Online Appendix

A Supplementary Analyses

Figure A1: Data Source

(A) Procurement website

(B) Bid-winner information

Figure A2: M2 year-on-year Growth

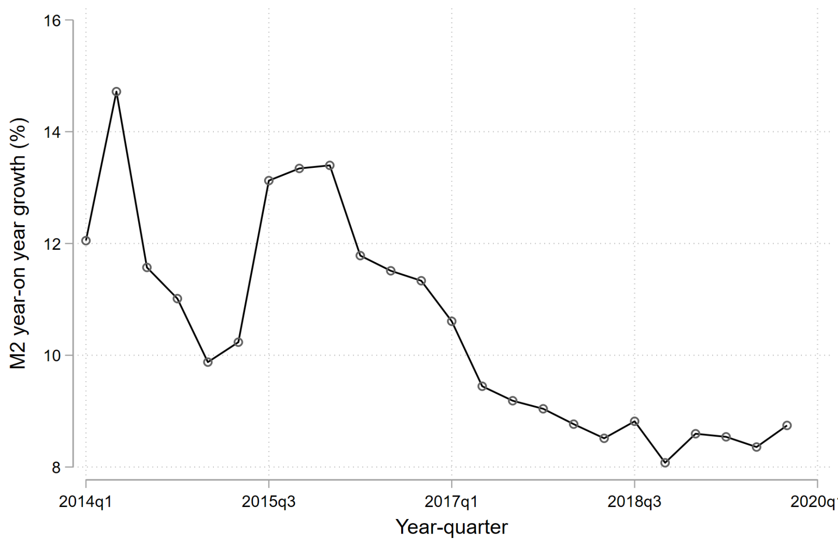
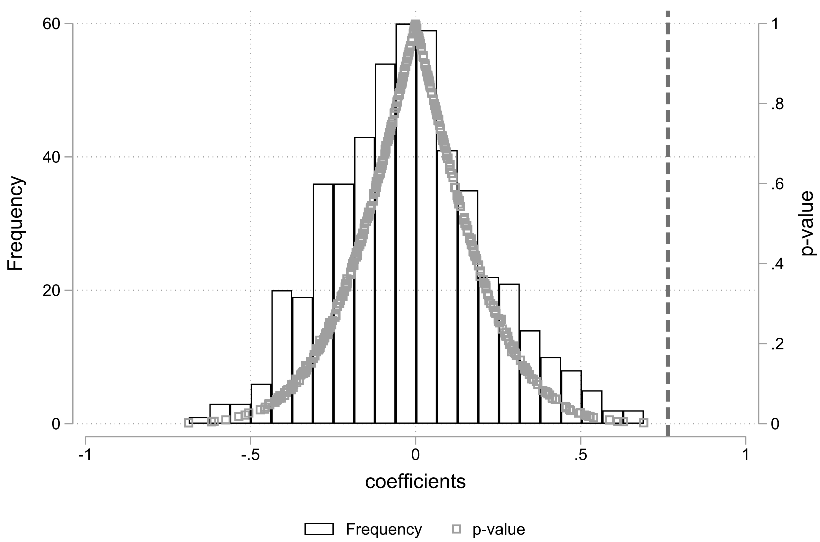


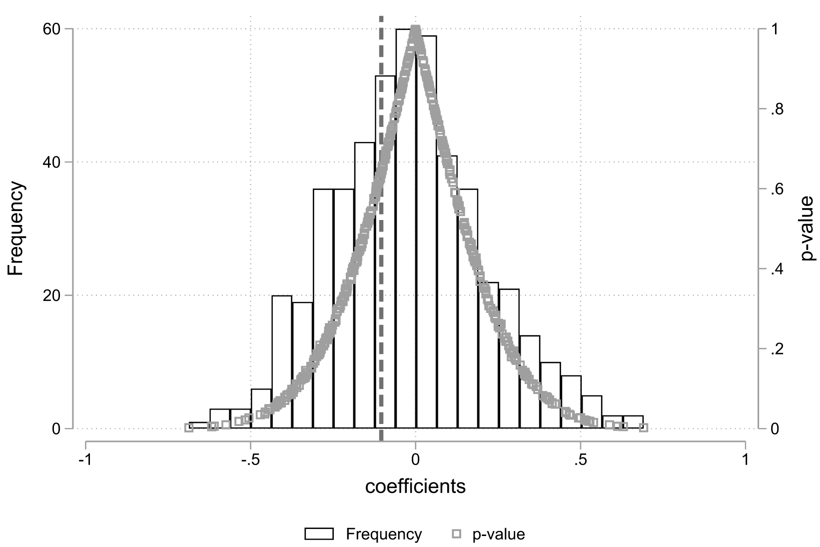
Figure A3: Placebo Tests: Random Draws of the Treatment Group

Note: This figure plots the regression results of placebo tests with the distribution (bars) of the regression coefficients and the corresponding p-values (gray squares) for the key variable ($GPfirm_i^R \times post2017_t$). We keep the proportion of GP firms in the sample of non-SOEs and SOEs unchanged, then redistribute GP firms through random sampling and perform regression according to specification A3. We repeat random sampling and regression 500 times. The gray dashed lines mark the coefficients in the baseline regression.

$$A/R_{it} = \alpha + \beta GPfirm_i^R \times Post2017Q2_t + \eta \mathbf{X}_{it-1} + \gamma_i + \gamma_t + \gamma_d * Quarter_t + \gamma_d * M2Growth_t + \epsilon_{it}$$



(A) Placebo test - Non-SOE



(B) Placebo test - SOE

Figure A4: Share Pledging and Stock Market Returns

Note: This figure shows a binned scatter plot of the relationship between the annual stock returns and pledge ratios of controlling shareholders using panel data of A-share listed companies between 2014 and 2019. The y-axis is the annual stock return data obtained from CSMAR for firm i in year t. The x-axis is the year-end percentage of controlling shareholders' pledged equity ratio $Pledgeratio_{it-1}$ for firm i in year $t-1$.

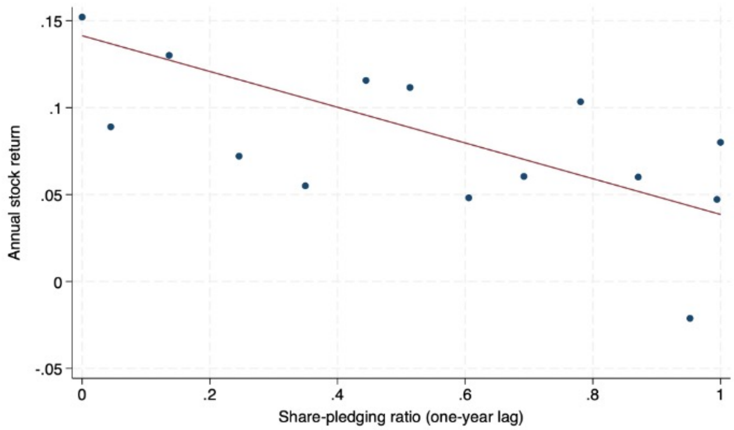


Table A1: Summary Statistics: Firm-Quarter Panel, Non-SOEs vs. SOEs

	Non-SOE						SOE					
VARIABLES	N	mean	sd	min	p50	max	N	mean	sd	min	p50	max
Firm Characteristics												
Top5_gov_client	37,387	0.0590	0.236	0	0	1	21,340	0.0755	0.264	0	0	1
Mean_top5_gov_client	37,387	0.0629	0.333	0	0	4.667	21,340	0.0887	0.414	0	0	4.667
Dependent Variables												
A/R (asset ratio,%)	37,387	13.82	9.735	0.326	12.36	33.83	21,340	9.646	9.364	0.326	6.272	33.83
Payable (asset ratio,%)	33,819	8.087	5.731	0.912	6.796	23.43	19,566	9.779	6.714	0.912	8.141	23.43
Inventory (asset raito,%)	36,958	13.38	10.11	0.405	11.10	40.49	21,297	14.38	11.96	0.405	11.65	40.49
Cash holding (asset ratio,%)	37,386	15.90	11.80	0.872	12.72	67.35	21,340	15.01	10.76	0.872	12.28	67.35
Leverage (%)	37,387	39.18	20.48	4.589	37.51	97.73	21,340	50.75	21.03	4.589	50.93	97.73
Lev short (asset ratio,%)	37,387	31.77	16.39	7.264	30.12	67.45	21,340	37.95	17.27	7.264	36.72	67.45
Lev short2 (asset ratio,%)	33,819	23.30	14.08	3.503	21.38	54.80	19,566	27.75	14.63	3.503	26.18	54.80
Lev long (asset ratio,%)	36,780	7.023	8.074	0.0732	3.550	31.22	21,230	11.43	10.11	0.0732	8.336	31.22
Invest (million RMB)	37,262	318.2	550.8	0	91.71	2,528	21,304	449.0	727.5	0	110.7	2,528
Invest (asset ratio, %)	37,262	6.181	8.116	0	2.561	29.25	21,304	3.615	5.905	0	1.291	29.25
Revenue (asset ratio,%)	37,384	14.68	10.62	0.439	12.45	65.33	21,340	15.86	12.20	0.439	12.73	65.33
Revenue growth(%)	37,362	28.79	86.69	-83.64	11.96	555.6	21,337	19.79	78.67	-83.64	5.818	555.6
Cost (asset ratio,%)	37,387	13.37	8.380	2.155	11.45	35.36	21,340	14.53	9.470	2.155	12.29	35.36
Gross profit (asset ratio,%)	37,387	1.241	1.625	-2.116	1.076	4.588	21,340	0.931	1.457	-2.116	0.770	4.588
ROA	37,387	1.024	1.424	-2.025	0.906	3.909	21,340	0.736	1.276	-2.025	0.611	3.909
ROE	37,387	1.680	2.508	-4.371	1.562	6.823	21,340	1.456	2.546	-4.371	1.404	6.823
Control Variables												
Size (ln, lag)	37,387	21.91	1.062	20.18	21.81	24.98	21,340	22.77	1.265	20.18	22.68	24.98
Fixed asset ratio (%, lag)	37,385	18.29	13.04	0.696	16.07	51.08	21,339	24.12	16.70	0.696	21.07	51.08
Leverage (%, lag)	37,387	38.73	19.68	9.636	37.01	82.15	21,340	50.41	20.10	9.636	51.02	82.15
Revenue ratio (%, lag)	37,387	14.19	8.721	1.974	12.45	36.59	21,340	15.09	9.768	1.974	12.77	36.59
Revenue growth (%, lag)	37,387	19.23	40.51	-47.43	12.38	116.2	21,340	11.89	37.15	-47.43	5.888	116.2
Control Variables (Only with firm-year level variations												
Top 10 share ratio (%)	37,387	56.47	14.44	23.33	57.36	92.29	21,304	57.54	15.45	23.33	57.27	92.29
IDP director ratio (%)	37,387	38.01	5.597	20.00	36.36	75.00	21,300	37.30	5.823	23.08	35.71	80.00
Employment (ln, lag)	37,379	7.436	1.215	1.946	7.415	12.34	21,302	8.144	1.395	2.890	8.120	13.21

Table A2: Robustness Tests

Note: This table reports the robustness test results of the impact of government deleveraging on firms' accounts receivable. We estimate the following DID model using a firm-quarter panel of non-financial firms listed on China's A-share stock market between 2014Q1 and 2019Q4:

$$A/R_{it} = \alpha + \beta GPfirm_i \times Post2017Q2_t + \eta X_{it-1} + \gamma_i + \gamma_t + \gamma_d * Quarter_t + \gamma_d * M2Growth_t + \epsilon_{it}$$

where A/R measures accounts receivable divided by total assets of firm i (with industry d) in year-quarter t. $Post2017Q2_t$ equals one for year-quarters in the post-deleveraging period between 2017Q2 and 2019Q4 and zero for the pre-deleveraging period between 2014Q1 and 2017Q1. $GPfirm_i$ equals one if firm i obtained at least one GP contract between 2014 and 2016 and zero if firm i never obtained any GP contracts throughout our sample period. $GPfirm12_i$ equals one if firm i had obtained GP contracts between 2010 and 2012 and zero if firm i had never obtained any GP contracts throughout our sample period. Initial firm size and leverage refer to the values at the beginning of our sample period in 2014. $\mathbf{X}_{it-1}$ is a vector of control variables, including firm size ($SizeL$, log scale), employment ($EmployL$, log scale), financial leverage ($LevL$), fixed asset ratio ($FixedassetL$, divided by total assets), total revenue ratio ($RevenueL$, divided by total assets), the growth rate of total revenue ($RevGrowthL$), the shareholding ratio of top 10 major shareholders ($Top10ShareL$) and the fraction of independent directors ($IDPdirectorL$), all lagged by one period. $EmployL$, $Top10ShareL$ and $IDPdirectorL$ vary at firm-year level and other control variables vary at firm-year-quarter level. γ_i and γ_t denote firm fixed effects and year-quarter fixed effects, respectively. $\gamma_d * Quarter_t$ are industry-by-quarter fixed effects. $\gamma_d * M2Growth_t$ are the industry times M2 growth fixed effects, with $M2Growth_t$ measured by the quarterly year-on-year M2 growth released by the central bank. ϵ_{it} represents the error term. Standard errors are adjusted for firm-level clustering and reported in parentheses. ***, **, * denote statistical significance levels at 1%, 5%, and 10%, respectively.

VARIABLES	**A/R (divided by assets,%)**				
	OLS	OLS	OLS	OLS	IV
	(1)	(2)	(3)	(4)	(5)
GPfirm × Post2017Q2	0.854***		0.965***		0.872**
	(0.233)		(0.193)		(0.361)
GPfirm12 × Post2017Q2				0.675**	
				(0.280)	
GPfirm × Post2016Q2		0.552**	-0.157		
		(0.241)	(0.205)		
Initial Firm Size × Post2017Q2	-0.510***	-0.478***	-0.508***	-0.410***	-0.433***
	(0.126)	(0.126)	(0.126)	(0.141)	(0.142)
Initial Firm Leverage × Post2017Q2	0.018***	0.018***	0.018***	0.015**	0.015**
	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
Observations	37,349	37,220	37,220	28,853	28,853
R-squared	0.872	0.871	0.872	0.868	0.060
First Stage F					1186.10
Mean of D.V.	13.82	13.82	13.82	13.82	13.82
Controls	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES
Year-Quarter FE	YES	YES	YES	YES	YES
Industry × Quarter FE	YES	YES	YES	YES	YES
Industry FE × M2Growth	YES	YES	YES	YES	YES

Table A3: Government Deleveraging and Discretionary vs. Non-discretionary Spending

Note: This table reports the impact of government deleveraging on different types of government spending: general fiscal expenditures, local investments, and government procurements. We estimate the following DID model using a city-year panel of 298 cities between 2014 and 2019:

$$Y_{ct} = \alpha + \beta HighRepayRatio_p \times Post2017_t + \eta \mathbf{X}_{ct-1} + \gamma_c + \gamma_t + \gamma_{pt} + \epsilon_{ct}$$

Y_{ct} measures general-budget fiscal expenditures, urban investments, the number of government procurements, and the money value of government procurements of city c of province p in year t, all in natural log scale. $HighRepayRatio_p$ equals one for cities in province p with an above-median average repayment ratio of MCBs issued in the post-deleveraging period (the high-repayment-pressure group) and zero otherwise (the low-repayment-pressure group). $Post2017_t$ equals one for years in the post-deleveraging period between 2017 and 2019 and zero for the pre-deleveraging period between 2014 and 2016. $\mathbf{X}_{ct-1}$ is a vector of control variables, including GDP, population, average wage, and fiscal revenue (all lagged by one year and in log scale). γ_c, γ_t, and γ_{pt} denote city, year, and province-by-year fixed effects, respectively. ϵ_{it} represents the error term. Standard errors are adjusted for firm-level clustering and reported in parentheses. ***, **, * denote statistical significance levels at 1%, 5%, and 10%, respectively.

VARIABLES	Fiscal Expenditures (ln) (1)	Urban Investments (ln) (2)	Procurements (Number, ln) (3)	Procurements (Value, ln) (4)
HighRepayRatio × Post2017	-0.015	-0.087	-0.591***	-0.453**
	(0.011)	(0.103)	(0.109)	(0.182)
Observations	1,613	1,561	1,573	1,573
R-squared	0.987	0.882	0.906	0.777
Mean of D.V. (Level)	35,744	5,294	936.6	2,850
Controls	YES	YES	YES	YES
City FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Province ×Year Trend	YES	YES	YES	YES

Table A4: Mechanism: Firm's Dependence on the Government as Buyers

Note: This table reports the impact of local government deleveraging on non-SOE firms' working capital management. We use a firm-quarter panel of non-financial firms listed on China's A-share stock market between 2014 and 2019:

$$A/R_{it} = \alpha + \beta Top5ClientGov_i \times Post2017Q2_t + \eta \mathbf{X}_{it-1} + \gamma_i + \gamma_t + \gamma_d * Quarter_t + \gamma_d * M2Growth_t + \epsilon_{it}$$

A/R_{it} measures accounts receivable divided by total assets of firm i (with industry d) in year-quarter t. $Post2017Q2_t$ equals one for year-quarters in the post-deleveraging period between 2017Q2 and 2019Q4 and zero for the pre-deleveraging period between 2014Q1 and 2017Q1. $Top5ClientGov\_Dummy_i$ equals one if firm i revealed certain government departments as its top 5 clients between 2014 and 2016 and zero otherwise. $Top5ClientGov\_Number_i$ denotes the average number of government departments as its top 5 clients between 2014 and 2016. The first and second columns retain all samples. The third and fourth columns retain only samples that disclose information about the top five customers. The fifth and sixth columns retain only samples that disclose specific customer information, i.e., samples that disclose anonymous information such as "Customer 1" are deleted. $\mathbf{X}_{it-1}$ is a vector of control variables, including firm size ($SizeL$, log scale), employment ($EmployL$, log scale), financial leverage ($LevL$), fixed asset ratio ($FixedassetL$, divided by total assets), total revenue ratio ($RevenueL$, divided by total assets), the growth rate of total revenue ($RevGrowthL$), the shareholding ratio of top 10 major shareholders ($Top10ShareL$) and the fraction of independent directors ($IDPdirectorL$), all lagged by one period. $EmployL$, $Top10ShareL$ and $IDPdirectorL$ vary at the firm-year level and other control variables vary at the firm-year-quarter level. γ_i and γ_t denote firm fixed effects and year-quarter fixed effects, respectively.$\gamma_d * Quarter_t$ are industry-by-quarter fixed effects. $\gamma_d * M2Growth_t$ are the industry times M2 growth fixed effects, with $M2Growth_t$ measured by the quarterly year-on-year M2 growth released by the central bank. ϵ_{it} represents the error term. Standard errors are adjusted for firm-level clustering and reported in parentheses. ***, **, * denote statistical significance levels at 1%, 5%, and 10%, respectively.

VARIABLES	**A/R (divided by assets,%)**					
	Full Sample		Customers Disclosure		Specific Customers	
	(1)	(2)	(3)	(4)	(5)	(6)
Top5ClientGov_Dummy × Post2017Q2	0.839*		0.845*		1.006	
	(0.452)		(0.484)		(0.706)	
Top5ClientGov_Number × Post2017Q2		0.685***		0.522**		0.592
		(0.242)		(0.253)		(0.385)
Observations	37,373	37,373	28,640	28,640	5,919	5,919
R-squared	0.872	0.872	0.875	0.875	0.894	0.894
Mean of D.V.	13.82	13.82	13.84	13.84	11.88	11.88
Controls	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Year-Quarter FE	YES	YES	YES	YES	YES	YES
Industry × Quarter FE	YES	YES	YES	YES	YES	YES
Industry FE × M2 Growth	YES	YES	YES	YES	YES	YES

Table A5: Impacts on Leverage

Note: This table reports regression results showing the impact of government deleveraging on non-SOE firms' leverage. We use a firm-quarter panel of non-financial firms listed on China's A-share stock market between 2014 and 2019:

$$Y_{it} = \alpha + \beta GPfirm_i \times Post2017Q2_t + \eta \mathbf{X}_{it-1} + \gamma_i + \gamma_t + \gamma_d * Q_t + \gamma_d * M2Growth_t + \epsilon_{it}$$

Y_{it} include total liabilities divided by total assets ($Total$), current liabilities divided by total assets ($Current$), current liabilities minus accounts payable divided by total assets ($Current - A/P$), and non-current liabilities divided by total assets ($Long$) of firm i (with industry d) in year-quarter t. $Post2017Q2_t$ equals one for year-quarters in the post-deleveraging period between 2017Q2 and 2019Q4 and zero for the pre-deleveraging period between 2014Q1 and 2017Q1. $GPfirm_i$ equals one if firm i obtained at least one GP contract between 2014 and 2016 and zero if firm i never obtained any GP contracts throughout our sample period. $\mathbf{X}_{it-1}$ is a vector of control variables, including firm size ($SizeL$, log scale), employment ($EmployL$, log scale), financial leverage ($LevL$), fixed asset ratio ($FixedassetL$, divided by total assets), total revenue ratio ($RevenueL$, divided by total assets), the growth rate of total revenue ($RevGrowthL$), the shareholding ratio of top 10 major shareholders ($Top10ShareL$) and the fraction of independent directors ($IDPdirectorL$), all lagged by one period. $EmployL$, $Top10ShareL$ and $IDPdirectorL$ vary at the firm-year level and other control variables vary at the firm-year-quarter level. γ_i and γ_t denote firm fixed effects and year-quarter fixed effects, respectively. $\gamma_d * Q_t$ are industry-by-quarter fixed effects. $\gamma_d * M2Growth_t$ are the industry times M2 growth fixed effects, with $M2Growth_t$ measured by the quarterly year-on-year M2 growth released by the central bank. ϵ_{it} represents the error term. Standard errors are adjusted for firm-level clustering and reported in parentheses. ***, **, * denote statistical significance levels at 1%, 5%, and 10%, respectively.

VARIABLES	Liability-to-Asset Ratios			
	Total	Current	Current-A/P	Long
	(1)	(2)	(3)	(4)
GPfirm × Post2017Q2	0.560	1.308***	1.066**	-0.789***
	(0.585)	(0.490)	(0.423)	(0.300)
Observations	37,373	37,373	33,804	36,756
R-squared	0.825	0.795	0.770	0.689
Mean of D.V.	39.18	31.77	23.30	7.02
Controls	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Year-Quarter FE	YES	YES	YES	YES
Industry × Quarter FE	YES	YES	YES	YES
Industry FE × M2Growth	YES	YES	YES	YES

Table A6: Impact on Employment

Note: This table reports regression results showing the impact of government deleveraging on firms' employment using a firm-year panel data of non-financial firms listed on China's A-share stock market between 2014 and 2019:

$$Employ_{i(d)t} = \alpha + \beta GPfirm_i \times post2017_t + \eta X_{it-1} + \gamma_i + \gamma_t + \epsilon_{it}$$

$Employ_{i(d)t}$ is employment divided by the total assets (# per billion yuan) of firm i (with industry d) in year t. $Post2017_t$ equals 0 for pre-policy periods between 2014 and 2016 and takes the value of 1 for post-policy periods between 2017 and 2019. $GPfirm_i$ equals one if firm i obtained at least one GP contract between 2014 and 2016 and zero if firm i never obtained any GP contracts throughout our sample period. The vector of control variables X_{it-1} include lagged values of firm size ($SizeL$), lagged values of firm total employment (logged) ($EmployL$), financial leverage ($LevL$), fixed asset ratio ($FixedassetL$, divided by total assets), total revenue ratio ($RevenueL$, divided by total assets), the growth rate of total revenue ($RevGrowthL$), the shareholding ratio of top 10 major shareholders ($Top10ShareL$) and the fraction of independent directors ($IDPdirectorL$). γ_i and γ_t denote firm fixed effects and year fixed effects, respectively. ϵ_{it} represents the error term. Standard errors are adjusted for firm-level clustering and reported in parentheses. ***, **, * denote statistical significance levels at 1%, 5%, and 10%, respectively.

	Non-SOE	
	(1)	(2)
VARIABLES	Employment	
GPfirm × Post2017	-6.602	-8.211
	(13.221)	(10.769)
Observations	8,968	8,965
R-squared	0.865	0.885
Mean of dep. var.	711.678	711.678
Controls	NO	YES
Firm FE	YES	YES
Year FE	YES	YES

B Matching GP Contracts with Listed Firms

We adopt natural language processing (NLP) methods to address two empirical challenges in analyzing the unstructured text of procurement announcements.

First, to match procurement contracts with corresponding local governments, we use the CPCA package to extract administrative information from the title of each announcement, which usually includes the three-tiered provincial-prefecture-county name of the purchasing government. When our algorithm fails to identify a province name, it is usually because the procurement announcement came from the central government. There are 411,471 procurement announcements for which we cannot identify a province, accounting for approximately 11% of our observations.

Second, to match publicly traded firms with firms winning GP orders, we use the spaCy package to perform named entity detection to extract firm names from GP contracts. We also extract the date and budgetary expenditure amounts of each GP announcement. We successfully identify approximately 810,000 GP firm names from 85% of the procurement announcements. We then adopt both exact and fuzzy matching methods to match firms. While we have the full names of all listed firms and their affiliates, the exact names may not appear in the GP announcements, especially when the winning bidder is an affiliated company. To address discrepancies in firm names, we match procurement firms with listed firms with exact and fuzzy matching. We develop a customized fuzzy matching method based on Chinese word segmentation by first building a dictionary including common suffixes of company names, such as "Ltd." (*youxian gongsi*) or "Co. Ltd." (*gufen youxian gongsi*) in Chinese. We then segment companies' names and compare the differences between the core parts using three indicators, as shown by an example in Table B1. We keep all data for which the former-in-latter indicator or the latter-in-former indicator is one. We manually check the matching results and drop observations that are incorrectly matched via the industrial and commercial registration data query system provided by QICHACHA (https://www.qcc.com/).

Table B1: An Example of Fuzzy Matching

	Procurement Firms	Listed Firms
Original	沃森生物技术有限公司	云南沃森生物技术股份有限公司
Segmentation	沃森生物技术 \有限公司	云南沃森生物技术\ 股份有限公司
Core Part	沃森生物技术	云南沃森生物技术

Similarity Score	Former in Latter	Latter in Former
83.86	1	0

C A Case Study: Beijing Orient Landscape

A prominent example of the reverse crowding-in effect amid government deleveraging is the case of Beijing Orient Landscape and Environment Co., Ltd., (henceforth Orient Landscape), a Beijing-based company principally engaged in landscape construction and urban ecosystem repair projects. Orient Landscape's business is closely associated with infrastructure investments made by local governments in the form of public-private partnership (PPP) projects as a part of GP activities. According to its annual reports, Orient Landscape successfully bid on 50 PPP projects in 2017, amounting to a total of 71.6 billion RMB.

The GP projects come with substantial financial pressure because Orient Landscape is responsible for financing the construction of these projects. For instance, Orient Landscape won a 458.5 million RMB bid for a PPP project involving the development of rural tourism in Nanchong, Sichuan Province. According to a news report, Orient Landscape would hold a controlling stake of 88 percent in the project and would be responsible for the financing, operation, and overall management of the project. Thus, the financial health of Orient Landscape hinges on payments from local governments and external financing capacity backed by government projects.

Delayed payments from local governments eventually created a heavy financial burden on Orient Landscape. Orient Landscape noted in its 2017 annual report that "even though local governments have relatively high credit ratings, the accounts receivable collection efficiency is inevitably affected by factors such as the local government budget, financial conditions, and local government debt levels. The speed of capital turnover is related to local government office efficiency. There is a risk of collection delay due to settlement delay." In 2018, the company disclosed total accounts receivable of 8.9 billion RMB, representing 21.3% of its total assets. Making matters even worse, 60% of these accounts receivable would not be paid.[31] In addition to its increasing accounts receivable and deteriorated cash holdings, Orient Landscape experienced setbacks in the bond market and the stock market, which sent a public signal that the company was in financial distress. A landmark event was the failure of Orient Landscape's bond issuance plan in May 2018, which was intended to raise 1 billion RMB but ultimately raised only 5% of its target.

Following the announcement of the failed issuance, Orient Landscape's stock plunged nearly 9% in afternoon trading. Although the stock price later recovered some of its losses, the fluctuations were costly given that Qiaonv He, founder and chairperson of Orient Landscape, had pledged over 90% of her shares in the company. China Securities Regulatory Commission (CSRC), the regulator, advised creditors of Orient Landscape not to engage in forced sales of pledged shares. The distress of Orient Landscape was finally resolved in August 2018, when the SASAC of Beijing's Chaoyang District injected liquidity into Orient Landscape in exchange for controlling rights of the company, changing its ownership from private to state-owned.

D Calculation of the Average Product of Capital (APK)

We calculate the APK of firms following the procedure provided by Jurzyk and Ruane (2021):

1. Calculation of Value-Added

$$\begin{aligned}
\text{Value Added}_{i(s)t} &= \text{Total Revenues}_{i(s)t} - \text{Intermediate Inputs}_{i(s)t} \\
&= \text{Total Revenues}_{i(s)t} - (\text{Total Operating Costs}_{i(s)t} - \text{Labor Costs}_{i(s)t}) \\
\text{Labor Costs}_{i(s)t} &= \text{Employment}_{i(s)t} * \text{Average urban wages}_{st}
\end{aligned}$$

[31] For instance, one of its largest clients, the Management Committee of Binzhou Economic Development Zone, paid only 13 million of its total of 1.5 billion in unpaid procurements between 2014 and 2018.

where firm i in sector s in year t has Value Added$_{i(s)t}$. Data for Total Revenues$_{i(s)t}$, Employment$_{i(s)t}$ and Total Operating Costs$_{i(s)t}$ come from CSMAR, and data for Average urban wages$_{st}$ come from CEIC (https://www.ceicdata.com).

2. Calculation of the APK

$$\text{APK}_{i(s)t} = \frac{\text{Value-added}_{i(s)t}}{K_{i(s)t}}$$

where firm i in sector s in year t has APK$_{i(s)t}$. We use fixed assets as our measure of capital K$_{i(s)t}$, and data for K$_{i(s)t}$ come from CSMAR.