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Abstract

International experience points to the critical role of stable property markets in maintaining financial stability. In China, the real estate sector has become increasingly important for the economy, but existing evidence has likely understated its importance as its linkages with other sectors have not been taken into account. This paper attempts to shed some light on these linkages which occur through both real and financial channels. Our analysis based on input-output tables shows that the linkages between the real estate and other sectors have strengthened through real channels, and that the real estate sector has been much more important to the economy's output than suggested by the share of its value added in total value added. The real estate industry is also closely linked to other sectors through various financial channels, including serving as collateral in credit expansion. We quantify these financial linkages by studying the spill-overs of credit risk across sectors using data of listed firms. In general, we find that corporate credit risk has risen in recent years, and that credit risk in the real estate sector can potentially have large-scale spill-over effects onto other sectors. Consequently, shocks to the property market could have much larger impact on the Chinese economy than suggested by headline figures.

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1. Introduction

The real estate sector has become increasingly important to the Chinese economy. Real estate fixed asset investment (FAI) has been consistently high, accounting for around 25% of the economy's total FAI, while the share of value added generated from housing services in total value added has risen steadily from less than 4.5% in 2002 to over 5.5% in 2010 (Figure 1). On the financial side, mortgage loans and loans to developers have accounted for an increasing share of total bank loans (Figure 2), while the shadow banking system's exposure to the real estate sector is sizeable. For instance, real estate trusts have accounted for over 30% of total trust products in the past couple of years, while a survey by Morgan Stanley for 64 small-scale credit intermediaries including pawn shops in 2012 suggests close to 20% of credit was extended to real estate developers.[1]

However, such evidence likely understates the importance of the real estate sector primarily because intersectoral linkages are not taken into account. Against this backdrop, this paper attempts to shed some light on this issue by looking at real estate sector's linkages with other sectors through real and financial channels.[2] Real linkages can be explored through input-output (I-O) analysis, while financial linkages are more complicated.[3] There are at least three financial channels through which the real estate sector is linked with others.

First of all, shocks to the property market would affect the profitability of any sector that is vertically integrated with it and weaken its debt servicing capacity. Secondly, as it is common for firms to use property as collateral to borrow, so any adjustment in the property market could affect collateral values and hence debt quality. According to the International Monetary Fund (IMF), 30-45% of loans extended by the five largest Mainland banks have been backed by collateral in recent years, the majority of which is real estate.[4] Thirdly, local government debt in China has been in part supported by land sales revenue, suggesting that any property market adjustment would affect the quality of local government debt as well.

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1 See "Asia Insight: Informal Lending – Low Risk to the Financial Sector: Limited Impact on the Real Economy", 11 January 2012, Morgan Stanley Research.

2 On the 3rd April 2014, the Guardian reported that, China puts railway and houses at the heart of its new stimulus measures (see "http://www.theguardian.com/world/2014/apr/03/china-railways-new-economic-stimulus-measures"). Thus, understanding the linkages between the real estate and other sectors in China is important in estimating the effectiveness of the overall "new stimulus measures".

3 Financial linkages largely depend on the financial contracts being signed. In the economic literature there are several ways to model financial contracts. For instance, Hart (1995) advocates the "limited enforcement contract" (LEC) approach. Kiyotaki and Moore (1997) embed LEC in a dynamic, stochastic general equilibrium model (DSGE) and demonstrate how the fluctuations of collateral values will increase both the magnitude and persistence of business cycles. Cooley et al. (2004) show how LEC amplifies productivity shocks when firms repudiate contracts in a general equilibrium model. An alternative is the "costly state verification" (CSV) approach developed by Townsend (1979). Williamson (1987) and Bernanke (1999). Both apply CSV in their general equilibrium models to simulate the effects of financial intermediation on business cycles.

4 See "People's Republic of China: Financial system Stability Assessment", the IMF, 2011, page 17.

The real economy linkages are examined in a way similar to Song et al. (2008). While there are various I-O models and related methods that could be used to conduct such analysis, the method used here is straightforward and easy to be implemented.[5] By contrast, data constraints make it difficult to quantify the financial linkages across sectors, and we attempt to shed some light on this issue by studying the spill-overs of credit risks across sectors. There are two main approaches to modelling credit risks. One is the structural approach and the other is the reduced form approach. The former is based on option theory pioneered by Black and Scholes (1973) and Merton (1974) (henceforth the BSM model). The basic idea of the BSM model is that, a firm's equity is a call option on a firm's assets with the strike price equal to the book value of firm's liabilities. The reduced-form approach evolves from discriminant analysis to the binary response model, and more recently to the duration model.[6] [7] Both the structural approach and the reduced-form models have been extended to study cyclical default correlations, or credit contagion among firms given the obvious interdependence of firms' credit risks in recent financial crises. For instance, Cossin and Schellhorn (2007) extend the structural approach by applying queuing theory to model credit risk in a network economy. The reduced-form approach, on the other hand, directly puts economy-wide state variables measuring common risk factors and the counterparty risk terms into Logit or Probit models, or into an intensity function in hazard models, see for example Jarrow and Yu (2001), and Duffie et al. (2009).[8]

In addition to these model extensions, the recent work by Yang and Zhou (2012) applies the directed acyclic graph (DAG) method to structural VAR (SVAR) to identify the map and assess the magnitude of the credit risk transmission across financial institutions in the US on the eve of the global financial crisis. Our analysis combines the structural and reduced-from approach with a DAG-based SVAR to study sectoral credit risk correlations and spillovers in China. As historic data on China default events are rare, it is difficult to directly use Logit or hazard models to estimate default probabilities. In addition, as the bond market is under-developed and the credit default swap market is not yet established, it is

[5] As an application of standard I-O analysis to China, Yuan et al. (2010) estimate the energy consumption structure and the impact of export changes on energy consumption respectively. Extensions of a standard Leontief model include: I-O price models by Sharify and Sancho (2012); Sharify (2013) which studies the effect of price shocks originating from taxation and subsidies on general prices; the I-O variable model by Liew and Liew (1988) applied to gauge the impact of primary input prices on industrial prices and outputs. In addition, Rose (1995) explains how I-O table is related to CGE models. More discussion and various applications of I-O table to CGE models can be found, for instance, in Dixon and Jorgenson (2012), Kehoe and Serra-Puche (1983), and Elekdag and Muir (2013). Liu et al. (2010) and Horridge and Wittwer (2008) are examples of applying such CGE models to evaluate the impact of the agricultural sector on general prices, and the regional impacts of region-specific shocks in China respectively.

[6] Discriminant analysis in early studies by Beaver (1968) and Altman (1968) primarily relies on accounting measures to generate credit scores such as the Z-score, which is still widely used by the academic and financial community. While the binary response model employs Logit or Probit regressions to explain the likelihood of firm failure or default with fundamental variables, the duration analysis uses discrete-time or Cox proportional hazard function to link default probability or default intensity to a set of explanatory variables. See Ohlson (1980), Zmijewski (1984), Campbell et.al. (2008), and Altman (2011), Shumway (2001), Hillegeist et al. (2004), and Duan et al. (2012).

[7] There are pros and cons to modelling issues using these approaches. Shumway (2001) proves that a discrete-time hazard model is equivalent to a multiperiod logit model when hazard function is the cumulative density function of failure or default in logit model. Both Shumway (2001) and Chava and Jarrow (2004) find that a duration model is more accurate than early generations of reduced-form models in predicting failure or default. On the other hand, by comparing structural and reduced-form models, Hillegeist et al. (2002) find that the structural model is more powerful in failure prediction. In contrast, Campbell and Szilagyi (2008) show that, when market variables, in addition to accounting variables, are used to construct independent variables, the logit model has higher failure predictive power than the structural model.

[8] Giesecke and Weber (2004) employ the theory of interacting particle systems to Bernoulli mixture model in their studies, which accommodates Logit and Probit models.

not feasible to use credit swap spreads to measure default risks. Applying the BSM framework to estimate default likelihood is a good alternative. Following Altman et al. (2011), we estimate firm-level default likelihood within the BSM framework, and then examine the link between default likelihood and firm-specific characteristics using a reduced-form approach. Credit risk spillovers are analysed at industry-level in the DAG-based SVAR framework. To our knowledge, this is the first paper in the literature to focus on the linkages between the real estate and other sectors in China, particularly from a financial perspective.

Our analysis shows that the linkages between real estate and other sectors have strengthened through real economy channels. The real estate sector has been much more important to the economy's output than suggested by the share of its value added in the economy's total value added. Credit risks across sectors show a clear pattern of co-movement, and have generally increased in recent years, particularly for those sectors with overcapacity problems. Of particular note, our estimates show that credit risks of the real estate sector can potentially generate large-scale spill-over effects onto other sectors, suggesting it is closely linked with other sectors through financial channels as well.

The rest of the paper is organized as follows. Section 2 studies inter-sectoral linkages through real channels. Section 3 outlines the BSM framework, presents the default likelihood estimation, and discusses the relationship between default likelihood and firm-specific characteristics. Section 4 investigates credit risk contagion, and Section 5 concludes.

2. Linkages between Real Estate and Other Sectors through Real Channels

Inter-sectoral linkages through real channels have been typically explored via marginal-impact analysis using input-output tables. An input-output model can be represented by the following linear equations:

$$\begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} = \begin{bmatrix} z_{11} & \cdots & z_{1n} \\ \vdots & \ddots & \vdots \\ z_{n1} & \cdots & z_{nn} \end{bmatrix} \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix} + \begin{bmatrix} f_1 \\ \vdots \\ f_n \end{bmatrix} \tag{1}$$

where x_i is the gross output of sector *i*, z_{ij} is the intermediate input from sector *i* to sector *j*, and f_i is the total final demand for sector *i*'s product. In matrix notation, an input-output model can be represented as:

$$X_{n\times1} = Z_{n\times n} i_{n\times1} + F_{n\times1} \tag{2}$$

The direct input coefficient a_{ij}, which measures the amount of intermediate input from sector *i* used to produce one unit of output in sector *j* with only direct input demand considered, is calculated by dividing the intermediate input from sector *i* to sector *j* by the total output of sector *j*:

$$a_{ij} = \frac{z_{ij}}{x_j}. \tag{3}$$

Substituting a_{ij} into equations (1) and (2), the input-output model can be rearranged as:

$$\begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} = \left(\begin{bmatrix} 1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 1 \end{bmatrix} - \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nn} \end{bmatrix} \right)^{-1} \cdot \begin{bmatrix} f_1 \\ \vdots \\ f_n \end{bmatrix} \tag{4}$$

$$X_{n\times 1} = (I_{n\times n} - A_{n\times n})^{-1} \cdot F_{n\times 1} \tag{5}$$

where I is an identity matrix and $(I_{n\times n} - A_{n\times n})^{-1}$ is known as the Leontief inverse or the total requirements matrix.

Specifically, total input coefficients, which illustrate how much output from each sector is used as intermediate inputs to meet a unit of increase in the final demand of a specific sector, with both direct and indirect effects considered, are a good summary of inter-sectoral linkages. The total input coefficient b_{ij} that describes the amount of output from sector *i* used as intermediate input to meet one unit increase in the final demand of sector *j* is calculated as:

$$B_{n\times n} = (I_{n\times n} - A_{n\times n})^{-1} - I_{n\times n} \tag{6}$$

The real estate sector in Mainland input-output tables mainly refers to housing services and excludes housing construction activities. Therefore, the research in this section combines the real estate and construction sectors in input-output tables to explore how a change in real estate related activities can affect other sectors.

Our research suggests that the linkages between the real estate-construction sector and other sectors have tightened, as evidenced by the increase in total input coefficients during 2005 to 2010 (Figure 3). Metal, construction materials, and the chemistry sector have been most closely linked with the real estate-construction sector, followed by transportation and storage, electrical and heat equipment, and the fuel sector. A one Yuan increase in the final demand of the real estate-construction sector leads to around a quarter of a yuan increase in the gross output of the metal sector in 2010, compared with one fifth of a Yuan in 2005.

We also explore the relative importance of each individual sector's linkage with the real estate-construction sector by estimating the loss in the economy's value added caused by a hypothetical elimination of the linkage on an isolated basis.[9] For example, if we want to calculate the importance of the linkages between sectors 1 and 2 in an economy, we replace a_{12} and a_{21} in equation (4) with 0 and obtain a new level of output x_i':

$$\begin{bmatrix} x_1' \\ x_2' \\ x_3' \\ \vdots \\ x_n' \end{bmatrix} = \left(\begin{bmatrix} 1 & 0 & 0 & \cdots & 0 \\ 0 & 1 & 0 & \cdots & 0 \\ 0 & 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & 1 \end{bmatrix} - \begin{bmatrix} a_{11} & 0 & a_{13} & \cdots & a_{1n} \\ 0 & a_{22} & a_{23} & \cdots & a_{2n} \\ a_{31} & a_{32} & a_{33} & \cdots & a_{3n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & a_{n3} & \cdots & a_{nn} \end{bmatrix} \right)^{-1} \cdot \begin{bmatrix} f_1 \\ f_2 \\ \vdots \\ f_n \end{bmatrix} \tag{7}$$

The loss in gross output caused by the elimination of the linkage between sectors 1 and 2 is the sum of the changes in output across all sectors: $\sum_{i=1}^{n}(x_i - x_i')$, and the value added change is then calculated according to the share of value added in gross output.

Our analysis shows the economy's value added would experience the largest loss of 5.7% in 2010 if the linkages between real estate-construction and construction material sectors were eliminated (Figure 4). The economy's value added would also see significant losses if the linkages between the real estate-construction and iron & steel or transport & storage sectors were eliminated.

To explore the overall importance of the real estate-construction sector because of its linkages with other sectors, we estimate the loss in the economy's value added caused by a hypothetical elimination of this sector from the input-output tables, following Song et al. (2008). For instance, in examining the importance of sector 1 in an economy, we set a_{i1} and a_{1j} at 0 in equation (4) for all *i* and *j* and calculate the new output level x_i^* for all sectors:

$$\begin{bmatrix} x_1^* \\ x_2^* \\ \vdots \\ x_n^* \end{bmatrix} = \left(\begin{bmatrix} 1 & \cdots & \cdots & 0 \\ \vdots & \ddots & & \vdots \\ \vdots & & \ddots & \vdots \\ 0 & \cdots & \cdots & 1 \end{bmatrix} - \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & a_{22} & \cdots & a_{2n} \\ 0 & \vdots & \ddots & \vdots \\ 0 & a_{n2} & \cdots & a_{nn} \end{bmatrix} \right)^{-1} \cdot \begin{bmatrix} f_1 \\ f_2 \\ \vdots \\ f_n \end{bmatrix} \tag{8}$$

The change in total output is then obtained by aggregating the change in output $(x_i - x_i^*)$ across all sectors. The importance of sector 1 in the economy is the sum of the change in total output and final demand for sector 1:

$$\sum_{i=1}^{n}(x_i - x_i^*) + f_1 \tag{9}$$

The value added change is then calculated according to the share of value added in gross output.

[9] See Song et al. (2008).

Overall, our analysis shows the real estate-construction sector has been much more important to the economy's output than suggested by its share of value added in the economy's total value added. The Chinese economy's value added would be around one third less in 2010 if the real estate-construction sector were eliminated, much larger than the share of its value added in the economy's total value added of around 12% (Figure 5). This is because eliminating the real estate-construction sector would also reduce the production of other sectors. Similarly, a hypothetical elimination of the real estate-construction sector would mean a loss of 29% and 27% in the economy's total value added in 2007 and 2005 respectively, much higher than the share of this sector's value added in the economy's total value added of around 10% over the same two years.

3. Financial Linkages between Real Estate and Other Sectors

We quantify intersectoral financial linkages by studying the spill-over of credit risks across sectors as it is difficult to directly quantify these linkages due to data constraints. Credit risks are proxied by default likelihoods estimated using financial data of all listed firms, such as stock prices, equity and liabilities. As a shock to one sector can affect financial variables of other sectors owing to intersectoral financial linkages, it seems reasonable to use default likelihood spill-overs across sectors to capture intersectoral financial linkages. For instance, a shock to one sector may not only affect this sector's stock prices, but could in turn spill-over to the share prices of closely connected sectors. As stock prices are a major variable used to estimate a firm's default likelihood, credit risk spill-overs should reflect the intersectoral financial linkages underlying them.

3.1 Estimation of Default Likelihood

To use a structural model to estimate default likelihood, we need to construct a daily debt and market-implied equity series. Stock prices are of daily frequency, and data from companies' financial reports (i.e., balance sheets and income statements) are quarterly. Because of time lags in quarterly data releases, we take a firm's liabilities and the number of shares in the previous quarter to calculate its debt and equity in the current quarter. Following Duan (1994), Altman et al. (2011) and other related research, we take the sum of short-term liabilities and a half of long-term liabilities as daily debt values.[10]

Corporate default likelihood is estimated according to the Black-Scholes-Merton option theory, which treats a firm's equity (E) as a call option on a firm's assets, with the strike price D equal to the firm's debt. Let V denote a firm's total assets with volatility of δ, and T the time horizon. The equity value can be expressed as:

[10] The number of shares for one stock in the previous quarter is obtained by dividing the company's total equity in the previous quarter by its stock price at the end of that quarter. The current quarter's daily equity for one stock is proxied by its last quarter's number of shares times its current quarter's daily stock price.

$$E= VN(d)-DN(d - \delta\sqrt{T}) \qquad (10)$$

where $N(.)$ denotes normal distribution with:

$$d =[ln(V/D)+(\delta^2/2)T]/(\delta\sqrt{T}) \qquad (11)$$

Equation (10) maps the unobserved asset value to the observed equity value in a one-to-one manner. According to Duan (1994), the unobserved asset value V and its volatility δ as well as its expected return μ can be estimated from a log-likelihood function along with Equations (10)-(11):[11]

$$L(\mu,\delta) = -[(n-1)/2]ln(2\pi)-[(n-1)/2]ln(\delta^2)$$

$$- \sum_{t=2}^{n} \ln V_t(\delta) - \sum_{t=2}^{n} \ln N(d_t) - \sum_{t=2}^{n} (\ln V_t(\delta) - \ln V_{t-1}(\delta) - u)^2 \qquad (12)$$

The default likelihood in a one-year horizon is defined as a Normal distribution:

$$DL = N(-(\hat{V}/D + (\mu - \delta^2/2))/\delta) \qquad (13)$$

with $\hat{V}/X + (\mu - \delta^2/2))/\delta$ being the distance to default.[12]

Our estimates suggest corporate default likelihood has generally risen in recent years. Sectoral default likelihood seems to co-move with business cycles (see Figures A-1 and A-2 in the appendix). In other words, credit risks would rise in nearly all sectors during an economic downturn and decline when the economy strengthens. Specifically, the default likelihood of all sectors surged on the eve of the global financial crisis but declined afterwards. Overall, however, credit risks are still higher than during the period of 2003-2007 (Figure 6).

Of particular note, the sectors with severe overcapacity problems, such as Metal, Coal, Cement, and Ship, have higher default risks than other sectors (Figures 7-8), mainly reflecting higher leverage of these sectors. Indeed, as shown in Figure A-3 in the appendix, the debt-to-asset ratio for these

11 Alternatively, V and δ could be estimated simultaneously by using equations (10)-(11) and $\delta_E = \frac{V}{E}\frac{\partial E}{\partial V}\delta$, where δ_E is equity volatility. However, this methodology is subject to criticism (Duan, 1994), stemming from the fact that the volatility function is derived from Equation (10) by Ito's lemma, and is redundant.

12 The maximum likelihood estimation is implemented with Gauss in line with Duan (1994). The estimation procedure is taken quarter by quarter over a one-year rolling window. Month-by-month estimation will be conducted later on.

sectors has been growing faster than for other sectors with the exception of real estate developers. It reached 65% in recent years, compared with around 60% for listed firms as a whole.

Moreover, we find state-owned enterprises (SOEs) do not necessarily feature lower credit risks although they are supported by government. As shown in Figure 9, firms with higher state ownership had a slightly lower default likelihood during 2003Q1-2008Q1, but the picture has changed in the past few years. Firms with state ownership of above 50% have a default likelihood of around 0.17, compared with around 0.15 for those firms with state ownership of below 50%. State ownership appears to be a double-edge sword: on the one hand, SOEs are protected by the government, and hence it should be less likely that they default. On the other hand, it is easier for SOEs to borrow under the current financial regime, and therefore, they can have higher leverage suggesting a higher default risk. Indeed, our analysis shows that the debt-to-asset ratio of firms with state ownership of over 50% was similar to that for firms with lower state ownership before 2009, but it is notably higher afterwards (Figure 10). This possibly reflects the fact that banks were encouraged to lend to SOEs to boost economic growth, and the launch of the big stimulus package in 2009-2010.

3.2 What Indicators are Informative of Default Risks?

To study which indicators are informative of default risks, we follow Altman et. al. (2010) and regress the default likelihood of firm i at time t, $DL_{it,}$ as a logistic function of firm size and major financial indicators as well as a monetary policy variable:

$$y_{it} = a_0 + a_1 ln(1\text{-}RE/TAE)_{it\text{-}1} + a_2 ln(CA/TAE)_{it\text{-}1}$$

$$+ a_3(1+ln(TAE/TL))_{it\text{-}1} + a_4(TA/IDX)_{i,t\text{-}1} + a_5 X_t \qquad (14)$$

where the dependent variable is the transformed default likelihood $y_{it} = ln((1\text{-}DL_{it})/DL_{it})$. The explanatory variables $ln(1\text{-}RE/TAE)$, $ln(CA/TAE)$, $ln(TAE/TL)$, and TA/IDX measure a firm's profitability, liquidity condition, leverage, and firm size respectively, with RE, TAE, CA, TL, and IDX denoting retained earnings, the implied asset value, current assets, total liabilities, and stock market index. We use different monetary instruments (X_t), including the change in real interest rates (dR, which is the nominal lending rate net of CPI inflation), the change in required reserve ratio ($dRRR$), bond yield spreads ($SPRD$), or a monetary conditions index (MCI) to capture policy effects. By definition, the coefficient to $ln(1\text{-}RE/TAE)$ should have a negative sign, as higher retuned earnings are usually associated with a lower default risk. Similarly, the coefficient on the monetary policy variables except the MCI should also have a negative sign. The coefficients on other independent variables should be positively signed, as high liquidity, low leverage, high asset values, and favorable monetary conditions provide a buffer against adverse shocks.

Leverage and liquidity appear to be the most informative indicators of credit risks.[13] Table A-1 in the appendix presents the estimates using different monetary policy variables, and Table A-2 reports the relative importance of each independent variable in explaining default likelihood variation accordingly. In the model with the real interest rate, leverage accounts for over 50% of the default likelihood variation, followed by liquidity (over 20%) and firm size (around 15%), while profitability and interest rate seem to be much less informative (Figure 11).

4. How Important Could the Real Estate Sector be in Spreading Credit Risks across Sectors?

4.1 How to Identify the Directions of Contemporaneous Spill-Overs across Sectors?

To explore the extent to which credit risk in the real estate sector spreads to other sectors, we need to identify the direction and size of possible spill-overs of credit risks across sectors. We use a network analysis and set up a structural vector auto-regression (SVAR) model to do so. The direction of spill-over effects is determined by the correlation and predictive causality of the default likelihood variation across sectors. Simply put, if a sector's default likelihood variation is correlated with, and adds explanatory power to, that of another sector, then there are spill-overs from the former to the latter. The size of spill-over effects is estimated with forecast error variance decomposition.

We need first to run a regression for a reduced-form VAR, which, together with the directed acyclical graph (DAG) techniques, helps to identify the contemporaneous causality across sectors. Let's start with the following SVAR, with L denoting the lag operator:

$$A_0 Y_t = A(L)Y_{t-1} + W_t \tag{15}$$

where the covariance matrix $\Phi = E(WW')$ is assumed to be diagonal, and matrix A_0 contains contemporaneous causal information among variables. In practice, the SVAR is transformed into the reduced-form VAR by premultiplying A_0^{-1}:

$$Y_t = A_0^{-1}A(L)Y_{t-1} + A_0^{-1}W_t = \mathrm{B}(L)Y_{t-1} + U_t \tag{16}$$

Given that the covariance matrix of the error term in this reduced form VAR, $\Omega = E(UU')$, is not diagonal in general, certain methodologies should be used to find the contemporaneous structure specified in A_0 in order to properly orthogonalize the error terms for impulse response analysis and

13 The relative importance of each individual indicator in explaining default risks is measured by $s_k = |\hat{a}_k|\delta_k \Big/ \sum_{j=1}^{4} \hat{a}_j \delta_j$ according to Altman et al., (2011), where $\hat{a}_k$ and δ_k (k =1,2, …,5) are coefficient estimates for, and the standard deviation of, each fundamental variable respectively.

forecast error variance decomposition.[14] The model structure embedded in A_0 should be tested in the first place when it is unknown. One can do so once the reduced form VAR is estimated, as the estimated covariance matrix Ω of the error term U contains relevant information for the contemporaneous causal ordering of the SVAR (Swanson and Granger, 1997). The DAG method, which uses arrows connecting causal variables to their effect variables to represent causal relationships in a graph, is one method to identify the structure of A_0.[15] The details of the algorithms of the DAG approach are given in the appendix. The average default likelihood of each sector is treated as the endogenous variable in the reduced-form VAR,[16] and the residual correlation matrix used for the DAG analysis is presented in Table A-3 in the appendix.

Our estimates suggest upstream industries such as Plastic, Cement, Coal, Glass, and IT, are in general credit risk *receivers*, and Glass, Plastic, while machinery, Auto, Real Estate, Chemistry, and Electric sectors are in general *sources* of credit risks. The contemporaneous causal relationships are shown in Figure 12. This possibly reflects the fact that shocks to downstream industries can affect the demand for products in upstream industries, and spread the credit risks along the chain accordingly. A caveat is that as the DAG approach assumes acyclical spill-overs, so the graph may not fully capture inter-sectoral spill-overs, nonetheless, it helps us to understand the major spill-overs across sectors.

Moreover, the real estate and machinery sector are the two industries that potentially spread credit risks to the largest number of industries. The real estate sector potentially spreads its credit risks directly to four sectors, compared with three sectors for the machinery sector and a smaller number for most of other sectors (Figure 13). When indirect spill-overs are considered, the real estate sector spreads its credit risks to ten sectors, the same as the machinery sector, while other sectors spill-over to a much smaller number of industries (Figure 14). Specifically, credit risks of the real estate sector can directly spill-over to construction, chemistry, ship-building and iron sectors, which would in turn spread risks to cement, coal, glass, information, aluminium, and plastic sectors (Figure 15). Credit risks of the machinery sector can directly spread to auto, glass and ship-building industries, which would further spread risks to other major upstream industries (Figure 16).

14 If a SVAR is recursive (with Wold causal order), the Cholesky decomposition can be used to find a unique lower-triangular matrix with unit coefficients along the principal diagonal, $P = A_0^{-1}$, such that E(P-1U(P-1U)-1 is diagonal, although economic theories or priori knowledge is still required to help determine the proper variable ordering. For a non-recursive SVAR, A0 may be recovered from moments condition as proposed by Bernanke (1986): $\Phi = A_0 \Omega \ (A_0)'$.
Since in a n-variable VAR, Ω has n(n+1)/2 distinct values and Φ has n unknown parameters, the model generally has solution as long as A0 has no more than n(n-1)/2 parameters and the rank condition is satisfied. As pointed out by Bernanke, solution for over-identified non-recursive SVAR in some cases might be subject to variable ordering as in the recursive model, and one has to appeal to economic theories or priori knowledge for proper ordering as well.

15 The acyclicality assumption of the DAG method rules out simultaneous equations.

16 These series are transformed into first differences to ensure stationarity, and two lags are used in estimation.

4.2 How Large are the Spill-Over Effects?

Our analysis shows that the machinery and real estate sector generate the largest contemporaneous spill-over effects across all sectors. The magnitude of contemporaneous spill-over effects can be estimated once the matrix A_0 is constructed.[17] The contemporaneous marginal impact of each sector's default risk on others is shown in Tables A5-6 in the appendix, which illustrates the direct and total contemporaneous impact of a one percentage point increase in each sector's default likelihood on that of other sectors. Some sectors do not have much direct contemporaneous effect on others, but they generate contemporaneous effect on many other sectors through indirect channels. For example, Figure 17 suggests that the machinery sector generates the largest marginal contemporaneous effects across sectors. For instance, a one percentage point increase in this sector's default likelihood leads to 1.2 percentage points rise in the default likelihood for the auto sector.

The contemporaneous spill-over effects of the real estate sector appear to be generally smaller than those of the machinery sector, but are still large compared with those of other sectors. Specifically, a one percentage point increase in this sector's default likelihood could mean a 0.75 percentage point increase in the default likelihood for the construction sector, and over 0.4 percentage point increase in the default likelihood for the chemistry and cement sector (Figure 18).

The real estate and machinery sectors remain the most influential if dynamic spill-overs are taken into account. The overall spill-over effects of credit risks across sectors, including both contemporaneous and dynamic effects, are studied through forecast error variance decompositions. Table A-7 in the appendix reports the forecasting error variance decomposition on a 1-month, 3- month, 6-month, 9-month, and 12-month basis. Obviously, real estate and machinery remain the most influential sectors, as at least 30% of unexpected disturbances in each sector, and more than 40% of disturbances in sectors other than Glass and ship, are explained by shocks to these two sectors (Figure 19).

The significant spill-over effects of credit risks from the real estate sector not only reflect its close input-output linkages with other sectors, as analysed in the previous section, but possibly the fact that properties have been used as collateral to back loans to these sectors. Indeed, construction, iron, coal, auto, IT, chemistry, cement, and electric sectors, which are closely linked with the real estate sector, have been major borrowers in recent years (Figures 20-21).[18] In addition, as the cement, glass, construction, and coal industries are closely related to infrastructure investment, their significant exposure to the credit risks of the real estate sector might also reflect the importance of land sales revenue to local governments to support their debts used to finance infrastructure investment.

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17 Restrictions on A_0 are constructed as shown in Table A-4 in the appendix according to the DAG graph, where blank cells are set to be zero, and cells with stars correspond to non-zero causal conditions from DAG. If the value of a nonzero cell (i , j) of A_0 is a_{ij}, then the magnitude of contemporaneous impact of variable j on variable i through direct link is ($-a_{ij}$). The contemporaneous impact of variable j on variable i through the whole network is $\tilde{a}_{ij}$, where $\tilde{a}_{ij}$ is the i^{th}-row-j^{th}-column element of A_0^{-1}. Given the structure of A_0, the SVAR is actually over-identified, and the model is estimated by maximum likelihood method.

18 Debts for the charts are limited to listed firms.

5. Concluding Remarks

The main points of this paper are summarised as follows:

- Input-output analysis shows that the linkages between the real estate and other sectors have strengthened through real economy channels. Accordingly, the real estate sector has been much more important to the economy's output than suggested by the share of its value added in total value added.

- Corporate credit risks have generally risen in recent years. Of particular note, those sectors with severe overcapacity problems, such as Metal, Coal, Cement, and Ship-building, have higher default risks than other sectors, in large part reflecting higher leverage than in other sectors.

- The real estate industry is closely linked to other sectors through various financial channels as well. Specifically, our analysis shows that credit risks in the real estate sector can generate large-scale spill-over effects onto other sectors. As a result, the impact of any property market adjustment on the rest of the Chinese economy could be much larger than indicated by headline figures.

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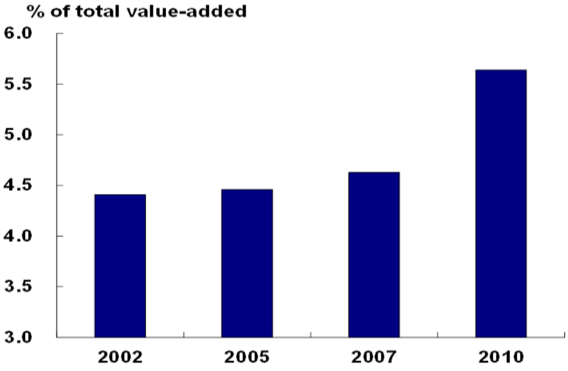
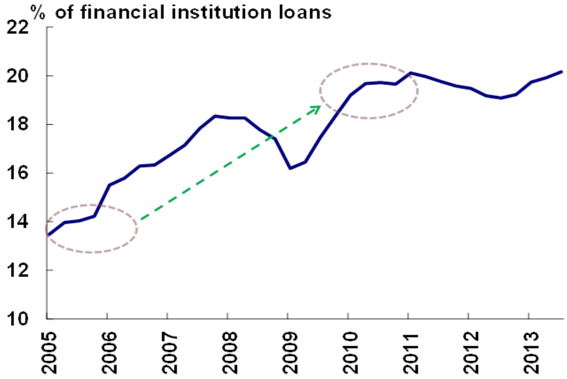
Figure 1. Share of Housing Service Value Added in Total Value Added



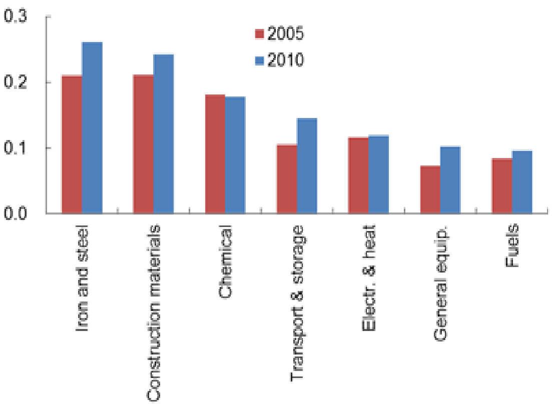
Sources: CEIC and staff estimates.

Figure 2. Share of Property-Related Loans in Total Bank Loans



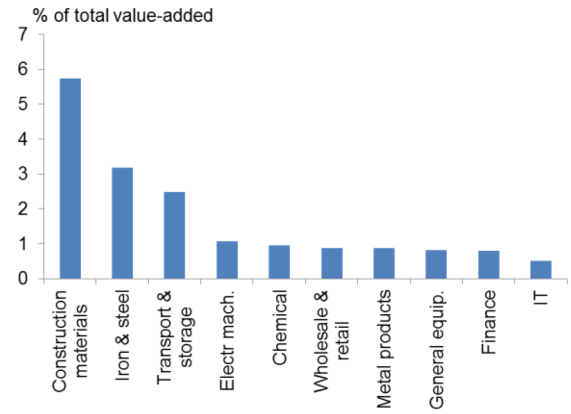
Sources: CEIC and staff estimates.

Figure 3. Total Input Coefficients for the Real Estate and Construction Sector



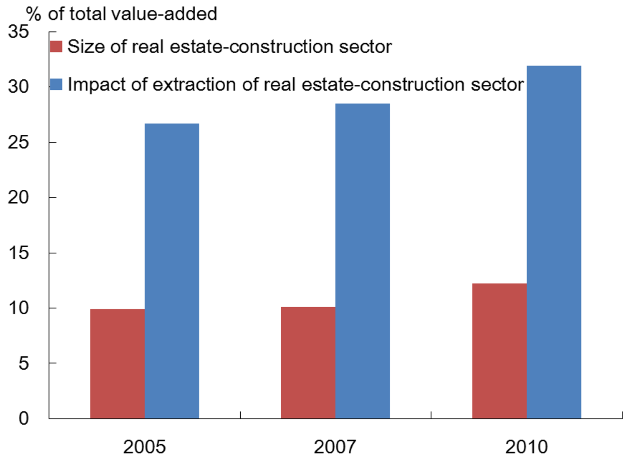
Sources: CEIC and HKMA staff estimates

Figure 4. Importance of Real Estate and Construction Sector's Linkages with Others



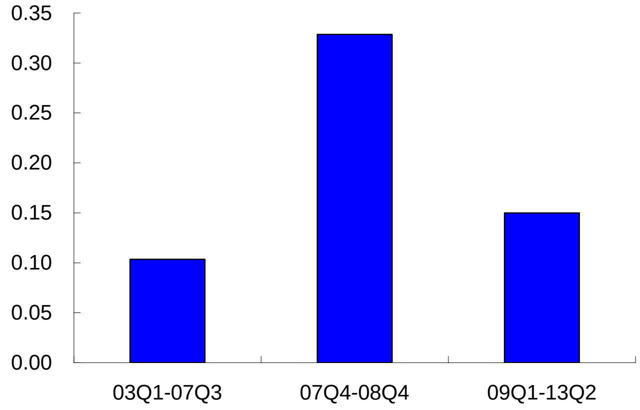
Sources: CEIC and HKMA staff estimates

Figure 5. Loss in Total Value Added Caused by Eliminating the Real Estate-Construction Sector



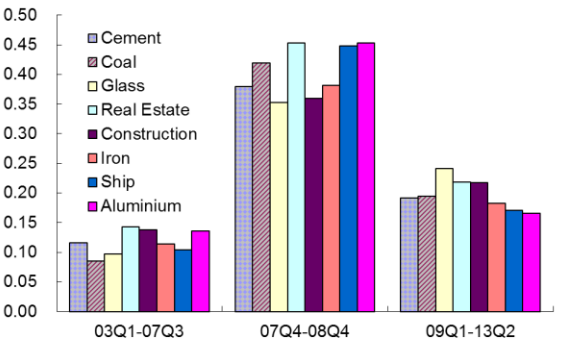
Sources: CEIC and HKMA staff estimates.

Figure 6. Overall Corporate Default Likelihood



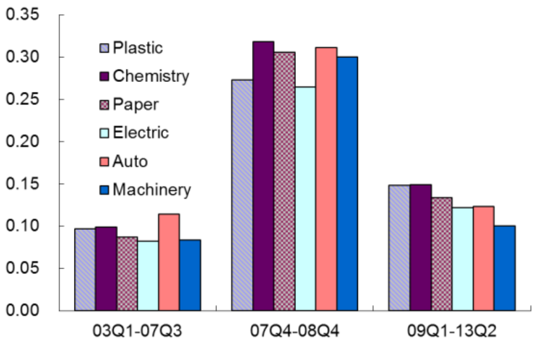
Sources: Bloomberg and authors' estimates.

Figure 7. Default Likelihood for Real Estate, Construction and Overcapacity Industries



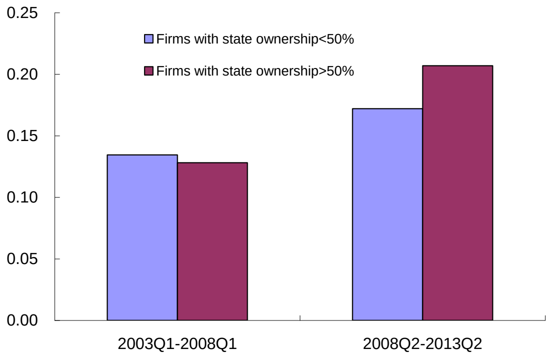
Sources: Bloomberg and authors' estimates.

Figure 8. Default Likelihood for Other Major Industries



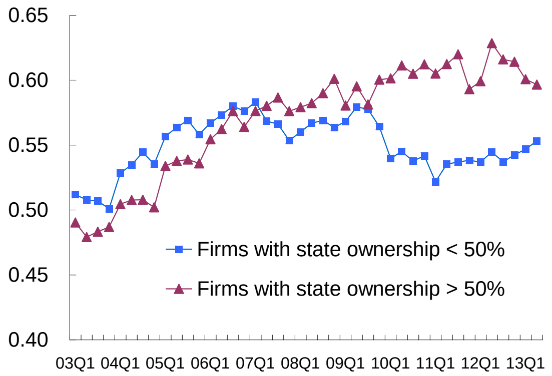
Sources: Bloomberg and authors' estimates.

Figure 9. Default Likelihood for Firms by Ownership



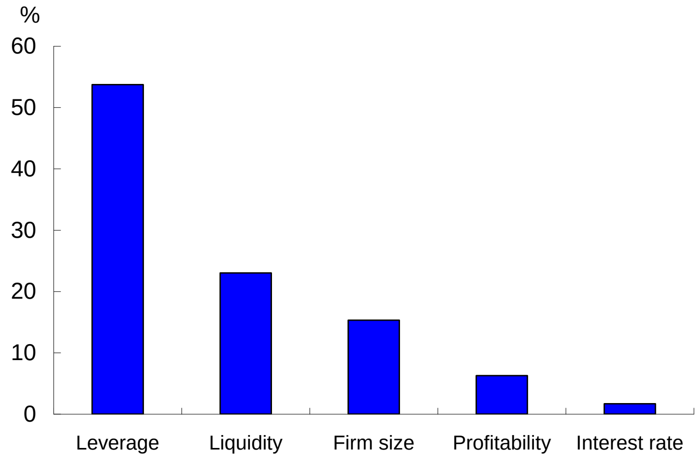
Sources: Bloomberg and authors' estimates.

Figure 10. Debt-to-Asset Ratio for Firms by Ownership



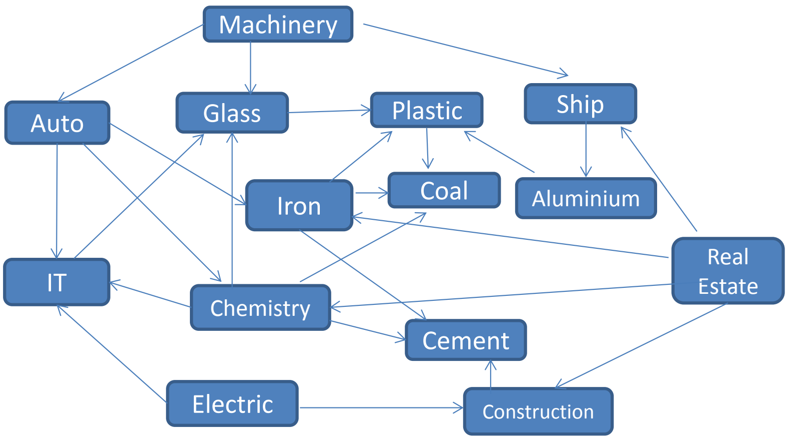
Sources: Bloomberg and authors' estimates.

Figure 11. Default Risk Variation by Firm Characteristics and Monetary Policy



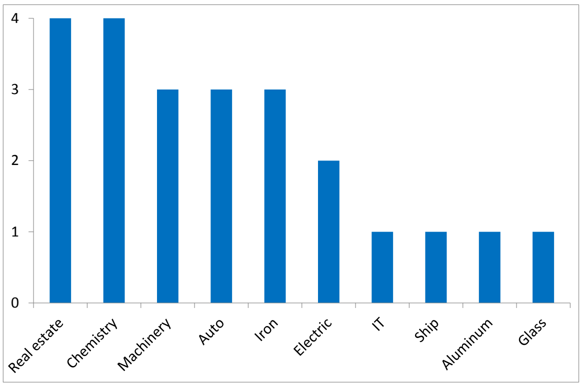
Sources: Bloomberg and authors' estimates.

Figure 12. Directions of Contemporaneous Credit Risk Spill-Overs across Sectors



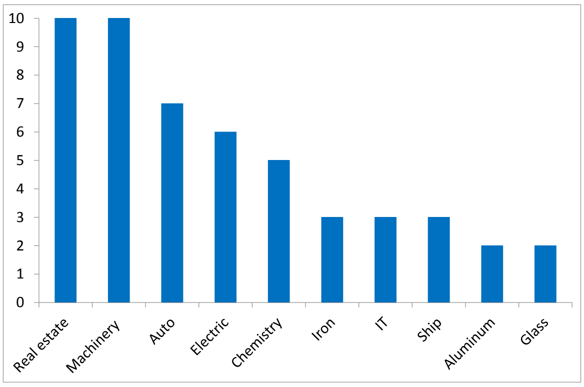
Sources: Bloomberg and authors' estimates.

Figure 13. Number of Direct Receivers of Credit Risk Spill-Overs



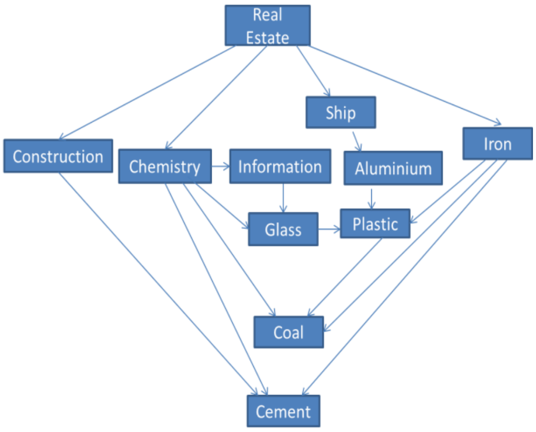
Sources: Bloomberg and authors' estimates.

Figure 14. Total Number of Receivers of Credit Risk Spill-Overs



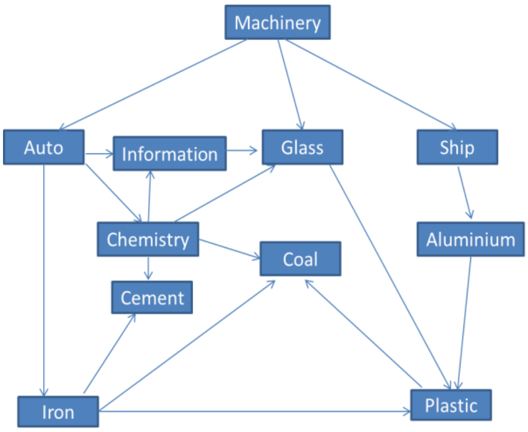
Sources: Bloomberg and authors' estimates.

Figure 15. Contemporaneous Spill-Over of Real Estate Sector's Credit Risks



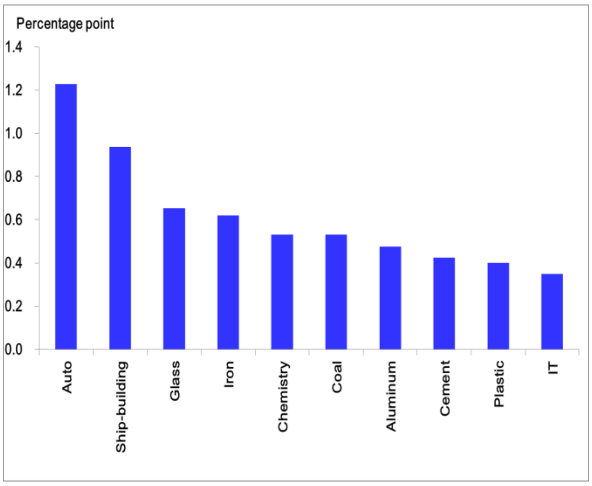
Sources: Bloomberg and authors' estimates.

Figure 16. Contemporaneous Spill-Over of Machinery Sector's Credit Risks



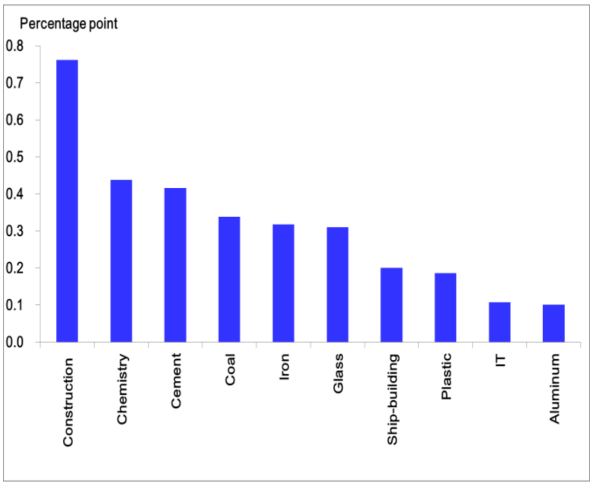
Sources: Bloomberg and authors' estimates.

Figure 17. Contemporaneous Marginal Effect of Machinery Default Likelihood



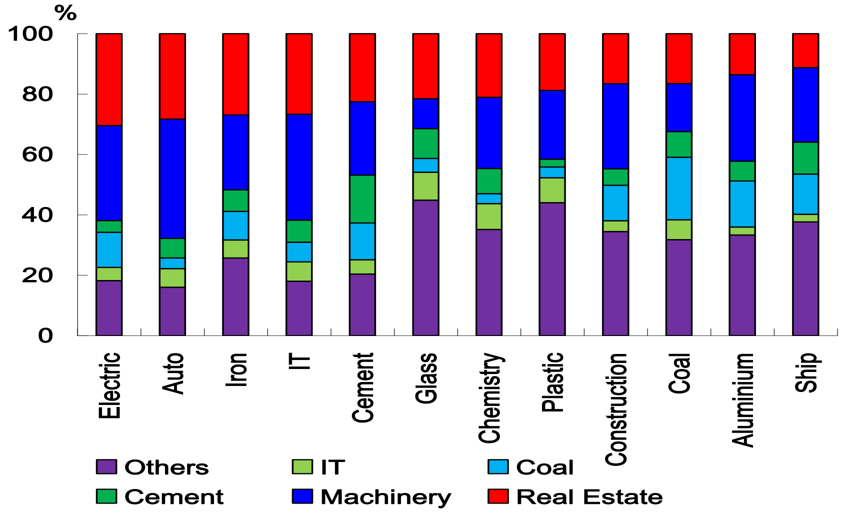
Sources: Bloomberg and authors' estimates.

Figure 18. Contemporaneous Marginal Effect of Real Estate Default Likelihood



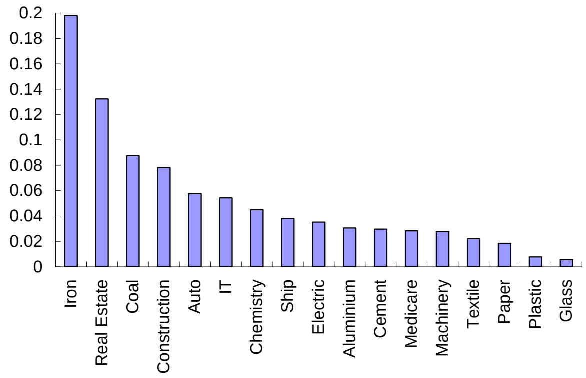
Sources: Bloomberg and authors' estimates.

Figure 19. Contributions to Volatility of Major Industries' Default Likelihood



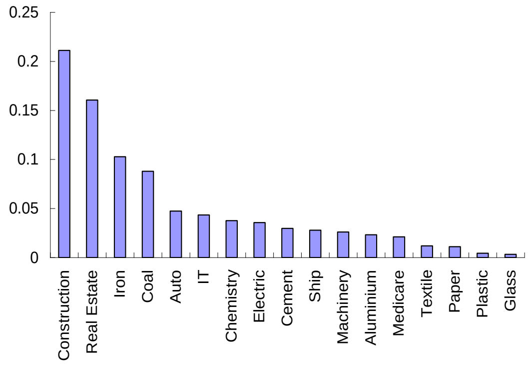
Sources: Bloomberg and authors' estimates.

Figure 20. Share of Debts by Industry in Total Debts in 2008 Q2



Sources: Bloomberg and authors' estimates.

Figure 21. Share of Debts by Industry in Total Debts in 2013 Q2



Sources: Bloomberg and authors' estimates.

Appendix 1. The Algorithm of the DAG

Working backward from statistical measures of conditional independence and dependence associated with residual covariance matrix Ω, it is possible to infer the class of graphs and identify A0 statistically (Hoover, 2005). The basic building block in the DAG method is unshielded collider, which adds causal directions to the initially undirected correlations of two variables, based on which other causal directions can be identified and built into the graph. Namely, if two unconditionally uncorrelated variables, x and z, are both correlated with a third variable y and, conditional on y they become correlated, then y is called the unshielded collider of x and z. In this case, the initially undirected link x ─ y ─ z becomes a directed link: "x $\rightarrow$ y $\leftarrow$ z".

According to (Hoover, 2005), directions of credit risk spill-overs across sectors can be identified as follows:

(1) Estimate the reduced-form VAR, where the endogenous variables are sectoral mean default likelihood. The residual covariance matrix is transformed into unconditional correlation matrix, which in turn is used to calculate conditional correlation of any pair of variables;

(2) Connect each pair of variables in the graph with undirected link if correlation of the pair of variables cannot be rejected;

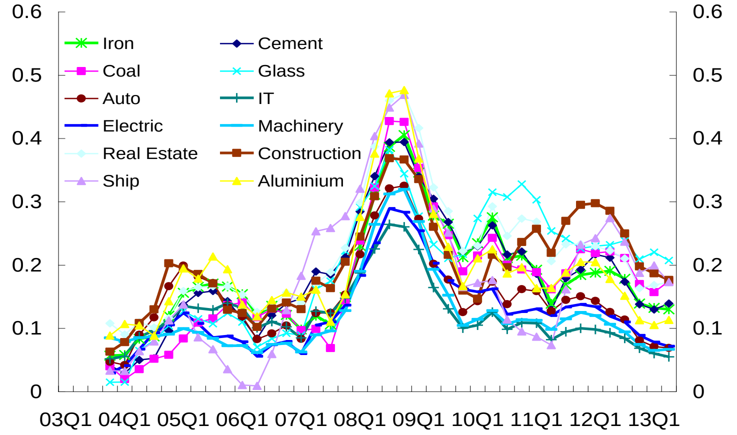
(3) Eliminate any link if correlation of the pair of variables conditional on a third variable (or on pairs, triples, and so forth), is statistically absent;

(4) Identify the unshielded colliders in the graph, and introduce causal directions (arrows) to replace the undirected links;

(5) Replace the half identified causal pattern "x $\rightarrow$ y ─ z" with fully identified causal pattern "x $\rightarrow$ y $\rightarrow$ z" (otherwise it should have been identified as an unshielded collider in the earlier step); Replace "x ─ z" with "x $\rightarrow$ z" if "x $\rightarrow$ y $\rightarrow$ z" (otherwise the pattern will be cyclical).

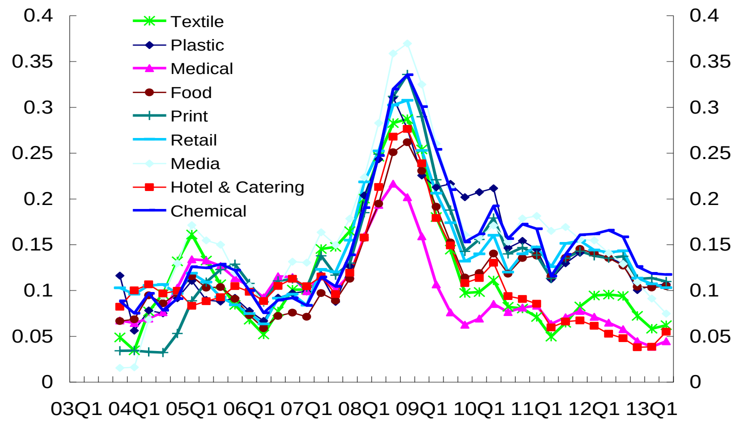
Appendix 2. Figures and Tables

Figure A-1. Default Likelihood (4-Quarter Moving Average)



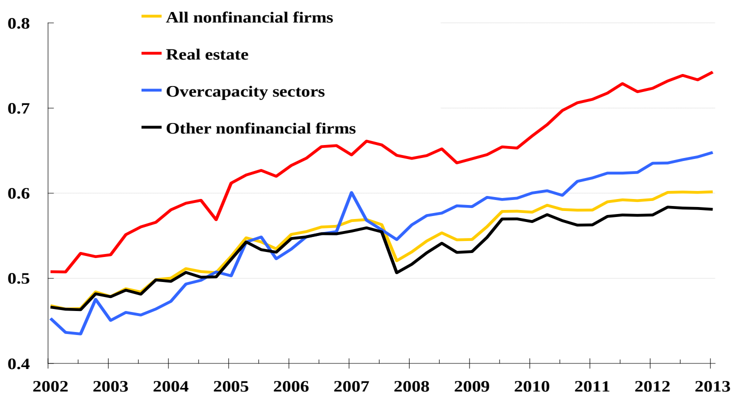
Sources: Bloomberg and authors' estimates.

Figure A-2. Default Likelihood (4-Quarter Moving Average)



Sources: Bloomberg and authors' estimates.

Figure A-3. Debt-to-Asset Ratio for Listed Non-Financial Firms



Sources: WIND and authors' estimates

Table A-1. Default Likelihood and Fundamentals

	Model 1	Model 2	Model 3	Model 4
ln(1-RE/TAE)	-0.232*	-0.236*	-0.114	-0.153
	(-1.91)	(-1.93)	(-0.93)	(-1.25)
ln(CA/TAE)	1.038***	0.906***	0.939***	0.888***
	(10.43)	(9.05)	(9.41)	(8.90)
ln(TAE/TL)	3.518***	3.517***	3.577***	3.566***
	(54.34)	(51.08)	(51.78)	(55.81)
ln(TA/IDX)	1.549***	1.285***	1.375***	1.524***
	(34.92)	(27.01)	(31.41)	(33.58)
dR	-0.404***			
	(-21.77)			
dRRR		-0.132***		
		(-4.64)		
SPRD			-0.303***	
			(-8.90)	
MCI				0.202***
				(12.65)
Constant	-6.915***	-6.01***	-6.053***	-9.053***
	(-30.81)	(-25.67)	(-26.80)	(-29.18)
Observations	50613	50613	50613	50613
Adj R-square	0.40	0.39	0.39	0.39

Note: t-statistics in the parentheses. * and *** denote statistical significance at 10% and 1% confidence levels respectively.
Sources: Bloomberg and authors' estimates.

Table A-2. Share of Variation of Fundamental Variables in Explained Variation (%)

	Model 1	Model 2	Model 3	Model 4
ln(1-RE/TAE)	6.3	6.8	3.3	4.3
ln(CA/TAE)	23.0	21.2	22.1	20.8
ln(TAE/TL)	53.7	56.8	58.1	57.7
ln(TA/IDX)	15.3	14.3	14.2	16.3
dR	1.7			
dRRR		0.9		
SPRD			2.4	
MCI				0.8

Sources: Bloomberg and authors' estimates.

Table A-3. Correlation Matrix of Residuals of Reduced-Form VAR

	Plastic	Cement	Iron	Coal	Aluminium	Glass	Auto	Ship	IT	Electric	Chemistry	Machinery	Real Estate	Construction
Plastic	1.000													
Cement	0.690	1.000												
Iron	0.805	0.829	1.000											
Coal	0.748	0.693	0.796	1.000										
Aluminium	0.620	0.512	0.631	0.565	1.000									
Glass	0.702	0.742	0.769	0.721	0.522	1.000								
Auto	0.674	0.771	0.895	0.689	0.606	0.844	1.000							
Ship	0.481	0.639	0.737	0.573	0.583	0.638	0.749	1.000						
IT	0.691	0.792	0.832	0.752	0.552	0.862	0.910	0.727	1.000					
Electric	0.608	0.709	0.757	0.713	0.540	0.797	0.836	0.650	0.933	1.000				
Chemistry	0.734	0.871	0.874	0.795	0.552	0.855	0.904	0.722	0.912	0.815	1.000			
Machinery	0.538	0.735	0.813	0.686	0.494	0.836	0.926	0.754	0.884	0.821	0.847	1.000		
Real Estate	0.692	0.804	0.899	0.708	0.454	0.814	0.874	0.741	0.860	0.805	0.893	0.822	1.000	
Construction	0.488	0.835	0.768	0.654	0.378	0.714	0.787	0.643	0.810	0.783	0.844	0.769	0.816	1.000

Sources: Bloomberg and authors' estimates.

Table A-4. Restrictions on Matrix A0

	Plastic	Cement	Iron	Coal	Aluminium	Glass	Auto	Ship	IT	Electric	Chemistry	Machinery	Real Estate	Construction
Plastic	1		*		*	*								
Cement		1	*								*			*
Iron			1				*						*	
Coal	*		*	1							*			
Aluminium					1			*						
Glass						1			*		*	*		
Auto							1					*		
Ship								1				*	*	
IT							*		1	*	*			
Electric										1				
Chemistry							*				1		*	
Machinery												1		
Real Estate													1	
Construction										*			*	1

Note: * represents non-zero restriction.

Sources: Bloomberg and authors' estimates.

Table A-5. Direct Contemporaneous Impact of One PPT Increase in Each Sector's Default Likelihood on Others

	Plastic	Cement	Iron	Coal	Aluminium	Glass	Auto	Ship	IT	Electric	Chemistry	Machinery	Real Estate	Construction
Plastic			0.469		0.116	0.082								
Cement			0.325								0.420			0.169
Iron							0.505						0.318	
Coal	0.124		0.421								0.413			
Aluminium								0.507						
Glass									0.620		0.556	0.142		
Auto												1.228		
Ship												0.938	0.200	
IT							0.179			0.512	0.244			
Electric														
Chemistry							0.433						0.438	
Machinery														
Real Estate														
Construction										0.315			0.762	

Sources: Bloomberg and authors' estimates.

Table A-6. Overall Contemporaneous Impact of One PPT Increase in Each Sector's Default Likelihood on Others

	Plastic	Cement	Iron	Coal	Aluminium	Glass	Auto	Ship	IT	Electric	Chemical	Machinery	Real Estate	Construction
Plastic			0.469		0.116	0.082	0.271	0.059	0.051	0.026	0.058	0.400	0.186	
Cement			0.325				0.345			0.053	0.420	0.424	0.416	0.169
Iron							0.505					0.620	0.318	
Coal	0.124		0.479		0.014	0.010	0.425	0.007	0.006	0.003	0.420	0.530	0.338	
Aluminium								0.507				0.475	0.101	
Glass							0.417		0.620	0.317	0.707	0.654	0.310	
Auto												1.228		
Ship												0.938	0.200	
IT							0.284			0.512	0.244	0.349	0.107	
Electric														
Chemical							0.433					0.531	0.438	
Machinery														
Real Estate														
Construction										0.315			0.762	

Sources: Bloomberg and authors' estimates.

Table A-7. Forecast Error Variance Decomposition

Shock	Plastic	Cement	Iron	Coal	Aluminium	Glass	Auto	Ship	IT	Electric	Chemistry	Machinery	Real Estate	Construction
Variance Decomposition of Plastic														
1m	64.44	0.00	5.21	0.00	1.44	0.49	1.81	0.29	0.02	0.06	0.07	11.23	4.12	0.00
3m	59.35	0.20	2.00	2.44	4.55	0.20	1.01	0.09	0.46	2.29	0.04	14.90	3.09	1.08
6m	17.80	7.29	0.74	8.56	2.19	0.59	1.06	0.05	7.77	1.74	1.37	25.31	20.40	2.77
9m	12.15	8.22	0.52	8.98	2.73	0.56	0.80	0.27	11.47	1.26	2.72	24.97	19.11	2.47
12m	11.32	7.48	0.89	8.22	2.55	1.41	1.75	1.24	10.57	3.63	2.57	22.76	18.80	2.31
Variance Decomposition of Cement														
1m	0.00	41.72	2.62	0.00	0.00	0.00	3.09	0.00	0.00	0.26	3.66	13.31	21.66	3.37
3m	1.01	45.69	0.84	7.41	1.81	0.84	1.02	0.25	0.55	0.63	2.87	17.52	10.50	1.77
6m	0.19	24.48	0.27	13.06	1.41	0.48	0.31	1.12	4.07	0.55	1.95	26.46	21.02	2.84
9m	0.50	17.97	0.18	13.63	1.50	0.33	0.20	1.88	5.35	0.94	3.92	26.64	21.89	3.34
12m	0.99	15.85	0.42	12.16	1.67	0.75	0.56	2.68	4.73	4.55	4.01	24.31	22.54	3.00
Variance Decomposition of Iron														
1m	0.00	0.00	31.67	0.00	0.00	0.00	8.41	0.00	0.00	0.00	0.00	36.19	16.07	0.00
3m	0.10	0.47	26.34	6.65	2.45	0.38	4.10	3.73	0.47	2.50	0.54	38.29	9.02	0.50
6m	0.36	8.17	6.38	10.28	2.58	0.08	1.08	1.02	4.11	4.89	0.96	28.21	27.03	2.39
9m	0.48	7.86	4.21	10.74	1.97	0.07	0.82	0.71	6.64	3.58	3.40	27.26	25.87	3.20
12m	0.78	7.18	3.73	9.43	1.82	0.58	1.05	1.22	5.99	6.25	3.44	24.82	26.88	3.25
Variance Decomposition of Coal														
1m	0.95	0.00	5.20	46.94	0.02	0.01	4.26	0.00	0.00	0.00	3.34	18.91	12.99	0.00
3m	4.70	1.34	1.84	50.37	5.10	2.14	1.79	0.04	0.46	0.10	1.09	16.79	10.14	0.04
6m	2.68	10.01	0.75	37.01	6.56	1.76	7.91	0.21	5.18	1.55	2.59	15.08	6.10	0.94
9m	2.05	10.07	0.51	25.99	3.92	1.56	7.68	0.47	7.32	2.03	4.21	17.17	12.20	1.04
12m	2.08	8.52	0.50	20.73	3.35	2.74	6.96	1.25	6.59	4.77	3.94	15.93	16.49	1.39
Variance Decomposition of Aluminium														
1m	0.00	0.00	0.00	0.00	73.18	0.00	0.00	14.64	0.00	0.00	0.00	10.93	0.84	0.00
3m	0.28	1.68	0.08	9.69	53.03	0.74	0.74	4.18	0.48	1.28	0.28	25.72	0.94	0.70
6m	1.02	8.77	0.08	19.38	18.48	2.30	1.09	1.61	1.61	0.47	7.50	30.42	6.77	0.24
9m	2.10	7.68	0.23	17.82	11.22	1.76	1.36	1.02	3.01	0.75	9.73	30.76	9.98	0.60
12m	2.30	6.59	0.61	15.23	9.42	2.12	1.73	1.40	2.63	3.17	9.00	28.62	13.59	1.01
Variance Decomposition of Glass														
1m	0.00	0.00	0.00	0.00	0.00	50.18	2.95	0.00	1.72	5.95	6.81	20.75	7.88	0.00
3m	3.75	0.48	0.74	1.28	4.37	40.17	4.00	0.15	1.90	15.76	2.77	11.77	4.73	3.04
6m	1.54	7.97	0.82	3.63	4.16	19.40	7.77	0.77	2.86	16.30	4.70	7.84	18.46	1.77
9m	0.90	10.24	1.01	4.98	5.70	12.35	4.36	1.21	8.40	9.75	3.58	11.64	21.96	2.28
12m	0.79	9.90	0.84	4.56	6.38	11.28	3.57	3.02	9.29	11.29	3.14	9.89	21.53	2.77
Variance Decomposition of Auto														
1m	0.00	0.00	0.00	0.00	0.00	0.00	18.85	0.00	0.00	0.00	0.00	81.15	0.00	0.00
3m	0.35	0.15	0.01	2.92	0.37	0.51	14.17	1.45	0.01	0.80	0.60	68.73	8.54	0.06
6m	0.13	3.88	0.24	5.41	0.79	0.21	4.79	0.58	0.59	2.53	4.44	44.99	27.97	0.21
9m	0.29	4.35	0.28	6.45	0.99	0.16	3.43	0.43	1.33	2.14	6.60	41.76	28.54	0.70
12m	0.62	4.29	0.75	6.20	0.98	0.26	3.32	0.74	1.30	3.50	6.52	39.50	28.29	0.91
Variance Decomposition of Ship														
1m	0.00	0.00	0.00	0.00	0.00	0.00	0.00	54.60	0.00	0.00	0.00	40.75	3.15	0.00
3m	3.37	2.87	1.40	6.38	0.17	1.12	0.13	31.57	0.02	0.53	0.28	45.43	5.83	0.23
6m	4.74	12.68	1.96	11.55	0.13	0.58	0.99	12.02	1.21	1.69	3.61	30.36	17.11	0.15
9m	7.10	11.56	3.18	13.82	0.49	0.60	1.27	9.91	2.71	0.97	5.95	27.75	13.03	0.14
12m	8.11	10.61	5.34	13.30	0.47	0.55	2.80	10.40	2.57	0.96	5.95	24.66	11.24	0.13
Variance Decomposition of IT														
1m	0.00	0.00	0.00	0.00	0.00	0.00	4.66	0.00	15.23	52.59	2.75	20.07	3.18	0.00
3m	2.11	0.18	0.18	2.07	2.39	1.18	1.51	0.59	15.53	38.18	1.20	28.64	5.42	0.05
6m	0.62	3.59	0.30	3.45	2.76	0.88	0.44	0.16	3.93	11.07	6.14	35.68	27.50	1.30
9m	0.55	5.16	0.31	5.88	1.75	0.79	0.56	0.11	3.34	6.54	7.17	36.52	27.94	1.85
12m	0.88	5.52	1.29	6.42	1.60	0.80	0.57	0.33	3.13	6.52	7.32	35.05	26.72	2.09
Variance Decomposition of Electric														
1m	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	100.00	0.00	0.00	0.00	0.00
3m	2.04	0.08	0.11	1.49	0.18	0.03	0.10	0.15	0.04	66.41	0.84	14.35	12.94	0.15
6m	1.18	1.84	0.91	2.05	0.10	0.14	0.03	0.08	2.36	18.43	3.56	34.77	32.38	0.36
9m	0.98	3.19	0.79	4.05	0.30	0.12	0.06	0.19	4.62	12.24	3.81	33.99	32.88	0.84
12m	1.48	3.46	1.83	4.40	0.29	0.12	0.83	0.81	4.53	11.64	3.85	31.46	30.45	1.17
Variance Decomposition of Chemistry														
1m	0.00	0.00	0.00	0.00	0.00	0.00	5.92	0.00	0.00	0.00	25.34	25.47	29.31	0.00
3m	2.12	0.23	0.87	2.34	5.55	3.57	3.02	1.61	0.09	0.17	20.70	24.91	22.20	0.05
6m	0.70	6.95	0.55	6.52	8.76	2.46	6.43	0.73	4.70	0.74	9.41	24.38	22.68	1.16
9m	1.73	6.11	0.48	8.99	4.86	1.29	4.40	0.65	6.96	0.55	9.30	26.45	22.46	1.47
12m	3.56	5.36	1.51	8.53	3.97	1.30	4.90	1.41	6.06	3.27	8.35	23.57	21.10	1.49
Variance Decomposition of Machinery														
1m	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	100.00	0.00	0.00
3m	2.49	0.16	0.06	2.79	0.96	1.56	2.77	0.75	0.53	1.59	0.65	78.93	6.07	0.21
6m	2.96	2.02	0.06	6.11	3.87	1.03	7.16	0.42	1.76	2.15	4.80	45.21	20.24	0.69
9m	4.59	2.61	0.92	7.57	2.70	0.74	7.33	0.62	2.52	1.36	7.53	37.09	17.45	1.74
12m	5.76	3.11	2.80	7.07	2.31	0.65	8.20	1.24	2.22	2.14	7.67	32.25	15.78	1.66
Variance Decomposition of Real Estate														
1m	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	67.72	0.00
3m	2.17	0.34	1.89	2.43	5.18	1.02	3.84	0.98	0.07	0.42	0.04	0.44	50.83	0.30
6m	1.31	9.15	0.98	6.30	8.52	0.41	7.08	0.47	1.47	2.93	2.33	18.10	31.33	0.46
9m	1.74	8.24	0.59	8.43	4.72	0.23	4.57	0.61	4.44	1.68	4.88	23.75	27.95	1.38
12m	2.14	7.70	1.04	8.27	4.16	0.42	4.18	1.42	4.61	3.42	4.69	21.79	27.00	2.01
Variance Decomposition of Construction														
1m	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.82	0.00	0.00	31.09	50.27
3m	1.23	1.02	1.11	5.34	0.09	0.59	0.29	0.82	0.12	1.43	0.58	8.76	21.74	48.76
6m	1.09	6.16	0.77	11.01	0.14	0.24	0.09	0.71	2.59	0.37	3.96	33.65	18.27	13.90
9m	1.91	5.95	0.63	12.72	0.21	0.50	0.48	1.46	3.89	0.45	5.60	31.00	18.29	9.92
12m	2.32	5.45	1.33	11.77	0.20	1.05	2.53	1.91	3.54	1.97	5.35	28.18	16.58	9.00

Sources: Bloomberg and authors' estimates.