtained with generalized impulse responses. They show that shock to China's trading partners GDP growth affects both business confidence and Chinese GDP growth significantly.



Source: Own calculations.

Fig. 14. Robustness Check. Impulse responses DLNGDP_CH, BC to DLNGDP_TP.

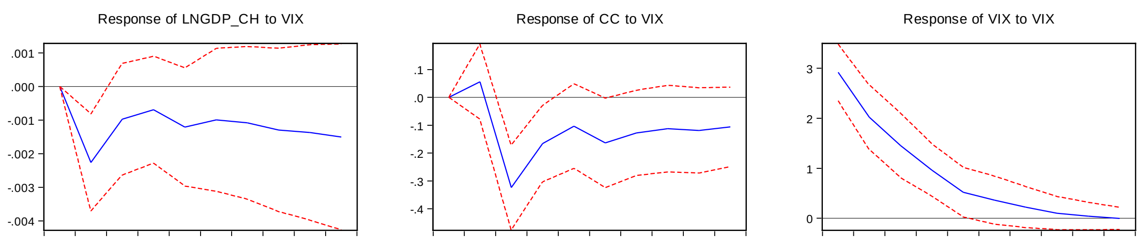
Additionally, we test the robustness of our results for the confidence channel (using CC) with the variables in levels. This should qualitatively produce the same results as our estimations in first differences. We use the same ordering and two dummies to account for the financial crisis (2008:04, 2009:01). Figure 15 displays the corresponding impulse responses. Again our findings are in line with our previous estimations.



Source: Own calculations.

Fig. 15. Robustness Check. Impulse response of CC to LNGDP_TP.

Finally, we check for the impact of the VIX on CC and China's GDP in levels. We are again able to reproduce our previous results (displayed in Fig. 16).



Source: Own calculations.

Fig. 16. Robustness Check. Impulse responses of LNGDP_CH, CC to VIX.

5. Conclusion and policy implications

In this paper, we have investigated the effect of external shocks on China's total real growth and real growth in its main sectors from the perspective of structural change and rebalancing. Generally, China is significantly affected in the short run by external shocks. Shocks appear to work through the trade, financial, and confidence channels alike. When we account for extreme values with intervention dummies, the impact of trade and financial shocks appears to be somewhat smaller in comparison to the results in previous literature (see Erten, 2012). However, we are generally able to reproduce the qualitative results of previous analyses and our results are robust if we remove our dummy variables. What is more, we are to our knowledge the first to extend the analysis to a sector level and find that the industrial sector especially is affected by external shocks. This can be explained by the fact that this is the most relevant sector for Chinese exports. While the agricultural sector is less important for China's overall growth perspective, an important result from our research is that the agricultural and the service sectors have thus far not been affected at all by external shocks, while there is limited evidence that liquidity conditions have had some effect on these two sectors according to our empirical models. Hence tertiarization could have a positive effect on China's resilience to external shocks as long as the major share of services is not industry-related to a large extent. But developments which further interconnect the industry and the service sector, like an increasing share of industry-related services in the service sector, could also increase the comovement of in these two sectors and at the same time the susceptibility towards external shocks. Furthermore, we add to the literature as we find strong evidence for the existence of confidence channels, which are affected by trade and financial shocks. While the concrete way in which confidence is affected is not clear, a possible explanation might be that the industrial sector is still very important for overall growth in China (see Fig. 3). Hence, investors and consumers closely observe the performance of China's industry, which is in turn affected by global developments. Thus, external shocks influence future income expectations, and hence consumption and demand in general. Additionally, there is some evidence for sentiment spillovers from China to trading partner countries.

While we do not wish to overinterpret our findings, some general policy implications seem to be quite clear. With a still very dominant industrial sector, China is directly affected by global events that affect demand for Chinese exports. Policymakers and companies could consider diversifying production.

In terms of our results, they question the perspective of rebalancing toward a more (domestic) consumption-driven model without accounting for global developments. In particular, confidence measures in China seem to be affected both by external demand shocks and financial shocks. Hence, greater consumer spending will currently only be possible if the relation between future income expectations in China and global economic developments is relaxed. However, our results also show that China has become an important trading partner as some of our results point toward sentiment spillovers from China into its trading partner countries. The effects of external shocks via trade and financial channels as described in the present paper, and the effects of the financial crisis raised the awareness of China's vulnerability to external shocks. China could mitigate the effects by corresponding fiscal policies at the same time reducing short-term negative consequences for commodity producers and trading partners. Hence, Made in China 2025 as a strategic plan is an ambitious project in this direction. If the initiative is successful this will lead to a more diversified industry sector with a key focus on producing products of higher value and thus make China's industry sector internationally more competitive. This could lead to a less strong impact of external shocks on the Chinese economy. The necessary promotion of IT services could however also increase the comovement between the industry and service sector and amplify future shocks from outside China.

The financial channel could work in different ways. Possible mechanisms could be portfolio reallocations in times of financial stress (flight to quality) and the withdrawal of capital or just a reduction in current and future FDI. This could perhaps be reduced by further developing domestic capital markets and domestic financing, hence reducing the dependence on international capital, and—through sound equity markets—offering domestic savers a possibility to invest their savings. The gradual elimination of capital controls will however increase the future impact of financial shocks.

The management of expectations will necessarily play a very prominent role. Creating confidence in the resilience of the Chinese economy, and ensuring financial and economic stability in China, for example by means of macroprudential policies, could also have beneficial effects.

Finally, the rebalancing of the Chinese economy towards a more service- and domestic consumption-oriented growth model, will decrease demand for resources and put additional reform pressure on countries with abundant natural resources.

Future research could try to draw a more detailed picture of the underlying dynamics we address in our models. Promising extensions could be to explicitly account for non-linarites in the estimations and hence to explicitly test for the functional form beforehand (Beckmann et al., 2013). Other possible extensions could consist in trying to model the sectoral structure of the Chinese economy in a global VAR framework thus increasing the complexity of the modelling approach by accounting for additional higher-order spillovers channels. Lastly, in the light of the restructuring of the Chinese industry sector under the initiative China 2025, a subsector analysis could shed more light on the underlying dynamics of the industry sector.

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Tables

Table 1
Unit root tests.

Time Series	Levels		First differences	
	ADF (SIC)	PP	ADF (SIC)	PP
LNGDP_CH (trend & intercept)	-1.437	-1.299	-10.516***	-10.433***
LNGDP_CH_1 (trend & intercept)	-1.448	-1.523	-11.604***	-12.746***
LNGDP_CH_2 (trend & intercept)	-0.718	-0.684	-10.193***	-10.070***
LNGDP_CH_3 (trend & intercept)	-2.374	-2.251	-9.147***	-9.435***
LNGDP_TP (trend & intercept)	-2.253	-1.716	-4.120***	-4.061**
VIX (intercept)	-3.615***	-3.589***	-8.278***	-10.925***
I_TP (intercept)	-1.531267	-1.373	-4.583***	-4.540***
BC (intercept) (1999:01-2014:04)	-3.801***	-2.814*	-6.681***	-6.681***
CC (intercept) (2001:01-2014:04)	-0.496	-1.146	-11.295***	-10.850***

Source: Own calculations.

Table 2
Tace Test

Trace Statistic
(sample: 1996:01-2014:04; series: LNGDP_CH LNGDP_TP I_TP, based on a VAR(1).

r	Eigenvalue	Trace Statistic	5% Critical Value	p-value**
0	0.348	42.366	42.915	0.057
1	0.102	9.802	25.872	0.933
2	0.021	1.619	12.518	0.987

Trace test indicates 0 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
** MacKinnon-Haug-Michelis (1999) p-values

Table 3
Diagnostic tests for the trade channel for China.

Variables	DLNGDP_CH DLNGDP_TP		
Lags	4		
Dummies	None		
Residual autocorrelation test: (H0: No serial autocorrelation)	Lags	p-value	
	1	0.173	
	2	0.596	
	3	0.060	
	4	0.841	
Heteroscedasticity test (H0: No cross terms)	p-value		
	0.082		
Univariate normality			
	Skewness	Kurtosis	Normality (p-value)
DLNGDP_CH	-0.193	3.826	0.268
DLNGDP_TP	-0.547	5.857	0.000

Table 4

Granger causality tests for the trade channel for China.

Null: DLNGDP_TP does not Granger cause DLNGDP_CH	
Lags	96Q1–14Q4[a]
1	0.616
2	0.056*
3	0.115
4	0.008***

[a]Models include no dummies;
*,**,*** indicate rejection of the null at the 10%, 5%, and 1%levels

Table 5

Variance decompositions for the trade channel for China.

Quarters	Decomposition of	DLNGDP_CH	DLNGDP_TP
1	DLNGDP_CH	100.000	0.000
		(0.000)	(0.000)
	DLNGDP_TP	13.952	86.048
		(7.107)	(7.107)
2	DLNGDP_CH	90.160	9.840
		(6.588)	(6.588)
	DLNGDP_TP	11.311	88.689
		(7.008)	(7.008)
4	DLNGDP_CH	84.927	15.073
		(7.730)	(7.730)
	DLNGDP_TP	9.924	90.076
		(7.015)	(7.015)
8	DLNGDP_CH	85.786	14.214
		(7.758)	(7.758)
	DLNGDP_TP	10.177	89.823
		(7.919)	(7.919)
12	DLNGDP_CH	85.911	14.089
		(7.977)	(7.977)
	DLNGDP_TP	10.283	89.717
		(8.531)	(8.531)

Table 6
Diagnostic tests for the trade channel for China's subsectors.

Variables	DLNGDP_CH_1 DLNGDP_CH_3 DLNGDP_CH_2 DLNGDP_TP		
Lags	4		
Dummies	None		
Residual autocorrelation test (H0: No serial autocorrelation)	Lags 1 2 3 4	p-value 0.146 0.619 0.671 0.887	
Heteroscedasticity test (H0: No cross terms)	p-value 0.513		
Univariate normality			
	Skewness	Kurtosis	Normality (p-value)
DLNGDP_CH_1	0.184	4.698	0.008
DLNGDP_CH_3	0.100	3.515	0.617
DLNGDP_CH_2	-0.092	2.694	0.817
DLNGDP_TP	-0.451	4.020	0.053

Table 7
Granger causality tests for the trade channel for China's subsectors.

	Null: DLNGDP_TP does not Granger-cause DLNGDP_CH_1	Null: DLNGDP_TP does not Granger-cause DLNGDP_CH_2	Null: DLNGDP_TP does not Granger-cause DLNGDP_CH_3
Lags	96Q1–14Q4[a]	96Q1–14Q4[a]	96Q1–14Q4[a]
1	0.551	0.184	0.633
2	0.754	0.117	0.455
3	0.806	0.229	0.412
4	0.884	0.016**	0.372

[a] Models include no dummies;
*,**,*** indicate rejection of the null at the 10%, 5%, and 1%levels

Table 8
Variance decompositions for the trade channel for China's subsectors.

Quarters	Decomposition of	DLNGDP_CH_1	DLNGDP_CH_2	DLNGDP_CH_3	DLNGDP_TP
1	DLNGDP_CH_1	100.000	0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.000)
	DLNGDP_CH_2	0.177	99.441	0.382	0.000
		(1.951)	(3.103)	(2.509)	(0.000)
	DLNGDP_CH_3	4.158	0.000	95.842	0.000
		(4.810)	(0.000)	(4.810)	(0.000)
	DLNGDP_TP	1.408	17.373	4.334	76.885
		(3.070)	(7.298)	(4.590)	(8.266)
2	DLNGDP_CH_1	98.937	0.000	0.079	0.000
		(3.653)	(0.000	(1.967)	(0.000)
	DLNGDP_CH_2	0.762	88.899	0.519	9.820
		(3.149)	(7.497)	(3.156)	(6.880)
	DLNGDP_CH_3	4.100	0.843	93.333	1.723
		(4.865)	(2.502)	(6.170)	(3.466)
	DLNGDP_TP	1.209	17.664	2.825	78.302
		(3.549)	(8.133)	(3.898)	(8.992)
4	DLNGDP_CH_1	96.096	1.450	1.988	0.466
		(6.391)	(4.002)	(3.967)	(3.744)
	DLNGDP_CH_2	5.720	79.712	2.045	12.523
		(6.112)	(8.026)	(4.319)	(6.607)
	DLNGDP_CH_3	9.306	0.731	83.871	6.092
		(5.963)	(2.931)	(7.575)	(5.571)
	DLNGDP_TP	3.758	15.544	2.678	78.020
		(5.726)	(7.944)	(4.667)	(9.828)
8	DLNGDP_CH_1	93.404	1.774	3.089	1.733
		(8.111)	(5.009)	(5.113)	(4.577)
	DLNGDP_CH_2	8.199	78.035	1.934905	11.831
		(7.562)	(9.039)	(4.567)	(6.343)
	DLNGDP_CH_3	10.793	2.832	78.932	7.443
		(6.523)	(4.616)	(8.765)	(5.788)
	DLNGDP_TP	9.177	14.850	3.442	72.531
		(8.520)	(7.918)	(5.080)	(11.014)
12	DLNGDP_CH_1	93.044	1.973	3.186	1.797
		(9.180)	(5.829)	(5.614)	(4.987)
	DLNGDP_CH_2	8.508	77.848	1.960	11.684
		(8.375)	(9.918)	(4.919)	(6.502)
	DLNGDP_CH_3	10.970	2.979	78.461	7.589
		(6.917)	(5.467)	(9.495)	(5.861)
	DLNGDP_TP	9.135	15.017	3.590	72.258
		(8.611)	(8.488)	(5.261)	(11.403)

Table 9
Diagnostic tests for the financial channel (VIX) for China.

Variables	DLNGDP_CH VIX		
Lags	2		
Dummies	2002:03, 2008:04, 2011:03		
Residual autocorrelation test (H0: No serial autocorrelation)	Lags	p-value	
	1	0.958	
	2	0.025	
Heteroscedasticity test (H0: No cross terms)	p-value		
	0.237		
Univariate normality			
	Skewness	Kurtosis	Normality (p-value)
DLNGDP_CH	0.166	3.381	0.667
DLNGDP_TP	0.602	3.864	0.031

Table 10
Granger causality tests for the financial channel (VIX) for China.

Null: VIX does not Granger cause DLNGDP_CH	
Lags	96Q1–14Q4[a]
1	0.072*
2	0.042**
3	0.100*
4	0.075*

[a] Models include dummies:dum0203, dum0804, dum1103;
*,**,*** indicate rejection of the null at the 10%, 5%, and 1%levels

Table 11
Variance decompositions for the financial channel (VIX) for China.

Quarters	Decomposition of	DLNGDP_CH	VIX
1	DLNGDP_CH	100.000	0.000
		(0.000)	(0.000)
	VIX	0.227	99.773
		(2.102)	(2.102)
2	DLNGDP_CH	97.329	2.671
		(2.224)	(2.224)
	VIX	0.673	99.327
		(3.022)	(3.022)
4	DLNGDP_CH	97.170	2.830
		(2.426)	(2.426)
	VIX	0.613	99.387
		(3.934)	(3.934)
8	DLNGDP_CH	97.161	2.839
		(2.474)	(2.474)
	VIX	0.604	99.396
		(4.225)	(4.225)
12	DLNGDP_CH	97.161	2.839
		(2.477)	(2.477)
	VIX	0.604	99.396
		(4.242)	(4.242)

Table 12

Diagnostic tests for the financial channel (VIX) for China’s subsectors.

Variables	DLNGDP_CH_1 DLNGDP_CH_3 DLNGDP_CH_2 VIX		
Lags	2		
Dummies	2002:03, 2008:04, 2011:03		
Residual autocorrelation test (H0: No serial autocorrelation)	Lags p-value 1 0.694 2 0.623		
Heteroscedasticity test (H0: No cross terms)	p-value 0.748		
Univariate normality			
	Skewness	Kurtosis	Normality (p-value)
DLNGDP_CH_1	0.297	5.201	0.000
DLNGDP_CH_3	0.058	3.522	0.636
DLNGDP_CH_2	0.507	3.339	0.163
VIX	0.203	3.671	0.378

Table 13

Granger causality tests for the financial channel (VIX) for China’s subsectors.

Null: VIX does not Granger-cause DLNGDP_CH_1		Null: VIX does not Granger-cause DLNGDP_CH_2	Null: VIX does not Granger-cause DLNGDP_CH_3
Lags	96Q1–14Q4[a]	96Q1–14Q4	96Q1–14Q4
1	0.979	0.088*	0.256
2	0.841	0.004***	0.096*
3	0.406	0.002***	0.239
4	0.196	0.000***	0.278

[a] Models include dummies for 2002:03, 2008:04, 2011:03;
*,**,*** indicate rejection of the null at 10%, 5%, and 1%levels

Table 14

Variance decompositions for the financial channel (VIX) for China's subsectors

Quarters	Decomposition of	DLNGDP_CH_1	DLNGDP_CH_2	DLNGDP_CH_3	VIX
1	DLNGDP_CH_1	100.000	0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.000)
	DLNGDP_CH_2	0.341	99.650	0.009	0.000
		(2.537)	(3.042)	(1.764)	(0.000)
	DLNGDP_CH_3	4.294	0.000	95.706	0.000
		(4.820)	(0.000)	(4.820)	(0.000)
	VIX	0.058	0.368	3.895	95.679
		(1.913)	(2.364)	(4.164)	(4.967)
2	DLNGDP_CH_1	99.299	0.621	0.030	0.050
		(2.888)	(2.330)	(1.666)	(0.585)
	DLNGDP_CH_2	1.340	94.35518	0.650014	3.654475
		(3.870)	(5.033)	(2.858)	(2.296)
	DLNGDP_CH_3	4.088	2.816	91.294	1.803
		(4.897)	(4.031)	(6.453)	(1.699)
	VIX	3.434	0.276	3.456	92.835
		(4.749)	(2.837)	(4.336)	(6.467)
4	DLNGDP_CH_1	99.000	0.640	0.151	0.209
		(4.401)	(3.264)	(2.716)	(0.874)
	DLNGDP_CH_2	5.823	89.469	1.014	3.694
		(6.467)	(7.265)	(3.446)	(2.206)
	DLNGDP_CH_3	8.305	2.582	87.455	1.658
		(6.143)	(3.991)	(7.251)	(1.596)
	VIX	2.599	1.890	12.541	82.970
		(4.631)	(4.961)	(8.466)	(9.915)
8	DLNGDP_CH_1	98.950	0.641	0.197	0.211
		(4.773)	(3.438)	(2.883)	(0.921)
	DLNGDP_CH_2	6.452	88.495	1.172	3.881
		(7.172)	(7.912)	(3.470)	(2.293)
	DLNGDP_CH_3	8.643	2.572	87.121	1.664
		(6.337)	(4.000)	(7.536)	(1.607)
	VIX	3.145	2.810	12.582	81.463
		(5.168)	(6.441)	(8.525)	(10.993)
12	DLNGDP_CH_1	98.950	0.641	0.197	0.211
		(4.817)	(3.469)	(2.897)	(0.924)
	DLNGDP_CH_2	6.452	88.483	1.175	3.889
		(7.238)	(7.979)	(3.483)	(2.303)
	DLNGDP_CH_3	8.644	2.573	87.119	1.664
		(6.349)	(4.011)	(7.557)	(1.610)
	VIX	3.149	2.840	12.586	81.425
		(5.190)	(6.487)	(8.543)	(11.047)

Table 15
Diagnostic tests for the financial channel (I_TP) for China.

Variables	DLNGDP_CH I_TP		
Lags	4		
Dummies	2001:01, 2008:01, 2009:01		
Residual autocorrelation test (H0: No serial autocorrelation)	Lags	p-value	
	1	0.381	
	2	0.795	
	3	0.310	
	4	0.970	
Heteroscedasticity test (H0: No cross terms)	p-value		
	0.103		
Univariate Normality			
	Skewness	Kurtosis	Normality (p-value)
DLNGDP_CH	-0.056	3.336	0.819
I_TP	-0.057	5.403	0.000

Table 16
Granger causality tests for the financial channel (I_TP) for China.

Null: I_TP does not Granger cause DLNGDP_CH	
Lags	96Q1–14Q4[a]
1	0.579
2	0.833
3	0.910
4	0.670
5	0.818
6	0.836

[a] Models include dummies for 2001:01, 2008:01, 2009:01;
*,**,*** indicate rejection of the null at the 10%, 5%, and 1%levels

Table 17
Diagnostic tests for the financial channel (I_TP) for China's subsectors.

Variables	DLNGDP_CH_1 DLNGDP_CH_3 DLNGDP_CH_2 I_TP		
Lags	4		
Dummies	1997:03, 2001:01, 2008:01, 2009:01		
Residual autocorrelation test (H0: No serial autocorrelation)	Lags	p-value	
	1	0.168	
	2	0.291	
	3	0.268	
	4	0.640	
Heteroscedasticity test (H0: No cross terms)	p-value		
	0.209		
Univariate Normality			
	Skewness	Kurtosis	Normality (p-value)
DLNGDP_CH_1	0.537	3.391	0.126
DLNGDP_CH_3	-0.165	3.204	0.788
DLNGDP_CH_2	-0.200	3.376	0.620
I_TP	0.144	4.613	0.014

Table 18

Granger causality tests for the financial channel (I_TP) for China's subsectors.

	Null: I_TP does not Granger cause DLNGDP_CH_1	Null: I_TP does not Granger cause DLNGDP_CH_2	Null: I_TP does not Granger cause DLNGDP_CH_3
Lags	96Q1–14Q4[a]	96Q1–14Q4[a]	96Q1–14Q4[a]
1	0.126	0.463	0.076*
2	0.130	0.787	0.061*
3	0.139	0.505	0.060*
4	0.089*	0.372	0.265

[a] Models include dummies for 1997:03, 2001:01, 2008:01, 2009:01;
*,**,*** indicate rejection of the null at the 10%, 5%, and 1%levels

Table 19

Variance decompositions for the financial channel (I_TP) for China.

Quarters	Decomposition of	DLNGDP_CH_1	DLNGDP_CH_2	DLNGDP_CH_3	I_TP
1	DLNGDP_CH_1	100.000	0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.000)
	DLNGDP_CH_2	0.021	99.947	0.032	0.000
		(2.117)	(2.795)	(1.944)	(0.000)
	DLNGDP_CH_3	2.624	0.000	97.376	0.000
		(3.964)	(0.000)	(3.964)	(0.000)
	I_TP	0.506	2.546	9.588	87.360
		(2.370)	(3.740)	(6.160)	(7.147)
2	DLNGDP_CH_1	95.045	0.002	3.053	1.899
		(5.397)	(1.880)	(4.317)	(2.424)
	DLNGDP_CH_2	2.114	97.441	0.382	0.063
		(3.992)	(4.821)	(3.073)	(1.159)
	DLNGDP_CH_3	2.563	0.742	95.985	0.709
		(4.028)	(2.808)	(4.982)	(1.879)
	I_TP	0.759	7.661	7.230	84.350
		(2.866)	(6.528)	(5.919)	(8.578)
4	DLNGDP_CH_1	91.229	0.473	5.802	2.497
		(7.108)	(3.298)	(5.524)	(3.058)
	DLNGDP_CH_2	4.189	90.323	2.575	2.913
		(5.125)	(6.9132)	(5.275)	(3.616)
	DLNGDP_CH_3	4.022	0.905	92.156	2.917
		(4.580)	(3.516)	(5.940)	(2.991)
	I_TP	0.533	13.307	5.574	80.586
		(3.614)	(9.358)	(6.732)	(10.989)
8	DLNGDP_CH_1	89.676	0.845	6.637	2.842
		(8.305)	(4.276)	(6.479)	(3.369)
	DLNGDP_CH_2	5.415	89.059	2.782	2.744
		(6.353)	(8.260)	(6.102)	(3.913)
	DLNGDP_CH_3	4.130	1.708	90.818	3.344
		(5.014)	(4.476)	(6.862)	(2.987)
	I_TP	0.579	20.706	9.366	69.348
		(5.111)	(14.364)	(10.255)	(16.022)
12	DLNGDP_CH_1	89.259	0.984	6.684	3.074
		(9.158)	(5.153)	(6.722)	(3.652)
	DLNGDP_CH_2	5.813	88.642	2.771	2.774
		(7.006)	(9.168)	(6.489)	(4.370)
	DLNGDP_CH_3	4.112	1.940	90.222	3.726
		(5.168)	(4.958)	(7.414)	(3.191)
	DLNGDP_TP	0.951	25.953	10.337	62.759
		(5.998)	(17.697)	(11.479)	(19.103)

Table 20

Diagnostic tests for the confidence channel (trade shocks) with business confidence.

Variables	BC DLNGDP_TP		
Lags	2		
Dummies	2008:04, 2009:01, 2009:02		
Residual autocorrelation test (H0: No serial autocorrelation)	Lags 1 2	p-value 0.041 0.201	
Heteroscedasticity test (H0: No cross terms)	p-value 0.8166		
Univariate normality			
	Skewness	Kurtosis	Normality (p-value)
BC	-0.190	3.400	0.674
DLNGDP_TP	-0.499	3.477	0.206

Table 21

Granger causality tests for the confidence channel (trade shocks) with business confidence.

Null: DLNGDP_TP does not Granger cause BC

Lags	1999Q1–14Q44
1	0.010***
2	0.028**
3	0.005***
4	0.013**

*,**,*** indicate rejection of the null at the 10%, 5%,and 1%levels

Table 22

Variance decompositions for the confidence channel (trade shocks) with business confidence.

Quarters	Decomposition of	BC	DLNGDP_TP
1	BC	100.000	0.000
		(0.000)	(0.000)
	DLNGDP_TP	6.172	93.828
		(6.192)	(6.192)
2	BC	92.929	7.071
		(5.047)	(5.047)
	DLNGDP_TP	5.052	94.948
		(5.971)	(5.971)
4	BC	85.781	14.219
		(9.836)	(9.836)
	DLNGDP_TP	6.799	93.201
		(6.089)	(6.089)
8	BC	81.488	18.512
		(13.361)	(13.361)
	DLNGDP_TP	11.967	88.033
		(8.757)	(8.757)
12	BC	81.317	18.683
		(13.641)	(13.641)
	DLNGDP_TP	12.478	87.522
		(9.275)	(9.275)

Table 23

Diagnostic tests for confidence channel (trade shocks) with consumer confidence.

Variables	DCC DLNGDP_TP		
Lags	3		
Dummies	2008:04, 2009:01		
Residual autocorrelation test (H0: No serial autocorrelation)	Lags	p-value	
	1	0.011	
	2	0.059	
	3	0.022	
Heteroscedasticity test (H0: No cross terms)	p-value 0.125		
Univariate normality			
	Skewness	Kurtosis	Normality (p-value)
DCC	-0.073	2.917	0.970
DLNGDP_TP	-0.591	4.415	0.025

Table 24

Granger causality tests for the confidence channel (trade shocks) with consumer confidence.

Null: DLNGDP_TP does not Granger cause DCC	
Lags	2001Q1–14Q[a]
1	0.000***
2	0.000***
3	0.001***
4	0.001***

[a] Models include dummies for 2008:04, 2009:01

*,**,*** indicate rejection of the null at the 10%, 5%, and 1%levels

Table 25

Variance decompositions for the confidence channel (trade shocks) with consumer confidence.

Quarters	Decomposition of	DCC	DLNGDP_TP
1	DCC	100.000	0.000
		(0.000)	(0.000)
	DLNGDP_TP	0.316	99.684
		(2.662)	(2.662)
2	DCC	88.839	11.161
		(7.878)	(7.878)
	DLNGDP_TP	12.753	87.247
		(8.113)	(8.113)
4	DCC	88.959	11.041
		(7.132)	(7.132)
	DLNGDP_TP	24.639	75.361
		(11.907)	(11.907)
8	DCC	88.935	11.065
		(7.229)	(7.229)
	DLNGDP_TP	24.901	75.099
		(12.643)	(12.643)
12	DCC	88.936	11.065
		(7.243)	(7.243)
	DLNGDP_TP	24.907	75.093
		(12.797)	(12.797)

Table 26

Diagnostic tests for the confidence channel (VIX shocks) with consumer confidence.

Variables	DCC VIX		
Lags	3		
Dummies	2002:03, 2008:04, 2011:03		
Residual autocorrelation test	Lags	p-value	
(H0: No serial autocorrelation)	1	0.070	
	2	0.173	
	3	0.347	
Heteroscedasticity test	p-value		
(H0: No cross terms)	0.1812		
Univariate Normality			
	Skewness	Kurtosis	Normality (p-value)
DCC	-0.357	2.951	0.407
VIX	0.604	3.039	0.577

Table 27

Granger causality tests for the confidence channel (VIX shocks) with consumer confidence.

Null: VIX does not Granger cause DCC	
Lags	2001Q1–14Q4 [a]
1	0.171
2	0.013**
3	0.000***
4	0.000***

[a] Models include dummies for 2002:03, 2008:04, 2011:03;
*,**,*** indicate rejection of the null at the 10%, 5%,and 1%levels

Table 28

Variance decompositions for the confidence channel (VIX) with consumer confidence.

Quarters	Decomposition of	DCC	VIX
1	DCC	100.0000	0.0000
		(0.00000)	(0.000)
	VIX	8.935910	91.06409
		(7.55206)	(7.55206)
2	DCC	99.95301	0.046993
		(0.91687)	(0.91687)
	VIX	11.83360	88.16640
		(9.43993)	(9.43993)
4	DCC	87.95557	12.04443
		(6.42213)	(6.42213)
	VIX	9.858035	90.14197
		(8.17657)	(8.17657)
8	DCC	88.15028	11.84972
		(6.30373)	(6.30373)
	VIX	10.15450	89.84550
		(8.78261)	(8.78261)
12	DCC	87.91006	12.08994
		(6.46857)	(6.46857)
	VIX	10.12839	89.87161
		(8.88715)	(8.88715)

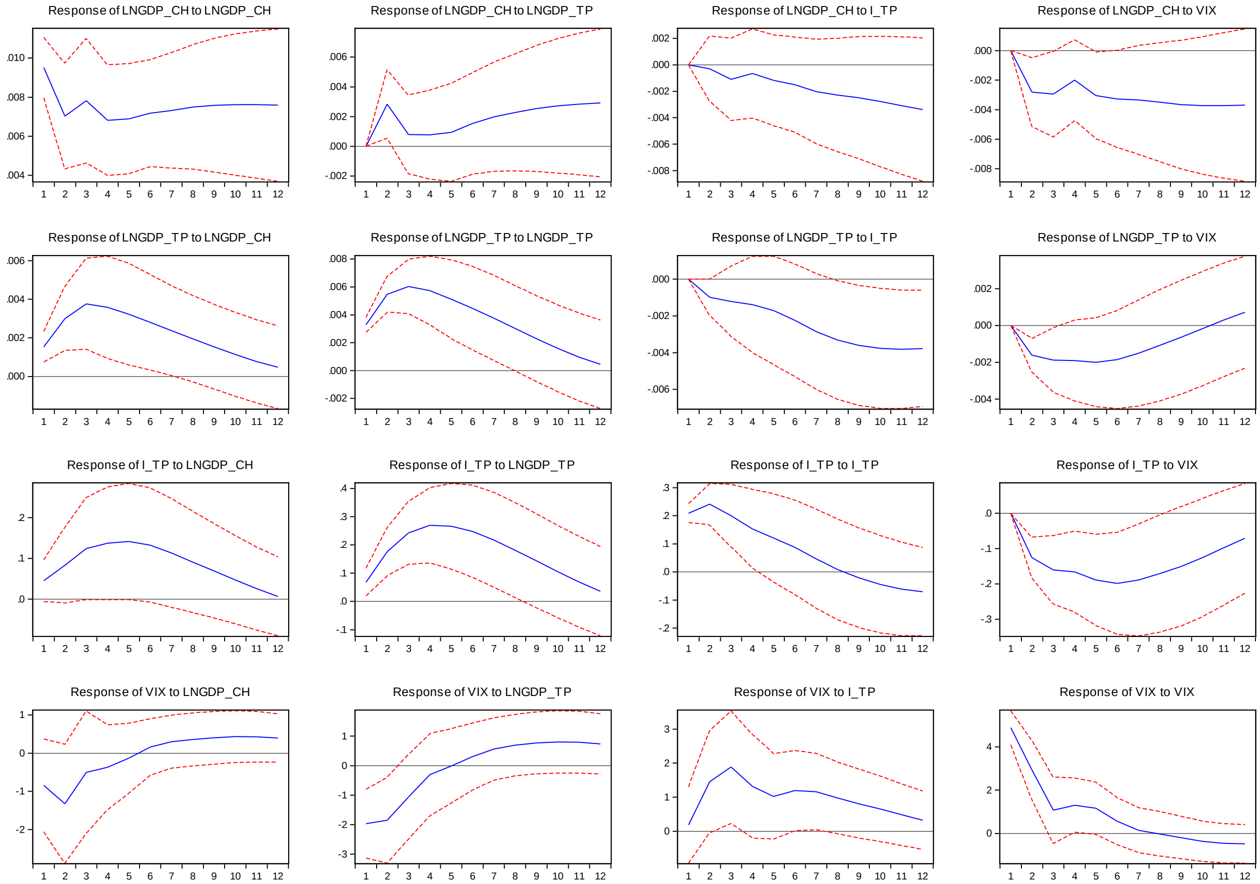
Table 29
Data sources.

Series	Source
GDP	
China, GDP	Datastream (DS Mnemonic: CHGDP...A)
China, GDP –Primary industry	Datastream (DS Mnemonic: CHGDPPN.A)
China, GDP –Secondary industry	Datastream (DS Mnemonic: CHGDPSN.A)
China, GDP –Tertiary industry	Datastream (DS Mnemonic: CHGDPTN.A)
US, GDP	Datastream (DS Mnemonic: USGDP...B)
Eurozone, GDP	Datastream (DS Mnemonic: EKGDP...B) and data from EABCN (http://www.eabcn.org/area-wide-model)
UK, GDP	Datastream (DS Mnemonic:UKGDP...B)
Japan, GDP	Datastream (DS Mnemonic: JPGDP...B)
GDP deflators	
China, price deflator	Datastream (DS Mnemonic: CHXPGDP.F)
US, implicit price deflator	Datastream (DS Mnemonic: USGDPIPDE)
Eurozone, implicit price deflator	Datastream (DS Mnemonic: EKGDPIPDE)and data from EABCN (http://www.eabcn.org/area-wide-model)
UK, implicit price deflator	Datastream (DS Mnemonic: UKGDPIPDE)
Japan, implicit price deflator	Datastream (DS Mnemonic: JPGDPIPDE)
Interest rates	
US, interbank rate – 3-month (London) (month average)	Datastream (DS Mnemonic: USINTER3)
European Monetary Union, Euro Interbank Offered Rate –3-month (mean), euro	Datastream (DS Mnemonic: EMINTER3)
UK, interbank rate – 3-month (month average)	Datastream (DS Mnemonic: UKINTER3)
Japan, 3-month interbank rate (EP)	Datastream (DS Mnemonic: JPINTER3)
Exchange rates	
Euro to USdollar exchange rate	Datastream (DS Mnemonic: EMXRUSD.)
Pound sterling to USdollar exchange rate	Datastream (DS Mnemonic: UKXRUSD.)
Yen to USdollar exchange rate	Datastream (DS Mnemonic: JPXRUSD.)
VIX	
CBOE Spx volatility VIX (New)	Datastream (DS Mnemonic: CBOEVIX)
Confidence measures	
China business climate index: Industry	Datastream (DS Mnemonic: CHNBCIINR)
China consumer confidence – future income confidence	Datastream (DS Mnemonic: CHCNFFUIF)
Data were either already seasonally adjusted or we used the x12_arima procedure to achieve seasonal adjustment (We did not seasonally adjust the VIX). If data were of a lower frequency than quarterly, we used averages of the sub-periods. All calculations were performed with the greatest care. Chinese GDP Data were downloaded in May 2015.	

Table 30

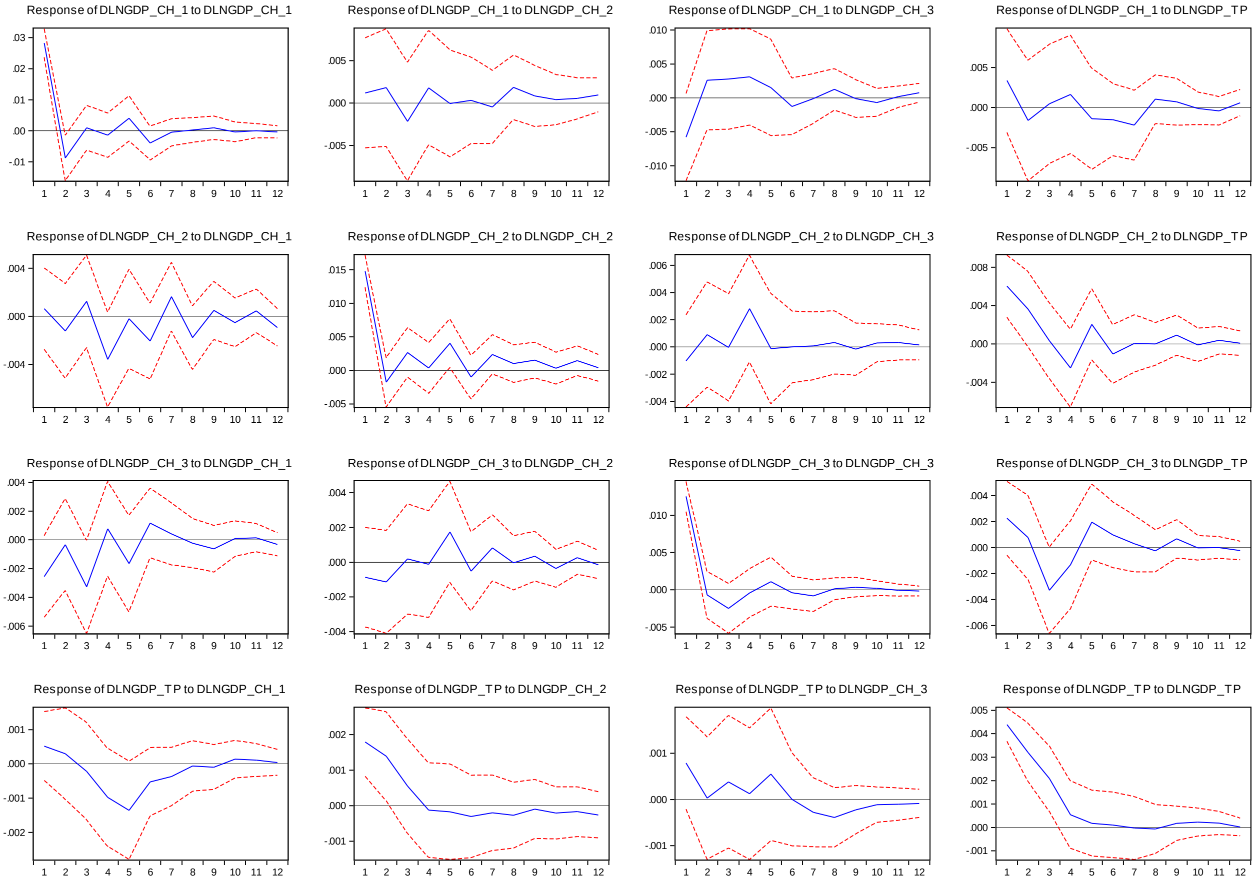
Dummy variables.

Dummy	Comment
1997:03	Dummy to account for outlier in China's real GDP growth rate
2001:01	Dummy to account for outlier in interest rate
2002:03	Outlier in VIX, possibly related to WorldCom Inc. Bankruptcy
2008:01	Dummy to account for outliers in interest rate
2008:04	Financial crisis
2009:01	Financial crisis
2009:02	Financial crisis
2011:03	Outlier in VIX, possibly related to concerns about Europe's debt crisis



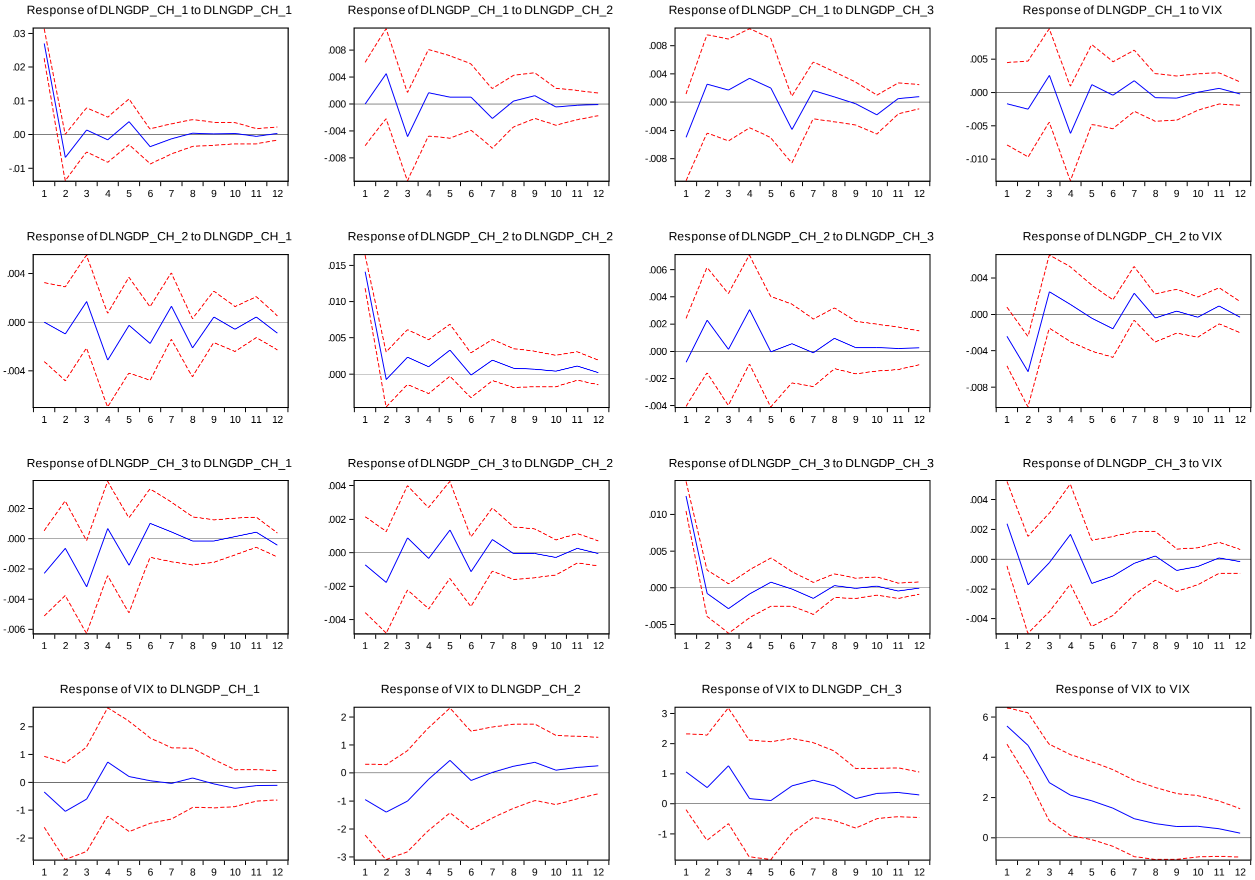
Source: Own calculations.

Fig. A1. Robustness Check; VAR in Levels; Impulse responses of LNGDP_CH, LNGDP_TP, I_TP, VIX.



Source: Own calculations.

Fig. A2. Robustness Check; VAR with generalized impulse responses; Impulse responses of DLNGDP_CH_1, DLNGDP_CH_2, DLNGDP_CH_3, DLNGDP_TP.



Source: Own calculations.

Fig. A3. Robustness Check; VAR with generalized impulse responses; Impulse responses of DLNGDP_CH_1, DLNGDP_CH_2, DLNGDP_CH_3, VIX.