TRENDS AND CYCLES IN CHINA’S MACROECONOMY

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Abstract. We make three contributions in this paper. First, we provide a core of macroeconomic time series usable for systematic studies on China’s macroeconomy. Second, we document, through various empirical methods, the robust findings about the striking patterns of trend and cycle. Third, we build a theoretical model that accounts for these facts. The model’s mechanism and assumptions are supported by institutional details and disaggregated time series distinctive of Chinese characteristics.

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Growth has been the hallmark for China. In recent years, however, rapid 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; 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 trends and cycles 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.

Our robust empirical findings about China’s macroeconomy since the late 1990s are composed of two parts. The first concerns trend patterns and the second pertains to cyclical patterns. The key trend facts are:

(T1) A simultaneous rise in the investment-to-output ratio and a decreasing trend in the consumption-to-output ratio (the top chart of Figure 1).

(T2) A decline of the labor share of income.

(T3) An increase in the ratio of long-term loans (for financing fixed investment) to short-term loans (for financing working capital).

(T4) A rise in the ratio of capital in the capital-intensive sector to that in the labor-intensive sector.

(T5) An increase in the ratio of total revenues in the capital-intensive industry to those in the labor-intensive sector.

The key cyclical patterns are:
(C1) No comovement or negative comovement between aggregate investment and consumption (the bottom chart of Figure 1).

(C2) No comovement between aggregate investment and labor compensation.

(C3) A negative comovement between long-term loans and short-term loans.

To explain both trend and cyclical patterns listed above, we build a theoretical model on Song, Storesletten, and Zilibotti (2011, SSZ henceforth). 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 the last decade. Their model replicates disinvestment of state-owned enterprises (SOEs) in the labor-intensive sector as privately-owned enterprises (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. In the second stage, SOEs disappear from the labor-intensive sector and POEs become the sole producers in that sector.

We extend their two-sector model by introducing two new ingredients into our model: a collateral constraint for capital-intensive goods producers and lending frictions in the banking sector. We show that with this two new ingredients, our model can replicate trend patterns (T1)-(T5) and cyclical patterns (C1)-(C3).

Our counterfactual economy shows that the key to generating the trend patterns is the presence of collateral constraint for the capital-intensive goods producer. With the collateral constraint, the borrowing capacity of capital-intensive firms grows with their net worth. Accordingly, the demand for capital from the capital-intensive sector accelerates during the transition, which leads to an increase in the share of value of capital-intensive sector in the 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 constant elasticity of substitution (CES), the demand for capital from capital-intensive goods producers is proportional to output produced by the labor-intensive sector. As output growth of the labor-intensive sector slows down over time due to the diminishing returns to capital, the capital-intensive sector would experience a declining investment rate. Moreover, the investment rate in the labor-intensive sector tends to decline during the transition due to either the resource reallocation from SOEs to POEs.

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1To highlight our key mechanism, we abstract from their first transition stage, in which SOEs’ employment share keeps declining in the labor-intensive sector. Our results would hold in a generalized economy that incorporates the first stage of transition.
(in the first stage of transition, which we abstract from our model) or decreasing returns to capital when the reallocation is completed.\textsuperscript{2}

The cyclical patterns uncovered in this paper, an issue silent in SSZ, are also a product of our model mechanism. The key to accounting for these important cyclical patterns is the presence of bank lending friction in our model, which interacts with the aforementioned collateral constraint to deliver a negative externality on the labor-intensive sector from credit injections into capital-intensive sector. In response to the government’s credit injection, the expansion of credit demand by the capital-intensive sector tends to crowd out the labor-intensive sector’s demand for working-capital loans by pushing up the loan rate for working capital. In an economy absent of such a banking lending friction as in SSZ, credit injection into the capital-intensive sector tends to push up the wage income and therefore household consumption due to the imperfect substitutability between capital-intensive output and labor-intensive output, a result that is again at odds with what we observe in China (see fact (C2)).\textsuperscript{3} Specifically, it generates the following counterfactual predictions:

- A positive comovement between aggregate investment and consumption.
- A positive comovement between aggregate investment and labor compensation
- A positive comovement between investment loans and working-capital loans.

More generally, our theory contributes to the emerging literature on the role of financial-market imperfections on economic development (Buera and Shin, 2013; Moll, Forthcoming). 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

\textsuperscript{2}SSZ overcome such deficiency in their quantitative model by feeding in an \textit{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 compensation tend to comove positively, which is inconsistent with fact (T2).

\textsuperscript{3}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 capital-intensive or labor-intensive producers, as in SSZ.
an increasing share of revenues generated by capital-intensive goods producers in aggregate output as they become larger with their expanded borrowing capacity. Such an explanation is consistent with the heavy industrialization experienced in China (see facts (T4) and (T5)) and perhaps by other economies in the later stage of their development such as Korea and Japan. We view our model mechanism as a useful complement to the larger literature.\footnote{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 and a looming issue for China in the present time.}

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 study on China’s macroeconomy.

II.1. Data sources. There are earlier works on Chinese monetary policy and fiscal policy, some taking an econometric approach and others employing historical perspectives or narrative approaches (Chow, 2011; Lin, 2013; Fernald, Spiegel, and Swanson, 2013). 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’ total factor productivities (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 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 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 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).

II.2. Construction. This paper is not about the quality of these 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). The most serious data problem, in our view, is the absence of a standard set of annual and quarterly macroeconomic time series that correspond to those commonly used in the macroeconomic literature on Western economies. Our goal is to first construct such a standard set and then use it as a starting point for promoting both improvement and transparency of China’s core macroeconomic dataset 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.\(^5\) Our construction method emphasizes the consistency across data frequencies and serves as a foundation for improvements in future research.\(^6\)

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.\(^5\) 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 (based on censuses conducted by the NBS) for historical data). 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 the most important 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.

\(^5\)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).

\(^6\)For the detailed description of all the problems we have discovered, how best to correct them and then construct the time series used in this paper, see Higgins and Zha (2015).
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. 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

\[
\frac{y_{t}}{y_{t-4}} \quad \text{(Q1)}, \quad \frac{y_{t+1}+y_{t+2}+y_{t+3}+y_{t+4}}{y_{t-3}+y_{t-4}} \quad \text{(Q2)}, \quad \frac{y_{t+2}+y_{t+3}+y_{t+4}+y_{t+5}}{y_{t-2}+y_{t-3}+y_{t-4}+y_{t-5}} \quad \text{(Q3)}, \quad \text{and} \quad \frac{y_{t+3}+y_{t+4}+y_{t+5}+y_{t+6}}{y_{t-1}+y_{t-2}+y_{t-3}+y_{t-4}} \quad \text{(Q4)}.
\]

The QTD changes for the same four quarters are

\[
\frac{y_{t}}{y_{t-4}} \quad \text{(Q1)}, \quad \frac{y_{t+1}}{y_{t-3}} \quad \text{(Q2)}, \quad \frac{y_{t+2}}{y_{t-2}} \quad \text{(Q3)}, \quad \text{and} \quad \frac{y_{t+3}}{y_{t-1}} \quad \text{(Q4)}.
\]

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, as shown in Higgins and Zha (2015), we keep 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 large retail establishments with annual sales above RMB 5 million or with more than 60 employees at the end of the year.\(^7\) 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.

II.3. Core time series. In Appendix A we list the standardized annual and quarterly time series. In this section we display several key variables. Figure 2 plots four price level series with the CPI and the investment price index lagging behind the GDP deflator. Figure 3 reports 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 1952. At the end of the “Great Leap Forward” movement in 1958-60, real GDP tanked by 30% while inflation increases by 14% (the first row of the figure). Since the economic reforms introduced in 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 3). 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.\footnote{The correlation of household consumption and retail sales of consumer goods is very low, especially for cyclical fluctuations.} The other measure of total investment, fixed-asset investment, takes up nearly 80% of GDP by 2012 (the bottom row of Figure 3). 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.
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.

Figure 4 displays year-over-year changes of the quarterly series: real GDP, the GDP deflator, M2, and total bank loans outstanding. The first row of this figure matches the first row of Figure 3. 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 adopted very tight credit policy. 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 slowing down the economy too drastically, the PBC cut interest rates twice in May and August of 1996 and loosened credit policy. Consequently, total bank loans shot up by about 40% in 1996Q1-1996Q3.

Figures 3 and 4 together present a broad perspective of trends and cycles for the Chinese economy. In next two sections we uncover the key facts from these trends and cycles and verify the robustness of these facts.

III. Econometric evidence

Figures 3 and 4 together present a broad perspective of trends and cycles for the Chinese economy. These data exhibit both volatility and trend changes. The trend patterns represent a host of economic reforms undergone by the Chinese government. Table 1 displays the major reform dates that 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 the framing of a credible theoretical model.

To this end we estimate a large set of models with various combinations of switching dates reported in Table 1 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 3 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. Modeling trends and cycles. 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:

$$A_0 Y_t = a_t + \sum_{t=1}^{p} A_t y_{t-t} + D_{s_t} \varepsilon_t,$$

(1)
where \( s_t \), taking a discrete value, is a composite index for regime switches in volatility and \( D_{s_t} \) is a diagonal matrix. 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).

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 distinctly different characteristic: cyclical variations coexist with trend drifts as shown in Figure 3. The time-varying intercept vector \( a_t \), monotone and bounded in \( t \) for each element, captures continuous trend drifts. 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. To this end, unit roots and cointegration are imposed on system (1). These restrictions are made explicit in the error-correction representation as follows

\[
F_0 \Delta Y_t = c_t + R y_{t-1} + \sum_{\ell=1}^{p-1} F_\ell \Delta y_{t-\ell} + D_{s_t} \varepsilon_t, \tag{2}
\]

where \( R \) is an \( n \times n \) matrix of reduced rank such that \( \text{rank}(R) = r \) with \( r < n \), implying that there are at most \( r \) cointegration vectors (i.e., the number of cointegration relationships and the number of stationary relationships sum to \( r \)). The relation between (1) and (2) is

\[
A_0 = F_0, \quad A_1 = R + F_1 + F_0, \quad A_\ell = F_\ell - F_{\ell-1} (\ell = 2, \ldots, p - 1), \quad A_p = -F_{p-1}, \quad c_{s_t} = a_{s_t}.
\]

We consider the following three functional forms of \( c_t \) in the order of importance.

- We specify the 4-parameter process as

\[
c_t \in \mathbb{R}^n = \left[ c_1 + \beta_1 (t - \gamma_1)^{\lambda_1} e^{-\alpha_1 t}, \ldots, c_n + \beta_n (t - \gamma_n)^{\lambda_n} e^{-\alpha_n t} \right]',
\]

where \( \alpha_j > 0 \) and \( \lambda_j > 0 \) for all \( j = 1, \ldots, n \). We consider the restriction \( \alpha_j = \alpha \), \( \beta_j = \beta \), \( \gamma_j = \gamma \), or \( \lambda_j = \lambda \) for all \( j = 1, \ldots, n \) or some of \( j \)'s. We also consider different combinations of these restrictions.

- \( c_t = c_{s_t} \).

- The following specification is for our record, but may not be used for our paper so we will not discuss how to form the prior for this specification in our first attempt.

\[
c_t \in \mathbb{R}^n = \left[ \frac{c_1}{1+\beta_1 \alpha_1 t^\alpha_1}, \ldots, \frac{c_n}{1+\beta_n \alpha_n t^\alpha_n} \right]',
\]

where \( 0 \leq \alpha_j < 1 \) for all \( i = 1, \ldots, n \). We also 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

\[ Y_t = b_{st} + \sum_{\ell=1}^{p} B_\ell y_{t-\ell} + M_{st} \xi_t, \]  

where \( b_{st} = A_0^{-1} a_{st} \), \( B_\ell = A_0^{-1} A_\ell \), and \( M_{st} = A_0^{-1} D_{st} \). Let \( \Sigma_{st} = M_{st} M_{st}' \) be a regime-switching covariance matrix.

### III.2. Design of the prior

Since the representation (2) is expressed in log difference and cointegration, it embodies the prior of Sims and Zha (1998) already (in fact, it implies the sharp Sims and Zha prior in a degenerate way). Therefore we should begin with the prior directly on \( F_\ell (\ell = 0, \ldots, p-1) \), \( c_j \), \( \alpha_j \), \( \beta_j \), \( \gamma_j \), and \( D_{st} \). The only difficult part is to have a prior that maintains the reduced rank \( r \) for \( R \).

**Prior on \( F_\ell (\ell = 0, \ldots, p-1) \), \( c_j \), \( \beta_j \), \( \gamma_j \), and \( D_{st} \).** The prior can be simply a normal-distribution prior on each of those elements. For \( F_\ell (\ell = 1, \ldots, p-1) \), we need a lag decay factor.

**Prior on \( \alpha_j \) and \( \lambda_j \).** Each parameter has a Gamma prior.

**Prior on \( R \).** Because \( R \) is a reduced rank matrix, the usual decomposition is \( R = \alpha \beta' \), where both \( \alpha \) and \( \beta \) are \( n \times r \) matrices of rank \( r \). But a more effective decomposition is the singular value decomposition:

\[ R = UDV', \]

where both \( U \) and \( V \) are \( n \times r \) matrices with orthonormal columns and \( D \) is an \( r \times r \) diagonal matrix. Let both the prior on \( U \) and on \( V \) has the uniform distribution and the diagonal elements of \( D \) have a prior Gamma distribution. These diagonal elements may be interpreted as inverses of standard deviations.

If the diagonal elements are distinct, the singular value decomposition is unique up to the ordering of the diagonal elements. The algorithm for simulating the prior is as follows.

1. Draw \( U \) and \( V \) from the uniform distribution (see Rubio-Ramírez, Waggoner, and Zha (2010) for the exact procedure).
2. Draw the diagonal elements \( d_1, \ldots, d_r \) from independent Gamma distributions with appropriate hyperparameters. Because the matrix \( R \) must be of rank \( r \), the density of \( d_i \) should be zero when \( d_i = 0 \). If we use the parametrization of the Gamma distribution given by \( \text{gamma}(d_i, a, b) \propto d_i^{a-1} \exp(-d_i/b) \), then \( a \) should be chosen to be larger than one.
3. Reorder the \( d \)'s (the diagonal elements) so that they are in descending order.

Since there are \( r! \) ways of ordering the diagonal elements, the prior can easily be evaluated as

\[ \prod_{i=1}^{r} \frac{\text{gamma}(d_i, a, b)}{r!}, \]
where \( \text{gamma}(x, a, b) \) is the gamma probability density function with hyperparameters \( a \) and \( b \).

Our prior has some similarity to the prior specified by Villani (2005). Working directly with the reduced-form parameters, Villani (2005) uses the \( F_0^{-1}R = \alpha * \beta' \) decomposition with normalization such that the upper \( r \times r \) block of \( \beta \) is the identity matrix. Such a prior on \( \beta \) implies a uniform distribution on the Grassman manifold of \( r \)-frames in \( R^n \) (similar to our uniform distribution). Villani (2005) does not work directly with \( \alpha \) but instead with \( \tilde{\alpha} = \alpha * (\beta' * \beta)^{1/2} \).

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

Since we begin with the primitive error-correction form, our prior is on \( R \) directly, not on \( F_0^{-1}R \). All the reduced-form parameters can be derived, through the relation between (3) and (2), as

\[
B_1 = F_0^{-1}(R + F_1 + F_0), \quad B_\ell = F_0^{-1}(F_\ell - F_{\ell-1}) (\ell = 2, \ldots, p - 1), \quad B_p = -F_0^{-1}F_{p-1},
\]

\[
b_{st} = F_0^{-1}c_{st}, \quad M_{st} = F_0^{-1}D_{st}.
\]

### III.3. Decomposing trend and cycle.

We first estimate system (2) and then convert it to system (3). We express system (3) in companion form:

\[
\begin{bmatrix}
Y_t \\
y_{t-1} \\
\vdots \\
y_{t-p+1}
\end{bmatrix} =
\begin{bmatrix}
b_{st} \\
0 \\
\vdots \\
0
\end{bmatrix} +
\begin{bmatrix}
B_1 & \ldots & B_{p-1} & B_p \\
I_n & \ldots & 0_n & n_n \\
\vdots & \ddots & \vdots & \vdots \\
0_n & \ldots & I_n & 0_n
\end{bmatrix}
\begin{bmatrix}
y_{t-1} \\
y_{t-2} \\
\vdots \\
y_{t-p}
\end{bmatrix} +
\begin{bmatrix}
M_{st} \\
0 \\
\vdots \\
0
\end{bmatrix} \varepsilon_t,
\]

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. 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.\(^9\)

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

\[
B = \begin{bmatrix}
W_1 & W_2 \\
np \times m_1 & np \times m_2
\end{bmatrix}
\begin{bmatrix}
T_{11} & T_{12} \\
0 & T_{22}
\end{bmatrix}
\begin{bmatrix}
W_1' & W_2' \\
m_2 \times m_2 & m_2 \times m_2
\end{bmatrix},
\]

where \( \begin{bmatrix} W_1 & W_2 \end{bmatrix} \) is an orthogonal matrix and the diagonal elements of \( T_{22} \) are equal to one.

\(^9\)Shocks within each block are not uniquely determined.
Our first task is to find the largest column space in which transitory shocks lie. That is, we need to find a $V_{1,s_t}$ such that the column space of

$$
\begin{bmatrix}
M_{s_t} \\
0 \\
\vdots \\
0
\end{bmatrix}
V_{1,s_t}
$$

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 rows. Hence, 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 $[M'_{s_t}, 0, \ldots, 0]'$. In other words, there exists an $m_1 \times \ell_1$ matrix of real values, $A$, such that

$$
\begin{bmatrix}
M_{s_t} \\
0 \\
\vdots \\
0
\end{bmatrix}
V_{1,s_t} = W_1A.
$$

Since $W_1 \perp W_2$, we have

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

It follows that

$$
V_{1,s_t} = \text{Null}
\begin{pmatrix}
\begin{bmatrix} M_{s_t} \\ 0 \end{bmatrix} \\
W_2'
\end{pmatrix}
$$

and $\ell_1 \geq n - m_1$.

We perform the QR decomposition of $V_{1,s_t}$ such that $Q_{s_t}R_{s_t} = V_{1,s_t}$, where

$$
Q_{s_t} = \begin{bmatrix} Q_{1,s_t} & Q_{2,s_t} \end{bmatrix}_{n \times \ell_1}
$$

Since $\ell_1 \geq n - m_1$, it must be that $\ell_2 = n - \ell_1 \leq m_2$. The impact matrix is

$$
M_{s_t} \begin{bmatrix} Q_{1,s_t} & Q_{2,s_t} \end{bmatrix}
$$

with the first $\ell_1$ columns corresponding to the contemporaneous responses to transitory shocks and the second $\ell_2$ columns corresponding to those to transitory shocks.

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

$$
\tilde{M}_{s_t} = \begin{bmatrix} \tilde{Q}_{1,s_t} & \tilde{Q}_{2,s_t} \end{bmatrix}
$$
with $\tilde{M}_{s_1} \tilde{Q}_{i,s_1} = M_{s_1} Q_{i,s_1} P_{i,s_1}$ for $i = 1, 2$, where $[P_{i,s_1} P_{2,s_1}]$ is an orthogonal matrix.

III.4. Results. We estimate a 3-variable time-varying BVAR model with 5 lags and the sample 1995Q1-2013Q4, where the three quarterly seasonally-adjusted variables are log values of household consumption, SOE investment, and POE investment. The 5 lags are used to eliminate any residual of possible seasonality. All the variables are deflated by the seasonally-adjusted quarterly GDP deflator. The time-varying intercept terms are essential to improvement of the model’s fit to the data. Since POE investment grows faster than SOE investment, the matrix $\mathcal{R}$ appears to be of rank 2. We find 2 stochastic regimes for the shock variances. 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 highest peak as our posterior mode.

For each posterior draw of model parameters (including a draw of a regime for shock variances), we use the model structure and these parameter values to back out a smoothed sequence of shocks, $\varepsilon_t$. For the three shocks at each time $t$, one of them is permanent and the other two are stationary. Conditional on the three variables for the initial 5 periods, the trend component of each variable is computed recursively by making the predictions from the model by feeding the smoothed permanent shock at each time $t$. The stationary component, by construction, is the difference between the data and the trend component.

We focus on the relationship between household consumption and (aggregate) investment, where aggregate investment is simply the sum of SOE investment and POE investment. From all the posterior draws, the median correlation between stationary components of consumption and investment (the cyclical part) is $-0.384$ with the 0.68 probability interval $(-0.409, -0.352)$. We compute the median trend components of consumption and investment and plot in Figure 1 the ratio of $C/Y$ and $I/Y$, where "$C$" is household consumption, "$I$" is aggregate investment, and $Y = C + I$, alongside the cyclical (stationary) components (the top chart).

The government’s stimulation of investment after the 2008 financial crisis shows up as a large spike in 2009 in the cyclical movement; the stimulation dies out when the government’s credit expansion ends after 2010, while consumption shoots up (the top chart of Figure 1). The trend pattern is equally striking with the consumption-to-output ratio declines steadily since 2001 and the mirror image is the steady rise of investment as a share of output since 2001 (the bottom chart). The opposite cyclical comovement between consumption and investment and the opposite trends of consumption and investment as shares of output are the robust

\footnote{For the model with the rank of $\mathcal{R}$ being 1, the median correlation is $-0.588$.}
findings not only from different BVAR models but also from other empirical studies presented in Section IV.

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 are reported in Figure 5. Since 2000, household consumption as a share of GDP has steadily declined from 45% in 2000 to 36% in 2013 (the top left chart), while aggregate investment (total business investment) has risen from 26% in 2000 to 34% in 2013 (the top right chart). This striking trend pattern is robust when we use the narrow definition of output as the sum of household consumption and aggregate investment (the bottom chart). More telling is the decline pattern of both household disposable personal income and labor compensation as share of GDP since 2000.11

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) and between GFCF and real GDP. 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.

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 SOE or POE fixed investment and household consumption tends to be more negative than not across time with the 10-year moving window (the top right corner 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

11The series of “labor compensation” 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 2000. There are, however, serious data problems associated with this alternative measure. See Bai and Qian (2003) for detailed discussions.
similar pattern in which investment has either low or negative correlation with consumption as well as with labor income (Table 2).

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 economies, household disposable income is different from household labor income because of interest payments and capital gains (household 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 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 expansion, as shown in Figures 3 and 4. 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 positive correlation between investment and household income. This is inconsistent with the fact presented in Figure 7.

V. 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.

V.1. Environment. The economy is populated by two-period lived agents with overlapping generations (OLGs).\textsuperscript{12} 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

\textsuperscript{12}While one can extend it to the economy with multiple-period-lived agents, one may lose both tractability and intuition.
are inherited from parents. Without loss of generality we do not allow transition between social classes.

V.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 as well as 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.” In Section VIII, we provide disaggregated data to support this assumption.

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

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

\[ Y^k_t = K^k_t, \quad Y^l_t = (K^l_t)^\alpha (\chi L_t)^{1-\alpha}, \]

where \( Y^j_t \) and \( K^j_t \) 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.

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

\[ Y_t = \left[ \phi \left( Y^k_t \right)^{\frac{\sigma-1}{\sigma}} + \left( Y^l_t \right)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{1}{\sigma-1}} \]

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

\[ \frac{Y^k_t}{Y^l_t} = \left( \frac{P^l_t}{P^k_t} \right)^\sigma \]  \tag{6} \]

where \( P^k_t \) is the price of the intermediate goods \( Y^k_t \), and \( P^l_t \) is the price of the intermediate goods \( Y^l_t \). Normalizing the final-goods price to one and using the zero-profit condition for final goods, we have

\[ \left[ \phi^\sigma \left( P^k_t \right)^{1-\sigma} + \left( P^l_t \right)^{1-\sigma} \right]^{\frac{1}{1-\sigma}} = 1. \]  \tag{7} \]

V.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, \((1 - \theta_t)Y^k_t\). The varying parameter \( \theta_t \) reflects the changing loan quota targeted by the government. A higher value of \( \theta_t \) 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

$$P^k_k t - R (K^k_k - N_t) \geq (1 - \theta_t) P^k_k t K^k_k.$$  (8)

The problem of K-firm is

$$\Pi^k_t \equiv \max_{K^k_k t} P^k_k t K^k_k - R (K^k_k - N_t) + (1 - \delta) K^k_k t$$

subject to (8). Denote the investment loan to the K-firm by $B^k_k t = K^k_k t - N_t$. At the end of the period, the K-firm turns in its profit to the government and dies.

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

$$\theta_t P^k_t < R < P^k_t$$

The first inequality is necessary; otherwise, the K-firm has no incentive to default on the debt payment. 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 $K^k_k t \leq N_t / (1 - \theta_t)$ with $R = P^k_t$. If, on the other hand, $K^k_k t > N_t / (1 - \theta_t)$, the financial constraint must bind. With the binding constraint, we obtain from (8)

$$K^k_k t = \frac{R}{R - \theta_t P^k_t} N_t.$$  (9)

Accordingly, the amount borrowed by the K-firm is

$$B^k_k t = \frac{\theta_t P^k_t}{R - \theta_t P^k_t} N_t.$$  (10)

V.4. L-firms’ problem. Before production takes place, the L-firm must finance its working capital from intratemporal (short-term) bank loans. L-firms, however, have no access to intertemporal (longer-term) bank loans to fund its fixed investment and must self-finance it through their own savings. The amount of the L-firm’s working capital is constrained by the bank’s loan supply, $B^l_l t$, which we discuss in Section V.6. We leave to Section VIII the discussion of these assumptions in light of the Chinese disaggregated data.

Following SSZ, we assume that the old entrepreneur pays the young entrepreneur a management fee, $m_t$, as a fixed fraction of output produced, $m_t = \psi P^l_l t (K^l_l t)^\alpha (\chi L_t)^{1-\alpha}$, where
Therefore the old entrepreneur’s problem becomes
\[ \Pi_l^t \equiv \max_{L_t} P_l^t \left(1 - \psi\right) (K_l^t)^\alpha \left(\chi L_t\right)^{1-\alpha} - R_l^t w_t L_t + (1 - \delta) K_l^t, \]  
(11)

where \(R_l^t\) is the loan rate on working capital \(w_t L_t\). In equilibrium, \(B_l^t = w_t L_t\). The first-order condition gives
\[ (1 - \psi) \left(1 - \alpha\right) P_l^t \left(\frac{K_l^t}{L_t}\right)^\alpha \left(\chi\right)^{1-\alpha} = R_l^t w_t. \]  
(12)

The gross return of the L-firm’s capital is
\[ \rho_l^t \equiv \Pi_l^t / K_l^t = (1 - \psi) \alpha P_l^t \left(\frac{K_l^t}{L_t}\right)^{\alpha-1} \left(\chi\right)^{1-\alpha} + 1 - \delta. \]  
(13)

The young entrepreneur’s problem is to decide on consumption and a portfolio allocation between bank deposit and physical capital investment. Since the rate of return to capital investment is \(\rho_{l+1}^t + 1\) and \(\rho_l^t > R\) in steady state, we assume, without loss of generality, that the young entrepreneur always prefers investing in capital to depositing in the bank. Specifically, the young entrepreneur’s consumption-saving problem is
\[
\max_{s^t, E^t} \left(\frac{m_t - s^t E^t}{1 - \gamma} \right)^{1-\gamma} + \beta E^t \left(\frac{\rho_{l+1}^t s^t E^t}{1 - \gamma}\right)^{1-\gamma}.
\]

First-order conditions determine the optimal saving of young entrepreneurs:
\[ s^t E^t = m_t / \left(1 + \beta^{-\gamma} E^t \left(\rho_{l+1}^t\right)^{1-\gamma}\right). \]
Since \(s^t E^t = K_{l+1}^t\), the law of motion for the L-firm’s capital becomes
\[ K_{l+1}^t = \frac{\psi}{1 + \beta^{-\gamma} E^t \left(\rho_{l+1}^t\right)^{1-\gamma}} P_l^t \left(\frac{K_l^t}{\chi L_t}\right)^{1-\alpha}. \]  
(14)

V.5. **Workers’ problem.** Workers deposit their savings into the representative bank and earn the fixed interest rate \(R\). Workers cannot lend directly to the K-firms or L-firms—this is an assumption commonly used in the literature on western economies, but it is even more suitable for the Chinese economy.

The worker’s consumption-saving problem is
\[
\max_{c_{1t}^w, c_{2t+1}^w} \left(\frac{c_{1t}^w}{\alpha} \right)^{1-\gamma} + \beta \left(\frac{c_{2t+1}^w}{1 - \gamma}\right)^{1-\gamma}
\]

\footnote{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.}
subject to
\[ c_{1t}^w + s_{tt}^w = w_t, \]
\[ c_{2t+1}^w = s_{tt}^w R, \]
where \( w_t \) is the market wage rate, \( c_{1t}^w, c_{2t+1}^w \), and \( s_{tt}^w \) denote consumption when young, consumption when old, and the worker’s savings.

V.6. The bank’s problem. Each period the bank receives deposits \( D_t \) from old 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 \( R_l \). The bank, however, is subject to a convex cost of loan processing, \( C(B_t) \), which increases in the total amount of loans, denoted as \( B_t \equiv B_l^t + B_k^t \). 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 privately-owned 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).\(^\text{14}\) Since bank loans to state-owned enterprises are always given priority in China, we assume that the bank always meets K-firms’ demand for investment loans prior to lending to L-firms. The bank’s problem is therefore
\[ \Pi_B^B = R_l^t B_l^t + R B_l^k + R(D_t - B_l^k) - R D_t - C(B_t) - B_l^t, \]
where \( B_t = B_l^t + B_k^t \). In equilibrium, \( D_t = s_{tt}^w L_t \). The first-order condition
\[ R_l^t = 1 + C'(B_t) \tag{15} \]
reveals that the loan rate for working capital increases with the total amount of loans.

V.7. The government’s problem. The government lives forever. At the end of each period, the government decides on how much of its revenues to be advanced to K-firms in 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 K-firms’ net worth
\[ N_{t+1} = \frac{R^\xi}{R - \theta R_t^k} N_t. \tag{17} \]
\(^\text{14}\)Reports from various Chinese financial papers confirm these situations.
The government’s budget constraint is

$$B_{t+1}^G + N_{t+1} = \Pi_t^k + \Pi_t^b + RB_t^G,$$

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

VI. Characterizing the equilibrium

In this section we characterize the equilibrium. We first discuss the parameter restrictions for the collateral constraint of the capital-intensive sector to bind at the steady state. We then explore the determinants of the investment-output ratio and the share of labor income during the transition.

VI.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 the steady state. Denote

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

Note that $P^k \bar{\theta} < R$. For the necessary condition for the collateral constraint to bind, i.e. $R < P^k$, we must have the following assumption

$$1 - \xi > \bar{\theta}.$$  (19)

Intuitively, the smaller $\theta$ is, the stronger the default incentive is, and thus the more binding the collateral constraint is. Similarly, the smaller $\xi$ is, the slower the net worth accumulates, and the more binding the collateral constraint becomes. Assumption (19) implies that the collateral constraint always binds along the transition path. Under this assumption, therefore, it is always profitable for K-firms to borrow up to the maximum to expand their production.

VI.2. Transition paths. We are interested in 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 labor compensation to aggregate output. For tractability we set $\theta_t = \bar{\theta}$ 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

$$\frac{I_t}{Y_t} = \frac{I_t^k}{P_t^k Y_t^k} + \frac{I_t^l}{P_t^l Y_t^l}.$$  (20)

In our model, dynamic paths of the investment rate depend on two channels: the reallocation effect and the sector-specific effect. If the investment rate in the capital-intensive sector is

\footnote{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 $Y_t - C(B_t)$.}
higher than the investment rate in the labor-intensive sector, a 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).\(^{16}\)

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

\[
\frac{w_t L_t}{Y_t} = \frac{(1 - \psi) (1 - \alpha)}{1 + P^k_t Y^k_t / (P^l_t Y^l_t)}.
\]

Equation (21) 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.\(^{17}\)

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. Such a structural change, as we argue below, is due to 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.** 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

\[
\Delta \log \frac{P^k_t Y^k_t}{P^l_t Y^l_t} = \left(1 - \frac{1}{\sigma}\right) \Delta \log \frac{Y^k_t}{Y^l_t}.
\]

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

\[
\frac{Y^k_t}{Y^l_t} = \left(\frac{\varphi (1 - \varphi^\sigma (P^k_t)^{1-\sigma})^{1-\sigma}}{P^k_t}\right)^\sigma
\]

Therefore, the ratio of output of the capital intensive to labor intensive sector moves in opposite direction with the price of capital intensive goods. As the net worth of capital intensive sector increases, the capital demand increases, which reduces the price of capital intensive goods towards the first-best level \(R\). Therefore, the ratio \(Y^k_t / Y^l_t\) increases monotonically during the transition path. Given that \(\sigma > 1\), the ratio \(P^k_t Y^k_t / (P^l_t Y^l_t)\) increases along the transition path. \(\square\)

\(^{16}\)Due to the OLG structure and the complete capital depreciation, the investment rate in the labor-intensive sector is constant. Relaxing the assumption of full depreciation tends to predict a declining investment rate in the labor intensive sector due to diminishing marginal returns to capital.

\(^{17}\)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.
The intuition for the above proposition is as follows. Accumulation of the 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 (22) 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 resource reallocations 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 Section VIII) 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 of capital deepening increases with the borrowing capacity of the capital-intensive sector. Consequently, resources are reallocated from the labor-intensive sector to the capital-intensive sector. Such a mechanism is important for explaining not only the trend patterns but also the cyclical patterns, as we show in Section VII. Without such a borrowing constraint, however, 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.

VII. Quantitative results and the mechanism

In this section we report quantitative results for both the transition paths, holding \( \theta \) constant, and the impulse responses following an expansionary shock to \( \theta \), discuss the mechanism in our model, and conduct counterfactual exercises to illustrate how the mechanism works.

VII.1. Trend and cyclical patterns. We set both the initial capital stock in the labor-intensive sector and the initial net worth of capital-intensive firms 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.

Figure 8 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. An increase in the investment rate is puzzling from the perspective of neoclassical models. As Equation (20) 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 8 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 VII.

We now explore the impulse responses to an increase in the credit quota, that is, an unexpected increase in $\theta_t$. Figure 9 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 9). As a result, aggregate investment increases, while aggregate consumption decreases moderately. This outcome leads to a hump-shaped increase in aggregate output. Interestingly, the wage rate and thus labor compensation declines as well.

VII.2. **Key mechanism.** 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.

Over the business cycle, if the government decides to increase the loan quota à la an increase of $\theta_t$, 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

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18 The aggregate investment rate falls initially because the investment rate in the capital-intensive sector falls initially as the leverage ratio becomes smaller.
positive externality on the cost of working-capital loans for labor-intensive firms. According to (12), an increase in $R_l$ 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 compensation, 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.

VII.3. Understanding the mechanism further. We explore in this section two counterfactual economies to understand the role of the two key ingredients in our model: the collateral constraint on capital-intensive firms and 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.

VII.3.1. Economy without banking 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 the 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 and the demand for working capital loans (Figure 10). Consequently, working-capital loans increase with investment loans, inconsistent with the data that will be discussed in Section VIII.

More important is the result that both aggregate consumption (both entrepreneur’s and worker’s) and aggregate investment increase (Figure 10), which 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.

VII.3.2. Frictionless economy. 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 SZZ 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 without banking frictions. The intuition is simple. Without the collateral constraint on capital-intensive firms, the economy behaves essentially as a neoclassical economy: as capital-intensive firms accumulate capital, marginal returns to capital fall, thus reducing output growth in the labor-intensive sector. The fall of output growth would in turn reduce the investment rate in the capital-intensive sector because of the imperfect substitutability of outputs between the two sectors.\textsuperscript{19} Meanwhile, the investment rate in the labor-intensive sector is constant with the complete capital depreciation.\textsuperscript{20} Since the share of revenues in the two sectors in total output is constant, the decline of the investment rate in the capital-intensive sector leads to the simultaneous decline in the aggregate investment rate and the rise in the consumption-output ratio (the first row of Figure 11).

The middle row of Figure 11 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 ratios of revenue and capital stock in the capital-intensive sector to those 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 11).

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 capital-intensive revenue to labor-intensive revenue, and (5) an increasing ratio of long-term loans to short-term loans. Without such a friction (in addition to the bank-lending friction), the economy would become essentially neoclassical, which predicts (1) a declining investment rate and an increasing consumption-output ratio, (2) a constant ratio of capital-intensive revenue to labor-intensive revenue, (3) a declining ratio of capital stock in the capital-intensive sector to that in the labor-intensive sector, (4) a secular decline of long-term loans relative to short-term loans, and (5) a constant labor income share. All these trend patterns are at odds with the Chinese data.

\textsuperscript{19}Specifically, the investment rate in the capital-intensive sector is

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

\textsuperscript{20}With incomplete capital depreciation, the investment rate in the labor-intensive sector declines due to diminishing marginal returns to capital.
The Chinese economy has undergone two types of transitions simultaneously. One transition is privatization that allows many SOEs previously engaged in labor-intensive (light) industries to become POEs. This transition is the focus of the SSZ work. The other transition is the concentration of SOEs in capital-intensive (heavy) industries, such as petroleum, commodities, electricity, water, and gas. It is this transition that becomes the focus of our paper. We corroborate the assumptions and features in our theoretical model using the disaggregated data that characterize this notable transition of the Chinese economy.

Table 3 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 4 reports the weight and the rank by capital intensity for each of the all 39 industries for 1999, 2006, and 2011. Those years give us a clear picture of the SOE transition into the heavy sector from the end of the 1990s to the beginning of the 2010s; and Tables 3 and 4 are used in conjunction with Figures 12, 13, and 14 to understand this transition. 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 capital intensity for each industry.

The rank of industries by capital intensity changes over time (Table 4), 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, less SOEs engaged in those industries; and in 2011, even less SOEs engaged. Take “Manufacture of General Purpose Machinery” (industry identifier 29 in Table 3) as example. In 1999, the SOE share was over 60% (the bar chart in Figure 12); in 2006, the SOE share dropped to 25% (the bar chart in Figure 13); and in 2011, the SOE share dropped even further to less than 20% (the bar chart in Figure 14).

What is most striking is the concentration of SOEs in the capital-intensive industry over time. On the right column of each figure from Figure 12 to 14, we mark the top-10 value-weighted industries with dark circles and fit the quadratic curve through these dark circles. In 1999, 6 of those industries were labor intensive (i.e., the capital-labor ratio is below 20) with the SOE share between 40% and 80% (Figure 12); in 2006, except one labor-intensive industry with 53% share of SOEs, all other 5 had the SOE participation rate less than 25%
TRENDS AND CYCLES IN CHINA’S MACROECONOMY

(Figure 13); by 2011, the SOE share in those labor-intensive industries dropped even further (Figure 14). Instead, the SOEs have concentrated on capital-intensive industries, revealed by the dark circles and fitted quadratic lines. The two sectors in our theoretical model, capital intensive K-firms and labor intensive L-firms, are modeled to capture the essence shown in these disaggregated data.

The SOEs enjoy easy access to bank loans for long-term investment in the heavy sector. Since large banks in China are state-owned, investment loans to the SOEs, often in the form of “medium & long term loans,” take priority over other loans to the POEs, often in the form of “short-term loans and bill financing.” A reading of China Monetary Policy Report prepared by Monetary Policy Analysis Group of the Peoples Bank of China (the CMP report hereafter) reveals that the government often increases medium & long term loans at the sacrifice of short-term loans. Figure 15 presents evidence that is consistent with the CMP reports. 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. This negative correlation is most conspicuous right after the 2008 financial crisis, when the government injected massive credits into SOE investment 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.

There are two shortcomings of these loan series. First, the series include loans made to financial institutions. Second, the series include loans made to households. One possible 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 exist from 2007Q1 to 2014Q3. Figure 16 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 15, with the correlation being −0.744. The right column of Figure 16 reports the

21Brandt and Zhu (2007) discuss how bank loans to the SOEs and those to the POEs changed over time. Their results are consistent with the CMP reports about short-term vs. long-term loans. It appears that the series for loans to the SOEs and POEs no longer exist after 2003.
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 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 to household
consumption.

The link between the government’s investment in the heavy sector and its priority in
injecting long-term bank loans into this sector is a unique institutional arrangement in China
central to our storyline. It is this link that becomes the key architecture of our theoretic
framework. Figure 17 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. This ratio fluctuated around one until the mid 1990s and since then
has steadily increased to the factor of 2.5. The next chart reports the ratio of capital stock
in heavy sector over that in light sector, which shows a pattern similar to the top chart. The
increasing importance of heavy industry 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 uprising trend has been reversed since 2010 because the
government ceased to inject long-term credits in 2010.\textsuperscript{22} The results from our theoretical
model are consistent with the facts presented by Figure 17.

\textsuperscript{22}As shown in the middle chart, the patterns for NFE loans and total loans track each other very closely,
indicating that total loans can be used to approximate new loans when the data for new loans are unavailable.
Table 1. Chronology of structural switches

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

Table 2. Correlations between HP-filtered log quarterly series

<table>
<thead>
<tr>
<th>Panel A: Real variables deflated by own price index</th>
<th>(C, I)</th>
<th>(I, LaborComp)</th>
<th>Correlation</th>
<th>p-value</th>
<th>Correlation</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>(C, I)</td>
<td></td>
<td>(I, LaborComp)</td>
<td>-0.140</td>
<td>0.256</td>
<td>0.165</td>
<td>0.179</td>
</tr>
<tr>
<td>Correlation</td>
<td>-0.035</td>
<td>(I, LaborComp)</td>
<td>0.165</td>
<td>0.775</td>
<td>0.178</td>
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</tr>
<tr>
<td>p-value</td>
<td></td>
<td>(I, LaborComp)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B: Real variables deflated by GDP price deflator</th>
<th>(C, I)</th>
<th>(I, LaborComp)</th>
<th>Correlation</th>
<th>p-value</th>
<th>Correlation</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>(C, I)</td>
<td></td>
<td>(I, LaborComp)</td>
<td>-0.035</td>
<td>0.775</td>
<td>0.165</td>
<td>0.178</td>
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<tr>
<td>Correlation</td>
<td>-0.035</td>
<td>(I, LaborComp)</td>
<td>0.165</td>
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<td>p-value</td>
<td></td>
<td>(I, LaborComp)</td>
<td></td>
<td></td>
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<td></td>
</tr>
</tbody>
</table>

Notes: Labor compensation (LaborComp) is deflated by the GDP deflator. The sample runs from 1996Q1 to 2012Q4. “C” stands for household consumption and “I” for aggregate investment.
Table 3. Industry identifiers

<table>
<thead>
<tr>
<th>Identifier</th>
<th>Industry</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Mining and Washing of Coal</td>
</tr>
<tr>
<td>2</td>
<td>Extraction of Petroleum and Natural Gas</td>
</tr>
<tr>
<td>3</td>
<td>Mining and Processing of Ferrous Metal Ores</td>
</tr>
<tr>
<td>4</td>
<td>Mining and Processing of Non-Ferrous Metal Ores</td>
</tr>
<tr>
<td>5</td>
<td>Mining and Processing of Nonmetal Ores</td>
</tr>
<tr>
<td>6</td>
<td>Mining of Other Ores</td>
</tr>
<tr>
<td>7</td>
<td>Processing of Food from Agricultural Products</td>
</tr>
<tr>
<td>8</td>
<td>Manufacture of Foods</td>
</tr>
<tr>
<td>9</td>
<td>Manufacture of Beverages</td>
</tr>
<tr>
<td>10</td>
<td>Manufacture of Tobacco</td>
</tr>
<tr>
<td>11</td>
<td>Manufacture of Textile</td>
</tr>
<tr>
<td>12</td>
<td>Manufacture of Textile Wearing Apparel, Footware, and Caps</td>
</tr>
<tr>
<td>13</td>
<td>Manufacture of Leather, Fur, Feather and Related Products</td>
</tr>
<tr>
<td>14</td>
<td>Processing of Timber, Manufacture of Wood, Bamboo, Rattan, Palm, and Straw Products</td>
</tr>
<tr>
<td>15</td>
<td>Manufacture of Furniture</td>
</tr>
<tr>
<td>16</td>
<td>Manufacture of Paper and Paper Products</td>
</tr>
<tr>
<td>17</td>
<td>Printing, Reproduction of Recording Media</td>
</tr>
<tr>
<td>18</td>
<td>Manufacture of Articles For Culture, Education and Sport Activity</td>
</tr>
<tr>
<td>19</td>
<td>Processing of Petroleum, Coking, Processing of Nuclear Fuel</td>
</tr>
<tr>
<td>20</td>
<td>Manufacture of Raw Chemical Materials and Chemical Products</td>
</tr>
<tr>
<td>21</td>
<td>Manufacture of Medicines</td>
</tr>
<tr>
<td>22</td>
<td>Manufacture of Chemical Fibers</td>
</tr>
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<td>Manufacture of Rubber</td>
</tr>
<tr>
<td>24</td>
<td>Manufacture of Plastics</td>
</tr>
<tr>
<td>25</td>
<td>Manufacture of Non-metallic Mineral Products</td>
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<tr>
<td>26</td>
<td>Smelting and Pressing of Ferrous Metals</td>
</tr>
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<td>27</td>
<td>Smelting and Pressing of Non-ferrous Metals</td>
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<td>28</td>
<td>Manufacture of Metal Products</td>
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<td>29</td>
<td>Manufacture of General Purpose Machinery</td>
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<td>30</td>
<td>Manufacture of Special Purpose Machinery</td>
</tr>
<tr>
<td>31</td>
<td>Manufacture of Transport Equipment</td>
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<tr>
<td>32</td>
<td>Manufacture of Electrical Machinery and Equipment</td>
</tr>
<tr>
<td>33</td>
<td>Manufacture of Communication Equipment, Computers and Other Electronic Equipment</td>
</tr>
<tr>
<td>34</td>
<td>Manufacture of Measuring Instruments and Machinery for Cultural Activity and Office Work</td>
</tr>
<tr>
<td>35</td>
<td>Manufacture of Artwork and Other Manufacturing</td>
</tr>
<tr>
<td>36</td>
<td>Recycling and Disposal of Waste</td>
</tr>
<tr>
<td>37</td>
<td>Production and Distribution of Electric Power and Heat Power</td>
</tr>
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<td>Production and Distribution of Gas</td>
</tr>
<tr>
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<td>Production and Distribution of Water</td>
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Table 4. Weights and capital-intensity ranks for various industries

<table>
<thead>
<tr>
<th>Industry identifier</th>
<th>1999 Weight (%) by value added</th>
<th>2006 Weight (%) by value added</th>
<th>2011 Weight (%) by gross output</th>
<th>1999 Capital intensity rank</th>
<th>2006 Capital intensity rank</th>
<th>2011 Capital intensity rank</th>
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<td>35</td>
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Figure 1. Trend and cyclical patterns of household consumption and aggregate investment, estimated from the 3-variable time-varying BVAR model.
Figure 2. Various price levels, normalized to 1 for 2000.
Figure 3. Time-series history of trends and cycles in China’s macroeconomy. “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 4. Year-over-year growth rates of key quarterly time series. Total bank loans are deflated by the GDP deflator.
Figure 5. Trend patterns for household consumption, investment, GDP, household disposable personal income, and household labor compensation. “Investment” is total business investment, which is calculated as gross fixed capital formation excluding household investment and equals to the sum of SOE investment and POE investment. “Output” is the sum of household consumption and total 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. The legend “exp” means that GDP is measured by expenditure and “va” means that GDP is measured by value added.
**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 aggregate investment (deflated by the investment price index), “SOE” is real SOE investment, “POE” is real POE investment, “Disposable” stands for household disposable personal income, “Labor” stands for household labor compensation, and “Before tax” stands for household before-tax labor income.
Figure 8. 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 9. Impulse responses to an expansionary credit shock in the benchmark theoretical model.
Figure 10. Impulse responses to an expansionary credit shock in the economy without the bank-lending friction.
Figure 11. The trend patterns for the frictionless economy. “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 12. 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 3. 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 13. 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 3. 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 14. 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 3. 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 15. 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 16. 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 17. Secular patterns for heavy vs light sectors and for medium and long term bank loans vs. short term bank loans. The top first 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 data and the bottom chart is based on the WIND data (the source of both data is the People’s Bank of China).
Appendix A. Core macroeconomic variables

The quarterly macroeconomic time series we have collected and constructed are listed as follows.

(1) Population. 1991Q1-. Seasonally adjusted.
(2) Number of people with high school diploma or higher education. 1996Q1-. Seasonally adjusted.
(7) Employment: urban and other non-private enterprises (million persons). 1992Q1-. Seasonally adjusted.
(8) Nominal industrial production: value added (RMB billion). 1991Q1-. Seasonally adjusted.
(20) Nominal GDP (RMB billion). 1991Q1-. Value added. Seasonally adjusted.
(22) Fixed-assets investment: total (RMB billion). 1990Q1-. Value added. Seasonally adjusted.
(23) Fixed-assets investment: private enterprises (RMB billion). 1990Q1-. Value added. Seasonally adjusted.
(32) CPI (2008Q1=100). 1985Q1-. Seasonally adjusted.
(34) Price index for retail consumption (2008Q1=100). 1985Q1-. Seasonally adjusted.
(35) Average nominal wage per employed person: urban private (RMB). 1991Q1-. Seasonally adjusted.
(37) Producer price index (2008Q1=100). 1991Q1-. Seasonally adjusted.
(38) Exchange rate (RMB/USD). 1991Q1-. Seasonally adjusted.
(39) M2 (RMB billion). 1990Q1-. Seasonally adjusted.
(40) Base money (RMB billion). 1990Q1-. Seasonally adjusted.
(41) M0 (RMB billion). 1990Q1-. Seasonally adjusted.
(42) Foreign reserves (USD billion). 1989Q1-. Seasonally adjusted.
(43) Bank loans: total (RMB billion). 1991Q1-. Seasonally adjusted.
(47) Social aggregate finance: loan in local currency (RMB billion). 2002Q1-. Seasonally adjusted.
(49) Social aggregate finance: entrusted loan (RMB billion). 2002Q1-. Seasonally adjusted.
(50) Social aggregate finance: trusted loan (RMB billion). 2006Q1-. Seasonally adjusted.
(51) Social aggregate finance: banker’s acceptance bill (RMB billion). 2002Q1-. Seasonally adjusted.
(52) Social aggregate finance: net corporate bond financing (RMB billion). 2002Q1-. Seasonally adjusted.
(53) Social aggregate finance: non financial enterprise equity financing (RMB billion). 2002Q1-. Seasonally adjusted.
(54) Social aggregate finance: insurance compensation (RMB billion). 2002Q4-. Seasonally adjusted.
(55) Social aggregate finance: insurance property investment (RMB billion). 2002Q4-. Seasonally adjusted.
(56) Social aggregate finance: other financing (RMB billion). 2002Q4-. Seasonally adjusted.
(57) Required reserve ratio (percent). 1985Q1-. Seasonally adjusted.
(58) Bank deposit rate: 3 months (percent). 1996Q1-. Seasonally adjusted.
(59) Market interest rate: 1-day CHIBOR/Repo rate (most traded). 1996Q1-. Seasonally adjusted.
(60) Market interest rate: 7-day CHIBOR/Repo rate. 1996Q1-. Seasonally adjusted.
(61) Market interest rate: overall CHIBOR/Repo rate. 1996Q1-. Seasonally adjusted.
(63) Real estate prices: total (RMB billion). 1991Q1-. Seasonally adjusted.
(64) Real estate prices: residential (RMB billion). 1991Q1-. Seasonally adjusted.

All these series exist on annual frequency with the first observations available back to much earlier dates. Additional annual series are

(1) Gross capital formation (RMB billion). 1952-. Flow of funds by expenditure.
(2) Gross capital formation: fixed (RMB billion). 1952-. Flow of funds by expenditure.
(3) Gross capital formation: changes in inventory (RMB billion). 1952-. Flow of funds by expenditure.
(14) Average nominal wage per employed person: urban private (RMB). 1952-.
(15) Producer price index. 1978-.
(16) Reserve: required & excessive (RMB billion). 1992-.
(17) Foreign reserves (USD billion). 1950-.
(18) Commodity building selling price: average. 1995-.
(19) Commodity building selling price: residential. 1995-.
References


