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Local Crowding-Out in China

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ABSTRACT

In China, between 2006 and 2013, local public debt crowded out the investment of private firms by tightening their funding constraints while leaving state-owned firms' investment unaffected. We establish this result using a purpose-built data set for Chinese local public debt. Private firms invest less in cities with more public debt, with the reduction in investment larger for firms located farther from banks in other cities or more dependent on external funding. Moreover, in cities where public debt is high, private firms' investment is more sensitive to internal cash flow.

IN CHINA, LOCAL GOVERNMENT DEBT almost quadrupled from 5.8% to 22% of GDP over the 2006 to 2013 period. This increase in local public debt was due largely to the fiscal stimulus program carried out after 2008, worth US$590 billion, together with much-reduced reliance on central government debt and transfers to local governments. Based on a novel, purpose-built database on the public debt of prefecture-level Chinese cities from 2006 to 2013, we show that the increase in local public debt crowded out private investment in the

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corresponding cities by inducing banks to tighten credit supply to local firms, which led to a reallocation of capital from private firms to the local public sector. We also show that the credit crunch spared state-owned enterprises (SOEs). As private firms are the most dynamic component of the Chinese economy, such reallocation of credit is likely to exacerbate the detrimental effects of crowding-out on growth, with public debt issuance reducing not only firm investment, but also its efficient allocation.

The Chinese credit market provides an ideal setting to test this local crowding-out hypothesis because of its geographical segmentation. In an integrated, nationwide market, there would be no reason to expect local government debt to affect local investment—its issuance would trigger an increase in local interest rates, drawing capital from the rest of the country and possibly increasing local saving, but eventually, the greater stock of local public debt would be held by investors throughout the country and hence any crowding-out of private investment would occur at the national level. If the credit market is geographically segmented, however, the imbalance and its impact on investment would be localized. In China, debt issuance by local governments ends up being absorbed by local banks and, owing to interest rate ceilings, does not trigger an increase in local interest rates and thus a local savings response.

Not all borrowers are expected to be affected equally, however. If banks maximize profits, they will tighten credit more to riskier borrowers, such as those with less collateral to pledge and higher monitoring costs. If, in contrast, banks allocate credit preferentially to politically connected borrowers, such as state-owned firms, then firms with no political ins will be rationed more strongly. In China, these two scenarios may well coincide, as state-owned firms are often assisted by implicit or explicit government guarantees.

We provide complementary firm-level evidence on this local crowding-out hypothesis. We start by showing that the investment of private manufacturing firms is negatively correlated with local government debt, while this is not the case for the investment of state-owned manufacturers. We next employ three different approaches to assess whether this relationship is causal and to identify the mechanism through which local government debt affects investment. Importantly, each of these approaches exploits a source of within-city firm heterogeneity, which allows us to control for city-year-level correlations between investment and public debt and thereby mitigate concerns about spurious correlation and reverse causality between these variables.

The first of these three approaches exploits variation in the location of firms within their respective cities. Firms close to neighboring cities—and to banks located in those cities—should be able to access credit outside their local market and hence should be less exposed to crowding-out due to debt issuance in their own city. Consistent with this view, we find that the investment of these firms drops less in response to government debt issuance in their city. Moreover, what appears to drive this result is firms' distance from the closest banks in nearby cities, rather than their distance from neighboring cities' borders. This finding suggests that crowding-out is due specifically to financing, rather than more generally to firms' access to other inputs available in nearby cities. As these regressions include city-year fixed effects, they rule out the most obvious problems related to omitted variables and reverse causality between city-level investment and public debt issuance.

The second approach exploits firm-level variation in firms' funding needs due to technological differences between industries. Specifically, we test whether local government debt has a disproportionate effect on the investment of firms whose technology requires more external funding. This approach, akin to that of Rajan and Zingales (1998), allows us to investigate whether government debt affects investment by tightening credit constraints. It also further mitigates endogeneity problems by permitting the inclusion of city-year, industry-year, and industry-city fixed effects. We find that local government debt is associated with lower investment by more financially dependent private firms but not by state-owned firms.

Our third approach tests whether local government debt affects the sensitivity of firms' investment to internally generated funds, which is taken to be an indicator of the severity of firms' financing constraints. This approach requires no assumptions about the external financing requirements of firms in different industries. We find that local government debt increases the sensitivity of investment to internally generated funds for private firms but not for state-owned firms, and for small firms but not large firms. To address the weaknesses of exogenous sample separation rules based on firm characteristics, we also rely on a switching regression model with endogenous sample separation, where firms' investment sensitivities are estimated jointly with their likelihood of being credit-constrained. Consistent with the previous results, local government debt affects cash-flow investment sensitivity for credit-constrained firms but not for unconstrained firms, with credit constraints being significantly more likely to bind for private than for state-owned firms and for small than for large firms.

This paper is related to the vast literature on the effect of government debt on investment and growth. While there is evidence of a negative correlation between public debt and growth (see Reinhart and Rogoff (2011)), establishing causality has been more difficult, as international comparisons are plagued by problems of reverse causality, omitted variables, and limited degrees of freedom.[1] As noted above, the geographical segmentation and interest rate ceilings of China's credit market enable us to identify a local crowding-out channel whereby government debt reduces investment by tightening financing constraints on private firms. As such, our work also relates to the corporate finance literature on investment and credit constraints.

We also contribute to research on the effects of the Chinese fiscal stimulus in the wake of the global financial crisis (see Deng et al. (2014), Ouyang and Peng (2015), and Wen and Wu (2019), among others). The stimulus plan appears to have exacerbated the fact that in China, high-productivity private firms tend to fund their investment mainly out of internal savings, while low-productivity

[1] Panizza and Presbitero (2014) survey the literature on debt and growth with particular emphasis on causality and measurement issues.

state-owned firms survive due to easier access to credit (Song, Storesletten, and Zilibotti (2011)). Under the stimulus plan, new bank credit was allocated disproportionately to state-owned firms rather than more productive private firms (Cong et al. (2019)).[2] According to Bai, Hsieh, and Song (2016), funding the stimulus plan via local government financing vehicles (LGFVs) led to reallocation of credit that favored politically connected firms, which likely had a negative effect on long-run productivity growth. Such reallocation is consistent with our finding that public debt issuance constrained the investment of private firms but not that of SOEs, which by definition are politically connected. Indeed, our estimates of the extent of such credit reallocation are conservative, since the private firms that we examine include some politically connected firms that may have been spared by the reallocation, and may even have gained from it.

Finally, our paper improves our understanding of local government debt in China. Previous studies estimate total local government debt with no geographical breakdown (National Audit Office (2013), Zhang and Barnett (2014)) or focus only on bond issuances, which account for a small part of total borrowing by LGFVs (Liang et al. (2017)). In contrast, we build a detailed data set on total borrowing by LGFVs in 261 prefecture-level cities between 2006 and 2013. The only other recent comprehensive studies of China's local government debt are Gao, Ru, and Tang (2018), who document that distressed local governments prefer to default on commercial bank loans than on politically sensitive policy bank loans, and Bai, Hsieh, and Song (2016), whose estimate of local government debt focuses mostly on measuring national aggregates rather than city-level aggregates.

The paper is organized as follows. Section I describes our data. Section II discusses the determinants of geographical segmentation in the Chinese credit market. Section III shows that investment by private-sector manufacturing firms is negatively correlated with local government debt. In Sections IV and V, we show how the relation between local public debt issuance and investment is affected by firms' within-city location and external funding needs, respectively. Sections VI and VII provide evidence on how local public debt issuance affects the investment cash-flow sensitivity of credit-constrained firms. Finally, Section VIII concludes.

I. Data

A key element of our study is the purpose-built data set on Chinese local government debt. Our data correspond to prefecture-level cities, the second tier of

[2] Papers on capital misallocation in China include Bai, Hsieh, and Qian (2006), Chang et al. (2014), Chong, Lu, and Ongena (2013), Cull and Xu (2003), and Song and Wu (2015). There is also a vast literature on the connections between economic growth and finance in China, with papers focusing on the transformation of the state sector (Hsieh and Song (2015), the role of government credit (Ru (2018)), bank competition (Gao et al. (2019)), and the side effects of financial interventions (Brunnermeier, Sockin, and Xiong (2017)).

Chinese local government bodies, below provinces. These cities are administrative units that comprise continuous urban areas and their surrounding rural districts, which include smaller towns and villages.[3] While we collect debt data for all 293 prefecture-level cities from 2006 to 2013, our statistical analysis is limited to 261 such cities, as macroeconomic data are not available for 32 of these cities.

Prefecture-level cities (henceforth, "cities") tend to be large. Populations range from 176,000 to 29.7 million, and 196 (75%) of our sample cities have at least 1.5 million inhabitants, with a median population of 3.7 million. Our sample also includes 100 cities with over five million inhabitants and 25 cities with more than eight million.

In 2013, the cities in our sample had a total population of 1.2 billion, or 91% of China's total population. Total GDP across the 261 cities amounted to 60.7 trillion yuan in 2013, which exceeded China's estimated GDP of 58.8 trillion yuan for the year. The discrepancy can be explained in part by the incentive of local politicians to overestimate economic growth (Koch-Weser (2013)), and in part by double-counting due to the difficulty of tracking value-added across city borders. According to the head of the Chinese National Statistics Bureau, in 2011, local government GDP numbers were approximately 10% higher than the corresponding central government figures.[4] Dividing 60.7 trillion by 1.1 yields 55.2 trillion, which suggests that the cities in our sample produce about 93% of China's GDP.

A. Local Government Debt in China

There have been a good many attempts to estimate the total amount of local government debt in China (e.g., Zhang and Barnett (2014)), but no public source offers time series for either city- or province-level government debt. One contribution of this paper consists precisely in the construction of such series.

Before going into the details of this data set, it is worth briefly recounting the manner in which Chinese local governments issue debt. Municipalities cannot borrow from banks or issue bonds directly, but rather can set LGFVs, transfer assets to them (usually land), and instruct them to borrow from banks or issue bonds, possibly posting the transferred assets as collateral (Clarke (2016)).[5] Our measure of local government debt is the volume of loans and bonds issued by these LGFVs.

As LGFVs are not generally required to disclose their financial information, efforts to collect data on local government debt from publicly available sources have generally turned to bond issuance by these entities (Bai and Zhou (2018)).

[3] Prefecture-level cities are further divided into counties or county-level cities. Cities in the strict sense of the term (i.e., contiguous urban areas) are referred to as urban areas (shiqu in Chinese).

[4] For an article in the Financial Times documenting this discrepancy, see http://blogs.ft.com/beyond-brics/2012/02/15/chinese-gdp-doesnt-add-up/. The original Chinese source is available at http://finance.china.com.cn/news/gnjj/20120215/534298.shtml.

[5] Bai, Hsieh, and Song (2016) provide a description of two LFGVs' activities.

While bond issuance has grown dramatically in recent years (from 6% of total LGFV debt in 2006 to 21% in 2013), the volume of bonds outstanding is far less than that of total debt, which consists mostly of bank loans, as shown by the top left panel of Figure 1.

To estimate the total financial liabilities of LGFVs, we exploit the fact that all entities that request an authorization to issue a bond in a given year are required to disclose their balance sheets for the current year as well as (at least) the three previous years. Accordingly, if an entity issues a bond in year t, we have data on its total outstanding debt back to year $t-3$. As the number of LGFVs issuing bonds soared between 2007 and 2014, this method provides a much more accurate and comprehensive lower bound for local government debt than bond issuance alone. The Internet Appendix describes our methodology in more detail.[6,7]

When aggregated to the national level, our data for local government debt can be compared with the official data provided by the National Audit Office (NAO) and China International Capital Corporation Limited (CICC), which are available for the period 2009 to 2013. As shown by the top right panel of Figure 1, our estimates are slightly lower than the official figures (consistent with our estimates being a lower bound) but match the trend in the official data, and in 2012 and 2013 are within 5% of the official figures. Our data also closely match the geographic distribution of local public debt at the province level, as shown by the two bottom panels of Figure 1: when the cities for which we have data on local government debt are aggregated at the level of the 30 Chinese provinces, their province-level total debt is closely correlated with province-level official data from the NAO surveys in 2012 and 2013.[8]

[6] Bai, Hsieh, and Song (2016) estimate local government debt starting from bond-issuing LGFVs, though mostly to estimate national aggregate figures. Both their and our estimates are based on the Wind database, but we complement this information by manually collecting balance sheet data for the LGFVs that are absent from the Wind database but present in the China Banking Regulatory Commission (CBRC) data. This data collection strategy allows us to decompose LGFV debt into different categories (short- and long-term debt, accounts payable, bank loans, and bond issuances), identify the rare cases in which the central government issued special bonds for the local government, and avoid double-counting in aggregating data at the city level (as we exclude issues of LGFVs belonging to a holding group). Another difference between the two data sets is that Bai, Hsieh, and Song (2016) use a statistical procedure to infer the debt of hidden LGFVs (i.e., LGFVs that never issued bonds), so as to estimate time series of total debt at the national level, including off-balance-sheet hidden debt. In contrast, we choose to be conservative and only count debt observed on LGFVs' balance sheets, as our research question and estimation strategy is based on the cross-sectional distribution of local government debt.

[7] The Internet Appendix is available in the online version of this article on *The Journal of Finance* website.

[8] In the bottom panels of Figure 1, most provinces are below the 45-degree line, which confirms that our measure is a lower bound. Beijing, Tianjin, Jiangsu, and Zhejiang are exceptions. Beijing and Tianjin, which are both cities and provinces, are two of the four Chinese municipalities under the direct control of the central government; in their case, our overestimate compared to the NAO data may result from our assigning to them some issuances that in reality are central government debt. For Jiangsu and Zhejiang, our estimates are only slightly higher than those of the NAO, as the difference ranges from 5% to 15%. Our results are robust to dropping the observations for these cities.

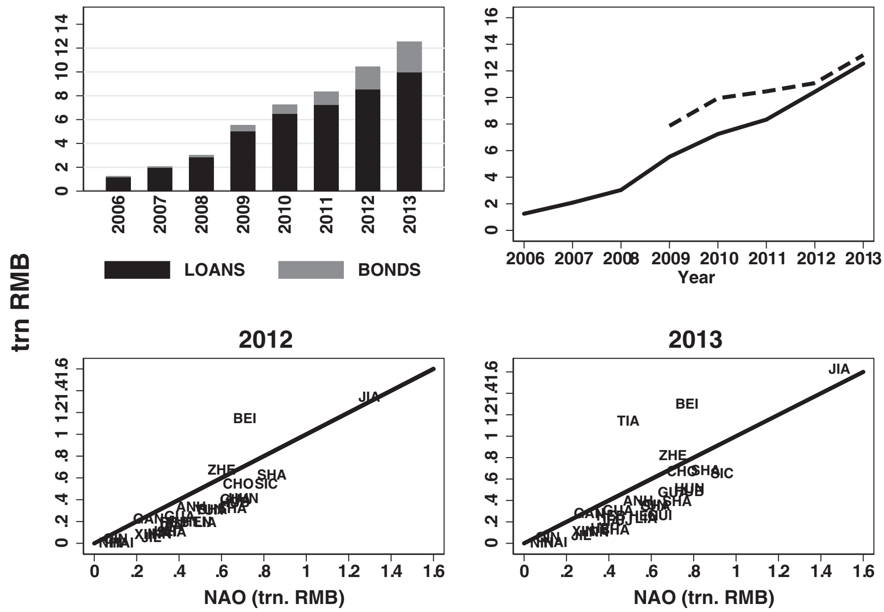

Figure 1. Local government debt in China. Top left panel: composition of local government debt. Top right panel: total local government debt according to our data (solid line) and NAO data (dashed line). Bottom panels: our data for province-level local government debt plotted against NAO data in 2012 (left) and 2013 (right).

The top panels of Figure 1 show that local government debt grew rapidly in the wake of the global financial crisis, when local governments were asked to contribute to the central government's massive fiscal stimulus but were not given additional fiscal resources with which to do so (Lu and Sun (2013), Zhang and Barnett (2014)). Competition between local governors may also have contributed to the rise in local government debt: since local officials are promoted via a tournament, they have an incentive to deliver the highest local growth rate and thus to increase local public debt (Xiong (2018)). Table I shows that between 2006 and 2010, local government debt outstanding jumped sixfold from 1.2 trillion to 7.2 trillion yuan—in proportion to GDP, it tripled from 5.8% to 18.1%—and it continued to grow thereafter, reaching 12.5 trillion yuan or 22% of Chinese GDP in 2013. Moreover, the share of cities with some debt outstanding rose from less than half in 2007 to nearly 100% in 2011, while their average debt expanded from 7 billion to 28 billion yuan.[9]

B. Other City-Level and Firm-Level Data

In addition to data on local public debt, our empirical analysis relies on other city- and firm-level data that come from a variety of sources. City-level data

[9] Figure IA.1 in the Internet Appendix illustrates how the geography of China's local debt-to-GDP ratio changed between 2006 and 2012.

Table I
Local Government Debt in China

This table summarizes our data for local government debt. Columns (2) to (5) are based on city-level variables. Columns (6) and (7) report annual totals in RMB and as a % of China's GDP.

	μ	σ	Min.	Max.	Total China		N. Cities	
Year	Bill. RMB				Bill. RMB	(% GDP)	All	$D > 0$
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
2006	4.3	18.1	0.0	173	1,255	5.7	293	92
2007	7.1	27.6	0.0	268	2,087	7.9	293	144
2008	10.4	38.4	0.0	383	3,036	9.7	293	189
2009	18.9	62.8	0.0	589	5,535	15.8	293	248
2010	24.7	80.5	0.0	789	7,249	17.4	293	281
2011	28.5	93.7	0.0	951	8,336	16.8	293	291
2012	35.6	113.0	0.0	1,145	10,425	18.8	293	292
2013	42.9	132.1	0.0	1,303	12,556	20.1	293	291

such as GDP, total bank loans, and population and economic growth come from the China City Statistical Yearbook. Upon merging these data with our data for city-level public debt, we obtain a data set covering 261 cities from 2006 to 2013. Table II summarizes our variables and data sources.

Firm-level data come from the Annual Survey of Industrial Firms (ASIF), also known as the Chinese Industrial Enterprise Database (CIED). This database covers the universe of manufacturing firms with annual sales above five million yuan until 2009 (about \$750,000 at the 2009 exchange rate) and 20 million yuan thereafter (\$3,200,000 at the 2015 exchange rate). This survey reports firms' location, ownership structure, and balance sheet variables, and has been used by Bai, Hsieh, and Song (2016), Brandt, Van Biesebroeck, and Zhang (2012), Hsieh and Song (2015), Song, Storesletten, and Zilibotti (2011), and Song and Wu (2015), among others.

ASIF covers 90% of China's manufacturing output in 2004 (Brandt, Van Biesebroeck, and Zhang (2012)) and 70% in 2013. This broad coverage reflects the fact that firms larger than the thresholds listed above are required to file detailed annual reports to their local statistics bureaus. The data are then transmitted to the National Bureau of Statistics (NBS), which aggregates them in the China Statistical Yearbook. Our sample spans the period 2005 to 2013 and contains the same number of observations as the NBS during these years. Unfortunately, however, the survey is not available for 2010, which deprives us of three years' worth of data from this source—besides 2010, we lose observations for 2011 because we need data at time $t-1$ to compute investment at time t, and also for 2012, because our regressions include lagged variables.[10]

[10] We compute investment in year t as fixed assets in year t plus depreciation in year t minus fixed assets in year $t-1$. We compute cash flow as net profits (profits minus taxes) plus depreciation.

Table II
Data Description and Sources

Variable	Description and Sources
Age	Firm age. Source: ASIF and ATS.
Assets	Firm total assets. *SIZE* is the log of total assets. Source: ASIF and ATS.
BD	Dummy variable that equals 1 for firms within the 25th percentile of firms closer to the city border, and 0 otherwise. In robustness checks, it equals 1 for firms at the 50th percentile of the distribution or within 20 km of the border, and 0 otherwise. Source: own calculations using ASIF and China Banking Regulatory Commission (CBRC) data and their matched GPS coordinates from Gaode(AMap) Maps Geocoding API.
BK	Dummy variable that equals 1 if the average distance between the firm and the 10 closest bank branches in another city is less than 20 km, and 0 otherwise. *PX* is a continuous measure of proximity to banks based in another city defined as 100 minus the average distance of the 10 closest banks located in another city. Source: own calculations using ASIF and China Banking Regulatory Commission (CBRC) data and their matched GPS coordinates from Gaode(AMap) Maps Geocoding API.
BL	City-level bank loans scaled by city-level GDP. *NBL* measures bank loans over GDP in neighboring cities. Source: China City Statistical Yearbook.
CF	Cash flow (profits minus taxes plus depreciation) scaled by beginning-of year total assets. Source: ASIF and ATS.
EF	Industry-level index of external finance requirements computed as the industry median ratio of capital expenditures minus cash flow from operations to capital expenditures for all firms based in Beijing, Shanghai, Hangzhou, and Wenzhou. Source: own calculation based on ASIF and ATS data.
GB	City-level budget balance over GDP. Source: China City Statistical Yearbook.
GDP PC	City-level GDP per capita. Source for GDP and population: China City Statistical Yearbook.
GR	City-level GDP growth. *NBL* measures GDP growth in neighboring cities. Source: China City Statistical Yearbook.
I	Fixed investment scaled by beginning-of-year total assets. Fixed investment is computed as the first difference of total fixed assets at historical prices. Source: ASIF and ATS.
LB	Dummy variable that equals 1 if in the relevant city the share of the branches of the four largest Chinese banks in the total number of city branches exceeds the sample median, and 0 otherwise. Source: own calculations using data for bank branches from the China Banking Regulatory Commission (CBRC), and their matched GPS coordinates from Gaode(AMap) Maps Geocoding API.
LEV	Firm-level leverage, computed as total debt over total assets. Source: ASIF and ATS.
LGD	City-level local government debt scaled by city-level GDP. *NLGD* measures local government debt over GDP in neighboring cities. See Section II for the construction of local government debt. Sources: own calculations based on data of the China Banking Regulatory Commission (CBRC) and the Wind Information Co. (WIND) database.
LP	City-level land prices computed as the average of auction prices and administered prices fixed by the local government. Source: Chinese Yearbook of Land and Resources, published annually by the Ministry of Land and Resources.

(*Continued*)

Table II—*Continued*

Variable	Description and Sources
Private	Dummy variable that equals 1 if the firm belongs to the private sector and is not foreign-owned, and 0 otherwise. Firms in which the public sector or foreigners own less than 30% of total shares are classified as private. Source: ASIF and ATS.
RC	City-level return to capital. Source: data provided by Chong-En Bai.
REV	Change in operating revenues scaled by total assets at the beginning of the period. Source: ASIF and ATS.
State	Dummy variable that equals 1 if the firm is state-owned, and 0 otherwise. Firms in which the public sector owns more than 30% and foreigners own less than 30% of total shares are classified as state-owned. Source: ASIF and ATS.
Z-score	Firm distance to default computed as in Altman (2005). Source: ASIF and ATS.

To compensate for this loss of information, we merge our ASIF data with the Annual Tax Survey (ATS), conducted by the Ministry of Finance between 2007 and 2011. The ATS gives detailed financial statements for manufacturing firms but also for agriculture, construction, and services. By exploiting the overlap in coverage between the two databases, we retrieve data for a large number of firms. Notwithstanding, our sample from 2010 to 2012 still remains considerably smaller on average than from 2006 to 2009 or in 2013 (61,000 versus 387,000 firms per year).

Dropping observations for firms with negative assets and those in the top and bottom 1% of the revenue distribution, and Winsorizing all of our firm-level variables at the 5% level, we are left with 1,161,180 observations on more than 300,000 firms. Shanghai has the most observations (61,347), while Jiayuguan City has the fewest (167). The sample includes 30 cities with at least 10,000 observations, and 90% of the sample cities have over 1,700 observations. The median is 1,970 observations, the mean 4,407.

II. Geographical Segmentation

The geographical segmentation of China's credit market is an important element of our empirical strategy. China's financial system is heavily bank-based, with three policy banks, one postal bank, five large commercial banks, 12 joint-stock commercial banks, 40 locally incorporated foreign banks, 133 city commercial banks, and more than 2,000 rural banks or credit cooperatives. Policy banks hold some 10% of total Chinese banking assets, large commercial banks about 40%, joint-stock commercial banks 19%, and local banks (city-level and rural banks as well as credit cooperatives) 30%. Foreign banks control the remaining 1% of bank assets.[11]

[11] For details on the Chinese banking and capital markets, see Hachem and Song (2016), Hachem and Song (2017), Allen, Qian, and Qian (2005), Allen et al. (2012), Bailey, Huang, and Yang (2011), and Berger, Hasan, and Zhou (2009), among others.

Geographical segmentation arises from two characteristics of the Chinese banking system. First, city and rural financial institutions rarely operate outside their own city or province. Until 2006, local banks were prohibited from doing business outside their province of origin. Although reforms between 2006 and 2009 theoretically allow them to operate across provincial boundaries, very few inter province licenses have actually been approved. The city commercial banks that were authorized typically have branches only in a few of the wealthiest cities (Shanghai, Beijing, Tianjin, Hangzhou, and Ningbo).

Second, even the policy banks and large commercial banks, which are present throughout China and together account for 50% of total bank assets, often conduct business on a local basis. Anecdotal evidence suggests that, until recently, the local branches of large banks had substantial decision-making power and autonomy vis-a-vis their headquarters (Dobson and Kashyap (2006)), with their decision-making greatly affected by pressure to lend to local governments and local SOEs. According to Roach (2006), through their influence on bank branches, local Communist Party officials often had more say in investment project approval than the credit officers at the head offices of the major banks in Beijing. Furthermore, local authorities are crucial to bank managers' career advancement and thus may influence lending decisions.[12]

The geographical segmentation of the Chinese financial system is reflected in limited capital mobility across regions (Boyreau-Debray and Wei (2005)) and systematic dispersion in returns to capital across Chinese regions and cities (Dollar and Wei (2007)). Although this dispersion decreased between 1988 and 2006 (Brandt, Tombe, and Zhu (2013)), it rose again in 2009. Indeed, by 2013 (the last year of our sample), the dispersion in the return to capital across Chinese cities was as high as in 2003, as shown in the top panel of Figure 2.[13] The internal capital markets of large banks thus appear unable to balance out differences in the demand for credit across cities: Agarwal et al. (2020), who study the consumer credit granted by the branches of a large national bank, find that individual branches cannot access the bank's internal capital market to expand credit and as a result need to reduce lending to nonconnected individuals when they lend more to government bureaucrats. Typically, branch managers are assigned monthly and quarterly lending quotas (Cao et al. (2018)), so managers who fulfill their quota by lending to LGFVs are unlikely to make the effort required to screen private firms.

[12] Yeung (2009) documents that branch managers give priority to SOEs and to the government, and quotes a branch manager as stating that "I shall lend to an SOE first should there be two equally good applications for loans, one from the SOE and the other from a non-SOE" (p. 294). Ho et al. (2017) similarly quote a Chinese bank manager as stating that: "we have to manage the relationships with these government departments very carefully and skillfully. Otherwise, it will ruin our career" (p. 10).

[13] Gao et al. (2019) suggest that the increase in financial segmentation in 2009 was an unintended consequence of the procompetitive bank reform of April 2009: big banks entering new cities had limited knowledge of local conditions and hence lent only to state-owned firms. However, higher local debt may have also played a role.

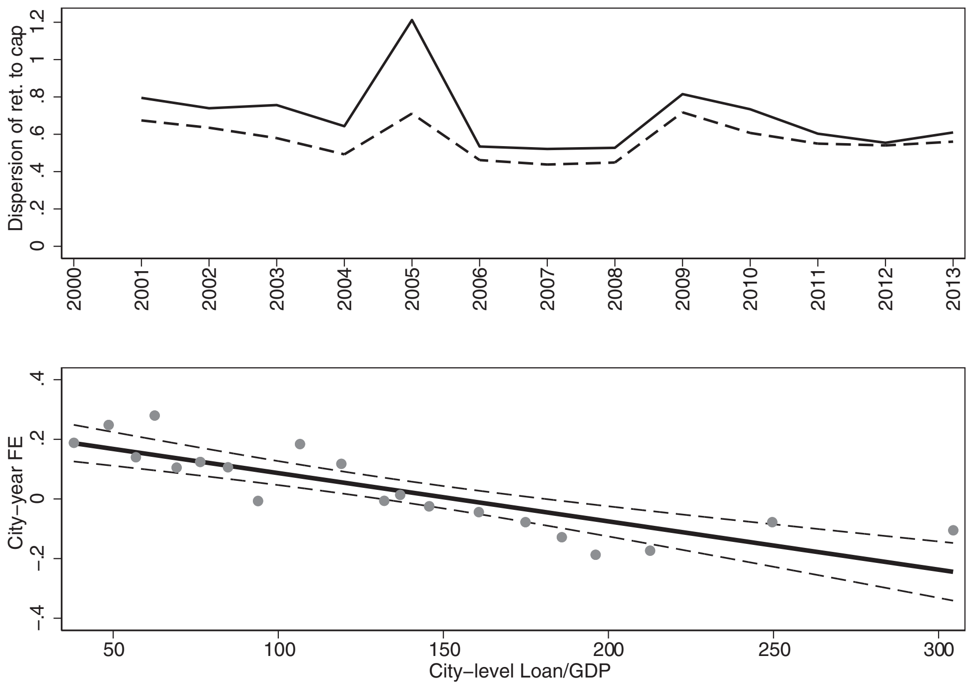

Figure 2. Geographic segmentation of China's credit market. Top panel: time series of the between-cities coefficient of variation on the return to capital; the solid line plots the raw data, and the dashed line plots the data after a 5% Winsorization of the return to capital. Bottom panel: binned scatterplot of estimated city-time effects from a regression of the residuals of LGFV bond yield residuals against the loan to GDP ratio of the corresponding cities and years.

A natural question that arises is why the interbank market does not help to fill local funding gaps. One reason is that regulation prevents Chinese banks from lending more than 75% of their deposits (Chen, Ren, and Zha (2013), Hachem and Song (2016, 2017)). This limits the scope for fund reallocation by banks, especially by small- and medium-size banks for which this constraint is typically binding (Hachem and Song (2016)). In addition, the repo market is dominated by the largest Chinese banks, which use their market power to limit competition from smaller banks (Hachem and Song (2017)). Limited access to the interbank market leads many banks to seek funding from off-balance-sheet wealth management products, the funding costs of which typically exceed the interbank market rate (Acharya et al. (2019)). Finally, the People's Bank of China and the China Banking Regulatory Commission set absolute caps on individual banks' lending volumes, which constrain the lending capacity of most banks even further (Elliott, Kroeber, and Qiao (2015)). For banks that face such constraints, underwriting additional local public debt requires a tightening of credit to the local private sector.

China's credit market also features interest rate ceilings on both deposits and loans. Such regulation was a factor in the rapid growth of a shadow banking sector whose assets increased from 4.5 trillion yuan (14% of GDP) in 2008 to 11 trillion (27%) in 2010 (Elliott, Kroeber, and Qiao (2015)), partly as a result of the 2009 stimulus package itself (Chen, He, and Liu (2017)). The doubling in size of this sector coincided with the jump in the spread between the shadow lending rate and the official lending rate following the postcrisis fiscal stimulus. While in the United States shadow banking is channeled mostly through money market and hedge funds, in China it operates via a wide array of (often opaque) financial instruments: informal lending accounts for 17% of the total, and entrusted loans (i.e., loans made by a nonfinancial corporation to another via a bank as servicing agent) comprise almost a third. However, the growth of shadow banking had little impact on credit market segmentation, as its transactions typically have limited geographical scope, and entrusted loans between firms in the same city carry a significantly lower interest rate (by more than 1 percentage point) than transactions between firms in different cities, other things equal (Allen et al. (2019)).

Credit market segmentation may also stem from asymmetric information between lenders and borrowers located in different jurisdictions as well as from the fact that it may be more difficult to enforce credit contracts when the lender and the borrower are located in different jurisdictions: Firth, Rui, and Wu (2011) and Lu, Pan, and Zhang (2015), for example, provide evidence of judicial bias across Chinese regions. From borrowers' viewpoint, this form of segmentation is functionally equivalent to that arising from regulatory frictions.[14]

A way to test for the presence of this additional cause of segmentation in the Chinese debt market is to examine whether even for local government bonds, which are traded in a centralized nationwide market, issuers located in some locations pay a price penalty that is not accounted by credit risk differentials. Toward this end, we collect the yield at issuance of 9,625 bonds issued by LGFVs between 2003 and 2014, and regress their yield on the bond maturity, amount issued, credit rating (to control for the issuer's credit risk), and time effects (to control for aggregate shocks). To provide a benchmark, we first estimate the same specification for the yields of 3,129 bonds issued over the period 2005 to 2015 by U.S. cities and counties, drawn from Thomson Reuters. The two regressions have the same explanatory power for the panels of Chinese and U.S. yields, with the R^2 equal to 0.57 for both. We then recover the residuals of these two models and regress them on a set of city-year fixed effects. The adjusted R^2 of this second regression is 0.10 for China and very close to zero for the United States. Hence, city-level characteristics have some residual explanatory power for Chinese local debt yields, even after controlling for bond characteristics, risk, and aggregate shocks, while this is not the case for U.S. local public debt yields.

When the residuals from the regressions for Chinese local debt yields are regressed on city fixed effects, the coefficients of these fixed effects turn out to be significantly negatively related to the depth of the respective credit markets,

[14] We would like to thank an anonymous Associate Editor for making this point.

as measured by the total loan-GDP ratio in the corresponding city and year. This result is illustrated by the binned scatterplot in the bottom panel of Figure 2. Hence, in cities with less developed credit markets, local governments pay higher yields irrespective of their credit risk. This is another indication that return differentials are not fully arbitraged across cities. If such differential funding costs exist in a centralized bond market, then a fortiori equally creditworthy firms located in different cities can be expected to face different costs of credit.

III. Investment and Local Public Debt

We start the empirical analysis by providing evidence on the correlation between city-level investment by manufacturing firms and local government debt. While in subsequent sections we pin causality and transmission channels down more firmly, these regressions provide preliminary evidence consistent with the local crowding-out hypothesis. We start by estimating the specification

$$I_{c,t} = \beta LGD_{c,t} + X_{c,t}\Gamma + \alpha_c + \tau_t + \varepsilon_{c,t}, \tag{1}$$

where $I_{c,t}$ is the ratio of investment to assets for manufacturing firms in city c and year t, $LGD_{c,t}$ is the ratio of local government debt to local GDP, $X_{c,t}$ is a vector of city-level controls (bank loans over GDP, local government balance over GDP, GDP growth, log of GDP per capita, log of population, and average price of land), and α_c and τ_t are city and year fixed effects.[15] We estimate this specification first for the entire manufacturing sector of city c in year t (i.e., $I_{c,t}$ is the weighted average of the investment-to-asset ratios of the city's manufacturing firms) and then separately for private-sector and state-owned manufacturing firms. We also estimate (1) separately for small and large firms.

Column (1) of Table III presents the results of specification (1) including only city and year fixed effects. The correlation between total manufacturing investment and local government debt is negative and statistically significant. The point estimate indicates that a one-standard-deviation increase in the debt-to-GDP ratio (14 percentage points) is associated with a 1.1 percentage-point decrease in investment ratio (whose sample average is 7%). Column (2) shows that the results are unchanged after controlling for other time-varying city characteristics. Among these, only GDP growth, GDP per capita, and population size are significantly correlated with firm investment.

Column (3) reproduces the specification of column (2) for the aggregate investment ratios of private-sector manufacturing firms only. We find that focusing on private investment leads to a slight increase (in absolute value) of the coefficient on local government debt. When the same specification is estimated for investment by state-owned manufacturing firms only (column (4)), the coefficient on local government debt is much lower and not statistically significant.

[15] The results are robust to scaling investment by fixed assets.

Table III

Investment and Local Government Debt: City-Level Regressions

This table reports results of regressions in which the dependent variable is the city-level investment ratio of the manufacturing sector (computed as the weighted average of investment scaled by total assets of all manufacturing firms in a given city and year) and the dependent variables are local government debt over GDP (*LGD*), bank loans scaled by GDP (*BL*), local government balance scaled by GDP (*GB*), GDP growth (*GR*), the log of GDP per capita (*GDP PC*), the log of population (*POP*), and the log of the price of land (*LP*). Columns (1) and (2) include all manufacturing firms, column (3) private-sector manufacturing firms only, column (4) state-owned manufacturing firms only, column (5) large manufacturing firms only, and column (6) small manufacturing firms only. Robust standard errors clustered at the firm and city-year levels are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

	(1)	(2)	(3)	(4)	(5)	(6)
LGD	−0.083**	−0.093*	−0.104**	−0.029	−0.081*	−0.229**
	(0.033)	(0.041)	(0.039)	(0.050)	(0.040)	(0.080)
BL		−0.011	−0.002	−0.027	−0.008	−0.028
		(0.022)	(0.025)	(0.016)	(0.021)	(0.074)
GB		0.019	0.028	−0.139	0.055	−0.430
		(0.218)	(0.234)	(0.242)	(0.233)	(0.600)
GR		0.408**	0.332*	0.632***	0.424**	0.084
		(0.146)	(0.143)	(0.163)	(0.140)	(0.310)
ln(*GDP PC*)		4.858*	6.761*	−5.851*	2.919	18.121
		(2.542)	(3.228)	(3.060)	(2.153)	(11.760)
ln(*POP*)		7.889**	9.774**	−5.674	5.761*	27.243*
		(3.077)	(3.822)	(3.237)	(2.480)	(13.491)
ln(*LP*)		0.583	0.489	−0.411	0.568	1.624
		(0.561)	(0.564)	(0.992)	(0.603)	(2.406)
N. Obs.	1,862	1,800	1,798	1,514	1,800	1,800
N. Cities	261	261	261	261	261	261
Firms	All	All	Private	State	Large	Small
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes

In the last two columns of Table III, the regression is re-estimated separately for large firms (column (5)) and small firms (column (6)), respectively, defined as those in the top and bottom quartiles of the distribution of firms by asset size.[16] The correlation between local government debt and investment is much smaller and only marginally significant for large firms, while for small firms it is nearly three times as large as for the full sample and more precisely estimated. These correlations are consistent with the view that local government debt crowds out firm investment, and that such crowding-out affects firms that are more likely to be credit-constrained, such as small private firms in contrast to state-owned firms, which enjoy preferential treatment by banks, or large firms, which may be politically connected or have greater access to credit in other cities.

[16] We do not include firms in the 25th to 75th percentile range to minimize the likelihood that firms endogenously transition from large to small, or vice versa.

Table IV

Capital Productivity and Local Government Debt

This table reports results of regressions in which the dependent variable is the city-level capital productivity of the manufacturing sector (computed as the average percentage deviation of firm-level capital productivity from the industry mean) and the dependent variables are local government debt scaled by GDP (*LGD*), bank loans scaled by GDP (*BL*), local government balance scaled by GDP (*GB*), GDP growth (*GR*), the log of GDP per capita (*GDP PC*), the log of population (*POP*), and the log of the price of land (*LP*). Columns (1) and (2) report estimates obtained using the sample of all manufacturing firms, columns (3) and (4) report estimates based on the subsample of private-sector manufacturing firms, and columns (5) and (6) report estimates based on the subsample of state-owned manufacturing firms. Robust standard errors clustered at the firm and city-year levels are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

	(1)	(2)	(3)	(4)	(5)	(6)
LGD	0.236***	0.271***	0.251***	0.275***	0.099	0.075
	(0.087)	(0.091)	(0.090)	(0.094)	(0.172)	(0.194)
BL		0.026		0.019		0.178*
		(0.059)		(0.062)		(0.091)
GB		−1.206**		−0.914		−1.923*
		(0.579)		(0.571)		(1.011)
GR		0.209		0.256		−0.096
		(0.319)		(0.331)		(0.855)
ln(*GDP PC*)		17.891*		14.673		49.286**
		(10.293)		(10.533)		(21.094)
ln(*POP*)		52.470***		53.205***		64.286**
		(17.591)		(18.136)		(28.770)
ln(*LP*)		0.352		0.609		−4.573
		(2.124)		(2.187)		(3.961)
N. Obs.	782	739	782	739	782	739
N. Cities	260	257	260	257	260	257
Firms	All	All	Private	Private	State	State
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes

Assuming that these correlations do indeed reflect crowding-out of private investment by local government debt, it is worth checking whether local government debt is also associated with less efficient capital allocation, as one would expect if private firms are more efficient than state-owned firms (Hsieh and Klenow (2009), Song, Storesletten, and Zilibotti (2011), Hsieh and Song (2015). Toward this end, we proxy for the marginal product of capital using its average product, following Hsieh and Song (2015). If capital markets are segmented and local government debt crowds out more efficient firms, the productivity of capital in private firms should be positively correlated with local government debt, as more public debt issuance should constrain private investment to a greater extent.[17] As can be seen in Table IV, this is exactly what we find: the correlation between capital productivity and local government debt is positive for all firms (columns (1) and (2)) and for private-sector firms only

[17] We thank an anonymous referee for suggesting this test.

(columns (3) and (4)), while it is not statistically significant for state-owned firms (columns (5) and (6)).[18] This finding is consistent with the view that local crowding-out affects private-sector firms only, since SOEs have preferential access to bank credit, as argued in Section II.

To better control for firm heterogeneity across and within cities, we turn to firm-level data and estimate

$$I_{i,c,t} = \beta LGD_{c,t} + X_{i,c,t}\Gamma + \alpha_i + \zeta_c + \tau_t + \varepsilon_{i,c,t}, \tag{2}$$

where $I_{i,c,t}$ is the ratio of investment to assets in firm i, city c, and year t, $LGD_{c,t}$ is the ratio of local government debt to local GDP in city c and year t, $X_{i,c,t}$ is a vector of firm-level controls, and α_i, ζ_c, and τ_t are firm, city, and year fixed effects, respectively.[19] In estimating equation (2), we double-cluster standard errors at the firm and city-year levels, the latter being the source of variation in our main variable of interest.

Column (1) of Table V presents the estimates of specification (2) controlling for the lagged investment ratio, the change in revenue, and lagged cash flow, where the latter two measures are scaled by total assets. The correlation between manufacturing investment and local government debt is again negative and statistically significant. The firm-level point estimate is smaller than that obtained with city-level data: a one-standard-deviation increase in the debt-to-GDP ratio is associated with a 0.8 percentage-point decrease in the investment ratio. In column (2), we find that the results are unchanged if we include a dummy variable that controls for state-owned firms. Since the specification includes firm fixed effects, this dummy captures the effect of firms that change ownership status—the negative point estimate suggests that privatization is associated with higher investment.

The specification in column (3) also includes the interaction between the debt-to-GDP ratio and the state ownership dummy. Here, β reflects the correlation between local government debt and private firms' investment, the coefficient on the interacted variable captures the differential effect of debt between private and state-owned firms, and the sum of the two coefficients reflects the correlation between local government debt and state-owned firms' investment. We find that the coefficient on the interacted variable is positive, statistically significant, and approximately half as large as β in absolute value. The sum of the two coefficients is not statistically significant, indicating that the correlation is significant only for private firms.

The last column of Table V reports results of a specification in which city and year fixed effects are replaced by city-year fixed effects. This model

[18] We compute city-level capital productivity as the average percentage deviation between firm-level capital productivity and the country-wide industry mean, so as to purge the variable from variation arising from city-level industry composition effects. This variation would not be fully absorbed by city-level effects if city-level industry composition changes over time. Since computing the average product of capital requires data on value-added that are available only in the ASIF firm survey, the regressions of Table IV omit the period 2008 to 2010.

[19] We include both city and firm fixed effects to allow for the possibility that firms change city. The results are identical if we only include firm fixed effects.

Table V

Investment and Local Government Debt: Firm-Level Regressions

This table reports results of regressions in which the dependent variable is the firm-level investment ratio (computed as investment scaled by total assets at the beginning of the year), and the explanatory variables are the lagged investment ratio (I_{t-1}), change in revenue scaled by total assets (REV_{t-1}), lagged cash flow scaled by total assets (CF_{t-1}), a state ownership dummy ($STATE$), local government debt scaled by city-level GDP (LGD), and the interaction between LGD and $STATE$. The regressions in columns (1)-(3) control for firm, city, and year fixed effects, while the regression in column (4) controls for firm and city-year fixed effects. Robust standard errors clustered at the firm and city-year levels are reported in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

	(1)	(2)	(3)	(4)
I_{t-1}	−0.271***	−0.271***	−0.271***	−0.274***
	(0.006)	(0.006)	(0.006)	(0.002)
REV_{t-1}	4.050***	4.050***	4.050***	3.772***
	(0.089)	(0.089)	(0.089)	(0.079)
CF_{t-1}	7.779***	7.780***	7.780***	6.987***
	(0.519)	(0.519)	(0.519)	(0.195)
$STATE$		−0.386**	−0.697***	−0.253
		(0.174)	(0.224)	(0.176)
LGD	−0.055***	−0.055***	−0.056***	
	(0.016)	(0.016)	(0.016)	
$STATE \times LGD$			0.027***	0.013*
			(0.009)	(0.007)
N. Obs.	1,035,427	1,035,427	1,035,427	1,035,400
N. Cities	261	261	261	261
Firm FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	No
Year FE	Yes	Yes	Yes	No
City-Year FE	No	No	No	Yes
$LGD + STATE \times LGD$			−0.029	
p-Value			0.12	

absorbs the effect of local government debt, but still yields an estimate of how local government debt correlates with the differential investment of private and state-owned firms while controlling for omitted time-varying city-level variables. The results of this specification confirm that the correlation between investment and local government debt is significantly lower for state-owned firms than for private firms.

In the Internet Appendix, we subject these correlations to a battery of robustness checks. The baseline results of Table V survive when the model is estimated using the standard difference and system Generalized Method of Moments (GMM) estimators, and when the explanatory variables include both fixed effects and the lagged dependent variable. The results are also robust to including additional time-varying city-level variables (size of the banking sector, GDP per capita, and GDP growth) and additional firm-level variables (firm size, leverage, average product of capital, export status, and firm age), as well as to replacing the debt-to-GDP ratio with the change in debt over GDP and replacing total local public debt with its bank-funded component only. Interestingly, in regressions in which local public debt does not include bonds, its coefficient is larger in absolute value terms than in regressions in which it is measured as total debt (−0.62 instead −0.56), consistent with the view that the bond market is less segmented than bank credit.[20]

Two further pieces of evidence about firm leverage support the idea that the negative correlation between private investment and local government debt that we document is driven by binding financing constraints in geographically segmented credit markets. First, not only private investment but also firm leverage is negatively correlated with local government debt. The first three columns of Table VI show that such negative correlation obtains for the leverage of private manufacturing firms only, as it is absent for state-owned firms. Second, firm leverage is negatively correlated with total bank lending to LGFVs divided by total bank lending to corporations (which includes lending to LGFVs). The latter correlation is also statistically significant only for private-sector firms, as shown by the regressions reported in columns (4) to (7) of Table VI .[21]

These results are consistent with the view that banks have less funds to lend to private firms when they lend more to local LGFVs. In principle, this result could also be driven by local governments implementing countercyclical policies and thus borrowing more when private firms deleverage, but it is worth noting that, in addition to controlling for year and city fixed effects, our specifications control for city-level GDP growth, total bank loans, and a host of other variables that capture local economic conditions. Moreover, if high government debt were driven by low private-sector demand for credit, firm leverage should be positively correlated with city-level return to capital, while the last two columns of Table VI show no statistically significant correlation between these two variables.[22]

While the results reported in this section are consistent with the hypothesis that local government debt crowds out private investment, these are simple correlations that are likely to suffer from endogeneity bias. The direction of the bias is unclear. On the one hand, local politicians may respond to negative shocks to private investment by instructing LGFV managers to borrow and invest more, so that the negative correlation could be due to reverse causality

[20] The results are reported in Tables IA.V to IA.IX of the Internet Appendix.

[21] We thank Chong-en Bai and Jun Qian for help accessing data on the composition of bank lending at the city level.

[22] Consistent with these results on firm-level leverage, the city-level share of corporate bank lending to private firms is negatively correlated with local government debt, controlling both for other factors and for city and year fixed effects. In contrast, the share of bank lending to non-LGFV SOEs is uncorrelated with local government debt (see Table IA.X in the Internet Appendix). This is also consistent with the fact that at city-level banks, bank credit growth to private corporations is negatively correlated with bank credit growth to LGFVs, controlling for city fixed effects and for total bank credit growth (see Figure IA.2 in the Internet Appendix).

Table VI

Firm Leverage, Local Government Debt, and Share of Local Bank Lending to LGFVs

This table reports results of regressions in which the dependent variable is firm-level leverage, and the explanatory variables are local government debt scaled by GDP (*LGD*), local bank lending to local government financing vehicles scaled by total local bank lending to corporates (*LGFV*), total bank loans scaled by GDP (*BL*), budget balance (*GB*), log of GDP per capita (ln(*GDP PC*)), GDP growth (*GR*), land price (*LP*), and firm size (*SIZE*). Columns (1), (4), (7), and (8) report estimates based on the sample of all manufacturing firms, columns (2) and (5) focus on the subsample of private manufacturing firms, and columns (3) and (6) focus on the subsample of state-owned manufacturing firms. The specifications of columns (7) and (8) also control for city-level return to capital (*RC*). Robust standard errors clustered at the firm and city-year levels are reported in parentheses $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LGD	-0.009^{**}	-0.013^{***}	-0.001					
	(0.004)	(0.004)	(0.015)					
LGFV				-0.073^{***}	-0.077^{***}	0.003	-0.066^{***}	
				(0.006)	(0.007)	(0.027)	(0.022)	
BL	0.025^{***}	0.029^{**}	-0.006	0.022^{***}	0.025^{***}	-0.006	0.024^{***}	0.027^{***}
	(0.001)	(0.002)	(0.007)	(0.002)	(0.002)	(0.007)	(0.006)	(0.006)
GB	-0.067^{***}	-0.063^{***}	-0.234^{***}	-0.077^{***}	-0.075^{***}	-0.235^{***}	-0.058	-0.046
	(0.020)	(0.022)	(0.069)	(0.020)	(0.022)	(0.069)	(0.073)	(0.075)
ln(*GDP PC*)	-2.610^{***}	-2.776^{***}	-0.278^{***}	-2.671^{***}	-2.789^{***}	-0.277	-4.682^{***}	-4.710^{***}
	(0.214)	(0.238)	(0.821)	(0.214)	(0.238)	(0.821)	(1.050)	(1.053)
GR	0.058	0.065^{***}	-0.121^{***}	0.068^{***}	0.072^{***}	-0.121^{***}	0.102^{***}	0.089^{**}
	(0.011)	(0.013)	(0.044)	(0.011)	(0.013)	(0.044)	(0.036)	(0.038)
LP	0.163^{***}	0.057	0.735^{***}	0.111^{*}	-0.006	0.735^{***}	0.216	0.248
	(0.060)	(0.070)	(0.230)	(0.060)	(0.070)	(0.230)	(0.170)	(0.175)
SIZE	-0.454^{***}	-1.245^{***}	-1.677^{***}	-0.446^{***}	-1.228^{***}	-1.677^{***}	-0561^{*}	-0.568^{*}
	(0.050)	(0.057)	(0.264)	(0.050)	(0.057)	(0.264)	(0.335)	(0.336)
RC							0.932	0.619
							(2.389)	(2.455)
N. Obs	751,974	591,084	40,332	751,974	591,084	40,332	591,152	591,152
N. Cities	261	261	261	261	261	261	261	261
Sample	All	Private	State	All	Private	State	All	All
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

from investment to local public debt.[23] On the other hand, common shocks—such as spending on public infrastructure, which increases both private firms' profitability and public debt issuance—could be driving both variables, biasing the estimates in the opposite direction.

To see this, suppose that the equation capturing the effect of local government debt (D) on investment (I) is $I = \alpha + \beta D + \varepsilon$, but public debt reacts to investment according to $D = a + bI + e$. In estimating the parameter β, two

[23] While column (4) of Table V controls for all possible city-year shocks, it does not fully address the endogeneity problem because cities that implement a countercyclical policy may also require state-owned firms to invest more.

endogeneity problems arise: first, it may be the case that $b \neq 0$ (for instance, $b < 0$ due to countercyclical local fiscal policy), and second, there may be a positive correlation $\rho_{\varepsilon e}$ between ε and e (growth and local public debt being positively correlated in our data).[24] The bias of the OLS estimator of β is given by:

$$E(\widehat{\beta}) - \beta = \frac{1 - b\beta}{\sigma_D^2}\left(b\sigma_\varepsilon^2 + \rho_{\varepsilon e}\right). \tag{3}$$

Under the natural assumption $b\beta < 1$,[25] the direction of the bias depends on the relative importance of reverse causality ($b < 0$) and common unobservable shocks ($\rho_{\varepsilon e} > 0$).

In the next two following sections, we employ three strategies to address this endogeneity problem. In Section IV, we exploit information about the precise geographical location of each firm within its city to build firm-specific measures of access to the credit market of the closest city, which provide an indication of the firm's ability to escape crowding-out due to its own city's public debt issuance. In Sections V, VI, and VII, we further examine whether the channel through which public debt affects private investment is a tightening of credit constraints on private firms. Specifically, in Section V, we test whether higher government debt leads to tighter credit constraints for private firms more dependent on external funding. We show that this channel is not at work for state-owned firms. In Sections VI and VII, we show that higher government debt leads to tighter credit for firms that are more likely to face financing constraints.[26]

IV. Local Crowding-Out and Firm Location

In the analysis above, we assume that, conditional on their ownership and size, all firms located in the same city are equally affected by local government borrowing. However, firms that are closer to their city's border may find it easier to tap the capital market of a neighboring city and thus escape any credit shortage due to government borrowing in their own city. Such firms are thus expected to be less affected by local crowding-out.

Exploiting this within-city source of firm-level heterogeneity has two related advantages over the approach used in Section II. First, it allows the estimates

[24] If we assume that D is positively correlated with investment by LGFVs, the positive correlation between ε and e could be driven by common shocks to private and public investment. In other words, we could have $\varepsilon = \zeta + \epsilon$ and $e = \zeta + u$, with $E(\epsilon u) = 0$.

[25] This assumption obviously holds if β and b differ in sign. If, instead, they take the same sign, the assumption $b\beta < 1$ is necessary for the level of I and D solving these two equations to be positive.

[26] In a previous version of the paper, we also experimented with an instrumental variable (IV) estimation of the specifications reported in this section (Huang, Pagano, and Panizza (2016)). While the IV results corroborate the OLS estimates in this section, we dropped this exercise for brevity.

to be based on the *different* response to public debt issuance by otherwise-identical firms differently located within the same city, rather than on the city-level relationship between investment and local debt issuance. As such, this approach does not depend on whether causality at the city level goes from local debt issuance to investment or in the opposite direction. Second, by the same token, this strategy enables us to saturate our specification with city-time effects and thus purge the estimates from the effect of macroeconomic city-year-level variables, including those that may induce a spurious correlation between investment and local public debt issuance.

To implement this strategy, we use the address of each firm in our sample to measure its location within the relevant city and construct the dummy variable BD_i by setting it equal to one for firms that are within 20 km from the city border.[27] This border proximity variable is intended to measure the firm's potential access to funding outside the city borders. However, this measure is inappropriate if no banks are located next to the neighboring city's border, as in this case, firms located in high-debt cities cannot borrow elsewhere even if they are close to a neighboring city. To address this issue, we measure the average distance of each firm from the 10 closest bank branches located in another city and create the dummy BK_i by setting it equal to 1 if this distance is less than 20 km.[28]

The two proximity variables above enable us to test whether firms closer to banks in a neighboring city or to the border with a neighboring city are less likely to be crowded out by local debt issuance. Specifically, we estimate a model in which the investment of firm i depends on the interaction of BK_i and BD_i with the government debt-to-GDP ratio of firm i's city:

$$I_{i,c,t} = (\delta_1 BK_i + \delta_2 BD_i) \times LGD_{c,t} + X_{i,c,t}\Gamma + \alpha_i + \theta_{ct} + \varepsilon_{i,c,t}, \tag{4}$$

where the coefficients δ_1 and δ_2 capture the extent to which proximity to nearby-city banks and proximity to the city border mitigate the crowding-out effect of local public debt, while θ_{ct} captures city-year fixed effects and the other variables are defined as in equation (2). The inclusion of city-year fixed effects absorbs the main effect of local public debt but controls for all possible city-year shocks and thus rules out the most obvious sources of reverse causality or omitted variable bias.

Column (1) of Table VII shows that the point estimates of δ_1 and δ_2 are positive. This finding suggests that, controlling for all possible city-year shocks, the negative correlation between local government debt and investment is smaller (in absolute value terms) for firms that are closer to nearby-city banks and closer to the border. Of the two coefficients, only δ_1 is statistically significant at

[27] To illustrate how we compute a firm's distance from the border, assume that city C has borders with cities A, B, and D, and that in city C, there are 10 firms. For each of these firms, we check the distance from the border of each neighboring city (in this example, each firm will have three distances, one from the border with A, one from the border with B, and one from the border with D), and then assign to this firm the minimum value across the distances with all neighboring cities. Ideally, we would like to measure the distances in terms of driving times or road length, but our data do not allow this computation. We therefore proxy for driving time using the shortest line

Table VII

Investment, Local Government Debt, and Proximity to Other Cities

This table reports results of regressions in which the dependent variable is the firm-level investment ratio, and the explanatory variables are the lagged investment ratio (I_{t-1}), change in revenue scaled by total assets (REV_{t-1}), lagged cash flow scaled by total assets (CF_{t-1}), a dummy variable equal to 1 only for firms for which the average distance of the 10 closest bank branches located in another city is less than 20 km (*BK*), a dummy variable equal to 1 for firms located less than 20 km from the city border (*BD*), the interaction between each of *BK* and *BD* and local government debt scaled by GDP (*LGD*), bank loans over GDP (*BL*), and GDP growth (*GR*). In column (4), *BK* is replaced with a continuous measure of proximity (*PX*) defined as 100 minus the average distance of the 10 closest banks located in another city. Columns (6) and (7) also control for the interaction between *BK* and government debt (*NLGD*), growth (*NGR*), and bank loans (*NBL*) in the city in which the neighboring banks are located. Robust standard errors clustered at the firm, city-year, and neighboring city-year (in columns (7) and (8)) levels are reported in parentheses $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
I_{t-1}	-0.258^{***}	-0.258^{***}	-0.258^{***}	-0.258^{***}	-0.259^{***}	-0.263^{**}	-0.263^{**}
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
REV_{t-1}	2.187^{***}	2.187^{***}	2.187^{***}	2.187^{***}	2.186^{***}	2.210^{***}	2.224^{***}
	(0.047)	(0.047)	(0.047)	(0.047)	(0.048)	(0.054)	(0.056)
CF_{t-1}	4.409^{***}	4.408^{***}	4.412^{***}	4.408^{***}	4.437^{***}	4.650^{***}	4.642^{***}
	(0.330)	(0.330)	(0.330)	(0.330)	(0.333)	(0.371)	(0.378)
$LGD \times BK$	0.017^{*}	0.022^{**}			0.028^{**}	0.031^{**}	0.036^{**}
	(0.008)	(0.008)			(0.012)	(0.012)	(0.015)
$LGD \times BD$	0.015		0.023^{**}				
	(0.010)		(0.010)				
$LGD \times PX$				0.004^{***}			
				(0.001)			
$GR \times BK$					0.023		0.087^{**}
					(0.021)		(0.044)
$BL \times BK$					−0.003		−0.007
					(0.003)		(0.004)
$NLGD \times BK$						−0.002	−0.007
						(0.014)	(0.017)
$NGR \times BK$							-0.089^{*}
							(0.047)
$NBL \times BK$							0.006^{*}
							(0.004)
N. Obs.	792,900	792,900	792,900	792,900	769,328	603,127	581,973
N. Cities	251	251	251	251	251	251	251
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
C-Y FE	No	Yes	Yes	Yes	Yes	Yes	Yes
N. C-Y FE	No	No	No	No	No	Yes	Yes

between the firm location and the closest city border. As we are not able to recover the location for all firms in our sample, we lose about 240,000 observations in this exercise.

[28] We restrict the analysis to branches within 100 km from the firm. If there are no bank branches in neighboring cities within 100 km, we set the distance value to 100. This approach is similar to that used by Hau et al. (2019).

the 10% level. The low precision of the estimates is likely due to the high correlation (0.7) between BD_i and BK_i—an F-test shows that δ_1 and δ_2 are jointly statistically significant with a p-value of 0.02. If BK_i and BD_i are included separately (columns (2) and (3) of Table VII), they are both statistically significant with p-values of 0.013 and 0.017, respectively.[29]

The fact that when both interacted variables are included, a firm's proximity to nearby-city banks appears to dominate its proximity to the city border itself suggests that crowding-out operates specifically through firms' financing, rather than through access to other inputs available in nearby cities, such as land, workers, or construction materials.[30] Hence, in subsequent specifications of Table VII, we rely on distance from banks located in other cities rather than from the border (all results are robust to using distance from the border and to alternative thresholds in defining proximity to the border; see Table IA.XI in the Internet Appendix).

Column (4) of Table VII reruns the regression of column (2) using a continuous measure of proximity, PX_i, which we define as 100 km minus the average distance of firm i from the 10 closest banks located in another city. This finding confirms that our results do not depend on the particular choice of the threshold distance used to measure proximity.

A possible concern is that the investment of firms that are more peripheral in their city may respond less to their own city's growth and to the depth of the local financial market than firms located more centrally in the same city: insofar as these variables are correlated with local government debt issuance, this could bias the estimate of the proximity coefficient δ. To address this concern, we next expand the specification of column (2) by adding the interactions between the proximity dummy BK_i and both city-level growth (GR) and the ratio of local bank lending to GDP (BL). The coefficients on these interacted variables are not statistically significant, while the estimate of the interaction between the proximity dummy and LGD remains positive and significant (column (5)), and, in fact, becomes larger than in the baseline estimate of column (2).

Finally, the investment of firms close to banks in neighboring cities may be affected by the issuance of government debt in these cities. To control for this possibility, we construct a variable measuring the local government debt of the city in which the 10 banks closest to firm i are located ($NLGD_{i,t}$, where N refers to "neighbor") and expand the specification of column (2) by including the interaction between proximity variables and government debt in the

[29] To appreciate the extent to which the nearby-city bank attenuates the crowding-out effect of local government debt, we estimate a simpler specification in which city-year fixed effects are replaced by separate city and year fixed effects and we include LGD among the regressors. The estimated coefficient on LGD is approximately -0.06 (close to the estimate in the regressions of Table V) and that on δ_1 is about 0.03. Thus, the correlation between local government debt and investment for firms close to the border is about half as large as for other firms.

[30] If we split the sample between private and state-owned firms, we find that δ is statistically significant only for private firms. This finding is in line with the hypothesis that state-owned firms are less likely to be credit-constrained than private firms.

neighboring city. We expect this variable to carry a negative coefficient, capturing crowding-out of firm i 's investment in the credit market of the neighboring city. The specification also includes neighboring-city-year effects, to control for time-varying shocks in neighboring cities (including the main effect of $NLGD_{i,t}$). The estimates, reported in column (6), show that the proximity coefficient δ remains positive and significant, and actually becomes larger than in the previous specifications. Moreover, the coefficient on the interaction between the proximity variables and neighboring-city public debt issuance is negative, though not significantly different from zero, in line with neighboring cities' debt issuance crowding-out the investment of firms close to other cities' banks. The results are robust to including the interaction of the proximity dummy BK_i with GDP growth (*NGR*) and local bank lending (*NBL*) of the closest city (column (7)).

The regressions of Table VII focus on investment. However, if the mechanism operates through financing, being close to the border should mitigate the negative correlation between local government debt and leverage documented in Table VI. Table IA.XII in the Internet Appendix shows that this is the case for private-sector firms, but not for state-owned firms.[31]

V. Crowding-Out and Industry Financial Needs

As explained in the introduction, given the institutional features of China's financial market, in cities that issue more public debt, banks can be expected to allocate more funds to the public sector, which implies tightening credit to private firms, while state-owned firms are spared the crunch. One way to test whether the data are consistent with this conjecture is to examine whether government debt reduces investment more in industries that for technological reasons need more external funds—an approach akin to that used by Rajan and Zingales (1998) to test the effect of financial development on investment. Accordingly, we aggregate our data at the industry-city level and estimate

$$I_{j,c,t} = \beta I_{j,c,t-1} + \delta\big(EF_j \times LGD_{c,t}\big) + \alpha_{jt} + \theta_{ct} + \eta_{cj} + \varepsilon_{j,c,t}, \tag{5}$$

where $I_{j,c,t}$ is the investment-asset ratio in industry j, city c, and year t, EF_j is a time-invariant measure of the external fund dependence of industry j, $LGD_{c,t}$ is local government debt scaled by GDP in city c and year t, and α_{jt}, θ_{ct}, and η_{cj} are industry-year, city-year, and city-industry fixed effects, respectively.

The parameter δ measures the incremental impact of local government debt on the investment of industries that depend more heavily on external finance. Due to the inclusion of industry-year, city-year, and city-industry fixed effects, equation (5) controls for any industry- or city-level time-varying factor and therefore does not suffer from any obvious reverse causality from city-level investment to local public debt issuance. The estimate of δ could be biased only if equation (5) omitted some source of credit constraint that is itself correlated

[31] We would like to thank an anonymous referee for suggesting this test.

with local government debt. We address this potential problem by expanding the specification so as to control for the interaction between EF_j and a set of city-level time-varying variables potentially correlated with both local government debt and credit constraints.

The index of external financial dependence constructed by Rajan and Zingales (1998) is the industry median ratio of capital expenditures minus operating cash flow, scaled by total capital expenditures, for a sample of U.S. firms in the 1980s. Rajan and Zingales (1998) use data for U.S. firms as they are least likely to be credit-constrained, owing to the high degree of U.S. financial development. Hence, the amount of external funds used by U.S. firms is likely to be a good measure of their unconstrained demand for external financing.

There are two issues with using the original Rajan-Zingales index in our sample. First, in some cases, we are not able to match the Chinese three-digit industry code of our survey with the original Rajan and Zingales ISIC code. Second, the technological parameters of Chinese firms are likely to be different from those of large U.S. firms. To address these issues, we use the methodology used by Rajan and Zingales for U.S. firms to construct an industry-level measure of external financial dependence for Chinese firms based on data from the four cities with the most developed financial markets: Beijing, Shanghai, Hangzhou, and Wenzhou.[32] We then use this measure to estimate equation (5) for the remaining 257 cities in our sample. We test the robustness of our results, however, to using the original Rajan and Zingales index.

The baseline estimates, reported in column (1) of the top panel of Table VIII, indicate that the coefficient δ on the interaction between external financial dependence and local government debt is negative and statistically significant: local crowding-out is particularly severe for firms that belong to industries that need more external financial resources. Column (2) reports results based on the original Rajan-Zingales index. While this implies losing many observations because not all Chinese industries can be matched with the Rajan-Zingales index, we continue to find a negative and statistically significant coefficient.

Next, we explore heterogeneity by estimating separate regressions for the industry-level investment of private and state-owned manufacturing firms (columns (3) and (4), respectively). The interaction between local government debt and external financial dependence is statistically significant only for private-sector firms, and four times larger (in absolute value terms) than for state-owned firms. These findings corroborate our previous result that crowding-out does not affect state-owned firms.

Firms may differ in their exposure to projects funded by LGFVs: when local governments undertake large infrastructure projects, suppliers to these

[32] Among the large Chinese cities, these four cities have the highest ratios of bank loans to GDP. As this index of external finance is based on our institutional knowledge in choosing the cities over which we compute the index, we also employ an alternative strategy. Specifically, we first estimate the correlation between local government debt and corporate investment in each city. We then recompute the index of external financial dependence based on data for the three largest cities in which the correlation is estimated to be positive and statistically significant. Our results are robust to the use of this alternative measure of external financial dependence.

Table VIII

Industry-Level Regressions

This table reports results of regressions in which the dependent variable is the investment ratio (computed as investment over total assets at the beginning of the year) aggregated at the city-industry-year level. The regressions control for the initial investment ratio (I_{t-1}) and the interaction between the Rajan-Zingales index of external financial dependence (*EF*) computed on firms in Beijing, Shanghai, Hangzhou, and Wenzhou and each of the following variables: local government debt over GDP (*LGD*), bank loans over GDP (*BL*), the log of GDP per capita (*GDP PC*), GDP growth (*GR*), and the log of average land price (*LP*). The regression in column (1) reports estimates based on the sample of all manufacturing firms and the *EF* index computed using Chinese data, while column (2) reports estimates based on the same sample and on the original Rajan-Zingales *EF* index. The regressions reported in the subsequent columns are all based on the *EF* index computed using Chinese data but are estimated on different subsamples: private-sector manufacturing firms in column (3), state-owned manufacturing firms in column (4), firms in industries with below-median exposure to government expenditure in column (5), and firms in industries with above-median exposure to government expenditure in column (6). Robust standard errors clustered at the city-industry level are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

	(1)	(2)	(3)	(4)	(5)	(6)
I_{t-1}	-0.216^{***}	-0.168^{***}	-0.213^{***}	-0.394^{***}	-0.232^{***}	-0.221^{***}
	(0.007)	(0.011)	(0.007)	(0.031)	(0.011)	(0.011)
$EF \times LGD$	-0.017^{***}	-0.014^{**}	-0.017^{**}	-0.004	-0.018^{**}	-0.011
	(0.008)	(0.007)	(0.001)	(0.015)	(0.009)	(0.012)
N. Obs	46,379	18,398	44,527	3,655	21,461	17,370
N. Cities	257	257	257	197	256	256
			With Additional Interactions			
I_{t-1}	-0.217^{***}	-0.174^{***}	-0.214^{***}	-0.398^{***}	-0.234^{***}	0.220^{***}
	(0.006)	(0.011)	(0.007)	(0.111)	(0.001)	(0.011)
$EF \times LGD$	-0.021^{***}	-0.017^{***}	-0.021^{***}	-0.007	-0.023^{***}	-0.012
	(0.007)	(0.006)	(0.007)	(0.079)	(0.009)	(0.011)
$EF \times BL$	0.004^{***}	0.017^{***}	0.004^{***}	0.001	0.004	0.006^{***}
	(0.001)	(0.001)	(0.001)	(0.006)	(0.002)	(0.002)
$EF \times ln(GDP\ PC)$	0.4078*	-0.543^{***}	0.352	0.788	0.456	-0.062
	(0.22)	(0.166)	(0.223)	(2.501)	(0.327)	(0.380)
$EF \times GR$	0.025	0.104^{***}	0.030	0.083	0.067*	-0.015
	(0.019)	(0.013)	(0.020)	(0.189)	(0.034)	(0.034)
$EF \times LP$	-0.174	0.408^{***}	-0.175	-0.311	-0.018	-0.213
	(0.112)	(0.106)	(0.121)	(1.353)	(0.180)	(0.187)
N. Obs	45,753	18,138	43,958	3,554	21,161	17,138
N. Cities	257	257	257	197	255	255
City-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Ind.-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Ind.-City FE	Yes	Yes	Yes	Yes	Yes	Yes
Sample	All	All	Private	State	Low Exp.	High Exp.

projects are likely to need less external funding, as they may discount invoices or borrow directly from the LGFV that funds the projects. To account for this possibility, we build an industry-specific index of exposure to government spending and estimate separate regressions for total manufacturing investment of firms in sectors with high and low exposure to government spending.[33] The results in columns (5) and (6) of Table VIII are consistent with the hypothesis that local government debt is less important for firms that operate in industries with high exposure to government spending, as the coefficient on the interaction between local government debt and the index of external financial needs is not statistically significant.

The bottom panel of Table VIII shows that all of the results described above are robust to controlling for other city-level variables (bank loans, log of GDP per capita, GDP growth, and log of average land price) that may be jointly correlated with local government debt and credit constraints.[34]

To illustrate the economic significance of the parameter δ, we use the point estimates of Table VIII, column (3) (bottom panel), to evaluate the effect of local public debt for the industries at the 25th and 75th percentiles of the distribution of the external financial dependence index (the paper and batteries production industries, respectively).[35] The left panel of Figure 3 depicts the relationship between local government debt and the investment ratio for the industry at the 25th percentile of the distribution of the external financial dependence index. It also shows the average investment ratio in this industry (8% of total assets, indicated by the solid horizontal line). As the public debt-GDP ratio increases from its 10% nationwide average, the investment ratio in this industry with low financial dependence is not significantly different from the average (and rises slightly, as in this industry the external financial dependence index is negative). The right panel of Figure 3 depicts the relationship between debt and the investment ratio for the industry at the 75th percentile of the distribution of the external financial dependence index, comparing it with the average investment ratio for this industry (the horizontal line drawn at 10.5%). As local government debt rises, the investment ratio in this financially dependent industry decreases rapidly: it becomes significantly lower than its 10.5% industry average when local public debt exceeds 15% of GDP, and drops to about 9% when local public debt climbs to 50%.

[33] High- and low-exposure firms are, respectively, defined as those that belong to industries with above- and below-median values of the exposure index. Since most LGFVs manage public infrastructure projects, the sectors taken to be *directly* affected by LGFV-funded public spending are (i) electricity production and distribution, (ii) heat production and distribution, (iii) gas distribution, (iv) water supply and sewage treatment, (v) construction, (vi) environmental management, and (vii) public facilities management. We match these sectors with the input-output table constructed by the National Statistics Bureau and construct indexes of exposure to these seven sectors for the 135 sectors covered in the input-output table for 2007. Finally, we match these exposure indexes with the manufacturing firms in our survey.

[34] Table IA.XIII in the Internet Appendix shows that the results are robust to estimating the model using firm-level data instead of industry-level aggregates. In those regressions, we also use firm size and age as proxies for financial constraints (see Hadlock and Pierce (2010)). We thank an anonymous referee for suggesting this exercise.

[35] Industries with indexes of external financial dependence close to paper include cigarette manufacturing and glass manufacturing. Industries with indexes of external financial dependence close to batteries include transmission, distribution, and control equipment as well as communication equipment.

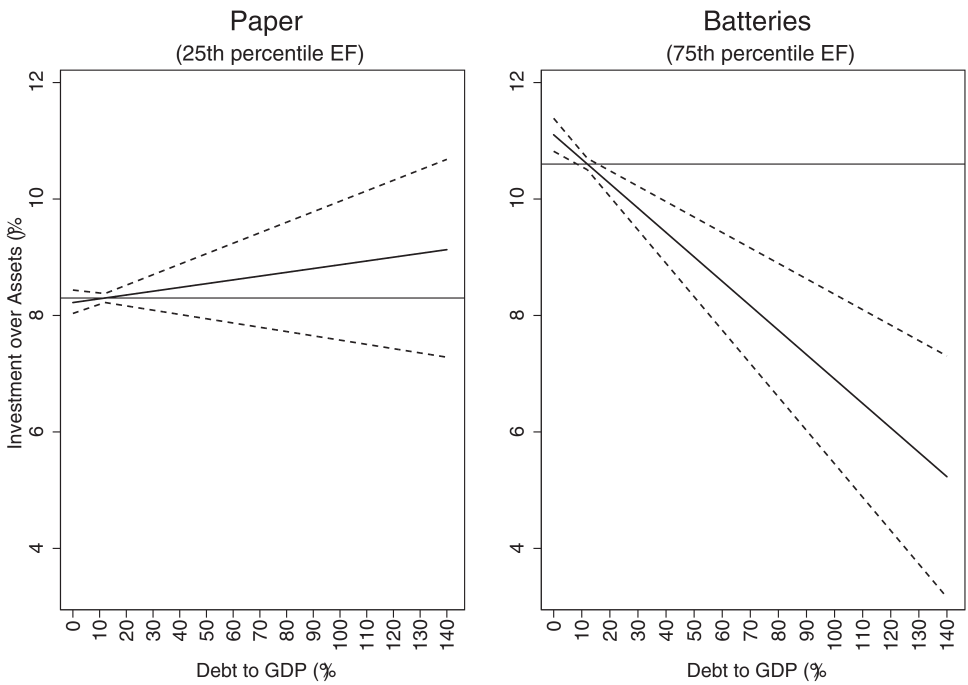

Figure 3. Local government debt and investment ratios in different industries. The figure shows how investment ratios vary with the level of government debt for manufacturing firms in the paper industry (25^{th} percentile of the distribution of the index of external financial dependence) and the battery industry (75^{th} percentile of the distribution of the index of external financial dependence). The graphs are based on the estimations of Table VIII, column (3). The dashed lines are 95% confidence intervals and the horizontal lines are the average investment ratios of the two industries (8.3% for paper and 10.6% for batteries).

VI. Cash-Flow Sensitivity with Exogenous Sample Split

The Rajan-Zingales approach enables us to identify credit rationing as the economic channel through which local crowding-out operates, but it is based on strong assumptions about the determinants of firms' external funding needs. For instance, it assumes that the external financing requirement of a paper-producing firm in Beijing is comparable to that of a paper producer in a small, isolated city. However, manufacturers in a given industry may well adapt their technologies to local conditions, so as to save on external funding. This would lead us to underestimate the impact of local government debt on manufacturing investment.[36]

To overcome this limitation, we adopt an empirical strategy that relies on firm-level estimates of cash-flow sensitivity to test whether government debt

[36] Moreover, the Rajan-Zingales methodology only measures the differential impact of government debt on firms that belong to industries characterized by different degrees of dependence, not the total effect of local government debt on investment.

tightens the financing constraints of private firms. Fazzari, Hubbard, and Petersen (1988) are the first to exploit the idea that investment sensitivity to internally generated funds should be greater for credit-constrained firms.[37] Love (2003) extends this approach to an international data set and shows that financial market depth is associated with lower sensitivity of investment to internal funds. Applying a variation of this approach to our sample of 261 Chinese cities, we demonstrate that local government debt tightens financing constraints on private-sector manufacturing firms, and we confirm Love (2003)'s finding that financial depth reduces the cash-flow sensitivity of investment.

The sensitivity of investment to cash flow has been criticized as a measure of financing constraints (Kaplan and Zingales (2000)), as cash flow may proxy for investment opportunities and the sensitivity could be driven by influential outliers or by firm distress.[38] We address this criticism in two ways. First, we split the sample into constrained versus unconstrained firms using an exogenous sample separation rule. In the Chinese case, it is natural to base such a sample split on private versus state ownership, since state-owned firms enjoy preferential treatment by banks and thus are less likely to be credit-constrained. Investment should therefore be more sensitive to cash flow in private firms than in state-owned firms, with such sensitivity greater, the larger is the debt-GDP ratio in the city in which the firm is located. We also explore differences between large and small firms.

Second, we endogenize the sample separation rule by estimating a switching model of investment in which the probability of a firm facing financing constraints is estimated jointly with firms' cash-flow investment sensitivity, along the lines of Hu and Schiantarelli (1998) and Almeida and Campello (2007). This approach does not hinge on a predetermined sample separation between constrained and unconstrained firms.

A. Baseline Regressions

Many studies model the effect of financing constraints on investment in the context of an Euler equation, that is, the optimality condition for a firm that maximizes the present value of dividends subject to adjustment costs and external financial constraints.[39] In particular, Love (2003) shows that linearizing the Euler equation yields a specification in which the investment-asset ratio depends on its lagged value, sales, cash flow, the interaction between cash flow,

[37] They capture credit constraints using average dividend payout. Bond and Meghir (1994) use the same proxy for credit constraints, while others apply a similar methodology but use other measures of financing constraints (Hoshi, Kashyap, and Scharfstein (1991), Whited (1992), Gertler and Gilchrist (1993)).

[38] Fazzari, Hubbard, and Petersen (2000) rebut Kaplan and Zingales (2000). Hadlock and Pierce (2010) criticize the Kaplan-Zingales index of financial constraints and suggest that firm size and age are most closely correlated with the presence of such constraints.

[39] See, for instance, Whited (1992), Hubbard and Kashyap (1992), and Gilchrist and Himmelberg (1995). The alternative approach of Hayashi (1982), based on the Q-theory of investment, requires share prices and therefore is unsuited to our sample, which consists mostly of unlisted firms.

and a measure of credit availability (i.e., an inverse measure of financing constraints), and a set of fixed effects.[40] We employ a similar model, but using city-level government debt as a measure of financing constraints:

$$I_{i,c,t} = \beta I_{i,c,t-1} + \delta REV_{i,c,t-1} + \big(\gamma_1 + \gamma_2 LGD_{c,t}\big) CF_{i,c,t-1} + \alpha_i + \theta_{ct} + \varepsilon_{i,c,t}, \qquad (6)$$

where $I_{i,c,t}$, $REV_{i,c,t}$, and $CF_{i,c,t}$ are the fixed capital investment, change in revenue, and cash flow of firm i in city c and year t (all scaled by beginning-of-year total assets), and $LGD_{i,c}$ is local government debt scaled by GDP in city c and year t. The specification also includes firm-level fixed effects (α_i) and city-year effects (θ_{ct}). The latter control for the direct effect of local government debt on firm-level investment, as well as for any other city-level time-variant macroeconomic variables. Hence, as in the regressions based on firms' differential within-city location in Section IV, identification in these regressions is driven by a within-city-year source of firm-level heterogeneity, which filters out macroeconomic city-level shocks that may induce spurious correlation between investment and local public debt.

In the presence of financing constraints, investment is expected to be positively correlated with internally generated funds (as proxied by cash flow), yielding a positive γ_1. A positive γ_2, instead, would be consistent with government debt crowding-out private investment via tighter financing constraints. This is the main hypothesis to be tested here.

Even though equation (6) exploits only within-firm and within-city-year variation in investment, cash flow, and the interaction between local public debt and cash flow, omitted variable bias could arise if the equation failed to control for sources of credit constraints correlated with local government debt. For instance, weak firms could become more credit-constrained during recessions, precisely when local governments increase borrowing for countercyclical reasons. If this were the case, our results would pick up this weakening effect and not the tightening of credit constraints brought about by higher government debt. To account for this possibility, we control for the interaction between cash flow and a host of variables that capture local economic conditions (local GDP growth, local budget balance, local bank loans, GDP per capita, and land prices) and show that our baseline results are robust to augmenting the model with all of these confounding variables.

When equation (6) is estimated for the full sample, γ_1 is positive and significant (column (1) in Table IX). The point estimate suggests that a one-standard-deviation increase in cash flow is associated with a 1.4 percentage-point increase in investment ratio. This is consistent with the presence of financing constraints for the average firm in a city with no public debt, although it may also result from cash flow capturing investment opportunities not captured by

[40] The model in Love (2003) does not allow for borrowing, and the external financial constraint involves the condition that the firm cannot pay negative dividends. Allowing for borrowing complicates the model but does not alter the first-order conditions for investment.

Table IX

Cash-Flow Sensitivity of Investment

This table reports results of regressions in which the dependent variable is the firm-level investment ratio (computed as investment scaled by total assets at the beginning of the year), and the explanatory variables are the lagged investment ratio (I_{t-1}), the change in revenue scaled by total assets (REV_{t-1}), lagged cash flow scaled by total assets (CF_{t-1}), and the interaction between CF_{t-1} and local government debt scaled by GDP (*LGD*). Column (1) reports estimates based on the full sample of manufacturing firms, column (2) those based on the subsample of private-sector manufacturing firms, column (3) those based on the subsample of state-owned manufacturing firms, column (4) those based on the subsample of large firms (top 25% of the distribution by assets), and column (5) those based on the subsample of small firms (bottom 25% of the distribution by assets). Robust standard errors clustered at the firm level are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

	(1)	(2)	(3)	(4)	(5)
I_{t-1}	-0.273^{***}	-0.280^{***}	-0.371^{***}	-0.230^{***}	-0.333^{***}
	(0.002)	(0.002)	(0.008)	(0.004)	(0.005)
REV_{t-1}	3.773^{***}	3.799^{***}	2.398^{***}	5.955^{***}	1.954^{***}
	(0.031)	(0.034)	(0.167)	(0.117)	(0.057)
CF_{t-1}	6.725^{***}	7.334^{***}	4.328^{***}	5.815^{***}	4.472^{***}
	(0.231)	(0.256)	(1.190)	(0.660)	(0.539)
$CF_{t-1} \times LGD$	0.028^{**}	0.029^{**}	-0.097	-0.020	0.075^{*}
	(0.011)	(0.013)	(0.055)	(0.026)	(0.030)
N. Obs.	1,035,400	858,624	45,922	110,091	107,694
N. Cities	261	261	261	261	261
Firm FE	Yes	Yes	Yes	Yes	Yes
City-Year FE	Yes	Yes	Yes	Yes	Yes
Sample	All	Private	State	Large	Small

other control variables (Kaplan and Zingales (2000)).[41] More importantly, for our purposes, γ_2 is positive and statistically significant. This result, which is immune to the Kaplan-Zingales critique, is consistent with the hypothesis that local government debt crowds out investment via tighter financial constraints. The point estimate implies that a one-standard-deviation increase in local government debt is associated with a 6% increase in the elasticity of investment to cash flow. The top left panel of Figure 4 plots the sensitivity of investment to cash flow at different levels of local government debt. The elasticity rises from 6.7 with zero government debt to 8.1 with a debt ratio of 50%.

If local public debt crowds out private investment by tightening local credit availability, this effect should be weaker for safer borrowers. As small firms are typically riskier than large firms, and private firms are riskier compared to state-owned firms that benefit from public guarantees, we split the sample along the size and ownership dimensions, and test whether γ_2 is larger for

[41] Kaplan and Zingales (2000) also suggest that the positive correlation between investment and cash flow could be driven by influential outliers or by a few firms in distress. However, such outliers are unlikely to be relevant in a sample like ours, with over 380,000 firms.

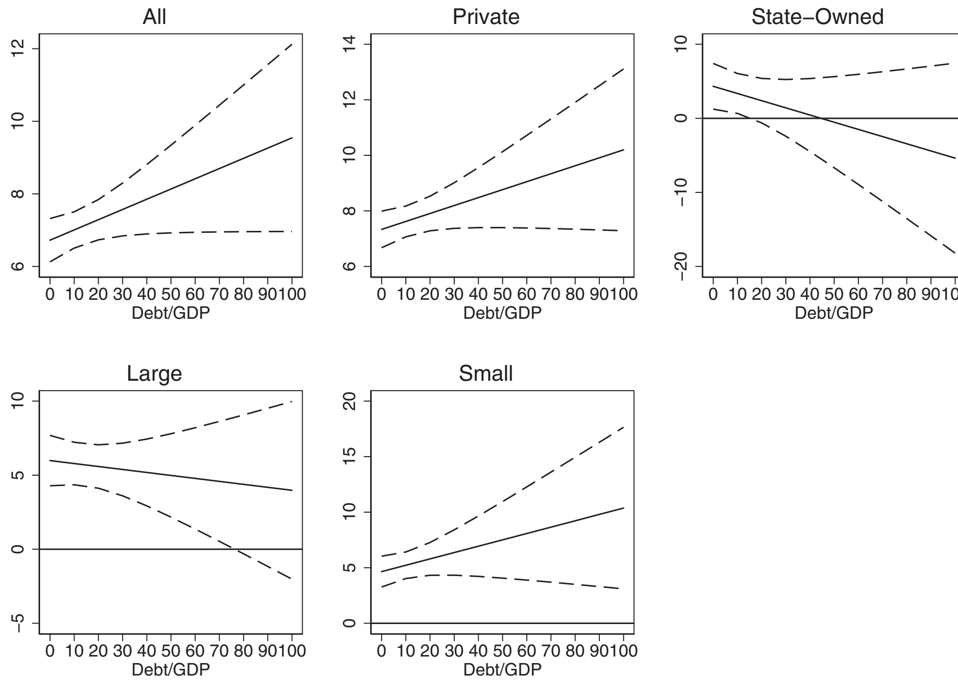

Figure 4. Investment sensitivity to cash flow. The figure shows how the sensitivity of investment to cash flow changes with the level of local government debt. These marginal effects are based on the estimates reported in Table IX.

private and small firms than for state-owned and large firms. We expect local government debt to lead to tighter credit for the former than for the latter.

When we estimate equation (6) for the subsample of private firms (column (2) of Table IX), the results are essentially the same as for the full sample but with tighter confidence intervals (see the top middle panel of Figure 4). For state-owned firms (column (3) of Table IX), the results are dramatically different. State-owned firms are less credit-constrained than the average firm (γ_1 decreases from 6.7 to 4.3), with the severity of the constraint inversely correlated with local government debt, so that state-owned firms essentially become unconstrained when local public debt reaches 20% of GDP; above that threshold, the correlation between cash flow and investment is no longer statistically significant (top right panel of Figure 4). This result suggests that at least some of the funds raised by Chinese cities via public debt issuance are channeled to local state-owned firms, mitigating or removing the credit constraints that they would otherwise face.

We obtain similar results upon splitting the sample between large firms (top quartile of the firm distribution by assets) and small firms (bottom quartile). The interaction between cash flow and local government debt is negative and not statistically significant for large firms (column (4) of Table IX, and bottom left panel of Figure 4), while it is positive and statistically significant for small firms (column (5) of Table IX and bottom right panel of Figure 4).

However, these specifications may omit an important variable, namely, the interaction between cash flow and total bank loans relative to GDP. Bank loans are likely to belong in equation (6) because they are correlated with both local government debt (as shown by Tables IA.II and IA.III in the Internet Appendix) and credit to the private sector, a variable that other studies find relaxes' credit constraints. As bank loans are positively correlated with local government debt and negatively correlated with credit constraints, their exclusion from the model should lead to a downward bias in the estimate of γ_2.[42] This is exactly what we find when we expand specification (6) by including the interaction between cash flow and bank loans as an explanatory variable. The point estimate of γ_2 almost triples (from 0.03 in column (1) of Table IX to 0.08 in column (1) of Table X): a one-standard-deviation increase in local government debt is thus associated with a 13 percentage-points increase in the elasticity of investment to cash flow. As expected, more bank lending also reduces the sensitivity of investment to cash flow, consistent with the view that bank loans proxy for local financial depth and thus relax credit constraints, as Love (2003) finds.

These results are robust to restricting the sample to private firms (column (2) of Table X), while government debt and bank loans have no statistically significant effect on the correlation between cash flow and investment in state-owned firms (column (3)). As before, government debt does not appear to tighten the credit constraints faced by large firms (column (4)), while it does do so for small firms (column (5)). Finally, the presence of large banks does not appear to mitigate the crowding-out effect of local government debt: the coefficient on the interaction between cash flow and government debt is slightly smaller in cities where the share of branches of large banks exceeds the sample median, but the difference between the two groups of cities is not statistically significant (column (6)). However, in these cities, the cash-flow sensitivity of firm investment is significantly lower, probably reflecting the greater financial development of these cities.

To explore how these results relate to credit market segmentation, we conduct an experiment analogous to that in Table IV: we use the city-level return to capital as a proxy for the geographic heterogeneity in credit frictions and check whether the credit scarcity due to local government debt issuance is particularly severe in cities with high return to capital, which presumably feature high barriers to capital flows. Specifically, we interact data on city-level return to capital (which are similar to those computed by Bai, Hsieh, and Qian (2006))

[42] Suppose that the true model is

$$y = \alpha + \beta LGD + \gamma BL + \epsilon,$$

where BL denotes bank loans, with $\gamma < 0$ and $\sigma_{LGD,BL} > 0$. If instead one estimates $y = a + bLGD + e$, the bias is

$$E(b) - \beta = \gamma \frac{\sigma_{LGD,BL}}{\sigma^2_{LGD}} < 0.$$

Table X

Cash-Flow Sensitivity of Investment: Controlling for Bank Loans

This table reports results of regressions in which the dependent variable is the firm-level investment ratio (computed as investment over total assets at the beginning of the year), and the explanatory variables are the lagged investment ratio (I_{t-1}), the change in revenue scaled by total assets (REV_{t-1}), lagged cash flow scaled by total assets (CF_{t-1}), and the interaction between CF_{t-1} and each of the following variables: local government debt scaled by GDP (LGD) and bank loans scaled by GDP (BL). Column (1) reports estimates based on the full sample of manufacturing firms, column (2) those based on the subsample of private-sector manufacturing firms, column (3) those based on the subsample of state-owned manufacturing firms, column (4) those based on the subsample of large firms (top 25% of the distribution by assets), and column (5) those based on the subsample of small firms (bottom 25% of the distribution by assets). In the specification reported in column (6), cash flow is interacted with a dummy (LB) that equals 1 if in the relevant city the share of the branches of the four largest Chinese banks in the total number of city branches exceeds the sample median, and 0 otherwise. Robust standard errors clustered at the firm level are reported in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

	(1)	(2)	(3)	(4)	(5)	(6)
I_{t-1}	−0.274***	−0.281***	−0.371***	−0.230***	−0.333***	−0.274***
	(0.002)	(0.002)	(0.008)	(0.004)	(0.005)	(0.002)
REV_{t-1}	3.770***	3.796***	2.393***	5.954***	1.951***	3.774***
	(0.031)	(0.033)	(0.168)	(0.135)	(0.067)	(0.031)
CF_{t-1}	8.343***	9.141***	6.020***	6.367***	7.062***	10.073***
	(0.374)	(0.411)	(1.902)	(1.193)	(1.037)	(0.447)
$CF_{t-1} \times LGD$	0.075***	0.083***	−0.044	−0.016	0.157***	0.073***
	(0.014)	(0.016)	(0.069)	(0.038)	(0.045)	(0.017)
$CF_{t-1} \times BL$	−0.022***	−0.025***	−0.023	−0.007	−0.035***	−0.031**
	(0.004)	(0.004)	(0.019)	(0.011)	(0.011)	(0.004)
$CF_{t-1} \times LGD \times LB$						−0.033
						(0.028)
$CF_{t-1} \times BL \times LB$						0.034***
						(0.007)
$CF_{t-1} \times LB$						−5.258***
						(0.708)
N. Obs.	1,035,400	868,624	45,922	110,091	107,694	1,035,383
N. Cities	261	261	261	261	261	261
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
City-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Sample	All	Private	State	Large	Small	All

with firm-level cash flow and local government debt, and we examine whether government debt triggers a larger increase in the cash-flow sensitivity of investment in cities where the return to capital is higher.[43]

Toward this end, we first split the sample into city-years with above- and below-median return to capital, and we estimate equation (6) separately for the two subsamples. Columns (1) and (2) of Table XI show that γ_2 is positive, large, and statistically significant in the subsample with high return to capital, while

[43] We thank an anonymous referee for suggesting this test, and Chong-En Bai for sharing his data on city-level return to capital.

Table XI

Cash-Flow Sensitivity of Investment and the Return to Capital

This table reports results of regressions in which the dependent variable is the firm-level investment ratio (computed as investment scaled by total assets at the beginning of the year), and the explanatory variables are the lagged investment ratio (I_{t-1}), change in revenue scaled by total assets (REV_{t-1}), lagged cash flow scaled by total assets (CF_{t-1}), and the interaction between CF_{t-1} and local government debt scaled by GDP (LGD). Columns (1) and (2) report estimates for the subsamples of manufacturing firms located in cities with above- and below-median return to capital, respectively. Columns (3) and (4) report estimates for the same models of columns (1) and (2) for the subsample of private-sector firms. Column (5) interacts government debt and cash flow with a continuous measure of city-level return to capital (RC), and column (6) also adds interactions with city-level bank loans scaled by GDP (BL). Robust standard errors clustered at the firm level are reported in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

	(1)	(2)	(3)	(4)	(5)	(6)
I_{t-1}	−0.304***	−0.228***	−0.313***	−0.235***	−0.272***	−0.272***
	(0.002)	(0.004)	(0.003)	(0.004)	(0.002)	(0.002)
REV_{t-1}	3.611***	4.151***	3.655***	4.137***	3.782***	3.782***
	(0.048)	(0.068)	(0.053)	(0.072)	(0.036)	(0.036)
CF_{t-1}	7.597***	6.500***	8.254***	6.851***	6.907***	6.791***
	(0.330)	(0.435)	(0.377)	(0.472)	(0.238)	(0.238)
$CF_{t-1} \times LGD$	0.167***	−0.018	0.162***	−0.019	0.051**	0.048***
	(0.033)	(0.020)	(0.037)	(0.022)	(0.021)	(0.021)
$CF_{t-1} \times RC$					−29.889***	−32.054***
					(3.065)	(3.170)
$CF_{t-1} \times LGD \times RC$					0.898***	0.868***
					(0.228)	(0.228)
$CF_{t-1} \times BL$						3.002***
						(0.6667)
$CF_{t-1} \times BL \times RC$						25.651***
						(8.521)
N. Obs	469,038	219,659	373,025	188,808	764,769	764,769
N. Cities	147	143	147	143	171	171
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
City-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Sample	High Ret. Cities All Firms	Low Ret. Cities All Firms	High Ret. Cities Private	Low Ret. Cities Private	All Cities All Firms	All Cities All Firms

it is negative, close to zero, and not statistically significant in the low-return subsample. Columns (3) and (4) show that the results are essentially identical if we limit our sample to firms in the private sector. In column (5), instead of relying on a sample split, we estimate the model with a triple interaction ($CF \times LGD \times RC$, where RC is a city-year continuous measure of return to capital) that aims to test if the estimated γ_2 is increasing in the return to capital. We find that the coefficient on this triple interaction is indeed positive and statistically significant, which supports the view that the credit scarcity due to high government debt issuance is more severe when return to capital is particularly high, which is also when the efficiency cost of local crowding-out is greatest. The results are unchanged when we also control for the interaction among return to capital, cash flow, and local financial depth (column (6)).

B. Robustness

We conduct a battery of robustness checks to ensure that the results reported so far survive additional controls, alternative subsamples, and different estimation techniques. None of the robustness tests alter our main finding, namely, that higher local government debt increases the sensitivity of investment to cash flow in private firms. The coefficient on the interaction between local government debt and cash flow is always positive, statistically significant, and almost equal to that in our baseline regression.

We start by showing that our results are robust to augmenting our model with the interactions between local government debt and city-level budget balance, GDP per capita, GDP growth, and land price (Table IA.XIV in the Internet Appendix). Next, we examine whether firms exposed to government projects have easier access to credit. While we find that private firms more exposed to LGFV-funded projects are less credit-constrained than less exposed firms, all of our baseline results are robust to controlling for exposure to LGFV-funded projects (Table IA.XV in the Internet Appendix).

In an additional battery of robustness tests, we find that our results are stronger if we focus on highly leveraged firms and that they are robust to: estimating our baseline models with a standard system GMM estimator, dropping the lagged dependent variable, dropping firms located in provinces for which our debt measure exceeds the official debt as published by the NAO (namely, Beijing, Tianjin, and 14 other cities located in Jiangsu and Zhejiang provinces), restricting the sample to 212 medium-sized cities (population of 1-10 million), restricting our estimates to the post-2007 period when local government borrowing began to soar, and restricting attention to data drawn from the Annual Survey of Industrial Firms.[44]

VII. Cash-Flow Sensitivity with Endogenous Sample Split

In the regressions presented so far, a firm's financing status—credit-constrained or not—is identified by exogenously splitting the sample. There are two problems with this approach (Hu and Schiantarelli (1998)): first, it does not jointly control for all of the factors that affect firms' substitution of external funds with internal funds, and second, it does not allow for firms switching from being credit-constrained to unconstrained or vice versa.

We address these issues by estimating an endogenous switching model with unknown sample separation. As in Hu and Schiantarelli (1998) and Almeida and Campello (2007), at each point in time, a firm is assumed to operate in one of two regimes: credit-constrained, where investment is sensitive to internal funds, or unconstrained, where it is not. The probability of a firm being in one

[44] See Tables IA.XVII to IA.XXII of the Internet Appendix.

regime or the other is determined by a switching function that depends on firm characteristics that capture the severity of the frictions the firm faces at a given point in time.

Formally, we jointly estimate the three equations

$$W^*_{i,c,t} = M_{i,c.t}\psi + u_{i,c,t}, \tag{7}$$

$$I_{1,i,c,t} = X_{i,c,t}\alpha_1 + \epsilon_{1,i,c,t}, \tag{8}$$

$$I_{2,i,c,t} = X_{i,c,t}\alpha_2 + \epsilon_{2,i,c,t}, \tag{9}$$

where W^* is a latent variable capturing the probability that firm i in period t is in one of the two regimes.

Equation (7) is the selection equation that estimates the likelihood that the firm is in the unconstrained regime 1 ($I_{i,c,t} = I_{1,i,c,t}$ if $W^*_{i,c,t} < 0$) versus the constrained regime 2 ($I_{i,c,t} = I_{2,i,c,t}$ if $W^*_{i,c,t} \geq 0$) as a function of variables M that proxy for financial strength and other factors that may amplify agency problems and thus lead to a tightening of financing constraints. Following the literature, we model selection into the two regimes as a function of the log of firm age, the log of total assets, distance to default (Altman Z-score), a time-invariant measure of industry-level asset intangibility, a dummy variable for firm type (one for private domestic firms, zero otherwise), and local government debt.[45] A firm's likelihood of being credit-constrained is expected to decrease with age, size, distance to default, and asset tangibility, and to increase with private ownership and local government debt.

Equations (8) and (9) are the investment equations for unconstrained and for constrained firms, respectively. Their specification is the same as in the baseline model of equation (6), but allows the coefficients of the two financing regimes to differ.[46] The regimes are not observable but are determined endogenously by the system of equations (7) to (9).

As in Hu and Schiantarelli (1998), the parameters ψ, α_1, and α_2 are jointly estimated by maximum likelihood, under the assumption that the error terms of the switching and investment equations are jointly normally distributed with zero mean, allowing for nonzero correlation between shocks to investment and shocks to the firm characteristics that determine the regime.

Column (1) of Table XII reports the results for a specification that includes city and year fixed effects. As expected, the selection equation (Panel A) shows

[45] Almeida and Campello (2007) also consider dividend payments, bond ratings, short- and long-term debt, and financial slack. Unfortunately, our data set does not contain these variables. In building the Z-score, we use emerging market-specific weights as suggested by Altman (2005). Specifically, we set $Z = 3.25 + 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4$, where $X_1 = \frac{(\textit{Current Assets}-\textit{Current Liabilities})}{\textit{Total Assets}}$, $X_2 = \frac{\textit{Retained Earnings}}{\textit{Total Assets}}$, $X_3 = \frac{\textit{EBIDTA}}{\textit{Total Assets}}$, and $X_4 = \frac{\textit{Book Value of Equity}}{\textit{Total Liabilities}}$. Which determinants of financial constraints are the true determinants is the subject of a lively debate in the literature (Farre-Mensa and Ljungqvist (2016)).

[46] The switching model does not converge when we include firm fixed effects.

Table XII

Switching Regression Model

This table reports results of the switching regression model described in equations (7) to (9). The selection equation (Panel A) controls for the log of firm age (ln(*Age*)), the log assets (ln(*Assets*)), distance to default (*Zscore*), a time-invariant industry-level measure of the share of tangible assets over total assets (*Tangible*), a dummy that takes a value of 1 for private-sector firms (*Private*), and a time-variant measure of city-level local government debt (*LGD*). The coefficients (and standard errors) in the selection equation are multiplied by 100 to facilitate readability. The investment equation (Panel B) controls for lagged cash flow (*CF*), the interaction between lagged cash flow and local government debt (*LGD*), lagged investment (not reported), and revenue growth (not reported). Model 1 includes city and year fixed effects, Model 2 includes city-year fixed effects, and Model 3 includes city-year and industry-year fixed effects. For each model, we report separate investment equations for firms that are not credit-constrained (regime 1) and credit-constrained firms (regime 2). Robust standard errors clustered at the firm level are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Panel A. Selection Equation

	(1)	(2)	(3)
ln(*Age*)	10.770***	7.176***	8.437***
	(0.077)	(0.072)	(0.066)
ln(*Assets*)	0.396**	0.685***	1.680***
	(0.034)	(0.002)	(0.027)
Zscore	0.097***	0.994***	0.918***
	(0.018)	(0.016)	(0.011)
Private	−8.943***	−5.063***	−4.248***
	(0.141)	(0.132)	(0.117)
Tangible	8.401***	4.642***	
	(0.280)	(0.261)	
LGD	−0.012*		
	(0.001)		
N. Obs	1,060,404	1,060,404	1,060,404

Panel B. Investment Equation

	(1.1) Not Constr.	(1.2) Constr.	(2.1) Not Constr.	(2.2) Constr.	(3.1) Not Constr.	(3.2) Constr.
CF_{t-1}	15.65***	4.158***	2.969***	8.208***	13.931***	7.125***
	(0.030)	(0.183)	(0.240)	(0.187)	(3.231)	(0.028)
$CF_{t-1} \times LGD$	−0.410***	0.142***	−0.056***	0.047***	−0.333***	0.114***
	(0.001)	(0.009)	(0.001)	(0.010)	(0.01)	(0.001)
LGD	−0.013***	−0.041***				
	(0.001)	(0.004)				
N. Obs.	305,603	754,800	2745,048	785,355	231,967	828,436
City FE	Yes		No		No	
Year FE	Yes		No		No	
City-Year FE	No		Yes		Yes	
Ind-Year FE	No		No		Yes	

that the likelihood of being unconstrained is increasing in firm age, size, distance to default, and asset tangibility, while it is lower for private-sector firms and in city-years with high local government debt.

The investment equations (Panel B) show that, for unconstrained firms (column (1.1)), the correlation between cash flow and investment is decreasing in local government debt: local public debt issuance allows these firms to decouple their investment from internal resources even more, probably because unconstrained firms are mostly state-owned and so enjoy more generous funding from local governments. For credit-constrained firms (column (1.2)), the correlation between investment and cash flow is positive and increasing in the level of government debt, confirming the results of the previous sections. Again, this finding reflects the fact that credit-constrained firms are disproportionately private.

Column (2) of Table XII reports the results for a model that includes city-year fixed effects, which absorb the variation in local government debt in the regime selection equation. The probability of being unconstrained is again estimated to be lower for private-sector firms and increasing in firm age, size, distance to default, and asset tangibility. Moreover, in unconstrained firms, the sensitivity of investment to cash flow is again decreasing in local government debt. The point estimates for unconstrained firms in column (2.1) show that the sensitivity of investment to cash flow is positive in city-years with no local government debt but drops to zero when local government debt reaches 5% of GDP. For credit-constrained firms (column (2.2)), the opposite holds: the sensitivity of investment to cash flow is much greater and is again increasing in local government debt.

Finally, column (3) reports estimates of a specification that includes city-year and industry-year effects, which absorb the effects of asset tangibility (defined at the industry level). The results are almost identical to those in column (2).

VIII. Conclusion

China reacted to the global financial crisis with a massive fiscal stimulus package, funded mainly by the issuance of local government debt and focused largely on public investment. In 2009, the growth rate of fixed capital formation was nearly twice its precrisis rate, with the contribution of fixed investment to Chinese GDP growth almost 90% (Wen and Wu (2019)). This surge in investment was achieved by injecting enormous financial resources into state-owned firms: the leverage of state-owned manufacturing firms rose from 57.5% in 2008Q1 (precrisis) to 61.5% in the first quarter of 2010, while for private-sector manufacturing firms, it slipped from 59% to 57% (Wen and Wu (2019)).

At first glance, the stimulus was a resounding success—China escaped the Great Recession and became one of the main drivers of world economic growth. However, our estimates suggest that the massive increase in local government debt had an adverse impact on investment by private manufacturing firms. As these are much more productive than their state-owned counterparts (Song, Storesletten, and Zilibotti (2011)), this reallocation of investment from the private to the public sector could undercut China's long-run growth potential, especially in the regions in which local governments have issued the largest amount of debt. Moreover, by increasing the share of public debt in banks' asset portfolios, this policy has strengthened the bank-sovereign nexus in China, which creates the potential for serious risks to systemic stability in the future, as the euro-area sovereign debt crisis has forcefully demonstrated (see Acharya, Drechsler, and Schnabl (2014), Acharya and Steffen (2015), and Altavilla, Pagano, and Simonelli (2017), among others).

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix.
Replication code.