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Can Consumption Growth in China Keep Up As Investment Slows?

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Abstract

Rebalancing away from investment to consumption has been on China's agenda in order to keep up higher growth rates. This paper uses both national- and provincial-level data to empirically answer the question how a slowdown in investment could have an impact on household consumption. Our empirical results from both the national- and provincial-level data using Bayesian vector autoregressions and panel regression methods suggest that investment has had a significant impact on household consumption beyond the standard household income channel. The effects are particularly strong in the post-global-financial-crisis period. Policy measures to encourage rebalancing away from investment should take the extra effect it may have on consumption beyond the impact on household income into account.

Keywords: Reforms · Investment · Consumption · China

JEL Classification: E21 · E22 · E27 · E44 · E47 · E52 · C12 · C32 · C33 · O53

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1 Introduction

"Over the past five years, new growth drivers have rapidly grown in strength. Economic growth, in the past mainly driven by investment and exports, is now being fueled by consumption, investment, and exports. In the past dependent mainly on secondary industry, growth is now powered by a combination of the primary, secondary, and tertiary industries. This is a major structural transformation that for years our sights had been set on, but we were never able to achieve."

Li Keqiang, First Session of the 13th National People's Congress of the People's Republic of China on March 5th, 2018

Over the past years, China's declining growth has increasingly been driven by consumption (Figure 1 left) despite its share in GDP still remaining at a relatively low level (Figure 1 right) compared to other economies. While investment propelled the economy in the aftermath of the global financial crisis (GFC), when the Chinese authorities engineered a large stimulus to mitigate the effects from the GFC (RMB 4 trillion, which is around US$ 600 billion and, hence, amounting to about the same size as the subsequently announced stimulus in the US with the Chinese economy being only a third of size), consumption has become a larger contributor to overall GDP growth more recently. Despite the slowdown in growth contribution of investment, the investment to GDP ratio reached unprecedented levels (Figure 1 right). Measuring the investment ratio using gross fixed capital formation (GFCF) these levels reach around 45 percent in recent years and measuring the ratio using fixed asset investment (FAI) as reported by firms these levels reach around 80 percent of GDP. However, since the latter measure also includes land purchases, part of this strong increase might be driven by a recent increase in land prices.

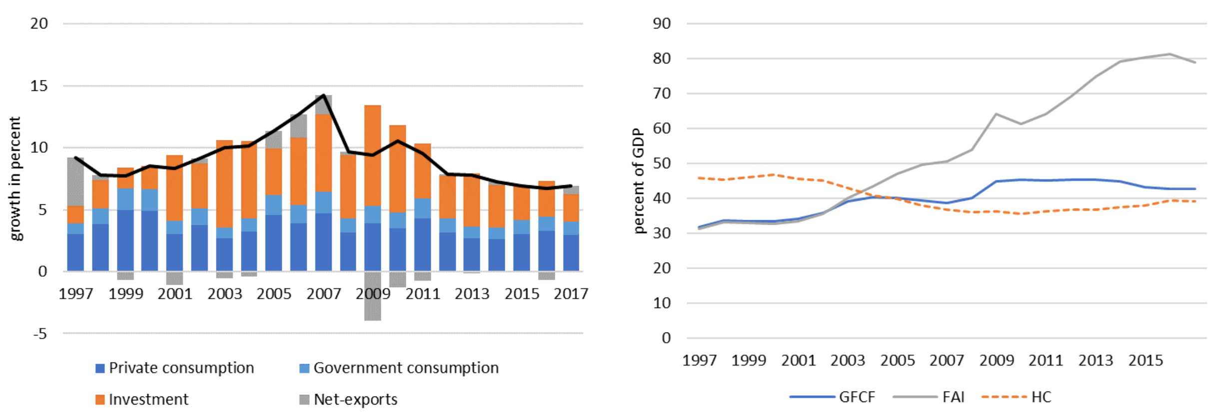

Figure 1: Contribution to GDP growth (left) and investment to GDP ratio (right; Household consumption to GDP ratio for reference). Source: CEIC.

Despite the capital stock per worker still being relatively low (Zhang (2016)), this means that the investment-driven growth in China has reached its limits. This is partly due to ever less efficient investment projects as observable by an increase in the incremental capital output ratio. At the same time as investment goes towards less profitable investments, credit intensity has increased markedly (Buysse et al. (2018)). A sizable part of the investment expenditures are financed via credit. Figure 2 (left) shows the credit to GDP gap for the private non-financial sector, which measures the gap between credit to GDP and its long-term trend. In 2009, when the Chinese government initiated the RMB 4 trillion stimulus, credits to non-financial firms (including privately owned firms and township and village enterprises (TVEs)) sharply increased and have been increasing since then, while credit to the general government and to households remained moderate. More recently, credit to GDP started to revert to its long-term trend. Since part of this funding takes place in the "shadow" banking sector, which is not regulated, this imposes threats to financial stability.

With investment-driven growth reaching its limits, China is now facing a big challenge of structural transformation after growth rates have started to decline towards a new normal in the last decade. Various studies on rebalancing scenarios have been put forth. Almost all of them, such as Ma et al. (2017), require resilience in consumption growth while investment growth is being detained. However, despite having been robust in the past, with declining GDP growth both household consumption and income growth started to slow down (Figure 2 right). Hence, as China continues to rebalance towards a more consumption-driven growth, questions arise whether household consumption itself would be adversely affected by a slowdown in investment. Therefore, this paper attempts to explain the drivers of Chinese household consumption and to address the channels through which an expected slowdown in investment could have an impact on household consumption. We use both country- and provincial-level data, in order to capture the heterogeneity of provinces, to empirically answer this question. Our empirical results suggest that investment has had a significant impact on household consumption beyond the household income channel. The effects were especially strong in the post-GFC period and in more salient sectors, indicating the that the stimulus has affected households' decision to consume. We propose, that investment in China functions as a proxy for expected future household income which affects consumption decisions today. Our findings are robust to various changes to the baseline estimation.

This paper is structured as follows: Section two reviews the literature and section three briefly develops theoretical links between investment and consumption in China. Section four discusses the data. In section five we use a Bayesian structural vector autoregression (BSVAR) to estimate the drivers of Chinese household consumption on the national level. Thereby we find that consumption growth reacts positively to a shock in investment growth.

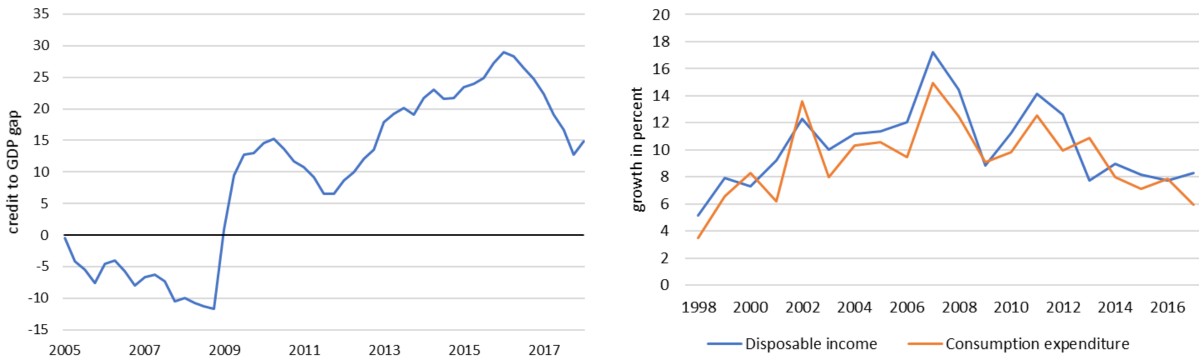

Figure 2: Credit to GDP gap of the private non-financial sector (left) and household income and consumption growth (right). Source: BIS, CEIC.

In section six we employ panel regression methods to account for the dispersion of investment across provinces. The results indicate, that there is a positive significant relation between investment growth and household consumption growth in the period since the GFC which goes beyond the household income channel. A panel Granger causality test affirms these findings. In section seven we discuss the nexus between investment, expected future income, and consumer confidence. Section eight concludes.

2 Literature Review

Household consumption and saving in China have been widely investigated in the context of a high household saving rate and a relatively low consumption ratio. Many theories have been put forth including the precautionary savings motive in conjunction with relatively high income risks and changes in the social safety net (Chamon et al. (2013)), sex-ratio imbalances (Wei and Zhang (2011)) which increase saving incentives, and demographic change (Curtis et al. (2015), Horioka (2010)).

Consumption dynamics at the macro level are less investigated. A few studies on monetary policy transmission, which is considered to be a key driver of household consumption, have touched on this. Chen, Chow and Tillmann (2017) examine the effectiveness of monetary policy in China using a Qual VAR and find that consumption growth falls and reaches its minimum about 8 months after a tightening shock, however, the impact is relatively small. Furthermore, the wealth effect on consumption has also been explored in several studies. Koivu (2012) uses a SVAR model and quarterly data between 1998 and 2008 to examine monetary policy transmission as well as asset price effects on consumption in China. She finds that a positive shock to income increases consumption. Following a positive shock in house prices, however, consumption initially drops and only after a lag of almost two years the reaction turns positive. The results reflect the relatively small role that asset markets play in household income and consumption at the aggregate level. Chen, Funke and Mehrotra (2017) find a significant and positive long-run relationship between property prices and consumption in China, beyond the expected relationship between household income and consumption, using city-level data from 1998 to 2009. Peltonen et al. (2012), however, do not find a significant relationship between property prices and consumption in China, using quarterly macro-level data from 1990 to 2008.

The relationship between investment and household consumption has not received much attention yet. Theory offers a direct channel where investment leads to a higher capital stock and eventually to higher growth and household income which in turn translates into higher consumption. However, there might be more indirect effects and channels through which consumption is affected. Lee et al. (2013) offer an alternative explanation. If investment is excessive, their hypothesis is that consumption would not be self-sustaining but dependent on recent investment. In addition, excessive investment should result in greater corporate profitability rather than boosting household income since wasted investment contributes to corporate income during the implementation period and to a lesser extent to household income, the scope of which would depend on the share of labor costs. Testing their hypothesis, Lee et al. (2013) find evidence that investment Granger-caused private consumption. Using provincial panel data, they find that investment has a significant impact on household consumption through household income. When adding investment to a panel estimation which includes household income investment turns out to be insignificant implying that investment only influenced consumption through the income channel. Their results also suggest that investment in the coastal areas elicits more of a sustained consumption response than in China's inland provinces, drawing the conclusion that investment in the inland area may be excessive and not self-sustaining.

3 Theoretical relationship between investment and consumption

The main drivers of consumption according to (neoclassical) theory are the level of (permanent) income, the distribution of wealth, expectations about prices, interest rates, changes in fiscal policy, the availability of goods, the attitude towards saving, and preferences. Investment, however, does not directly show up in the (neoclassical) consumption function. Nevertheless, investment leads to a higher capital stock and eventually to higher growth and household income which then translates into higher consumption. Taking into account that financial markets in China are still relatively underdeveloped and hence, one assumes that financial frictions exist, the standard permanent income hypothesis, in which consumption depends on the permanent level of income, does not hold and rather disposable income matters for consumption decisions. Taking all that into account, investment in China should affect household consumption through the household disposable income channel. This is not only in line with the permanent income hypothesis with financial frictions (borrowing constraint) where the agents cannot borrow against the future but also in an economy with a large fraction of hand-to-mouth consumers (e.g. Kaplan et al. (2014)), or with New Keynesian models with heterogeneous agents (e.g. Kaplan and Violante (2018)).

Another channel besides household income which may fit well with China's situation is that investment could be a good proxy for expected future household income. Beyond the current disposable income channel, investment may have an impact on the households' decision to consume through their income expectation. If this was the case, this effect should be stronger for more salient investment. As the government still has an important say in driving economic growth, especially through investment expenditure, households can expect that strong investment today could bring better job prospects and higher income in the future. There is evidence that household income expectation is an important factor in determining household consumption in other countries (see for example Pounder Demarco (2009) for the US and Estrada et al. (2015) for advanced economies). If this was the case, consumption should not only indirectly depend on investment through disposable income but also directly on investment with a stronger effect of more salient investment. We will further discuss this issue in Section 7.

4 Data

China's national accounts are still a work in progress. On the expenditure side, nominal consumption, investment, and net exports are published annually. Since 2015, growth rates and contribution to GDP growth are published on a quarterly basis. Moreover, the reliability of the Chinese official data is highly controversial. This prompts researchers to look beyond the national accounts and to estimate their own real and quarterly series.

There exist two measures for investment in China: gross fixed capital formation (GFCF) from the national accounts and fixed asset investment (FAI) as reported by firms subject to reporting. GFCF, available annually and since 2015 in quarterly growth rates, measures how much of the output of the economy is invested and excludes purchases of land, inventories, and other already pre-owned resources (ownership change). FAI, which is available monthly, measures investment in long-term assets as reported by firms and includes purchases of land, used facilities and equipment, and mergers and acquisitions. Since FAI is published in a year-to-date format, it is difficult to calculate period-over-period growth rates although first-differences could be applied. However, since the data also includes revisions and accounting problems could distort the monthly data, this approximation would be inaccurate (for a detailed discussion see Barnett and Brooks (2006)). This fact is revealed by a relatively low correlation between GFCF and FAI on a quarterly basis of about 0.33 whereas this correlation is relatively high on an annual basis of around 0.8 in our sample. Therefore, we use quarterly GFCF in the national-level estimations[1]. As FAI is available at the sectoral level and as the correlation is relatively high on an annual basis, we use annual FAI growth in the provincial-level estimations. We will check the robustness of our results with respect to the choice of the investment variable.

At the national level, we use quarterly data from 2002Q1 to 2015Q4 from the CEIC database. Data for household income and consumption is taken from the household survey since consumption from the national account is available only on an annual basis. Household income and consumption are measured as urban disposable income per capita and urban consumption expenditure per capita. Moreover, we use the deposit interest rate for savings as interest rate in the baseline estimation[2], which we transform into the real interest rate by subtracting the inflation rate. Since housing wealth is difficult to approximate for China (data on housing stock is not available), we use residential property prices to capture the wealth effect. All variables are in real terms. To account for political uncertainty and its effect on consumption decisions, we use the political uncertainty index by Baker et al. (2016).

Since there is no quarterly data available at the provincial level, we use annual data from 2000 to 2015 from the CEIC database. The variables remain basically the same as at the national level except for investment where we use annual FAI data as discussed before. Household income and consumption per capita are again taken from the household survey but at the provincial level. Real variables are obtained by deflating household income and consumption with provincial consumer price indices (CPIs) and investment with provincial fixed asset investment price indices. We use the deposit rate for savings[3] and the provincial residential property price series, both deflated by provincial inflation and provincial CPIs.

[1] Since it is only available on an annual basis, quarterly gross fixed capital formation (GFCF) estimates were derived from Soudan (forthcoming).

[2] In the robustness section, we will instead use the average lending rate for loans by the three biggest banks and show, that the results remain qualitatively the same. It has to be noted, that due to the large "shadow" banking sector in China, the official interest rates might not necessarily reflect the true interest rate. However, the true interest rates are difficult to infer and, therefore, we have to remain with this approximation. Since we focus on households, this choice seems to be justified as the "shadow" banking sector plays only a minor role for households.

[3] Since interest rates are only available at the national level, the real interest rates on the provincial level only differ with respect to the provincial inflation rate.

Similar to before we use the national political uncertainty index. Tibet is excluded from the estimations due to missing data. To account for different demographic dynamics across provinces, we use investment per capita. This might, however, not completely control for labor transfer dynamics in the light of the large migrant worker population in China. A large fraction of the income in regions where migrant workers originate from might consist of transfer payments from migrant workers to their families which in turn might increase consumption. At the same time these provinces have been subject to higher investment growth in the recent years and, therefore, our estimates could be confounded. Unfortunately, neither data on transfer payments from migrant works nor detailed data on the number and origin of migrant workers exists. We therefore approximate this dynamic by calculating the deviation of each province of the median share of residents holding a permit to the total population as estimated by the household survey across all provinces for every year[4]. A number below zero means that this province has a relatively higher population of non-residents whereas a number above zero means that this province has a relatively higher population holding a residence permit. We then assume, that a province with an indicator above zero, indicating an above median population holding a residence permit and, thus, a lower number of migrant workers, receives proportionally more transfers. Since a positive correlation between investment growth and consumption growth might capture this underlying dynamic, we will control for this proxy in the robustness section.

5 Results at the national level

5.1 Baseline estimation

As the sample is relatively short at the national level, we estimate a Bayesian vector autoregression (BVAR), which has proven to be more efficient with shorter samples, of the reduced form

$$y_t = C_B + A_1 y_{t-1} + ... + A_p y_{t-p} + \epsilon_t \qquad \text{where} \qquad \epsilon_t = B_0^{-1} u_t, A_i = B_0^{-1} B_i \tag{1}$$

to examine consumption dynamics using the BEAR toolbox (Dieppe et al. (2016)). The vector of variables includes our six variables: economic uncertainty pu_t, interest rate r_t, investment I_t, residential property prices pp_t, household income inc_t, and household consumption hc_t as discussed in the section before. Investment, household consumption, household income, and property prices are in real year-over-year percentage changes. The real interest

[4]More formally: $migrant = \frac{\frac{resident_p}{population_p} - median(\frac{resident}{population})}{median(\frac{resident}{population})}$ for each province p.

rate and the uncertainty index are in levels. The optimal lag length of four is determined by the Akaike information criterion. We use the independent normal-Wishart prior since this prior imposes less restrictions than the somewhat more standard Minnesota prior or the standard normal-Wishart prior. We checked our results with respect to the choice of the prior and the results seem to be robust. For the calibration of the BVAR we use standard values, i.e. an autoregressive-coefficient of 0.8, an overall tightness of 0.1, a cross-variable weighting of 0.5, and a lag decay of 1. We perform 2000 iterations of which 1000 are burn-in iterations.

The results from a VAR can only be interpreted structurally if the model is correctly identified. $N(N-1)/2$ further restrictions are needed to derive A_i. We identify the shocks by using a recursive Choleski ordering imposing zero short-run restrictions on the parameter matrix making it lower triangular. This orthogonalization is appropriate only if the recursive structure is justified on economic grounds. There is, however, no economic model which encompasses the variables we want to examine. Therefore, we rely on selective insights[5] from economic theory to arrive at the variable ordering $y_t = (pu_t, I_t, inc_t, pp_t, hc_t, r_t)$ which are discussed below.

Political uncertainty, as constructed by Baker et al. (2016), is measured by news about real politics and, hence, assuming that real policy takes time to adapt to a new economic situation by several rounds of consultations, should not react contemporaneously to the economic variables in the VAR. However, this uncertainty instantaneously influences the economic agents and their decisions by decreasing planning lags. Real investment is supposed to be inherently sluggish (Sims (1998)) and, hence, contemporaneously unaffected by the other economic variables at the time being conducted. This is due to a planning lag, i.e. it takes time for actual investment to materialize after the decision of investing. We assume, however, that this lag is relatively small if there are changes in the political environment and allow investment to contemporaneously react to political uncertainty. Household income is also sluggish (e.g. Ludvigson et al. (2002)) since for example interest rates only affect savings income at the end of the next period. Investment, however, increases the income of the workers responsible for the implementation of the projects. The contemporaneous effect of investment and household income on house prices are derived from a supply and demand model. An increase in demand for housing, either through an increase in real estate investment or through an increase in disposable income and hence in private demand, leads to higher property prices (e.g. Tsatsaronis and Zhu (2004)). However, house prices are

[5]These can be information delays, physical constraints (such as the process from making a decision on investment in a firm until realization), institutional knowledge, market structure, or parameter estimates from previous studies.

contemporaneously unaffected by consumption and by the interest rate as mortgages still play a relatively small role in China. Since the planning lag for household consumption is smaller than the one of investment, consumption can contemporaneously react to shocks in income, prices, and investment but only reacts with one lag to changes in the interest rate as consumer credits are still used relatively less in China as compared to other countries like the US (e.g. Bagliano and Favero (1998)). We allow monetary policy, which follows a policy rule taking into account the economic situation, to react contemporaneously to all economic variables in the model (e.g. Bernanke and Mihov (1998)). However due to the planning lag and the realization of interest income after one period, monetary policy affects the other variables only with one lag.

Since we are specifically interested in the effect of a shock to investment, the question of the nature of the shock arises. In the case of China, investment shocks can be either exogenously determined by a state-imposed increase or decrease in investment spending by state-owned enterprises (SOEs) or endogenously driven by financial shocks. The first represents a shock to the supply of capital whereas the latter represents a shock to the demand for capital. Furlanetto et al. (2017) examine the identification of financial factors in economic fluctuations and show that these two shocks only differ with respect to the effect on stock markets. They further disentangle financial shocks into housing market shocks and shocks to the credit market and show that investment reacts positively to both supply and demand shocks. Since we are interested in the drivers of household consumption growth and how it is affected by a slowdown in investment growth and since we abstract from stock markets, we can disregard this decomposition into supply and demand shocks and use the aggregate investment shock.

The impulse response functions of consumption and household income growth are depicted in Figure 3 (Figure A.4 in the appendix shows the full set of impulse response functions). The result of an income shock is as expected: a positive shock to income growth increases consumption growth on impact. A positive shock to investment growht significantly increases household consumption growth as well. The effect lasts about three quarters, just a little shorter than the impact of the income shock. A positive shock to residential property prices, however, leads to a negative impulse in consumption growth. This result is similar to the findings from Koivu (2012) and may be driven by the need for households to save more in order to be able to afford housing as residential property prices go up. Hence, the wealth effect of increasing residential property prices seems to be inferior. This reflects the relatively small role that asset markets play in household income and consumption decisions at the aggregate level.

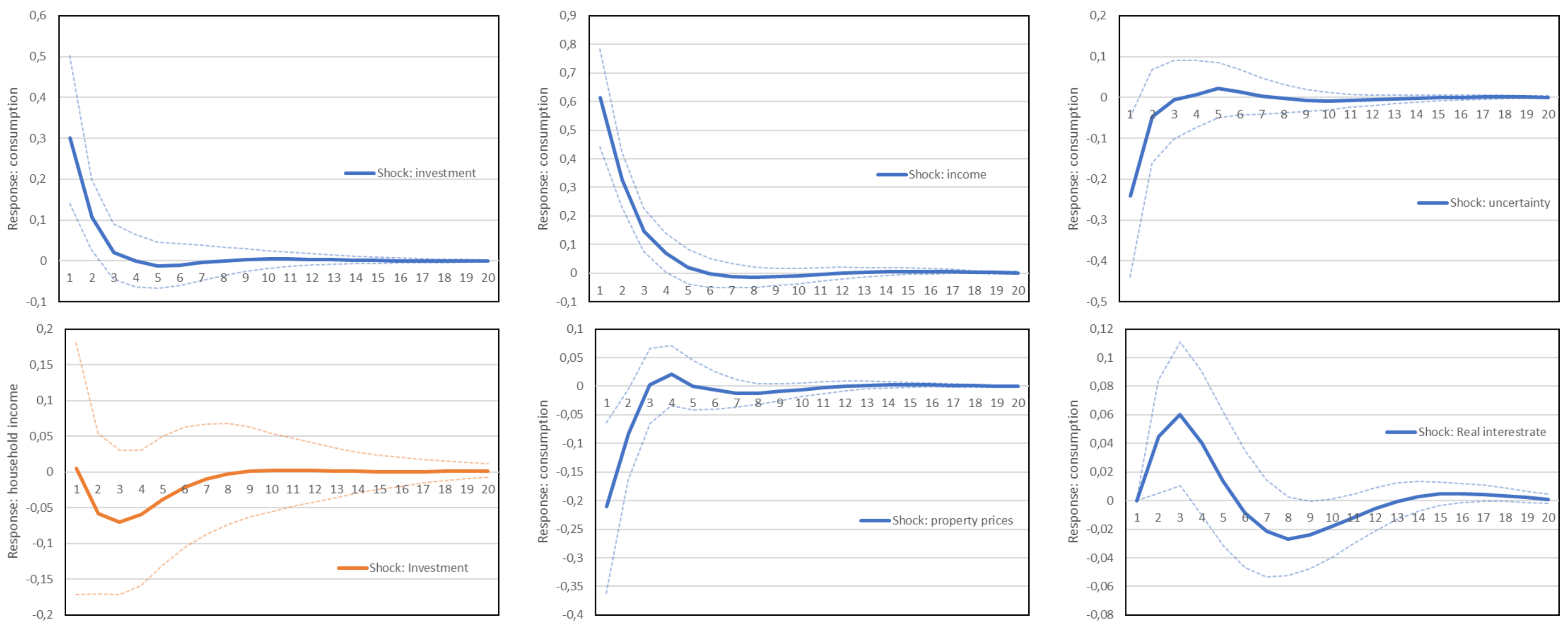

Figure 3: Impulse response functions of consumption (blue) and household income (orange) to different one-standard-deviation shocks. Dotted lines represent one-standard-deviation credibility bands.

Household consumption growth responds mildly in the positive direction to an interest rate shock. This is likely driven by two factors. First, borrowing for consumption in China remains relatively small and second, with a higher interest rate households may have to save less towards their targets (Nabar (2011)). The response of consumption growth to uncertainty is negative. Interestingly, household income growth is only weakly and insignificantly affected by an investment shock and the effect is rather short-lived.

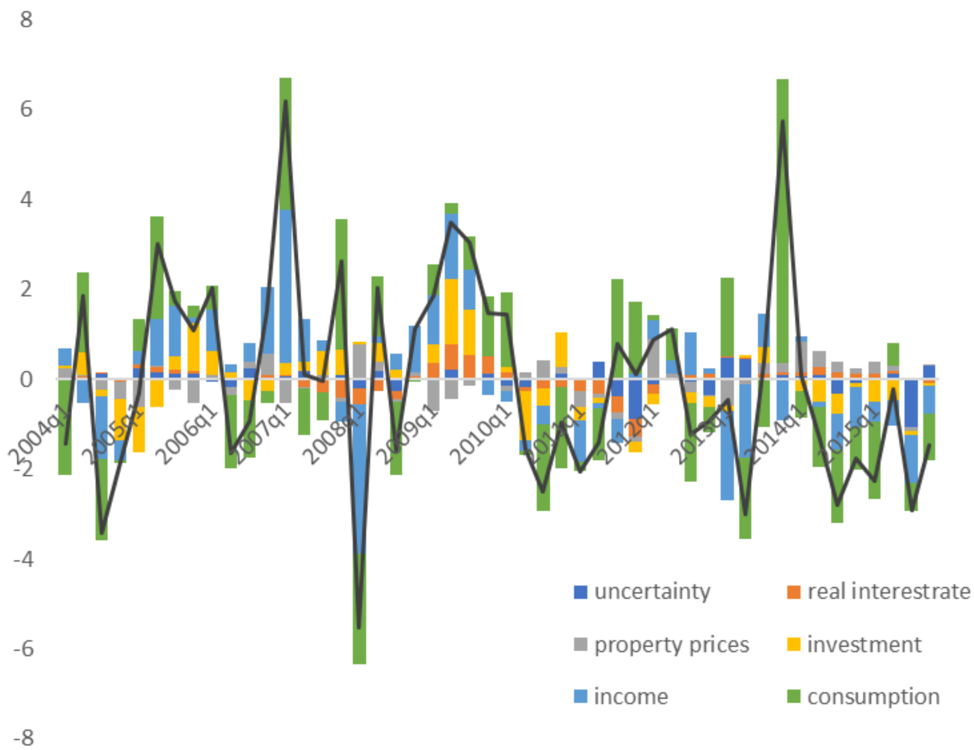

Figure 4: Historical decomposition (deviation from the unconditional model forecast).

Historical shock decomposition (Figure 4) suggests that the impact of an investment shock on household consumption growth was especially strong during the immediate aftermath of the GFC in 2009 when China ramped up investment to counter the effects of the GFC. In the most recent period, household income accounts for most of the deviation of household consumption. At the same time, investment also plays an important role, while uncertainty, which spiked in 2015, also contributed significantly to deviations in household consumption.

We furthermore conduct a forecast error variance decomposition for household consumption growth. The results presented in Table 1 suggest that, apart from the residual shock, income played the biggest role in the forecast error of household consumption. However, investment is the second biggest contributor. This suggests that investment has had a non-negligible positive direct impact on household consumption. Furthermore, this relationship seems to be relatively stable over time.

Table 1: **Household consumption forecast error variance decomposition**

	Percent of h-Step Ahead Forecast Error Variance Explained by shock in:					
	(1)	(2)	(3)	(4)	(5)	(6)
Horizon	uncertainty shock	investment shock	income shock	property price shock	interest rate shock	residual shock
1	.03	.05	.20	.02	.00	.64
2	.03	.05	.22	.02	.00	.62
3	.03	.05	.22	.03	.00	.61
4	.04	.05	.22	.03	.00	.61
8	.04	.05	.22	.03	.01	.60
∞	.04	.05	.22	.03	.01	.59

5.2 Robustness tests

We test the robustness of our baseline results to various changes of the specification. For the scope of this paper, we only report the impulse responses of consumption to various shocks in Figure A.5 in the appendix. Panel a) shows the baseline estimation results using the independent normal-Wishart prior, four lags of the endogenous variables and the deposit interest rate. Panel b) shows that the impulse response functions of consumption do not change much if we use the real lending rate instead of the real deposit rate as interest rate. In Panel c) we use the normal-Wishart prior instead of the independent normal-Wishart prior. The responses of consumption growth seem to get larger when using the normal-Wishart prior. Interestingly, the response of consumption growth to a shock in property prices reverts. Panel d) shows the result for a lag length of one instead of four as suggested by the Bayesian information criterion. The results seem robust with respect to the lag length with the responses being somewhat stronger. Only the response of consumption growth to a shock in property prices reverts. The response of consumption growth to a shock in investment remains qualitatively the same.

6 Results at the provincial level

6.1 Baseline estimations

To exploit variation across regions in China, we also use provincial-level data. Since quarterly data is not available, we use annual data to analyze the way investment interacts with consumption over a longer time horizon.

We estimate a dynamic panel model with of the form

$$y_{i,t} = \gamma y_{i,t-1} + x'_{i,t}\beta + \eta_i + \epsilon_{i,t} \tag{2}$$

with consumption growth measured in log first differences as dependent variable y and the same set of explanatory variables as at the national level covering the period from 2000 to 2015. However, as discussed in Section 4, we use FAI rather than GFCF in order to be able to estimate sectoral specific effects. We use investment in per capita terms to control for different demographic dynamics in the provinces. Investment, household consumption, property prices, and income are measured in log first differences. The interest rate and the uncertainty index are measured in levels whereby we take the logarithm of the uncertainty index in order to have an estimate of the elasticity.

We first conduct a fixed effects (FE) estimation with province fixed effects. However, as Nickell (1981) showed, the FE estimator is inconsistent in dynamic models if the number of time periods is finite even if the number of cross-sections goes to infinity. The estimator for the lagged variable is usually downward biased while in the standard OLS it is upwards biased due to the fixed effects. For dynamic panel data models with many cross-sections (large N), the difference GMM (Arellano and Bond (1991)) and system GMM (Arellano and Bover (1995); Blundell and Bond (1998)) are popular choices. Under appropriate assumptions, these GMM estimators are asymptotically unbiased as N goes to infinity and T is finite. The use of an instrument variable approach in these estimators often leads to poor small sample properties. Roodman (2009) shows that when T is large compared to N, many instruments are available. In our case with moderate number of both N and T the GMM estimator, which has become a standard approach to dynamic panel data, is not asymptotically unbiased and therefore may not be suitable. Hence, we consider another alternative: a bias-corrected Least Squares Dummy Variable (LSDVC) estimator (Kiviet (1995) and Kiviet (1999)). Due to the moderate number of cross-sections in our data ($N = 30$) and time-periods ($T = 15$ or less in some specifications), we use the LSDVC estimator for an unbalanced panel as proposed by Bruno (2005). The LSDVC estimator has been found to be appropriate for small T[6]. We

[6] Judson and Owen (1997) compare three groups of estimators for small N and finite T (small to moderate): (i) the Anderson and Hsiao (1982) estimator based on IV procedures; (ii) the one and two-step GMM by Arellano and Bond (1991); and (iii) the bias-corrected LSDV estimator by Kiviet (1995). They find that in general the one-step GMM outperforms the two-step GMM, but the LSDVC and Anderson-Hsiao estimators consistently outperform all other estimators. They find that the Anderson-Hsiao has a lower bias, but the LSDVC is more effective. Hence, there is a certain bias-effectiveness trade-off. They conclude that, for small T, the LSDVC estimator seems more appropriate while the Anderson-Hsiao estimator is more appropriate for larger T. A drawback of the LSDVC estimator as proposed by Kiviet (1995) is, that it cannot be applied to unbalanced panels. Bruno (2005) extends the version of Kiviets LSDVC to unbalanced panel data. De Vos et al. (2015) proposed a bootstrap-based bias corrected FE (BCFE) estimator which,

use bias correction for small T and for small N up to order $O(N^{-1}T^{-2})$ and bootstrapped standard errors clustered at the provincial level. The Anderson-Hsiao estimator is used for the initial consistent estimation of the error term.

Table 2: **Baseline regression results**

This table presents the results for the fixed effects regression and the bias-corrected LSDV estimation (Bruno (2005)) of the equation $y_{i,t} = \gamma y_{i,t-1} + x'_{i,t}\beta + \eta_i + \epsilon_{i,t}$ for the full sample from 2000 to 2015 and for different subsamples. The values in parenthesis are robust standard errors clustered at the provincial level for the fixed effects regression and bootstrapped standard errors for the LSDVC estimation. Stars indicate the significance level: * 10%, ** 5%, *** 1%. *cons* is real household consumption per capita, *disp_income* is real disposable income per capita, *pprice* are residential property prices, *inv* is real investment per capita as measured by FAI, *interest* is the real deposit interest rate, and *uncert* the uncertainty index by Baker et al. (2016).

Dependent variable: Δ ln($cons_t$)	(1) All years FE	(2) All years LSDVC	(3) All years LSDVC	(4) Pre-GFC LSDVC	(5) Post-GFC LSDVC	(6) Western LSDVC	(7) Eastern LSDVC
Δ ln($cons_{t-1}$)	-.1337***	-.0175	.0159	.1436	.3088**	.0412	.0473
	(.0295)	(.0447)	(.0450)	(.1890)	(.1229)	(.0643)	(.1416)
Δ ln($disp\_inc_t$)	.8451***	.8299***	.9217***	.8969***	.8884***	.9639***	.6017***
	(.0864)	(.0552)	(.0574)	(.0830)	(.0929)	(.0608)	(.1157)
Δ ln($pprice_t$)	.0007	.0041	.0115	.0397	-.0239	.0060	-.0070
	(.0189)	(.0212)	(.0225)	(.0395)	(.0294)	(.0219)	(.0348)
Δ ln(inv_t)	.0442***	.0402**	.0494**	.0101	.0722***	.0294	.0439*
	(.0144)	(.0205)	(.0199)	(.0398)	(.0252)	(.0225)	(.0295)
$interest_t$	.0014**	.0020***	-.0007	.0025	.0024*	.0015**	.0040***
	(.0006)	(.0007)	(.0023)	(.0021)	(.0012)	(.0008)	(.0013)
ln($uncert_t$)	-.00004	.0024		.0203	-.0156	.0056	-.0010
	(.0034)	(.0034)		(.0135)	(.0096)	(.0047)	(.0075)
Observations	417	417	417	180	237	238	179
Groups	30	30	30	30	30	17	13
Time fixed effects			yes				
R^2	.469	.469	.545	.568	.429	.548	.409

Column one to three in Table 2 show the results for the full sample. The results for the fixed effects as well as the bias-corrected LSDV estimation are similar except for the downward bias on the lagged dependent variable in the fixed effects estimation. The results suggest that there is a significant and positive correlation between investment growth and household consumption growth, even after controlling for household income growth. While the coefficients of investment may be moderate compared to the coefficients of household income, they are not negligible. Interestingly, the interest rate also has a significant and positive coefficient consistent with the result at the national level. We also note that neither the housing price variable nor the uncertainty index have a significant correlation with consumption growth.

The provinces are most likely subject to a common trend. We address this issue by

however, imposes more restrictions.

including time fixed effects into the estimation in column three of Table 2. Despite increasing the overall R^2, this comes at the cost of having to exclude the uncertainty index from the estimation since this index is measured on the national level and, thus, cross-sectional invariant. Moreover, since the nominal interest rate is also measured at the national level and, therefore, cross-sectional invariant, the coefficient of the interest rate only captures the deviation of the real interest rate from the nominal interest rate in each province and cannot be properly interpreted. Including time fixed effects seems to only slightly increase the coefficients of the significant variables but not to change the qualitative results and, thus, by excluding fixed effects we seem to estimate a lower bound. Since we are interested in the drivers of Chinese household consumption including the interest rate and the uncertainty index, we exclude time fixed effects in the subsequent estimations.

Since, according to theory, investment leads to an increase in the capital stock which in turn should translate into higher incomes and income growth has a strong correlation with consumption growth as shown above, investment growth also indirectly affects consumption growth. We conduct a back-of-the-envelope calculation to get an idea about the total relationship between investment growth and consumption growth. Therefore, we make use of the standard decomposition of income into a labor and capital part and regress real disposable income growth on real urban wage growth[7], our migrant worker population proxy in order to capture labor transfer dynamics, real investment per capita growth, the real interest rate, and individual and time fixed effects. By multiplying the coefficient of investment growth with the coefficient of income growth of the previous estimation[8] we obtain a rough estimate of the indirect effect which we then can add to the coefficient of investment growth of the previous estimation and arrive at a total estimate of .08.

When splitting the sample into pre- and post-GFC periods (column four and five in Table 2), the correlation between investment growth and household consumption growth is only significant in the post-GFC period. This result suggests a stronger correlation between investment growth and consumption growth after the GFC. The lagged consumption growth rate only has a significant coefficient in the post-GFC period suggesting some degree of habit formation in consumption. Even though not being significant in both periods, the coefficient of uncertainty as well as property prices turned negative in the period after the GFC. The interest rate is significant only after the GFC. Note, that only the difference of the investment coefficient between both samples is significant as calculated by an unpaired t-test.

The Chinese provinces differ strongly from each other. Provinces with higher per capita

[7]Since hours worked are not available, we have to remain with this approximation of the labor part of income.

[8]Here we include time fixed effects since we are only interested in the correlation between investment/income growth with consumption growth.

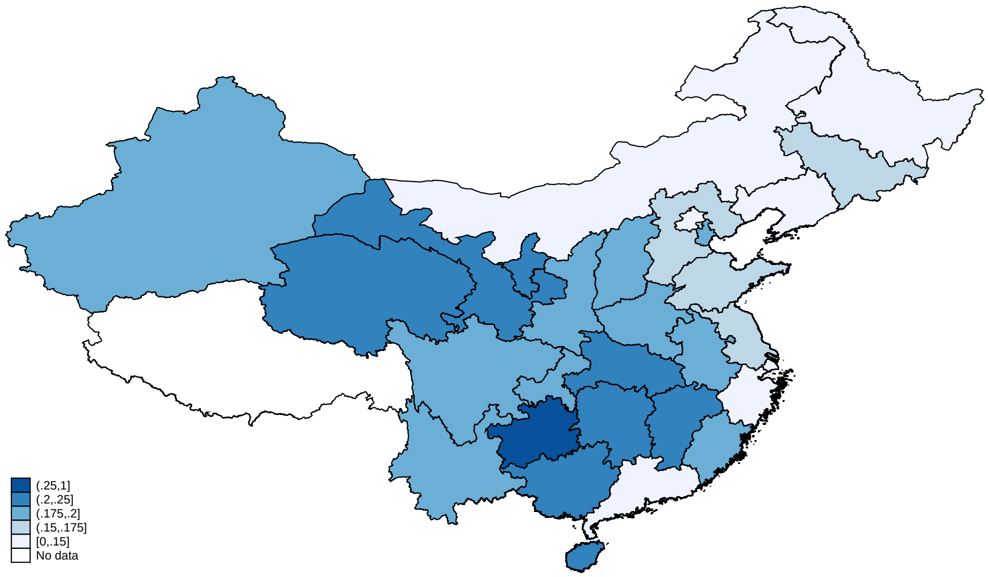

Figure 5: Average growth rates of FAI between 2008 and 2016. (Source: CEIC)

income along the coast in the east, provinces with a large heavy industry in the north-east, metropolitan areas such as Shanghai and Beijing and less developed rural provinces in the west. Especially these rural provinces have been subject to investment projects in recent years under the “Go-West” policy of the government. The regional dispersion of investment among the provinces can be seen in Figure 5, which shows the average growth rates of FAI between 2008 and 2016. In the baseline estimation, we will split the regions according to a slightly modified version of the geographical separation by the National Bureau of Statistics of China. We will group the eastern, north-eastern and municipal provinces Fujian, Guangdong, Jiangsu, Zhejiang, Hebei, Heilongjiang, Jilin, Liaoning, Shandong, Beijing, Chongqing, Shanghai, and Tianjin into a group called eastern provinces and the rest into a group called western provinces (see Figure A.1 in the appendix). In the robustness section we check our results with respect to different groupings. First, we will split the provinces according to the median income per capita in 2015 and to the median average growth rate of fixed asset investment from 2008 to 2015 (see Figure A.2 and Figure A.3 in the appendix).

When the sample is split into less-developed western regions and eastern regions (including the developed coastal regions as well as the industrial north-east and metropolitan areas), the results in column six and seven of Table 2 show that there is a positive significant correlation between investment growth and household consumption growth only for the eastern provinces with the difference being statistical insignificant. This contradicts the findings of Lee et al. (2013) who find that consumption is increasingly dependent on investment in the western regions. However, they do not control for disposable income and part of the effect for the inland provinces might be driven by transfer payments. If transfer payments by migrant workers confounded the estimate of investment growth, we would expect the opposite result and the coefficient to be larger for the less-developed western regions, as in Lee et al. (2013), since the regions with higher average investment growth in the recent years coincide with the regions where most of the migrant worker population originates from. Nevertheless, we will test the robustness of this result by including our proxy for the migrant worker population in the robustness section. The difference of the estimate of household income growth across both regions is significant with the coefficient being larger for the western provinces which comes hand in hand with a smaller and less significant coefficient on the deposit rate. This result is in line with larger financial frictions or a larger hand-to-mouth consumer population in the inland provinces.

To examine the effects of different investment channels, we replace overall investment growth with fixed asset investment growth of different types of industries[9]. In particular we group five categories of fixed asset investment: manufacturing, construction, real estate, infrastructure (including transportation, information transmission, utilities, and resident services), and other investment. Due to multicollinearity concerns we first estimate the investment channels separately. The results (Table 3) show that only real estate as well as infrastructure investment growth have a significant and positive correlation with household consumption growth, with larger coefficients for infrastructure.

These results suggest that investment growth has a significant correlation with household consumption growth beyond the household income channel. This effect has become stronger after the GFC with real estate and infrastructure having the largest and most significant coefficient. While the availability of sectoral FAI data (only available starting in 2004) makes it difficult to compare the effects of sectoral investment growth on consumption growth in the pre- and post-GFC period, the last set of regressions is mostly influenced by the post-GFC period. Overall, the results therefore suggest that the great stimulus package introduced after the GFC seems to have had a significant and positive impact on household consumption growth.

The results so far indicate correlations rather than causality. In order to exclude reverse causality, we conduct a Granger causality test adapted to a panel framework as proposed by Dumitrescu and Hurlin (2012). In general, Granger causality tests check whether the lags of the explanatory variable contain further information which is important for the current value of the dependent variable, conditional on its own lags. We use log-first-differences for all variables. The optimal number of lags is derived from the Akaike information criterion in the full sample from 2000 to 2015. The optimal number of lags found for the whole sample

[9]Since the detailed data is only available after 2004, the sample gets smaller.

Table 3: **Regression results for different investment channels**

This table presents the results for the bias-corrected LSDV estimation (Bruno (2005)) of the equation $y_{i,t} = \gamma y_{i,t-1} + x'_{i,t}\beta + \eta_i + \epsilon_{i,t}$ for the full sample from 2004 to 2015. The values in parentehsis are bootstrapped standard errors clustered at the provincial level. Stars indicate the significance level: * 10%, ** 5%, *** 1%. *cons* is real household consumption per capita, *disp_income* is real disposable income per capita, *pprice* are residential property prices, *inv* is real investment per capita as measured by FAI grouped into investment in the manufacturing sector (*manu*), construction sector (*cons*), real estate sector (*real*), infrastructre (*infra*), and others (*other*), *interest* is the real deposit interest rate on savings, and *uncert* the uncertainty index by Baker et al. (2016).

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	All years	All years	All years	All years	All years	All years
Δ ln($cons_t$)	LSDVC	LSDVC	LSDVC	LSDVC	LSDVC	LSDVC
Δ ln($cons_{t-1}$)	.1284	.1251	.1283	.1049	.1287	.1120
	(.0832)	(.0815)	(.0816)	(.0746)	(.0809)	(.0783)
Δ ln($disp\_inc_t$)	.8065***	.8201***	.8031***	.8289***	.8107***	.8107***
	(.0722)	(.0694)	(.0683)	(.0689)	(.0674)	(.0682)
Δ ln($pprice_t$)	.0205	.0249	.0170	.0205	.0259	.0121
	(.0227)	(.0226)	(.0237)	(.0230)	(.0228)	(.0234)
Δ ln(inv_manu_t)	.0149					0.0075
	(.0114)					(.0132)
Δ ln(inv_cons_t)		.0003				-.0001
		(.0027)				(.0027)
Δ ln(inv_real_t)			.0269**			.0207*
			(.0131)			(.0141)
Δ ln(inv_infra_t)				.0319**		.0277*
				(.0142)		(.0151)
Δ ln(inv_other_t)					.0149	-.0047
					(.0131)	(.0154)
$interest_t$	.0025**	.0023**	.0028***	.0009	.0020*	.0017
	(.0010)	(.0010)	(.0009)	(.0012)	(.0010)	(.0013)
ln($uncert_t$)	.0036	.0024	.0037	.0024	.0025	.0040
	(.0044)	(.0041)	(.0041)	(.0041)	(.0042)	(.0043)
Observations	328	328	328	328	328	328
Groups	30	30	30	30	30	30
Time fixed effects						
R^2	.416	.416	.424	.429	.416	.433

is also used for the according subsamples, as the results might be influenced by the number of lags and it would not be quite clear whether the different results come from the adaption of the number of lags or from a structural change in the Granger causality. We allowed for a maximum number of four lags as four lags represent about half of a business cycle. Due to the rather small samples and the economic interpretation, a higher number of lags seems to be unreasonable. The Granger causality test adapted to a panel framework as proposed by Dumitrescu and Hurlin (2012) takes heterogeneity between cross-section units into account allowing coefficients to differ. The following linear model is considered:

$$y_{i,t} = \alpha_i + \sum_{k=1}^{K} \gamma_i^{(k)} y_{i,t-k} + \sum_{k=1}^{K} \beta_i^{(k)} x_{i,t-k} + \epsilon_{i,t}$$

where the individual effects α_i are supposed to be time-invariant, and the lag orders K to be identical for all cross-section units of the balanced panel. The coefficients $\gamma_i^{(k)}$ and $\beta_i^{(k)}$ are allowed to differ across groups but are constant in time. The Granger causality test tests the Homogeneous Non-Causality hypothesis where the null hypothesis is defined as:

$$H_0 : \beta_i = 0 \qquad \forall i = 1, ..., N$$

which means, that x does not Granger-cause y.

Table 4: **Granger causality test on the provincial level**

This table shows the p-values standardized for fixed T of granger causality tests on the provincial level of the form $y_{i,t} = \alpha_i + \sum_{k=1}^{K} \gamma_i^{(k)} y_{i,t-k} + \sum_{k=1}^{K} \beta_i^{(k)} x_{i,t-k} + \epsilon_{i,t}$ as proposed by Dumitrescu and Hurlin (2012). The number of lags is determined by the AIC in the full sample from 2000 to 2015. Variables are in log first differences and per capita values. The groups refer to the geographical separation as described in section 6. Metro: Beijing, Tianjin, Shanghai. Coast: Guangdong, Fujian, Jiangsu, Zhezhiang. North-east: Liaoning, Jilin, Heilongjiang, Hebei, Shandong. Note that the lag length is determined in the full sample and, therefore, inaccurate for the subsamples.

H_0: Non causality						
Specification	All	Metro	Coast	Ind. NE	Less dev.	lags
Investment on consumption	.01**	.06*	.93	.51	.02**	3
Consumption on investment	.23					3
Investment on income	.00***	.20	.37	.00***	.00***	3
Income on investment	.40					3

The test results (Table 4) suggest that we can reject the null hypothesis of no causality from investment growth to consumption growth for the entire sample. We moreover can replicate the findings of Lee et al. (2013) that in less developed areas, consumption is reliant on investment. Overall, the empirical evidence suggests that the causality in the panel regression tends to go from investment to consumption. The results for investment growth and income growth are similar.

6.2 Robustness tests

We also test the baseline results for robustness to various changes. The results for the full sample can be found in Table A.1 in the appendix. Using GFCF per capita instead of FAI[10]

[10] Due to missing data we have to constrain the sample to the period up to 2014.

(column two) does not change the results significantly. We moreover include the migrant worker population proxy in the full sample in column three. The coefficient of investment growth only slightly decreases which means that some of the variation is indeed captured by the migrant worker proxy. However, qualitatively the results remains the same. Using the lending rate instead of the deposit rate does not change the results much. Table A.2 in the appendix shows robustness checks with respect to the regional subsample analysis where we include the migrant worker proxy and use the different groupings as discussed above. In the baseline geographical grouping, the results do not change much when including the migrant worker proxy (column three and four). When using different groupings (columns five to eight), the coefficient of income growth is larger for regions with below median income in 2015 and for regions with average investment growth below the median. For the investment variable the opposite holds. The correlation between investment growth and income growth seems to be larger for regions with above median income and for regions with above median average investment growth.

7 Investment, income expectations, and consumer confidence

The results that the effects are stronger for more salient investment suggest that investment in China may be a good leading indicator for expected future household income and, thus, affect consumption through consumer confidence (see Figure 6). Under the general permanent income hypothesis, household consumption should only react to unexpected changes in permanent income. If, however, households are liquidity constrained, as it is likely to be the case in China, consumer confidence could be related to consumption growth (Ludvigson (2004)).

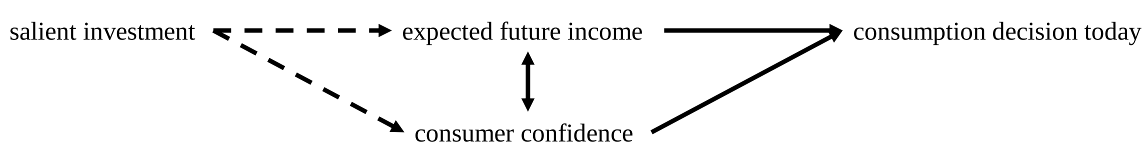

Figure 6: Schematic representation of the possible channel of an effect of salient investment on household consumption. Solid lines represent relationships found in the literature, dashed lines a possible explanation for the effect of investment on consumption.

There is evidence that household income expectation is an important factor in determining household consumption in other countries such as the US (Pounder Demarco (2009)) or advanced economies (Estrada et al. (2015)).

The effect of consumer confidence on consumer spending has been extensively examined mostly for developed economies. Ludvigson (2004) indeed finds for the US that consumer confidence has a significant predictive power for consumption spending. Moreover, evidence suggests that consumer confidence reflects households' expectations about future income since consumer confidence has some predictive power for future labor income. Dees and Soares Brinca (2013) find that in the US and the Euro area confidence indicators can be a good predictor for household consumption especially when there are large changes in these indicators. Dion (2006) discusses various aspects in the relationship between consumer confidence and consumption.

Since emerging economies are even more liquidity constrained than developed economies, the effect should be even stronger for emerging economies from a permanent income hypothesis view. There is, however, less empirical reasearch on this relationship in emerging markets, mostly due to data availability. Fan and Wong (1998) examine the relationship between consumer sentiment and household spending in Hong Kong and find little explanatory power of consumer sentiment. This is due to the fact that consumer sentiment rather measures well-being than expected future income.

The determinants of consumer confidence or income expectations have received less attention in the literature. Lopez and Durre (2003) examine standard drivers of consumer confidence for the US and Belgium, such as unemployment and wages, as well as the role of stock market returns. Celik et al. (2010) examine drivers for emerging markets and propose two important drivers: production and financial markets. If salient investment was a driver of consumer confidence, there should be a positive correlation between investment growth today and consumers expectations about the future. Heim (2010) indeed finds a positive relationship between investment spending and consumer confidence in the US.

Using a measure of consumer confidence with respect to expectations about the future in China in order to confirm our hypothesis seems straightforward. The National Bureau of Statistics of China publishes a consumer confidence index which is, however, remarkably stable over the whole time horizon and, hence, regarded as unreliable. Another measure, which seems to capture consumer confidence better, is the confidence indicator by Union Pay, a private credit card company. This series is, however, only available after 2010 and does not include the time of the great stimulus. Therefore, there exists no good measure to test this hypothesis and we have to remain with our proposition that investment in China might act as proxy for future household income which in turn influences the decision to consume today based on our empirical findings in the previous sections. This leaves room for future research about the drivers of consumer confidence and its relationship with household consumption in China once reliable statistics are available.

8 Conclusion

Investment propelled the Chinese economy in the aftermath of the GFC as the Chinese authorities introduced a large stimulus to mitigate the effects from the GFC. This sent the already high investment-to-GDP ratio to unprecedented levels. The inevitable rebalancing towards consumption has been on China's agenda during the last years. More recently, consumption has become more important in driving growth as investment started to slow down. Lower investment could have an impact on consumption beyond the standard channel through household income. This paper attempts to explain the drivers of Chinese household consumption and to address how an expected investment slowdown could have an impact on household consumption. We use both national-level (BVAR) and provincial-level data (panel regression) to empirically answer this question. Our empirical results from both the national- and provincial-level data suggest that investment growth has had significant impact on household consumption growth beyond the household income channel. The effects are especially strong in the post-GFC period and for more salient investment, indicating the extent that the stimulus has affected households' decision to consume. The results suggest that investment in China may be a good leading indicator for future household income. The rebalancing from investment-driven growth towards consumption-driven growth is very important considering the very high investment to GDP ratio and the very high credit to GDP ratio. A further increase in investment might have adverse effects for the financial stability of the corporate sector. However, policy to encourage rebalancing away from investment should consider the extra effect it may have on consumption beyond the impact on household income and foster household consumption via increasing consumer confidence by improving social inequality or the social safety net which in turn would decrease the high savings rate and increase consumption expenditure.

References

Anderson, T. W. and Hsiao, C. (1982), 'Formulation and estimation of dynamic models using panel data', *Journal of Econometrics* 18(1), 47–82.

Arellano, M. and Bond, S. (1991), 'Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations', *Review of Economic Studies* 58(2), 277–297.

Arellano, M. and Bover, O. (1995), 'Another look at the instrumental variable estimation of errorcomponents models', *Journal of Econometrics* 68(1), 29–51.

Bagliano, F. C. and Favero, C. A. (1998), 'Measuring monetary policy with VAR models: An evaluation', *European Economic Review* 42(6), 1069–1112.

Baker, S. R., Bloom, N. and Davis, S. J. (2016), 'Measuring Economic Policy Uncertainty', *The Quarterly Journal of Economics* 131(4), 1593–1636.

Barnett, S. A. and Brooks, R. (2006), 'Whats Driving Investment in China?', *IMF Working Paper No. 06/265* .

Bernanke, B. S. and Mihov, I. (1998), 'The liquidity effect and long-run neutrality', *Carnegie-Rochester Conference Series on Public Policy* 49(1), 149–194.

Blundell, R. and Bond, S. (1998), 'Initial conditions and moment restrictions in dynamic panel data models', *Journal of Econometrics* 87(1), 115–143.

Bruno, G. S. F. (2005), 'Approximating the bias of the LSDV estimator for dynamic unbalanced panel data models', *Economics Letters* 87(3), 361–366.

Buysse, K., Essers, D. and Vincent, E. (2018), 'Can china avoid the middle-income trap?', *NBB Economic Review* June 2018, 63–77.

Celik, S., Aslanoglu, E. and Uzun, S. (2010), 'Determinants of Consumer Confidence in Emerging Economies: A Panel Cointegration Analysis', *Topics in Middle Eastern and North African Economies* 12.

Chamon, M., Liu, K. and Prasad, E. (2013), 'Income uncertainty and household savings in China', *Journal of Development Economics* 105(C), 164–177.

Chen, H., Chow, K. and Tillmann, P. (2017), 'The effectiveness of monetary policy in China: Evidence from a Qual VAR', *China Economic Review* 43(C), 216–231.

Chen, H., Funke, M. and Mehrotra, A. (2017), 'What Drives Urban Consumption in Mainland China? The Role of Property Price Dynamics', *Pacific Economic Review* 22(3), 383–409.

Curtis, C. C., Lugauer, S. and Mark, N. C. (2015), 'Demographic Patterns and Household Saving in China', *American Economic Journal: Macroeconomics* 7(2), 58–94.

De Vos, I., Everaert, G. and Ruyssen, I. (2015), 'Bootstrap-based bias correction and inference for dynamic panels with fixed effects', *Stata Journal* 15(4), 986–1018.

Dees, S. and Soares Brinca, P. (2013), 'Consumer confidence as a predictor of consumption spending: Evidence for the United States and the Euro area', *International Economics* 134, 1–14.

Dieppe, A., van Roye, B. and Legrand, R. (2016), 'The BEAR toolbox', *ECB Working Paper Series 1934* .

Dion, D.-P. (2006), 'Does Consumer Confidence Forecast Household Spending?', *MPRA Paper 902* .

Dumitrescu, E.-I. and Hurlin, C. (2012), 'Testing for Granger non-causality in heterogeneous panels', *Economic Modelling* 29(4), 1450–1460.

Estrada, n., Garrote, D., Valdeolivas, E. and Valls, J. (2015), 'Household Debt and Uncertainty: Private Consumption after the Great Recession', *Monetaria* 0(1), 71–109.

Fan, C. S. and Wong, P. (1998), 'Does consumer sentiment forecast household spending? The Hong Kong case', *Economics Letters* 58(1), 77–84.

Furlanetto, F., Ravazzolo, F. and Sarferaz, S. (2017), 'Identification of Financial Factors in Economic Fluctuations', *The Economic Journal* .

Heim, J. J. (2010), ‘The Impact of Consumer Confidence on Consumption and Investment Spending’, *Journal of Applied Business and Economics* 11(2).

Horioka, C. Y. (2010), ‘Aging And Saving In Asia’, *Pacific Economic Review* 15(1), 46–55.

Judson, R. and Owen, A. L. (1997), ‘Estimating dynamic panel data models: a practical guide for macroeconomists’, *Finance and Economics Discussion Series 1997-3 Board of Governors of the Federal Reserve System (U.S.)* .

Kaplan, G. and Violante, G. L. (2018), ‘Microeconomic Heterogeneity and Macroeconomic Shocks’, *Journal of Economic Perspectives* 32(3), 167–194.

Kaplan, G., Violante, G. L. and Weidner, J. (2014), ‘The Wealthy Hand-to-Mouth’, *Brookings Papers on Economic Activity* 45(1), 77–153.

Kiviet, J. F. (1995), ‘On bias, inconsistency, and eciency of various estimators in dynamic panel data models’, *Journal of Econometrics* 68(1), 53–78.

Kiviet, J. F. (1999), ‘Expectation of Expansions for Estimators in a Dynamic Panel Data Model; Some Results for Weakly Exogenous Regressors’, *In: Hsiao, C., Lahiri, K., Lee, L.-F., Pesaran, M. H. (Eds.), Analysis of Panel Data and Limited Dependent Variables. Cambridge University Press, Cambridge* .

Koivu, T. (2012), ‘Monetary policy, asset prices and consumption in China’, *Economic Systems* 36(2), 307–325.

Lee, I. H., Syed, M. and Liu, X. (2013), ‘China’s path to consumer-based growth: Reorienting investment and enhancing efficiency’, *IMF Working Paper No. 13/83* .

Lopez, H. B. and Durre, A. (2003), ‘The determinants of consumer confidence: the case of United States and Belgium’, *CORE Discussion Papers* 2003053.

Ludvigson, S. C. (2004), ‘Consumer Confidence and Consumer Spending’, *Journal of Economic Perspectives* 18(2), 29–50.

Ludvigson, S., Steindel, C. and Lettau, M. (2002), ‘Monetary policy transmission through the consumption-wealth channel’, *Economic Policy Review* issue May, 117–133.

Ma, G., Roberts, I. and Kelly, G. (2017), ‘Rebalancing China’s Economy: Domestic and International Implications’, *China & World Economy* 25(1), 1–31.

Nabar, M. S. (2011), ‘Targets, Interest Rates, and Household Saving in Urban China’, *IMF Working Paper No. 11/223* .

Nickell, S. J. (1981), ‘Biases in Dynamic Models with Fixed Effects’, *Econometrica* 49(6), 1417–1426.

Peltonen, T. A., Sousa, R. M. and Vansteenkiste, I. S. (2012), ‘Wealth effects in emerging market economies’, *International Review of Economics & Finance* 24(C), 155–166.

Pounder Demarco, L. (2009), ‘Consumption response to expected future income’, *International Finance Discussion Papers 971 Board of Governors of the Federal Reserve System (U.S.)* .

Roodman, D. (2009), ‘How to do xtabond2: An introduction to difference and system GMM in Stata’, *Stata Journal* 9(1), 86–136.

Sims, C. A. (1998), ‘Comment on Glenn Rudebusch’s “Do Measures of Monetary Policy in a VAR Make Sense”’, *International Economic Review* 39(4), 933–941.

Soudan, M. (forthcoming), ‘Quarterly National Account for China’, *ECB (forthcoming)* .

Tsatsaronis, K. and Zhu, H. (2004), ‘What drives housing price dynamics: cross-country evidence’, *BIS Quarterly Review* .

Wei, S.-J. and Zhang, X. (2011), ‘The Competitive Saving Motive: Evidence from Rising

Sex Ratios and Savings Rates in China', *Journal of Political Economy* 119(3), 511–564.
Zhang, L. (2016), 'Rebalancing in China-Progress and Prospects', *IMF Working Papers* 16(183), 1.

A Appendix

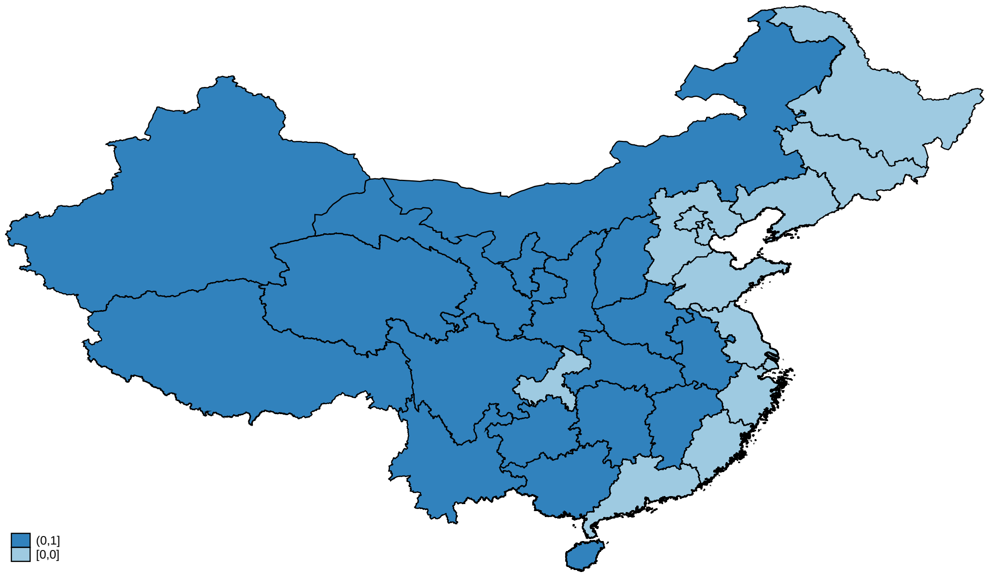

Figure A.1: Baseline classification of provinces according to geography. Darker areas refer to western provinces and lighter areas to eastern provinces in the classification.

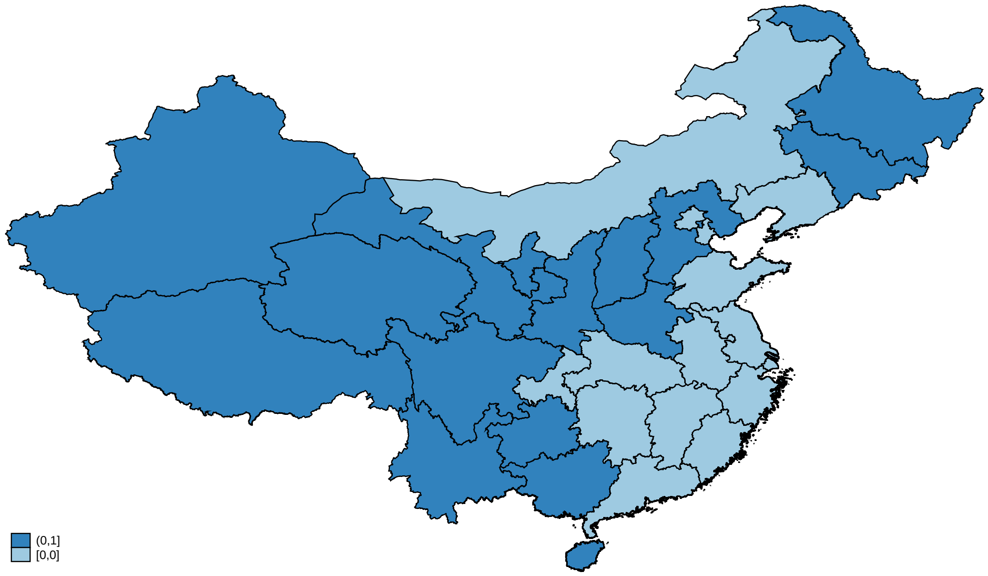

Figure A.2: Classification of provinces according to median income per capita in 2015. Darker shaded areas are below the median. (Source: Authors' calculations)

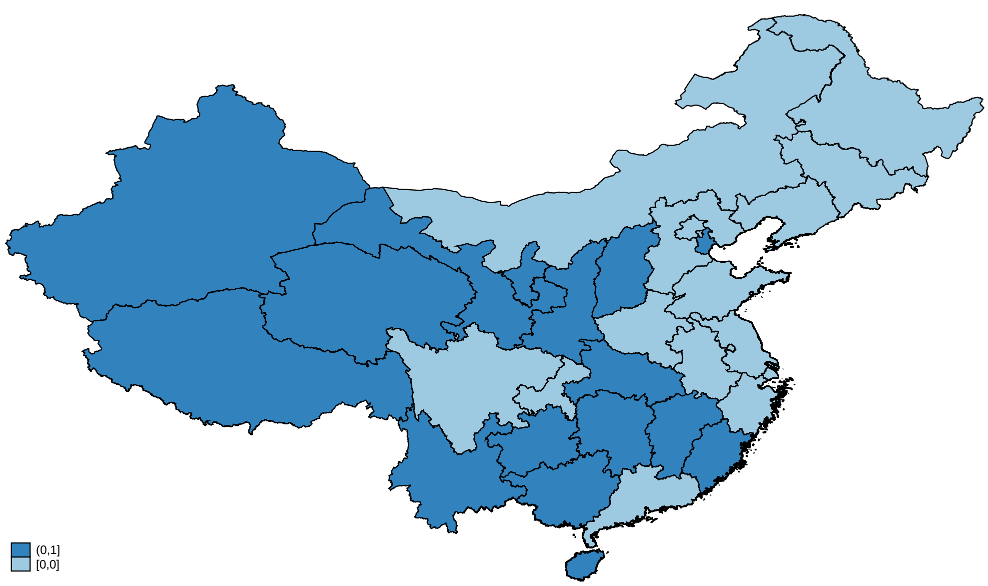

Figure A.3: Classification of provinces according to average annual fixed asset growth from 2008 to 2015. Darker shaded areas are provinces with above median average fixed asset growth. (Source: Authors' calculations)

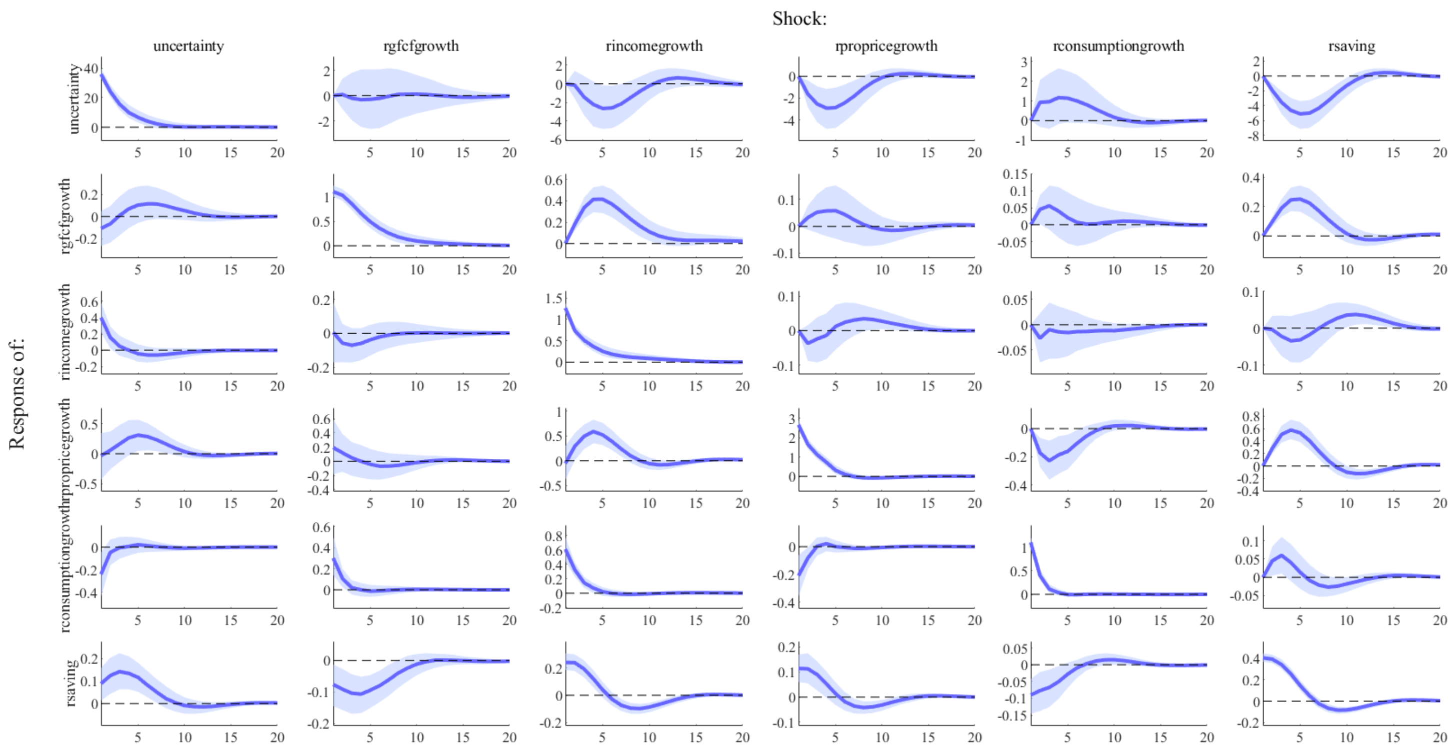

Figure A.4: Full set of impulse response functions to a one-standard-deviation shock. Dotted lines represent one-standard-deviation credibility bands.

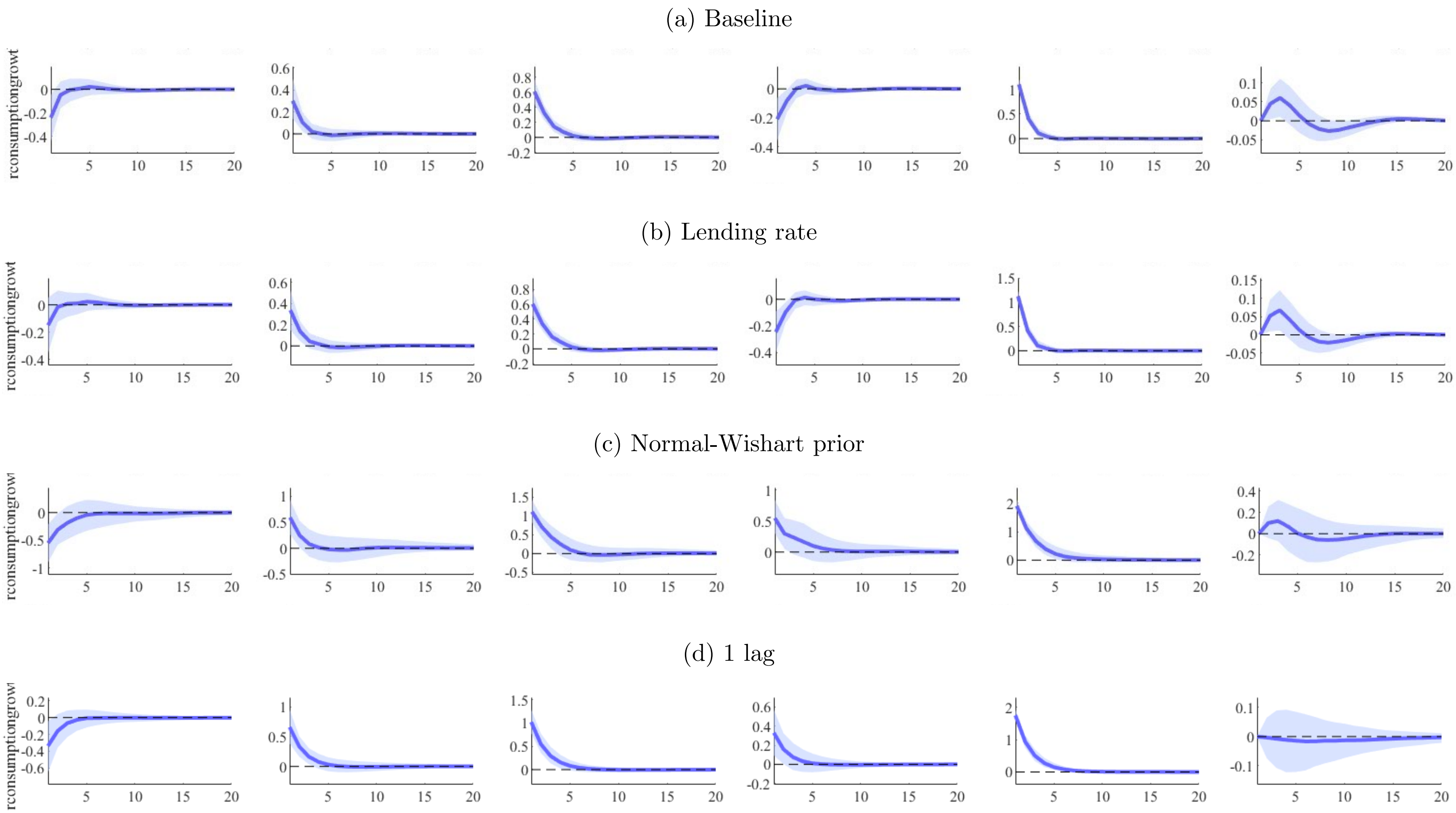

Figure A.5: Robustness tests of the BVAR on the national level

Impulse response functions of consumption to various one-standard-deviation shock. Dotted lines represent one-standard-deviation credibility bands. Baseline specification: independent normal-Wishart prior, 4 lags, deposit rate

Table A.1: Robustness tests for the full sample

This table presents the robustness test results for the bias-corrected LSDV estimation (Bruno (2005)) of the equation $y_{i,t} = \gamma y_{i,t-1} + x'_{i,t}\beta + \eta_i + \epsilon_{i,t}$ for the full sample from 2000 to 2015. The values in parenthesis are robust bootstrapped standard errors. Stars indicate the significance level: * 10%, ** 5%, *** 1%. *cons* is real household consumption per capita, *disp_income* is real disposable income per capita, *pprice* are residential property prices, *inv* is real investment per capita as measured by FAI, *interest* is the deposit interest rate, *migrant* is the migrant worker proxy and *uncert* the uncertainty index by Baker et al. (2016).

Dependent variable: Δ ln($cons_t$)	(1) Baseline LSDVC	(2) GFCF LSDVC	(3) Migration LSDVC	(4) Lending LSDVC
Δ ln($cons_{t-1}$)	-.0175	-.0281	-.0159	-.0200
	(.0447)	(.0497)	(.0448)	(0442)
Δ ln($disp\_inc_t$)	.8299***	.8026***	.8322***	.8209***
	(.0552)	(.0748)	(.0561)	(.0565)
Δ ln($pprice_t$)	.0041	.0069	.0048	.0038
	(.0212)	(.0170)	(.0214)	(.0212)
Δ ln(inv_t)	.0402**	.0441**	.0393*	.0395*
	(.0205)	(.0209)	(.0208)	(.0205)
$migrant_t$			-.0028	
			(.0257)	
$interest_t$	.0020***	.0024***	.0020***	.0024***
	(.0007)	(.0009)	(.0007)	(.0009)
ln($uncert_t$)	.0024	.0043	.0023	.0017
	(.0034)	(.0045)	(.0034)	(.0034)
Observations	417	388	417	417
Groups	30	30	30	30
Time fixed effects				
R^2	.469	.470	.472	.470

Table A.2: Robustness tests for the regional sample

This table presents the robustness test results for the bias-corrected LSDV estimation (Bruno (2005)) of the equation $y_{i,t} = \gamma y_{i,t-1} + x'_{i,t}\beta + \eta_i + \epsilon_{i,t}$ for the regional sample. The values in parenthesis are robust bootstrapped standard errors. Stars indicate the significance level: * 10%, ** 5%, *** 1%. *cons* is real household consumption per capita, *disp_income* is real disposable income per capita, *pprice* are residential property prices, *inv* is real investment per capita as measured by FAI, *interest* is the deposit interest rate, *migrant* is the migrant worker proxy and *uncert* the uncertainty index by Baker et al. (2016). The groupings are described in detail in Section 6.

Dependent variable: Δ ln($cons_t$)	(1) Baseline Western LSDVC	(2) Baseline Eastern LSDVC	(3) Migration Western LSDVC	(4) Migration Eastern LSDVC	(5) Income Below LSDVC	(6) Income Above LSDVC	(7) FAI Above LSDVC	(8) FAI Below LSDVC
Δ ln($cons_{t-1}$)	.0412	.0473	.0399	.0503	.0577	.0742	.0402	.0832
	(.0643)	(.1416)	(.0647)	(.1375)	(.0906)	(.0934)	(.1030)	(.0832)
Δ ln($disp\_inc_t$)	.9639***	.6017***	.9625***	.6123***	.8864***	.7431***	.6776***	.9391***
	(.0608)	(.1157)	(.0617)	(.1192)	(.0777)	(.0897)	(.0812)	(.0786)
Δ ln($pprice_t$)	.0060	-.0070	.0068	-.0041	.0107	-.0011	-.0047	.0195
	(.0219)	(.0348)	(.0219)	(.0354)	(.0272)	(.0300)	(.0297)	(.0219)
Δ ln(inv_t)	.0294	.0439*	.0306	.0404	.0223	.0458**	.0524**	.0027
	(.0225)	(.0295)	(.0231)	(.0307)	(.0246)	(.0218)	(.0253)	(.0288)
$migrant_t$			.0474	-.0013				
			(.0590)	(.0442)				
$interest_t$	.0015**	.0040***	.0015*	.0042***	.0014	.0035***	.0028**	.0019**
	(.0008)	(.0013)	(.0008)	(.0013)	(.0009)	(.0011)	(.0012)	(.0009)
ln($uncert_t$)	.0056	-.0010	.0056	-.0022	.0051	.0025	.0004	.0069
	(.0047)	(.0075)	(.0050)	(.0077)	(.0056)	(.0065)	(.0065)	(.0050)
Observations	238	179	238	179	210	207	207	210
Groups	17	13	17	13	15	15	15	15
Time fixed effects								
R^2	.548	.409	.544	.417	.497	.447	.542	.417