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Trends and Cycles in China's Macroeconomy

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Abstract: We make four contributions in this paper. First, we provide a core of macroeconomic time series usable for systematic research on China. Second, we document, through various empirical methods, the robust findings about striking patterns of trend and cycle. Third, we build a theoretical model that accounts for these facts. Fourth, the model's mechanism and assumptions are corroborated by institutional details, disaggregated data, and banking time series, all of which are distinctive Chinese characteristics. We argue that preferential credit policy for promoting heavy industries accounts for the unusual cyclical patterns as well as the post-1990s economic transition featured by the persistently rising investment rate, the declining labor income share, and a growing foreign surplus. The departure of our theoretical model from standard ones offers a constructive framework for studying China's modern macroeconomy.

JEL classification: E, F4, G1

Key words: reallocation, between-sector effect, total factor productivity growth, heavy versus light sectors, long-term versus short-term loans, labor share, lending frictions, incentive compatibility

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I. Introduction

Growth has been the hallmark for China. In recent years, however, China's GDP growth has slowed down considerably while countercyclical government policy has taken center stage. Never has this change been more true than after the 2008 financial crisis, when the government injected 4 trillion RMBs into investment to combat the sharp fall of output growth. Issues related to both trend and cycle are now on the minds of policymakers and economists;[1] yet there is a serious lack of empirical research on (1) the basic facts about trends and cycles of China's macroeconomy and (2) a theoretical framework that is capable of explaining these facts. This paper serves to fill this important vacuum by tackling both of these issues. The broad goal is to promote, among a wide research community, empirical studies on China's macroeconomy and its government policies.

Over the past two years we have undertaken a task of providing a core of annual and quarterly macroeconomic time series to be as consistent with the definitions of U.S. time series as possible, while at the same time maintaining Chinese data characteristics for understanding China's macroeconomy. We develop an econometric methodology to document China's trend and cyclical patterns. These patterns are carefully cross-verified by studying different frequencies of the data, employing other empirical methods, and delving into disaggregated time series relevant to our paper. We build a theoretical framework to account for the unique patterns of trend and cycle by integrating the disaggregated time series and institutional details with our theoretical model. All three ingredients—data, empirical facts, and theory—constitute a central theme of this paper; none of ingredients can be understood apart from the whole.

Since March 1996 the government has been actively promoting what is called "heavy industries," which are largely composed of big capital-intensive industries such as telecommunication, energy, and metal products.[2] The other industries, called "light industries," do not receive the same preferential treatment. Our robust empirical findings about China's macroeconomy since the late 1990s consist of two parts. The first concerns trend patterns and the second pertains to cyclical patterns. The key trend facts are:

- (T1) A simultaneous rise of the investment-to-output ratio (from 26% in 1997 to 36% in 2010) and a fall of the consumption-to-output ratio (from 45% in 1997 to 35% in 2010), as confirmed by Figure 1.
- (T2) A decline of the labor share of income from 53% in 1997 to 47% in 2010.
- (T3) An increase in the ratio of long-term loans (for financing fixed investment) to short-term loans (for financing working capital) from 0.4 in 1997 to 2.5 in 2010.
- (T4) A rise in the ratio of capital in heavy industries to that in light industries from 2.4 in 1997 to 4 in 2010.
- (T5) An increase in the ratio of total revenues in heavy industries to those in light industries from 1 in 1997 to 2.5 in 2010.

The key cyclical patterns are:

[1] See various official reports from the research group in China's National Bureau of Statistics (`http://www.stats.gov.cn/tjzs/tjsj/tjcb/zggqgl/200506/t20050620_37473.html`).

[2] Not every capital-intensive industry belongs in the heavy classification. For example, food and beverage industries are capital intensive, but are not strategically important to the government. In this paper we study two aggregate sectors and abstract from the heterogeneity of capital intensity within each sector. Despite the heterogeneity within each sector, the heavy sector is, on average, much more capital intensive than the light sector.

(C1) Weak or negative comovement between aggregate investment and consumption, ranging from -0.6 to 0.2 for the sample from the late 1990s on.
(C2) Weak or negative comovement between aggregate investment and labor income, ranging from -0.3 to 0.3 for the sample from the late 1990s on.
(C3) A negative comovement between long-term loans and short-term loans, around -0.2 for the quarterly sample and -0.4 for the annual sample from the late 1990s on.

To explain both trend and cyclical patterns listed above, we build a theoretical model on Song, Storesletten, and Zilibotti (2011, SSZ henceforth) but depart from the traditional emphasis on state-owned enterprises (SOEs) versus and privately-owned enterprises (POEs). SSZ construct an economy with heterogeneous firms that differ in both productivity and access to the credit market to explain the observed coexistence of sustained returns to capital and growing foreign surpluses in China in most of the 2000s. Their model replicates disinvestment of SOEs in the labor-intensive sector as POEs accumulate capital in the same sector. In this two-sector model, they characterize two transition stages. In the first stage, both SOEs and POEs coexist in the labor-intensive sector, while capital-intensive goods is produced exclusively by SOEs.[3] In the second stage, SOEs disappear from the labor-intensive sector and POEs become the sole producers in that sector. SSZ present a persuasive story about resource reallocations between SOEs and POEs within the labor-intensive sector and the source of TFP growth since the later 1990s.

Although discussions around SOEs versus POEs have dominated the literature on China, the SOE-POE classification does not help explain the rising investment rate, the decline of labor income share, and the weak or negative cyclical comovement between investment and consumption or between investment and labor income. Since the late 1990s, moreover, capital deepening has become the major source of GDP growth in China. To address these China's macroeconomic issues in one coherent and tractable framework, we take a different perspective by shifting an emphasis to resource reallocation between the heavy and light sectors. This shift of emphasis is grounded in China's institutional arrangements that took place in the late 1990s, when the Eighth National People's Congress passed a historic long-term plan to adjust the industrial structure for the next 15 years in favor of strengthening heavy industries. The plan was subsequently backed up by long-term bank loans given priority to the heavy sector. As discussed in Sections V.2 and VIII.2.4, heavy industries have been deemed to be of strategic importance to China since 1996. Our novel approach is to build a two-sector model with a special emphasis on resource and credit reallocations between the heavy versus light sectors *and* by introducing two new institutional ingredients into our model: a collateral constraint on producers in the heavy sector and a lending friction in the banking sector. We show that with these new ingredients, our model can replicate trend patterns (T1)-(T5) and cyclical patterns (C1)-(C3).

Frictionless neoclassical models rest on certain assumptions that are at odds with the Chinese facts. Models represented by Chang and Hornstein (2015) and Karabarbounis and Neiman (2014) require a fall of the relative price of investment to explain the rise of the investment rate in South Korea or the global decline of labor share across a large number of

[3]To keep our paper transparent and focused, we abstract from their first transition stage, in which SOEs' employment share keeps declining in the labor-intensive sector. As shown by Chen and Wen (2014), most of the increase in the share of private employment occurred between 1998 and 2004 (from 15% to 50%), while the share increased by only 10% between 2004 and 2011. Nonetheless, our results would hold in a generalized economy that incorporates the first stage of transition.

countries when the elasticity of substitution between capital and labor is greater than one. Evidence in China for such a simultaneous fall of the relative price and the labor income share is at best weak. Frictionless two-sector models of capital deepening à la Acemoglu and Guerrieri (2008) assume that (labor-augmented) total factor productivity (TFP) in the capital-intensive sector grows faster than TFP in the labor-intensive sector when the elasticity of substitution between two sectors is less than one, or TFP in the capital-intensive sector grows slower than TFP in the labor-intensive sector when the elasticity of substitution between two sectors is greater than one. With this assumption, the investment rate declines over time. For the investment rate to rise and the labor share of income to decline, it must be that the elasticity of substitution between two sectors is greater than one and TFP in the capital-intensive sector grows faster than TFP in the labor-intensive sector. As discussed in Section V.2, Chinese evidence is unsupportive of faster TFP growth in the heavy sector. The critical feature of our model is that it *does not rely on any TFP assumption* in explaining the trend patterns of China. What we do rely on is a host of key institutional details that are critical for understanding China's macroeconomy. This paper weaves these institutional details together to formulate our theoretical framework.

Our counterfactual economy shows that the key to generating the trend patterns is the presence of collateral constraint in the heavy sector. With the collateral constraint, the borrowing capacity of heavy firms grows with their net worth. Accordingly, the demand for capital from the heavy sector accelerates during the transition, which leads to an increase in the value share of the heavy sector in aggregate output. This structural change contributes to both an increasing aggregate investment rate and a declining labor income share along the transition path. In the absence of this financial friction as in SSZ, by contrast, the economy tends to predict a *declining* (aggregate) investment rate during the transition. This result occurs because, under the aggregate production function with the constant elasticity of substitution (CES), the demand for capital from producers in the heavy sector is proportional to output produced by the light sector. As output growth in the light sector slows down over time due to the diminishing returns to capital, the heavy sector would experience a *declining* investment rate. Moreover, the investment rate in the light sector tends to decline during the transition due to either the resource reallocation from SOEs to POEs (in the first stage of transition, which we abstract from our model) or decreasing returns to capital when this kind of reallocation is completed.[4]

The cyclical patterns uncovered in this paper, an issue silent in SSZ, constitute an integral part of our model mechanism. The key to accounting for these important cyclical patterns is the presence of bank lending frictions in our model, which interacts with the aforementioned collateral constraint to deliver a negative externality on the light sector from credit injections into the heavy sector. In response to the government's credit injection, the expansion of credit demand by the heavy sector tends to crowd out the light sector's demand for working-capital loans by pushing up the loan rate for working capital. In an economy absent such lending frictions, a credit injection into the heavy sector tends to push up the wage income and therefore household consumption due to the imperfect substitutability between output produced from the heavy sector and output produced by the light sector, a result that is

[4]SSZ overcome such deficiency in their quantitative model by feeding in an *exogenous* sequence of interest rate subsidies, which pushes up wages and capital-labor ratios for both types of firms. This modification, nonetheless, predicts that the growth rates of aggregate investment and labor income tend to comove positively, which is inconsistent with fact (C2).

again at odds with what we observe in China (fact (C2)).[5] Specifically, it generates the following counterfactual predictions:

- A strong, positive comovement between investment and consumption.
- A strong, positive comovement between investment and labor income.
- A strong, positive comovement between investment loans and working-capital loans.

Standard business cycle models have a number of shocks that are potentially capable of generating a negative comovement between aggregate investment and household consumption through the negative effect on consumption of rising interest rates in response to demand for investment. Primary examples are preference shocks, investment-specific technology shocks, and credit shocks. In those models, however, an increase of investment raises household income, contradictory to fact (C2). What is most important: most of these standard models are silent about the negative relationships between short-term and long-term loans (fact (C3)) and *are not designed* to address many of the trend facts (T1)-(T5). We view our model's capability of reproducing the cyclical patterns of China's macroeconomy a further support of our mechanism for the aforementioned trend facts.

More generally, our theory contributes to the emerging literature on the role of financial-market imperfections in economic development (Buera and Shin, 2013; Moll, 2014). It is a long-standing puzzle from the neoclassical perspective that the investment rate in emerging economies increases over time, since the standard neoclassical model predicts that the investment rate falls along the transition and quickly converges to the steady state due to decreasing returns to capital. The typical explanation in this literature is that in an under-developed financial market, productive entrepreneurs, thanks to binding collateral constraints and thus high returns to capital, have a higher saving rate, while the unproductive but rich entrepreneurs are financially unconstrained and have a low saving rate. Aggregate investment rate increases during the transition, when productive entrepreneurs account for a larger share of wealth and income in the aggregate economy over time through resource reallocations.

Our model provides a different explanation for an increase in aggregate investment for China. In our model, a persistent increase in aggregate investment is mainly caused by an increasing share of revenues generated by heavy industries in aggregate output as those firms become larger with their expanded borrowing capacity. Such an explanation is consistent with the heavy industrialization experienced in China (facts (T4) and (T5)). We view our model mechanism as a useful complement to the larger literature.[6]

The rest of the paper is organized as follows. Section II reviews how we construct the annual and quarterly data relevant to this paper. Section III develops an econometric method to uncover the key facts of trend and cycle. Section IV delivers a robustness analysis of these facts using different empirical approaches. Section V provides China's institutional details relevant to this paper. In light of these facts we build a theoretical framework in Section VI and characterize the equilibrium in Section VII. In Section VIII we discuss the quantitative

[5]Similar positive comovements between aggregate investment, labor income, and consumption would happen if there is a negative shock to the interest rate subsidy facing by either heavy or light producers, as in SSZ.

[6]Our mechanism might potentially explain why the observed fast increase in the ratio of corporate debt to GDP tends to beget a financial crisis, as many East Asian countries experienced in 1997-1998, because unproductive large firms accumulate debts at the cost of loans allocated to productive firms. A pace of rising debts in large firms is a looming issue for China at the present time (see, for example, the article "Digging into China's debts" published in the 2 February 2015 issue of *Financial Times*).

results from our model, corroborate the model's key assumptions and mechanism with further empirical evidence, and conduct a number of counterfactual exercises to highlight the model's mechanism. We offer some concluding remarks in Section IX.

II. Construction of macroeconomic time series

In this section we discuss how we construct a standard set of annual and quarterly macroeconomic time series usable for this study as well as for future studies on China's macroeconomy.

II.1. **Brief literature review and data sources.** There are earlier works on the Chinese economy, some taking an econometric approach and others employing historical perspectives or narrative approaches (Chow, 2011; Lin, 2013; Fernald, Spiegel, and Swanson, 2013). He, Chong, and Shi (2009) apply standard business cycle models to the linearly detrended 1978-2006 annual data for conducting business accounting exercises and conclude that productivity best explains the behavior of China's macroeconomic variables. Chakraborty and Otsu (2012) apply a similar model to the linearly detrended 1990-2009 annual data and conclude that investment wedges are increasingly important for China's business cycles in the late 2000s. But the questions of what explains the dynamics of investment wedges and what are the key cyclical patterns for China's economy are left unanswered. Shi (2009) finds that capital deepening is the major driving force of high investment rates after 2000, consistent with our own evidence presented in Section V.3.

Most of extensive empirical studies on China, however, take a microeconomic perspective (Hsieh and Klenow, 2009; Brandt and Zhu, 2010; Yu and Zhu, 2013), mainly because there are a variety of survey data that either are publicly available or can be purchased. Annual Surveys of Rural and Urban Households conducted by China's National Bureau of Statistics (NBS) provide detailed information about income and expenditures of thousands of households from at least 1981 through the present time (Fang, Wailes, and Cramer, 1998). The survey data on manufacturing firms for studying firms' TFPs come from Annual Surveys of Industrial Enterprises from 1998 to 2007 conducted by the NBS, which is a census of all nonstate firms with more than 5 million RMB in revenue as well as all state-owned firms (Hsieh and Klenow, 2009; Lu, Forthcoming). The longitudinal data from China's Health and Nutrition Surveys provide the distribution of labor incomes over 4,400 households (26,000 individuals) over several years starting in 1989 (Yu and Zhu, 2013). There have been recent efforts in constructing more micro data about China. For example, China's Household Finance Survey, conducted by Southwestern University of Finance and Economics, is a survey on 8,438 households (29,324 individuals) in 2011 and 28,141 households (more than 99,000 individuals) in 2013, with a special focus on households' balance sheets and their demographic and labor-market characteristics (Gan, 2014).

Macroeconomic time series are based on two databases: the CEIC (China Economic Information Center, now belonging to Euromoney Institutional Investor Company) database—one of the most comprehensive macroeconomic data sources for China—and the WIND database (the data information system created by the Shanghai-based company called WIND Co. Ltd., the Chinese version of Bloomberg). The major sources of these two databases are the NBS and the People's Bank of China (PBC). For the NBS data, in particular, we consult *China Industrial Economy Statistical Yearbooks* (including 20 volumes) and *China Labor Statistical Yearbooks* (including 21 volumes).

II.2. **Construction.** This paper is not about the quality of publicly-available data sources in China. The pros and cons associated with such quality have been extensively discussed in, for example, Holz (2013), Fernald, Malkin, and Spiegel (2013), and Nakamura, Steinsson, and Liu (2014). Notwithstanding possible measurement errors of GDP as well as other macroeconomic variables, one should *not* abandon the series of GDP in favor of other less comprehensive series, no matter how "accurate" one would claim those alternatives are. After all, the series of GDP is what researchers and policy analysts would pay most attention to when they need to gauge China's aggregate activity.

The most urgent data problem, in our view, is the absence of a standard set of annual and quarterly macroeconomic time series comparable to those commonly used in the macroeconomic literature on Western economies. Our goal is to provide as accurate as possible the series of GDP and other key variables, make them publicly available, and use such a dataset as a starting point for promoting both improvement and transparency of China's core macroeconomic series usable for macroeconomic analysis.

Construction of the annual and quarterly time series poses an extremely challenging task because many key macroeconomic series are either unavailable or difficult to fetch. We utilize both annual and quarterly macroeconomic data that are available and interpolate or estimate those that are publicly unavailable.[7] Our construction method emphasizes the consistency across data frequencies and serves as a foundation for improvements in future research.[8]

The difficulty of constructing a standard set of time series lies in several dimensions. The NBS—probably the most authoritative source of macroeconomic data—reports only percent changes of certain key macroeconomic variables such as real GDP. Many variables, such as investment and consumption, do not even have quarterly data that are publicly available . The Yearbooks published by the NBS have only annual data by the expenditure approach (with annual revisions for the most recent data and benchmark revisions every five years for historical data—benchmark revisions are based on censuses conducted by the NBS). Even for the annual data, the breakdown of the nominal GDP by expenditure is incomplete. The Yearbooks publish the GDP subcomponents such as household consumption, government consumption, inventory changes, gross fixed capital formation (total fixed investment), and net exports. But other categories, such as investment in the state-owned sector and investment in the nonstate-owned sector, are unavailable. These categories are estimated using the detailed breakdown of fixed-asset investment across different data frequencies.

Using the valued-added approach, the NBS publishes some quarterly or monthly series whose definitions are different from the same series by expenditure. For the value-added approach, moreover, the subcomponents of GDP do not add up to the total value of GDP. Many series on quarterly frequency are not available for the early 1990s. For that period, we extrapolate these series. Few macroeconomic time series are seasonally adjusted by the NBS or the PBC. We seasonally adjust all quarterly time series.

The most challenging part of our task is to keep as much consistency of our constructed data as possible by cross-checking different approaches, different data sources, and different data frequencies. One revealing example is construction of the quarterly real GDP series.

[7]One could in principle interpolate quarterly data using a large state-space-form model for a mixture of frequencies of the data. (A similar argument could be made about seasonal adjustments.) Since computation for such an interpolation is both costly and model-dependent, we opt for the approach proposed by Leeper, Sims, and Zha (1996) and Bernanke, Gertler, and Watson (1997).

[8]For the detailed description of all the problems we have discovered and of how best to correct them and then construct the time series used in this paper, see Higgins and Zha (2015).

Based on the value-added approach, the NBS publishes year-over-year changes of real GDP in two forms: a year-to-date (YTD) change and a quarter-to-date (QTD) change. Let t be the first quarter of the base year. The YTD changes for the four quarters within the base year are $\frac{y_t}{y_{t-4}}$ (Q1), $\frac{y_{t+1}+Y_t}{y_{t-3}+y_{t-4}}$ (Q2), $\frac{y_{t+2}+y_{t+1}+Y_t}{y_{t-2}+y_{t-3}+y_{t-4}}$ (Q3), and $\frac{y_{t+3}+y_{t+2}+y_{t+1}+Y_t}{y_{t-1}+y_{t-2}+y_{t-3}+y_{t-4}}$ (Q4). The QTD changes for the same four quarters are $\frac{y_t}{y_{t-4}}$ (Q1), $\frac{y_{t+1}}{y_{t-3}}$ (Q2), $\frac{y_{t+2}}{y_{t-2}}$ (Q3), and $\frac{y_{t+3}}{y_{t-1}}$ (Q4). The published data on QTD changes are available from 1999Q4 on, while the data on YTD changes begin on 1991Q4. Using the time series of both YTD and QTD changes we are able to construct the level series of quarterly real GDP. There are discrepancies between the real GDP series based on the QTD-change data and the same series based on the YTD-change data. We infer from our numerous communications with the NBS that the discrepancies are likely due to human errors when calculating QTD and YTD changes. The real GDP series is so constructed that the difference between our implied QTD and YTD changes and NSB's reported QTD and YTD changes is minimized. The quarterly real GDP series is also constructed by the CEIC, the Haver Analytics, and the Federal Reserve Board. In comparison to these sources, the method proposed by Higgins and Zha (2015) keeps to the minimal the deviation of the annual real GDP series aggregated by the constructed quarterly real GDP series from the same annual series published by the NBS.

Another example is the monthly series of retail sales of consumer goods, which has been commonly used in the literature as a substitute for household consumption. Constructing the annual and quarterly series from this monthly series would be a mistake because the monthly series covers only large retail establishments with annual sales above 5 million RMB or with more than 60 employees at the end of the year.[9] The annual series published by the NBS, however, includes smaller retail establishments and thus has a broader and better coverage than the monthly series. A sensible approach is to use the annual series (CEIC ticker CHFB) to interpolate the quarterly series with the monthly series (CEIC ticker CHBA) as an interpolater.

Many series such as M2 and bank loans are published in two forms: year-to-date change and level itself. In our communication with the People's Bank of China, we have learned that when the two forms do not match, it is the year-to-date change that is supposed to be more accurate, especially in early history. We thus adjust the affected series accordingly. Cross-checking various data sources to ensure accuracy is part of our data construction process. For example, the monthly bank loan (outstanding) series from the CEIC exhibits wild month-to-month fluctuations (more than 10%) in certain years (e.g., the first 3 months in 1999). These unusually large fluctuations may be due to reporting errors as they are absent in the same series from the WIND Database (arguably more reliable for financial data). Detecting unreasonable outliers in the data is another important dimension of our construction. One prominent example is the extremely low value of fixed-asset investment in 1994Q4. If this reported low value were accurate, we would expect the growth rate of gross fixed capital formation in 1995 to be unusually strong as the 1995Q4 value would be unusually strong relative to the 1994Q4 value. But this is not the case. Growth of gross fixed capital formation in 1995 is more in line with growth of fixed-asset investment in capital construction and innovation than does growth of total fixed-asset investment. Accordingly we adjust the extreme value of total fixed-asset investment in 1994Q4. The quarterly series of fixed-asset investment is used as one of the interpolators for interpolating the quarterly series of gross fixed-asset capital formation (Higgins and Zha, 2015).

[9]See *China's Statistical Yearbook 2001* published by the NBS.

II.3. **Core time series.** We report several key variables that are relevant to this paper. Table 1 reports a long history of GDP by expenditure, household consumption, gross capital formation (gross investment including changes of inventories), government consumption, and net exports. Since 1980, the consumption rate (the ratio of household consumption to GDP) has been trending down and the investment rate (the ratio of gross capital formation to GDP) has been trending up, while the share of government consumption in GDP has been relatively stable. China has undergone many dramatic phases. Table 2 displays major economic reforms from December 1978 onward. Economic reforms towards the market economy were not introduced until December 1978; the period prior to 1979 belongs to Mao's premarket command economy and is not a subject of this paper. The phase between 1980 and the late 1990s is marked by a gradual transition to the implementation of privatization of state-owned firms. Due to the lack of detailed time series prior to 1995, the focus of this paper is on the period since the late 1990s.

As indicated in Table 1, net exports as percent of GDP has become important since the late 1990s. Detailed breakdowns of GDP, as well as other relevant time series, become available from 1995 on, as reported in Table 3 and 4. From these tables one can see that the rapid increase of fixed investment (gross fixed capital formation) is driven by fixed investment of privately owned firms, while fixed investment of state-owned firms as a share of GDP has trended down steadily. Net exports as a share of GDP reached its peak in 2007 before it gradually descended. Household investment as a share of GDP reached its peak in 2005 and has since hovered around that level. Changes of inventories as a share of GDP have fluctuated around a low value since 1997.

Figure 2 displays the annual growth rate of real GDP, the annual change of the GDP deflator (inflation), and consumption, gross fixed capital formation (total fixed investment), retail sales of consumer goods, and fixed-asset investment as percent of GDP. The two measures of real GDP, by expenditure and by value added, have similar growth rates over the time span since 1980. After the economic reforms were introduced in December of 1978, China's growth has been remarkable despite its considerable fluctuations accompanied by the large rise and fall of inflation in the early 1990s. Rapid growth is supported by the steady decline of household consumption and the steady rise of gross fixed capital formation as percent of GDP (the middle row of Figure 2). Consumption as a share of GDP is now below 40% while total fixed investment is at 45% of GDP, prompting the question of how sustainable China's high growth will be in the future. The commonly used measure of consumption, retail sales of consumer goods, shows the same low share of GDP (around 40% by 2012), although this measure includes consumption goods purchased by government and possibly durable goods purchased by small business owners. The other measure of total investment, fixed-asset investment, takes up nearly 80% of GDP by 2012 (the bottom row of Figure 2). This measure exaggerates investment because it includes the value of used equipment as well as the value of land that has increased drastically since 2000.[10] Nonetheless, fixed-asset investment is available monthly and its subcomponent "investment in capital construction and innovation" plays a key role in interpolation of quarterly gross fixed capital formation.

[10] See Xu (2010) for more details. The author was deputy director of the NBS when that article was published.

Figure 3 displays (a) year-over-year changes of the quarterly series: real GDP, the GDP deflator, M2, and total bank loans outstanding and (b) new long-term and short-term quarterly loans to non-financial firms as percent of GDP by expenditure. The first row of this figure corresponds to the annual data displayed in the first row of Figure 2. The quarterly series clearly shows that the largest increase of inflation occurred in the early 1990s. Fueled by rapid growth in M2 and bank leading, GDP deflator inflation reached over 20% in 1993Q4-1994Q3 and CPI inflation reached over 20% in 1994Q1-1995Q1. The PBC began to adopt very tight credit policy in 1995. In 1996, inflation was under control with GDP deflator down to 5.45% and CPI down to 6.88% by 1996Q4 while GDP growth fell from 17.80% in 1993Q2 to 9.22% in 1996Q4. For fear of drastically slowing down the economy caused by rising counter-party risks ("Sanjiao Zhai" in Chinese), the PBC cut interest rates twice in May and August of 1996. While new long-term loans were held steady, short-term loans shot up in 1996 and in the first quarter of 1997 to achieve a soft landing ("Ruan Zhaolu" in Chinese). This increase proved to be short-lived while the decentralization of the banking system was underway. In subsequent years, whenever medium and long term loans increased sharply, short-term loans tended to decline. Another sharp spike of short-term loans (most of which was in the form of bill financing) took place in 2009Q1 right after the 2008 financial crisis. This sharp rise, however, lasted for only one quarter and was followed by sharp reversals for the rest of the year. By contrast, a large increase in medium and long term loans lasted for two years after 2008 as part of the government's two-year fiscal stimulus plan. Clearly, long-term and short-term loans tend *not* to move together.

III. Econometric evidence

In this section we uncover the key facts about trends and cycles. Cyclical facts are as important as trend facts because they help discipline the model with stochastic shocks and serve as an identification mechanism to distinguish between theoretical models. To be sure, separating the cyclical behavior from the trend behavior is inherently an daunting task, especially when the time series are relatively short. We do not view it as an option to abandon this enterprise. Rather, we take a two-pronged approach to safeguard our findings. First, we follow King, Plosser, Stock, and Watson (1991) and develop a Bayesian reduced-rank time-series method to separate trend and cycle components. The trend component is consistent with the trend definition in our theoretical model. We avail ourselves of quarterly data that range from 1997Q1 to 2013Q4,[11] a sample length comparable to many business-cycle empirical studies using the U.S. data only after the early 1990s to concentrate on the recent Great Moderation period discussed in Stock and Watson (2003).

Second, we use other empirical methods outlined in Section IV to build robustness of the findings uncovered in this section. We believe that the method employed in this section is methodologically superior to those used in Section IV because we treat all the relevant variables in one system. Nonetheless, other empirical methods reassure the reader that our robust findings do not hinge on one particular econometric method.

Figures 2 and 3 in Section II together present a broad perspective of trends and cycles for the Chinese economy. These charts exhibit changes in both volatility and trend. These

[11] *China's Statistical Yearbooks* have not published the subcomponents of GDP by expenditure for 2014. Some quarterly series in 2013 are extrapolated, and the quality of extrapolation is high. See Higgins and Zha (2015) for details.

changes could be potentially caused by a number of economic reforms undergone by the Chinese government. We use the major reform dates displayed in Table 2 to serve as candidate switching points for either volatility or trend changes. To take account of these date points, we use Sims, Waggoner, and Zha (2008)'s regime-switching vector autoregression (VAR) methodology that allows discrete (deterministic) switches in both volatility and trend.

Christiano, Eichenbaum, and Evans (1996, 1999, 2005) argue forcibly that the VAR evidence is the key to disciplining a credible theoretical model. To this end we estimate a large set of models with various combinations of switching dates reported in Table 2 and perform a thorough model comparison. We find strong evidence for discrete switches in volatility but not for any discrete switches in trend. But the steady decline of consumption and the steady rise of investment shown in Figure 2 indicate that our VAR model must take account of a possible continuous drift in trend. The model presented below is designed for this purpose.

III.1. **Econometric framework.** Let Y_t be an $n \times 1$ vector of (level) variables, p the lag length, and T the sample size. The multivariate dynamic model has the following primitive form:

$$A_0 y_t = a_t + \sum_{\ell=1}^{p} A_\ell y_{t-\ell} + \mathcal{D}_{s_t} \varepsilon_t, \tag{1}$$

where s_t, taking a discrete value, is a composite index for regime switches in volatility, $\mathcal{D}_{s_t}$ is an $n \times n$ diagonal matrix, and ε_t is an $n \times 1$ vector of independent shocks with the standard normal distribution. By "composite" we mean that the regime-switching index may encode distinct Markov processes for different parameters (Sims and Zha, 2006; Sims, Waggoner, and Zha, 2008) or deterministic discrete jumps according to different dates displayed in Table 2.

The previous literature on Markov-switching VARs, such as Sims, Waggoner, and Zha (2008), focuses on business cycles around the trend that is constant across time. Chinese macroeconomic data have a distinctively different characteristic: cyclical variations coexist with trend drifts as shown in Figure 2. The time varying intercept vector a_t, monotone and bounded in t for each element, captures a continuous trend drift. In contrast to the HP filter that deals with each variable in isolation, our methodology is designed to decompose the data into cycles and trends in one multivariate framework. Specifically, unit roots and cointegration are imposed on system (1). These restrictions are made explicit in the error-correction representation as follows

$$F_0 \Delta y_t = c_t + \mathcal{R} y_{t-1} + \sum_{\ell=1}^{p-1} F_\ell \Delta y_{t-\ell} + \mathcal{D}_{s_t} \varepsilon_t, \tag{2}$$

where $\mathcal{R}$ is an $n \times n$ matrix of reduced rank such that $rank(\mathcal{R}) = r$ with $r < n$, implying that there are $n-r$ unit roots and at most r cointegration vectors (i.e., the number of cointegration relationships and the number of stationary relationships sum to r). Long-run relationships are imposed in, for example, Hansen, Heaton, and Li (2008) who measure a long-run risk for the valuation of cash flows exposed to fluctuations in macroeconomic growth. The Bayesian framework developed here helps find the posterior peak by simulating Monte Carlo Markov Chain (MCMC) draws of model parameters.

The relation between (1) and (2) is

$$A_0 = F_0,\ A_1 = \mathcal{R} + F_1 + F_0,\ A_\ell = F_\ell - F_{\ell-1} (\ell = 2, \ldots, p-1),\ A_p = -F_{p-1},\ c_t = a_t.$$

We consider the following three functional forms of $c_{t,j}$, the j^{th} component of c_t, in the descending order of importance.

- We specify the 4-parameter process as
$$c_{t,j} = c_j + (d_j - c_j)(\alpha_j(t - \tau_j) + 1)e^{-\alpha_j(t-\tau_j)}$$
where $\alpha_j > 0$ for $j = 1, \ldots, n$. c_j is the limiting value of $c_{t,j}$ as t increases and d_j is the value of $c_{t,j}$ when $t = \tau_j$. Furthermore, if $d_j < c_j$, then d_j is the minimum value of $c_{t,j}$ and if $d_j > c_j$, then d_j is the maximum value of $c_{t,j}$. The parameter α_j controls how quickly $c_{t,j}$ converges to its limiting value. Our setup is flexible enough for researchers to entertain further restrictions of the form $\alpha_j = \alpha$, $c_j = c$, $d_j = d$, or $\tau_j = \tau$ for all or some of j's.
- $c_t = c_{s_t}$, where the discrete process s_t is either Markovian or deterministic.
- The following specification is an alternative that is not used for this paper:
$$\underset{n\times 1}{c_t} = \begin{bmatrix} \frac{c_1}{1+\beta_1\alpha_1^t}, & \ldots, & \frac{c_n}{1+\beta_n\alpha_n^t} \end{bmatrix}',$$
where $0 \leq \alpha_j < 1$ for all $i = 1, \ldots, n$. One could consider the restriction $\alpha_j = \alpha$ for all $i = 1, \ldots, n$ or the restriction $\beta_j = \beta$ for all $i = 1, \ldots, n$ or both.

The reduced-form representation of (1) is
$$y_t = b_{s_t} + \sum_{\ell=1}^{p} B_\ell y_{t-\ell} + \mathcal{M}_{s_t}\varepsilon_t, \tag{3}$$
where $b_{s_t} = A_0^{-1}a_{s_t}$, $B_\ell = A_0^{-1}A_\ell$, and $\mathcal{M}_{s_t} = A_0^{-1}\mathcal{D}_{s_t}$. Let $\Sigma_{s_t} = \mathcal{M}_{s_t}\mathcal{M}'_{s_t}$ be the regime-switching covariance matrix.

III.2. **Design of the prior.** Since the representation (2) is expressed in log difference and of reduced rank, it embodies the prior of Sims and Zha (1998) (with the implication that the Sims and Zha prior become degenerate along the dimension of reduced rank). Therefore we should begin with the prior directly on F_ℓ ($\ell = 0, \ldots, p-1$), c_j, d_j, τ_j, α_j, and $\mathcal{D}_{s_t}$. The only difficult part is to have a prior that maintains the reduced rank r for $\mathcal{R}$.

Prior on F_ℓ ($\ell = 0, \ldots, p-1$), c_j, d_j, and τ_j. The prior is Gaussian on each of those elements centered at zero. For F_ℓ ($\ell = 1, \ldots, p-1$), there is a lag decay factor such that the prior becomes tighter as the lag lengthens.

Prior on α_j and $\mathcal{D}_{s_t}$. The prior on α_j is of Gamma. The prior on each of the diagonal elements of $\mathcal{D}_{s_t}$ is of inverse Gamma.

Prior on $\mathcal{R}$. Because $\mathcal{R}$ is a reduced-rank matrix, the usual decomposition is $\mathcal{R} = \alpha\beta'$, where both α and β are $n \times r$ matrices of rank r. But a more effective decomposition is the singular value decomposition:
$$\mathcal{R} = \mathcal{U}\mathcal{D}\mathcal{V}',$$
where both $\mathcal{U}$ and $\mathcal{V}$ are $n \times r$ matrices with orthonormal columns and $\mathcal{D}$ is an $r \times r$ diagonal matrix. Let the prior on both $\mathcal{U}$ and on $\mathcal{V}$ be the uniform distribution and the prior on the diagonal elements of $\mathcal{D}$ be Gaussian.

The set of all $n \times r$ matrices with orthonormal columns is the Stiefel manifold, which is an $(nr - \frac{r(r+1)}{2})$-manifold in $\mathbb{R}^{nr}$. Instead of working directly with the elements of the Stiefel manifold, we work with arbitrary $n \times r$ matrices $\tilde{\mathcal{U}}$ and $\tilde{\mathcal{V}}$ and map $\tilde{\mathcal{U}}$ and $\tilde{\mathcal{V}}$ to $\mathcal{U}$ and $\mathcal{V}$ using the QR decomposition. In particular, we map $\tilde{\mathcal{U}}$ to $\mathcal{U}$ and $\tilde{\mathcal{V}}$ to $\mathcal{V}$ via the QR decompositions $\tilde{\mathcal{U}} = \mathcal{U}\mathcal{R}_{\mathcal{U}}$ and $\tilde{\mathcal{V}} = \mathcal{V}\mathcal{R}_{\mathcal{V}}$ with the positive diagonals of $\mathcal{R}_{\mathcal{U}}$ and $\mathcal{R}_{\mathcal{V}}$. If the prior on each column of $\tilde{\mathcal{U}}$ and $\tilde{\mathcal{V}}$ is any spherical distribution centered at the origin, then the induced prior on $\mathcal{U}$ and $\mathcal{V}$ is uniform as desired. Having the free parameters $\tilde{\mathcal{U}}$, $\tilde{\mathcal{V}}$, and

$\mathcal{D}$ defined over Euclidean space, as opposed to a complicated submanifold, makes numerical optimization tractable. While this parameterization is not unique in the sense that different values of $\tilde{\mathcal{U}}$, $\tilde{\mathcal{V}}$, and $\mathcal{D}$ can produce the same $\mathcal{R}$, it is inconsequential because we do not give $\tilde{\mathcal{U}}$, $\tilde{\mathcal{V}}$, and $\mathcal{D}$ any economic interpretation.

We propose a prior on each column of $\tilde{\mathcal{U}}$ and $\tilde{\mathcal{V}}$ to be

$$\frac{\Gamma(\frac{n}{2})}{\pi^{\frac{n}{2}} 2^{\frac{n+1}{2}} \Gamma(\frac{n+1}{2})} \rho e^{-\frac{\rho^2}{2}},$$

where ρ is the norm of a column of $\tilde{\mathcal{U}}$ or $\tilde{\mathcal{V}}$. This prior is spherical and centered at the origin, and thus induces the uniform prior distributions for $\mathcal{U}$ and $\mathcal{V}$. Moreover it is straightforward to sample independently from this distribution.

Our prior has some similarity to the prior specified by Villani (2005). Working directly with the reduced-form parameters, Villani (2005) uses the $F_0^{-1}\mathcal{R} = \alpha\beta'$ decomposition with normalization such that the upper $r \times r$ block of β is the identity matrix. The prior on β is chosen so that the prior on the Grassmannian manifold is uniform. The Grassmannian manifold is the space of all k-dimensional linear subspaces in $\mathbb{R}^n$ and the columns of β can be interpreted as the basis for an element in the Grassmannian manifold. This is analogous to our use of the uniform distribution on the Stiefel manifold. Villani (2005) does not work directly with α but instead uses

$$\tilde{\alpha} = \alpha(\beta'\beta)^{1/2}.$$

It follows that the prior on the i^{th} column of $\tilde{\alpha}$, conditional on Σ_{s_t}, is normally distributed with mean zero and variance matrix $v\Sigma_{s_t}$, where v is a positive hyperparameter.

Since we work with the primitive error-correction form for the purpose of taking into account time-varying shock variances, our prior is on $\mathcal{R}$ directly, not on $F_0^{-1}\mathcal{R}$. All the reduced-form parameters are derived, through the relations between (2) and (3), as

$$B_1 = F_0^{-1}\left(\mathcal{R} + F_1 + F_0\right), \ B_\ell = F_0^{-1}\left(F_\ell - F_{\ell-1}\right)(\ell = 2, \ldots, p-1), \ B_p = -F_0^{-1}F_{p-1},$$
$$b_{s_t} = F_0^{-1}c_{s_t}, \ \mathcal{M}_{s_t} = F_0^{-1}\mathcal{D}_{s_t}.$$

III.3. **Decomposing trends and cycles.** We first estimate system (2) and then convert it to system (3). We express system (3) in companion form:

$$\begin{bmatrix} y_t \\ y_{t-1} \\ \vdots \\ y_{t-p+1} \end{bmatrix} = \begin{bmatrix} b_{s_t} \\ 0 \\ \vdots \\ 0 \end{bmatrix} + \underbrace{\begin{bmatrix} B_1 & \ldots & B_{p-1} & B_p \\ I_n & \ldots & 0_n & n_n \\ \vdots & & & \\ 0_n & \ldots & I_n & 0_n \end{bmatrix}}_{B} \begin{bmatrix} y_{t-1} \\ y_{t-2} \\ \vdots \\ y_{t-p} \end{bmatrix} + \begin{bmatrix} \mathcal{M}_{s_t} \\ 0 \\ \vdots \\ 0 \end{bmatrix} \varepsilon_t, \tag{4}$$

where the companion matrix B is of $np \times np$ dimension, I_n is the identity matrix of dimension n, and 0_n is the $n \times n$ matrix of zeros. There are $m_2 = n - r$ unit roots and let $m_1 = np - m_2$. We follow the approach of King, Plosser, Stock, and Watson (1991) by maintaining their assumption that the innovations to permanent shocks are independent of those to transitory shocks. This assumption enables one to obtain a unique block of permanent shocks as well as a unique block of transitory shocks.[12]

[12]Shocks within each block are not uniquely determined.

To obtain these two blocks of shocks, we first perform a real Schur decomposition of B such that

$$B = \begin{bmatrix} \underset{np\times m_1}{W_1} & \underset{np\times m_2}{W_2} \end{bmatrix} \begin{bmatrix} \mathcal{T}_{11} & \mathcal{T}_{12} \\ 0 & \underset{m_2\times m_2}{\mathcal{T}_{22}} \end{bmatrix} \begin{bmatrix} W_1' & W_2' \end{bmatrix},$$

where $\begin{bmatrix} W_1 & W_2 \end{bmatrix}$ is an orthogonal matrix and the diagonal elements of $\mathcal{T}_{22}$ are equal to one.

Our first task is to find the largest column space in which transitory shocks lie. That is, we need to find an $np \times \ell_1$ matrix, V_{1,s_t}, such that the column space of

$$\begin{bmatrix} \mathcal{M}_{s_t} \\ 0 \\ \vdots \\ 0 \end{bmatrix} V_{1,s_t} \tag{5}$$

is contained in the column space of W_1, and V_{1,s_t} is of full column rank and has the maximal number of columns. Hence, the transitory shocks lie in the column space represented by (5). This column space must be equal to the intersection of the column space of W_1 and the column space of $\begin{bmatrix} \mathcal{M}_{s_t}', 0, \ldots, 0 \end{bmatrix}'$. In other words, there exists an $m_1 \times \ell_1$ matrix of real values, $\mathcal{A}$, such that

$$\begin{bmatrix} \mathcal{M}_{s_t} \\ 0 \\ \vdots \\ 0 \end{bmatrix} V_{1,s_t} = W_1 \mathcal{A}.$$

Since $W_1 \perp W_2$, we have

$$W_2' \begin{bmatrix} \mathcal{M}_{s_t} \\ 0 \\ \vdots \\ 0 \end{bmatrix} V_{1,s_t} = 0.$$

It follows that

$$V_{1,s_t} = \text{Null}\left(W_2' \begin{bmatrix} \mathcal{M}_{s_t} \\ 0 \\ \vdots \\ 0 \end{bmatrix} \right)$$

and $\ell_1 \geq n - m_1$.

Let

$$V_{1,s_t} = Q_{s_t} R_{s_t} = \begin{bmatrix} \underset{n\times \ell_1}{Q_{1,s_t}} & \underset{n\times \ell_2}{Q_{2,s_t}} \end{bmatrix} R_{s_t}$$

be the QR decomposition of V_{1,s_t}. Since $\ell_1 \geq n - m_1$, it must be that $\ell_2 = n - \ell_1 \leq m_2$. The impact matrix is

$$\mathcal{M}_{s_t} \begin{bmatrix} Q_{1,s_t} & Q_{2,s_t} \end{bmatrix}$$

with the first ℓ_1 columns corresponding to contemporaneous responses to the transitory shocks and the second ℓ_2 columns corresponding to those to the permanent shocks.

If we have a different identification represented by $\tilde{\mathcal{M}}_{s_t}$, we can repeat the same procedure to obtain the impact matrix as

$$\tilde{\mathcal{M}}_{s_t} = \begin{bmatrix} \tilde{Q}_{1,s_t} & \tilde{Q}_{2,s_t} \end{bmatrix}$$

with $\tilde{\mathcal{M}}_{s_t} \tilde{Q}_{i,s_t} = \mathcal{M}_{s_t} Q_{i,s_t} P_{i,s_t}$ for $i = 1, 2$, where $[P_{1,s_t} \; P_{2,s_t}]$ is an orthogonal matrix.

III.4. **Results.** The sample begins with 1997Q1 because this is the time when China had begun to swift its strategic priority to development of heavy industries as marked in Table 2 (see Section V.2 for a detailed discussion).

We estimate a number of 6-variable time-varying quarterly BVAR models with 5 lags and the sample 1997Q1-2013Q4. Out of these variables, four variables are log values of real household consumption, real total business investment, real GDP, and real labor income (all are deflated by the implicit GDP deflator); two variables are the ratio of new medium&long-term bank loans to GDP and the ratio of new short-term bank loans and bill financing to GDP. All the variables are seasonally-adjusted. The 5 lags are used to eliminate any residual of possible seasonality. For our benchmark BVAR, the rank of the matrix $\mathcal{R}$ is set to 3, implying one possible cointegration relationship and two stationary variables. We find 2 stochastic regimes for the shock variances. Finding the posterior mode proves to be a challenging task. The estimation procedure follows the DSMH method proposed by Waggoner, Wu, and Zha (2015). First, we use the DSMH method to obtain the sufficient sample of BVAR coefficients. From these posterior draws, we randomly select 100 starting points independently and use the standard optimization routine to find local peaks. From the 100 local peaks, we select the hight peak as our posterior mode.

We use the model structure and the estimated parameter values to back out a smoothed sequence of shocks, ε_t. Out of the six shocks at each time t, three of them are permanent and the other three are stationary.[13] Conditional on the values of the six variables for the initial 5 periods, the trend component of each variable is computed recursively by making the predictions from the model by feeding into the model the smoothed permanent shocks at each time t. The stationary component, by construction, is the difference between the data and the trend component.

Across different BVARs, we obtain robust results about cyclical patterns. For the benchmark BVAR, the estimated correlation between stationary components of investment and consumption (the cyclical part) is -0.05, the estimated correlation between investment and labor income is -0.23, and the estimated correlation between short-term loans and long-term loans is -0.51. The results are robust across various BVARs. For example, with the BVAR with all coefficients (including shock variances) being set to be constant across time, the estimated correlation is 0.18 between investment and consumption and -0.44 between investment and labor income; when the BVAR with time-varying intercept terms and regime-switching volatility, the estimated correlation is -0.50 between investment and consumption and 0.14 between investment and labor income. If we set $\text{rank}(\mathcal{R}) = 2$ (i.e., no cointegration is allowed) and allow for regime-switching volatility, the estimated correlation is 0.01 between investment and consumption and -0.33 between investment and labor income.

The government's stimulation of investment after the 2008 financial crisis shows up as a rapid run-up of the investment rate in 2009 in the trend movement; the stimulation has a long-last impact on sustaining the high investment rate even after the government ceased long-term credit expansions in 2011 (Figure 1). The high-volatility regime, characterized by the smoothed posterior probability as displayed in the bottom row of Figure 4, reflects the wild fluctuation of banks loans shown in Figure 3. After separating these short-lived high volatilities from the general trend, the trend pattern is equally striking with the consumption-to-GDP ratio steadily declining and the investment-to-GDP ratio steadily rising. Both the

[13]While the posterior mode is well estimated with our method, we still have not managed to obtain a convergence of MCMC posterior draws to provide an informative posterior distribution.

trend and cycle patterns uncovered here are robust findings not only from different BVAR models but also from other empirical studies presented in the next section.

IV. Robust empirical evidence

In this section we verify robustness of the key facts uncovered in Section III. Given how stark these findings are, it is essential to verify their robustness by other means. We pursue this task in two ways. First, we cross-verify the previous findings using the annual data. Second, we apply the HP filter to the relevant variables to verify the cyclical patterns previously obtained.

The trend patterns, reported in Figure 1, are confirmed by the raw annual data displayed in Figure 5. Since the late 1990s, household consumption as a share of GDP has steadily declined from 45% in 1997 to 35% in 2010 (the top left chart), while aggregate investment (total business investment) has risen from 26% in 2000 to 36% in 2010 (the top right chart).[14] This striking trend pattern is robust when we use the narrow definition of output as the sum of household consumption and business investment (the two charts at the bottom). More telling is the declining pattern of both household disposable personal income and labor income as a share of GDP since 1997.[15]

With the annual data we are able to study the transition with the longer period that covers the early years after the introduction of economic reforms in December 1978. The left column of Figure 6 reports the time series of the moving 10-year-window correlations of annual growth rates between household consumption (C) and gross fixed capital formation (GFCF). There is a clear structural break after the early 1990s when the correlations have declined to be extremely low or even negative. Such negative correlations after the mid 1990s are more pronounced for the HP-filtered series, reported in the right column of Figure 6. Note that for annual data we follow the analytical formula of Ravn and Uhlig (2002) by setting the smoothing parameter value of the HP filter to 6.25 so that this value is most compatible to the smoothing parameter value (1600) used for quarterly data.

The cyclical pattern uncovered in Section III supports a similar divergence between consumption on the one hand and investment and income on the other. This pattern is further confirmed by various 10-year moving-window correlations of the HP-filtered annual data as reported in Figure 7. First, the correlation between business investment and household consumption is more negative than not across time with the 10-year moving window (the first row of Figure 7). Second, the correlation of various household incomes with aggregate investment has been either very low or negative (the second row of Figure 7). The correlations among various HP-filtered quarterly time series present a similar pattern in which investment has either low or negative correlation with consumption as well as with labor income (Table 5).

Household disposable income is the sum of household before-tax income and net transfers. In China, taxes and transfers play a minor role in explaining the correlation between investment and disposable income because the correlation between investment and household before-tax income shows a similar pattern (the second row of Figure 7). For Western

[14]Total business investment is gross fixed capital formation bar household investment.

[15]The series of "labor income" is obtained from the *Flows of Funds*. Alternatively one could construct labor share of income by summing up "compensation of labor" across provinces and dividing by sum of "GDP by income" across provinces, which has also declined since the late 1990s. There are, however, serious data problems associated with this alternative measure because of large discrepancies between the national value and the sum of provincial values. For discussions of other data problems, consult Bai and Qian (2009).

economies, household disposable income is different from household labor income because of interest payments and capital gains (household disposable income is the sum of labor income, interest payments, realized capital gains, and net transfers). In China, however, labor income is the main driving force of household disposable income. This fact explains the similar pattern of the correlation of investment with labor income and with disposable income (the second row of Figure 7).

The low or negative correlation between investment and labor income, alongside the negative correlation between investment and consumption, poses a challenging task for macroeconomic modeling. Standard macroeconomic models for explaining the negative correlation of business investment and household consumption rely on intertemporal substitution of household consumption. Except for an aggregate TFP shock, which moves investment and consumption in the same direction, other shocks (such as preference, marginal efficiency of investment, and financial constraint) may be able to generate a negative comovement of investment and consumption, but they also generate a positive comovement between investment and labor income. For the Chinese economy, the government's policy for stimulating investment is typically through credit expansions, as shown in Figure 3. In the one-sector model à la Kiyotaki and Moore (1997), for example, a credit expansion triggers demand for investment and increases the interest rate. As a result, consumption in the current period declines. An increase in investment, however, tends to increase household disposable income as well as savings. Thus one should expect *not just positive but also strong* correlation between investment and household income. This is inconsistent with the fact presented in Figure 7. The discussion in Section VIII.3 at the end of this paper provides examples of how standard models cannot account for the key Chinese facts.

V. China in transition

Table 2 lists a number of major economic reforms. Out of these reforms we focus on the two most important dimensions of the transition that are relevant to both our empirical findings and our subsequent macroeconomic theory. One dimension, state-owned versus privately-owned firms, has been extensively studied in the literature on China. The other dimension, the heavy versus light sectors, is a new and enlightening angle that we argue is most helpful to an understanding of trends and cycles in China's aggregate economy.

V.1. **SOEs vs. POEs.** The Chinese economy has undergone two kinds of reforms in SOEs simultaneously, the so-called "grasp the large and let go of the small.". One transition is privatization that allows many SOEs previously engaged in unproductive labor-intensive industries to be privatized. This reform is the focus of the SSZ work. The other reform is a gradual concentration of SOEs in large industries, such as petroleum, commodities, electricity, water, and gas. We use disaggregated data on two-digit industries to quantify this reform. Table 6 lists the 39 two-digit industries. For each industry we obtain the value added, gross output, fixed investment, the capital stock, employment, and the share of SOEs from the NBS data source. We then compute the capital-labor ratio for each industry to measure the capital intensity. We also compute the weight of each industry by value added or by gross output if the value added is unavailable. Table 7 reports the weight and the rank by capital intensity for each of the all 39 industries for 1999, 2006, and 2011.[16] Those years give us an informative picture of how the SOE reforms took place from 1999 to 2011; and

[16]Since the sixth industry "Mining of Other Ores" receives almost zero weight in value added or gross output, there are effectively 38 active industries.

Tables 6 and 7 are used in conjunction with Figures 8, 9, and 10 to add understanding of the outcome of SOE reforms. In all these three figures, the left column of each figure displays the SOE share for each industry and the bars are sorted from the most capital-intensive industry (the highest capital-labor ratio) on the top to the least capital-intensive industry (the lowest capital-labor ratio) at the bottom. The right column of each figure plots the SOE share against the capital intensity for each industry.

The rank of industries by capital intensity changes over time (Table 7), but this change is not only gradual but also minimal. Indeed, the rank correlations between 1999, 2006, and 2011 are all above 0.93. The SOE share, however, has undergone a significant change. In 1999 many SOEs engaged in labor-intensive industries; in 2006 fewer SOEs engaged in those industries; and in 2011 even fewer SOEs engaged. Take "Manufacture of General Purpose Machinery" (the industry identifier 29 in Table 6) as an example.[17] In 1999 the SOE share was over 60% (the bar chart in Figure 8); in 2006 the SOE share dropped to 25% (the bar chart in Figure 9); and in 2011 the SOE share dropped even further to less than 20% (the bar chart in Figure 10). This trend is confirmed by the aggregate data displayed in Figure 11. The figure shows that the SOE share of total business investment has declined while the POE share has increased.

This pattern of change in SOE reforms is consistent with the fact that the SOE sector has become more productive over time by shedding unproductive small firms through privatization. As documented by Hsieh and Song (2015), the gap between the average TFP in *privatized* firms (i.e., state-owned in 1998 and privately owned in 2007) and the average TFP in surviving privately owned firms (i.e., privately owned in 1998 and in 2007) had narrowed from 1998 to 2007. For the same period, the TFP gap between surviving SOEs (i.e., state-owned in 1998 and in 2007) or newly entered SOEs and surviving privately owned firms had also narrowed. Of course, the definition of what constitutes a SOE is crucial. Hsieh and Song (2015) provide a careful analysis and argue that simply using the firm's legal registration as state owned is inaccurate. They propose to "define a firm as state-owned when the share of registered capital held directly by the state exceeds or equals 50 percent or when the state is reported as the controlling shareholder." Even within the SOE sector, there is a degree to which a firm is controlled by the state, depending on the actual share of capital owned by the sate. Nonetheless, Hsieh and Song (2015) find that the SOE share of total revenue, calculated according to their definition, is close to the official aggregate data in the *China's Statistical Yearbooks* from 1998 to 2007 published by the NBS.[18] Different SOE definitions notwithstanding, a robust finding is that privatization appears to be a critical factor in driving TFP growth of the SOE sector. As the SOE sector continues to reform[19], this reallocation from SOEs to POEs through privatization will persist. Despite Hsieh and

[17]Our evidence indicates that this industry is labor intensive. In Table 11, we classify 17 broad sectors according to their respective labor income shares. According to that classification, the sector "Machinery Equipment" belongs to the labor-intensive sector.

[18]The SOE definition we use for Figure 11 is consistent with the NBS's official definition except a fraction of limited liability companies (LLCs) excluding "state sole proprietors" should have been classified as SOE according to the *China's Statistical Yearbooks*'s definition of "State Owned & Holding" (Higgins and Zha, 2015). Note that LLCs excluding "state sole proprietors" in the series of fixed-asset investment are not further partitioned. For the disaggregate data on the two-digit industries, we use the NBS's official definition of SOE.

[19]For informative reading, see the recent article "State-owned enterprises: fixing China Inc" in the 30 August 2014 issue of the *Economist*.

Song (2015)'s finding that the average TFP of surviving SOEs had grown faster than the average TFP of surviving POEs, such reallocation gain is largely responsible for the continuing decline both in the SOE share of investment (Figure 11) and in the state-owned share of industrial revenues as reported in the *China's Statistical Yearbooks* (Figure 12).

V.2. **Heavy vs. light sectors.** Although discussions around the role of SOEs have dominated the literature on China's economy, the SOE-POE classification does not naturally lead up to an explanation of the steady rise of investment as a share of total output (Fact T1). This point is elaborated further in the context of our theoretical model in Section VI.

We place instead an emphasis on studying two distinct sectors: the heavy and light sectors. This shift of focus marks a major departure of our approach from the standard approach in the literature on China and affords a fruitful and tractable way of analyzing the Chinese aggregate economy; and it helps avoid the seemingly contradicting fact that the SOE investment share has declined over time but at the same time the SOE TFP has grown faster than the POE counterpart.

The gradual concentration of large firms or industries in the heavy sector has taken place since the late 1990s. In March 1996, the Eighth National People's Congress passed the *National Economic and Social Development* and *Ninth Five-Year Program: Vision and Goals for 2010*, prepared by the State Council (see the bold, italic line in Table 2). This program was the first medium and long term plan made after China switched to the market economy; it set up the policy goal to adjust the industrial structure for the next 15 years. Specifically, it urged continuation of strengthening the infrastructure (transportation, telecommunication—information transmission) and basic industries (electricity, coal, petroleum process, natural gas, smelting and pressing of ferrous and non-ferrous metals, chemical industry), boosting pillar industries (electrical machinery, petroleum process, automobile, real estate), and invigorating and actively developing the tertiary industry. Most of these industries belong to the heavy sector as illustrated in Section VIII.2.3. Indeed, the revenue ratio of the heavy sector to the light sector began to increase in 1996.

Our own analysis of disaggregate data reinforces this finding. On the right column of each figure from Figure 8 to 10, we mark the top-10 value-weighted industries with dark circles and fit the quadratic curve through these dark circles. In 1999 four of those industries were capital intensive (i.e., the capital-labor ratio is above 20, Figure 8); by 2011 not only more of the top-10 industries became capital intensive but also the ratio of capital to labor increased for these large industries (Figure 10). Large industries became more and more capital intensive during this transition.

Indeed, the reallocation of resources between heavy and light sectors has a profound effect on the upward trend of the overall investment rate. The NBS provides the time series of gross output, value added, and investment for the heavy and light sectors within the broad secondary industry bar the construction sector (we compute investment as the first difference of the gross value of fixed assets). The reallocation (between-sector) effect, relative to the sector-specific (within-sector) effect, on the overall investment rate is calculated as

$$\frac{\bar{i}^l P_t^l Y_t^l + \bar{i}^k P_t^k Y_t^k}{P_t^l Y_t^l + P_t^k Y_t^k} - \frac{i_t^l \overline{P^l Y^l} + i_t^k \overline{P^k Y^k}}{\overline{P^l Y^l} + \overline{P^k Y^k}},$$

where $P_t^l Y_t^l$ is value added or gross output for the light sector, $P_t^k Y_t^k$ for the heavy sector, i_t^l is the investment rate for the light sector, and i_t^k for the heavy industry. The bar line over each of the variables indicates the sample mean. The series for value added ends in 2007 and there is no published data from the NBS for later years. The relative reallocation effect between 1997 and 2007 is an increase of 16.8 percentage points. For the series of gross output, the relative reallocation effect between 1997 and 2011 is an increase of 11.1 percentage points.[20] These findings provide solid evidence about the importance of a between-sector contribution to the rise of the investment rate discussed in Sections III.4 and IV and displayed in Figures 1 and 5. In Section VIII.2.4 we discuss further the evolution of heavy vs. light sectors in connection with how each sector is financed.

Firms in the heavy sector are a mix of SOEs and POEs (especially large POEs). According to the 2012 report "Survey of Chinese Top 500 Private Enterprises" published by China's National Federation of Economic Ministry, there has been a trend for more large private firms (whose sales are all above 500 million RMB) to engage in heavy industries, partly because these activities are supported by the state. For instance, in 2007 there were only 36 large firms in the ferrous metal and processing industries; by 2011 there were 65 large firms; in 2007 there only 6 large firms in the industries of petroleum processing, coking, and nuclear fuel processing; by 2011 the number more than doubled. Indeed, out of 345 largest private firms in 2010, 64 were in the ferrous metal and processing industries (constituting the single largest fraction of all these large firms) while 54 were in the wholesale and retail trade industries.

As China's economic reforms deepen, the government no longer adheres to the practice of favoring SOEs and bias against POEs. As long as firms help boost growth of the local economy and create tax revenues, the local government would support them. Medium and long term bank loans treat large firms symmetrically no matter whether they are SOEs or POEs; labor-intensive firms, most of which tending to be small, have a difficult time to obtain loans, especially in the last ten years. One of the main reasons for heavy-industry firms to gain easy access to bank loans is the firms' ability to use their fixed assets for collateralizing the loans. This feature is built in our theoretical model.

Evidence shows that the labor-intensive sector is more productive than the capital-intensive sector. Using the dataset of manufacturing firms by bridging the Annual Surveys of Industrial Enterprises and the Database for Chinese Customs from 2000 to 2006, Ju, Lin, Liu, and Shi (2015) calculate the TFP growth rates for the import and export sectors, using both the Olley and Pakes (1996) method and the standard OLS method. In China, the export sector is much more labor intensive than the import sector. Ju, Lin, Liu, and Shi (2015) find that TFP growth in the export sector was higher than that in the import sector for the period from 2000 and 2006. More direct evidence comes from the careful study by Chen, Jefferson, and Zhang (2011) and Huang, Ju, and Yue (2015). Chen, Jefferson, and Zhang (2011) use the disaggregate data of 2-digit industries to document that the TFP in the light sector grew faster than that in the heavy sector.[21] Using the Chinese Annual Industrial Survey between

[20]For this calculation we adjust the average investment rate within the secondary sector bar the construction industry to match the average investment rate for the whole economy for the sample from 1997 to 2011. The investment rate for the whole economy is measured as the ratio of total business investment to GDP by expenditure. The NBS also provides the input-output tables that contain the series of output and the survey data that contain the series of labor compensation for each of 17 sectors covering the whole economy, but the investment series is not measured in accordance with our purpose. For each of the 17 sectors, the value of gross fixed capital formation is calculated according to how much of the goods produced by industry A is used for the production in industry B. If the output of the food industry is not used for the production of other industries, for example, investment in that industry receives the zero entry.

[21]According to their estimates, the result holds for labor-augmented TFP growth rates as well. Such a result does not necessarily contradict the findings of Hsieh and Song (2015) because privatized firms have

1999 and 2007, Huang, Ju, and Yue (2015) show that technology improved significantly in favor of more labor-intensive industries. To the extent that estimated TFP growth rates across different sectors are debatable, there is well-established evidence that the TFP level in the light sector is higher than that in the heavy sector. Nonetheless our benchmark model does not rely on *any TFP assumption*.

Despite the fact that the light sector is more productive than the heavy sector, the government has since 1997 abided by the Strategic Plan passed by the Eighth National People's Congress. Because a significant part of the heavy sector is comprised of large firms that possess an strategic importance to the state, the government assigns lending priorities to this sector. It is this unique institutional arrangement that forms a building block for development of our theoretical model.

V.3. **Aggregate economy.** Figure 6 shows the sharp break in the correlation between investment and consumption fluctuations since the late 1990s. This stark picture is not an accident. It is a consequence of both banking reforms in 1995 and a new government policy in promoting heavy industries started in 1996. Such preferential credit policy toward heavy industries also generated the sharp trend change in the consumption-output and investment-output ratios (Figure 5).

How important is the rise of the investment-output ratio to GDP growth? Table 8 reports the contribution of capital deepening and TFP growth to the GDP growth rate for various periods, where GDP is measured by value added. Capital deepening accounts for a majority of GDP growth, especially since 1998.[22] Clearly, this investment-driven growth has its negative consequences on consumption and labor income, which has caused concerns of the Chinese government.

China's capital deepening has its own unique characteristics when compared to other East Asian newly industrializing countries (NICs) studied by Young (1995) and Fernald and Neiman (2011). Figure 13 displays the consumption-output ratio, the investment-output ratio, and the labor share of income for the four NICs: Korea, Japan, Singapore, and Taiwan. The overall correlation between the labor income share and the investment rate is positive for Korea, Singapore, and Taiwan and negative for Japan. For the early years when the investment-output ratio rose, the correlation is almost zero for Japan and positive for Korea and Taiwan. The CEIC does not have the labor share data for Singapore in those early years, but Young (1995) reports that the labor share series were essentially flat. China is different: the labor share of income declined when the investment-output ratio rose as shown in Figure 5.

Another unique feature of China is the divergence between the rising investment rate and the diminishing ability to export capital-intensive goods as China moved toward a stage of heavy industrialization. Romalis (2004) finds that as other East Asian NICs (e.g. Korea, Singapore, Taiwan) accumulated physical capital, their export structure also moved toward capital-intensive goods (the so-called "quasi-Rybczynski" effect in the international trade literature). Ventura (1997) shows how a small open economy can sustain rapid growth without a diminishing marginal product of capital by exporting capital-intensive goods. The disaggregate evidence of China, however, suggests the pattern opposite to other East

proven to be very productive and there has been a trend for the largest private firms to engage in heavy industries prioritized by the National People's Congress.

[22]We compute the contribution from 1998 and 2007 to compare to a similar finding by Brandt and Zhu (2010). The difference in exact numbers is probably due to different vintage data.

Asian NICs. Between 1999 and 2007, according to Huang, Ju, and Yue (2015), labor-intensive firms increased their export shares and capital-intensive firms reduced their export share; and at the same time the capital intensity of export firms was reduced. All these reallocations occurred despite the fact that aggregate investment rate increased steadily during that period. Such a divergent pattern is at odds with the existing theory that explains a persistent increase in the investment rate among East Asian NICs based on the country's ability to export capital-intensive goods (e.g. Ventura (1997)). But the pattern, as we have argued, is rooted in the macro policy of China via the special credit channel under which firms in the heavy sector, instead of those in the light sector (constituting the bulk of the export sector), enjoy preferential access to bank credits.

VI. The theoretical framework

In this section we build a theoretical model that is tractable for understanding its mechanism but rich enough for capturing the salient facts presented in the preceding sections.

VI.1. **Environment.** The economy is populated by two-period lived agents with overlapping generations (OLGs).[23] Agents work when young and consume their savings when old. Agents have heterogeneous skills. In each cohort, half of the population consists of workers without entrepreneurial skills and the other half is composed of entrepreneurs. Entrepreneurial skills are inherited from parents. Without loss of generality we do not allow switching between social classes.

VI.2. **Technology.** There are two production sectors of intermediate goods and hence two types of firms. The key feature of our model is that these two production sectors differ in capital intensity and *especially their access to bank loans.* The first sector is composed of firms that are endowed with capital-intensive technology. We call these firms "K-firms," which stands for capital-intensive. Remember that the heavy sector is more capital intensive that the light sector.

The second sector is a newly emerging private sector composed of productive firms. We call these firms "L-firms" that are labor-intensive. The firms are managed and operated by entrepreneurs. Specifically, L-firms are owned by old entrepreneurs, who hire their own children as managers, are residual claimants on profits, and consume all the profits.

Technologies for both types of firms have constant returns to scale:

$$Y_t^k = K_t^k, \; Y_t^l = \left(K_t^l\right)^{\alpha} (\chi L_t)^{1-\alpha},$$

where Y_t^j and K_t^j denote per capita output and the capital stock for the type-j firm, $j \in \{k, l\}$. The superscript k stands for "capital-intensive" and l for "labor-intensive." L_t denotes the labor demand by labor-intensive firms. The parameter $\chi > 1$ captures the assumption that L-firms are more productive than K-firms, as supported by the analysis in Section V.2. The results implied by our benchmark model, however, do not reply on this assumption. This assumption is used only for the purpose of measuring the effects of misallocation of resources between the two sectors.

The production of final goods is a CES aggregator of the above two intermediate goods:

$$Y_t = \left[\varphi \left(Y_t^k\right)^{\frac{\sigma-1}{\sigma}} + \left(Y_t^l\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}.$$

[23]While one can extend it to the economy with multiple-period-lived agents, one may lose both tractability and intuition.

The perfect competition in the final goods market implies the following first-order condition

$$\frac{Y_t^k}{Y_t^l} = \left(\varphi \frac{P_t^l}{P_t^k}\right)^{\sigma}, \tag{6}$$

where P_t^k is the price of the intermediate goods Y_t^k, and P_t^l is the price of the intermediate goods Y_t^l. Normalizing the final-goods price to one and using the zero-profit condition for final goods, we have

$$\left[\varphi^{\sigma}\left(P_t^k\right)^{1-\sigma} + \left(P_t^l\right)^{1-\sigma}\right]^{\frac{1}{1-\sigma}} = 1. \tag{7}$$

VI.3. **K-firms' problem.** Each K-firm lives for one period only, an assumption that can be relaxed. At the beginning of each period, new born K-firms receive net worth N_t from the government. K-firms can borrow from the representative financial intermediary at a fixed interest rate (R) to finance investment in capital. K-firms, however, could default on loan payments and receive a fraction of output, $(1-\theta_t)P_t^k Y_t^k$. The time-varying parameter θ_t reflects the changing loan quota targeted by the government. A higher value of θ_t implies an increase of the targeted loan quota whose payment is implicitly guaranteed by the government. The incentive-compatibility constraint for the K-firm is

$$P_t^k K_t^k - R\left(K_t^k - N_t\right) \geq \left(1-\theta_t\right) P_t^k K_t^k. \tag{8}$$

The problem of the K-firm is

$$\Pi_t^k \equiv \max_{K_t^k} P_t^k K_t^k - R\left(K_t^k - N_t\right) + \left(1-\delta\right) K_t^k$$

subject to (8). Denote the investment loan to the K-firm by $B_t^k = K_t^k - N_t$. At the end of the period, the K-firm turns in its gross profit (which includes $(1-\delta)K_t^k$) to the government and dies.[24]

It is straightforward to show that for the financial constraint to bind, the following inequality must hold

$$\theta_t P_t^k < R < P_t^k.$$

The first inequality is necessary; otherwise, the incentive-compatibility constraint for the K-firm never binds in equilibrium, even when $N_t = 0$. The second inequality holds because it is always profitable for K-firms to expand the production until the financial constraint binds. If the financial constraint is not binding, (8) implies that the demand for capital satisfies the condition $K_t^k \leq N_t / \left(1-\theta_t\right)$ with $R = P_t^k$. If, on the other hand, $K_t^k > N_t / \left(1-\theta_t\right)$, the financial constraint must bind. With the binding constraint, we obtain from (8)

$$K_t^k = \frac{R}{R - \theta_t P_t^k} N_t. \tag{9}$$

Accordingly, the amount borrowed by the K-firm is

$$B_t^k = \frac{\theta_t P_t^k}{R - \theta_t P_t^k} N_t. \tag{10}$$

[24]Alternatively one can assume that K-firms may exist forever but with a certain surviving rate to prevent the accumulated net worth N_t from growing so large that the collateral constraint (8) is no longer binding.

VI.4. **L-firms' problem.** Before production takes place, L-firms must finance their working capital from intratemporal (short-term) bank loans. For simplicity, we assume that L-firms can borrow working-capital loans freely from the bank. L-firms, however, have no access to intertemporal (long-term) bank loans to fund its fixed investment and must self-finance it through their own savings. We leave to Section VIII.2.4 the discussion of how these assumptions are consistent with China's disaggregated banking data.

Following SSZ, we assume that the old entrepreneur pays the young entrepreneur a management fee as a fixed fraction of output produced, $m_t = \psi P_t^l \left(K_t^l\right)^{\alpha} \left(\chi L_t\right)^{1-\alpha}$, where $\psi < 1$.[25] Therefore the old entrepreneur's problem becomes

$$\Pi_t^l \equiv \max_{L_t} P_t^l \left(1-\psi\right) \left(K_t^l\right)^{\alpha} \left(\chi L_t\right)^{1-\alpha} - R_t^l w_t L_t + \left(1-\delta\right) K_t^l, \tag{11}$$

where R_t^l is the loan rate on the working capital $w_t L_t$. Note that old entrepreneurs do not choose K_t^l because, as shown below, it is determined when they are young.

The first-order condition gives

$$\left(1-\psi\right)\left(1-\alpha\right) P_t^l \left(K_t^l/L_t\right)^{\alpha} \left(\chi\right)^{1-\alpha} = R_t^l w_t. \tag{12}$$

The gross return to the L-firm's capital is

$$\rho_t^l \equiv \Pi_t^l/K_t^l = \left(1-\psi\right) \alpha P_t^l \left(K_t^l/L_t\right)^{\alpha-1} \left(\chi\right)^{1-\alpha} + 1 - \delta. \tag{13}$$

The young entrepreneur's problem is to decide on consumption and a portfolio allocation between bank deposits and physical capital investment. Since the rate of return to capital investment is ρ_{t+1}^l and $\rho^l > R$ in steady state, the young entrepreneur always prefers investing in capital to depositing in the bank. Specifically, the young entrepreneur's consumption-saving problem is

$$\max_{s_t^E} \frac{\left(m_t - s_t^E\right)^{1-\frac{1}{\gamma}}}{1-\frac{1}{\gamma}} + \beta E_t \frac{\left(\rho_{t+1}^l s_t^E\right)^{1-\frac{1}{\gamma}}}{1-\frac{1}{\gamma}}.$$

First-order conditions determine the optimal saving of young entrepreneurs:

$$s_t^E = m_t / \left(1 + \beta^{-\gamma} E_t \left(\rho_{t+1}^l\right)^{1-\gamma}\right).$$

Since $s_t^E = K_{t+1}^l$, the law of motion for the L-firm's capital becomes

$$K_{t+1}^l = \frac{\psi}{1 + \beta^{-\gamma} E_t \left(\rho_{t+1}^l\right)^{1-\gamma}} P_t^l \left(K_t^l\right)^{\alpha} \left(\chi L_t\right)^{1-\alpha}. \tag{14}$$

VI.5. **Workers' problem.** Workers deposit their savings into the representative bank and earn the fixed interest rate R. Workers cannot lend directly to K-firms or L-firms. This assumption is consistent with the fact that the banking sector in China plays a key role in intermediating business loans.

[25] SSZ provide a microfoundation for the young entrepreneur's management fee as a fixed fraction of output as follows. There exists an agency problem between the manager and the owner of the business. The manager can divert a positive share of the firm's output for her own use. Such opportunistic behavior can be deterred only by paying managers a compensation that is at least as large as the funds they could steal, which is a share of output. An alternative setup is for parents to leave voluntary bequests to their children, who in turn would invest in the family firm.

The worker's consumption-saving problem is

$$\max_{c_{1t}^w, c_{2t+1}^w} \frac{\left(c_{1t}^w\right)^{1-\frac{1}{\gamma}}}{1-\frac{1}{\gamma}} + \beta \frac{\left(c_{2t+1}^w\right)^{1-\frac{1}{\gamma}}}{1-\frac{1}{\gamma}}$$

subject to

$$\begin{aligned} c_{1t}^w + s_t^w &= w_t, \\ c_{2t+1}^w &= s_t^w R, \end{aligned}$$

where w_t is the market wage rate; c_{1t}^w, c_{2t+1}^w, and s_t^w denote consumption when young, consumption when old, and the worker's savings.

VI.6. **The bank's problem.** Each period the bank receives deposits D_t from young workers and uses these deposits for intertemporal (long-term) loans to K-firms' investment and intratemporal (short-term) loans to L-firms's working capital. The bank's interest rate for investment loans is simply R, but the loan rate for working capital is R_t^l. The bank is subject to a convex cost of loan processing, $C(B_t)$, which increases in the total amount of loans, denoted as $B_t \equiv B_t^l + B_t^k$. Specifically, $C(B_t) = B_t^\eta$ for $\eta > 1$. Remaining deposits, invested in foreign bonds, earn the interest rate R.

The convex cost of loan processing is discussed in Cúrdia and Woodford (2010). For China, this assumption is more pertinent because various legislative or implicit restrictions on bank loans to small but productive firms become more severe as the loan-to-deposit ratio approaches to the official limit, making loans to productive firms exceedingly expensive (Zhou and Ren, 2010).[26] Since bank loans to enterprises with large asset values are always given priority in China, we assume that that the bank always meets K-firms' demand for investment loans prior to lending to L-firms. The bank's problem is therefore

$$\Pi_t^b = \underset{B_t^l}{\mathrm{Max}}\, R_t^l B_t^l + R B_t^k + R(D_t - B_t^k) - R D_t - C(B_t) - B_t^l.$$

In equilibrium, $D_t = s_t^w L_t$ and $B_t^l = w_t L_t$. The first-order condition

$$R_t^l = 1 + C'(B_t) \tag{15}$$

reveals that the loan rate for working capital increases with the total amount of loans.

VI.7. **The government's problem.** The government lasts forever. At the end of each period, the government decides on how much of its revenues to be advanced to new-born K-firms as net worth in the beginning of the next period. For simplicity we assume that N_{t+1} advanced to new-born K-firms is a fraction of K-firms' capital stock at the end of the current period, i.e.,

$$N_{t+1} = \xi K_t^k, \tag{16}$$

where $0 \leq \xi \leq 1$. A combination of (9) and (16) gives the law of motion for the K-firm's net worth

$$N_{t+1} = \frac{R\xi}{R - \theta_t P_t^k} N_t. \tag{17}$$

The government's budget constraint is

$$B_{t+1}^G + N_{t+1} = \Pi_t^k + \Pi_t^b + R B_t^G, \tag{18}$$

[26]Reports from various Chinese financial papers confirm these institutional arrangements.

where B_t^G is the beginning-of-period government assets invested in foreign bonds, with the fixed interest rate R.

VI.8. **Equilibrium conditions.** The equilibrium conditions are listed as follows.

$$
\begin{aligned}
1 &= L_t = \left[\frac{(1-\psi)(1-\alpha) P_t^l \chi}{R_t^l w_t}\right]^{\frac{1}{\alpha}} K_t^l/\chi, \\
\Pi_t^l &= \rho_t^l K_t^l, \\
\rho_t^l &= (1-\psi)\,\alpha P_t^l \left(K_t^l\right)^{\alpha-1} \chi^{1-\alpha} + 1 - \delta, \\
R_t^l &= 1 + C'(B_t), \\
\Pi_t^k &= P_t^k K_t^k - R\left(K_t^k - N_t\right) + (1-\delta) K_t^k, \\
\Pi_t^B &= \left(R_t^l - 1\right) B_t^l - C(B_t), \\
m_t &= \psi P_t^l \left(K_t^l\right)^{\alpha} (\chi L_t)^{1-\alpha}, \\
s_t^E &= m_t / \left(1 + \beta^{-\gamma}\left(E_t \rho_{t+1}^l\right)^{1-\gamma}\right), \\
c_{1t}^E &= m_t - s_t^E,\; c_{2t}^E = \rho_t^l s_{t-1}^E, \\
B_t^k &= K_t^k - N_t, \\
B_t^l &= w_t L_t, \\
N_{t+1} &= \xi K_t^k, \\
Y_t &= \left[\varphi \left(Y_t^k\right)^{\frac{\sigma-1}{\sigma}} + \left(Y_t^l\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}, \\
Y_t^k &= K_t^k, \\
Y_t^l &= \left(K_t^l\right)^{\alpha} (\chi L_t)^{1-\alpha}, \\
1 &= \left[\varphi^{\sigma} \left(P_t^k\right)^{1-\sigma} + \left(P_t^l\right)^{1-\sigma}\right]^{\frac{1}{1-\sigma}}, \\
K_t^k &= \frac{R}{R - \theta_t P_t^k} N_t, \\
B_{t+1}^G &= \Pi_t^k + \Pi_t^b + R B_t^G - N_{t+1}, \\
P_t^l &= \frac{P_t^k}{\varphi}\left(\frac{Y_t^l}{Y_t^k}\right)^{\frac{1}{\sigma}}, \\
s_t^w &= w_t / \left(1 + \beta^{-\gamma} R^{1-\gamma}\right), \\
c_{1t}^w &= w_t - s_t^w,\; c_{2t}^w = s_t^w R, \\
B_t^w &= s_t^w - B_t^k.
\end{aligned}
$$

Combining the budget constraints of households, entrepreneurs, and the government, we obtain the following resource constraints

$$
C_t + I_t + S_t^f = \mathrm{GNP}_t = Y_t - C(B_t) + (R-1)\left(B_t^w + B_t^G\right), \tag{19}
$$

where S_t^f stands for a current account or foreign surplus and

$$
\begin{aligned}
C_t &= c_{1t}^w + c_{2t}^w + c_{1t}^E + c_{2t}^E, \\
I_t &= K_{t+1} - (1-\delta) K_t, \\
K_t &= K_t^k + K_t^l,
\end{aligned}
$$

$$S_t^f = B_{t+1}^w + B_{t+1}^G - \left(B_t^w + B_t^G\right).$$

VII. Characterizing the equilibrium

In this section we characterize the equilibrium. We first discuss the parameter restrictions for the capital-intensive sector's collateral constraint to bind at steady state. We then discuss the model's implication on a foreign surplus. We end the section by analyzing the determinants of the investment rate and the share of labor income during the transition.

VII.1. **Steady state.** In steady state, all aggregate variables are constant. We consider the case that the borrowing constraint for the K-firm is binding at steady state. Note that

$$P^k = \frac{R}{\overline{\theta}} (1 - \xi),$$
$$P^k \overline{\theta} < R.$$

For the collateral constraint to bind, i.e $R < P^k$, it must be

$$1 - \xi > \overline{\theta}. \tag{20}$$

Intuitively, the smaller $\overline{\theta}$ is, the stronger the firm's default incentive is, and thus the more binding the collateral constraint is. Similarly, the smaller ξ is, the slower the net worth accumulates, and the more binding the collateral constraint becomes. Condition (20) implies that the collateral constraint always binds along the transition path. It is, therefor, always profitable for K-firms to borrow up to the maximum to expand their production.

VII.2. **A growing foreign surplus.** Tables 3 and 4 show that net exports since 1997 has become large in comparison to earlier periods. A large current account surplus, part of the emphasis in SSZ, is a byproduct of our model but with a different mechanism. To see this result, we begin with workers' purchases of foreign bonds denoted as

$$B_t^w = s_t^w - (K_t^k - N_t),$$

where $K_t^k - N_t$ is workers' savings used for domestic capital investment. The net foreign surplus as a fraction of GDP is

$$\frac{B_{t+1}^w + B_{t+1}^G - (B_t^w + B_t^G)}{Y_t - C(B_t)}.$$

Two forces drive up the net foreign surplus: households' savings in foreign bonds ($B_{t+1}^w - B_t^w$) and the government's savings in foreign reserves ($B_{t+1}^G - B_t^G$). In China, the difference between savings and investment (GFCF) as percent of GDP by expenditure reached its peak at 9.48% in 2007 and declined to 0.69% in 2012. Although household savings is still the main component of national savings, its growth is much slower than that of the government's savings between 2000 and 2012. According to our calculation based on the NBS annual data, government savings as percent of GDP increased by seven percentage points between 2000 and 2012, contributing to 63.90% of an increase of 11 percentage points in the national saving rate during this period (from 37.47% to 48.43%). In our model, the worker's saving rate is constant and all entrepreneurial savings is used to finance investment in the labor-intensive sector. As a result, most of the *increase* in the national saving rate and thus the net foreign surplus are driven by an increase in government savings, consistent with the aforementioned fact for China.

VII.3. **Key transition paths.** We are interested in the dynamic paths of (a) the investment rate, measured as the ratio of aggregate investment to aggregate output, and (b) the share of labor income, measured as the ratio of wage income to aggregate output. For tractability we set $\theta_t = \overline{\theta}$ and assume the complete capital depreciation (i.e. $\delta = 1$) such that $I_t^j = K_{t+1}^j$ for $j \in \{k, l\}$. In our two-sector model, the investment rate can be decomposed as[27]

$$\frac{I_t}{Y_t} = \frac{I_t^k}{P_t^k Y_t^k} \frac{P_t^k Y_t^k}{Y_t} + \frac{I_t^l}{P_t^l Y_t^l} \frac{P_t^l Y_t^l}{Y_t}. \tag{21}$$

In our model, dynamic paths of the investment rate depend on two channels: the reallocation (between-sector) effect and the sector-specific (within-sector) effect. If the investment rate in the capital-intensive sector is higher than the investment rate in the labor-intensive sector, reallocation of resources from the labor-intensive sector to the capital-intensive sector tends to increase the investment rate (the reallocation effect). Given the ratio of revenue in the capital-intensive sector to that in the labor-intensive sector, a change in the investment rate in the capital-intensive sector tends to move the aggregate investment rate in the same direction (the sector-specific effect).[28]

The other key object is the share of labor income in total output:

$$\frac{w_t L_t}{Y_t} = \frac{(1-\psi)(1-\alpha)}{1 + P_t^k Y_t^k / \left(P_t^l Y_t^l\right)}. \tag{22}$$

Equation (22) indicates that an increase in the ratio of revenue in the capital-intensive sector to that in the labor-intensive sector reduces the share of labor income.[29]

In summary, an increase in the ratio of revenue in the capital-intensive sector to that in the labor-intensive sector tends to raise the investment rate and reduce the share of labor income simultaneously, as we observe in the data discussed in Sections V.2 and VIII.2. Such a trend pattern, as argued below, is driven by the increasing borrowing capacity of the capital-intensive sector.

We now establish the following proportion about the ratio of revenue in the capital-intensive sector to that in the labor-intensive sector during the transition.

Proposition 1. Given that $\sigma > 1$, during the transition the ratio of revenue in the capital-intensive sector to that in the labor-intensive sector increases monotonically towards the steady state.

Proof. The growth rate of the ratio of revenues in the two sectors can be expressed as

$$\Delta \log \frac{P_t^k Y_t^k}{P_t^l Y_t^l} = \left(1 - \frac{1}{\sigma}\right) \Delta \log \frac{Y_t^k}{Y_t^l}. \tag{23}$$

[27]For illustrative purposes we use Y_t in the denominator in this section. The correct measurement of GDP in our benchmark model, however, is $Y_t - C(B_t)$, which we adopt in our numerical analysis below. Because B_t increases over time, our results hold when the denominator is replaced by $Y_t - C(B_t)$.

[28]Because of the complete capital depreciation, the investment rate in the labor-intensive sector is constant when the risk-aversion parameter γ is set to one. Relaxing the assumption of full depreciation would predict a declining investment rate in the labor intensive sector due to diminishing marginal returns to capital.

[29]Such a prediction holds in a general setup in which the capital-intensive sector also uses labor as an input, as long as the share of labor income in the capital-intensive sector is less than that in the labor-intensive sector.

Along the transition path, the output ratio of the two sector is

$$\frac{Y_t^k}{Y_t^l} = \left(\frac{\varphi \left(1 - \varphi^\sigma \left(P_t^k\right)^{1-\sigma}\right)^{\frac{1}{1-\sigma}}}{P_t^k} \right)^\sigma . \tag{24}$$

Therefore, the ratio of output in the capital intensive sector to that in the labor intensive sector moves in opposite direction to the relative price of capital-intensive goods. As net worth of the capital-intensive sector increases, the collateral constraint becomes less binding, which reduces the price of capital-intensive goods towards the first-best level R. Therefore, the ratio Y_t^k/Y_t^l increases monotonically during the transition path. Given $\sigma > 1$, the ratio $P_t^k Y_t^k / \left(P_t^l Y_t^l\right)$ increases along the transition path. □

The intuition for the above proposition is as follows. Accumulation of net worth in the capital-intensive sector expands the borrowing capacity and henceforth causes output in the capital-intensive sector to grow faster than output in the labor-intensive sector. With the elasticity of substitution greater than one, the ratio of revenue in the capital-intensive sector to that in the labor-intensive sector increases along the transition.

Equation (23) is reminiscent of the finding of Acemoglu and Guerrieri (2008). In a frictionless two-sector model with different capital intensities, their paper explores the impact of capital deepening on the capital income share, and the *efficient* resource reallocation between the two sectors. The focus of their paper, however, is on the U.S. economy, characterized by a roughly constant labor income share and the increasing share of the labor-intensive sector's value in the long run as capital deepens. As a result, the elasticity of substitution of less than one is needed to reconcile these facts. The observation on China's two sectors (elaborated in Sections V.2 and VIII.2.3) clearly indicates that the ratios of both revenues and capital stocks in the capital-intensive and labor-intensive sectors increase while the share of labor income declines with capital deepening, suggesting that the elasticity of substitution of greater than one is consistent with the transition pattern of China's macroeconomy.

More important is our finding that the dynamics of the aggregate investment rate along the transition path depend on the source of capital deepening. In our benchmark model, the source of capital deepening is endogenous and the extent to which capital deepens increases with the borrowing capacity of the capital-intensive sector. Consequently, resources are reallocated from the labor-intensive sector to the capital-intensive sector. If the labor-intensive sector is more productive than the capital-intensive sector, the reallocation is *inefficient*. Such a mechanism, as we show in Section VIII, is crucial to explaining not only the trend patterns but also the cyclical patterns of China. Without the borrowing constraint, our economy would imply a declining aggregate investment rate and an increasing consumption output ratio along the transition path, due to diminishing returns to capital in the labor-intensive sector; and the economy would imply a positive comovement between investment and labor income under various shocks as well as a positive comovement between long-term and short-term loans.

VIII. Quantitative results and the mechanism

In this section we report quantitative results for both the transition paths, holding θ constant, and the impulse responses following an expansionary shock to θ. We then discuss the mechanism in our model in the context of disaggregated data and further empirical findings. We conclude this section with counterfactual exercises to illustrate how the mechanism works.

VIII.1. **Trend and cyclical patterns.** We set both the initial capital stock in the labor-intensive sector and the initial net worth of the capital-intensive sector to values smaller than the corresponding steady-state values. Moreover, the initial net worth of capital-intensive firms is such that the capital-intensive sector's collateral constraint binds in the initial period. The specific configuration of parameter values is set in Table 9.

Figure 14 shows the simulated results. Along the transition path, we see that the consumption-output ratio experiences a secular decline, while the investment-output ratio increases steadily after an initial fall.[30] An increase in the investment rate is puzzling from the perspective of neoclassical models. As Equation (21) suggests, the main channel for an increase in the investment rate is the increase in the value of the capital-intensive sector relative to that of the labor-intensive sector. In our model economy, the investment rate in the capital-intensive sector is higher than its counterpart in the labor-intensive sector because of capital-intensive firms' ability to leverage against their net worth. When capital-intensive goods producers' net worth increases, resources are reallocated towards the capital-intensive sector, measured by an increasing share of revenues of capital-intensive firms in total output. As a result, the aggregate investment rate tends to increase toward the steady state. The middle row of Figure 14 shows that the ratio of investment loans to working-capital loans increases steadily while the share of labor income declines, as we observe in the data. The last row of the figure shows that the ratios of revenue and capital stock in the capital-intensive sector to those in the labor-intensive sector increase steadily. These results are corroborated by the evidence from the disaggregated data presented in Section VIII.2.4.

We now explore the impulse responses to an increase in the credit quota, that is, an unexpected increase in θ_t. Figure 15 presents a set of impulses responses that are consistent with the empirical findings discussed in previous and later sections. One can see that loans to the capital-intensive sector (long-term loans) increase sharply on impact and the response is persistent. The increase of long-term loans crowds out working-capital loans due to the banking friction (the bottom row of Figure 15). As a result, aggregate investment increases, while aggregate consumption decreases moderately (the first row of Figure 15). This outcome leads to a hump-shaped increase in aggregate output. The decline of the wage rate and thus labor income is caused by the crowding effect on the labor-intensive sector (the second row of Figure 15).

VIII.2. **Key mechanism and data corroboration.** Along the transition path, as capital-intensive firms' net worth increases, their borrowing capacity increases as well. With the elasticity of substitution between the two sectors greater than one, the share of the capital-intensive sector's revenue in total output increases along the transition path. Given that the capital-intensive sector's investment rate is higher than that of the labor-intensive sector, such a resource reallocation leads to a higher aggregate investment rate. Meanwhile, the share of labor income declines and the ratio of the capital stock in the capital-intensive sector to that in the labor-intensive sector rises.

[30]The aggregate investment rate falls initially because the investment rate in the capital-intensive sector falls initially with the initial leverage ratio smaller than the leverage in later periods.

Over the business cycle, if the government decides to increase the loan quota à la an increase of θ_t, long-term credits to capital-intensive firms would expand. Equations (10) and (15) then imply that an increase in the capital-intensive firm's borrowing capacity exerts a positive externality on the cost of working-capital loans for labor-intensive firms. According to (12), an increase in R_t^l reduces labor demand, thereby crowding out working-capital loans and reducing wage income (the crowding-out effect). Thus, our theoretical model is able to generate a negative correlation between investment and labor income, a negative comovement of investment and consumption, and most importantly a negative comovement of long-term and short-term loans. For similar reasons, such comovement patterns hold during the economic transition (even without credit shocks) because capital-intensive firms' net worth continues to rise.

VIII.2.1. *Estimating the elasticity of substitution.* The fall of the labor income share generated by our model economy depends crucially on the magnitude of the elasticity of substitution in the aggregate production function to be greater than 1. The value greater than one accords with (a) the observed ratio of revenue in the capital-intensive sector to that in the labor-intensive sector and (b) the observed comovement between the ratio of revenues in the heavy and light sectors and the corresponding quantity ratio. Of course, one can directly estimate this important parameter by deriving from (6) the following relationship between the value ratio and the quantity ratio in the two sectors:

$$\log \frac{P_t^k Y_t^k}{P_t^l Y_t^l} = \log \varphi + \frac{\sigma - 1}{\sigma} \log \frac{Y_t^k}{Y_t^l}. \tag{25}$$

The annual data for the value and quantity ratios in the heavy and light sectors are available from 1996 to 2011. Following Acemoglu and Guerrieri (2008), we first HP-filter both variables in (25) with the smooth parameter being 6.25 and then regress the lefthand variable on the righthand variable. The regression estimate of $(\sigma - 1)/\sigma$ is 0.78 with the t-statistic 5.32, implying that the estimate of σ is 4.53 and significantly greater than 1. To examine the extent to which this estimate is affected by the HP filter, we also regress $\Delta \log \frac{P_t^k Y_t^k}{P_t^l Y_t^l}$ on $\Delta \log \frac{Y_t^k}{Y_t^l}$ by taking advantage of the relationship

$$\Delta \log \frac{P_t^k Y_t^k}{P_t^l Y_t^l} = \frac{\sigma - 1}{\sigma} \Delta \log \frac{Y_t^k}{Y_t^l}. \tag{26}$$

The regression estimate of $(\sigma - 1)/\sigma$ is 0.74 with the t-statistic 5.65. This implies that the estimate of σ is 3.86 and it is significantly greater than 1.

There are two criticisms for this simple regression exercise. One is that the number of data points is only 16. To address this criticism, we employ the monthly data for P_t^k, P_t^l, Y_t^k, and Y_t^l that are available from 2003:1 to 2012:5 (a total of 113 data points) when Y_t^k and Y_t^l are measured by gross output and from 1996:10 to 2012:12 (a total of 195 data points) when these variables are measured by sales. Running simple regressions on the HP-filtered seasonally-adjusted series (with the smooth parameter being 129600) according to equation (25) yields the estimate of σ being 1.38 for gross output and 1.92 for sales.

The second criticism, which is more serious, is that both variables in (25) or (26) are endogenously determined. Thus, simple-regression results may be biased. To take account of these criticisms and further establish the robustness of the result $\sigma > 1$, we model such a simultaneous relationship explicitly with the following two-variable restricted VAR:

$$A_0 y_t = a + \sum_{\ell=1}^{p} A_\ell y_{t-\ell} + \varepsilon_t,$$

where A_0 is an unrestricted 2×2 matrix allowing for full endogeneity, a is a 2×1 vector of intercept terms, ε_t is a 2×1 vector of independent standard-normal random shocks, and

$$A_0 = \begin{bmatrix} a_{0,11} & a_{0,12} \\ a_{0,21} & a_{0,22} \end{bmatrix},\ A_\ell = \begin{bmatrix} a_{\ell,11} & a_{\ell,12} \\ 0 & 0 \end{bmatrix},\ y_t = \begin{bmatrix} \log \frac{P_t^k Y_t^k}{P_t^l Y_t^l} & \log \frac{Y_t^k}{Y_t^l} \end{bmatrix}'. \tag{27}$$

It follows from (25) and (27) that $\sigma = a_{0,21}/(a_{0,21} + a_{0,22})$. By Theorems 1 and 3 of Rubio-Ramírez, Waggoner, and Zha (2010), the simultaneous system (27) is globally identified almost everywhere. We estimate this model with $p = 13$.[31] Likelihood-based estimation of system (27) is analogous to utilizing a large number of lagged variables as instrumental variables (Sims, 2000).

The monthly data for gross output gives us 100 data points (excluding all the lagged variables)—a respectable degrees of freedom for estimation. We use the MCMC method of Zha (1999) and Sims and Zha (1999) to obtain maximum-likelihood estimation of the VAR parameters as well as the 68% and 95% posterior probability intervals of the estimated parameter σ, as reported in Table 10. Estimation results are robust to whether we first seasonally-adjust the four monthly data P_t^k, P_t^l, Y_t^k, and Y_t^l or we do not adjust theses series seasonally. Because the estimation applies to the value and quantity *ratios*, the seasonality is largely eliminated. The estimate of σ is 2.32 for seasonally-adjusted monthly data and 2.15 for original monthly data. The probability intervals are very tight around these estimates. None of the million MCMC simulations we have generated gives the value of σ that comes even close to being less than or equal to 1.[32]

The robustness of our advanced estimation method is further tested by applying the method to the alternative relationship

$$\log \frac{P_t^k Y_t^k}{P_t^l Y_t^l} = \sigma \log \varphi + (1 - \sigma) \log \frac{P_t^k}{P_t^l}. \tag{28}$$

Thus, the system represented by (27) becomes

$$A_0 = \begin{bmatrix} a_{0,11} & a_{0,12} \\ a_{0,21} & a_{0,22} \end{bmatrix},\ A_\ell = \begin{bmatrix} a_{\ell,11} & a_{\ell,12} \\ 0 & 0 \end{bmatrix},\ y_t = \begin{bmatrix} \log \frac{P_t^k Y_t^k}{P_t^l Y_t^l} & \log \frac{P_t^k}{P_t^l} \end{bmatrix}'. \tag{29}$$

One can show that the estimation result for σ is invariant to whether system (27) or (29) is used. The invariance is confirmed by our MCMC simulations. This robust result is critical because the invariance property breaks down when one estimates this alternative relationship via simple regressions or swaps the lefthand variable and the righthand variable in the regression. We recommend that the estimated results reported in Table 10 be used.

[31] The quantity Y_t^k or Y_t^l is measured by gross output. The lag length 13, instead of 12, is used to take account of any residual seasonality. Estimation results are robust to a choice of lag length.

[32] As a robust check we also apply our estimation method to the monthly data in which the quantity and revenue are measured by sales in each of the heavy and light industries. Again, all of the posterior draws deliver the robust result that $\sigma > 1$.

VIII.2.2. *Relative prices of investment.* In a recent paper, Karabarbounis and Neiman (2014) argue for the elasticity of substitution between capital and labor to be greater than 1 to explain the decline of labor income share. Their model requires that the relative price of investment declines simultaneously. Our model economy for China does not rest on the decline of the relative price of investment to explain the decline of labor income share. Specifically, the relative price is assumed to be flat so that it does not play a dominant role in explaining either trend or cyclical facts.[33] This feature marks a major departure of our model from the standard model so as to account explicitly for Chinese unique characteristics in which we establish, below, a robust finding that there is weak or little relationship between the labor income share and the relative price of investment in China.

Figure 16 displays various measures of relative prices of investment goods to consumption goods following Karabarbounis and Neiman (2014). In the top chart of the figure, we use two investment price series and two consumption price seres. The investment price series are the price indices for fixed-asset investment (FAI) and gross fixed-asset capital formation (GFCF); the consumption price series are CPI and the price index for the retail sales of consumer goods. As one can see from these various measures, the relative price of investment since 1997 has either increased or stayed flat. This pattern is robust to other measures of the relative price of investment. In the bottom chart of Figure 16, we report the two other data sources used by Karabarbounis and Neiman (2014): the PWT measure (Penn World Tables) and the WDI measure (World Bank's World Development Indices). Both measures use the price of GFCF. The PWT price index of consumption is the purchasing-power-parity (PPP) price of consumption that is suitably adjusted by the exchange rate. The PWT price index of investment is adjusted by the PPP in the same way. The WDI price index of consumption is the price of retail sales of consumer goods. As evident in this chart, the relative price of investment has been increasing or flat since 1997.[34]

VIII.2.3. *Between-sector contribution to the labor share decline.* The assumption of two sectors in our model accords with the fact that the between-sector contribution to the aggregate labor-share decline is empirically significant for the Chinese economy. The disaggregated data we use are the surveys from 1995 to 2010 of the 17 disaggregated sectors (sub-sectors), published by the NBS in years ending with 0, 2, 5, and 7. This dataset contains four variables: labor income (remuneration of employees), net production tax, profits (operational surplus), and depreciation of fixed assets. The value added of each disaggregated sector is calculated as the sum of these four variables.[35] Table 11 ranks the 17 detailed sectors according to the

[33]In fact, our results hold both along the transition path and in dynamic responses to a positive credit shock, even if we expand our benchmark model to an economy either with decreasing relative prices of investment to reflect technological advances in the production of investment goods or with endogenously *increasing relative prices* of investment goods due to a fixed input (e.g., land) in the production, .

[34]Hsieh and Klenow (2007) find that for poor countries, the relative price of investment measured by the domestic price tends to be larger than that measured by the PPP price. Our finding, however, is not subject to such a measurement issue, since our interest is the time series pattern of the relative price of investment for a given country, i.e. China.

[35]The sum of values added over the 17 sectors is very close to GDP by value added from 2002 on, although there are some discrepancies between these two measures prior to 2002. Discrepancies also exist between the sum of labor compensations over the 17 sectors and the labor income reported by the NBS's Flow of Funds (FOF). The labor income series reported in the Flow of Funds contains two components: (a) wage and (b) social insurance payment by company. The discrepancies may be driven mainly by social insurance payments. Despite all these discrepancies, the decline of China's labor income share since the late 1990s is a robust fact, as further confirmed by Bai and Qian (2009) and Qian and Zhu (2012) who have made data

average labor share between 1995 and 2010. Although the ranking within each broad sector differs between China and the U.S., a comparison of our Table 11 and Acemoglu and Guerrieri (2008)'s Table 1 shows the broad consistency of separating the capital-intensive sector from the labor-intensive sector across the two countries.[36] We then group the 17 sectors into two aggregate sectors: the heavy sector and the light sector according to the strategic plan of the Eighth National People's Congress to develop infrastructure, real estate, basic industries (metal products, autos, and high-tech machinery), and other heavy industries (petroleum and telecommunication).

Figure 17 plots the labor shares in the heavy and light sectors, along with the labor share at the aggregate level. The aggregate labor share from the survey data and input-output tables shows a pattern similar to the trend pattern displayed in the middle row of Figure 5 in which the *Flow of Funds* aggregate data are utilized; its decline over time is attributed to a combination of within-sector and between-sector effects. The within-sector effect concerns the decline of the labor share in each of the heavy and light sectors and the between-sector effect reflects the difference between the two sectors. To calculate these two effects, note that

$$\mathrm{LS}_t \equiv \frac{w_t L_t}{Y_t} = \frac{w_t L_t^k + w_t L_t^l}{P_t^k Y_t^k + P_t^l Y_t^l} = \alpha_t^l \, \frac{1 + \beta_t \frac{P_t^k Y_t^k}{P_t^l Y_t^l}}{1 + \frac{P_t^k Y_t^k}{P_t^l Y_t^l}},$$

where $\alpha_t^l = \frac{w_t L_t^l}{P_t^l Y_t^l}$, $\alpha_t^k = \frac{w_t L_t^k}{P_t^k Y_t^k}$, and $\beta_t = \frac{\alpha_t^k}{\alpha_t^l} < 1$. The between-sector effect is measured by

$$B_t^{\text{effect}} = \bar{\alpha}^l \, \frac{1 + \bar{\beta} \frac{P_t^k Y_t^k}{P_t^l Y_t^l}}{1 + \frac{P_t^k Y_t^k}{P_t^l Y_t^l}},$$

where $\bar{\alpha}^i$ is the average of α_t^i over t for $i = l, k$ and $\bar{\beta} = \frac{\bar{\alpha}^k}{\bar{\alpha}^l}$, while the within-sector effect is measured by $W_t^{\text{effect}} = \mathrm{LS}_t - B_t^{\text{effect}}$. A change in the labor share, denoted by $\Delta\mathrm{LS} \equiv \mathrm{LS}_{t=t_1} - \mathrm{LS}_{t=t_0}$ where t_0 is the beginning year and t_1 is the end year in consideration, is decomposed into

$$\Delta\mathrm{LS} = \Delta B^{\text{effect}} + \Delta W^{\text{effect}}, \tag{30}$$

where $\Delta B^{\text{effect}} = B_{t=t_1}^{\text{effect}} - B_{t=t_0}^{\text{effect}}$ and $\Delta W^{\text{effect}} = W_{t=t_1}^{\text{effect}} - W_{t=t_0}^{\text{effect}}$. It is straightforward to prove that (30) is equivalent to the decomposition formula proposed by Karabarbounis and Neiman (2014) such that

$$\Delta B^{\text{effect}} = \sum_{i=k,l} \bar{\alpha}^i \Delta\omega^i, \; \Delta W^{\text{effect}} = \sum_{i=k,l} \Delta\alpha^i \bar{\omega}^i, \tag{31}$$

where $\omega_t^i = \frac{P_t^i Y_t^i}{P_t^k Y_t^k + P_t^l Y_t^l}$ and $\bar{\omega}^i$ is the average of ω_t^i over t.

A necessary condition for the between-sector effect on the declining labor share is for the ratio of value added in the heavy sector to value added in the light sector to rise over time. Figure 18 plots this ratio, which shows a strong upward trend since 1990. As shown in Figure 17, the labor share α_t^i for both $i = k$ (the heavy sector) and $i = l$ (the light sector) did

adjustments to take account of changes in statistical coverage of labor compensation over time. To make definition distinctive, therefore, we use the term "labor income" when the data is from the Flow of Funds and "labor compensation" when it is from the survey data for the 17 disaggregated sectors.

[36]To make grouping of different industries more compatible between China and the U.S., one may proceed further by matching sic codes for similar four-digit industries. The results reported in Table 11, however, serve our purpose of separating the two general sectors.

not change much between 1995 and 2010, while the overall (aggregate) labor share declined from 0.5 in 1995 to 0.47 in 2010. This presents a very informative case—it illustrates that even when the labor share *changes little* in the heavy sector and *even rises* in the light sector, the aggregate labor share may still decline entirely due to the between-sector effect. If we use 1997 instead as an initial year, the labor share did experience a decline over time for each of the two sectors and the question is whether the between-sector effect is still empirically significant.[37] Table 12 reports that with 1997 as an initial year for comparison, the between-sector effect continues to be significant in explaining the decline of the overall labor income share.[38] The table documents the results with and without the agricultural sector for 1995 as an initial year, 1997 as an initial year, 2007 as an ending year, and 2010 as an ending year. The reason for excluding agriculture is to eliminate the potential bias introduced by the extremely high value of labor share in that sector. Our findings are very robust. For a majority of cases, the between-sector effect contributes at least 40% of the decline to the aggregate labor share. In the cases when the initial year is 1995 and the ending year is 2010, the between-sector effect is the only effect that contributes the labor share decline because the within-sector effect has a *wrong sign* (i.e., causing the labor share to increase rather than decrease). These robust results reinforce the overriding importance of modeling the heavy and light sectors as two separate sectors for the Chinese economy.

VIII.2.4. *Short-term vs. long-term loans.* Figure 19 summarizes the key loan structure in China. Heavy industries, given the priority by the "Five-Year Program" of the Eighth National People's Congress, have enjoyed easy access to bank loans for medium and long term investment. One main reason for rapid increases of bank loans towards heavy industries is the persistent monopoly held by large banks (most of them are state-owned) in the credit market. According to Yu and Ju (1999), the share of the four largest national banks ("the Big Four") in total bank loans was 70.0% in 1997. This monopolistic power has been hardly changed ever since. According to our calculation using the monthly data from 2010:1 to 2014:12 published by the PBC, the share of large national banks in total bank loans was on average 67.4% (with a share of 51.2% for the Big Four). This monopoly is more severe for medium and long term loans, with an average share of 75.7% between 2010 and 2014 (55.2% for the Big Four).

When assessing the loan applications, these large national banks favor loans to large firms and are biased against small firms. This practice is not only because of the asymmetric information problem for small firms when banks assess loan applications, but also because large firms gain implicit government guarantees from local governments (Jiang, Luo, and Huang, 2006). In Figure 19 we call this type of banking "green banking." As a result, banks favor lending to large firms in heavy industries targeted by the state (e.g. steel and petroleum). Compared to small firms, large firms produce more sales, provide more tax

[37]To keep our model both transparent and focused, we abstract from entering labor in the production function of the heavy sector. For the same reason, we abstract from factors that might potentially explain the changes in the labor income share within the sector. We could, for example, allow for the heterogeneity of technologies and endogenous technology adoption within each sector as in Ngai (2004). Adding these components would *not* change our qualitative results but may blunt our emphasis on the between-sector contribution to changes in the labor income share.

[38]The year 1997 marks the regime switch intended in March 1996 by the "Five-Year Program" of the Eighth National Peoples Congress to give priority to the heavy industry. All our results about the importance of the between-sector effect hold if we also choose 2000 as an initial year for comparison.

revenues, and help boost the GDP of the local economy, an important criterion for the promotion of local government officials.

Most small firms are concentrated in labor-intensive industries (Lin and Li, 2001). Given the monopoly of large banks in the credit market, their preferential loan advances to large firms in the heavy sector, often in the form of "medium & long term loans," take priority over other loans to small firms in the light industry, often in the form of "short-term loans and bill financing." A reading of various *China Monetary Policy Reports* prepared by Monetary Policy Analysis Group of the Peoples Bank of China (the CMP reports hereafter) reveals that the government often increases medium & long term loans at the sacrifice of short-term loans. The purpose of short-term loans is to finance working capital. In fact, the CMP reports sometimes interexchange the terms "short-term loans" and "working capital loans." Costs of short-term loans are much higher than those of long-term loans and we call this type of banking "yellow banking" in Figure 19.

Figure 20 presents evidence that is consistent with the CMP reports and with the divergence between green baking and yellow banking . Two series are plotted in the figure: one is the short-term loan series as percent of GDP and the other is the medium&long-term loan series as percent of GDP. Given the fact that the total loan volume is targeted by the government, whenever there is a rise in new long-term loans, there is a tendency for new short-term loans to fall. The overall correlation of new long-term and short-term loans is negative (about -0.4), consistent with our model's prediction in response to a credit expansion.[39] These annual data accord with the quarterly data displayed in the bottom row of Figure 3 and the discussion in Section III.4. This negative correlation is most conspicuous right after the 2008 financial crisis, when the government injected massive credits into medium&long-term investment projects with a spike of new long-term loans to blunt the impact on China of the severe global recession, while new short-term loans were left unchanged. When this prodigious government credit expansion ceased in 2010, new short-term loans began to rise. Indeed, the loan structure in our theoretical model is designed to approximate these unique characteristics of short-term versus long-term loans.

These new loan series have one potential shortcoming: it does not have the data on *new* loans made to households. An alternative hypothesis is that when the government makes loans to firms, loans to households get crowded out, which leads to the negative comovement between consumption and investment. To entertain this hypothesis, we obtain a breakdown of the quarterly time series of loans *outstanding* into loans to non-financial enterprises (NFE) and to households. These disaggregated series are available from 2007Q1 to 2014Q3. Figure 21 plots year-over-year growth rates of these quarterly series. The left column of the figure displays the growth rates of short-term and long-term loans to NFEs. This plot confirms the negative-correlation pattern displayed in Figure 20, with the correlation being -0.744. The right column of Figure 21 reports the growth rates of short-term and long-term loans to household consumption, alongside the growth rates of long-term loans to NFEs. As one can see clearly, an increase of long-term loans to non-financial firms does not crowd

[39]Brandt and Zhu (2007) discuss how bank loans to the SOEs and POEs changed over time (it appears that these breakdown series for loans no longer exist after 2003). The high volume of short-term loans before 1997 reflected the government's loose credit policy for funding small firms (including unproductive SOE firms) in the form of working capital. After the 1995 banking reform, such easy credit policy has ceased. We see from Figure 20 a sharp fall of new short-term loans in 1997 and 1998. Since 1997 new short-term loans to small firms, including privatized small firms, have been restrictive and received lower priority than new medium&long-term loans to large firms.

out long-term loans to household consumption nor does it crowd out short-term loans to household consumption. To the contrary, all three series comove together with the correlation being 0.725 between short-term and long-term household consumption loans and 0.769 between long-term loans to NFEs and those to household consumption.

The negative correlation between short-term and long-term loans in China is in sharp contrast to the positive one for the U.S. economy. Table 13 reports the correlation between short-term and long-term loans in terms of both the year-over-year growth rate of outstanding loans and the ratio of new loans to GDP by expenditure. All these loans are for non-financial institutions. The quarterly U.S. series of short-term and long-term loans outstanding extend back all the way to the first quarter of 1960, while the corresponding Chinese series go back to only the first month of 1994 according to the WIND dataset.[40] We consider three subsamples relevant to our study: the whole sample period for the U.S. but unavailable (N/A) in early periods for China (1961:1-2014:3), the sample period for most of our empirical analysis (1997:1-2014:3 or 1997:1–2014:4), and the sample period in which a host of monthly data are available for China (2000:1-2013:4 or 2000:1-2014:3). For the U.S., the correlation is highly positive and stable (around 0.60) across all the three subsamples; for China, the correlation is significantly negative for both growth of outstanding loans and the ratio of new loans to GDP (above -0.26) for the two subsamples. These negative correlations for the Chinese economy reflects the government's policy priority that supports heavy industries at the cost of crowding out short-term loans to labor-intensive industries.

The link between the government's investment in the heavy sector and its priority in injecting long-term bank loans into this sector is an unusual institutional arrangement central to our storyline. It is this link that constitutes the key architecture of our theoretic framework. From our calculation based on the 2010:1-2014:4 quarterly series of loan classifications reported by the PBC, 89% of medium&long-term loans is allocated on average to heavy industries and this number has been stable over the years. Figure 22 presents further facts along this dimension but over the longer span of periods. The top chart shows that the ratio of gross output in heavy sector over gross output in light sector based on the NBS's own classification of heavy vs light sectors within the broad secondary industry bar the construction sector. This ratio fluctuated around one until the mid 1990s and since then has steadily increased to the factor of 2.5 in recent years, consistent with the upward trend displayed in Figure 18 based on all the 17 sectors covering the entire economy. The next chart reports the ratio of the capital stock in the heavy sector over that in the light sector within the broad secondary industry bar the construction sector. This chart shows a pattern similar to the top chart. The increasing importance of heavy industries is supported by the rising long-term loans relative to short-term loans until 2010, both in the form of new loans and by the outstanding measure (the third and bottom charts). The upward trend has been

[40]There is no good comprehensive source of aggregate loan originations (new loans) for the U.S. One source we are aware of is the Survey of Terms of Business Lending (STBL) from the Federal Reserve Board, which collects data on commercial and industrial loan originations. It is not a comprehensive count (about 350 banks are surveyed each quarter), and to our knowledge the largest banks are surveyed with certainty and smaller banks are randomly sampled. Consult `http://www.federalreserve.gov/apps/reportforms/reportdetail.aspx?sOoYJ+5BzDaSCesXTb1UmHCoyU8rIHWr` for details. The aim of the STBL survey is to collect data on terms of new business loans (e.g. lending rates), although the survey collects data on the amount of loan originations (or new loans) as well. Unfortunately there is no breakdown of short-term vs. long-term loan originations.

reversed since 2010 because the government ceased to inject long-term credits in 2010.[41] The results from our theoretical model are consistent with the facts presented by Figure 22.

VIII.3. **Understanding the mechanism further.** We explore in this section three counterfactual economies to understand the role of the two key ingredients in our model: the collateral constraint on capital-intensive firms and the financial friction in the banking sector. To isolate the role of each ingredient, we drop one friction at a time. We first drop the banking-sector friction. We then drop both banking-sector friction and collateral constraint on capital-intensive firms so that this counterfactual economy mimics the SSZ two-sector economy. Last, we allow firms in the labor-intensive sector to borrow to finance their investment so that this counterfactual economy becomes a standard frictionless small-open economy.

VIII.3.1. *Economy without lending frictions.* We remove the convex lending cost from our benchmark model. This isolates the role of the financial friction on capital-intensive firms. We find that the transition path of this counterfactual economy is qualitatively similar to our benchmark economy. But the cyclical patterns following a credit expansion differs.

A credit expansion, through on capital-intensive firms, leads to an increase in demand for output produced by the labor-intensive sector. Without the banking-sector friction, the labor demand by labor-intensive firms would increase, which would push up the wage rate as well as the demand for working capital loans (Figure 23). Consequently, working-capital loans increase with investment loans, inconsistent with the data discussed in Section VIII.2.4.

More important is the result that both aggregate consumption (both entrepreneur's and worker's) and aggregate investment increase (Figure 23), which again is inconsistent with the empirical facts. This exercise suggests that the banking-sector friction holds the key to explanation of the cyclical patterns we observe in China.

VIII.3.2. *Economy without lending and collateral frictions.* We now remove the collateral constraint faced by capital-intensive firms as well. With these two types of frictions removed, our economy is reduced to the SSZ two-sector economy. We explore transition paths of this counterfactual economy to quantify the role of the collateral constraint.

Let the starting point be the low initial capital stock below the steady state for labor-intensive firms. Similar to a neoclassical model, the investment-output ratio declines over time while the consumption-output ratio increases. This is opposite of the transition pattern of the economy with collateral constraints. The intuition is simple. Without the collateral constraint on capital-intensive firms, the economy behaves essentially as a neoclassical economy. As the economy grows, output growth in the labor-intensive sector slows down due to the diminishing marginal return to capital. The fall of output growth in the labor-intensive sector in turn reduces the investment rate in the capital-intensive sector because of the imperfect substitutability of outputs between the two sectors. To see this point, consider the case of complete capital depreciation and the risk-aversion parameter $\gamma = 1$. Because there

[41]As shown in the third chart, the patterns for new NFE loans and total new loans track each other very closely, suggesting that total new loans can be used to approximate NFE loans when subcategories of the NFE data are unavailable. For these loan data, it is often inquired by the reader as to why a large fall of new short-term loans in 1997 shown in Figure 20 is not visible in the third chart of Figure 22. This is because the large fluctuations in 1996 and 1997 observed in Figure 20 are small in scale when compared to those in 2008 and 2009. Indeed, the ratio of new medium&long-term loans to new short-term loans in 1996 is $4.53/14.14 = 0.32$ and that the same ratio in 1997 increases to only $3.58/9.18 = 0.39$.

there is no collateral constraint on capital-intensive firms, we have $P_t^k = R$ and consequently P_t^l is constant according to (7). The investment rate in the capital-intensive sector becomes

$$\frac{K_{t+1}^k}{P_t^k Y_t^k} = \frac{K_{t+1}^k}{P_{t+1}^k Y_{t+1}^k} \frac{P_{t+1}^k Y_{t+1}^k}{P_t^k Y_t^k} = \frac{1}{R} \frac{Y_{t+1}^l}{Y_t^l}.$$

Even though the investment rate in the labor-intensive sector remains constant, because the share of revenues in the two sectors in total output is constant, a decline of the investment rate in the capital-intensive sector leads to a simultaneous decline in the aggregate investment rate and a rise in the consumption-output ratio (the first row of Figure 24).[42]

The middle row of Figure 24 displays the pattern of loan structure changes during this transition. When investment for labor-intensive firms falls, it leads to a fall in investment for capital-intensive firms as well. As a result, the demand for investment loans (relative to working-capital loans) declines over time. Due to the constant ratio of revenue in the capital-intensive sector to that in the labor-intensive sector and the constant fraction of wage incomes in output produced by labor-intensive firms, the share of labor income is constant throughout the transition (the middle and last rows of Figure 24).

To summarize, the collateral constraint faced by capital-intensive firms is the key to generating the following trend patterns observed in the Chinese economy: (1) an increasing investment rate, (2) a decreasing consumption-output ratio, (3) a decreasing labor income share, (4) an increasing ratio of the capital-intensive sector's revenue to the labor-intensive sector's revenue, and (5) an increasing ratio of long-term loans to short-term loans. Without such a friction (in addition to the absence of the bank-lending friction), the economy would become essentially neoclassical, which predicts (1) a declining investment rate, (2) an increasing consumption-output ratio, (3) a constant labor income share, (4) a constant ratio of the capital-intensive sector's revenue to the labor-intensive sector's revenue, and (5) a secular decline of long-term loans relative to short-term loans. All these counterfactual trend patterns are at odds with the Chinese data.

VIII.3.3. *Frictionless economy.* In addition to remove both lending and collateral constraints from the benchmark model, we allow the labor-intensive sector to have free access to the financial market. This is essentially a standard frictionless small-open economy with an exogenous interest rate. Assume, without loss of generality, that the old entrepreneur owns the L-firm that is able to borrow from the bank at the fixed interest rate R for capital input. Note that the interest rate for short-term loans to finance wage bills is $R^l = 1$. Similar to our benchmark model, the young entrepreneur is the manager of the L-firms, and the managerial compensation is a fraction ψ of the L-firm's total output. At the end of the period, the young entrepreneur decides on how much to consume and how much to save or deposit in the bank at the fixed interest rate R.

Solving this frictionless economy is straightforward. Because the labor-intensive sector can borrow freely to finance its production with the constant interest rate R, this economy is at the steady state in all periods. In particular, both the consumption rate and the investment rate are constant across time, which implies that the ratio of long-term loans to short-term loans is constant. Similar to the economy without lending and collateral frictions, the labor income share and the ratio of the capital-intensive sector's revenue to the labor-intensive sector's revenue is constant. Thus, all the financial frictions introduced in our benchmark

[42]With incomplete capital depreciation or the risk-aversion parameter $\gamma > 1$, the investment rate in the labor-intensive sector would decline due to diminishing marginal returns to capital.

model as a way to encapsulate China's unique financing arrangements play an indispensable role in accounting for the key facts laid out in this paper.

IX. Conclusion

We have provided a core set of annual and quarterly time series to promote transparency and consistency of the data usable for studying China's macroeconomy. We have styled the key facts that are robust to disparate empirical analyses. These facts represent the core aspects of trend and cycle in the Chinese economy. Macroeconomic models for China should aim to account for all these facts. We have developed a theoretical framework capable of explaining the stylized facts documented in this paper. This framework does not rest on declining prices of investment or a particular assumption about the TFPs between the heavy and light sectors.

There are a host of important dimensions we have not considered, in which one might consider to extend our model for future studies. One important extension is to collect the relevant micro banking data to see how a particular loan is made to a firm, including the information on the type of loan, the type of firm, and the terms of new loans. This extension also allows us to study the aggregate impact of current financial reforms. Another extension is to refine and enrich the model for day-to-day policy analysis, an analysis much needed by the People's Bank of China.

Perhaps the most relevant extension is to explore policy implications and banking reforms. The Eighteenth National People's Congress in 2012, when discussing various policy goals, explicitly expressed concerns about low consumption growth and low labor share of income in China.[43] Our theoretical framework sheds light on a potential cause of the twin first-order problems facing China's macroeconomy today: (a) low consumption and income growth and (b) overcapacity of heavy industries with rising debt risks. How to resolve these problems might have profound policy implications. Our paper suggests that both problems have stemmed from preferential credit policy for promoting the heavy industrialization since the late 1990s. Going forward, effective policy would aim at reducing the *preferential* credit access given to large firms and especially those in the heavy sector. Indeed, financial reforms geared for eliminating such a distortion would go a long way toward making both short-term and long-term loans function efficiently *and* putting the economy on a more balanced path. We hope that this paper will stimulate further research on China's macroeconomy.

[43]See the third point at http://news.xinhuanet.com/18cpcnc/2012-11/17/c_113711665_5.htm and http://news.xinhuanet.com/18cpcnc/2012-11/17/c_113711665_8.htm.

Table 1. Annual GDP series and its subcomponents

Year	GDP	C	I	Govt	Nex	C	I	Govt	Nex
	Billion RMB					Percent of GDP			
1980	459.3	233.1	160.0	67.7	-1.5	50.8	34.8	14.7	-0.3
1981	500.9	262.8	163.0	73.4	1.7	52.5	32.5	14.6	0.3
1982	559.0	290.3	178.4	81.2	9.1	51.9	31.9	14.5	1.6
1983	621.6	323.1	203.9	89.5	5.1	52.0	32.8	14.4	0.8
1984	736.3	374.2	251.5	110.4	0.1	50.8	34.2	15.0	0.0
1985	907.7	468.7	345.8	129.9	-36.7	51.6	38.1	14.3	-4.0
1986	1050.8	530.2	394.2	152.0	-25.5	50.5	37.5	14.5	-2.4
1987	1227.7	612.6	446.2	167.8	1.1	49.9	36.3	13.7	0.1
1988	1538.9	786.8	570.0	197.1	-15.1	51.1	37.0	12.8	-1.0
1989	1731.1	881.3	633.3	235.2	-18.6	50.9	36.6	13.6	-1.1
1990	1934.8	945.1	674.7	264.0	51.0	48.8	34.9	13.6	2.6
1991	2257.7	1073.1	786.8	336.1	61.8	47.5	34.8	14.9	2.7
1992	2756.5	1300.0	1008.6	420.3	27.6	47.2	36.6	15.2	1.0
1993	3693.8	1641.2	1571.8	548.8	-68.0	44.4	42.6	14.9	-1.8
1994	5021.7	2184.4	2034.1	739.8	63.4	43.5	40.5	14.7	1.3
1995	6321.7	2837.0	2547.0	837.9	99.9	44.9	40.3	13.3	1.6
1996	7416.4	3395.6	2878.5	996.4	145.9	45.8	38.8	13.4	2.0
1997	8165.9	3692.2	2996.8	1121.9	355.0	45.2	36.7	13.7	4.3
1998	8653.2	3922.9	3131.4	1235.9	362.9	45.3	36.2	14.3	4.2
1999	9112.5	4192.0	3295.2	1371.7	253.7	46.0	36.2	15.1	2.8
2000	9874.9	4585.5	3484.3	1566.1	239.0	46.4	35.3	15.9	2.4
2001	10902.8	4943.6	3976.9	1749.8	232.5	45.3	36.5	16.0	2.1
2002	12047.6	5305.7	4556.5	1876.0	309.4	44.0	37.8	15.6	2.6
2003	13661.3	5765.0	5596.3	2003.6	296.5	42.2	41.0	14.7	2.2
2004	16095.7	6521.8	6916.8	2233.4	423.6	40.5	43.0	13.9	2.6
2005	18742.3	7295.9	7785.7	2639.9	1020.9	38.9	41.5	14.1	5.4
2006	22271.3	8257.5	9295.4	3052.8	1665.5	37.1	41.7	13.7	7.5
2007	26659.9	9633.2	11094.3	3590.0	2342.3	36.1	41.6	13.5	8.8
2008	31597.5	11167.0	13832.5	4175.2	2422.7	35.3	43.8	13.2	7.7
2009	34877.5	12358.5	16446.3	4569.0	1503.7	35.4	47.2	13.1	4.3
2010	40281.6	14075.9	19360.4	5335.6	1509.8	34.9	48.1	13.2	3.7
2011	47261.9	16895.7	22834.4	6315.5	1216.3	35.7	48.3	13.4	2.6
2012	52939.9	19058.5	25277.3	7140.9	1463.2	36.0	47.7	13.5	2.8
2013	58667.3	21218.8	28035.6	7997.8	1415.1	36.2	47.8	13.6	2.4

Note: "C" stands for household consumption, "I" for gross capital formation (aggregate investment), "Govt" government consumption, and "Nex" net exports.

TABLE 2. Chronology of structural switches

Dates	Major structural changes
December 1978	Introduction of economic reforms
Early 1990s	Price controls and rationing
Beginning of 1992	Advanced the reforms by Deng Xiaoping
January 1994	Ended the two-tiered foreign exchange system
1994	Major tax reforms and devaluation of RMB
1995-1996	Phased out price controls and rationing
1995	Enacted People's Bank of China law and other banking laws with decentralization of the banking system
March 1996	***Strategic plan to develop infrastructure and other heavy industries***
July 1997	Asian financial crises started in Thailand
November 1997	Began privatization
November 2001	Joined the WTO and trade liberalization
July 2005	Ended an explicit peg to the USD
September 2008	U.S. and world wide financial crisis
2009-2010	Fiscal stimulus of 4 trillion RMB investment

Table 3. Annual GDP series and further breakdowns (billion RMB)

Year	GDP	C	SOE	POE	HH I	Govt C	Nex	Invty
1995	6321.7	2837.0	926.8	810.7	351.0	837.9	99.9	458.5
1996	7416.4	3395.6	1016.6	963.4	424.8	996.4	145.9	473.7
1997	8165.9	3692.2	1090.9	1032.8	472.8	1121.9	355.0	400.3
1998	8653.2	3922.9	1215.7	1086.8	554.4	1235.9	362.9	274.5
1999	9112.5	4192.0	1263.5	1156.5	632.7	1371.7	253.7	242.4
2000	9874.9	4585.5	1289.2	1345.9	749.3	1566.1	239.0	99.8
2001	10902.8	4943.6	1324.2	1549.7	901.5	1749.8	232.5	201.5
2002	12047.6	5305.7	1409.3	1927.4	1026.4	1876.0	309.4	193.3
2003	13661.3	5765.0	1525.6	2504.5	1318.9	2003.6	296.5	247.2
2004	16095.7	6521.8	1654.4	3155.2	1702.1	2233.4	423.6	405.1
2005	18742.3	7295.9	1695.7	3577.1	2150.5	2639.9	1020.9	362.4
2006	22271.3	8257.5	2055.1	4728.6	2011.7	3052.8	1665.5	500.0
2007	26659.9	9633.2	2327.6	5839.3	2228.0	3590.0	2342.3	699.5
2008	31597.5	11167.0	2928.3	7388.3	2491.8	4175.2	2422.7	1024.1
2009	34877.5	12358.5	3892.9	8571.1	3204.0	4569.0	1503.7	778.3
2010	40281.6	14075.9	4388.6	10156.8	3816.1	5335.6	1509.8	998.9
2011	47261.9	16895.7	4323.5	11855.9	5388.7	6315.5	1216.3	1266.2
2012	52939.9	19058.5	4708.6	13460.3	6006.8	7140.9	1463.2	1101.6
2013	58667.3	21218.8	4991.9	15111.7	6803.3	7997.8	1415.1	1128.1

Note: "C" stands for household consumption, "SOE" for the SOE portion of gross fixed capital formation, "POE" the POE portion of gross fixed capital formation, "HH I" household investment, "Govt C" government consumption, "Nex" net exports, and "Invty" changes of inventories.

Table 4. Detailed GDP subcomponents as percent of GDP

Year	C	SOE	POE	HH I	Govt C	Nex	Invty
1995	44.9	14.7	12.8	5.6	13.3	1.6	7.3
1996	45.8	13.7	13.0	5.7	13.4	2.0	6.4
1997	45.2	13.4	12.6	5.8	13.7	4.3	4.9
1998	45.3	14.0	12.6	6.4	14.3	4.2	3.2
1999	46.0	13.9	12.7	6.9	15.1	2.8	2.7
2000	46.4	13.1	13.6	7.6	15.9	2.4	1.0
2001	45.3	12.1	14.2	8.3	16.0	2.1	1.8
2002	44.0	11.7	16.0	8.5	15.6	2.6	1.6
2003	42.2	11.2	18.3	9.7	14.7	2.2	1.8
2004	40.5	10.3	19.6	10.6	13.9	2.6	2.5
2005	38.9	9.0	19.1	11.5	14.1	5.4	1.9
2006	37.1	9.2	21.2	9.0	13.7	7.5	2.2
2007	36.1	8.7	21.9	8.4	13.5	8.8	2.6
2008	35.3	9.3	23.4	7.9	13.2	7.7	3.2
2009	35.4	11.2	24.6	9.2	13.1	4.3	2.2
2010	34.9	10.9	25.2	9.5	13.2	3.7	2.5
2011	35.7	9.1	25.1	11.4	13.4	2.6	2.7
2012	36.0	8.9	25.4	11.3	13.5	2.8	2.1
2013	36.2	8.5	25.8	11.6	13.6	2.4	1.9

Note: "C" stands for household consumption, "SOE" for the SOE portion of gross fixed capital formation, "POE" the POE portion of gross fixed capital formation, "HH I" household investment, "Govt C" government consumption, "Nex" net exports, and "Invty" changes of inventories.

Table 5. Correlations between HP-filtered log quarterly series

Panel A: Real variables deflated by own price index		
	(C, I)	(I, LaborIncome)
Correlation	−0.140	0.165
p-value	0.256	0.179
Panel B: Real variables deflated by GDP price deflator		
	(C, I)	(I, LaborIncome)
Correlation	−0.035	0.165
p-value	0.775	0.178

Note: Labor income (LaborIncome) is deflated by the GDP deflator. The sample runs from 1996Q1 to 2012Q4. "C" stands for household consumption and "I" for total business investment.

Table 6. Industry identifiers

Identifier	Industry
1	Mining and Washing of Coal
2	Extraction of Petroleum and Natural Gas
3	Mining and Processing of Ferrous Metal Ores
4	Mining and Processing of Non-Ferrous Metal Ores
5	Mining and Processing of Nonmetal Ores
6	Mining of Other Ores
7	Processing of Food from Agricultural Products
8	Food
9	Wine, Beverage & Refined Tea
10	Tobacco
11	Textile
12	Textile Product, Garment, Shoes & Hat
13	Leather, Fur, Feather & Its Product
14	Wood Processing, Wood, Bamboo, Rattan, Palm & Grass Product
15	Manufacture of Furniture
16	Manufacture of Paper and Paper Products
17	Printing, Reproduction of Recording Media
18	Cultural, Education & Sport
19	Processing of Petroleum, Coking, Processing of Nuclear Fuel
20	Chemical Material & Product
21	Manufacture of Medicines (Pharmaceutical)
22	Manufacture of Chemical Fibers
23	Manufacture of Rubber
24	Manufacture of Plastics
25	Manufacture of Non-metallic Mineral Products
26	Smelting and Pressing of Ferrous Metals
27	Smelting and Pressing of Non-ferrous Metals
28	Manufacture of Metal Products
29	Manufacture of General Purpose Machinery
30	Manufacture of Special Purpose Machinery
31	Manufacture of Transport Equipment
32	Manufacture of Electrical Machinery and Equipment
33	Computer, Communication & Other Electronic Equipment
34	Instrument, Meter, Culture & Office Machinery
35	Manufacture of Artwork and Other Manufacturing
36	Recycling and Disposal of Waste
37	Electricity, Heat Production & Supply
38	Gas Production & Supply
39	Water Production & Supply

TABLE 7. Weights and capital-intensity ranks for various industries

	1999		2006		2011	
Industry identifier	Weight (%) by value added	Capital intensity rank	Weight (%) by value added	Capital intensity rank	Weight (%) by gross output	Capital intensity rank
1	2.66	23	3.93	22	3.42	16
2	6.77	2	6.57	2	1.52	2
3	0.25	30	0.64	23	0.93	12
4	0.59	24	0.74	24	0.59	15
5	0.55	22	0.41	28	0.45	27
6	N/A	N/A	0.00	16	0.00	8
7	3.59	19	3.83	21	5.22	22
8	1.62	18	1.61	18	1.66	23
9	2.76	11	1.58	12	1.40	17
10	4.20	4	2.61	6	0.80	7
11	5.26	29	4.35	30	3.86	33
12	2.38	35	2.01	38	1.60	37
13	1.33	36	1.28	39	1.05	39
14	0.62	28	0.75	32	1.06	31
15	0.36	33	0.55	35	0.60	35
16	1.67	12	1.52	11	1.43	13
17	0.93	16	0.61	17	0.45	26
18	0.66	34	0.51	37	0.38	38
19	2.78	3	2.54	4	4.36	4
20	5.73	10	5.92	10	7.20	10
21	2.42	13	1.98	13	1.76	21
22	1.19	7	0.66	8	0.79	11
23	0.95	20	0.78	20	0.86	20
24	1.82	21	1.83	26	1.84	30
25	4.73	17	4.01	15	4.75	14
26	5.09	8	7.69	7	7.58	6
27	1.90	9	3.51	9	4.25	9
28	2.54	31	2.44	33	2.76	28
29	3.50	27	4.17	29	4.85	25
30	2.43	25	2.52	27	3.09	24
31	5.62	15	5.41	14	7.49	18
32	4.72	26	5.07	31	6.09	29
33	6.35	14	7.77	19	7.55	32
34	0.85	32	1.06	34	0.90	34
35	N/A	N/A	0.77	36	0.85	36
36	N/A	N/A	0.10	25	0.31	19
37	10.18	1	7.58	1	5.60	1
38	0.17	5	0.21	3	0.37	5
39	0.68	6	0.34	5	0.13	3

Table 8. Growth accounting of China's economy

Growth rate (in percent)	1978-1998	1998-2011	1998-2007
GDP per worker	6.78	9.48	9.42
capital per worker	3.56	7.00	6.13
TFP	3.23	2.48	3.29
Contribution by capital deepening	52.4%	73.9%	65.1%

Note: The computation uses the value of the capital share set at 0.5 as in SSZ and Brandt and Zhu (2010).

Table 9. Parameter values

Parameter	Definition	Value
α	Capital Income Share in L-Sector	0.40
β	Utility Discount Factor	$(0.96)^{30}$
ξ	Speed of Net Worth Accumulation for K-sector	0.56
θ	Leverage Ratio for K-Sector	0.30
ψ	Fraction of L-sector Revenue to Young Entrepreneurs	0.20
δ	Capital Depreciate Rate	1
χ	Relative TFP of L-sector	4.98
σ	Elasticity of Substitution Between K and L Sectors	2
R	Interest Rate for K-sector Investment Loan	1.04
φ	Share of K-sector output in Final Output Production	0.85
η	Curvature Parameter in Banking Cost of Borrowing	20
γ	Intertemporal Elasticity of Substitution	1

Table 10. Estimate and probability intervals of σ using system (27) or (29)

Seasonally adjusted monthly data		
Point estimate	68% interval	95% interval
2.32	(2.11, 2.54)	(1.94, 2.79)
Original (not seasonally adjusted) monthly data		
Point estimate	68% interval	95% interval
2.15	(1.96, 2.35)	(1.80, 2.57)

Note: The simulated results are based on one million MCMC posterior probability draws.

Table 11. Labor shares across 17 sectors

Labor share	Detailed sector	Broad sector
0.199	Real Estate, Leasing and Commercial Service	H
0.238	Electricity, Heating and Water Production and Supply	H
0.243	Coking, Coal Gas and Petroleum Processing	H
0.266	Food, Beverage and Tobacco	L
0.316	Wholesale, Retail, Accommodation and Catering	H
0.330	Banking and Insurance	H
0.335	Chemical	H
0.336	Other manufacturing	L
0.365	Mining	H
0.370	Transportation, Information Transmission, Computer Services & Software	H
0.375	Metal Product	L
0.399	Machinery Equipment	L
0.414	Construction Material and Non Metallic Mineral Product	L
0.448	Textile, Garment and Leather	L
0.580	Construction	L
0.738	Other Services	L
0.886	Farming, Forestry, Animal Husbandry, Fishery	L

Note: "H" stands for the heavy sector and "L" the light sector. The labor share in each disaggregated sector is calculated as labor compensation from the survey data, divided by value added from the NBS input-output tables. The labor-share number reported is the average value between 1995 and 2010.

TABLE 12. Between-sector and within-sector decompositions of changes in the labor share

All 17 sectors, ΔLS relative to the 1995 labor share					
Year	ΔLS	Between	Within	Between (%)	Within (%)
2007	-0.085	-0.052	-0.032	61.84 (−)	38.15 (−)
2010	-0.025	-0.052	0.027	65.81 (−)	34.19 (+)
All 17 sectors, ΔLS relative to the 1997 labor share					
Year	ΔLS	Between	Within	Between (%)	Within (%)
2007	-0.147	-0.057	-0.089	39.00 (−)	61.00 (−)
2010	-0.088	-0.057	-0.030	65.59 (−)	34.40 (−)
Excluding agriculture, ΔLS relative to the 1995 labor share					
Year	ΔLS	Between	Within	Between (%)	Within (%)
2007	-0.043	-0.019	-0.024	43.30 (−)	56.69 (−)
2010	0.028	-0.019	0.047	29.01 (−)	70.99 (+)
Excluding agriculture, ΔLS relative to the 1997 labor share					
Year	ΔLS	Between	Within	Between (%)	Within (%)
2007	-0.119	-0.026	-0.093	21.76 (−)	78.23 (−)
2010	-0.048	-0.027	-0.021	55.84 (−)	44.16 (−)

Note: "ΔLS" stands for change of the labor share relative to the value in the initial year (1995 or 1997). The "−" sign in parentheses indicates contribution to a decline in labor share and the "+" sign indicates contribution to an increase in labor share. "Excluding agriculture" means all 16 sectors excluding the sector of farming, forestry, animal husbandry, and fishery.

TABLE 13. Correlation between short-term and long-term loans (quarterly data)

Start of the sample	Loan growth (yoy) U.S.	Loan growth (yoy) China	New loans as % of GDP China
1961:1-	0.63 (2014:3)	N/A	N/A
1997:1-	0.60 (2014:3)	-0.26 (2014:4)	-0.27 (2013:4)
2000:1-	0.59 (2014:3)	-0.40 (2014:4)	-0.27 (2013:4)

Note: "Loan growth (yoy)" means the year-over-year growth rate of loans outstanding. "New loans as % of GDP" means the ratio of new loans to GDP. For the Chinese data, the term "long-term loans" means medium&long-term loans. The date in parentheses indicates the end period of the sample. These end-of-sample dates are different for different series, depending on when the latest data of each series is released to the public.

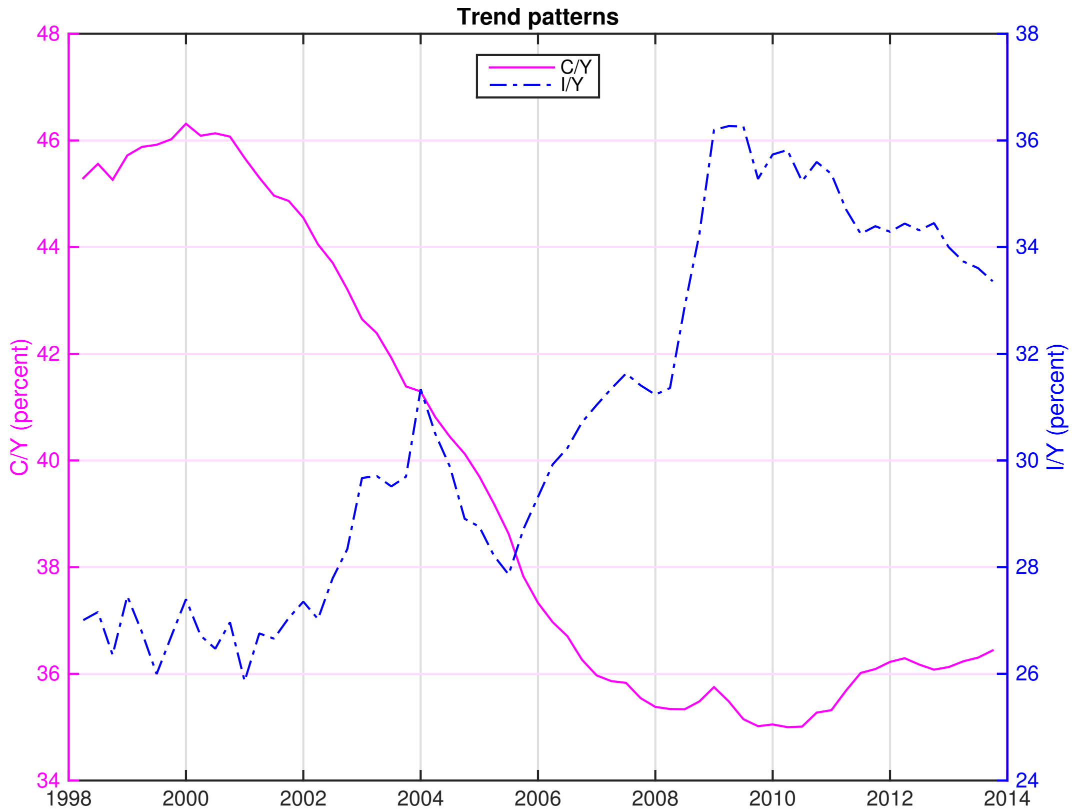

FIGURE 1. Trend patterns of household consumption and business investment, estimated from the 6-variable regime-switching BVAR model.

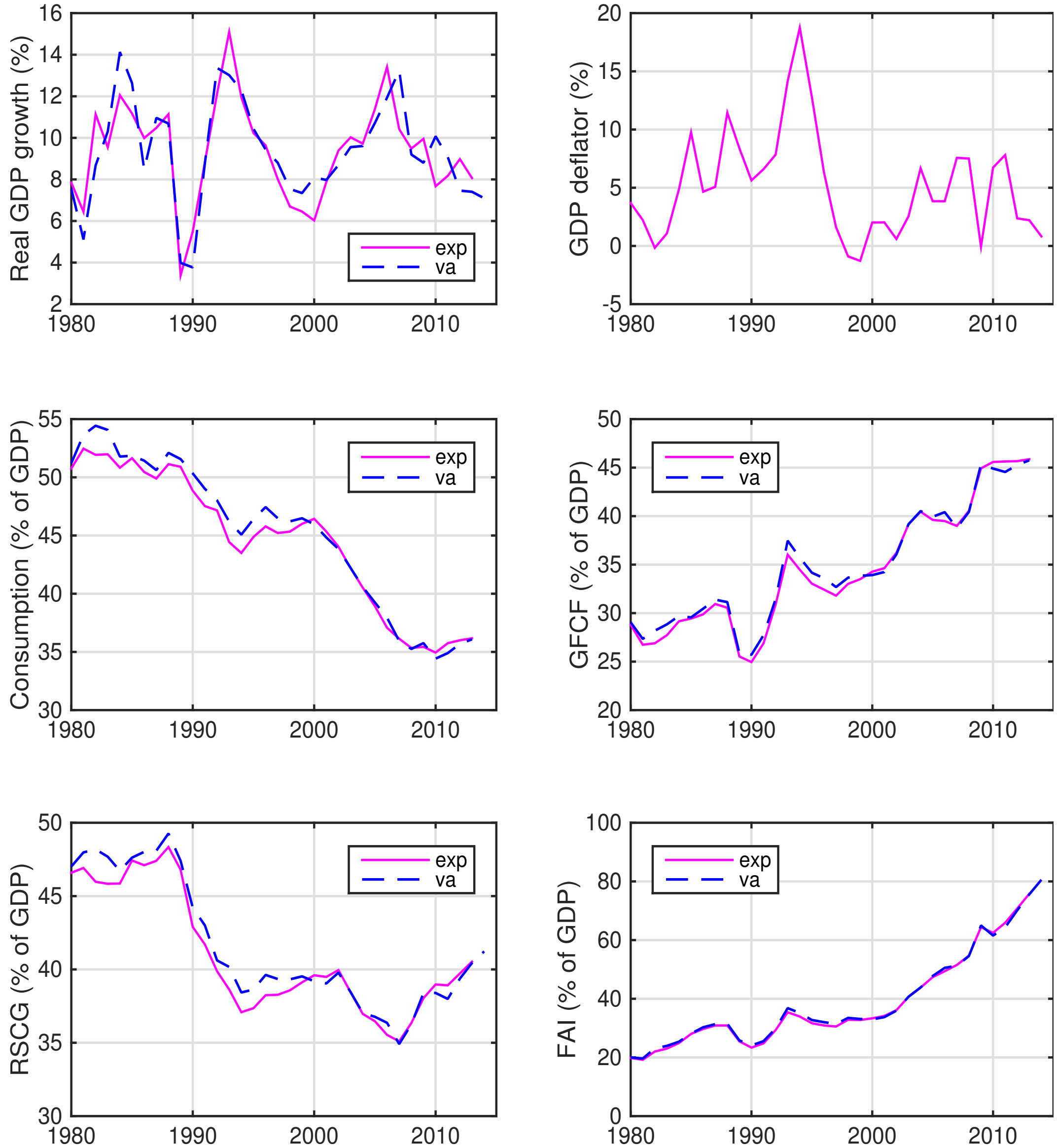

FIGURE 2. Time-series history of trends and cycles in China's macroeconomy: annual data. "Consumption" is household consumption, "GFCF" stands for gross fixed capital formation, "RSCG" stands for retail sales of consumer goods, and "FAI" stands for fixed-asset investment. The legend "exp" means that GDP is measured by expenditure and "va" means that GDP is measured by value added.

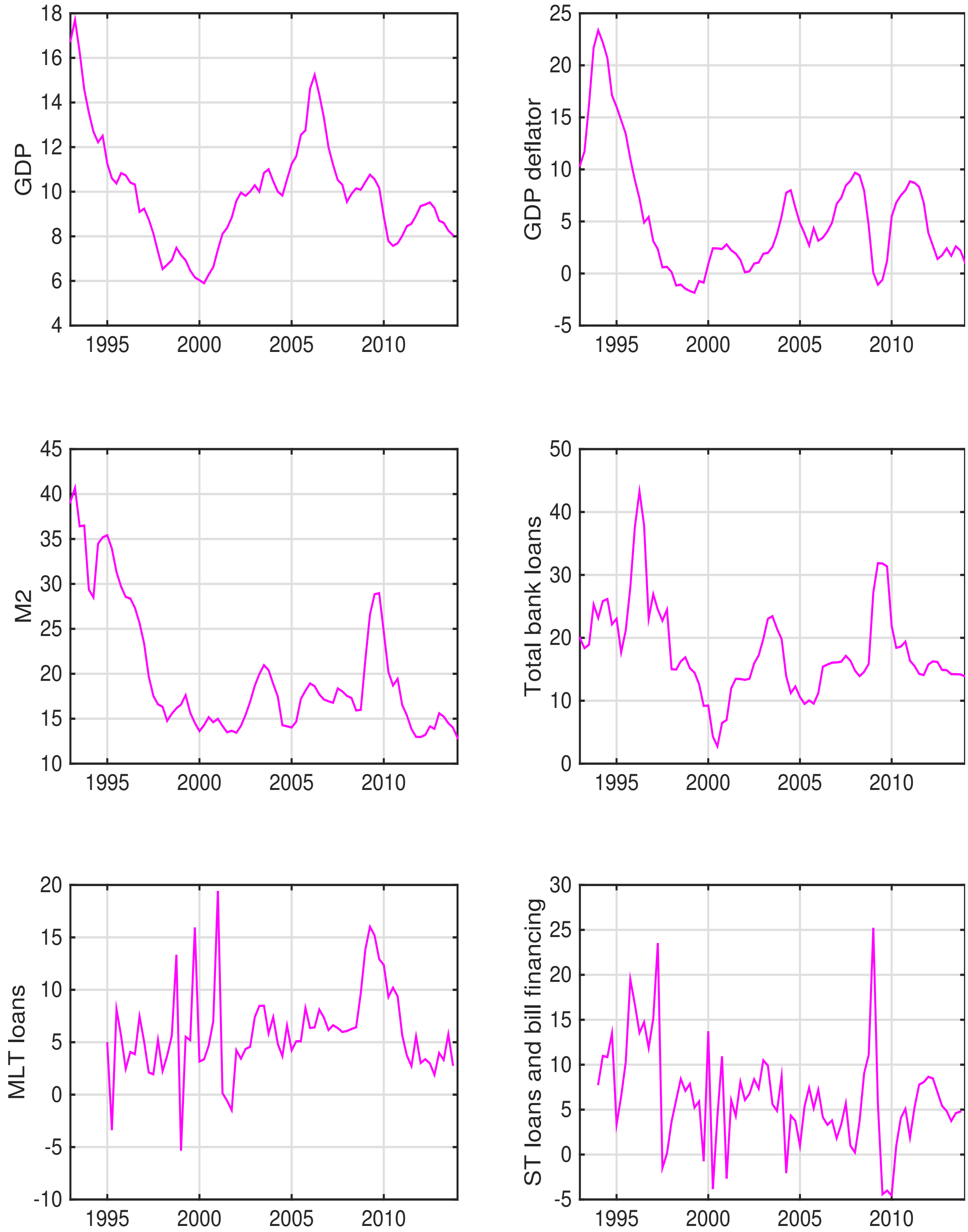

FIGURE 3. The top first two rows: year-over-year growth rates (%) of key quarterly time series; the bottom row: quarterly variables as percent of GDP. Total bank loans are delated by the implicit GDP deflator. "MLT loans" stands for medium and long term bank loans to non-financial firms and "ST loans and bill financing" stands for short term bank loans and bill financing to non-financial firms.

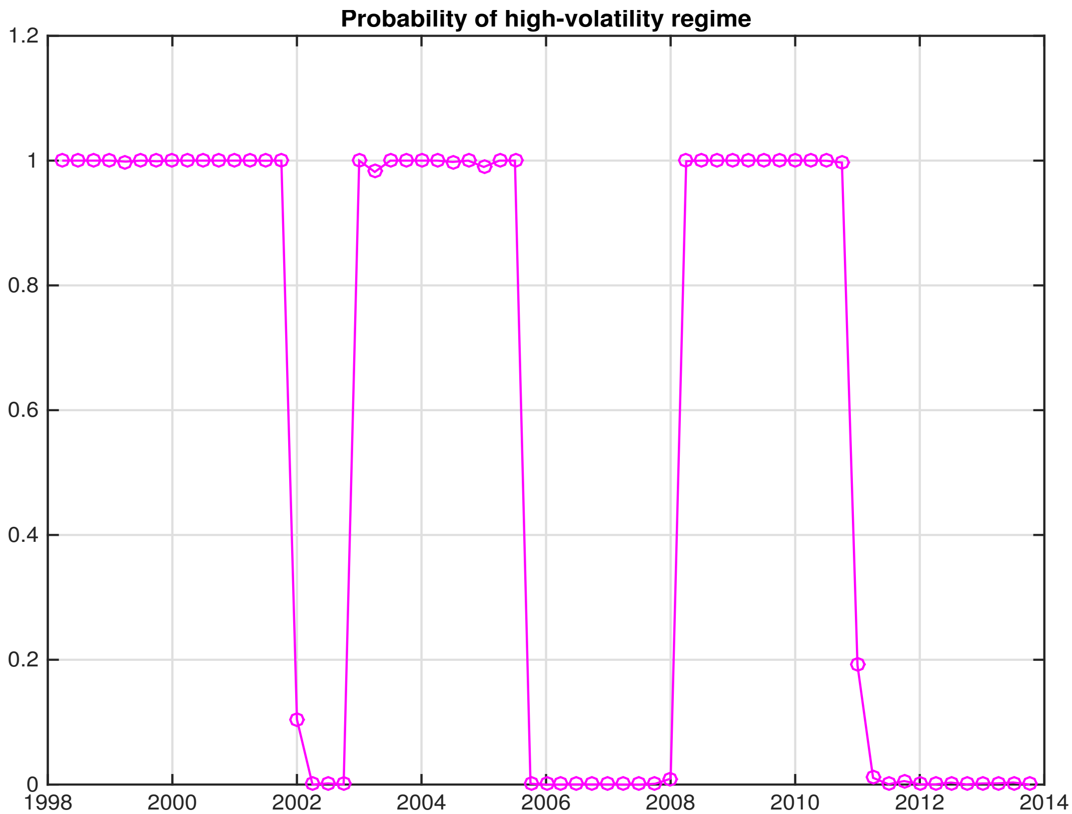

FIGURE 4. Estimated smoothed posterior probabilities of the high-volatility regime.

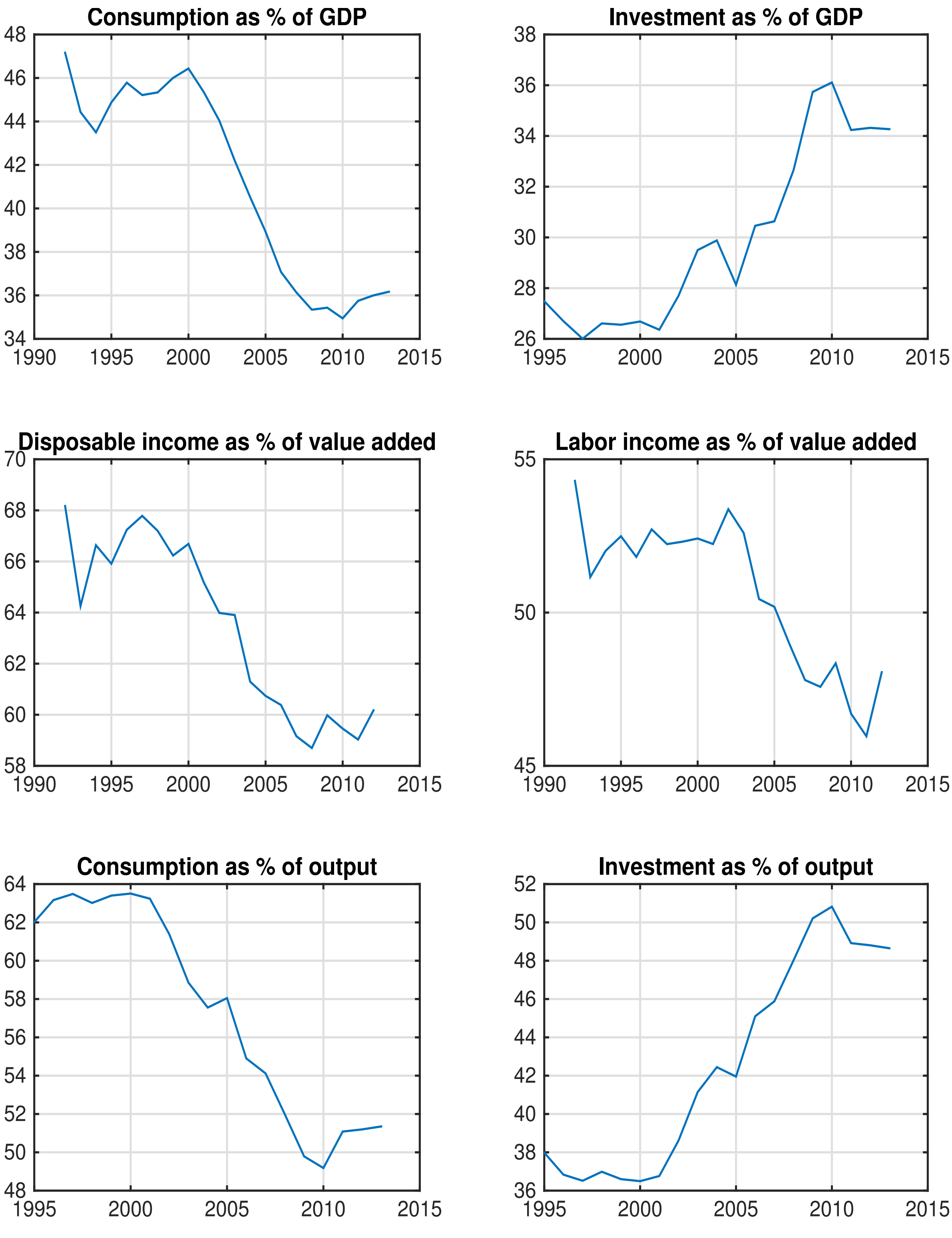

FIGURE 5. Annual data: trend patterns for household consumption, investment, GDP, household disposable personal income, and household labor income. "Investment" is total business investment, calculated as gross fixed capital formation excluding household investment. "Output" is the sum of household consumption and business investment.

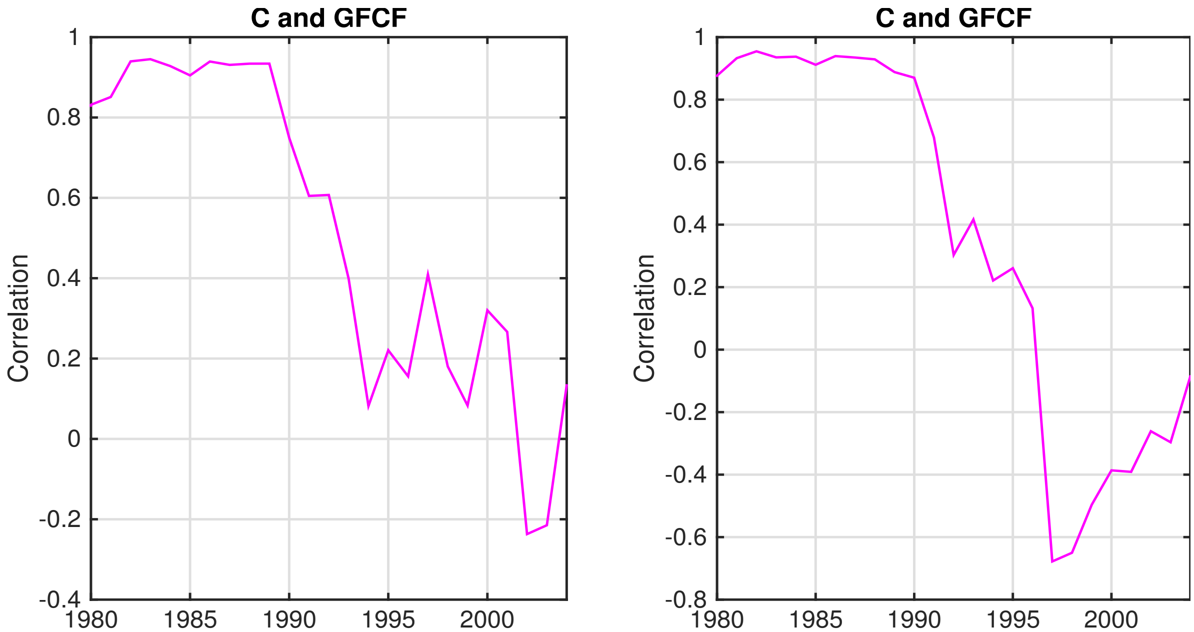

FIGURE 6. Time series of correlations with the 10-year moving window. The left-column graphs represent the correlation of annual growth rates. The right-column graphs represent the correlation of HP-filtered log annual values.

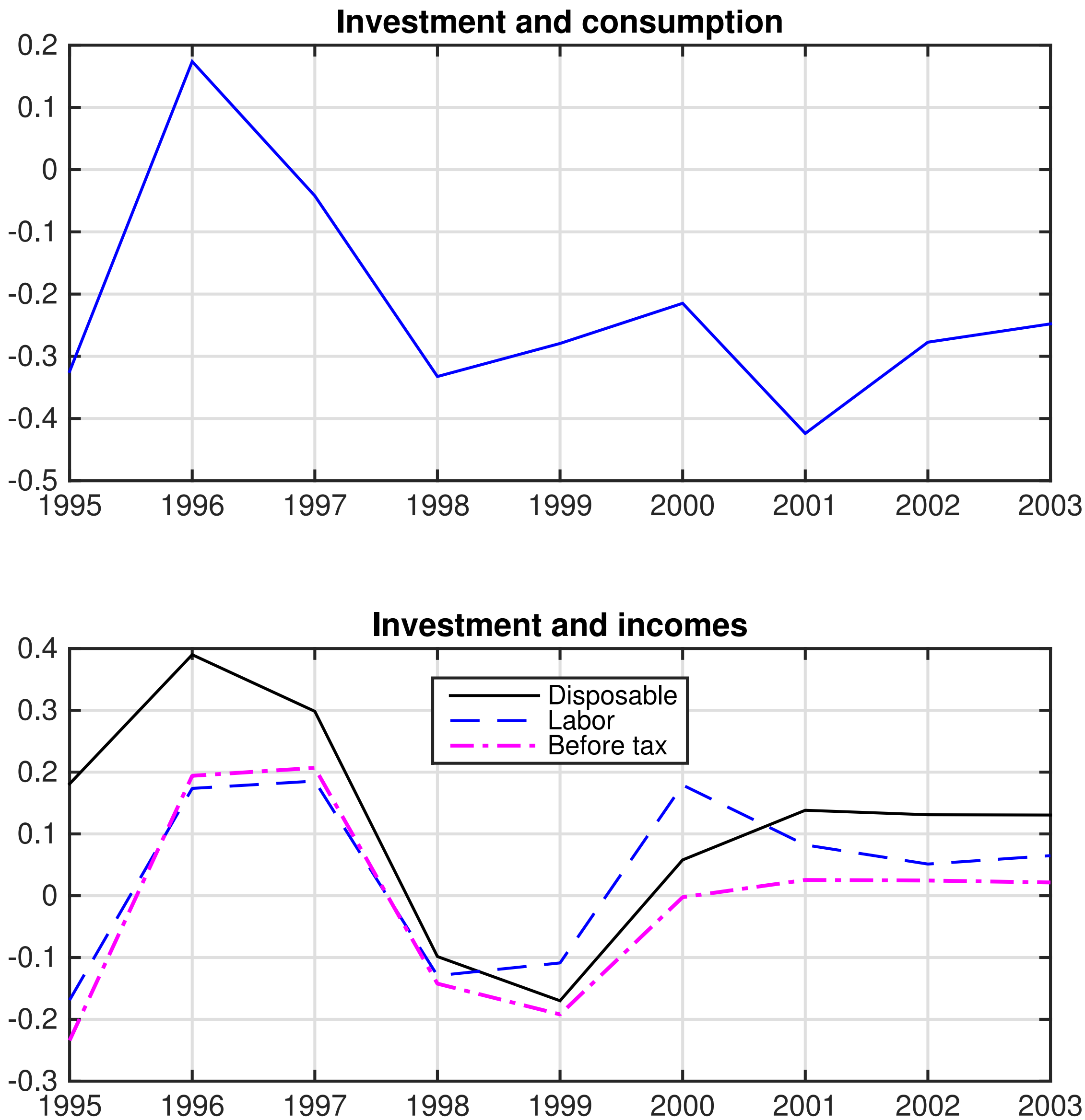

FIGURE 7. Correlations between HP-filtered log annual series with the moving window of 10 years. "Consumption" is real household consumption (deflated by the CPI), "Incomes" are various measures of household personal incomes (deflated by the GDP deflator), "Investment" is real total business investment (deflated by the investment price index), "Disposable" stands for household disposable personal income, "Labor" stands for household labor income, and "Before tax" stands for household before-tax labor income.

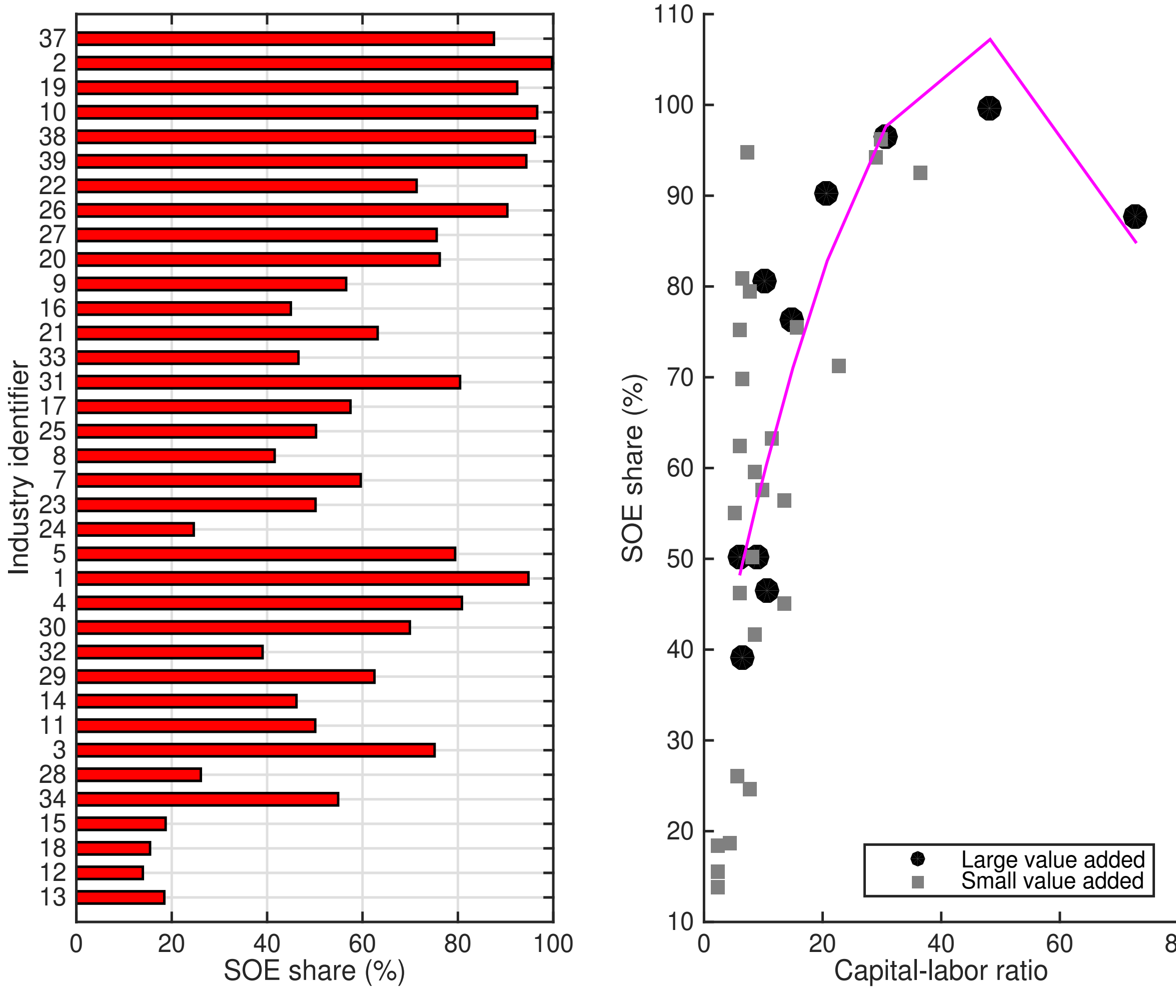

FIGURE 8. The 1999 characteristics of various industries in China. The industries identified by the numerical numbers on the vertical axis of the left-hand graph are listed in Table 6. The dark circles in the right-hand graph indicate the top-10 industries by added value to output; the curve line is a fitted quadratic regression of the SEO share on the capital-labor ratio for these top-10 industries.

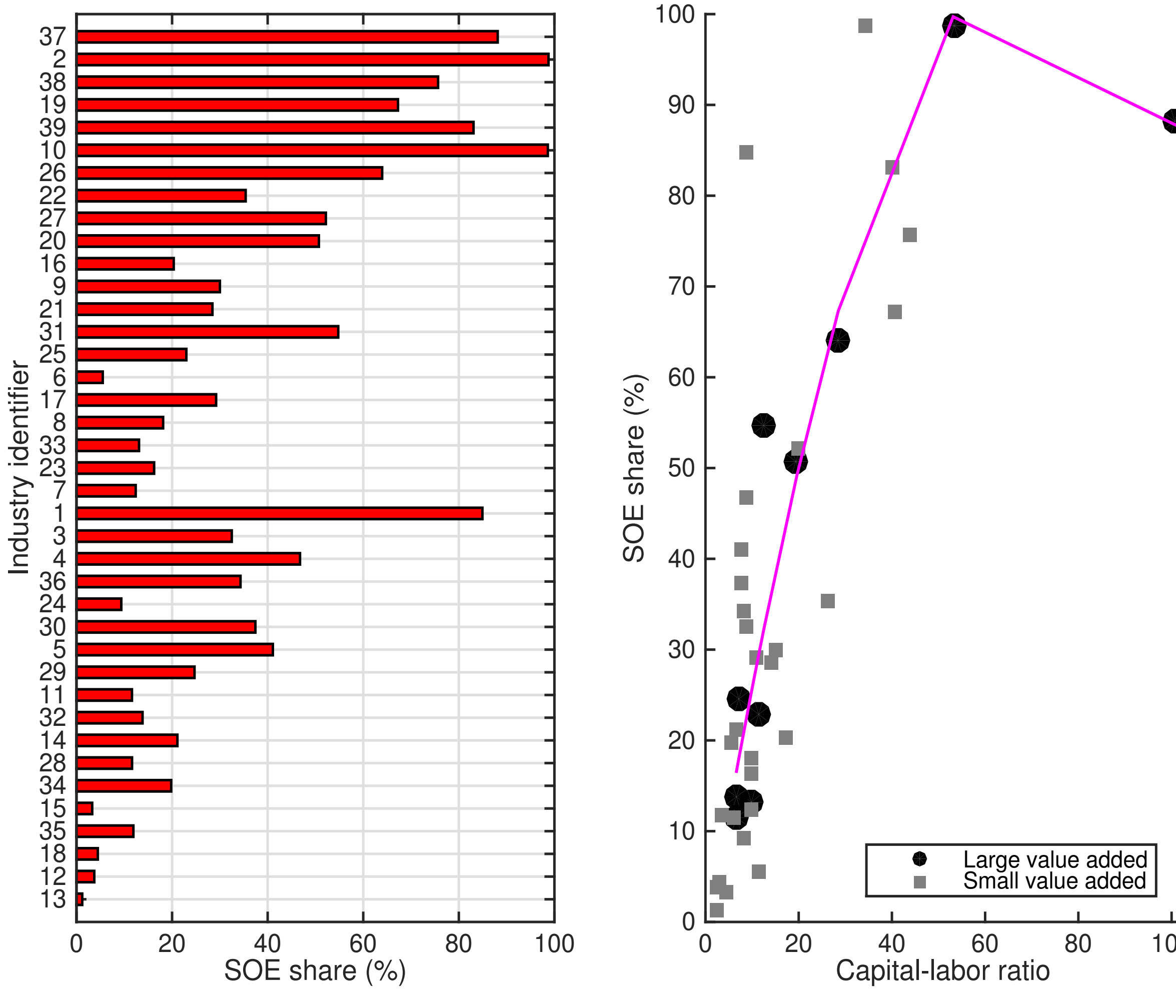

FIGURE 9. The 2006 characteristics of various industries in China. The industries identified by the numerical numbers on the vertical axis of the left-hand graph are listed in Table 6. The dark circles in the right-hand graph indicate the top-10 industries by added value to output; the curve line is a fitted quadratic regression of the SEO share on the capital-labor ratio for these top-10 industries.

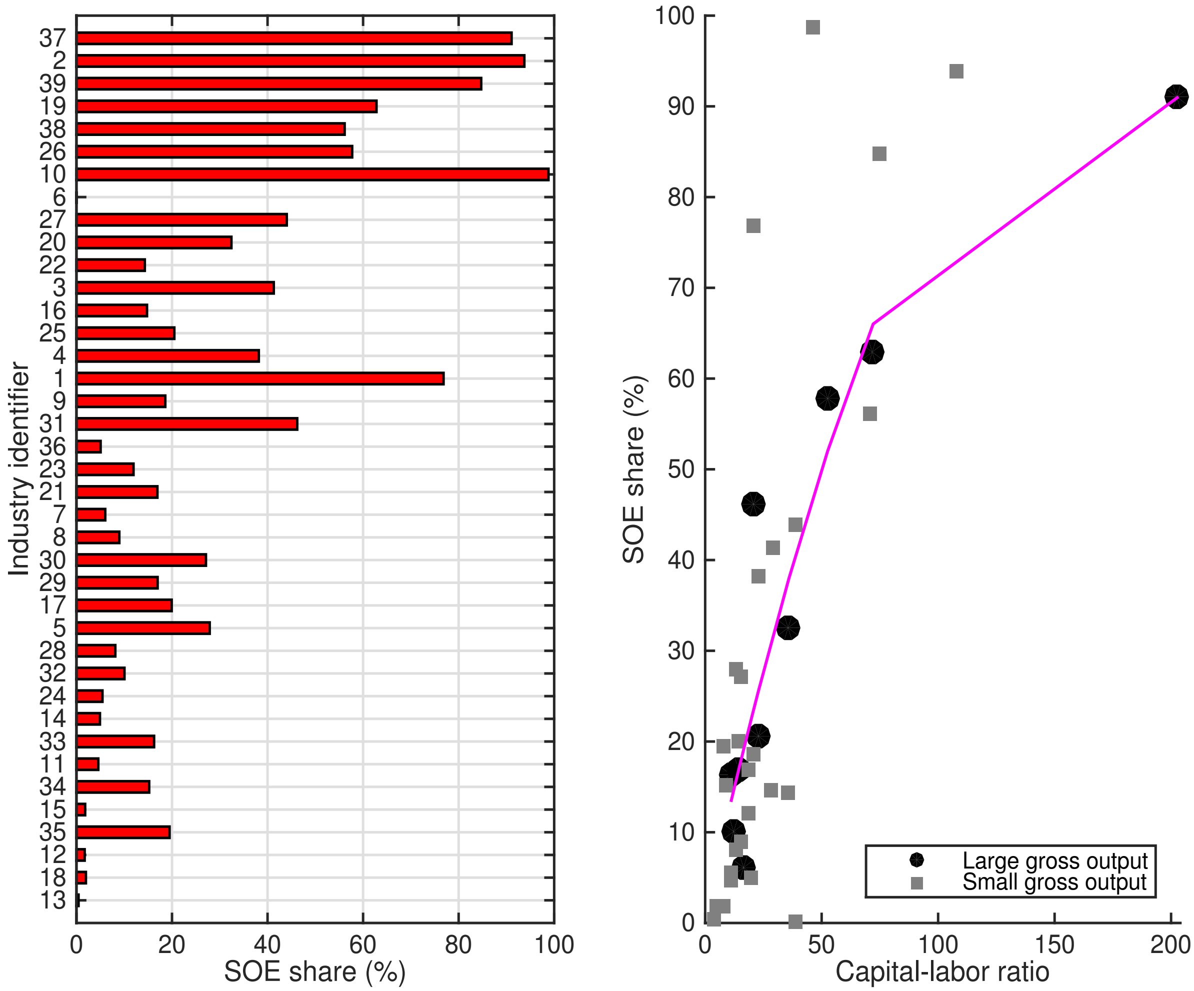

FIGURE 10. The 2011 characteristics of various industries in China. The industries identified by the numerical numbers on the vertical axis of the left-hand graph are listed in Table 6. The dark circles in the right-hand graph indicate the top-10 industries by gross output; the curve line is a fitted quadratic regression of the SEO share on the capital-labor ratio for these top-10 industries.

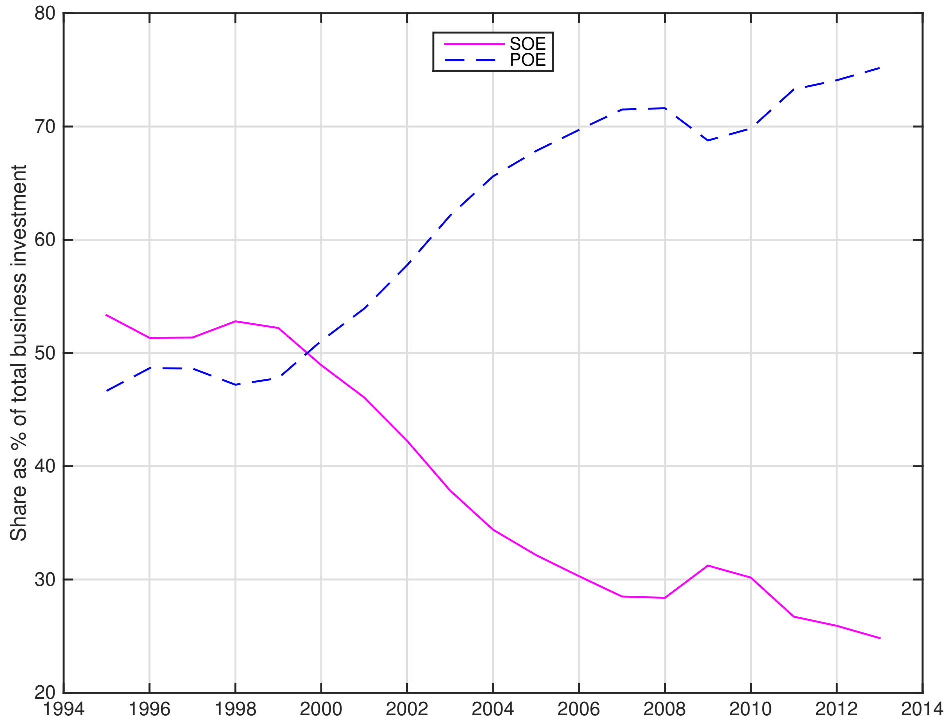

FIGURE 11. The share of SOE investment and POE investment as percent of total business investment, where total business investment equals the sum of SOE investment and POE investment.

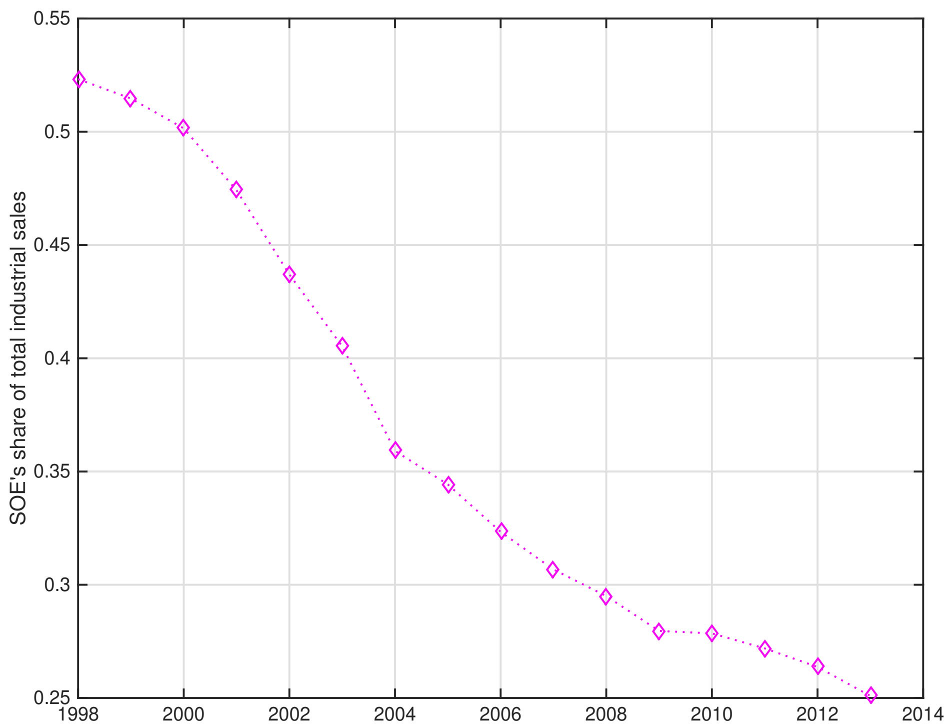

FIGURE 12. The ratio of sales revenue in the SOEs to the total sales revenue in all industrial firms.

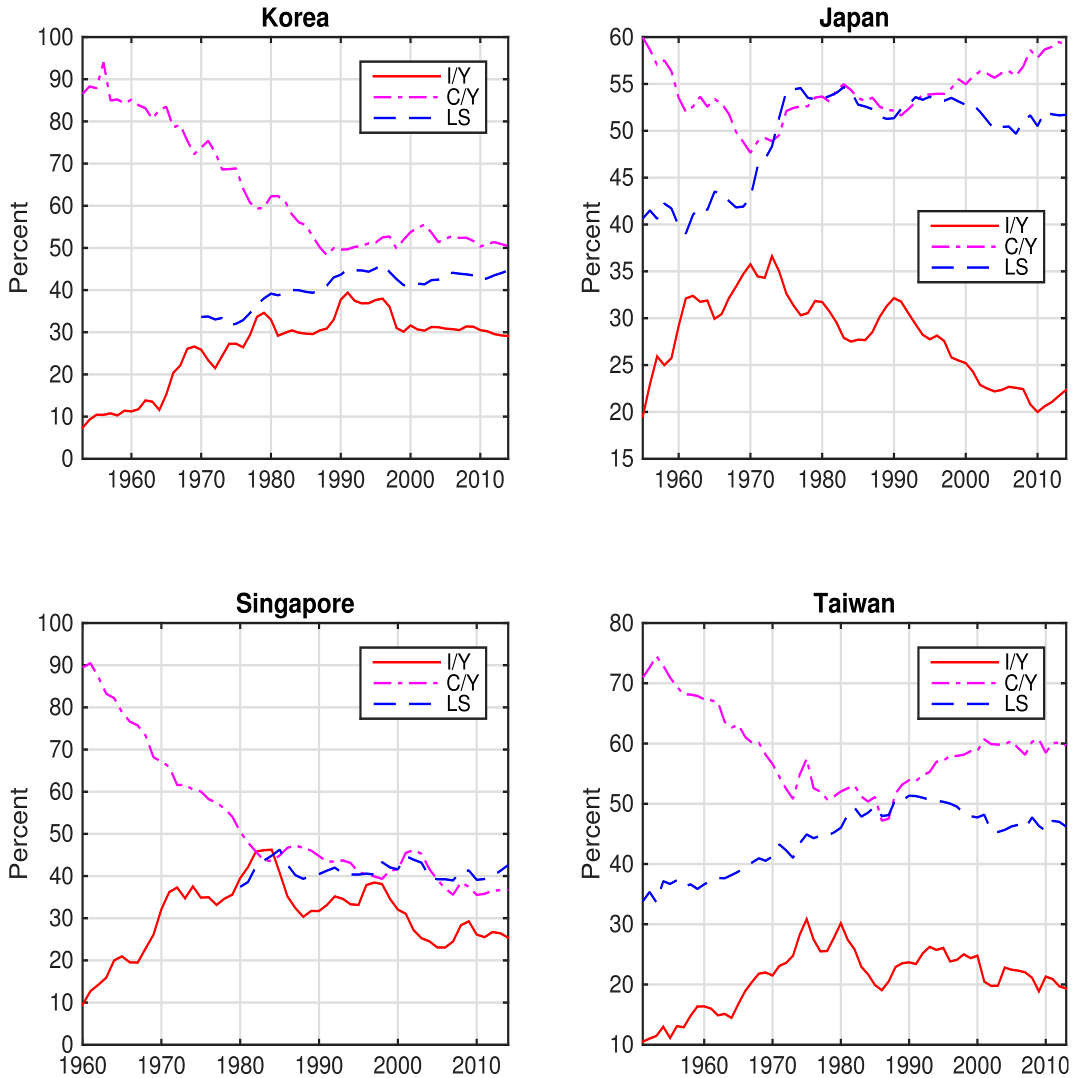

FIGURE 13. C: private personal consumption; I: gross fixed domestic investment (gross fixed capital formation); LS: labor income share; Y: GDP. Source: CEIC. Overall correlation between LS and I/Y: 0.718 (Korea), -0.174 (Japan), 0.353 (Singapore), 0.740 (Taiwan).

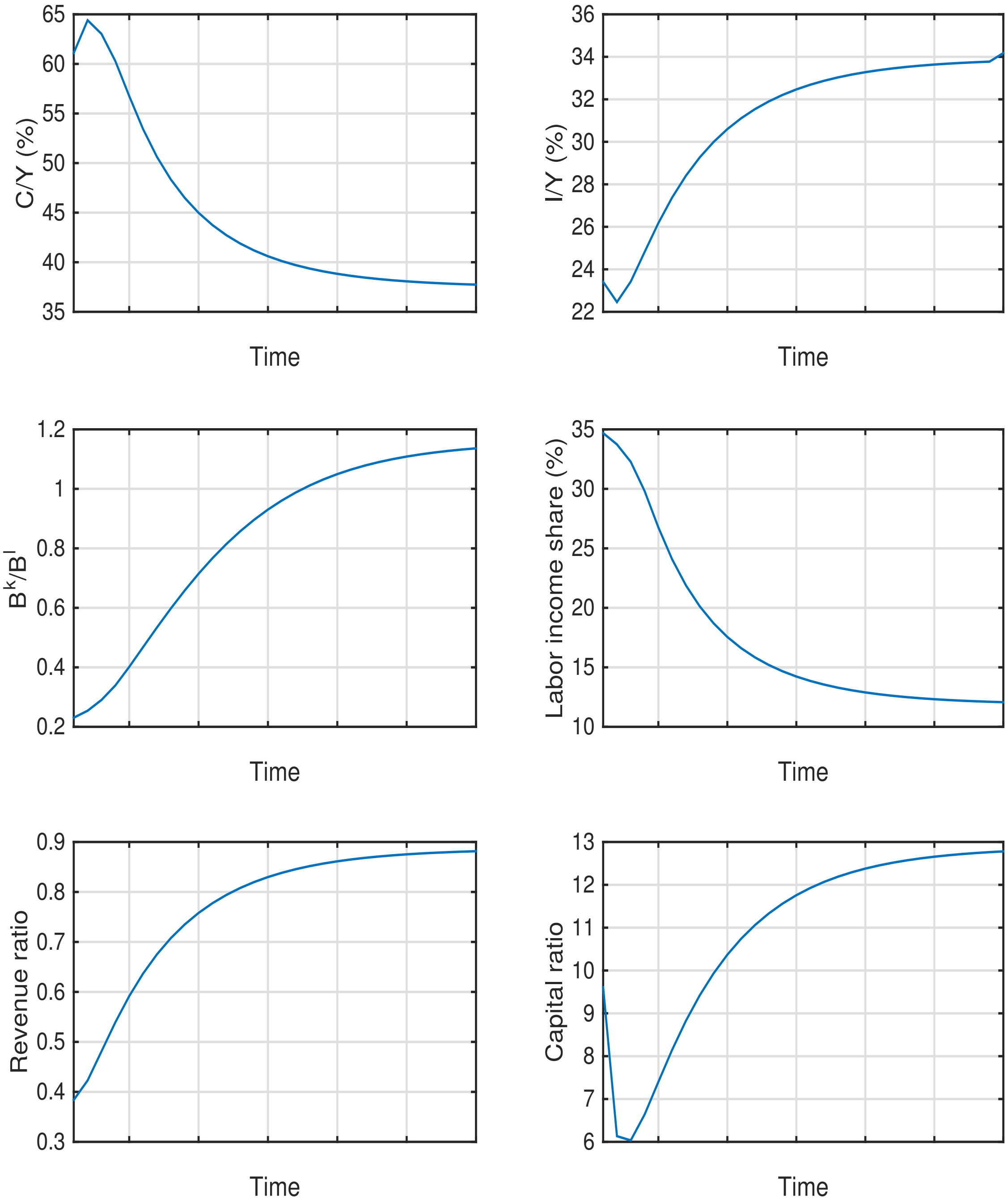

FIGURE 14. The trend patterns for the benchmark theoretical model. "C" stands for aggregate consumption, "I" for aggregate investment, "Y" for aggregate output, "B^k" for long-term loans, "B^l" for short-term loans, "Revenue ratio" means the ratio of the capital-intensive sector's revenue to that of the labor-intensive sector, and "Capital ratio" means the ratio of capital stock in the capital-intensive sector to that in the labor-intensive sector.

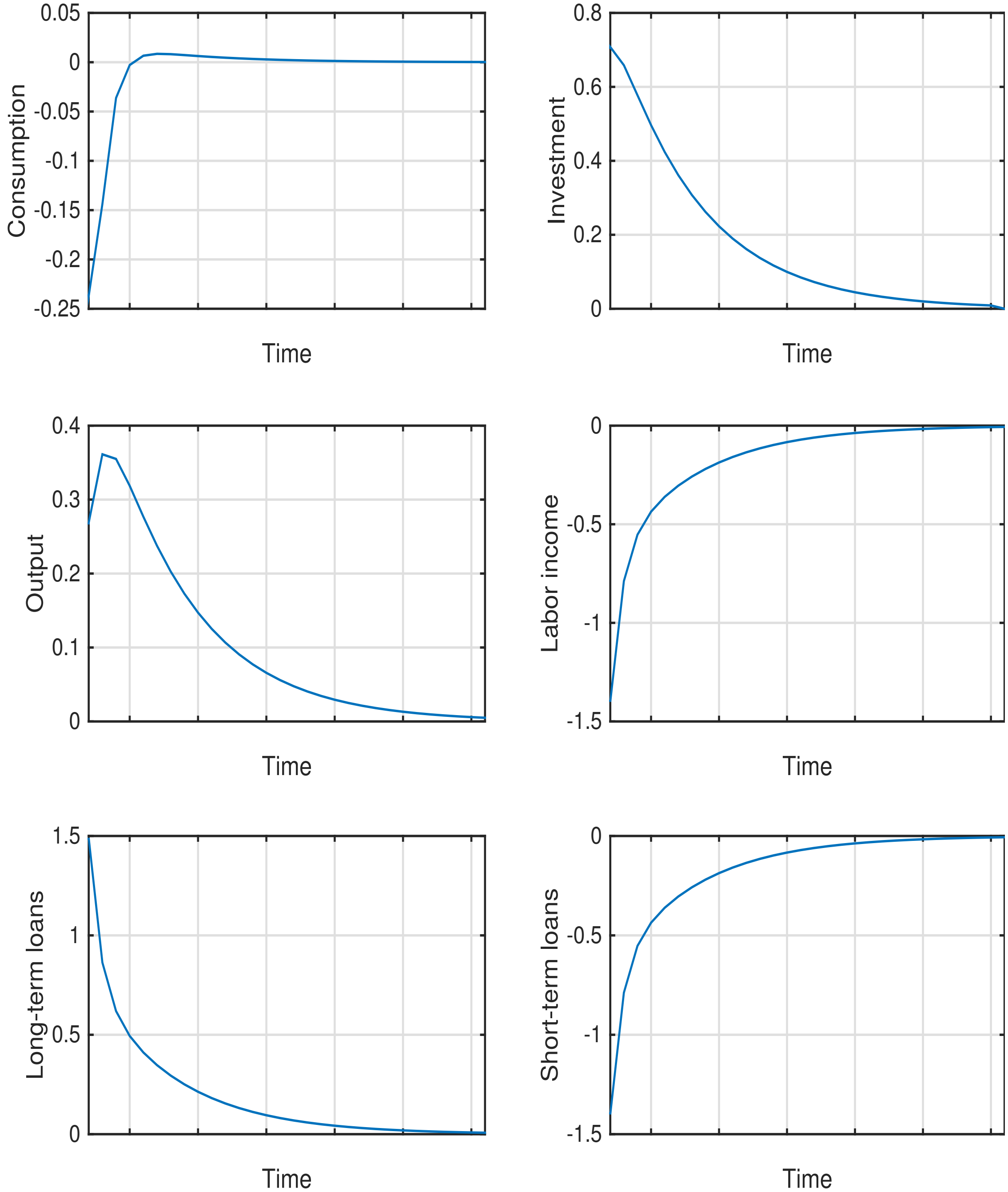

FIGURE 15. Impulse responses to an expansionary credit shock in the benchmark theoretical model.

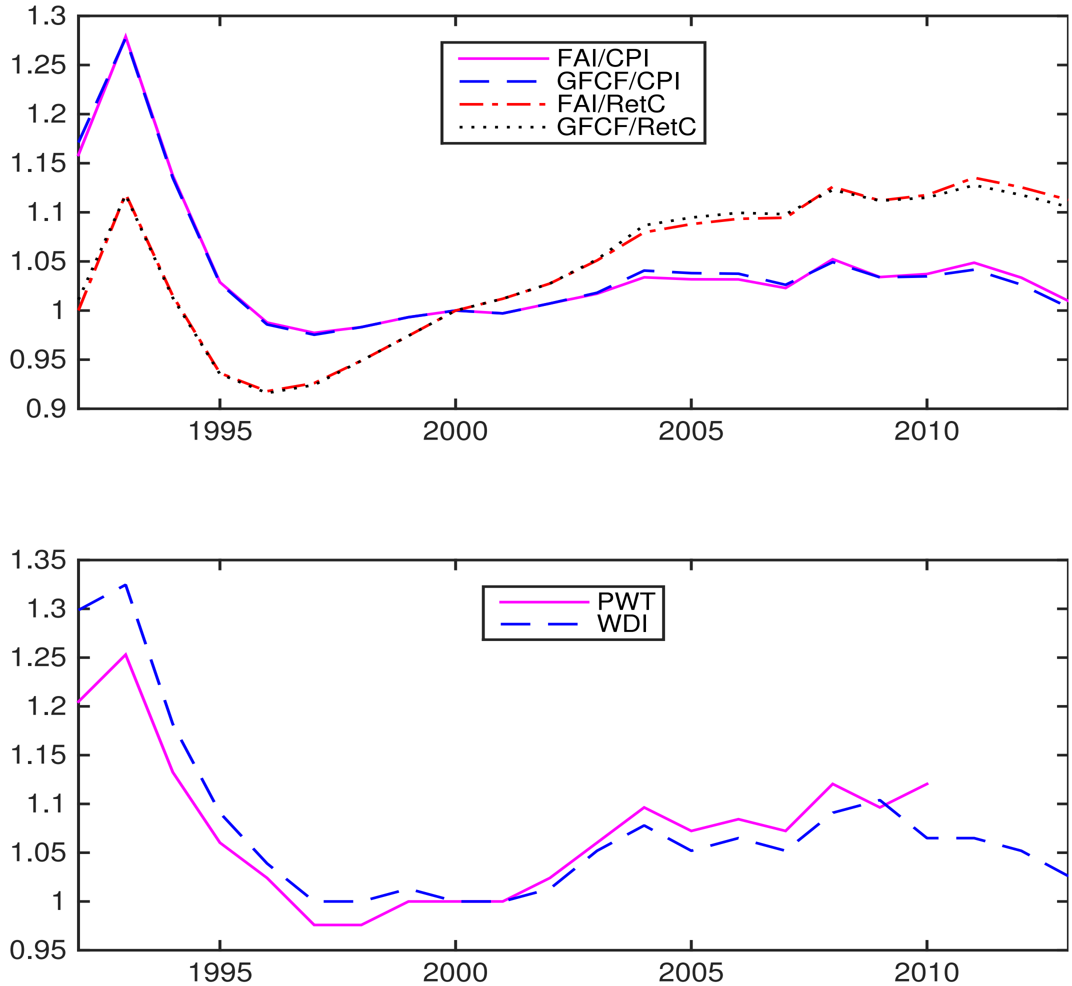

FIGURE 16. Various relative prices of investment goods to consumption goods, normalized to 1 for 2000. "FAI" stands for the price of fixed-asset investment, "GFCF" the price of gross fixed-asset capital formation, and "RetC" the price of retails sales of consumer goods. The data of relative prices of investment goods to consumption goods from the PWT and WDI are suggested by Karabarbounis and Neiman (2014), where "PWD" stands for the Penn World Tables and "WDI" the World Bank's World Development Indices. For the PWT data source, the price of investment goods is the price of GFCF and the price of consumption goods is CPI; for the WDI data source, the price of investment goods is the same as in the PWT data source, but the price of consumption goods is the price of retail sales of consumer goods.

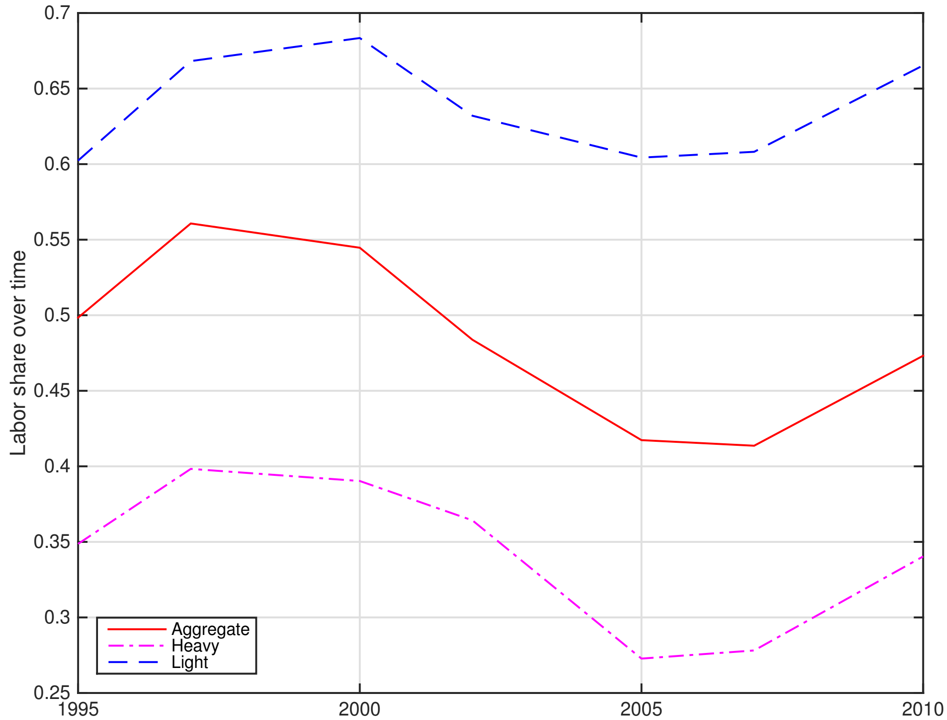

FIGURE 17. Labor shares in the heavy and light sectors. The calculation is based on the NBS input-output data for the 17 sectors in China.

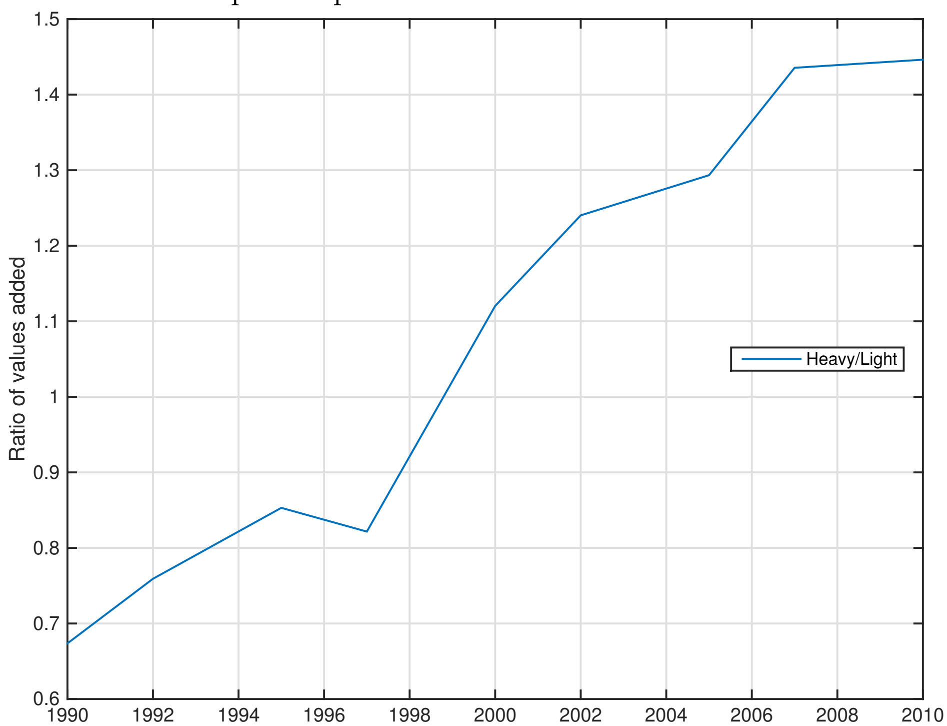

FIGURE 18. Ratio of values added in the heavy and light sectors grouped from the 17 sectors in the NBS input-output data.

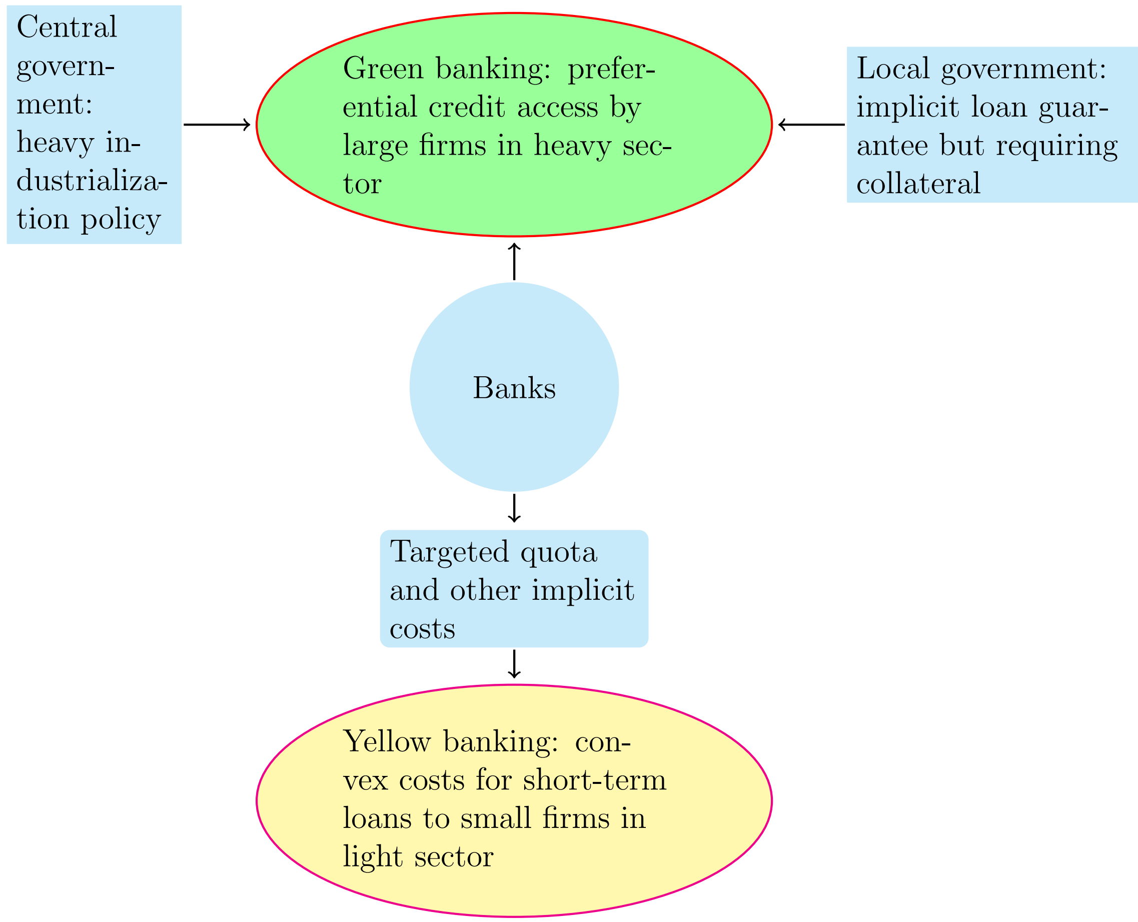

FIGURE 19. Loan structures in China.

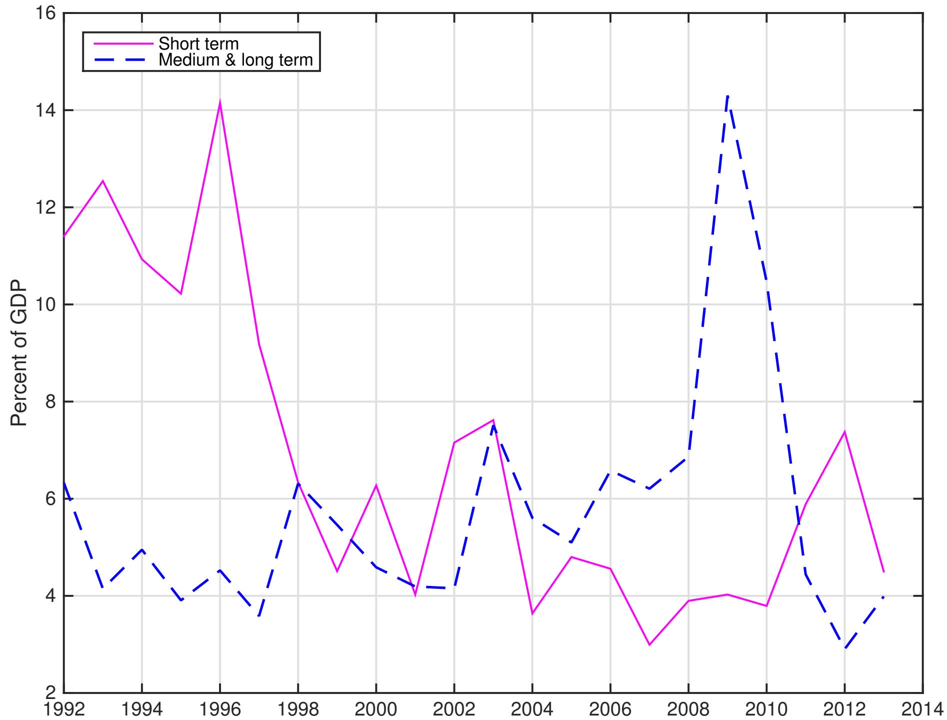

FIGURE 20. New bank loans to non-financial enterprises as percent of GDP. The correlation between the two types of loans is −0.403 for 1992-2012 and −0.405 for 2000-2012.

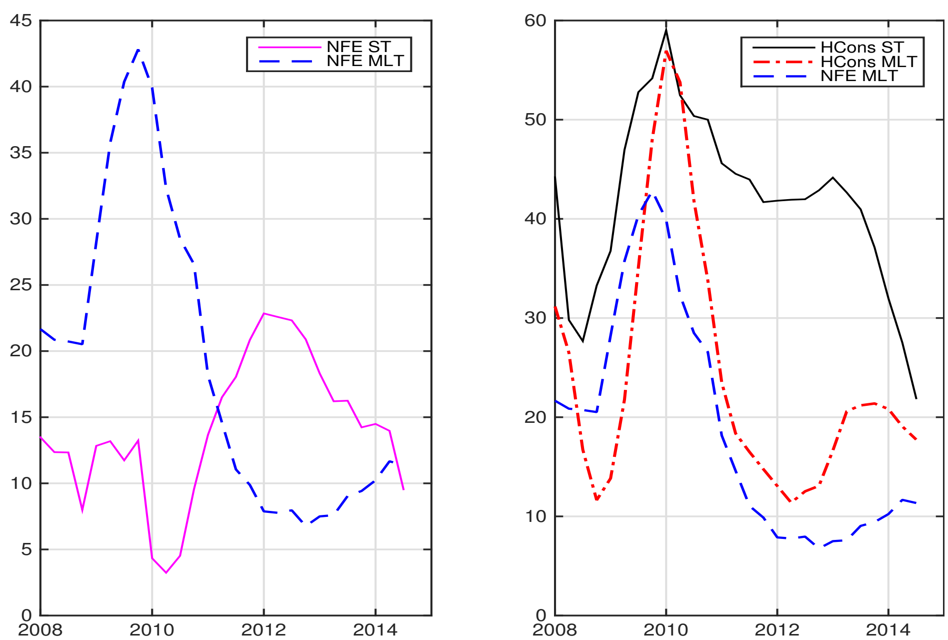

FIGURE 21. Year-over-year growth rates of short term (ST) and medium and long term (MLT) bank loans (outstanding) to household consumption (HCons) and non-financial enterprises (NFE) from 2008Q1 to 2014Q3. The correlation is −0.744 between short-term and medium&long-term NFE loans, 0.725 between short-term and medium&long-term household consumption loans, and 0.769 between medium&long-term NFE and household consumption loans.

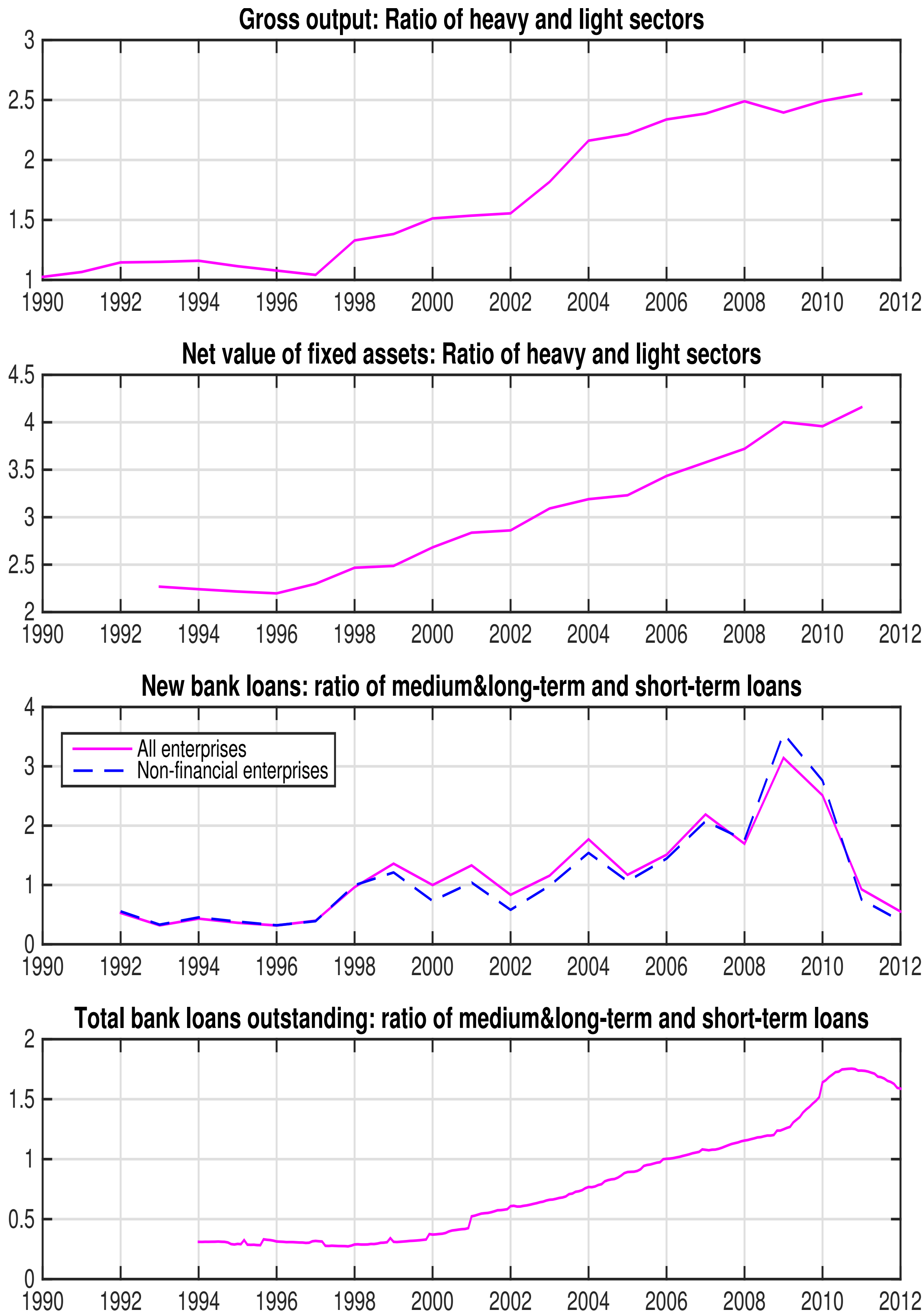

FIGURE 22. Secular patterns for heavy vs light sectors and for medium and long term bank loans vs. short term bank loans. The top two charts are based on the NBS data and the 39 industries. The third chart (counting from the top) is based on the Flow of Funds annual data and the bottom chart is based on the monthly WIND data (the source of both data is the People's Bank of China).

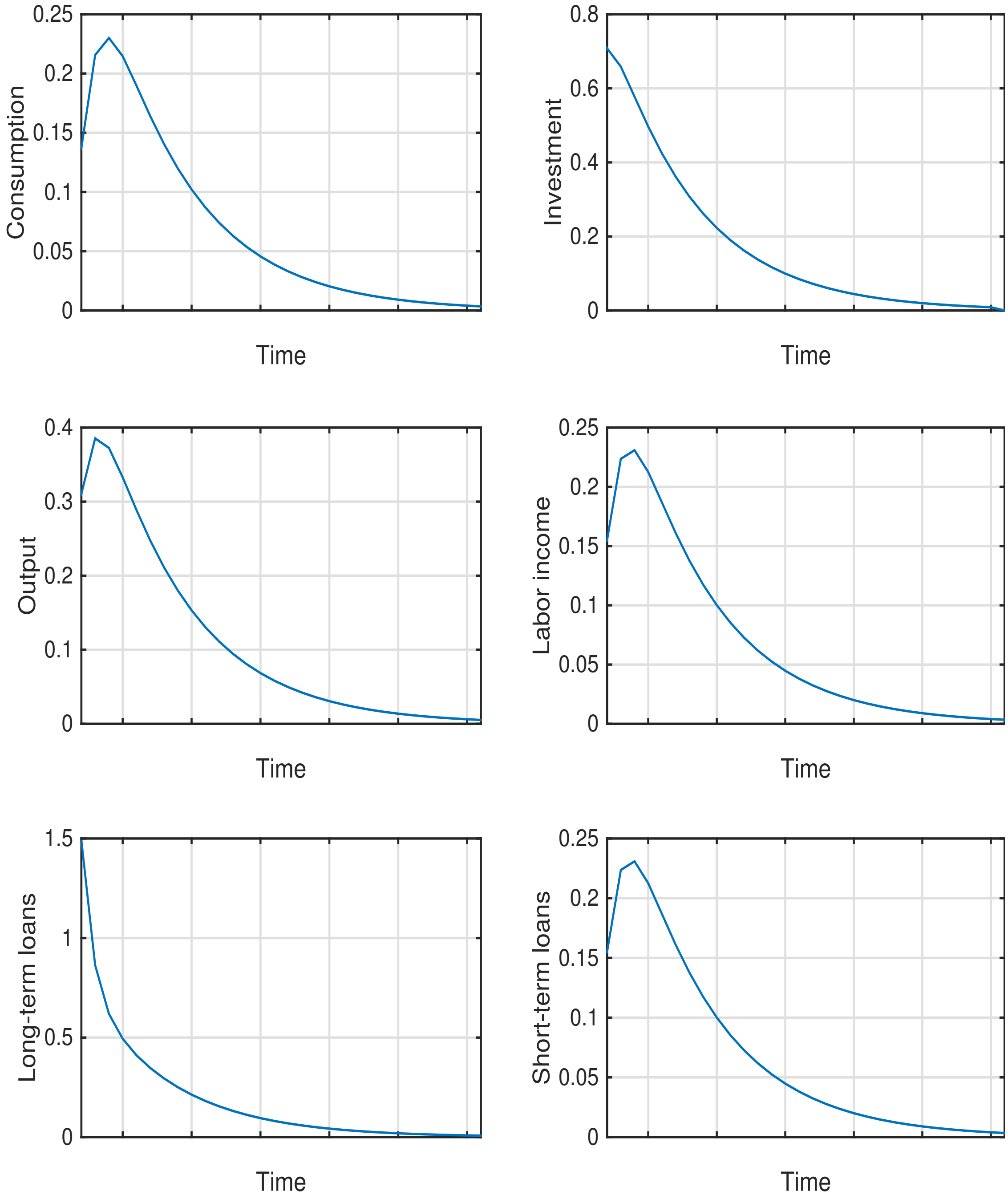

FIGURE 23. Impulse responses to an expansionary credit shock in an economy without the bank-lending friction.

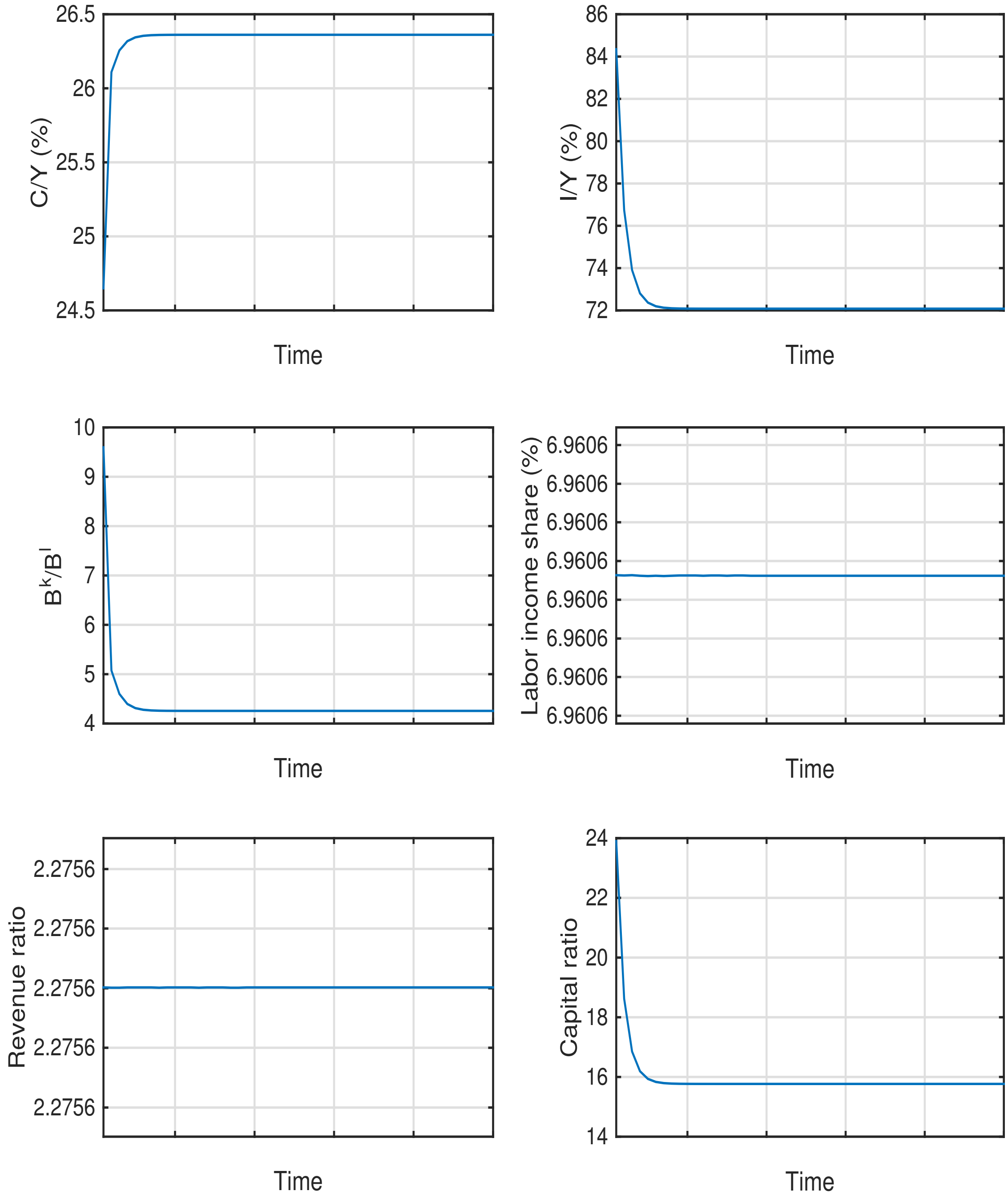

FIGURE 24. The trend patterns for an economy without lending frictions and collateral constraints. "C" stands for aggregate consumption, "I" for aggregate investment, "Y" for aggregate output, "B^k" for long-term loans, "B^l" for short-term loans, "Revenue ratio" means the ratio of the capital-intensive sector's revenue to that of the labor-intensive sector, and "Capital ratio" means the ratio of capital stock in the capital-intensive sector to that in the labor-intensive sector.

References

Acemoglu, D., and V. Guerrieri (2008): "Capital Deepening and Nonbalanced Economic Growth," *Journal of Political Economy*, 116(3), 467–498.

Bai, C., and Z. Qian (2009): "Factor Income Share in China: The Story Behind the Statistics," *Economic Research Journal (in Chinese)*, 3, 27–41.

Bernanke, B. S., M. Gertler, and M. W. Watson (1997): "Systematic Monetary Policy and the Effects of Oil Price Shocks," *Brookings Papers on Economic Activity*, 1, 91–142.

Brandt, L., and X. Zhu (2007): "China's Banking Sector and Economic Growth," in *China's Financial Transition at a Crossroads*, ed. by C. W. Calomiris, chap. 2. Columbia University Press, New York.

——— (2010): "Accounting for China's Growth," Working Paper 394, Department of Economics, University of Toronto.

Buera, F. J., and Y. Shin (2013): "Financial Frictions and the Persistence of History: A Quantitative Exploration," *Journal of Political Economy*, 121(2), 221–272.

Chakraborty, S., and K. Otsu (2012): "Business Cycle Accounting of the BRIC Economies," Unpublished Manuscript.

Chang, Y., and A. Hornstein (2015): "Transition Dynamics in the Neoclassical Growth Model: the Case of South Korea," *The B.E. Journal of Macroeconomics*, Forthcoming.

Chen, K., and Y. Wen (2014): "The Great Housing Boom of China," Unpublished Manuscript, Emory University.

Chen, S., G. H. Jefferson, and J. Zhang (2011): "Structural Change, Productivity Growth, and Industrial Transformation in China," *China Economic Review*, 22(1), 133–150.

Chow, G. C. (2011): *China As A Leader Of The World Economy*. World Scientific Publishing Company, New Jersey, USA.

Christiano, L. J., M. S. Eichenbaum, and C. L. Evans (1996): "The Effects of Monetary Policy Shocks: Some Evidence from the Flow of Funds," *Review of Economics and Statistics*, 78(1), 16–34.

——— (1999): "Monetary Policy Shocks: What Have We Learned and To What End?," in *Handbook of Macroeconomics*, ed. by J. B. Taylor, and M. Woodford, vol. 1A, pp. 65–148. North-Holland, Amsterdam, Holland.

——— (2005): "Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy," *Journal of Political Economy*, 113, 1–45.

Cúrdia, V., and M. Woodford (2010): "Credit Spreads and Monetary Policy," *Journal of Money, Credit and Banking*, 42(S1), 3–35.

Fang, C., E. Wailes, and G. Cramer (1998): "China's Rural and Urban Household Survey Data: Collection, Availability, and Problems," CARD Working Paper 98-WP 202, Center for Agricultural and Rural Development, Iowa State University.

Fernald, J., I. Malkin, and M. Spiegel (2013): "On the Reliability of Chinese Output Figures," *Federal Reserve Bank of San Francisco Economic Letter*, 8.

Fernald, J., and B. Neiman (2011): "Growth Accounting with Misallocation: Or, Doing Less with More in Singapore," *American Economic Journal: Macroeconomics*, 3, 29–74.

Fernald, J., M. M. Spiegel, and E. Swanson (2013): "Monetary and Fiscal Policy Effectiveness in China: Evidence from a FAVAR Model," Unpublished Manuscript, Federal Reserve Bank of San Francisco.

Gan, L. (2014): "Income Inequality and An Economy in Transition," Presentation Slides, Texas A&M University and Southwestern University of Finance and Economics.

Hansen, L. P., J. C. Heaton, and N. Li (2008): "Consumption Strikes Back? Measuring Long-Run Risk," *Journal of Political Economy*, 116(2), 260–302.

He, Q., T. Chong, and K. Shi (2009): "What accounts for Chinese Business Cycle?," *China Economic Review*, 20, 650–661.

Higgins, P. C., and T. Zha (2015): "China's Macroeconomic Time Series: Method and Implications," Unpublished Manuscript, Federal Reserve Bank of Atlanta.

Holz, C. (2013): "The Quality of China's GDP Statistics," Working Paper No. 487, Stanford Center for International Development.

Hsieh, C.-T., and P. J. Klenow (2007): "Relative Prices and Relative Prosperity," *The American Economic Review*, 97(3), 562–585.

——— (2009): "Misallocation and Manufacturing TFP in China and India," *Quarterly Journal of Economics*, CXXIV(4), 1403–1448.

Hsieh, C.-T., and Z. M. Song (2015): "Grasp the Large, Let Go of the Small: The Transformation of the State Sector in China," Unpublished Manuscript.

Huang, H., J. Ju, and V. Z. Yue (2015): "A Unified Model of Structural Adjustments and International Trade: Theory and Evidence from China," Unpublished Manuscript.

Jiang, S., J. Luo, and J. Huang (2006): "Credit Concentration and Expansion, Soft Budget Constraints, and Systemic Credit Risks of Banks," *Journal of Financial Research (in Chinese)*, 4, 40–48.

Ju, J., Y. Lin, Q. Liu, and K. Shi (2015): "A Dynamic Structural Analysis of Real Exchange Rate: Theory and Evidences from China," Unpublished Manuscript.

Karabarbounis, L., and B. Neiman (2014): "The Global Deciine of the Labor Share," *Quarterly Journal of Economics*, 129(1), 61–103.

King, R. G., C. I. Plosser, J. H. Stock, and M. W. Watson (1991): "Stochastic Trends and Economic Fluctuations," *American Economic Review*, 81(4), 819–840.

Kiyotaki, N., and J. Moore (1997): "Credit Cycles," *Journal of Political Economy*, 105(2), 211–248.

Leeper, E. M., C. A. Sims, and T. Zha (1996): "What Does Monetary Policy Do?," *Brookings Papers on Economic Activity*, 2, 1–78.

Lin, J. Y. (2013): *Demystifying the Chinese Economy*. Cambridge University Press, New York, USA.

Lin, J. Y., and Y. Li (2001): "Promoting the Growth of Medium and Small-sized Enterprises through the Development of Medium and Small-sized Financial Institutions," *Economic Research Journal (in Chinese)*, 1, 10–18.

Lu, D. (Forthcoming): "Exceptional Exporter Performance? Evidence from Chinese Manufacturing Firms," *Journal of Monetary Economics*.

Moll, B. (2014): "Productivity Losses from Financial Frictions: Can Self-financing Undo Capital Misallocation?," *American Economic Review*, 104(10), 3186–3221.

Nakamura, E., J. Steinsson, and M. Liu (2014): "Are Chinese Growth and Inflation Too Smooth? Evidence from Engel Curves," Unpublished Manuscript, Columbia University.

Ngai, L. R. (2004): "Barriers and the Transition to Modern Growth," *Journal of Monetary Economics*, 51, 1353–1383.

Olley, G. S., and A. Pakes (1996): "The Dynamics of Productivity in the Telecommunications Equipment Industry," *Econometrica*, 64(6), 1263–1297.

Qian, Z., and X. Zhu (2012): "Why Is Labor Income Share So Low in China?," Unpublished Presentation Slides.

Ravn, M. O., and H. Uhlig (2002): "Notes On Adjusting the Hodrick-Prescott Filter for the Frequency of Observations," *Review of Economics and Statistics*, 84(2), 371–380.

Romalis, J. (2004): "Factor Proportions and the Structure of Commodity Trade," *American Economic Review*, 94(1), 67–79.

Rubio-Ramírez, J. F., D. F. Waggoner, and T. Zha (2010): "Structural Vector Autoregressions: Theory of Identification and Algorithms for Inference," *Review of Economic Studies*, 77, 665–696.

Shi, H. (2009): "Understanding Chinas Economy During 1979-2007: A Business Cycle Accounting Approach," Unpublished Manuscript.

Sims, C. A. (2000): "Using a likelihood perspective to sharpen econometric discourse: Three examples," *Journal of Econometrics*, 95, 443–462.

Sims, C. A., D. F. Waggoner, and T. Zha (2008): "Methods for Inference in Large Multiple-Equation Markov-Switching Models," *Journal of Econometrics*, 146(2), 255–274.

Sims, C. A., and T. Zha (1998): "Bayesian Methods for Dynamic Multivariate Models," *International Economic Review*, 39(4), 949–968.

——— (1999): "Error Bands for Impulse Responses," *Econometrica*, 67(5), 1113–1155.

——— (2006): "Were There Regime Switches in US Monetary Policy?," *American Economic Review*, 96, 54–81.

Song, Z., K. Storesletten, and F. Zilibotti (2011): "Growing Like China," *American Economic Review*, 101(1), 196–233.

Stock, J. H., and M. W. Watson (2003): "Has the Business Cycles Changed? Evidence and Explanations," in *Monetary Policy and Uncertainty: Adapting to a Changing Economy*, pp. 9–56. Federal Reserve Bank of Kansas City, Jackson Hole, Wyoming.

Ventura, J. (1997): "Growth and Independence," *Quarterly Journal of Economics*, 112(1), 57–84.

Villani, M. (2005): "Bayesian Reference Analysis of Cointegration," *Econometric Theory*, 21, 326–357.

Waggoner, D. F., H. Wu, and T. Zha (2015): "Dynamic Striated Metropolis-Hastings Sampler for High-Dimensional Models," Unpublished Manuscript, Federal Reserve Bank of Atlanta.

Xu, X. (2010): "An Accurate Understanding of Chinas Economic Statistics," *Economic Research Journal (in Chinese)*, 5, 21–31.

Young, A. (1995): "The Tyranny of Numbers: Confronting the Statistical Realities of the East Asia Growth Experience," *Quarterly Journal of Economics*, 110(3), 641–680.

Yu, J., and G. Zhu (2013): "How Uncertain Is Household Income in China," *Economics Letters*, 120, 74–78.

Yu, L., and Y. Ju (1999): "Monopoly and Competition: The Reform and Development of China's Banking Industry," *Economic Research Journal (in Chinese)*, 8, 48–57.

Zha, T. (1999): "Block Recursion and Structural Vector Autoregressions," *Journal of Econometrics*, 90(2), 291–316.

Zhou, M., and R. Ren (2010): "A Time Series Analysis of the Relationship between Banking Interest Rates and Private Lending Interest Rates," *Statistics and Decision (in*

Chinese), 1, 126–129.