The Falling Rate of Profit Hypothesis: Evidence from China and the United States

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Preliminary draft. Comments welcome.

Abstract

Marx's law of the tendency of the rate of profit to fall holds that a rising organic composition of capital depresses the general rate of profit. Although the law has been debated extensively, most empirical studies measure profit rates and their trends, and few examine the causal relationship between the organic composition of capital and the rate of profit directly. This paper studies that relationship in two economies with different institutional structures. For the U.S. nonfinancial corporate sector, we estimate vector autoregressive and vector error-correction models on annual data for 1929–2022. For China, we estimate dynamic panel models with difference and system GMM on a balanced panel of 21,987 industrial enterprises for 1999–2007. In the United States, the rate of profit and the organic composition of capital are cointegrated and negatively related in the long run. Deviations from this relationship, however, are corrected through the organic composition of capital, while the rate of profit is weakly exogenous. This implies that long-run causation runs from the rate of profit to the organic composition of capital, the opposite of the direction the hypothesis posits, and Granger-causality tests in first differences indicate short-run causation in both directions. In China, both the rate of profit and the composition of capital rise over the sample period, and our preferred GMM estimates show no significant negative long-run effect of the composition of capital on profitability. We discuss the limitations of the present specifications, including the definitional link between the U.S. measures of the rate of profit and the organic composition of capital and the use of a bivariate system, and outline how future work can address them.

Keywords: rate of profit, organic composition of capital, Marxian crisis theory, vector error correction, dynamic panel GMM
JEL codes: B51, E11, E32, O47

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1 Introduction

Economic crises recur throughout the history of capitalist economies. They typically involve falling profitability, declining investment, stalled accumulation, and slowing or falling growth of demand and output. As for their causes, Marx and Engels famously located them in "too much civilisation, too much means of subsistence, too much industry, too much commerce" (Marx and Engels, 1848). More specific explanations differ across schools of thought. Underconsumption and disproportionality theories locate the source of crises in difficulties of realizing value. Yet, as Xie et al. (2010) point out, problems of realization are a permanent feature of capitalist economies, whereas crises are not, so these theories cannot by themselves explain why crises occur when they do. A third explanation places the source of crises in production itself, through the law of the tendency of the rate of profit to fall (LTRPF).

The LTRPF occupies a central place in Marx's theory of capital accumulation. Marx summarizes it as a "relative decrease of the variable capital as compared to the constant capital, and consequently a continuously rising organic composition of the total capital," whose result is that "the rate of surplus value, at the same, or even a rising, degree of labour exploitation, is represented by a continually falling general rate of profit" (Marx, 1998). The pursuit of surplus value drives capitalists to raise labor productivity and adopt cost-reducing techniques. As accumulation and technical change proceed, the living labor used in production declines relative to the means of production, raising the organic composition of capital. Because living labor is the only source of surplus value, surplus value falls relative to total capital, and with it the rate of profit. In this sense, the engine that drives capitalist expansion also generates the conditions for its periodic crises (Sweezy, 1942; Grossmann, 1992).

Since its formulation in the third volume of *Capital*, the law has been the subject of extensive controversy, and it has been established neither mathematically nor empirically. Much of the empirical literature measures the rate of profit and inspects its trend, or decomposes it into components whose effects are inferred from accounting identities. Few studies test directly whether a rising organic composition of capital causes the rate of profit to fall, and those that do rely almost exclusively on data from advanced capitalist economies such as the United States.

This paper examines the relationship between the organic composition of capital and the rate of profit in two economies with different institutional structures: the United States and China. The comparison is informative because the mechanism Marx describes rests on accumulation and technical change, which are not unique to any one institutional setting, while the integration of China into the global economy exposes its enterprises to many of the same competitive pressures. For the United States, we use annual aggregate data on the nonfinancial corporate sector for 1929–2022 and estimate vector autoregressive (VAR), vector error-correction (VEC), and structural VAR models. For China, we use enterprise-level data from the China Industry Business Performance Database for 1998–2007 and estimate dynamic panel models with difference and system GMM, which address the endogeneity of the composition of capital.

Neither economy provides evidence that a rising composition of capital causes the rate of profit to fall. In the United States, the rate of profit and the organic composition of capital are cointegrated, and the long-run relationship is negative. The adjustment dynamics, however, reverse the causal reading that the hypothesis suggests: deviations from the long-run relationship are corrected through changes in the organic composition of capital, while the adjustment coefficient of the rate of profit is small and insignificant. The rate of profit is therefore weakly exogenous, and long-run causation runs from profitability to the composition of capital rather than the other way round. Granger-causality tests on first differences indicate short-run causation in both directions. In China, both the rate of profit and the composition of capital rise over the period we observe. Our preferred difference GMM estimates show a positive but insignificant long-run effect of the composition of capital on the rate of profit, and therefore provide no evidence for the hypothesis.

These results should be read as provisional. In the U.S. data, the product of our measures of the rate of profit and the organic composition of capital equals the ratio of profits to wages, so the two variables are linked by an accounting identity, and the bivariate system omits the rate of exploitation and other determinants of profitability. We discuss these limitations in Section 8 and outline how future work can address them.

The rest of the paper is organized as follows. Section 2 reviews the theoretical debate, and Section 3 the empirical literature. Section 4 sets out our empirical strategy, and Section 5 describes the data. Sections 6 and 7 present the results for the United States and China, and Section 8 concludes.

2 Theoretical Background

Marx formulated the LTRPF against the background of a long-term decline in the general rate of profit during the era of liberal capitalism, from the late eighteenth to the mid-nineteenth century, a phenomenon observed by other classical economists as well. Their explanations differed. Smith (2007) attributes the decline to the growing abundance of capital and its decreasing "productivity." Ricardo (1891) attributes it instead to rising wage pressure caused by diminishing returns in agriculture. Marx, from the perspective of the labor theory of value, regards the rising *organic composition of capital* (OCC), the ratio of constant capital (means of production) to variable capital (the value of labor power), as the dominant cause (Marx, 1998). The LTRPF states that a rising OCC lowers the general rate of profit when the *rate of exploitation*, the ratio of surplus value to variable capital, is held constant. Marx also argues that the law can hold even when the rate of exploitation rises. He recognizes countertendencies that can check the decline, including the "cheapening of elements of constant capital" brought about by "the same development which increases the mass of the constant capital in relation to the variable," but maintains that, on balance, the law dominates, so that the rate of profit exhibits a long-run downward trend.

The subsequent debate has focused on three issues. The first concerns the assumption of a constant rate of exploitation. With increasing mechanization, the value of the workers' consumption bundle, and hence the value of labor power, tends to fall, which raises the rate of exploitation even if the length and intensity of the working day are unchanged (Sweezy, 1942). Marx attempted to incorporate a rising rate of exploitation into the law but, according to exegetical evidence, did not arrive at a determinate answer (Heinrich, 2013).

The second issue is the charge that the LTRPF is a tautology. In aggregate value terms, the general rate of profit r can be written as

$$r = \frac{S}{C+V} = \frac{S/V}{C/V+1} = \frac{e}{C/V+1}, \tag{1}$$

where C, V, and S denote constant capital, variable capital, and surplus value, and $e = S/V$ is the rate of exploitation. The OCC is usually measured as C/V. Since a rising C/V lowers r by definition as long as e is constant, the proposition "needs no ghost come from the grave to tell us this" (Robinson, 1966). This objection can be partly answered by Marx's distinction between the *technical*, *value*, and *organic* compositions of capital (Fine and Harris, 1976).

The third issue is whether the rate of profit falls at all. Okishio (1961) analyzes the question in an input-output framework, holding the real wage constant and allowing relative prices to adjust endogenously, and shows that a technical change that is profitable for the individual capitalist raises rather than lowers the general rate of profit. The Okishio theorem has proved robust in a variety of settings, including fixed capital (Roemer, 1979), joint production (Bidard, 1988), product innovation (Nakatani and Hagiwara, 1997; Fujimori, 1998), and historical cost accounting (Laibman, 2001). Nonetheless, the assumption of a constant real wage is restrictive, as Okishio (2001) himself acknowledges, and the theorem does not rule out a falling rate of profit with a constant or even rising rate of exploitation when the real wage is allowed to vary.

3 Empirical Literature

The empirical literature on the LTRPF can be divided into three strands according to method. The first strand measures the rate of profit and inspects its trend visually (Weisskopf, 1979; Wolff, 1986; Moseley, 1991; Tsoulfidis and Paitaridis, 2019). These studies examine whether the profit rate of a given economy trends downward and use decomposition analysis to infer the causes of its movements. They have contributed substantially to the measurement of the rate of profit and other Marxian categories, but their inferences do not meet contemporary statistical standards.

The second strand uses econometric methods to test for deterministic or stochastic trends in the rate of profit, usually controlling for short-run fluctuations in demand or for countertendencies that could raise the rate of profit (Nordhaus, 1974; Feldstein and Summers, 1977; Downe, 1986; Michl, 1988; Basu and Manolakos, 2013; Trofimov, 2018). Among these contributions, Basu and Manolakos (2013) stand out for controlling for all the countertendencies that Marx outlines in the third volume of *Capital*. They find a declining trend in the rate of profit for the postwar U.S. economy, but, as they acknowledge, their finding only "draws attention to the existence of possible mechanisms, like the inexorable mechanization under capitalist production or the long-run labor-saving bias of technological change that drive the rate of profit to conditionally decline over time."

The third strand investigates causal relationships directly. To our knowledge, only Kalogerakos (2017) examines the causal relationship between the OCC and the rate of profit. He finds a cointegrating relationship among the chosen variables, but this result is probably a statistical artifact, since the econometric model is specified on the basis of an accounting identity, a problem well documented in the literature (Shaikh, 1974; Felipe et al., 2008; Sánchez Vidal, 2015; Liang, 2021).

Our paper belongs to this third strand. Its objective is to test the empirical relevance of the LTRPF in a mature capitalist economy and in China's socialist market economy. The theoretical indeterminacy of the law does not rule out its empirical relevance, since it may hold at a more concrete level. We therefore examine directly whether a rising OCC, a stylized fact in advanced capitalist economies, has had a negative long-run effect on the general rate of profit.

Moving from theory to evidence poses two challenges. The first is that economic data are recorded in price rather than value terms, except in some historical periods of former socialist economies. Following conventional practice, we use price analogues as proxies for variables that are theoretically defined in value terms. The second challenge is simultaneity. The rate of profit guides investment and other decisions of the firm, so it may in turn affect the choice of technique. We therefore rely on econometric methods that are robust to simultaneity.

4 Empirical Strategy

4.1 Causal channels

Studies of the determinants of the rate of profit often decompose it into components and then either infer the effect of each component through growth accounting (e.g., Weisskopf, 1979) or specify an econometric model on the basis of the decomposition (e.g., Kalogerakos, 2017). Because decompositions rest on accounting identities, they are ill suited to studying causal relationships among variables that appear in the same identity, and doing so produces statistical artifacts. We instead begin from the behavioral relationships among the relevant variables, summarized in Figure 1.

Our primary goal is to estimate the causal effect of the OCC on the rate of profit. The OCC can affect the rate of profit through three channels. The first is the *labor productivity channel*: rising mechanization raises labor productivity, which increases the surplus value produced per worker and thus tends to raise the rate of profit (Marx, 1996, ch. 15). The second is the *price channel*. In the long run, the prices of output, capital goods, and wage goods are determined by the technique of production. Mechanization cheapens wage goods and, by displacing workers into the reserve army of labor, weakens workers' bargaining power; both effects tend to lower the real wage and raise the rate of profit (Marx, 1996, ch. 25). At the same time, mechanization changes the relative price of capital goods, so the net effect of these price changes on the rate of profit is ambiguous. The third is the *capital requirement channel*: a higher level of mechanization raises the capital that must be advanced per worker, which increases the denominator of the rate of profit and tends to lower it,

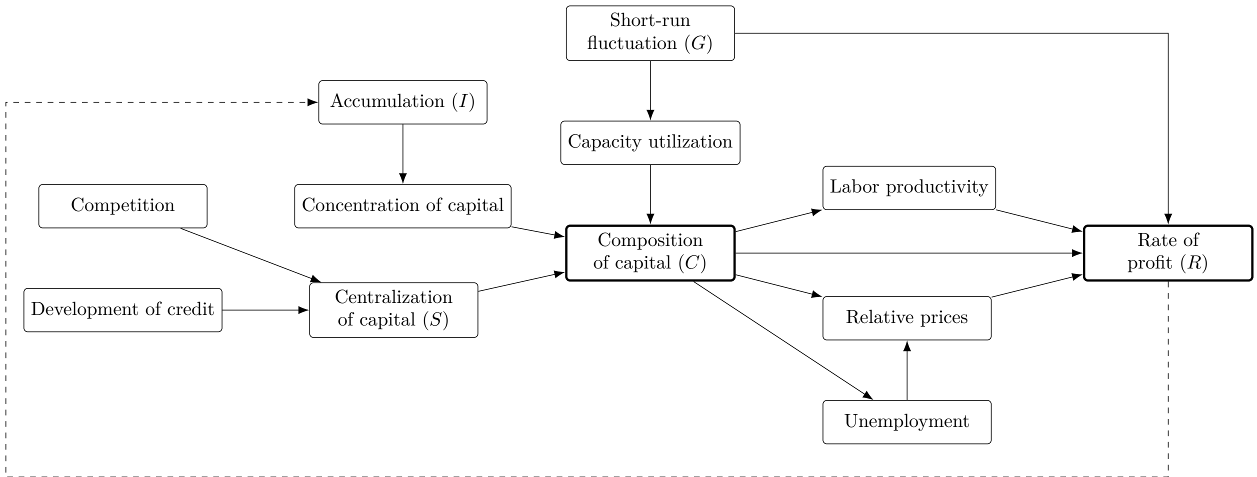


Figure 1: Causal channels linking the composition of capital and the rate of profit. The dashed arrow indicates the feedback from profitability to accumulation.

at least when the technical change takes place (Marx, 1998, chs. 13–15). The first two channels therefore tend to raise the rate of profit and the third to lower it. This is the tension at the center of the debate reviewed in Section 2, and it is why the sign of the overall effect is an empirical question.

The causal effect of the OCC on the rate of profit can be confounded by other mechanisms that affect both variables. Short-run fluctuations in demand, for example, affect the price levels and hence the rate of profit, and at the same time affect the measured OCC through fluctuations in employment. Such fluctuations do not change the technique of production that the OCC is meant to represent, but they are reflected in its measurement unless the OCC is adjusted for capacity utilization. Other confounding mechanisms involve the drivers of the OCC. Marx (1996) identifies two causes of a rising OCC: the concentration of capital through accumulation, and the centralization of capital through competition and the development of the credit system, since new investment and larger capitals tend to adopt techniques with a higher OCC. These factors may also affect the rate of profit through channels other than the OCC. Most importantly, the rate of profit may have a reverse causal effect on the OCC through accumulation.

In estimating the effect of the OCC on the rate of profit, we therefore do not control for variables that lie on the causal path between them, such as price levels and labor productivity, since doing so would conceal the effect of interest. We do control for the rate of accumulation (I), the degree of centralization of capital (S), and short-run fluctuations in aggregate demand (G) to avoid omitted variable bias. We are able to include these controls in the enterprise-level panel for China. For the U.S. aggregate time series, we begin with a bivariate system of the rate of profit and the OCC, in which the VEC approach addresses reverse causality by treating both variables symmetrically as endogenous. Extending the U.S. system to include the control variables is left for future work.

4.2 Time-series methods for the United States

Estimating a VAR model requires the series to be stationary. Economic theory often implies, however, that variables share equilibrium relationships in levels, so that a linear combination of nonstationary series is stationary, a property known as *cointegration*. Vector error-correction models (VECMs) capture such relationships. A VECM can be written as

$$\Delta X_t = \mu_0 + \sum_{i=1}^{p-1} \Pi_i \Delta X_{t-i} + \Pi X_{t-1} + e_t, \tag{2}$$

where $X_t = (R_t, C_t)'$ is the vector of the rate of profit and the OCC, ΔX_t its first difference, Π_i the coefficient matrices on the lagged differences, μ_0 an unrestricted constant, p the lag order of the model in its VAR form, and e_t an error term with zero mean.

What distinguishes the VECM from a VAR in differences is the error-correction term ΠX_{t-1}, which captures how the growth rate of each variable responds when the system departs from its long-run equilibrium. The matrix Π can be decomposed as $\Pi = \alpha\beta'$, so that the error-correction term becomes $\alpha\beta' X_{t-1}$. The *cointegrating vector* β describes the equilibrium relationship among the variables in levels, and $\beta' X_{t-1}$ measures the distance of the variables from their equilibrium values. The *loading matrix* α describes the speed at which each variable adjusts back toward equilibrium.

4.3 Dynamic panel methods for China

To address the small sample of the U.S. time series and to broaden the scope of the analysis, we use enterprise-level panel data for China. Since the rate of profit may be persistent and the effect of the OCC is likely to unfold over several periods, we estimate a panel autoregressive distributed lag (ARDL) model,

$$R_{i,t} = \sum_{j=1}^{p} \rho_j R_{i,t-j} + \sum_{j=0}^{q_1} \mu_j C_{i,t-j} + \sum_{j=0}^{q_2} \gamma_j I_{i,t-j} + \sum_{j=0}^{q_3} \theta_j S_{i,t-j} + \sum_{j=0}^{q_4} \delta_j G_{i,t-j} + \alpha_i + \tau_t + \epsilon_{i,t}, \tag{3}$$

where i indexes enterprises and t years; R is the rate of profit, C the composition of capital, I the rate of accumulation, S the centralization of capital, and G short-run fluctuations in demand. The lag orders are p for R and $q_1, \ldots, q_4$ for C, I, S, and G; α_i is an enterprise fixed effect, τ_t a year effect, and $\epsilon_{i,t}$ an independently and identically distributed disturbance with zero mean.

Removing the fixed effect by first differencing yields

$$\Delta R_{i,t} = \sum_{j=1}^{p} \rho_j \Delta R_{i,t-j} + \sum_{j=0}^{q_1} \mu_j \Delta C_{i,t-j} + \sum_{j=0}^{q_2} \gamma_j \Delta I_{i,t-j} + \sum_{j=0}^{q_3} \theta_j \Delta S_{i,t-j} + \sum_{j=0}^{q_4} \delta_j \Delta G_{i,t-j} + \Delta\tau_t + \Delta\epsilon_{i,t}. \tag{4}$$

By construction, $\Delta R_{i,t-1}$ is correlated with the transformed error $\Delta\epsilon_{i,t}$ through $\epsilon_{i,t-1}$, and the same holds for the other regressors if they are endogenous. This gives rise to dynamic panel bias (Nickell, 1981), so that equation (4) cannot be estimated by least squares. The *difference GMM*

(DGMM) estimator uses the untransformed lagged levels of the endogenous variables, dated $t-2$ and earlier, as instruments. It is valid as long as these lagged levels are uncorrelated with $\Delta\epsilon_{i,t}$ and there is no serial correlation of order two or higher in $\Delta\epsilon_{i,t}$, and it is consistent for fixed T as N grows (Holtz-Eakin et al., 1988; Arellano and Bond, 1991). Because the DGMM estimator can be inefficient when the endogenous variables are close to random walks, we also use the *system GMM* (SGMM) estimator, which is more efficient provided the first differences of the endogenous variables are uncorrelated with the fixed effects (Blundell and Bond, 1998). SGMM combines the differenced equation with the level equation (3), using lagged first differences as instruments for the levels. The two-step versions of both estimators are robust to arbitrary heteroskedasticity (Roodman, 2009). We implement both estimators in two steps with `xtabond2`, treating lags of R, C, I, G, and S as GMM-style instruments, collapsing the instrument matrix to limit instrument proliferation, and including year effects.

For model selection, we use the model and moment selection criteria MBIC and MAIC developed by Andrews and Lu (2001) for dynamic panel models estimated by GMM, which are analogues of the conventional BIC and AIC. We also report the Arellano–Bond test for second-order autocorrelation, AB(2), and the Hansen (1982) J test of the validity of the instruments. In addition, we use the OLS and fixed-effects (FE) estimates of the coefficient on the first lag of R as benchmarks for detecting misspecification. Absent omitted variables other than the fixed effects, the OLS estimate is biased upward and the FE estimate downward (Nickell, 1981; Bond, 2002), so a well-specified GMM estimate should lie between them.

Once a model is selected, we test the long-run effect of C on R,

$$\lambda = \frac{\sum_{j=0}^{q_1} \mu_j}{1 - \sum_{j=1}^{p} \rho_j}, \tag{5}$$

using a Wald test, computed as a nonlinear χ^2 test of $\lambda = 0$. For comparison, we report pooled OLS estimates both without year effects (OLS0) and with year effects (OLS). A significantly negative λ supports the LTRPF. If λ is not significantly negative, the LTRPF is not supported, and it is contradicted if λ is significantly positive.

5 Data

5.1 United States

For the United States, we use annual aggregate time series for the nonfinancial corporate sector from 1929 to 2022, drawn from official sources listed in Table 1. The rate of profit can be measured in many ways (Basu and Vasudevan, 2013). For the numerator, profits, we use the non-wage part of net value added, that is, net of depreciation. For the denominator, capital advanced, we use the stock of nonresidential fixed assets. We measure the OCC as the ratio of nominal nonresidential fixed assets to the wage bill, including benefits. Both variables enter in logarithms.

These measures are not independent of each other. Since $R = (\text{NVA} - \text{CE})/\text{NRFA}$ and

$C = \text{NRFA/CE}$, their product is

$$R \times C = \frac{\text{NVA} - \text{CE}}{\text{CE}}, \tag{6}$$

the ratio of profits to wages, which is the empirical counterpart of the rate of exploitation e in equation (1). In logarithms, $\log R = \log e - \log C$ holds by construction. A negative relationship between R and C is therefore partly built into the measures, and it reflects the underlying economic mechanism only to the extent that movements in C are not offset by movements in e. This is the same problem that affects econometric models specified on the basis of accounting identities, discussed in Section 3. Our bivariate specification does not resolve it, and we return to it in Section 8.

Table 1: U.S. data: measurement and sources

Period	Series	Description	Source
1929–2022	NVA	Net value added	BEA NIPA Table 1.14
1929–2022	CE	Compensation of employees	BEA NIPA Table 1.14
1925–2022	NRFA	Private nonresidential fixed assets	BEA Fixed Assets Table 4.1

Note: The rate of profit is $R = (\text{NVA} - \text{CE})/\text{NRFA}$ and the organic composition of capital is $C = \text{NRFA/CE}$.

Table 2 reports summary statistics and Figure 2 plots the two series. The OCC is highly cyclical and may contain structural breaks, which is not surprising for a series that spans 94 years, including the Great Depression and the Second World War. It shows an upward trend only from the Second World War onward, which makes the choice of sample period consequential. The rate of profit shows a pronounced downward trend. This trend is stronger than in most of the literature, which typically finds no significant long-run decline, and its levels in the early decades are implausibly high, both of which suggest that it partly reflects the measure used here. The capital stock is also not adjusted for capacity utilization, and its coverage is not fully aligned with the nonfinancial corporate sector. Refining these measures is an important task for future work.

Table 2: U.S. data: summary statistics, 1929–2022

Variable	Unit	Obs.	Min.	Mean	Max.
R	Log of ratio	94	−2.91	−0.41	1.31
C	Log of ratio	94	0.94	1.31	1.88

5.2 China

The data for China come from the China Industry Business Performance Database for 1998–2007. The database is compiled annually by the National Bureau of Statistics from industrial legal entities with annual main business income of 5 million yuan or more. By 2007 it covered more than 330,000 industrial enterprises, accounting for about 95 percent of China's total industrial output (Nie et al., 2012).

Each enterprise is identified by its legal person code, which generally does not change over time. Although enterprises enter and exit the database each year, most are observed continuously.

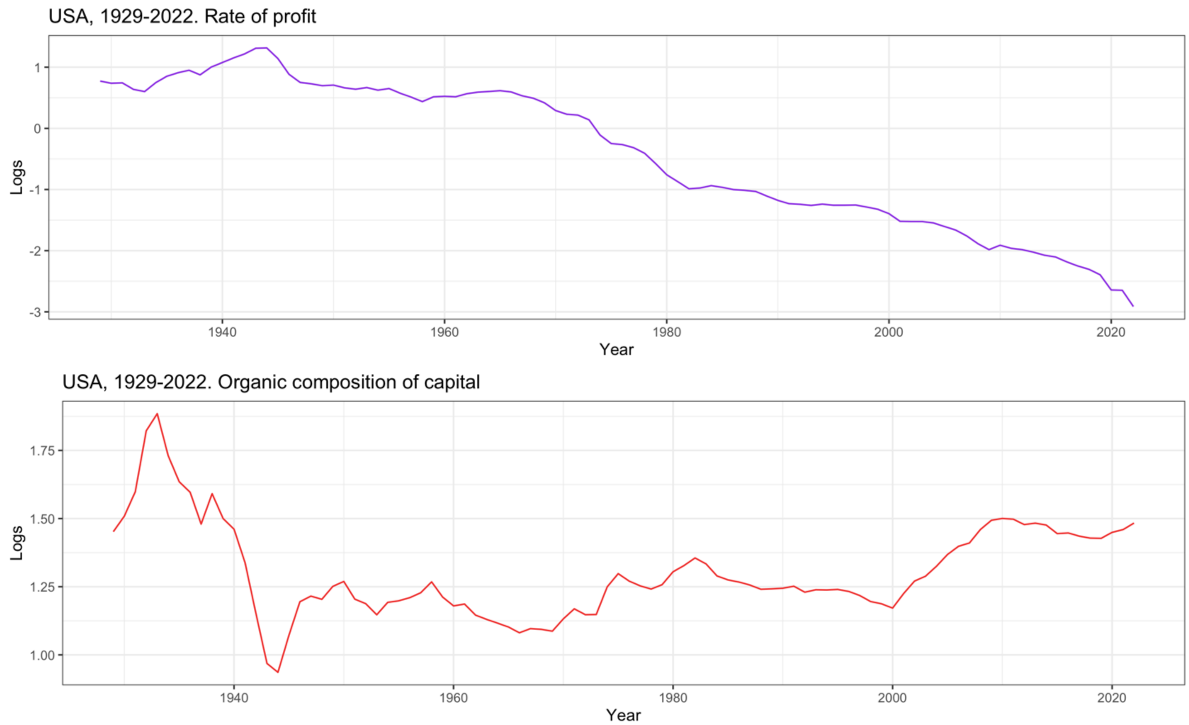


Figure 2: Rate of profit and organic composition of capital, U.S. nonfinancial corporate sector, 1929–2022 (logarithms).

We drop 1996 and 1997, which contain only slightly more than 20,000 enterprises, to retain more enterprises in a panel covering ten years. We also exclude 2008, because the data for that year lack legal person codes and cannot be matched to earlier years, and because 2008 was an exceptional year owing to the global financial crisis. The sample therefore covers 1998–2007.

We match enterprises across years by legal person code to form a balanced panel of 32,481 enterprises and 324,810 observations. Following standard practice for this database, we remove observations with missing, zero, or negative total assets or total fixed assets, and observations with fewer than eight employees. To treat outliers, we drop observations below the first quartile minus three times the interquartile range or above the third quartile plus three times the interquartile range of each variable. This leaves a balanced panel of 220,980 observations on 22,098 enterprises. Since I and G depend on values from the previous year, they are missing for 1998, so the final balanced panel covers 1999–2007 and contains 197,883 observations on 21,987 enterprises. Total fixed assets are deflated by the fixed asset investment price index, with 1998 as the base year, from the National Bureau of Statistics of China.

Table 3 defines the variables. We measure the composition of capital as fixed assets per employee. This is closer to the technical than to the value composition of capital, and we interpret the estimates with this limitation in mind.

Table 4 reports summary statistics, and Table 22 in the Appendix reports the means of R and C by industry. Mining has the highest rate of profit, followed by manufacturing, while electricity and

Table 3: China: variable definitions

Variable	Concept	Measurement
R	Rate of profit	Operating profit / total assets
C	Composition of capital	Total fixed assets / number of employees
I	Rate of accumulation	Growth rate of total fixed assets, $(\text{FA}_t - \text{FA}_{t-1})/\text{FA}_{t-1}$
S	Centralization of capital	Gini coefficient of total assets
G	Short-run fluctuation	Inventory turnover time: inventory at the beginning of the year / average daily cost of sales

heat production and supply has the lowest. Most enterprises in electricity and heat are state-owned, which suggests that the rate of profit of state-owned enterprises is lower than that of other enterprises. Compared with manufacturing, mining has both a high C and a high R, whereas electricity and heat has a high C but a low R.

Table 4: China: summary statistics, 1999–2007

Variable	Unit	Obs.	Mean	S.D.	Min.	Max.
R	Percent	197,883	3.51	7.86	−36.39	43.79
C	Ratio	197,883	79.34	82.08	0.01	553.10
I	Ratio	197,883	0.14	4.44	−1.00	1,694.85
G	Days	197,883	114.96	207.94	−354.73	9,448.52
S	Ratio	197,883	0.82	0.01	0.81	0.84

Figure 3 shows the aggregate trends of the composition of capital and the rate of profit. The composition of capital grows at an average annual rate of about 4.6 percent, and the rate of profit at about 14 percent. The rate of profit rises throughout the decade, at varying rates, with no sign of decline. The composition of capital fluctuates within a narrow range from 1998 to 2002, with an overall upward tendency, and rises steadily from 2003 to 2007. After 2002, both variables grow together. The sources of the rising rate of profit are a subject for future research.

Each enterprise is assigned to an industry using the 2007 industry codes, which yields 38 industries. We classify enterprises by ownership using their registration type: following Yang (2015), enterprises with registration types 110, 141, 143, and 151 are classified as state-owned and all others as non-state-owned. State-owned enterprises account for a high share of enterprises in tobacco manufacturing, electricity and heat, gas, and water production and supply (Table 22).

6 Results for the United States

6.1 Unit roots and the VAR model

We first test the stochastic properties of the series. To establish the possibility of cointegration, both series must be integrated of order one. Since unit root tests have low power in small samples and in the presence of structural breaks, we use a battery of tests: the augmented Dickey–Fuller (ADF) test, the generalized least squares Dickey–Fuller (DF-GLS) test, and the KPSS test. The

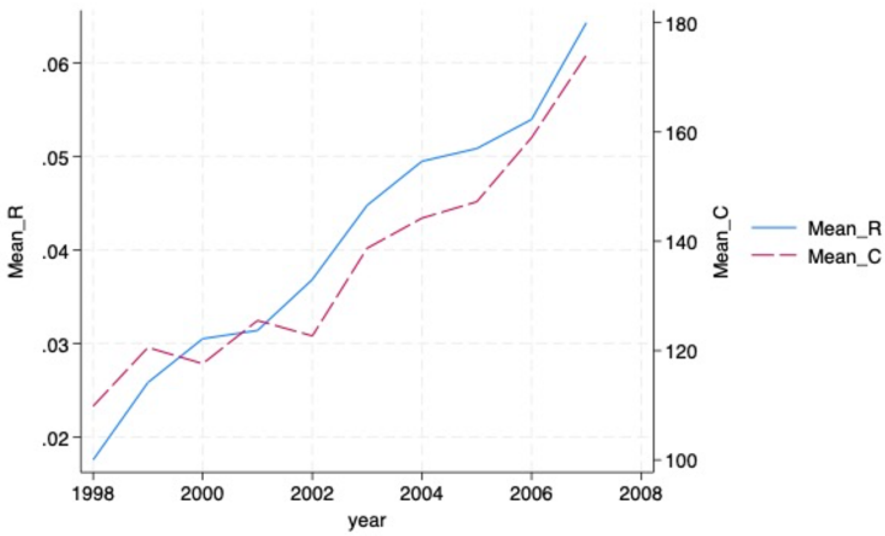


Figure 3: Average rate of profit (ratio, left axis) and average composition of capital (right axis), Chinese industrial enterprises, 1998–2007.

results, reported in Table 15 in the Appendix, indicate that both variables contain one unit root.

To select the lag length of the VAR, we use four information criteria. The AIC and the final prediction error (FPE) select four lags, while the Hannan–Quinn (HQ) criterion and the BIC select two. The Breusch–Godfrey LM test and the portmanteau test detect serial correlation in the VAR(2) residuals but not in the VAR(4) residuals (Table 16). We therefore use the VAR(4). The Jarque–Bera test rejects normality of the residuals, which affects the confidence intervals but not the consistency of the estimates, while the ARCH test does not reject homoskedasticity at the 5 percent level (Table 17). The CUSUM test indicates that the parameters are stable over time (Figure 5). Table 5 reports the VAR(4) estimates.

6.2 Cointegration and the VEC model

To estimate a VEC model, we first test for cointegration between the two variables. Johansen's trace and maximum eigenvalue tests both indicate one cointegrating relationship (Table 18). With the first element normalized to one, the estimated cointegrating vector is $\hat{\beta}' = (1,\ 19.671,\ -18.893)$ for $(R_{t-1}, C_{t-1}, 1)$, which implies the long-run relationship

$$R_{t-1} = 18.893 - 19.671\, C_{t-1} + e_{t-1}. \tag{7}$$

The rate of profit and the OCC are thus negatively related in the long run, as the LTRPF predicts.

The estimated loading coefficients are $\hat{\alpha}_R = 0.0003$ and $\hat{\alpha}_C = -0.0031$ (Table 6). The OCC adjusts toward the long-run equilibrium, and its adjustment coefficient is highly significant. The adjustment coefficient of the rate of profit is small and insignificant, so the rate of profit is *weakly exogenous* with respect to the long-run relationship: deviations from equilibrium are corrected

Table 5: VAR(4) estimates, United States

	R_t	C_t
R_{t-1}	1.371***	−0.117
	(0.153)	(0.101)
C_{t-1}	0.110	1.179***
	(0.190)	(0.125)
R_{t-2}	−0.304	0.216
	(0.273)	(0.180)
C_{t-2}	0.070	−0.270
	(0.329)	(0.217)
R_{t-3}	0.122	−0.344*
	(0.296)	(0.195)
C_{t-3}	0.271	−0.264
	(0.340)	(0.224)
R_{t-4}	−0.172	0.237**
	(0.173)	(0.114)
C_{t-4}	−0.337	0.254*
	(0.205)	(0.135)
Constant	−0.157**	0.115**
	(0.069)	(0.045)

Note: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

through the OCC rather than through the rate of profit. This has a direct implication for the direction of causation. When the system departs from its long-run relationship, it is the OCC that moves to restore it, while the rate of profit does not respond. In the long run, then, the rate of profit drives the OCC, and not the other way round. This is the opposite of the causal direction posited by the LTRPF. It is consistent instead with the view that profitability governs accumulation and the choice of technique, and hence the composition of capital. The negative sign of the long-run relationship alone should therefore not be read as evidence for the hypothesis. Table 6 reports the full VEC(3) estimates, which can be written as

$$\begin{aligned}\Delta R_t = {} & 0.0003\,(R_{t-1} - 18.89 + 19.67\,C_{t-1}) + 0.504\,\Delta R_{t-1} + 0.140\,\Delta C_{t-1} + 0.125\,\Delta R_{t-2} \\ & + 0.173\,\Delta C_{t-2} + 0.342\,\Delta R_{t-3} + 0.514\,\Delta C_{t-3} + e_{R,t}, \qquad (8)\\ \Delta C_t = {} & -0.0031\,(R_{t-1} - 18.89 + 19.67\,C_{t-1}) - 0.164\,\Delta R_{t-1} + 0.227\,\Delta C_{t-1} + 0.080\,\Delta R_{t-2} \\ & - 0.030\,\Delta C_{t-2} - 0.300\,\Delta R_{t-3} - 0.320\,\Delta C_{t-3} + e_{C,t}. \qquad (9)\end{aligned}$$

Transforming the VEC(3) into its VAR(4) representation in levels gives

$$\begin{aligned}\begin{pmatrix} R_t \\ C_t \end{pmatrix} = {} & \begin{pmatrix} -0.006 \\ 0.059 \end{pmatrix} + \begin{pmatrix} 1.504 & 0.146 \\ -0.167 & 1.165 \end{pmatrix}\begin{pmatrix} R_{t-1} \\ C_{t-1} \end{pmatrix} + \begin{pmatrix} -0.379 & 0.033 \\ 0.244 & -0.256 \end{pmatrix}\begin{pmatrix} R_{t-2} \\ C_{t-2} \end{pmatrix} \\ & + \begin{pmatrix} 0.216 & 0.341 \\ -0.379 & -0.290 \end{pmatrix}\begin{pmatrix} R_{t-3} \\ C_{t-3} \end{pmatrix} + \begin{pmatrix} -0.342 & -0.514 \\ 0.300 & 0.320 \end{pmatrix}\begin{pmatrix} R_{t-4} \\ C_{t-4} \end{pmatrix} + \begin{pmatrix} e_{R,t} \\ e_{C,t} \end{pmatrix}. \qquad (10)\end{aligned}$$

Table 6: VEC(3) estimates, United States

	ΔR_t	ΔC_t
Error-correction term	0.0003	-0.0031^{***}
	(0.0012)	(0.0008)
ΔR_{t-1}	0.504^{***}	-0.164^{*}
	(0.149)	(0.095)
ΔC_{t-1}	0.140	0.227^{*}
	(0.189)	(0.121)
ΔR_{t-2}	0.125	0.080
	(0.177)	(0.113)
ΔC_{t-2}	0.173	-0.030
	(0.209)	(0.134)
ΔR_{t-3}	0.342^{**}	-0.300^{***}
	(0.167)	(0.107)
ΔC_{t-3}	0.514^{**}	-0.320^{**}
	(0.196)	(0.125)
R^2	0.441	0.373
Residual standard error	0.069	0.044

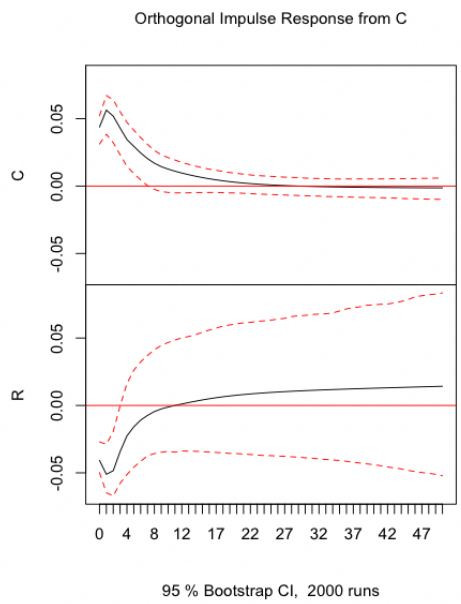
Note: The error-correction term is $R_{t-1} + 19.671\, C_{t-1} - 18.893$. Standard errors in parentheses; 83 degrees of freedom. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

6.3 Impulse responses and variance decomposition

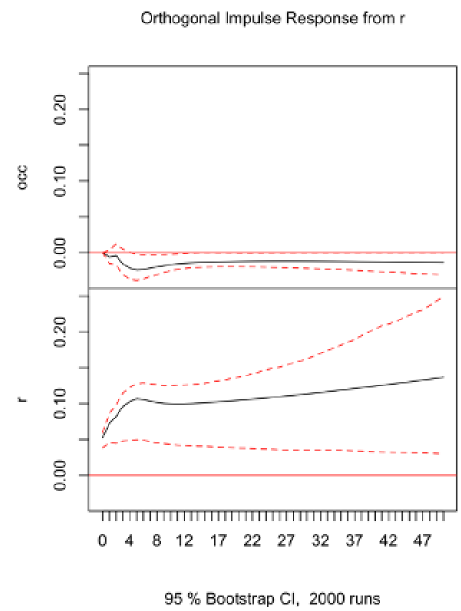
To analyze the dynamic interaction between the two variables, we transform the reduced-form model into a structural form. Imposing a long-run restriction to obtain a structural VEC model did not yield well-behaved impulse responses and variance decompositions, so we use a structural VAR(4) identified by a Cholesky ordering with C ordered before R. Under this ordering, a shock to the OCC can affect the rate of profit contemporaneously, but not vice versa.

Figure 4 shows the orthogonalized impulse responses. After a shock to the OCC, both variables respond immediately. The response of the rate of profit is negative on impact and turns positive and persistent after about ten years, although its confidence band includes zero beyond the first few years, while the effect on the OCC itself dies out. After a shock to the rate of profit, the OCC does not respond contemporaneously, by the Cholesky ordering, but subsequently declines persistently, while the response of the rate of profit itself grows and persists. These impulse responses depend on the recursive ordering, which imposes rather than tests the contemporaneous direction of causation, and they are estimated from a VAR in levels that does not impose the cointegrating restriction. We therefore regard them as descriptive of the short-run dynamics and rely on the VEC model for the long-run direction of causation.

Table 7 reports the forecast error variance decomposition. On impact, the OCC accounts for about 38 percent of the forecast error variance of the rate of profit, and the rate of profit itself for 62 percent. After ten years, the share explained by the OCC falls to 8 percent. By construction of the Cholesky ordering, the OCC accounts for all of its own forecast error variance on impact; after ten years, the rate of profit accounts for about 20 percent of it.



(a) Shock to C



(b) Shock to R

Figure 4: Orthogonalized impulse responses from the structural VAR(4), with 95 percent bootstrap confidence intervals (2,000 replications).

Table 7: Forecast error variance decomposition, structural VAR(4)

	Variance of R due to		Variance of C due to	
Horizon	C	R	C	R
0	0.376	0.624	1.000	0.000
1	0.350	0.650	0.993	0.007
2	0.311	0.689	0.993	0.007
3	0.246	0.754	0.970	0.030
4	0.194	0.806	0.934	0.066
5	0.158	0.842	0.897	0.103
6	0.132	0.868	0.866	0.134
7	0.115	0.885	0.843	0.157
8	0.101	0.899	0.825	0.175
9	0.091	0.909	0.811	0.189
10	0.082	0.918	0.799	0.201

6.4 Granger causality

To test for Granger causality, we estimate a VAR in first differences, since both series contain a unit root, with ΔC ordered before ΔR. The AIC and FPE select three lags and the HQ criterion and BIC one lag. Serial correlation tests reject white-noise residuals for the VAR(1) but not for the VAR(3) (Table 16), so we use the VAR(3). Its residuals are non-normal and heteroskedastic (Table 17), which affects the confidence intervals, and the CUSUM test indicates stable parameters (Figure 6). Table 8 reports the estimates.

Table 8: VAR(3) in first differences, United States

	ΔR_t	ΔC_t
ΔC_{t-1}	0.081	0.207
	(0.195)	(0.130)
ΔR_{t-1}	0.452***	−0.181*
	(0.155)	(0.103)
ΔC_{t-2}	0.160	−0.066
	(0.209)	(0.140)
ΔR_{t-2}	0.110	0.071
	(0.177)	(0.118)
ΔC_{t-3}	0.480**	−0.383***
	(0.200)	(0.133)
ΔR_{t-3}	0.293*	−0.331***
	(0.172)	(0.115)
Constant	−0.008	−0.019***
	(0.010)	(0.007)

Note: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 9 reports the Granger-causality tests. Both null hypotheses are rejected at the 5 percent level: changes in the rate of profit Granger-cause changes in the OCC, and changes in the OCC Granger-cause changes in the rate of profit. In the short run, the relationship between the two variables is therefore one of mutual causation rather than a one-directional effect of the OCC on the rate of profit. Because the two series are cointegrated, a VAR in first differences omits the error-correction term, so these tests capture only short-run causation and may be misspecified. Tests that account for cointegration, such as causality tests within the VEC model or the procedure of Toda and Yamamoto (1995), would be more appropriate. The VEC estimates above indicate that long-run causation runs from the rate of profit to the OCC.

Table 9: Granger-causality tests

Null hypothesis	F	df_1	df_2	p-value
ΔR does not Granger-cause ΔC	4.900	3	166	0.003
ΔC does not Granger-cause ΔR	3.732	3	166	0.012

7 Results for China

7.1 Model selection

We consider lag orders from one to three for each variable. Table 10 reports the model selection statistics. For every lag order, the DGMM and SGMM estimates of the coefficient on the first lag of R lie between the OLS and FE estimates, as expected. The MAIC selects three lags for both GMM estimators. At the 5 percent level, the AB(2) test does not reject the absence of second-order autocorrelation for DGMM with one or three lags, but rejects it for SGMM at every lag order. The Hansen J test does not reject the validity of the instruments at the 5 percent level for DGMM with three lags, but rejects it for SGMM. We therefore select the model with three lags, setting $p = q_1 = q_2 = q_3 = q_4 = 3$ in equations (3) and (4).

Table 10: China: model selection

Lags	Statistic	OLS0	OLS	FE	DGMM	SGMM
1	L.R	0.682***	0.682***	0.305***	0.341***	0.426***
	AB(2)				1.431	4.955***
	J				99.456***	317.995***
	MAIC				57.456	267.995
	MBIC				−110.507	68.040
2	L.R	0.570***	0.571***	0.277***	0.416***	0.488***
	AB(2)				−4.512***	−4.563***
	J				124.718***	247.912***
	MAIC				90.718	205.912
	MBIC				−45.251	37.949
3	L.R	0.559***	0.559***	0.230***	0.472***	0.531***
	AB(2)				1.606	2.319**
	J				21.961*	67.221***
	MAIC				−4.039	33.221
	MBIC				−108.015	−102.749

Note: L.R is the coefficient on the first lag of R. AB(2) is the Arellano–Bond test for second-order autocorrelation and J the Hansen test of overidentifying restrictions. OLS0 is pooled OLS without year effects; OLS, FE, DGMM, and SGMM include year effects. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

7.2 Regression results

Table 11 reports the estimates for the selected model with three lags. The DGMM estimator, which passes the specification tests at the 5 percent level, is our preferred estimator. Its estimate of the long-run effect of C on R is positive but insignificant, and therefore provides no evidence for the hypothesis of a falling rate of profit. The SGMM estimator fails both the test of overidentifying restrictions, which indicates invalid instruments, and the AB(2) test, so its estimates are not reliable. The OLS and FE estimates of the long-run effect are negative but also insignificant.

For comparison, Tables 20 and 21 in the Appendix report the results with two lags and one lag. With two lags, both GMM estimators fail the tests of overidentifying restrictions and second-order

Table 11: China: regression results, three lags

	OLS0	OLS	FE	DGMM	SGMM
L.R	0.559***	0.559***	0.230***	0.472***	0.531***
	(0.003)	(0.003)	(0.003)	(0.014)	(0.011)
L2.R	0.126***	0.126***	$-$0.040***	0.095***	0.108***
	(0.003)	(0.003)	(0.003)	(0.007)	(0.007)
L3.R	0.092***	0.092***	$-$0.068***	0.058***	0.063***
	(0.003)	(0.003)	(0.003)	(0.006)	(0.006)
C	$-$0.006***	$-$0.006***	$-$0.005***	$-$0.008	0.023
	(0.000)	(0.000)	(0.000)	(0.022)	(0.022)
L.C	0.002***	0.002***	0.001	0.007	$-$0.020
	(0.001)	(0.001)	(0.001)	(0.018)	(0.018)
L2.C	0.003***	0.003***	0.002***	0.003	$-$0.001
	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)
L3.C	0.001	0.001	0.001**	0.001	$-$0.000
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
I	0.081***	0.079***	0.029	1.939	1.497
	(0.019)	(0.019)	(0.020)	(1.392)	(1.439)
L.I	0.113***	0.114***	0.076***	0.020	$-$0.014
	(0.019)	(0.019)	(0.020)	(0.039)	(0.042)
L2.I	0.086***	0.086***	0.064***	0.032	0.011
	(0.018)	(0.018)	(0.018)	(0.026)	(0.029)
L3.I	$-$0.000	0.000	$-$0.001	$-$0.003**	$-$0.003**
	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)
G	$-$0.003***	$-$0.003***	$-$0.003***	0.002	$-$0.004*
	(0.000)	(0.000)	(0.000)	(0.003)	(0.002)
L.G	0.000	0.000	$-$0.001***	$-$0.001	0.001
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
L2.G	0.000***	0.000***	$-$0.001***	$-$0.000	0.001*
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
L3.G	0.000***	0.000***	$-$0.001***	0.000	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
S	8.335	$-$15.969**	$-$3.342	14.645***	
	(6.616)	(7.233)	(6.671)	(3.533)	
L.S	$-$18.577*	27.087**	23.748**		
	(10.043)	(11.448)	(10.555)		
L2.S	23.973**	18.778*	15.947*		30.888***
	(9.721)	(9.738)	(8.982)		(6.845)
L3.S	16.583***	22.518***	15.345***	30.228***	
	(4.633)	(4.687)	(4.326)	(6.017)	
Constant	$-$23.611***	$-$41.701***	$-$38.527***		$-$24.292***
	(3.370)	(4.012)	(3.707)		(5.547)
N	131,922	131,922	131,922	109,935	131,922
AB(2)				1.606	2.319**
J				21.961*	67.221***
Long-run effect λ	$-$0.001	$-$0.001	$-$0.001	0.007	0.006
Wald test of $\lambda = 0$	2.006	2.023	2.259	1.107	1.045

Note: Standard errors in parentheses. Blank cells denote terms omitted from the estimation. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

autocorrelation, so their results are inconclusive. The FE estimator, which does not require these tests, yields a negative long-run effect that is significant at the 5 percent level. With one lag, DGMM passes the autocorrelation test but fails the Hansen J test, and SGMM fails both, so the GMM results are again disregarded; the FE estimate of the long-run effect is negative and significant at the 1 percent level. In summary, the preferred DGMM estimates show a positive but insignificant long-run effect of the composition of capital on the rate of profit, whereas the FE estimates at shorter lag orders show a significant negative effect.

7.3 Robustness

We assess the stability of these results in two ways. First, we split the sample into two subperiods, 1998–2003 and 2004–2007, and construct a separate panel for each. Because each panel spans fewer years, more enterprises remain in the balanced panel, making the results more representative of Chinese enterprises as a whole. The short time span, however, does not permit the AB(2) test that validates the GMM estimates, so we consider only the FE estimates, which do not require it. In both subperiods, the FE estimates show a significant negative long-run effect of C on R at both lag orders (Table 19). The subperiod GMM estimates are reported for completeness but are not informative, since the AB(2) test cannot be computed in three of the four specifications.

Second, we estimate the model separately for state-owned and non-state-owned enterprises. Table 12 reports the model selection statistics. For state-owned enterprises, the GMM estimates of the coefficient on the first lag of R again lie between the OLS and FE estimates. The MAIC selects three lags for both GMM estimators, while the MBIC selects one lag. With one lag, the GMM estimates pass the AB(2) test but fail the Hansen J test, whereas with three lags DGMM passes both tests. We therefore base our conclusions on the model with three lags (Table 13). Only the DGMM estimate of the long-run effect is significant, and it is negative at the 10 percent level, which provides some support for the hypothesis among state-owned enterprises.

For non-state-owned enterprises, the GMM estimates of the coefficient on the first lag of R also lie between the OLS and FE estimates, and both the MAIC and the MBIC select three lags. With three lags, DGMM passes both the AB(2) and Hansen J tests, while SGMM passes only the AB(2) test (Table 14). The DGMM estimate of the long-run effect is positive but insignificant, consistent with the full-sample results. SGMM yields a significant positive long-run effect, but since it fails the Hansen J test we do not rely on it. The FE estimate is negative and significant at the 5 percent level.

Overall, the FE estimates show a significant negative long-run effect in both robustness exercises. The DGMM estimates show a significant negative effect for state-owned enterprises and a positive but insignificant effect for non-state-owned enterprises, which account for more than four-fifths of the sample.

Table 12: China: model selection by ownership

		OLS0		OLS		FE		DGMM		SGMM	
Lags	Statistic	SOE	Non-SOE	SOE	Non-SOE	SOE	Non-SOE	SOE	Non-SOE	SOE	Non-SOE
1	L.R	0.695	0.665	0.695	0.666	0.293	0.293	0.339	0.372	0.420	0.433
	AB(2)							0.752	3.643***	0.313	5.411***
	J							40.929***	158.528***	49.318***	360.050***
	MAIC							−1.071	116.528	−2.682	308.050
	MBIC							−138.414	−47.844	−174.555	104.489
2	L.R	0.570	0.563	0.571	0.563	0.253	0.269	0.388	0.435	0.474	0.488
	AB(2)							−1.592	−5.087***	−1.164	−5.033***
	J							25.857*	116.495***	48.316***	228.296***
	MAIC							−8.143	82.495	4.316	184.296
	MBIC							−118.571	−50.555	−139.567	12.096
3	L.R	0.558	0.554	0.558	0.554	0.205	0.224	0.426	0.485	0.520	0.536
	AB(2)							−1.182	1.638	−0.287	2.217**
	J							15.755	17.434	26.495*	64.343***
	MAIC							−10.245	−8.566	−9.505	28.343
	MBIC							−93.879	−110.288	−126.429	−112.534

Note: SOE denotes state-owned and Non-SOE non-state-owned enterprises. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

8 Conclusion

This paper has examined the relationship between the organic composition of capital and the rate of profit, the core mechanism of Marx's law of the tendency of the rate of profit to fall, in the United States and China.

For the United States, we use annual data on the nonfinancial corporate sector for 1929–2022. The rate of profit and the OCC are cointegrated, and their long-run relationship is negative. The rate of profit, however, does not adjust toward the long-run equilibrium, so it is weakly exogenous in the cointegrated system, while the OCC bears the adjustment. Long-run causation therefore runs from the rate of profit to the OCC, the opposite of the direction the LTRPF posits. Granger-causality tests on first differences indicate short-run causation in both directions. The U.S. evidence thus does not support the proposition that increases in the OCC drive subsequent declines in profitability.

For China, we construct a balanced panel of 21,987 enterprises in 38 industries from the China Industry Business Performance Database for 1999–2007 and measure the rate of profit, the composition of capital, the centralization of capital, the rate of accumulation, and short-run fluctuations. Although the period is short, it shows an upward trend in both the rate of profit and the composition of capital. The estimated long-run effect of the composition of capital on the rate of profit depends on the estimator. The preferred GMM estimates show a positive but insignificant effect and thus provide no evidence for a falling rate of profit. The FE estimates show a significant negative effect, but this result is at odds with the aggregate trends of the two variables, and the FE estimator is more exposed to endogeneity than GMM. We therefore do not read the FE results as support for the hypothesis. Overall, the Chinese enterprise data do not support a negative relationship between the composition of capital and the rate of profit.

Our analysis has important limitations, and we regard its results as provisional. The most

Table 13: China: state-owned enterprises, three lags

	OLS0	OLS	FE	DGMM	SGMM
L.R	0.558^{***}	0.558^{***}	0.205^{***}	0.426^{***}	0.520^{***}
	(0.007)	(0.007)	(0.008)	(0.040)	(0.020)
L2.R	0.149^{***}	0.149^{***}	-0.030^{***}	0.099^{***}	0.122^{***}
	(0.008)	(0.008)	(0.008)	(0.019)	(0.017)
L3.R	0.098^{***}	0.098^{***}	-0.060^{***}	0.048^{***}	0.059^{***}
	(0.007)	(0.007)	(0.008)	(0.016)	(0.016)
C	-0.000	-0.000	-0.000	0.004	0.004
	(0.001)	(0.001)	(0.001)	(0.013)	(0.010)
L.C	-0.001	-0.001	-0.002	-0.013	-0.004
	(0.001)	(0.001)	(0.001)	(0.009)	(0.008)
L2.C	0.001	0.001	0.000	-0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
L3.C	0.001	0.001	0.001	-0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
I	0.017	0.016	0.052^{*}	0.955	3.085^{***}
	(0.030)	(0.030)	(0.032)	(0.717)	(0.372)
L.I	-0.028	-0.029	-0.004	0.007	0.016
	(0.029)	(0.029)	(0.031)	(0.034)	(0.027)
L2.I	0.015	0.015	0.029	0.063^{***}	0.061^{***}
	(0.029)	(0.029)	(0.031)	(0.020)	(0.018)
L3.I	-0.001	-0.001	-0.002	-0.001	-0.002^{**}
	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)
G	-0.001^{***}	-0.001^{***}	-0.001^{***}	-0.002	-0.004
	(0.000)	(0.000)	(0.000)	(0.003)	(0.003)
L.G	-0.000	-0.000	-0.000^{*}	0.001	0.002
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
L2.G	0.000	0.000	-0.000^{**}	0.001	0.001^{*}
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
L3.G	0.000^{**}	0.000^{**}	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
S	22.795^{*}	5.196	13.467		
	(12.922)	(14.240)	(13.230)		
L.S	-14.537	18.562	20.749	21.593^{***}	
	(19.781)	(22.759)	(21.066)	(7.226)	
L2.S	-14.893	-19.379	-9.361		1.483
	(19.475)	(19.532)	(18.109)		(11.765)
L3.S	7.326	12.276	3.269		
	(9.150)	(9.302)	(8.710)		
Constant	-0.329	-13.394^{*}	-22.325^{***}		-1.080
	(6.584)	(7.943)	(7.454)		(9.617)
N	24,500	24,500	24,500	19,901	24,500
AB(2)				-1.182	-0.287
J				15.755	26.495^{*}
Long-run effect λ	0.000	0.000	-0.000	-0.025	-0.002
Wald test of $\lambda = 0$	0.057	0.060	0.108	3.543^{*}	0.093

Note: Standard errors in parentheses. Blank cells denote terms omitted from the estimation. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 14: China: non-state-owned enterprises, three lags

	OLS0	OLS	FE	DGMM	SGMM
L.R	0.554^{***}	0.554^{***}	0.224^{***}	0.485^{***}	0.536^{***}
	(0.003)	(0.003)	(0.004)	(0.014)	(0.010)
L2.R	0.120^{***}	0.120^{***}	-0.043^{***}	0.093^{***}	0.110^{***}
	(0.004)	(0.004)	(0.004)	(0.008)	(0.008)
L3.R	0.087^{***}	0.086^{***}	-0.070^{***}	0.058^{***}	0.066^{***}
	(0.003)	(0.003)	(0.004)	(0.007)	(0.006)
C	-0.007^{***}	-0.007^{***}	-0.006^{***}	0.012	0.018
	(0.001)	(0.001)	(0.001)	(0.025)	(0.022)
L.C	0.003^{***}	0.003^{***}	0.001	-0.008	-0.015
	(0.001)	(0.001)	(0.001)	(0.020)	(0.018)
L2.C	0.003^{***}	0.003^{***}	0.002^{***}	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)
L3.C	0.001	0.001	0.001^{*}	0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
I	0.099^{***}	0.098^{***}	0.020	0.188	0.159
	(0.023)	(0.023)	(0.024)	(0.902)	(0.942)
L.I	0.161^{***}	0.163^{***}	0.105^{***}	-0.010	0.005
	(0.024)	(0.024)	(0.025)	(0.044)	(0.045)
L2.I	0.099^{***}	0.098^{***}	0.070^{***}	0.012	0.002
	(0.021)	(0.021)	(0.022)	(0.029)	(0.030)
L3.I	0.003	0.003	-0.001	-0.005	-0.007^{*}
	(0.006)	(0.006)	(0.006)	(0.004)	(0.004)
G	-0.004^{***}	-0.004^{***}	-0.004^{***}	0.007	-0.009
	(0.000)	(0.000)	(0.000)	(0.008)	(0.006)
L.G	0.000^{**}	0.000^{**}	-0.001^{***}	-0.005	0.002
	(0.000)	(0.000)	(0.000)	(0.004)	(0.003)
L2.G	0.001^{***}	0.001^{***}	-0.001^{***}	-0.001	0.001
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
L3.G	0.001^{***}	0.001^{***}	-0.001^{***}	-0.000	0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
S	3.164	-22.581^{***}	-8.650	8.884^{**}	
	(7.551)	(8.239)	(7.612)	(3.726)	
L.S	-18.806	29.605^{**}	24.443^{**}		1.371
	(11.438)	(13.009)	(12.013)		(5.988)
L2.S	33.239^{***}	27.959^{**}	20.856^{**}		
	(11.029)	(11.047)	(10.207)		
L3.S	20.108^{***}	26.172^{***}	20.773^{***}	34.624^{***}	
	(5.277)	(5.332)	(4.935)	(8.878)	
Constant	-29.406^{***}	-48.601^{***}	-42.266^{***}		0.606
	(3.849)	(4.567)	(4.232)		(4.844)
N	107,422	107,422	107,422	90,034	107,422
AB(2)				1.638	2.217^{**}
J				17.434	64.343^{***}
Long-run effect λ	0.002	0.002	-0.002	0.013	0.014
Wald test of $\lambda = 0$	2.745^{*}	2.727^{*}	5.081^{**}	2.108	3.311^{*}

Note: Standard errors in parentheses. Blank cells denote terms omitted from the estimation. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

fundamental concerns the U.S. measures. Because the product of our rate of profit and organic composition of capital equals the ratio of profits to wages, as shown in equation (6), the two variables are linked by an accounting identity, and part of the negative long-run relationship between them is definitional rather than behavioral. Future work should use measures of the composition of capital that are not mechanically related to the measured rate of profit, such as a real capital stock per worker, which is closer to the technical composition of capital and is the measure we use for China, or the output–capital ratio, which bounds the maximum rate of profit. It should also model the rate of exploitation explicitly, so that the effect of the composition of capital can be separated from changes in distribution.

The U.S. analysis has further limitations. A bivariate system is unlikely to be an adequate model of the rate of profit, and the U.S. system does not yet include the rate of exploitation or the control variables used in the Chinese panel, so its results should be regarded as subject to revision once a larger system is estimated. The sample of at most 94 annual observations limits the precision of inference and spans the Great Depression and the Second World War, so the results should be checked on a postwar sample, beginning in 1947, over which the OCC shows a sustained upward trend. We have not tested for structural breaks, which are likely in a series of this length; unit root tests that allow for breaks, such as that of Zivot and Andrews (1992), and cointegration tests with regime shifts, such as that of Gregory and Hansen (1996), are natural extensions. The capital stock should be restricted to the nonfinancial corporate sector and adjusted for capacity utilization, and the levels of the measured rate of profit, which are implausibly high in the early decades, should be checked against alternative measures. Finally, causality tests that account for cointegration would provide a more reliable account of the short-run dynamics than the Granger-causality tests on first differences reported here.

The Chinese evidence has limitations of its own. The panel covers only ten years, which may not capture long-run tendencies, and our measure of the composition of capital, fixed assets per employee, is closer to the technical than to the value composition of capital. Extending the panel to more years and constructing measures that correspond more closely to Marxian categories are natural next steps.

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A Additional Tables and Figures

Table 15: Unit root tests, United States

Variable	Test	Statistic	5% critical value	Result
R	ADF	−1.708	−3.45	Fail to reject unit root
	DF-GLS	−1.176	−3.03	Fail to reject unit root
	KPSS	0.157	0.146	Reject stationarity
ΔR	ADF	−4.753	−3.45	Reject unit root
	DF-GLS	−3.126	−3.03	Reject unit root
	KPSS	0.072	0.146	Fail to reject stationarity
C	ADF	−2.271	−3.45	Fail to reject unit root
	DF-GLS	−2.507	−3.03	Fail to reject unit root
	KPSS	0.172	0.146	Reject stationarity
ΔC	ADF	−7.989	−3.45	Reject unit root
	DF-GLS	−3.363	−3.03	Reject unit root
	KPSS	0.049	0.146	Fail to reject stationarity

Table 16: Serial correlation tests of VAR residuals (p-values)

	Levels		First differences	
Test	VAR(2)	VAR(4)	VAR(1)	VAR(3)
Breusch–Godfrey LM, lag 1	0.795	0.387	0.271	0.609
Breusch–Godfrey LM, lag 2	0.309	0.329	0.130	0.313
Breusch–Godfrey LM, lag 3	0.028	0.233	0.010	0.429
Portmanteau	0.907	0.872	0.885	0.925

Note: The null hypothesis is that the residuals are white noise.

Table 17: Normality and heteroskedasticity tests of VAR residuals (p-values)

Test	VAR(4), levels	VAR(3), differences
Jarque–Bera (null: normality)	3.66×10^{-15}	2.41×10^{-8}
ARCH (null: homoskedasticity)	0.078	8.26×10^{-5}

Table 18: Johansen cointegration tests

Test	Null hypothesis	Statistic	10%	5%	1%
Trace	$r \leq 1$	8.33	7.52	9.24	12.97
	$r = 0$	32.14	17.85	19.96	24.60
Maximum eigenvalue	$r \leq 1$	8.33	7.52	9.24	12.97
	$r = 0$	23.81	13.75	15.67	20.20

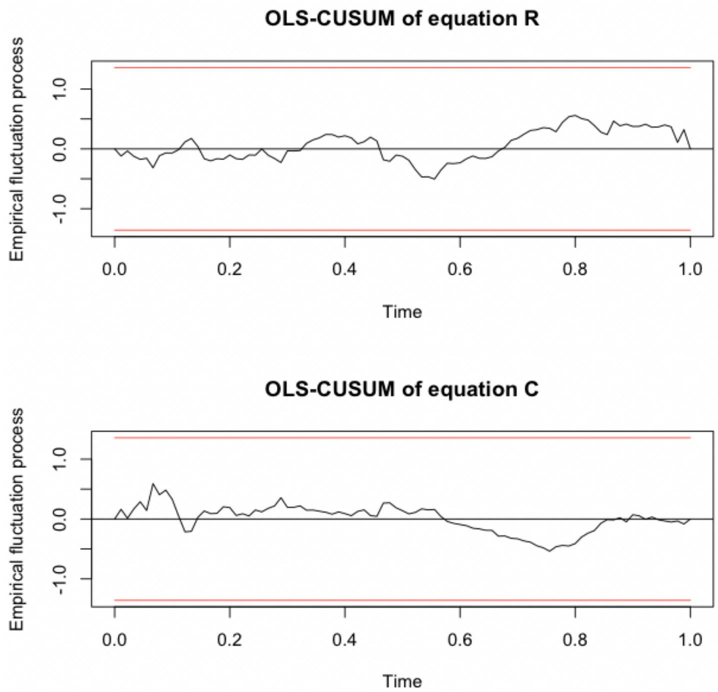

Figure 5: OLS-CUSUM parameter stability test, VAR(4) in levels.

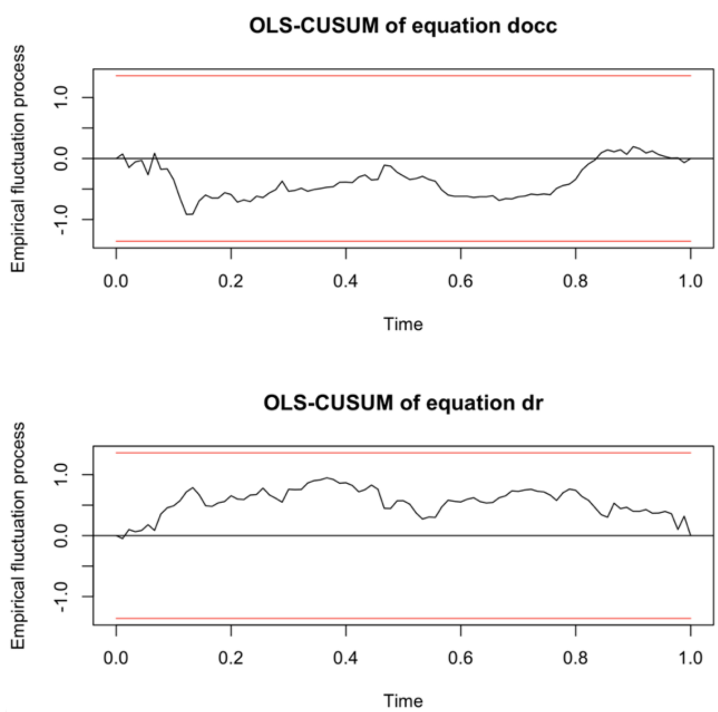

Figure 6: OLS-CUSUM parameter stability test, VAR(3) in first differences.

Table 19: China: long-run effect of C on R in subperiod panels

Panel		OLS0	OLS	FE	DGMM	SGMM
A. 1998–2003, one lag						
	λ	−0.020	−0.020	−0.008	0.026	−0.025
	Wald	91.930***	92.010***	17.465***	0.389	1.217
	N	123,280	123,280	123,280	92,460	123,280
	AB(2)				2.039**	3.594***
	J				19.577***	57.448***
A. 1998–2003, two lags						
	λ	−0.023	−0.023	−0.007	0.621	−0.051
	Wald	43.074***	43.074***	8.564***	0.838	6.826***
	N	92,460	92,460	92,460	61,640	92,460
	J				2.338	20.160***
B. 2004–2007, one lag						
	λ	−0.006	−0.006	−0.011	0.068	−0.044
	Wald	69.275***	69.275***	121.889***	3.401*	12.538***
	N	173,769	173,769	173,769	115,846	173,769
	J				11.929***	317.237***
B. 2004–2007, two lags						
	λ	−0.005	−0.005	−0.010	−0.070	−0.056
	Wald	12.501***	12.501***	43.208***	4.392**	3.026*
	N	115,846	115,846	115,846	57,923	115,846
	J				0.000	5.547**

Note: λ is the long-run effect of C on R and Wald the χ^2 statistic for $\lambda = 0$. The AB(2) test cannot be computed where it is not reported. Full regression results are available on request. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 22: China: distribution of enterprises by industry

Code	Industry	Firms	Non-SOE	SOE	Mean R (%)	Mean C
06	Coal mining and washing	391	0.501	0.499	11.04	140.49
07	Oil and gas extraction	4	0.750	0.250	10.44	189.49
08	Ferrous metal mining and processing	46	0.652	0.348	23.08	131.70
09	Non-ferrous metal mining and processing	89	0.528	0.472	38.12	252.57
10	Non-metallic mineral mining and processing	117	0.513	0.487	4.62	68.22
13	Agricultural and sideline food processing	772	0.865	0.135	3.80	100.65
14	Food manufacturing	421	0.895	0.105	4.03	94.60
15	Beverage manufacturing	330	0.882	0.118	5.34	118.60
16	Tobacco products	27	0.407	0.593	12.73	201.45
17	Textiles	1,626	0.941	0.059	3.41	72.81
18	Textile garments, footwear, and headwear	860	0.963	0.037	3.49	32.80
19	Leather, fur, feather, and related products	429	0.981	0.019	4.25	37.75
20	Wood processing and wood, bamboo, rattan, palm, and straw products	172	0.907	0.093	1.81	87.47

Note: Non-SOE and SOE are the shares of non-state-owned and state-owned enterprises in each industry.

Code	Industry	Firms	Non-SOE	SOE	Mean R (%)	Mean C
21	Furniture manufacturing	172	0.942	0.058	3.85	60.16
22	Paper and paper products	582	0.954	0.046	3.85	89.83
23	Printing and reproduction of recording media	521	0.651	0.349	1.75	98.28
24	Cultural, educational, and sporting goods	338	0.976	0.024	3.01	38.68
25	Petroleum processing, coking, and nuclear fuel	105	0.857	0.143	5.10	136.33
26	Chemical raw materials and chemical products	1,590	0.887	0.113	5.94	100.89
27	Pharmaceutical manufacturing	657	0.884	0.116	5.09	125.37
28	Chemical fiber manufacturing	90	0.956	0.044	4.24	119.67
29	Rubber products	295	0.942	0.058	4.47	65.66
30	Plastic products	866	0.958	0.042	3.80	75.88
31	Non-metallic mineral products	1,656	0.877	0.123	3.57	88.78
32	Ferrous metal smelting and rolling	318	0.896	0.104	5.87	121.52
33	Non-ferrous metal smelting and rolling	312	0.865	0.135	4.17	107.05
34	Metal products	925	0.932	0.068	4.81	65.22
35	General equipment manufacturing	1,718	0.860	0.140	5.05	71.43
36	Special equipment manufacturing	880	0.774	0.226	4.27	79.31
37	Transportation equipment manufacturing	1,191	0.751	0.249	3.68	85.51
39	Electrical machinery and equipment	1,365	0.933	0.067	4.92	76.60
40	Communication equipment, computers, and other electronic equipment	829	0.920	0.080	3.88	80.66
41	Instruments and cultural and office machinery	415	0.855	0.145	4.25	68.42
42	Crafts and other manufacturing	346	0.945	0.055	4.89	43.28
43	Waste resources and materials recycling	9	1.000	0.000	3.62	57.01
44	Electricity and heat production and supply	898	0.228	0.772	2.27	192.63
45	Gas production and supply	63	0.270	0.730	−0.81	206.91
46	Water production and supply	562	0.103	0.897	−0.52	167.82
	Total	21,987	0.828	0.172		

Note: Non-SOE and SOE are the shares of non-state-owned and state-owned enterprises in each industry.

Table 20: China: regression results, two lags

	OLS0	OLS	FE	DGMM	SGMM
L.R	0.570^{***}	0.571^{***}	0.277^{***}	0.416^{***}	0.488^{***}
	(0.003)	(0.003)	(0.003)	(0.012)	(0.010)
L2.R	0.175^{***}	0.174^{***}	-0.032^{***}	0.077^{***}	0.094^{***}
	(0.003)	(0.003)	(0.003)	(0.006)	(0.006)
C	-0.006^{***}	-0.006^{***}	-0.005^{***}	-0.001	0.012
	(0.000)	(0.000)	(0.000)	(0.016)	(0.014)
L.C	0.002^{***}	0.002^{***}	0.001^{*}	0.004	-0.011
	(0.001)	(0.001)	(0.001)	(0.013)	(0.012)
L2.C	0.004^{***}	0.004^{***}	0.003^{***}	0.002	-0.000
	(0.000)	(0.000)	(0.000)	(0.002)	(0.002)
I	0.079^{***}	0.078^{***}	0.020	2.432^{*}	1.529
	(0.018)	(0.018)	(0.018)	(1.409)	(1.310)
L.I	0.095^{***}	0.096^{***}	0.050^{***}	-0.034	-0.035
	(0.017)	(0.017)	(0.017)	(0.022)	(0.023)
L2.I	-0.002	-0.001	-0.002	-0.006^{***}	-0.007^{***}
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
G	-0.003^{***}	-0.003^{***}	-0.003^{***}	0.002	-0.003
	(0.000)	(0.000)	(0.000)	(0.002)	(0.002)
L.G	0.000^{*}	0.000^{*}	-0.001^{***}	-0.001	0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
L2.G	0.000^{***}	0.000^{***}	-0.000^{***}	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
S	30.022^{***}	25.165^{*}	23.487^{*}	33.407^{***}	
	(5.966)	(14.740)	(13.734)	(5.450)	
L.S	-29.577^{***}	-6.596	9.382		4.390
	(9.620)	(25.222)	(23.486)		(4.807)
L2.S	5.594	3.295	-2.093	11.352^{**}	
	(4.460)	(8.086)	(7.536)	(5.206)	
Constant	-3.802	-16.828	-22.108^{*}		-1.824
	(2.466)	(13.806)	(12.855)		(3.959)
N	153,909	153,909	153,909	131,922	153,909
AB(2)				-4.512^{***}	-4.563^{***}
J				124.718^{***}	247.912^{***}
Long-run effect λ	-0.000	-0.000	-0.002	0.009	0.001
Wald test of $\lambda = 0$	0.078	0.098	5.907^{**}	3.159^{*}	0.096

Note: Standard errors in parentheses. Blank cells denote terms omitted from the estimation. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 21: China: regression results, one lag

	OLS0	OLS	FE	DGMM	SGMM
L.R	0.682^{***}	0.682^{***}	0.305^{***}	0.341^{***}	0.426^{***}
	(0.002)	(0.002)	(0.003)	(0.015)	(0.010)
C	-0.006^{***}	-0.006^{***}	-0.005^{***}	-0.013	-0.001
	(0.000)	(0.000)	(0.000)	(0.009)	(0.008)
L.C	0.005^{***}	0.005^{***}	0.003^{***}	0.023^{***}	0.000
	(0.000)	(0.000)	(0.000)	(0.008)	(0.006)
I	0.087^{***}	0.086^{***}	0.025	12.852^{***}	4.956^{***}
	(0.016)	(0.016)	(0.016)	(2.428)	(1.495)
L.I	0.005^{*}	0.005^{*}	0.003	-0.010^{***}	-0.005^{***}
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
G	-0.002^{***}	-0.002^{***}	-0.003^{***}	0.004^{**}	0.001
	(0.000)	(0.000)	(0.000)	(0.002)	(0.001)
L.G	0.000	-0.000	-0.001^{***}	-0.002^{**}	-0.001^{***}
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
S	-2.793	-8.556^{**}	6.830^{**}	55.986^{***}	19.658^{***}
	(2.554)	(3.505)	(3.264)	(6.161)	(5.155)
L.S	19.919^{***}	35.575^{***}	28.217^{***}		
	(3.637)	(11.175)	(10.359)		
Constant	-12.503^{***}	-20.598^{***}	-25.715^{***}		-14.434^{***}
	(1.805)	(7.219)	(6.689)		(4.347)
N	175,896	175,896	175,896	153,909	175,896
AB(2)				1.431	4.955^{***}
J				99.456^{***}	317.995^{***}
Long-run effect λ	-0.001	-0.001	-0.003	0.016	-0.002
Wald test of $\lambda = 0$	1.899	2.041	26.784^{***}	7.049^{***}	0.337

Note: Standard errors in parentheses. Blank cells denote terms omitted from the estimation. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.