Pricing Collateralizable Growth*

Lei Guo†, Hening Liu‡, and He Nie§

May 31, 2026

Abstract

In a bank-dominated economy where collateral shapes access to external finance, the accumulation of collateralizable assets can expose firms to systematic credit-cycle risk. We incorporate asset heterogeneity and collateral-based financing constraints into the dividend-discount framework, showing that the return implications of asset growth depend on whether newly accumulated assets support external borrowing. Using Chinese A-share data, we find that collateralizable growth (CG) predicts higher future returns, whereas non-collateralizable growth (NCG) does not. The CG return spread remains positive after controlling for established Chinese factor models. Credit-cycle innovations carry a significant price of risk for CG-sorted portfolios, but not for NCG-sorted portfolios. High-CG firms experience larger financing and investment contractions when credit tightens. These findings suggest that the CG premium reflects systematic compensation for credit-cycle risk embedded in collateralizable asset accumulation.

Keywords: Collateralizable Growth, Credit Cycle, Macro Credit Risk, Financing Frictions

JEL Classification: G12, G11, G32, E22

*Nie He acknowledges financial support from the National Natural Science Foundation of China (Grant No. 72403186). We thank Shijie Deng, Bin Li, Le Wang, Vincent Yao, and Tao Zha for their valuable comments.

†Department of Finance, School of Economics and Management, Wuhan University. Contact: pythonwantong@gmail.com

‡Alliance Manchester Business School, The University of Manchester. Contact: Hening.Liu@manchester.ac.uk

§Department of Finance, School of Economics and Management, Wuhan University. Contact: henieecon@gmail.com

I Introduction

In China's bank-dominated financial system, the composition of a firm's assets shapes not only its productive capacity but also its access to external finance, because collateral remains central to bank lending decisions (Allen et al., 2005). Chinese firms often expand by accumulating assets that both increase productive capacity and support collateral-based bank financing. Yet this financing role also tightens the link between a firm's refinancing capacity and aggregate credit conditions. The more a firm has expanded through collateralizable asset growth, the more its refinancing capacity depends on the borrowing value of those assets, leaving such firms more exposed when credit tightens. Recent episodes of corporate distress suggest that this exposure becomes especially important when credit conditions deteriorate.[1] The pattern points to a question: does the growth of collateralizable assets constitute a systematic source of risk, and is it priced in the cross-section of returns?

The existing literature has not fully addressed this question. Research on collateral shows that collateralizable assets shape borrowing capacity, investment, and real outcomes (Gan, 2007; Chaney et al., 2012; Brandt and Li, 2003). Research on expected returns typically studies investment through aggregate asset growth or production-based models that treat capital as homogeneous and external finance as approximately frictionless (Fama and French, 2015; Hou et al., 2015). Neither line speaks directly to the asset-pricing implications of how investment is composed when borrowing depends on collateral. In China, fixed assets, construction in progress, and increasingly accounts receivable can support bank borrowing, whereas cash and many residual operating assets do not enter the core collateral-based borrowing base and may even substitute for external funds.[2] Once capital is no longer treated as homogeneous and borrowing

[1] Several recent cases illustrate this exposure. China Evergrande Group accumulated large liabilities partly through collateral-backed borrowing against land reserves and property inventories, and defaulted in 2021 after the "Three Red Lines" policy restricted new borrowing for overleveraged developers. Similar refinancing pressure also appeared among other highly leveraged firms that had expanded through debt-financed asset accumulation. Related evidence on the real effects of financing constraints in China's real estate market is provided by Agarwal et al. (2026).

[2] Accounts receivable are legally pledgeable in China (*Civil Code*, Article 441), and a centralized registry operated by the People's Bank of China facilitates their use in bank lending; see Wang et al. (2020).

constraints depend on balance-sheet composition, the composition of investment becomes relevant for expected returns.[3]

This insight finds direct expression in the cross-section of returns. When stocks are sorted each month on the growth of individual balance-sheet items, the resulting high-minus-low portfolios diverge sharply along the collateral dimension. Fixed asset growth and accounts receivable growth, the two items that carry explicit collateral status under the Chinese Civil Code and routinely enter commercial bank lending decisions, generate cumulative excess returns of 55 to 60 percent between 2000 and 2022. Cash growth, which provides internal liquidity rather than external borrowing capacity, generates a cumulative spread of roughly negative 45 percent. Total asset growth, which combines items with different financing roles, produces no meaningful pattern, consistent with the weak aggregate asset-growth effect documented in the Chinese market (Lin, 2017; Huang, 2019; Liu et al., 2019).

To rationalize this pattern, we bring two features, asset heterogeneity and collateral-based financing constraints, into the dividend-discount framework of Fama and French (2015). Total asset growth is decomposed into collateralizable and non-collateralizable components, and new borrowing is allowed to depend on the amount of newly accumulated collateralizable assets, with a time-varying credit-state variable governing how much of this investment can be debt financed in a given period. Collateralizable growth still requires investment outlays, as in the standard framework, but it also relaxes the financing constraint by expanding the borrowing capacity supported by collateral. This additional borrowing-capacity term is absent for non-collateralizable growth and varies with aggregate credit conditions. The framework therefore delivers two related implications. First, collateralizable growth should carry positive pricing content because it expands collateral-based borrowing capacity. Second, this premium is interpreted as compensation for systematic macro credit risk.

[3]The most closely related asset-pricing study is Ai et al. (2020), who study the level of collateralizable capital and show that its insurance value against aggregate shocks lowers expected returns. We focus on a different margin: the accumulation of collateralizable assets. This growth margin can increase firms' exposure to credit-cycle fluctuations and therefore points toward a positive premium. We discuss this distinction in detail in the contribution section below.

Taking the model to the data requires translating its abstract distinction between collateralizable and non-collateralizable assets into specific items on the balance sheet of Chinese listed firms. Our classification rests on three considerations: whether an item carries collateral status under Chinese collateral law, whether banks accept it as collateral in lending practice, and whether its growth predicts future net debt inflows in firm-level data. Fixed assets, construction in progress, and accounts receivable satisfy all three. They are explicitly recognized as collateral under the Chinese Civil Code, they are routinely accepted by banks in commercial lending, and their growth strongly predicts subsequent debt inflows in panel regressions.[4] We aggregate them into collateralizable growth (CG), scaled by lagged total assets. Cash and other residual operating assets are not classified as part of the core collateralizable borrowing base under our conservative legal-institutional criteria; cash growth in fact predicts less subsequent borrowing, consistent with cash substituting for external finance rather than supporting it. We aggregate these items into non-collateralizable growth (NCG). Inventory and intangible assets carry collateral status legally but their use in lending practice is institutionally heterogeneous, so we exclude them from the baseline measure and reintroduce them through an extended collateral measure in robustness tests.[5] Our empirical sample covers all non-financial A-share firms from January 2000 to June 2022.

We use these two measures to test the model's predictions in the cross-section of A-share returns. Fama-MacBeth regressions that control for size, earnings-to-price, and interest-bearing leverage assign CG a positive and statistically significant coefficient, whereas the coefficient on NCG is indistinguishable from zero. To complement this linear specification, we sort firms each month into quintiles by CG and form value-weighted portfolios. The high-minus-low spread is statistically significant and is concentrated among small and medium firms, where reliance on

[4]Article 395 of the Civil Code recognizes buildings, machinery, and construction in progress as legally collateralizable property; Article 441 grants the same status to accounts receivable. A centralized registry operated by the People's Bank of China facilitates the use of receivables as bank collateral; see Wang et al. (2020).

[5]The treatment of inventory was severely affected by the 2014 Qingdao Port collateral fraud, after which banks substantially curtailed inventory-collateralized lending. Among intangibles, land use rights are widely accepted as collateral, while patents and trademarks face valuation difficulties and are rarely accepted in practice (Crouzet et al., 2022).

bank credit is likely to be stronger, and is much weaker among large firms with more diversified sources of external finance. This size pattern is consistent with a collateral-based borrowing interpretation, since bank credit is likely to matter more for smaller firms. Portfolios formed on NCG display no comparable spread. The CG hedge portfolio's alpha also survives the Liu et al. (2019) three- and four-factor models, indicating that the premium is not a relabeling of size, value, or a turnover-based factor.

A positive cross-sectional premium is consistent with the model, but the model makes a sharper claim: the premium should be linked to exposure to the macroeconomic credit cycle. We test this claim in two complementary ways. At the macro level, we estimate a stochastic discount factor in which innovations in the aggregate credit cycle, measured from the cyclical component of total loan growth, enter as a candidate priced factor. The credit-cycle factor carries a significant price of risk for portfolios sorted on CG and is much weaker for portfolios sorted on NCG, consistent with the model. At the firm level, financing and investment quantities show a corresponding state-dependent pattern. High-CG firms face larger contractions in borrowing and investment when credit tightens. This pattern is much weaker for NCG portfolios. Taken together, the pricing and quantity evidence support a risk-based interpretation: the CG premium reflects the credit-cycle exposure embedded in collateralizable growth.

The paper's central contribution is to show that collateralizable asset accumulation carries distinct cross-sectional pricing information that is closely linked to aggregate credit risk. Earlier work has documented how collateral shapes borrowing, investment, and real outcomes, as well as how financing frictions affect expected returns (Gan, 2007; Chaney et al., 2012; Hahn and Lee, 2009). The most closely related asset-pricing study is Ai et al. (2020), who study U.S. firms and show that the level of collateralizable capital can provide insurance against aggregate shocks and is associated with lower expected returns. Two features distinguish our paper from theirs. The first is institutional: U.S. firms have access to more developed capital markets and more diverse external financing channels, whereas China's bank-dominated system makes collateralizable

assets central to bank borrowing capacity. The second distinction concerns the relevant margin. In our setting, collateralizable assets are not only a stock that may protect firms in bad states; they are also a basis for credit allocation. The accumulation of collateralizable assets therefore matters because it ties marginal borrowing capacity more closely to the aggregate credit cycle. These two margins can have opposite return implications: collateral stocks may lower expected returns by providing insurance, whereas collateralizable growth may raise expected returns by increasing credit-cycle exposure.

The framework also helps clarify why aggregate asset growth has weak pricing power in the Chinese market, as documented in prior studies (Lin, 2017; Huang, 2019; Liu et al., 2019). We argue that the weakness of the aggregate measure reflects an aggregation problem rather than the absence of investment-related pricing information. Total asset growth combines balance-sheet components with different financing roles, so the aggregate measure can fail to capture the pricing content of its underlying components. Decomposing asset growth by collateralizability recovers a clear return pattern that is not visible in total asset growth, and complements recent evidence that the information in asset growth is concentrated in specific balance-sheet items rather than in the aggregate measure itself (Cooper et al., 2024).

China provides an institutionally useful setting for studying this mechanism because bank intermediation dominates external finance and collateral remains central to corporate lending. The mechanism, however, need not be specific to China. In economies where external finance is largely bank-mediated and borrowing capacity depends heavily on collateralizable assets, investment composition may similarly affect firms' exposure to aggregate credit conditions (Fernald and Rogers, 2002; Carpenter et al., 2021). By embedding heterogeneity in asset collateralizability into an otherwise standard valuation framework, the paper offers a way to uncover pricing effects that are not visible when capital is treated as homogeneous.

The remainder of the paper proceeds as follows. Section II documents the motivating stylized facts. Section III develops the theoretical framework. Section IV describes the data and

sample. Section V presents the balance-sheet decomposition and variable construction. Section VI reports the cross-sectional evidence, the credit-cycle pricing tests, the quantity evidence across credit states, and the robustness of the premium to alternative factor models. Section VII concludes.

II Motivating Evidence

In China, bank credit remains a central source of external finance for listed firms. Because collateral plays an important role in bank lending decisions, the composition of a firm's assets can affect both its productive capacity and its access to external borrowing. This makes asset growth difficult to interpret as a single homogeneous measure. An increase in collateralizable assets may expand the firm's borrowing capacity, whereas an increase in cash or other non-collateralizable assets may mainly change the firm's reliance on internal funds. Asset growth can therefore have different implications depending on which balance-sheet item expands.

The analysis begins with simple evidence from individual balance-sheet items. The purpose is to examine whether the return patterns of A-share firms differ across asset components with different financing roles. If all asset growth were economically similar, sorting on the growth of different items should produce similar return spreads. If the spreads differ systematically across items, then the composition of asset growth contains information that is not captured by total asset growth. This exercise provides a useful first look at whether balance-sheet composition matters for the return patterns of Chinese listed firms.

This exercise uses monthly stock returns and annual financial statements for all non-financial firms listed on the Chinese A-share market between January 2000 and June 2022, drawn from the CSMAR database. The sample excludes financial firms, ST and *ST stocks, firms with fewer than fifteen trading days in the prior month, firms with negative year-end shareholder

equity or missing key financial items, and stocks below the thirtieth percentile of tradable market capitalization in each monthly cross-section. Full details of data sources, screening criteria, and the Fama-French annual-to-monthly mapping convention appear in Section IV.

We sort firms each month into quintiles based on the growth rate of each individual balance-sheet item. For each asset item j, firms are ranked on $g^j_{i,t} = \Delta\text{Item}^j_{i,t}/TA_{i,t-1}$ within the monthly cross-section. A value-weighted high-minus-low portfolio is constructed as the return spread between the top and bottom quintiles, and cumulative excess returns are computed arithmetically over the entire sample period. We examine four balance-sheet items whose collateral functions in Chinese bank lending differ markedly: fixed assets and accounts receivable, which carry explicit collateral status under the *Civil Code* and are routinely accepted as collateral in commercial bank lending; inventory, which is legally collateralizable but constrained in banking practice; and cash, which provides internal liquidity rather than supporting external borrowing. Figure 1 plots the resulting cumulative high-minus-low returns.

The figure displays a sharp divergence along the collateralizability dimension. The cumulative returns of the portfolios sorted on fixed asset growth and accounts receivable growth climb steadily over the sample period, reaching cumulative excess returns of roughly 55 to 60 percent by mid-2022. Both items are the core collateralizable items in Chinese bank lending: fixed assets typically receive favorable loan-to-value treatment under direct legal protection, and accounts receivable benefit from the centralized registration system operated by the People's Bank of China, which has supported the expansion of receivables-based supply-chain finance (Wang et al., 2020). The cash-sorted portfolio moves in the opposite direction, drifting downward throughout the sample and ending at roughly −45 percent. This pattern is consistent with cash functioning as an internal substitute for external finance rather than as an asset that expands debt-financing capacity. Inventory traces a more irregular path, falling below zero for roughly a decade before recovering after 2016, reflecting the ambiguous collateral status of inventory in Chinese banking practice. By contrast, the total asset growth portfolio displays no discernible

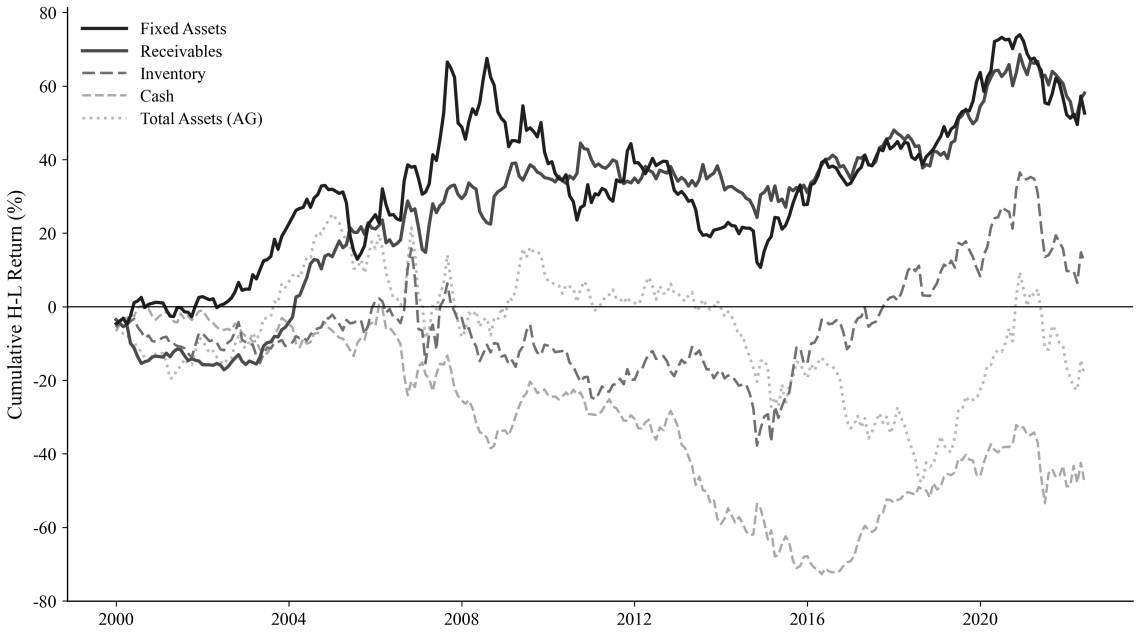


Figure 1: Cumulative High-Minus-Low Returns by Balance-Sheet Item

Note: This figure plots the cumulative value-weighted high-minus-low returns of portfolios sorted on the growth of individual balance-sheet items. Each month, firms are independently ranked into quintiles based on the growth of fixed assets, accounts receivable, inventory, or cash, normalized by lagged total assets. The high-minus-low return is defined as the value-weighted return spread between the top and bottom quintiles. Cumulative returns are computed arithmetically from January 2000 to June 2022. The sample excludes financial firms, ST and *ST stocks, firms with fewer than 15 trading days in the prior month, and stocks below the 30th percentile of tradable market capitalization in each monthly cross-section.

pattern over the same period, oscillating around zero throughout the sample, consistent with the idea that aggregating components with different financing roles can dilute the underlying return patterns.

Several features of the time series merit comment. The cumulative returns of the fixed-asset and receivables portfolios are slightly negative during the first three years of the sample, when China's listed universe was still relatively small and the market structure was changing quickly. The large oscillation around 2008 and 2009 coincides with the four-trillion stimulus program and the subsequent tightening episodes, and is consistent with the view that shifts in credit supply amplify return dispersion between firms with different collateralizable asset bases.

The stretch from 2010 to 2015 is also informative, but should be read descriptively.

During these years, the fixed-asset and receivables portfolios plateau, while the cash-sorted portfolio experiences its most pronounced drawdown. These years include the 2013 interbank cash crunch and the easing cycles that followed. The timing is consistent with the view that credit-cycle variation may amplify return dispersion across firms with different balance-sheet compositions. The divergence across the groups widened substantially and reached its maximum gap around 2016.

Two features of Figure 1 together pose a challenge to canonical investment-pricing models. The first is that asset-component spreads carry opposite signs: items that support debt financing earn persistent positive excess returns, while items that substitute for external borrowing earn persistent negative ones. The second is that the side carrying positive returns is the collateralizable side. Both features are difficult to reconcile with the Fama and French (2015) dividend-discount logic and the neoclassical q-theory of Hou et al. (2015), which treat capital as homogeneous and external finance as approximately frictionless. In these frameworks, different forms of asset growth enter expected returns through the same investment margin and are therefore expected to carry the same sign, traditionally negative under the investment-anomaly interpretation. The data deliver opposite signs across components, and the positive sign appears precisely on the collateralizable side.

The persistence of the divergence makes it difficult to view the pattern as a purely transitory return fluctuation. More importantly, the return spreads correspond to a dimension that these frameworks do not explicitly consider: whether the expanding asset item can support external debt financing. Because canonical models abstract from both asset heterogeneity and collateral-based borrowing constraints, they have little to say about why asset growth should have different return implications depending on the collateral function of the underlying asset. The next section introduces this asset heterogeneity and the associated financing constraint into the dividend-discount framework. The goal is to provide a simple structure for understanding why collateralizable and non-collateralizable asset growth can have different pricing implications, and

to guide the empirical analysis that follows.

III Theoretical Framework

Section II documents two features of the data that are difficult to explain within the canonical framework: collateralizable and non-collateralizable balance-sheet expansions earn opposite cross-sectional spreads, and the positive spread sits on the collateralizable side. In standard investment-pricing models, capital is homogeneous and external financing is approximately frictionless, so every form of asset growth enters the valuation equation through the same investment margin. Explaining this pattern therefore calls for introducing the institutional feature that distinguishes the two sides of the balance sheet, namely that one supports debt financing under bank-based credit allocation and the other does not.

We formalize this insight by extending the dividend-discount model (DDM) to include financing constraints based on collateralizable assets. The purpose of the model is deliberately narrow. It does not seek to characterize the firm's full dynamic financing problem. Instead, it clarifies how asset growth enters valuation when newly accumulated assets also expand collateral-based borrowing capacity. In a bank-dominated financial system, this borrowing capacity depends on aggregate credit conditions, so firms with greater collateralizable growth become more exposed to adverse credit states. The resulting framework separates two ideas that are conceptually distinct. The DDM delivers a valuation-level cross-sectional prediction, while the risk-premium interpretation comes from the exposure of high-CG firms to adverse credit states.

A key point is that the model concerns the growth margin rather than the total stock of collateral. Existing collateral stocks may support borrowing or provide insurance in adverse states. CG instead measures newly accumulated collateralizable assets and therefore captures how recent investment links future borrowing capacity to the aggregate credit environment. This distinction is

central for both the empirical design and the interpretation of the premium.

III.A Model Setup

We follow the valuation framework of Fama and French (2015) but introduce asset heterogeneity and financing frictions. Firm i's equity market value $M_{i,t}$ is the present value of expected future dividends:

$$M_{i,t} = \sum_{\tau=1}^{\infty} \frac{\mathbb{E}_t(D_{i,t+\tau})}{(1+r_i)^{\tau}}, \tag{1}$$

where r_i is the internal rate of return that equates current market value to expected future payouts. Using the accounting identity, the dividend payout $D_{i,t}$ equals corporate earnings $Y_{i,t}$ minus the change in book equity $\Delta B_{i,t}$. Applying the balance-sheet identity $\Delta B_{i,t} = \Delta A_{i,t} - \Delta L_{i,t}$, dividends can be written as

$$D_{i,t} = Y_{i,t} - \Delta A_{i,t} + \Delta L_{i,t}. \tag{2}$$

The standard DDM treats asset growth as homogeneous. Our departure is to decompose total asset expansion into a collateralizable component and a non-collateralizable component,

$$\Delta A_{i,t} = \Delta CA_{i,t} + \Delta NCA_{i,t}. \tag{3}$$

The distinction is economic rather than purely accounting-based. Collateralizable asset growth, $\Delta CA_{i,t}$, captures newly accumulated assets that banks can credibly accept as part of the collateralizable borrowing base. Non-collateralizable asset growth, $\Delta NCA_{i,t}$, captures asset growth that is not classified as part of this core borrowing base under the paper's conservative legal-institutional criteria.

In China's bank-dominated financial system, the marginal availability of external debt financing depends on the collateralizable assets newly accumulated on the firm's balance sheet. Yet this collateral-based borrowing capacity is not fixed: aggregate credit conditions affect how banks set lending standards for collateral-based borrowing. Following Jermann and Quadrini (2012), we represent the collateral-based financing constraint as[6]

$$\Delta L_{i,t} \leq \tilde{\theta}_t \Delta CA_{i,t}, \tag{4}$$

where $\tilde{\theta}_t \in (0, 1)$ is a reduced-form aggregate credit-state variable that summarizes the time-varying debt capacity supported by one unit of newly accumulated collateralizable assets. Higher values of $\tilde{\theta}_t$ correspond to credit expansions, when banks are more willing or able to provide external debt financing against collateralizable assets. Lower values correspond to credit contractions, when the same collateralizable assets support less external borrowing.

This interpretation is important. The variable $\tilde{\theta}_t$ is not a collateral-price shock, a firm-specific loan-to-value ratio, a collateral haircut, or a bank relationship parameter. It is a macroeconomic credit-state variable common to all firms. Cross-sectional heterogeneity in exposure comes primarily from $\Delta CA_{i,t}$, the amount of collateralizable assets a firm has accumulated.[7] By contrast, $\Delta NCA_{i,t}$ does not provide the same debt-financing support and therefore does not transmit aggregate credit conditions into the firm's debt capacity.

The constraint in equation (4) is a reduced-form representation of incremental borrowing capacity under a financing constraint based on collateralizable assets. It should be read as describing dependence on a particular borrowing-capacity margin rather than as a prediction that

[6]The empirical measure of $\Delta CA_{i,t}$ can be positive or negative. The model uses $\Delta CA_{i,t}$ as an ordered measure of collateralizable accumulation: higher values imply stronger borrowing-capacity exposure to the credit state, while lower or negative values indicate weaker or declining collateralizable accumulation.

[7]A more general constraint can be written as $\Delta L_{i,t} \leq \kappa_i \tilde{\theta}_t \Delta CA_{i,t}$, where κ_i captures persistent firm-level differences in collateral quality, bank relationships, or enforcement frictions. The baseline model normalizes κ_i to one because the empirical mechanism does not require estimating firm-specific collateral rates. The central prediction requires only that the common credit-state variable $\tilde{\theta}_t$ varies over time and loads more strongly on firms with larger collateralizable asset growth.

high-CG firms are always more levered. Firms that accumulate more collateralizable assets rely more on this financing capacity when credit is available and are more exposed when that capacity contracts.

When the financing constraint binds, the firm borrows up to the debt capacity supported by collateralizable assets,

$$\Delta L_{i,t} = \tilde{\theta}_t \Delta CA_{i,t}.$$

Substituting this expression into the dividend identity in equation (2) gives

$$D_{i,t} = Y_{i,t} - \Delta NCA_{i,t} - (1 - \tilde{\theta}_t)\Delta CA_{i,t}. \tag{5}$$

Equation (5) is the central object of the model. Non-collateralizable growth reduces current distributable resources one-for-one because it requires internal funding but does not relax the financing constraint. Collateralizable growth also requires investment outlays, but part of that outlay can be financed with debt backed by collateralizable assets. The share supported externally is governed by the aggregate credit state $\tilde{\theta}_t$.

Substituting equation (5) into the valuation equation gives the augmented DDM:

$$\frac{M_{i,t}}{B_{i,t}} = \frac{\sum_{\tau=1}^{\infty} \mathbb{E}_t \left[Y_{i,t+\tau} - \Delta A_{i,t+\tau} + \tilde{\theta}_{t+\tau} \Delta CA_{i,t+\tau} \right] / (1 + r_i)^{\tau}}{B_{i,t}}. \tag{6}$$

Relative to the standard DDM, equation (6) contains one new term, $\tilde{\theta}_{t+\tau} \Delta CA_{i,t+\tau}$. This term is the key addition to the valuation framework. It preserves the standard negative investment effect through $-\Delta A$, but adds a borrowing-capacity term that applies only to the collateralizable component of asset growth.

III.B Implications

Equation (6) is a valuation equation. Following the logic of Fama and French (2015), it links expected returns to current valuation and expected future payouts. The equation does not by itself identify a risk premium. Rather, it shows how expected returns adjust when expected payouts differ, holding valuation and other fundamentals fixed.

This logic is useful for interpreting collateralizable growth. Consider two firms with the same market-to-book ratio, expected profitability, and total asset growth, but different compositions of asset growth. In the standard dividend-discount logic, higher investment reduces current distributable resources and is therefore associated with lower expected returns, other things equal. In equation (6), however, collateralizable growth enters not only through the standard investment term $-\Delta A_{i,t+\tau}$, but also through the borrowing-capacity term $\tilde{\theta}_{t+\tau}\Delta CA_{i,t+\tau}$. A firm with more collateralizable growth therefore has higher expected payouts than an otherwise similar firm whose asset growth does not expand collateral-based borrowing capacity. Holding current valuation and expected profitability fixed, this difference points to a higher internal rate of return for high-CG firms.

Implication 1 (Positive Pricing Effect of Collateralizable Growth). Holding valuation, expected profitability, and total asset growth fixed, collateralizable growth should carry a positive expected-return premium because it expands collateral-based borrowing capacity in the valuation equation.

This implication does not mean that collateralizable investment is costless. CG remains part of total asset growth and therefore still absorbs resources through the standard investment term. The difference is that CG also supports external borrowing, whereas NCG does not. When assets are treated as homogeneous and all investment is financed in the same way, this distinction disappears. When borrowing capacity depends on collateralizable assets, the composition of asset

growth becomes relevant for expected returns.

The risk interpretation comes from the state dependence of the same borrowing-capacity term. In equation (6), $\tilde{\theta}_t$ is a common credit-state variable. It affects all firms, but its effect is stronger for firms that have accumulated more collateralizable assets. A high-CG firm therefore has future payouts and refinancing capacity that are more exposed to aggregate credit conditions than an otherwise similar low-CG firm. This exposure is summarized by equation (5):

$$\frac{\partial D_{i,t}}{\partial \tilde{\theta}_t} = \Delta CA_{i,t}. \tag{7}$$

A decline in the credit state lowers distributable resources more for firms with larger $\Delta CA_{i,t}$, because a larger share of their financing capacity is tied to collateralizable assets.

The economic logic is direct. When credit expands, newly accumulated collateralizable assets support external borrowing. When credit contracts, the same dependence exposes high-CG firms to a larger adjustment in internal funds, refinancing capacity, or payouts. Firms whose asset growth is concentrated in non-collateralizable components do not acquire the same exposure, because $\Delta NCA_{i,t}$ does not support external borrowing. CG therefore links the firm's marginal financing capacity to aggregate credit conditions.

Implication 2 (Credit-Cycle Risk Compensation). The positive CG premium is interpreted as compensation for aggregate credit-cycle risk, because the financing value of collateralizable growth varies with aggregate credit conditions and declines when credit tightens.

This formulation separates the valuation implication from the risk interpretation. The first implication predicts a positive return premium for collateralizable growth. The second implication links this premium to systematic exposure to aggregate credit conditions. The empirical analysis that follows is organized around these two implications: it first examines whether CG is priced in the cross-section, and then asks whether the pricing pattern is consistent with credit-cycle risk

compensation rather than a mechanical investment effect or a generic growth anomaly.

IV Data and Sample

The primary sample spans the period from January 2000 to June 2022. We source all firm-level financial information, including monthly stock returns, tradable market capitalization, and accounting data, from the China Stock Market & Accounting Research (CSMAR) database. To capture aggregate credit conditions, we obtain the year-over-year growth rate of total financial institution loans from the Wind Financial Terminal. This series serves as our primary proxy for the aggregate credit environment. Following standard practice, we apply the Hodrick-Prescott (HP) filter to isolate its cyclical component (Drehmann et al., 2011; Borio, 2014). Appendix E additionally uses quarterly TFP innovations as a robustness control for broad productivity-side macroeconomic shocks. Following standard practice in empirical asset-pricing studies, our initial universe comprises all non-financial firms listed on the Chinese A-share market. Table 1 outlines the annual evolution of the sample.

The sample window of January 2000 to June 2022 deserves a note. Our analysis focuses on how collateralizable asset growth links firms' financing capacity to the aggregate credit cycle. The baseline state variable is therefore the macro credit environment, not a separate collateral-price or real-estate valuation shock. Ending the sample in mid 2022 also avoids placing weight on later property-sector-specific disruptions that are less closely aligned with the broad bank-credit channel modeled in the paper.

Monthly stock returns are computed with cash dividend reinvestment to reflect investors' compound returns (Liu et al., 2024). Following standard practice in the Chinese market literature, we use the annualized one-year time deposit interest rate, converted to a monthly rate, as a proxy for the risk-free rate (r_f). The value-weighted average return of the filtered stock universe defines

Table 1: Annual Sample Characteristics (2000–2022)

Year	N	Market Cap (Billion RMB)	Total Assets (Million RMB)	EP	BM	Leverage
2000	516	514.43	196,321.78	0.30	3.23	0.41
2001	568	500.67	220,659.75	0.25	2.64	0.41
2002	650	410.82	246,002.42	0.20	2.74	0.42
2003	708	404.46	304,977.84	0.25	3.62	0.43
2004	764	423.91	332,074.60	0.32	4.30	0.41
2005	837	320.83	339,381.37	0.35	5.04	0.39
2006	887	428.31	374,271.97	0.35	6.28	0.41
2007	922	1,267.18	423,424.07	0.36	5.88	0.56
2008	971	949.85	501,807.96	0.25	3.29	0.44
2009	1,050	1,223.12	664,967.19	0.27	3.57	0.51
2010	1,075	1,518.12	829,428.66	0.27	3.72	0.48
2011	1,195	1,471.72	923,878.53	0.25	2.56	0.42
2012	1,438	1,120.80	960,251.54	0.36	3.58	0.40
2013	1,629	1,086.55	991,192.32	0.43	4.44	0.38
2014	1,721	1,217.35	1,069,185.31	0.43	4.51	0.37
2015	1,826	2,108.46	1,183,575.60	0.38	3.91	0.36
2016	1,873	1,840.96	1,204,874.01	0.25	2.91	0.35
2017	2,009	1,997.87	1,262,492.71	0.25	2.98	0.34
2018	2,229	1,698.03	1,285,445.89	0.32	3.56	0.33
2019	2,505	1,631.77	1,292,378.91	0.39	4.76	0.34
2020	2,633	2,020.98	1,347,006.93	0.41	5.19	0.34
2021	2,827	2,488.40	1,399,941.09	0.33	4.65	0.35
2022	3,211	2,139.15	1,411,643.28	0.33	4.21	0.34

Note: This table reports annual characteristics of the initial A-share sample. N denotes the number of firms in each year. Market Cap reports aggregate sample market capitalization in billion RMB, and Total Assets reports aggregate sample book assets in million RMB. EP, BM, and Leverage are cross-sectional means of unadjusted firm-level data.

the market return (r_m). Financial data are matched to returns following the classic Fama-French annual mapping rules to eliminate look-ahead bias (Fama and French, 1993): annual financial statement data from the end of December in year $t-1$ are mapped to the monthly return cross-section from July of year t to June of year $t+1$. The market capitalization denominator for valuation metrics is taken from December of year $t-1$, while the tradable market capitalization for size sorting is taken from June of year t.

We apply standard procedural screens to the initial A-share sample: (i) stocks listed for at least six months; (ii) stocks with at least 15 trading days in the previous month, to exclude highly illiquid or suspended samples (Acharya and Pedersen, 2005); (iii) removal of ST and *ST stocks;

and (iv) exclusion of firms with negative year-end shareholder equity or missing key financial data.

Beyond these procedural screens, we further exclude stocks below the 30th percentile of tradable market capitalization in each monthly cross-section. This filter follows the standard practice in the Chinese asset-pricing literature. Lee et al. (2017) show that small listed firms in China contain substantial shell value because tight IPO constraints make listing status valuable in reverse mergers. Liu et al. (2019) further document that this shell-value component is concentrated in the bottom 30% of the size distribution and can distort the relation between returns and operating fundamentals. Excluding these firms allows our empirical tests to focus on the part of the market where stock returns are more likely to reflect cash-flow and risk exposures rather than regulatory option value. Appendix C reports parallel results using 25% and 35% cutoffs, which are quantitatively close to the baseline.

V Asset Structure Decomposition and Variable Construction

Taking the augmented DDM to the data requires translating its abstract distinction between collateralizable and non-collateralizable capital into a concrete classification of balance-sheet items reported by Chinese listed firms. The classification proceeds in three steps. We first delimit the universe of major operating or financing-relevant balance-sheet items, excluding financial investments and accounting residuals. Within this universe, we then partition items by whether they support the debt-financing base through which firms depend on bank credit, using a triple criterion that combines legal status, banking practice, and empirical predictive content for forward debt inflows. Items that pass all three criteria enter our baseline collateralizable measure; items that clearly do not expand collateral-based borrowing capacity enter the non-collateralizable category; and items whose collateral status is institutionally heterogeneous are held aside for the baseline measure and reintroduced through an extended robustness measure.

V.A Asset Item Selection

We restrict attention to non-financial listed firms and exclude all financial-specific accounts such as loans and advances. The inclusion of an asset item in our main analysis must satisfy three principles. The first is scale significance: the item must constitute a substantial portion of total assets so that variation in its growth carries measurable cross-sectional content. The second is economic clarity: the item must represent a major operating or financing-relevant balance-sheet category rather than financial portfolio allocation or accounting residuals. The third is financing relevance: the item must have a plausible theoretical link to the collateral-based borrowing margin studied in the paper.

Five major balance-sheet items meet these principles. *Cash and cash equivalents* represent the firm's immediate liquidity reserves and typically account for 15 to 20 percent of total assets, providing a critical baseline for analyzing financing constraints. *Accounts and notes receivable*, including the post-2019 "receivables financing" subcategory, represent operational claims generated from sales and constitute 10 to 20 percent of assets. *Inventory*, comprising raw materials, work in process, and finished goods, accounts for 10 to 15 percent of total assets. *Fixed assets*, taken together with construction in progress because the latter represents physical capital that will eventually transition into fixed assets on completion, form the largest non-current asset category at 30 to 45 percent. *Intangible assets* include patents, trademarks, and land use rights. These five categories collectively cover 82 to 88 percent of a typical non-financial firm's total assets.

We deliberately exclude financial assets such as trading assets and held-to-maturity investments, long-term equity investments that reflect strategic mergers and acquisitions rather than capital expenditures, goodwill as an accounting residual, and deferred taxes. These items follow economic logics that differ fundamentally from operational investment, and we collect them with the residual of the balance sheet under a non-collateralizable category to keep the

baseline classification conservative.

V.B Classification Criteria for Asset Collateralizability

We classify the selected operational items into collateralizable and non-collateralizable categories on the basis of three considerations: legal eligibility under Chinese collateral law, the bank lending practice that determines whether eligibility translates into actual borrowing capacity, and the empirical relation between each item and subsequent debt inflows in firm-level panel regressions. An item is assigned to the collateralizable group only if it satisfies all three.

1. Collateralizable Assets (CG)

Fixed Assets and Construction in Progress. Physical capital is the canonical form of collateralizable assets. Article 395 of the Civil Code of the People's Republic of China explicitly recognizes buildings, production equipment, and buildings under construction (i.e., CIP) as legally collateralizable property. In banking practice, physical assets are widely preferred because of their tangibility and relatively transparent valuation, typically receiving high loan-to-value ratios and low haircuts (Jiang et al., 2017). Empirically, as shown in our dynamic validation tests in Appendix B, fixed asset growth significantly predicts future net debt inflows.

Accounts and Notes Receivable. Including receivables as collateralizable assets is important in China's institutional setting. Article 441 of the Civil Code explicitly permits the use of accounts receivable as collateral. The People's Bank of China operates a unified movable-property financing registration system through its Credit Reference Center, which reduces duplicate pledging risk and helps banks verify receivables used as collateral. This infrastructure has supported the rapid expansion of receivables-based supply-chain finance in China (Wang et al., 2020). Consistent with the financing role of receivables, the Ministry of Finance introduced the "receivables financing" accounting category in 2019, recognizing certain

receivables as more liquid financing-eligible claims. Empirically, accounts receivable growth is closely related to forward debt inflow (Appendix Table B1, Model 2).

2. Debated Assets

Inventory. We treat inventory as a debated item for three reasons, despite its theoretical potential. First, using inventory as collateral often requires third-party warehousing, monitoring, or other control arrangements, incurring prohibitive friction costs for most firms. Second, the 2014 Qingdao Port metal financing fraud severely eroded banking confidence, causing banks to become more cautious toward inventory-collateralized lending (Narayanan et al., 2025). Third, and most importantly for our model, inventory value is highly procyclical and may decline or become harder to liquidate precisely when credit conditions tighten. While inventory growth is positively related to future debt inflows in Appendix B, these institutional frictions make inventory less suitable as a systematic collateral-based borrowing base. To keep the baseline classification conservative, we exclude inventory from the baseline classification. Acknowledging its theoretical potential, we reincorporate it into an extended collateralizable asset measure (CG^{ext}) in the Appendix to verify the robustness of our pricing results.

Intangible Assets. Intangibles present unique heterogeneity. While land use rights are often accepted as collateral (Civil Code Article 395), patents and trademarks are difficult to collateralize at scale because of valuation uncertainty and thin secondary markets (Crouzet et al., 2022). Because standard databases such as CSMAR aggregate different types of intangible assets, treating the combined item as uniformly collateralizable is problematic. This conservative treatment likely attenuates the measured pricing effect of collateralizable growth, since some land use rights may be collateralizable in practice. To avoid mixing assets with heterogeneous collateral functions into the baseline measure, we exclude intangibles from the baseline components and reserve them for the extended collateralizable-growth measure in Appendix D.

3. Non-Collateralizable Assets (NCG)

Cash and Cash Equivalents. In our baseline classification, cash is not treated as collateralizable growth; it primarily serves as internal liquidity and can substitute for external borrowing. Under the pecking order theory (Myers and Majluf, 1984), firms use internal cash before seeking external debt. In frictional markets, firms accumulate cash for precautionary liquidity rather than to secure loans (Han and Wang, 2023). Our dynamic tests confirm this: cash growth strongly and *negatively* predicts future net debt inflows ($t = -5.95$ in Appendix Table B1), consistent with cash substituting for external finance rather than supporting new borrowing.

Residual Assets. The remaining assets on the balance sheet, excluding fixed assets, construction in progress, receivables, inventory, intangibles, and cash, are not classified as part of the core collateralizable borrowing base under our conservative legal-institutional criteria. Some residual items may have limited financing relevance in specific transactions, but they do not provide systematic and comparable collateral-based borrowing capacity in the way physical assets and pledgeable receivables do. We group them with cash to form the baseline NCG measure.

V.C Variable Definition

Following the classification established above, we decompose total asset growth into distinct dimensions. Throughout this subsection, $TA_{i,t}$ denotes the book value of total assets of firm i at the end of fiscal year t. For any balance-sheet item X, we define its annual change as $\Delta X_{i,t} = X_{i,t} - X_{i,t-1}$, and scale all growth measures by lagged total assets, $TA_{i,t-1}$.

We first define total asset growth (AG) as the benchmark measure:

$$AG_{i,t} = \frac{TA_{i,t} - TA_{i,t-1}}{TA_{i,t-1}}. \tag{8}$$

AG is retained as a horse-race control in the empirical tests, following the convention of the investment anomaly literature. It is not the focus of our analysis because it aggregates asset components with different financing roles.

Collateralizable Growth (CG) aggregates the expansion of the core balance-sheet items that satisfy the legal, institutional, and empirical criteria for collateralizability:

$$CG_{i,t} = \frac{\Delta FA_{i,t} + \Delta CIP_{i,t} + \Delta AR_{i,t}}{TA_{i,t-1}}. \tag{9}$$

Here, FA denotes fixed assets, CIP denotes construction in progress, and AR denotes accounts and notes receivable. These items constitute the baseline collateralizable asset category because they are legally pledgeable, routinely accepted in bank lending practice, and empirically related to subsequent debt inflows.

Non-Collateralizable Growth (NCG) captures the expansion of assets that are not classified as part of the core collateralizable borrowing base in our baseline design:

$$NCG_{i,t} = \frac{\Delta Cash_{i,t} + \Delta RA_{i,t}}{TA_{i,t-1}}. \tag{10}$$

Here, $Cash$ denotes cash and cash equivalents, and RA denotes residual assets, defined as total assets excluding fixed assets, construction in progress, accounts and notes receivable, inventory, intangible assets, and cash. We deliberately exclude the debated items from the baseline NCG measure to preserve a clean distinction between the core collateralizable borrowing base and assets whose collateral status is institutionally ambiguous.

To address the debated nature of inventory and intangible assets, and to ensure that our findings are not driven by their exclusion from the baseline measure, we construct an extended collateralizable growth measure, CG^{ext}, for robustness tests in the Appendix. This extended measure treats inventory and intangible assets as collateralizable and therefore provides an

intentionally broader version of CG:

$$CG^{ext}_{i,t} = \frac{\Delta FA_{i,t} + \Delta CIP_{i,t} + \Delta AR_{i,t} + \Delta INV_{i,t} + \Delta IA_{i,t}}{TA_{i,t-1}}. \tag{11}$$

Here, INV denotes inventory and IA denotes intangible assets. Since both items have institutionally heterogeneous collateral status, CG^{ext} is used only as a robustness measure rather than as the baseline definition.

The decomposition builds directly on the motivating evidence in Figure 1. The items that generate the clearest positive spreads in the stylized figure, fixed assets, construction in progress, and accounts receivable, are aggregated into CG. The item that generates the clearest negative spread, cash, is included in NCG together with residual non-collateralizable assets. Inventory and intangible assets are held outside the baseline decomposition because their collateral role is less uniform across firms, banks, and institutional settings. Before testing the asset-pricing implications of CG, Appendix B provides panel regressions showing that CG predicts future net debt inflows, while the non-collateralizable components either predict lower subsequent borrowing or fail to operate as systematic collateral. Before we ask whether CG is priced, this validation establishes that CG captures a meaningful economic construct: incremental borrowing capacity supported by collateralizable assets.

V.D Validating the Collateralizable Growth Measure

The decomposition above is grounded in collateral law and bank lending practice, but the continuous measure constructed from balance-sheet items still requires a simple validation exercise. The purpose of this subsection is to describe the type of firms selected by CG and to verify that sorting on CG separates firms along the balance-sheet dimension emphasized by the theory. If CG captures collateralizable accumulation, high-CG firms should have more pledgeable operating assets, should not simply be larger firms, and should be more common in activities

where collateral-intensive bank finance is institutionally relevant.

We construct a firm-year panel from the same monthly sample used in the asset-pricing tests. Each firm contributes one observation per sorting year under the Fama-French July-to-June mapping. Within each year, firms are sorted into five groups based on CG. Continuous variables are winsorized at the 1% and 99% levels within annual cross-sections. Table 2 reports group means together with the Q5 minus Q1 difference in levels and relative to the Q1 mean. The table summarizes four dimensions of firm characteristics: scale and age, asset structure, financing position, and industry composition.

The key asset-structure variable reported in the table is fixed assets plus receivables scaled by total assets. Construction in progress is included in CG but is not reported as a separate row in this descriptive profile because it is a transitional physical-capital account and is much more uneven across firms. Inventory is institutionally debated in our classification and is therefore reported separately rather than bundled into the core collateral ratio. Listing age is computed from the listing date in the firm information file.

Panel A shows that high-CG firms are not simply large firms. The difference in log total assets between Q5 and Q1 is only 0.021, and the difference in log market capitalization is 0.126, both economically small. The sharper difference is listing age: high-CG firms are about three years younger than low-CG firms. This age pattern is consistent with the idea that CG captures firms still building pledgeable operating assets, rather than mature firms whose balance sheets are large but stable.

Panel B describes the asset composition behind the CG sort. The FA-and-receivables ratio rises from 25.4% in Q1 to 39.5% in Q5, a 14.1 percentage point increase. Both fixed assets and receivables contribute to this gap, with the receivables share almost doubling from the bottom to the top quintile. High-CG firms therefore hold substantially more of the assets that form the core collateralizable category. At the same time, they do not look like firms that simply lack liquidity:

Table 2: Firm Characteristic Profile across CG Quintiles

Variable	Q1 (Low)	Q2	Q3	Q4	Q5 (High)	Q5 − Q1 (Abs.)	Q5 − Q1 (Rel.)
Panel A: Scale and Age							
log(Total Assets)	21.788	21.940	22.032	21.833	21.809	0.021	+0.1%
log(Market Cap)	15.600	15.722	15.812	15.687	15.725	0.126	+0.8%
Listing Age	10.62	12.28	12.31	9.02	7.52	−3.10	−29.2%
Panel B: Asset Structure							
FA and receivables / assets	0.254	0.168	0.154	0.285	0.395	0.141	+55.3%
Fixed assets / assets	0.159	0.114	0.096	0.159	0.210	0.051	+31.8%
Receivables / assets	0.094	0.054	0.058	0.125	0.183	0.088	+93.5%
Cash / assets	0.125	0.119	0.122	0.146	0.145	0.020	+16.3%
Inventory / assets	0.074	0.057	0.058	0.090	0.097	0.023	+31.5%
Intangible assets / assets	0.025	0.019	0.016	0.023	0.024	−0.001	–[†]
Panel C: Financing Position							
Total leverage	0.386	0.359	0.342	0.370	0.398	0.012	+3.1%
Interest-bearing leverage	0.162	0.152	0.146	0.144	0.147	−0.015	−9.2%
Current ratio	2.858	3.845	6.118	2.687	2.387	−0.471	−16.5%
Panel D: Industry Composition							
Manufacturing share	0.370	0.307	0.323	0.441	0.433	0.063	+16.9%
Real estate share	0.057	0.113	0.129	0.044	0.027	−0.030	−52.5%
Construction share	0.022	0.025	0.025	0.021	0.015	−0.007	–[†]

Note: This table reports firm-year group means across CG quintiles. Firms are sorted into five groups by CG within each sorting year. Continuous variables are winsorized at the 1% and 99% levels within annual cross-sections. FA and receivables/assets is fixed assets plus accounts receivable scaled by total assets; construction in progress is included in CG but not reported separately in this descriptive profile. The Q5 − Q1 (Abs.) column reports the difference in original units; the Q5 − Q1 (Rel.) column reports the difference relative to the Q1 mean.
[†] Relative difference is suppressed when the absolute value of the Q1 mean is below 0.05, because small denominators make percentage differences difficult to interpret.

cash/assets is slightly higher in Q5 than in Q1. Inventory also rises with CG, but its collateral role is more heterogeneous, so it remains outside the baseline measure and is examined in robustness tests. Intangible assets are essentially flat across the extreme groups.

Panel C separates the CG profile from a static leverage story. Total leverage is only modestly higher in Q5 than in Q1, while interest-bearing leverage is lower in the top quintile. High-CG firms are therefore not simply firms with larger debt stocks. The lower current ratio in Q5 may be consistent with greater reliance on refinancing and working-capital rollover, rather

than mechanically higher leverage. This distinction matters for the mechanism: the relevant exposure is the marginal debt capacity created by collateralizable accumulation, not the unconditional amount of debt already on the balance sheet.

Panel D shows that high-CG firms are concentrated in activities where collateralizable operating assets are naturally important. The manufacturing share is higher in the top CG group, consistent with the capital-intensive and receivables-intensive nature of manufacturing supply chains. By contrast, real estate and construction shares are not higher in Q5, which alleviates the concern that CG is merely a proxy for property or construction exposure.

Taken together, Table 2 shows that CG identifies a distinct balance-sheet exposure. High-CG firms are not primarily larger firms, nor are they simply firms with higher debt stocks. They are younger firms with substantially more fixed assets and receivables, lower current ratios, and a greater concentration in manufacturing activity. This profile is consistent with the collateral-based borrowing interpretation: CG selects firms whose asset growth is more likely to support borrowing capacity backed by collateralizable assets and whose financing is more exposed to shifts in aggregate credit conditions.

VI Empirical Evidence

This section takes the two implications of Section III to the data and then asks whether the resulting premium is distinct from established Chinese factor models. Subsection VI.A tests Implication 1, the positive cross-sectional premium of CG, in three steps: Fama-MacBeth regressions, double-sorted portfolios, and an alpha test of the CG hedge portfolio against alternative factor models. Subsection VI.B tests Implication 2 by using a stochastic discount factor framework as an empirical testing device. Subsection VI.C then examines whether firm financing and investment quantities display the state dependence implied by the model.

VI.A The Cross-Sectional CG Premium

We test Implication 1 using parametric Fama-MacBeth regressions, non-parametric portfolio sorts, and alpha regressions against established Chinese factor models. The three exercises probe the same prediction along complementary dimensions: the regressions ask whether CG carries pricing content after controlling for size, value, and the firm's existing debt burden; the sorts ask whether the same content survives without any functional-form assumption; and the alpha regressions ask whether the remaining return spread is absorbed by established Chinese factor models.

VI.A.1 Fama-MacBeth Cross-Sectional Regressions

We adopt the Fama and MacBeth (1973) two-step framework, exploring specifications that isolate which component of balance-sheet expansion carries the marginal pricing signal. For each month t:

$$R^{exc}_{i,t+1} = a_t + \sum_k b^k_t X_{k,i,t} + \varepsilon_{i,t}, \tag{12}$$

where $R^{exc}_{i,t+1}$ is the excess return of stock i in month $t+1$. We report time-series means of monthly slope coefficients with Newey-West t-statistics (4 lags). EP enters as EP^+ (positive part) and $D(EP<0)$ (negative earnings dummy). Investment variables (CG, NCG, and AG) undergo monthly cross-sectional z-score standardization. To address the concern that the collateralizable growth signal merely reflects firms' broader leverage profile, we further introduce the interest-bearing leverage ratio (Lev) as a stock-side control, defined as interest-bearing debt over total assets and likewise z-score standardized monthly. The choice of a stock-level rather than flow-level leverage control is deliberate: contemporaneous changes in liabilities are by accounting identity the mirror image of asset-side investment, so any flow-side debt measure would mechanically share variation with CG and obscure rather than test the underlying mechanism. The

level of leverage, by contrast, captures the firm's standing debt burden and is conceptually distinct from any single year's collateralizable accumulation. Coefficients are multiplied by 100. Table 3 reports the eleven specifications.

Table 3: Fama-MacBeth Cross-Sectional Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Intercept	3.56	3.43	3.59	4.89*	4.85*	4.90*	4.83*	4.87*	4.82*	4.87*	4.81*
	(1.29)	(1.23)	(1.30)	(1.92)	(1.90)	(1.92)	(1.89)	(1.93)	(1.90)	(1.93)	(1.90)
log ME	−0.16	−0.15	−0.16	−0.26*	−0.26*	−0.26*	−0.26*	−0.26*	−0.26*	−0.26*	−0.26*
	(−1.01)	(−0.95)	(−1.03)	(−1.84)	(−1.82)	(−1.84)	(−1.81)	(−1.84)	(−1.81)	(−1.84)	(−1.81)
EP^+				7.02***	7.25***	7.04***	6.94***	7.09***	7.34***	7.13***	7.02***
				(2.70)	(2.77)	(2.73)	(2.72)	(2.79)	(2.87)	(2.83)	(2.81)
$D(EP < 0)$				−0.14	−0.18	−0.16	−0.14	−0.11	−0.15	−0.13	−0.11
				(−0.95)	(−1.19)	(−1.11)	(−1.01)	(−0.85)	(−1.10)	(−1.02)	(−0.88)
CG	0.11***			0.08**			0.09**	0.07**			0.09**
	(2.71)			(2.32)			(2.32)	(2.21)			(2.23)
NCG		−0.01			−0.02		0.01		−0.02		0.00
		(−0.27)			(−0.66)		(0.09)		(−0.61)		(0.00)
AG			0.04			0.01	−0.02			0.01	−0.01
			(0.91)			(0.26)	(−0.26)			(0.21)	(−0.16)
Lev								−0.05	−0.05	−0.05	−0.06
								(−1.04)	(−1.05)	(−1.04)	(−1.09)
Avg. Adj. R^2	0.027	0.026	0.027	0.040	0.039	0.040	0.041	0.044	0.043	0.044	0.045

Note: Average slope coefficients from monthly Fama-MacBeth regressions. EP^+, $D(EP < 0)$, and log ME enter with raw values; investment variables (CG, NCG, AG) and the leverage stock control (Lev, defined as interest-bearing debt over total assets) are z-score standardized monthly. Coefficients × 100. Sample: January 2000 to June 2022. Newey-West t-statistics (4 lags) in parentheses. *, **, ***: 10%, 5%, 1% significance levels.

The table is organized as a stepwise comparison. Specifications 1 through 3 examine each growth measure separately, controlling only for firm size. Specifications 4 through 6 add the value controls EP^+ and $D(EP < 0)$ to each single-growth-measure specification. Specification 7 forces all three growth measures into a single horse race. Specifications 8 through 10 reintroduce the three growth measures one at a time but now alongside the leverage stock control. Specification 11 places everything together: size, value, all three growth measures, and leverage. Reading the table from left to right traces a clean stepwise narrative.

The single-growth-measure specifications in Columns 1 through 3 already deliver the central message of the table. CG carries a coefficient of 0.11 with $t = 2.71$, in line with Implication 1 that high collateralizable growth predicts higher future returns. NCG takes a coefficient of −0.01 with $t = -0.27$, providing no evidence of positive pricing content. AG, the

conventional aggregate measure, takes a small and statistically insignificant coefficient of 0.04 with $t = 0.91$. The contrast between Specifications 1 and 3 is consistent with the augmented DDM: CG contains the pricing-relevant component of balance-sheet expansion, whereas the aggregate AG measure dilutes this information by combining assets with different financing roles. This suggests that the weak asset-growth effect in the Chinese market may reflect the aggregation of components with distinct pricing implications rather than a simple absence of investment-related pricing information.

Adding value controls in Specifications 4 through 6 leaves the contrast intact. CG retains a coefficient of 0.08 with $t = 2.32$ under the EP controls. The magnitude is lower than the slope in Specification 1, indicating that the value controls absorb part of the raw CG-return relation, but the coefficient remains positive and statistically significant at the 5% level. The collateral growth premium is therefore not subsumed by the traditional value effect. NCG remains flat at -0.02 ($t = -0.66$), and AG remains flat at 0.01 ($t = 0.26$). Neither alternative shows evidence of meaningful pricing information once value is controlled for.

Specification 7 places all three growth measures into direct competition with size and value controls. The result is clear. CG remains positive and significant at 0.09 with $t = 2.32$, while NCG stays close to zero at 0.01 ($t = 0.09$), and AG turns slightly negative at -0.02 ($t = -0.26$) but remains insignificant. When the three growth measures compete simultaneously, the aggregate AG measure carries no independent pricing information; the pricing signal is concentrated in CG. The horse race indicates that the asset-composition information resides primarily in CG.

Specifications 8 through 10 address a natural objection: the CG premium might simply be a relabeling of leverage-related risk, since the mechanism we propose involves bank borrowing. We test this by adding the interest-bearing leverage ratio as a control to each of Specifications 4 through 6. Under this control, CG still prices the cross-section at 0.07 with $t = 2.21$ in Specification 8, while Lev itself takes a small negative loading (-0.05 with $t = -1.04$) that does not approach significance. NCG and AG remain insignificant in Specifications 9 and 10. The

leverage stock variable shows no evidence of independent pricing power in these specifications, and it does not displace the CG signal. This weighs against the reading that CG is merely a noisy proxy for firm-level debt burden.

Specification 11 is the most demanding test. With all three growth measures and Lev in the regression alongside size and value, CG holds at 0.09 with $t = 2.23$, remaining significant at the 5% level. NCG, AG, and Lev all carry small coefficients with t-statistics well below conventional thresholds. The CG signal survives each increasingly demanding combination of controls, while the alternative growth and leverage variables remain insignificant in specifications where they compete head-to-head with CG.

Overall, CG remains positive and statistically significant across the specifications in which it appears, whereas NCG and AG do not exhibit comparable pricing content.[8] The evidence indicates that the pricing content of asset growth is concentrated in collateralizable balance-sheet expansion.

VI.A.2 Portfolio Sorts

To ensure that our findings are not driven by linear functional form assumptions, we supplement the analysis with non-parametric double-sorted portfolios, including EP sorts as a benchmark (Liu et al., 2019). Table 4 reports the results.

In Panel A, the full-sample H-L spread for CG is 0.33%/month ($t = 2.77$), corresponding to an annualized premium of approximately 3.96%. Returns increase from the Low to the High quintile (0.64% to 0.97%). This pattern is quantitatively consistent with the positive cumulative trajectories of the fixed-asset and receivables portfolios in Figure 1, reinforcing the view that the pricing signal resides in the collateralizable components. The premium is particularly

[8]The CG coefficient also meets the $|t| \geq 2.0$ benchmark often used for factor discovery in Harvey et al. (2016) in each specification in which it appears.

Table 4: Double-Sorted Portfolio Returns

Size Group	Low	2	3	4	High	H-L	t(H-L)
Panel A: Size × Collateralizable Growth (CG)							
Small	0.85	1.00	0.90	1.07	1.17	0.32	(2.98)
Medium	0.62	0.75	0.65	0.81	1.08	0.47	(3.74)
Large	0.44	0.66	0.43	0.62	0.65	0.21	(1.49)
All	0.64	0.80	0.66	0.83	0.97	0.33	(2.77)
Panel B: Size × Non-Collateralizable Growth (NCG)							
Small	0.93	0.96	1.12	0.94	0.95	0.03	(0.20)
Medium	0.74	0.87	0.72	0.72	0.84	0.11	(1.09)
Large	0.51	0.42	0.53	0.51	0.61	0.10	(0.60)
All	0.73	0.75	0.79	0.72	0.80	0.08	(1.01)
Panel C: Size × Earnings-to-Price Ratio (EP Benchmark)							
Small	0.74	1.15	1.31	1.21	1.26	0.51	(3.00)
Medium	0.46	0.82	0.86	1.05	1.10	0.63	(3.37)
Large	0.24	0.33	0.55	0.44	0.85	0.60	(1.80)
All	0.48	0.77	0.91	0.90	1.07	0.58	(3.03)

Note: Monthly value-weighted excess returns (%/month) from independent 3 × 5 double sorts on tradable market capitalization and the corresponding characteristic. H-L is the spread of highest minus lowest group. Newey-West t-statistics (6 lags) in parentheses.

concentrated among small and medium-sized firms: the medium-size group reaches 0.47% ($t = 3.74$), while large-cap firms show a weaker effect. This size distribution is consistent with the idea that the financing constraint based on collateralizable assets binds more tightly for smaller firms, which rely more heavily on the accumulation of new collateralizable assets to expand credit access (Berger and Udell, 2006; Jiang et al., 2015), while large firms enjoy more diversified financing channels (Belo et al., 2019). Panel B shows that NCG generates no comparable return spread, with an all-stock H-L spread of 0.08% per month ($t = 1.01$). Panel C confirms the value premium as a benchmark, showing that the sort methodology detects known pricing signals when they exist.

The positive CG premium departs from standard q-theory logic, in which high investment

implies low expected returns (Liu et al., 2009). The augmented DDM helps reconcile this apparent tension by introducing the collateral-based borrowing-capacity term, $+\tilde{\theta}\Delta CA$, which competes against the conventional $-\Delta A$ investment effect. In a bank-dominated system, this borrowing-capacity term can offset the standard investment effect and generate a positive premium for CG. The same decomposition logic also helps explain why the conventional aggregate investment effect tends to be weak or absent in the Chinese market (Lin, 2017; Huang, 2019; Liu et al., 2019): total asset growth mixes the two opposing components and the net signal is muted, while a clean positive pattern emerges once the collateralizable subset is isolated.

VI.A.3 Alpha Tests against Alternative Factor Models

A natural concern at this point is that the cross-sectional spread documented above could be a relabeling of established Chinese asset-pricing factors rather than an independent pricing signal. If size, value, or turnover-based sentiment exposures already span the CG return spread, the previous evidence would not survive a more demanding factor-adjustment test. We confront this concern by regressing CG hedge portfolio returns on three progressive factor models and examining whether a significant alpha survives.

The first model is the Capital Asset Pricing Model, which projects portfolio returns on the market factor alone. The second is the Liu et al. (2019) three-factor model, hereafter Liu-3, which augments the market factor with a size factor (SMB) and a value factor (VMG) constructed for the Chinese A-share market. The third is the corresponding four-factor model, hereafter Liu-4, which adds the turnover-based sentiment factor (PMO) to capture retail speculation effects in the Chinese market.

The Liu-3 model is our central benchmark because it is widely used in Chinese asset-pricing research. Liu et al. (2019) demonstrate that direct application of the Fama and French (1993) framework to China produces misleading results for two reasons. First, the smallest

decile of listed firms in China exhibits returns dominated by shell-value speculation and reverse-merger expectations rather than fundamental risk pricing (Hsu et al., 2018), which contaminates any size-based factor constructed from the full universe. Second, the book-to-market ratio is a weak pricing signal in China because accounting conservatism and the dominance of tangible assets in book equity reduce its informativeness, so EP substantially outperforms BM as a value proxy. Liu-3 addresses both issues by excluding the bottom 30 percent of firms by tradable market capitalization before factor construction and by using earnings-to-price rather than book-to-market as the value sorting variable. These modifications have made Liu-3 the preferred workhorse benchmark for asset pricing tests on Chinese data.

Our factor construction follows the standard procedure. The MKT factor is the value-weighted excess return of the filtered A-share universe described in Section IV. SMB and VMG are constructed from 2×3 independent double sorts on size and EP, following Liu et al. (2019). Each June, stocks are first sorted into two size groups by median tradable market capitalization, and independently into three EP groups using the 30th and 70th percentiles as breakpoints, with loss-making firms assigned to the growth category.[9] The six resulting portfolios are held for twelve months and their returns value-weighted by beginning-of-month market capitalization. SMB is the average return of the three small portfolios minus the average return of the three large portfolios; VMG is the average return of the two high-EP portfolios minus the average return of the two low-EP portfolios. The PMO factor follows the same 2×3 structure but uses monthly turnover as the second sorting variable, with monthly rebalancing to reflect its high-frequency nature. PMO is the average return of the two low-turnover portfolios minus the average return of the two high-turnover portfolios.

A simple alpha test on the full-sample H-L spread would ignore the size heterogeneity already documented in Section VI.A.2, where the CG premium concentrates in small and medium

[9]Assigning loss-making firms to the growth (low EP) category follows Liu et al. (2019) and is consistent with the treatment in Fama and French (2015). This procedure prevents negative EP values from distorting the value-growth ranking.

firms and weakens in large firms. The heterogeneity is itself an implication of our framework, because small and medium firms face tighter financing constraints based on collateralizable assets and larger refinancing vulnerability. A pooled alpha test would obscure this pattern. We therefore conduct alpha tests separately within each size group using a conditional sort. Each month, stocks are sorted into three size groups (Small, Medium, Large) by tradable market capitalization, and within each size group, stocks are independently sorted into five CG quintiles. The within-group H-L portfolio is the value-weighted spread between the highest and lowest CG quintile. For each size group, we estimate

$$R_t^{H-L} = \alpha + \boldsymbol{\beta}' \mathbf{F}_t + \epsilon_t, \tag{13}$$

where $\mathbf{F}_t$ is the vector of factor returns from CAPM, Liu-3, or Liu-4. The *All* column reports the average H-L alpha across the three size groups as a pooled benchmark. All standard errors use the Newey-West correction with six lags. Table 5 reports the results.

Three findings in Table 5 warrant attention. The first is that the CG premium remains positive after adjustment by each factor model we consider. In the Small group, the Liu-3 alpha reaches 0.451% per month with a t-statistic of 3.57, corresponding to an annualized premium of 5.4% that remains after controlling for market, size, and value exposure. In the Medium group, the Liu-3 alpha is 0.344% per month with $t = 2.46$. Across the three models, the alphas remain positive and economically meaningful. The Liu-4 estimates reach 0.643% in Small and 0.870% in Medium, indicating that the CG spread is not driven to zero by adding established Chinese factors. The pooled *All* estimate is 0.380% per month under Liu-3 ($t = 3.39$) and 0.712% under Liu-4 ($t = 3.38$). The fact that the alpha remains positive and significant after factor adjustment indicates that the CG return spread is not absorbed by established Chinese factor models. This suggests that CG contains independent pricing information.

The second finding concerns the β_{SMB} coefficient in the Small group, which is -0.133

Table 5: CG Hedge Portfolio Alpha under Alternative Factor Models

	Small	Medium	Large	All
Panel A: H−L Alpha across Size Groups (%/month)				
α_{CAPM}	0.261^{**}	0.411^{***}	0.239	0.303^{***}
	(2.36)	(3.21)	(1.20)	(2.84)
$\alpha_{\text{Liu-3}}$	0.451^{***}	0.344^{**}	0.344	0.380^{***}
	(3.57)	(2.46)	(1.62)	(3.39)
$\alpha_{\text{Liu-4}}$	0.643^{***}	0.870^{***}	0.623	0.712^{***}
	(2.92)	(3.56)	(1.54)	(3.38)
Panel B: Factor Loadings under Liu-3 Model				
β_{MKT}	−0.010	−0.026	0.031	−0.002
	(−0.60)	(−1.59)	(0.86)	(−0.11)
β_{SMB}	-0.133^{***}	0.042	−0.077	−0.056
	(−2.77)	(0.90)	(−1.09)	(−1.36)
β_{VMG}	−0.031	0.072	0.047	0.029
	(−0.68)	(1.57)	(0.54)	(0.69)
Adj. R^2	0.024	0.011	0.005	0.013
N	265	265	265	265

Note: This table reports alpha tests of CG hedge portfolios formed under conditional size-CG sorts. Each month, sample stocks are first sorted into three size groups (Small, Medium, Large) by tradable market capitalization, and within each size group, stocks are independently sorted into five CG quintiles. The within-group H−L portfolio is the value-weighted return spread between the highest (Q5) and lowest (Q1) CG quintile. The *All* column averages the H−L returns across the three size groups. Panel A reports alpha estimates from time-series regressions on CAPM, the Liu et al. (2019) three-factor model with MKT, SMB, and VMG, and the four-factor model that adds the PMO turnover-based sentiment factor. Panel B reports the factor loadings of each H−L portfolio under the Liu-3 model. Newey-West t-statistics with six lags in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

with $t = -2.77$. A negative loading on SMB for an H-L portfolio formed within a single size group is informative. Recall that the hedge portfolio longs Q5 (high CG) and shorts Q1 (low CG) within the Small tercile. A negative β_{SMB} means that Q1 firms behave more like smaller stocks than Q5 firms do. Economically, this is consistent with the collateral-based borrowing interpretation: within the set of small firms, those with very low collateralizable growth are the most constrained and least able to scale, so their returns are even more tilted toward the small-firm factor. The Liu-3 control thus accounts for the size-related component of the return spread, yet the alpha rises

rather than falls when SMB enters. This pattern is consistent with our framework, where the CG premium reflects credit-risk exposure that is not absorbed by size-based risk pricing.

The third finding concerns the Large group relative to the other two. The Large-group H-L alpha is positive in every model but never statistically significant, with t-statistics of 1.20 under CAPM, 1.62 under Liu-3, and 1.54 under Liu-4. This mirrors the pattern already documented in the raw portfolio sorts of Table 4. Large firms access credit through diversified channels, stronger bank relationships, or direct bond market participation, so the accumulation of collateralizable assets does not determine the incremental borrowing margin in the same way. Within large firms, the collateral-based borrowing mechanism is likely to be weaker, so the CG premium is correspondingly muted. The absence of a significant large-firm alpha is therefore consistent with the mechanism rather than a contradiction of it.

The factor alpha tests address a specific concern about the cross-sectional finding. The premium is robust to progressively more demanding factor benchmarks, the factor loadings carry economically sensible signs, and the size-conditional heterogeneity is consistent with the theoretical framework. Collateralizable growth captures pricing information in the Chinese A-share market that is not spanned by existing factor models.

VI.B The Premium and Macro Credit Risk

The cross-sectional tests in Section VI.A show that CG carries a positive premium that NCG does not, and that the premium is not absorbed by established factor models. These tests do not, on their own, identify why the premium arises. A positive cross-sectional spread is consistent with many possibilities: behavioral mispricing, exposure to a growth factor unrelated to credit, or industry-specific risks correlated with asset composition. Implication 2 makes a sharper prediction. Since the financing value of CG depends on the common credit-state variable $\tilde{\theta}_t$, firms with larger collateralizable asset growth should be more exposed to aggregate credit-cycle

fluctuations. This subsection tests whether the cross-sectional premium is associated with that credit-cycle exposure.

VI.B.1 SDF Tests

The fundamental no-arbitrage condition $\mathbb{E}_t[m_{t+1}R^e_{p,t+1}] = 0$ implies that the cross-section of expected excess returns is determined by the covariance between the stochastic discount factor and asset payoffs. We use a parsimonious linear SDF as an empirical testing device. The main specification contains only the market factor and the credit-cycle factor, because the theoretical framework has a single aggregate state variable: the credit environment. Broader macroeconomic controls, including TFP, are examined in Appendix E.

Let $R_{m,t+1}$ denote the market factor, defined as the value-weighted excess return of the filtered A-share universe described in Section IV. Let Credit_{t+1} denote the innovation in the aggregate credit-cycle proxy, where positive values correspond to credit expansions relative to trend and negative values correspond to credit contractions. We project the empirical SDF onto these two candidate risk factors:

$$m_{t+1} = 1 - b_{MKT}R_{m,t+1} - b_{Credit}\text{Credit}_{t+1}, \tag{14}$$

where b_{MKT} and b_{Credit} denote the SDF coefficients associated with the market and credit-cycle factors, respectively. Since the candidate factors are standardized, the coefficients are directly comparable in magnitude. Under the sign convention in equation (14), a positive b_{Credit} implies that assets with higher covariance with credit-expansion innovations require higher expected returns, or equivalently, that they perform relatively poorly when credit conditions deteriorate.

For each test portfolio p, the unconditional moment condition becomes

$$\mathbb{E}\left[(1 - b_{MKT}R_{m,t+1} - b_{Credit}\text{Credit}_{t+1})R^e_{p,t+1}\right] = 0, \tag{15}$$

which we estimate via Generalized Method of Moments (GMM). Implication 2 has a sharp prediction in this empirical framework: the credit-cycle factor should price CG-sorted portfolios more strongly, because CG is the balance-sheet component that transmits aggregate credit conditions into firms' financing capacity. The same factor should not play an analogous role for NCG-sorted portfolios, since non-collateralizable growth does not support external borrowing.

The credit-cycle factor Credit_{t+1} serves as the empirical counterpart to the model's macro credit state $\tilde{\theta}_t$. We compute the year-over-year growth rate of total RMB loans extended by financial institutions, then apply the Hodrick-Prescott filter with smoothing parameter $\lambda = 14400$ for monthly data to extract its cyclical component. This construction follows the BIS literature on the financial cycle (Drehmann et al., 2011; Borio, 2014), where deviations of credit aggregates from trend identify periods of credit expansion versus contraction. To isolate unanticipated credit shocks, the credit-cycle proxy is fitted with an AR(1) process; we extract the residual innovation and standardize it to have unit variance.

We construct two independent sets of test portfolios, each containing 25 portfolios formed from independent 5×5 sorts on the earnings-to-price ratio (EP) and one of the two growth proxies, CG or NCG. The choice of EP as the first sorting dimension follows the value-factor convention in the Chinese market literature (Liu et al., 2019), where EP outperforms book-to-market as a value proxy due to shell-value contamination of the latter. The use of two parallel sets of test assets allows us to isolate which type of asset growth is priced by macro credit risk. If the credit-cycle factor prices CG-sorted portfolios more strongly than NCG-sorted portfolios, the evidence is consistent with a link between the cross-sectional premium documented in Section VI.A and the macroeconomic credit exposure identified in the theoretical framework.

With $N = 25$ test assets and up to $K = 2$ parameters in the main specification, the system is over-identified. We estimate the parameters using two-stage efficient GMM. In the first stage, we minimize the unweighted criterion $g_T(b)' I g_T(b)$ to obtain a consistent initial estimate $\hat{b}_1$. Using $\hat{b}_1$, we estimate the long-run covariance matrix $\hat{S}$ of the moment conditions via the Newey-West

kernel with 6 lags. In the second stage, we re-minimize the criterion using $\hat{S}^{-1}$ as the optimal weighting matrix, yielding the asymptotically efficient estimate $\hat{b}_2$. Standard errors and t-statistics are computed from the Newey-West-adjusted asymptotic covariance of $\hat{b}_2$. Model specification is assessed via Hansen's J-statistic, which follows a χ^2_{N-K} distribution under the null of correct specification. Table 6 reports the market-only benchmark and the main market-plus-credit specification.

Table 6: SDF Factor Prices: Macro Credit Risk Exposure

Variable	(1) MKT Only	(2) MKT + Credit
Panel A: Test Assets = 25 EP × CG Portfolios		
MKT	0.45***	0.00
	(2.72)	(0.03)
Credit		0.39**
		(2.34)
J-statistic	22.21	17.44
J-test p-value	0.567	0.787
Panel B: Test Assets = 25 EP × NCG Portfolios		
MKT	0.49***	0.27**
	(3.31)	(2.09)
Credit		0.01
		(0.19)
J-statistic	21.72	22.17
J-test p-value	0.596	0.510

Note: This table reports two-stage efficient GMM estimates of the SDF coefficients in equation (14). The test assets are 25 portfolios independently sorted on EP and CG in Panel A, and 25 portfolios independently sorted on EP and NCG in Panel B. The Credit factor is the standardized innovation in the cyclical component of total RMB loan growth; positive values indicate credit expansions relative to trend. Newey-West t-statistics with 6 lags are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

The credit-cycle factor is significantly priced for CG portfolios. In the specification that adds Credit to the market factor, the estimated coefficient is positive and significant ($b = 0.39$, $t = 2.34$). By contrast, the credit coefficient is close to zero and statistically insignificant for NCG portfolios ($b = 0.01$, $t = 0.19$). This contrast is consistent with Implication 2. The credit-cycle factor prices portfolios sorted on collateralizable growth, the component of asset growth tied to collateral-based borrowing capacity, but does not play the same role for portfolios sorted on

non-collateralizable growth.

The SDF result is not intended as a generic macro-factor exercise. It is tied to the specific state variable emphasized by the model. Innovations in aggregate credit conditions price the CG test assets more strongly than the NCG test assets. Appendix E shows that this pattern is robust to adding a TFP shock as an additional production-side macroeconomic factor. The main text keeps the two-factor SDF as the baseline specification because the paper's theoretical mechanism is about credit-cycle exposure rather than general productivity risk. The next subsection examines whether firm financing and investment variables display the corresponding state dependence.

VI.C Quantity Evidence across Credit States

The SDF evidence indicates that the CG premium is associated with aggregate credit-cycle risk. This subsection examines the corresponding quantity-side evidence. The mechanism in Section III implies that collateralizable growth links a firm's financing capacity to the aggregate credit environment. When credit conditions tighten, this dependence on collateral-based borrowing capacity should expose high-CG firms to larger financing and investment adjustments. Non-collateralizable growth should not display the same state dependence because it does not expand borrowing capacity through collateralizable assets.

Firms are sorted annually on predetermined CG or NCG, and portfolio-level financing and investment quantities are compared across aggregate credit states. In each year, firms are assigned to terciles based on lagged CG or lagged NCG. The bottom tercile is denoted Low (T1), and the top tercile is denoted High (T3). Loose credit states are years in the top tercile of the aggregate credit-cycle innovation, while tight credit states are years in the bottom tercile. The middle tercile of credit states is omitted so that the comparison focuses on periods of clear credit expansion and credit tightening.

We examine three quantity margins. Total liability flow captures broad liability expansion and is defined as the annual change in total liabilities scaled by lagged total assets. Bank-related debt flow is a balance-sheet proxy for bank-related credit expansion, defined as the annual change in short-term loans, notes payable, the current portion of non-current liabilities, and long-term loans, scaled by lagged total assets. Bonds payable are excluded from the baseline measure because they represent market-based debt financing rather than the bank-related borrowing margin emphasized in the paper. Capital expenditure captures real investment and is measured as cash paid for acquiring fixed assets, intangible assets, and other long-term assets, scaled by lagged total assets.

For each outcome variable Y, the table reports the high-minus-low quantity spread within each credit state,

$$\Delta_{H-L}^{Loose} = Y_{High}^{Loose} - Y_{Low}^{Loose}, \qquad \Delta_{H-L}^{Tight} = Y_{High}^{Tight} - Y_{Low}^{Tight}.$$

The main statistic is the state difference in the high-minus-low spread,

$$\Delta_{State} = \Delta_{H-L}^{Tight} - \Delta_{H-L}^{Loose}.$$

A negative value of Δ_{State} indicates that the quantity spread between high- and low-growth firms is smaller in tight credit states than in loose credit states. The model predicts this compression for CG-sorted portfolios, but not for NCG-sorted portfolios.

Table 7 reports the credit-state quantity spreads. Panel A first examines financing quantities. For portfolios sorted on CG, total liability flow rises from 6.00% of lagged assets for Low (T1) firms to 13.53% for High (T3) firms in loose credit states, producing a high-minus-low spread of 7.52 p.p. In tight credit states, the corresponding spread falls to 2.23 p.p. The state difference, Δ_{State}, is therefore −5.30 p.p. Thus, the liability expansion of high-CG firms relative to low-CG firms is weaker when aggregate credit conditions tighten.

Table 7: Credit-State Quantity Spreads

		Loose Credit States			Tight Credit States			State Difference
Outcome	Sort	Low (T1)	High (T3)	Δ_{H-L}^{Loose}	Low (T1)	High (T3)	Δ_{H-L}^{Tight}	Δ_{State}
Panel A: Financing Quantities								
Total liability flow	CG sort	6.00	13.53	7.52	6.93	9.16	2.23	−5.30
	NCG sort	9.40	13.43	4.03	4.78	11.27	6.50	2.47
Bank-related debt flow	CG sort	0.55	4.40	3.85	2.33	2.50	0.17	−3.68
	NCG sort	3.40	1.78	−1.62	0.79	1.80	1.02	2.64
Panel B: Real Investment								
Capital expenditure	CG sort	3.36	6.04	2.69	4.21	6.46	2.26	−0.43
	NCG sort	4.36	1.91	−2.46	3.08	2.89	−0.19	2.27

Note: Firms are sorted annually into terciles using lagged CG or lagged NCG. Low (T1) and High (T3) denote the bottom and top terciles. Loose and tight credit states are the top and bottom terciles of the aggregate credit-cycle innovation, respectively; the middle tercile is omitted. There are seven loose years and seven tight years. Total liability flow is Δ total liabilities$/TA_{t-1}$. Bank-related debt flow is Δ(short-term loans + notes payable + current portion of non-current liabilities + long-term loans)$/TA_{t-1}$; bonds payable are excluded. Capital expenditure is cash paid for acquiring fixed assets, intangible assets, and other long-term assets, scaled by TA_{t-1}. Entries are portfolio-level aggregate ratios, reported in % of lagged assets; spread columns are in p.p. $\Delta_{State} = \Delta_{H-L}^{Tight} - \Delta_{H-L}^{Loose}$.

The bank-related debt margin displays a sharper pattern. In loose credit states, the high-minus-low spread for CG-sorted portfolios is 3.85 p.p. In tight credit states, the spread falls to only 0.17 p.p., yielding a state difference of −3.68 p.p. This result is closely aligned with the model because bank-related debt flow captures the balance-sheet debt instruments most directly related to bank-based financing. High-CG firms expand bank-related debt more strongly when credit is loose, but this relative financing advantage nearly disappears when credit tightens.

The NCG-sorted portfolios do not show the same state-dependent compression. For total liability flow, the NCG high-minus-low spread increases from 4.03 p.p. in loose credit states to 6.50 p.p. in tight credit states, implying a positive state difference of 2.47 p.p. For bank-related debt flow, the spread rises from −1.62 p.p. to 1.02 p.p., with a state difference of 2.64 p.p. These patterns suggest that the tightening-state compression is more closely associated with collateralizable growth than with balance-sheet expansion in general.

Panel B turns to real investment. The investment response is smaller than the financing

response, consistent with the smoother adjustment of capital expenditure. Nevertheless, the direction remains consistent with the proposed mechanism. For CG-sorted portfolios, the capital-expenditure spread declines from 2.69 p.p. in loose credit states to 2.26 p.p. in tight credit states, giving a state difference of −0.43 p.p. By contrast, the NCG-sorted capital-expenditure spread moves in the opposite direction, increasing from −2.46 p.p. to −0.19 p.p.

Taken together, the evidence is consistent with the quantity-side interpretation of the CG premium. The same balance-sheet characteristic associated with a positive return premium also identifies firms whose financing quantities are more sensitive to aggregate credit conditions. The financing advantage of high-CG firms over low-CG firms compresses sharply in tight credit states. The absence of a similar pattern for NCG is consistent with the model's distinction between collateralizable and non-collateralizable growth. The evidence therefore connects the return premium on CG to a concrete balance-sheet exposure: high-CG firms appear more vulnerable to contractions in collateral-based borrowing capacity during adverse credit states.

VII Conclusion

This paper starts from a simple empirical pattern in the Chinese A-share market. Portfolios sorted on fixed asset growth and accounts receivable growth earn substantial positive high-minus-low returns over more than two decades, while portfolios sorted on cash growth move in the opposite direction and aggregate asset growth contains little pricing information. The divergence is organized not by investment intensity alone, but by whether the underlying balance-sheet item supports external debt financing in a bank-dominated system. This fact motivates a decomposition of asset growth by financing function.

We develop a financing-constraint explanation based on collateralizable assets. In the augmented dividend-discount framework, total asset growth is decomposed into collateralizable

growth and non-collateralizable growth. The key new term is $\tilde{\theta}_t \Delta CA_{i,t}$, where $\tilde{\theta}_t$ is a common aggregate credit-state variable that governs the debt financing supported by a unit of collateralizable asset growth. This term has two distinct roles. At the valuation level, it explains why CG can carry positive pricing content. At the risk level, its dependence on $\tilde{\theta}_t$ implies that high-CG firms are more exposed when aggregate credit conditions deteriorate.

The empirical evidence is consistent with this interpretation. CG predicts higher future returns in Fama-MacBeth regressions, portfolio sorts, and alpha tests against established Chinese factor models, whereas NCG does not. In SDF tests, innovations in the aggregate credit cycle price portfolios sorted on CG more strongly than portfolios sorted on NCG. Quantity evidence based on firm financing and investment variables points in the same direction: high-CG firms experience a sharper compression in financing and investment when credit conditions tighten. The mechanism is therefore not that high-CG firms are permanently more levered. It is that recent collateralizable accumulation makes their marginal financing capacity more sensitive to aggregate credit conditions.

The paper also clarifies why aggregate asset growth has weak pricing power in China. Aggregate asset growth combines items with very different financing roles. Cash accumulation, residual asset growth, fixed asset growth, construction in progress, and receivables growth are not equivalent in a bank-dominated credit system. Once asset growth is decomposed by collateralizability, the pricing signal becomes visible. This decomposition complements standard investment-based asset pricing by showing that the financing function of investment can matter as much as the scale of investment itself.

Several limitations should be kept in mind. The mechanism tests are state comparisons based on portfolio-level quantities, so they should be interpreted as quantity-side support for the proposed mechanism rather than as stand-alone causal evidence. The collateral classification is intentionally conservative, and the extended tests show that adding inventory and intangibles weakens the pricing signal. Future work could refine the measurement of collateralizable assets

using loan-level collateral records, receivables-pledge registries, or bank-firm relationship data. These data would allow a more direct test of how the financing value of specific asset classes changes over the credit cycle.

The broader message is that the asset-pricing content of investment depends on institutional financing frictions. When borrowing capacity is tied to collateralizable assets, the composition of asset growth becomes a source of systematic credit-cycle exposure. Treating capital as homogeneous can therefore mask a pricing relation that becomes visible only after the balance sheet is decomposed by financing function.

References

Acharya, V. V. and Pedersen, L. H. (2005). Asset pricing with liquidity risk. *Journal of financial Economics*, 77(2):375–410.

Agarwal, S., Sarkar, A., Zhang, Y., and Zong, Z. (2026). Financing constraints, implicit government guarantee, and real estate market. SSRN working paper.

Ai, H., Li, J. E., Li, K., and Schlag, C. (2020). The collateralizability premium. *The Review of Financial Studies*, 33(12):5821–5855.

Allen, F., Qian, J., and Qian, M. (2005). Law, finance, and economic growth in china. *Journal of Financial Economics*, 77(1):57–116.

Belo, F., Lin, X., and Yang, F. (2019). External equity financing shocks, financial flows, and asset prices. *The Review of Financial Studies*, 32(9):3500–3543.

Berger, A. N. and Udell, G. F. (2006). A more complete conceptual framework for sme finance. *Journal of Banking & Finance*, 30(11):2945–2966.

Borio, C. (2014). The financial cycle and macroeconomics: What have we learnt? *Journal of Banking & Finance*, 45:182–198.

Brandt, L. and Li, H. (2003). Bank discrimination in transition economies: ideology, information,

or incentives? *Journal of Comparative Economics*, 31(3):387–413.

Carpenter, J. N., Lu, F., and Whitelaw, R. F. (2021). The real value of china's stock market. *Journal of Financial Economics*, 139(3):679–696.

Chaney, T., Sraer, D., and Thesmar, D. (2012). The collateral channel: How real estate shocks affect corporate investment. *The American Economic Review*, 102(6):2381–2409.

Cooper, M., Gulen, H., and Ion, M. (2024). The use of asset growth in empirical asset pricing models. *Journal of Financial Economics*, 151:103746.

Crouzet, N., Eberly, J. C., Eisfeldt, A. L., and Papanikolaou, D. (2022). The economics of intangible capital. *Journal of Economic Perspectives*, 36(3):29–52.

Drehmann, M., Borio, C., and Tsatsaronis, K. (2011). Anchoring countercyclical capital buffers: the role of credit aggregates. *International Journal of Central Banking*, 7(4):189–240.

Fama, E. F. and French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of financial economics*, 33(1):3–56.

Fama, E. F. and French, K. R. (2015). A five-factor asset pricing model. *Journal of financial economics*, 116(1):1–22.

Fama, E. F. and MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy*, 81(3):607–636.

Fernald, J. and Rogers, J. H. (2002). Puzzles in the chinese stock market. *Review of Economics and Statistics*, 84(3):416–432.

Gan, J. (2007). Collateral, debt capacity, and corporate investment: Evidence from a natural experiment. *Journal of Financial Economics*, 85(3):709–734.

Hahn, J. and Lee, H. (2009). Financial constraints, debt capacity, and the cross-section of stock returns. *The Journal of Finance*, 64(2):891–921.

Han, H. and Wang, X. (2023). Monetary policy uncertainty and corporate cash holdings: Evidence from china. *Journal of Financial Stability*, 67:101138.

Harvey, C. R., Liu, Y., and Zhu, H. (2016). … and the cross-section of expected returns. *The Review of financial studies*, 29(1):5–68.

Hou, K., Xue, C., and Zhang, L. (2015). Digesting anomalies: An investment approach. *The Review of Financial Studies*, 28(3):650–705.

Hsu, J., Viswanathan, V., Wang, M., and Wool, P. (2018). Anomalies in chinese a-shares. *Journal of Portfolio Management*, 44(7):108–123.

Huang, T.-L. (2019). Is the fama and french five-factor model robust in the chinese stock market? *Asia Pacific Management Review*, 24(3):278–289.

Jermann, U. and Quadrini, V. (2012). Macroeconomic effects of financial shocks. *American Economic Review*, 102(1):238–271.

Jiang, F., Jiang, Z., and Kim, K. A. (2017). Capital markets, financial institutions, and corporate finance in china. *Journal of Corporate Finance*, 45:1–20.

Jiang, F., Kim, K. A., Nofsinger, J. R., and Zhu, B. (2015). Product market competition and corporate investment: Evidence from china. *Journal of Corporate Finance*, 35:196–210.

Lee, C. M. C., Qu, Y., and Shen, T. (2017). Reverse mergers, shell value, and regulation risk in chinese equity markets. Stanford University Graduate School of Business Research Paper No. 17-63. SSRN working paper.

Lin, Q. (2017). Noisy prices and the fama–french five-factor asset pricing model in china. *Emerging Markets Review*, 31:141–163.

Liu, J., Stambaugh, R. F., and Yuan, Y. (2019). Size and value in china. *Journal of financial economics*, 134(1):48–69.

Liu, L. X., Whited, T. M., and Zhang, L. (2009). Investment-based expected stock returns. *Journal of Political Economy*, 117(6):1105–1139.

Liu, Y., Zhou, G., and Zhu, Y. (2024). Trend factor in china: The role of large individual trading. *The Review of Asset Pricing Studies*, 14(2):348–380.

Myers, S. C. and Majluf, N. S. (1984). Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics*, 13(2):187–221.

Narayanan, P., Somasundaram, J., and Seifert, M. (2025). Risk-averse algorithmic support and inventory management. *European Journal of Operational Research*, 322(3):993–1004.

Peters, R. H. and Taylor, L. A. (2017). Intangible capital and the investment-q relation. *Journal of Financial Economics*, 123(2):251–272.

Shan, J. and Zhu, K. (2013). Inventory management in china: An empirical study. *Production and Operations Management*, 22(2):302–313.

Wang, Z., Wang, Q., Lai, Y., and Liang, C. (2020). Drivers and outcomes of supply chain finance adoption: an empirical investigation in china. *International journal of production economics*, 220:107453.

Online Appendix

A Investment q-Theory Intuition with Financing Frictions

This appendix provides an investment-based intuition for the main DDM argument. It is not intended to replace the valuation framework in Section III. The purpose is narrower: to show that once collateralizable investment relaxes a financing constraint whose tightness varies with the aggregate credit state, collateralizable and non-collateralizable investment need not have the same return implication.

Consider a firm that operates two forms of capital, collateralizable capital K_t^C and non-collateralizable capital K_t^N. Investment in the two assets is denoted I_t^C and I_t^N, and capital evolves according to

$$K_{t+1}^j = (1-\delta)K_t^j + I_t^j, \qquad j \in \{C, N\}. \tag{A1}$$

Adjustment costs are quadratic,

$$\Phi_j(I_t^j, K_t^j) = \frac{a_j}{2}\left(\frac{I_t^j}{K_t^j}\right)^2 K_t^j, \tag{A2}$$

so the marginal cost of investment in asset j is $1 + a_j(I_t^j/K_t^j)$.

The firm receives operating profit $\Pi(K_t^C, K_t^N, X_t)$ and finances investment through internal funds and debt. Let B_{t+1} denote next-period debt. The financing constraint reflects the fact that only collateralizable capital supports borrowing capacity:

$$B_{t+1} \le \tilde{\theta}_t K_{t+1}^C, \tag{A3}$$

where $\tilde{\theta}_t$ is the same aggregate credit-state variable used in the main text. A high value of $\tilde{\theta}_t$ represents a loose credit state; a low value represents a tight credit state. Let m_{t+1} denote the stochastic discount factor and let $\mu_t \geq 0$ be the multiplier on the financing constraint.

The first-order condition for non-collateralizable investment takes the standard form:

$$1 + a_N \left(\frac{I_t^N}{K_t^N} \right) = \mathbb{E}_t \left[m_{t+1} \, \text{Payoff}_{t+1}^N \right] \equiv q_t^N. \tag{A4}$$

For collateralizable investment, the marginal unit of capital also relaxes the financing constraint:

$$1 + a_C \left(\frac{I_t^C}{K_t^C} \right) = \mu_t \tilde{\theta}_t + \mathbb{E}_t \left[m_{t+1} \, \text{Payoff}_{t+1}^C \right] \equiv \mu_t \tilde{\theta}_t + q_t^{C,Fund}. \tag{A5}$$

The extra term $\mu_t \tilde{\theta}_t$ is the financing value of collateralizable capital. It has no analogue for I_t^N. The comparison between equations (A4) and (A5) is the investment-based counterpart to the DDM term $\tilde{\theta}_t \Delta CA_{i,t}$ in the main text.

This formulation should be read cautiously. The first-order conditions do not, by themselves, prove a risk premium. They show that collateralizable investment has a financing value whose magnitude depends on the aggregate credit state. The risk interpretation follows only if shocks to $\tilde{\theta}_t$ are systematic and priced. In that case, firms with larger collateralizable investment growth have returns and financing capacity that are more sensitive to credit-cycle innovations. Non-collateralizable investment lacks the corresponding financing-value term and therefore does not acquire the same exposure through this financing margin.

The appendix therefore delivers the same qualitative implication as the main DDM framework. Treating capital as homogeneous misses an important institutional margin: collateralizable investment both uses resources and expands borrowing capacity, while non-collateralizable investment mainly uses resources. When the borrowing-capacity component varies with aggregate credit conditions, CG can carry a credit-cycle exposure that is absent from

NCG.

B Dynamic Validation of the Borrowing-Capacity Interpretation

To empirically validate our classification of collateralizable assets, we track the dynamic evolution of firms' debt positions following asset expansions. This exercise is a prerequisite for the asset-pricing tests in the main text rather than a test of the pricing mechanism itself: it confirms that CG indeed captures incremental borrowing capacity before we ask whether that capacity is priced. We estimate panel regressions with firm and year fixed effects to predict *Forward Debt Inflow*, defined as the change in total interest-bearing debt in year $t + 1$ scaled by total assets in year t:

$$FwdDebtInflow_{i,t+1} = \frac{Debt_{i,t+1} - Debt_{i,t}}{TA_{i,t}}. \tag{B1}$$

By regressing $FwdDebtInflow_{i,t+1}$ on asset growth variables measured at year t, we avoid look-ahead bias and capture the sequence implied by the borrowing-capacity interpretation: firms first invest in collateralizable assets, which then enables them to secure new bank loans in the subsequent period. The regressions control for firm size and current leverage, and include both firm and year fixed effects to absorb unobservable time-invariant characteristics and macroeconomic shocks. Standard errors are clustered at the firm level.

The results in Table B1 support our classification. In Models 1 and 2, fixed asset growth is marginally significant ($t = 1.85$), while receivable growth strongly predicts future net debt inflows ($t = 4.97$), consistent with their role as collateralizable assets that support external debt financing. Cash growth (Model 3) functions more like a substitute for external financing, displaying a significant negative relationship ($t = -5.95$) with future net debt inflows. In the competitive horse-race specification (Model 10), Collateralizable Growth (CG) remains a significant positive predictor of future net debt inflows, while Total Asset Growth (AG) and Non-Collateralizable

Table B1: Predicting Forward Debt Inflows with Asset Components

Variable	M1: FA	M2: Rec	M3: Cash	M4: Inv	M5: Int	M6: AG	M7: CG	M8: NCG	M9: CG+NCG	M10: Full
Fixed Asset Growth	0.0016*									
	(1.85)									
Receivable Growth		0.0047***								
		(4.97)								
Cash Growth			−0.0047***							
			(−5.95)							
Inventory Growth				0.0065***						
				(6.92)						
Intangible Growth					0.0013					
					(1.58)					
Asset Growth (AG)						0.0042***				0.0035
						(4.07)				(0.78)
CG							0.0038***		0.0041***	0.0029*
							(3.91)		(4.19)	(1.65)
NCG								0.0028***	0.0032***	−0.0001
								(2.93)	(3.30)	(−0.01)
Size (log Asset)	−0.022***	−0.022***	−0.021***	−0.022***	−0.022***	−0.024***	−0.022***	−0.023***	−0.023***	−0.024***
	(−8.49)	(−8.52)	(−8.14)	(−8.52)	(−8.46)	(−8.99)	(−8.59)	(−8.75)	(−9.01)	(−9.02)
Leverage	−0.256***	−0.256***	−0.256***	−0.257***	−0.256***	−0.253***	−0.256***	−0.254***	−0.254***	−0.254***
	(−31.93)	(−31.90)	(−31.88)	(−31.94)	(−31.93)	(−31.44)	(−31.91)	(−31.38)	(−31.36)	(−31.40)
N (Firm-Years)	55,720	55,720	55,720	55,720	55,720	55,720	55,720	55,720	55,720	55,720
R^2 (within)	0.0722	0.0735	0.0727	0.0734	0.0722	0.0731	0.0728	0.0727	0.0733	0.0733
Firm FE / Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster SE (Firm)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents panel regressions with firm and year fixed effects predicting *Forward Debt Inflow* ($t \rightarrow t+1$). Independent growth variables are z-score standardized and measured at year t. Standard errors are clustered at the firm level, and corresponding t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Growth (NCG) lose their explanatory power, suggesting that the borrowing-capacity content is concentrated in the CG component.

C Robustness to Alternative Size Cutoffs

The baseline sample excludes stocks below the 30th percentile of tradable market capitalization in each monthly cross-section, following the procedure proposed in Liu et al. (2019). The 30th percentile is the threshold those authors recommend for constructing factor models that price the remaining cross-section, but it is by construction a calibrated choice rather than a sharp boundary in the underlying data. A natural concern is whether our central finding hinges on this particular cutoff. To address this concern, we re-estimate the core Fama-MacBeth regressions using two alternative thresholds, 25% and 35%, that bracket the baseline value. Lowering the threshold to 25% reintroduces a layer of micro-cap firms whose returns may carry residual shell-value content; raising it to 35% removes additional small-firm observations and shrinks the sample at the bottom. If the CG premium reflects the collateral-based borrowing interpretation rather than an artifact of where the size cutoff is drawn, the coefficient on CG should remain positive and significant under both alternatives, and CG should continue to dominate the alternative growth measures.

Table C1 reports four representative specifications drawn from the eleven we run on each alternative sample. Column (1) is the simplest CG specification, regressing returns on size and CG alone. Column (2) adds the EP value controls. Column (3) is the horse race that places CG, NCG, and AG into direct competition. Column (4) is the most demanding setup, adding the interest-bearing leverage stock on top of the horse race. The four columns track the same stepwise tightening of controls used in the main text, allowing readers to verify that the CG signal survives at every level of severity under both alternative cutoffs.

The two panels deliver a consistent message. The CG slope in Column (1) is 0.08 ($t = 2.25$) under the 25% cutoff and 0.09 ($t = 2.50$) under the 35% cutoff, both statistically significant and close to the baseline estimate reported in Table 3. Adding the EP controls in Column (2) reduces the slope to 0.06 in both panels, with t-statistics of 1.68 and 1.95 respectively.

Table C1: Fama-MacBeth Regressions under Alternative Size Cutoffs

	(1) logME+CG	(2) +EP+CG	(3) Horse Race	(4) HR + Lev
Panel A: 25% Cutoff				
Intercept	2.26	3.65	3.53	3.44
	(0.88)	(1.55)	(1.49)	(1.47)
log ME	−0.09	−0.19	−0.19	−0.18
	(−0.62)	(−1.49)	(−1.42)	(−1.40)
EP^{+}		7.26***	7.16***	7.46***
		(3.15)	(3.15)	(3.37)
$D(EP<0)$		−0.07	−0.08	−0.04
		(−0.40)	(−0.52)	(−0.25)
CG	0.08**	0.06*	0.08*	0.09*
	(2.25)	(1.68)	(1.72)	(1.74)
NCG			−0.05	−0.07
			(−0.39)	(−0.49)
AG			0.01	0.03
			(0.10)	(0.21)
Lev				−0.05
				(−1.02)
$\bar{R}^2$	0.024	0.038	0.040	0.043
Panel B: 35% Cutoff				
Intercept	2.01	3.42	3.29	3.19
	(0.78)	(1.43)	(1.37)	(1.35)
log ME	−0.08	−0.18	−0.17	−0.17
	(−0.51)	(−1.37)	(−1.30)	(−1.27)
EP^{+}		7.20***	7.10***	7.34***
		(3.11)	(3.10)	(3.29)
$D(EP<0)$		−0.07	−0.09	−0.05
		(−0.41)	(−0.52)	(−0.35)
CG	0.09**	0.06*	0.11*	0.11**
	(2.50)	(1.95)	(1.93)	(2.02)
NCG			0.02	0.01
			(0.14)	(0.05)
AG			−0.06	−0.05
			(−0.39)	(−0.31)
Lev				−0.03
				(−0.62)
$\bar{R}^2$	0.023	0.039	0.040	0.044

Note: This table replicates four core specifications of Table 3 using two alternative size-based screens. Panel A excludes stocks below the 25th percentile of tradable market capitalization in each monthly cross-section; Panel B excludes those below the 35th percentile. The dependent variable is the next-month excess return. Column (1) regresses returns on size and CG alone; Column (2) adds the EP value controls; Column (3) adds NCG and AG to form a horse race; Column (4) further adds the interest-bearing leverage ratio (Lev). EP^{+}, $D(EP<0)$, and log ME enter as raw values; CG, NCG, AG, and Lev are z-score standardized monthly. Coefficients are multiplied by 100. Sample period: January 2000 to June 2022. Newey-West t-statistics with four lags are reported in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

The horse race in Column (3) shows that the CG coefficient remains positive under both alternative cutoffs: under the 35% cutoff the CG coefficient climbs to 0.11 (t = 1.93), and under the 25% cutoff it sits at 0.08 (t = 1.72). Column (4), which adds Lev to the horse race, leaves the CG slope essentially unchanged in both panels, at 0.09 (t = 1.74) and 0.11 (t = 2.02). Across all four columns and both panels, NCG and AG remain indistinguishable from zero, and the leverage stock variable carries no independent pricing power. CG remains the only growth measure with consistent pricing content at every cutoff value we examine.

The mild monotonicity in CG coefficients deserves comment. Tightening the cutoff from 25% to 35% raises the CG slope in three of the four columns, particularly in the horse-race specifications where the move is from 0.08 to 0.11 in Column (3) and from 0.09 to 0.11 in Column (4). This direction is what the underlying logic predicts. The 25% sample retains an extra layer of small-cap stocks whose returns are partly driven by shell-value option pricing rather than collateral mechanics, and including them dilutes the CG signal in the same way the bottom 30% would in the unfiltered universe. Tightening the cutoff to 35% removes more observations whose returns are likely to reflect shell-value effects, leaving a sample whose returns track operating fundamentals more closely, so the CG signal sharpens. The 30% baseline strikes the balance Liu et al. (2019) originally identify, and the results in either direction confirm that the CG premium is not an artifact of where this balance is struck. The collateral-based borrowing interpretation is robust to reasonable variation in how the small-firm tail of the cross-section is handled.

D Robustness: Extended Collateralizable Asset Definition

This appendix examines how cross-sectional predictability changes when inventory and intangible assets are added to the collateralizable asset group, to assess the robustness of the baseline classification criteria in Section V. As discussed in the main text, although inventory can be used as collateral, it faces valuation haircuts and liquidation difficulties (Shan and Zhu, 2013; Narayanan et al., 2025), while intangibles are difficult to value and lack secondary markets (Crouzet et al., 2022; Peters and Taylor, 2017). To keep the baseline classification conservative, we hold them outside the core collateralizable category. A natural question is whether incorporating these marginal assets into the collateralizable group strengthens or weakens the pricing signal.

To address this, we construct an extended collateralizable growth measure (CG^{ext}), defined as the sum of fixed assets, construction in progress, accounts receivable, inventory, and intangible asset growth, scaled by lagged total assets. The purpose of this exercise is to examine whether a broader CG definition strengthens or weakens the pricing signal relative to the baseline measure. We conduct tests over the identical sample period and report the results of double-sorted portfolio returns below, benchmarking against the corresponding baseline CG results from the main text.

D.1 Double-Sorted Portfolio Returns

Table D1 reports the monthly value-weighted excess returns of independent 3×5 double-sorted portfolios based on the extended collateralizable growth measure (CG^{ext}).

Compared to the baseline CG sorting results in Table 4, the extended definition produces a weaker pricing signal. The full-sample H-L spread narrows from 0.33% ($t = 2.77$) for the baseline CG to 0.29% ($t = 2.63$) for the extended measure. This reflects a decline in both economic magnitude and statistical significance. The extended definition also introduces prominent non-monotonic fluctuations within size subsets. The return progression in the small-cap and

Table D1: Double-Sorted Portfolio Returns using Extended Collateralizable Growth (3×5)

Size Group	Low(1)	2	3	4	High(5)	H-L	t(H-L)
Size × Extended Collateralizable Growth (CG^{ext})							
Small(1)	0.98	0.93	1.09	1.29	1.16	0.18	(1.58)
Medium(2)	0.74	0.74	0.82	0.87	1.10	0.36	(2.36)
Large(3)	0.58	0.69	0.48	0.43	0.90	0.32	(1.62)
All	0.77	0.79	0.80	0.86	1.05	0.29	(2.63)

Note: This table reports the monthly value-weighted excess returns (unit: %/month) of portfolios constructed by independent 3×5 double sorts based on tradable market capitalization (three groups) and extended collateralizable growth CG^{ext} (five groups). CG^{ext} additionally includes inventory and intangibles on top of the baseline CG (fixed assets + construction in progress + accounts receivable). H-L is the monthly spread of the highest minus the lowest group. Newey-West adjusted t-statistics (6 lags) are in parentheses.

large-cap groups becomes less monotonic, suggesting a weaker pricing signal. Within the medium-cap subset, the baseline CG achieved a highly significant 0.47% ($t = 3.74$), whereas the extended measure falls to 0.36% ($t = 2.36$), suggesting weaker predictive power.

This deterioration is consistent with the theoretical classification. In the augmented framework, the CG premium is expected to be strongest for assets with clear collateral functionality. The market value of inventory is strongly impacted by non-credit factors such as industry cycles, technological turnover, and consumer trends (Shan and Zhu, 2013), making its price volatility less directly tied to macro credit cycles. Pulling inventory into the collateralizable group introduces cross-sectional variation less directly related to aggregate credit conditions. The issue with intangibles is more fundamental. A substantial gap exists between the book values of goodwill or patents and their actual collateral functions (Crouzet et al., 2022), and banks often apply steep haircuts or hesitate to accept these assets as collateral in practice. Categorizing them as collateralizable weakens the institutional premise of our collateral-based borrowing interpretation, which requires that marginal borrowing capacity be closely tied to collateralizable asset accumulation. Including these asset components less tightly linked to the credit cycle can dilute the pricing signal emphasized by the model. These components therefore add variation that is less closely related to the credit-cycle exposure captured by baseline CG.

D.2 Summary

The findings show that incorporating inventory and intangibles into the collateralizable asset pool weakens cross-sectional pricing performance. The H-L spread in portfolio sorts narrows from 0.33% (t = 2.77) to 0.29% (t = 2.63).

These outcomes support the conservative baseline classification. The baseline CG encompasses fixed assets, construction in progress, and accounts receivable, which are the core balance-sheet components with clear collateral functionality in Chinese bank lending practice and close links to macro credit conditions. Although inventory and intangible assets show some relation to financing outcomes in prior tests, their collateral utility in actual banking operations encounters steep discount rates, significant appraisal subjectivity, and severe liquidation difficulties. Consequently, their growth rates are less directly tied to the credit-cycle exposure captured by physical collateral and receivables. Incorporating these marginal assets into CG mixes the clearer baseline signal with cross-sectional variation less closely connected to collateral-based borrowing capacity, thereby diluting the clearer pricing signal captured by the baseline CG measure. The main text therefore adopts a conservative baseline classification that isolates the clearest collateral-based borrowing margin, while the extended measure serves as a useful robustness check.

E SDF Robustness with a Productivity Shock

The main SDF test in Section VI.B focuses on the market factor and the aggregate credit-cycle factor, because the theoretical model has a single macroeconomic state variable: credit conditions. This appendix adds a TFP shock as a production-side macroeconomic control. The purpose is to check whether the credit-cycle result is robust to controlling for broad productivity-side macroeconomic shocks. If the CG premium reflects credit-cycle risk, the credit factor should retain pricing content for CG-sorted portfolios after controlling for broad productivity innovations, while the contrast between CG and NCG test assets should remain visible.

We estimate the extended empirical SDF

$$m_{t+1} = 1 - b_{MKT} R_{m,t+1} - b_{Credit} \text{Credit}_{t+1} - b_{TFP} \text{TFP}_{t+1}, \tag{E1}$$

where TFP_{t+1} is the standardized AR(1) innovation in aggregate total factor productivity, computed at quarterly frequency and interpolated to monthly frequency. The test assets, GMM procedure, and standard-error construction are the same as in Section VI.B. Table E1 reports both single-addition specifications and the joint model.

The extended specification leaves the main message intact. For CG portfolios, the credit coefficient is positive and significant when added to the market factor, and remains positive and marginally significant in the joint model with TFP. For NCG portfolios, the credit coefficient is close to zero in the market-plus-credit specification and remains insignificant after TFP is included. Adding TFP therefore does not eliminate the credit-cycle interpretation of the CG premium. The productivity shock has some pricing content for CG portfolios, but the credit-cycle factor remains most relevant for the part of the cross-section emphasized by the theory, namely portfolios sorted on collateralizable growth.

Table E1: SDF Robustness: Adding a Productivity Shock

Variable	(1) MKT Only	(2) Add Credit	(3) Add TFP	(4) Joint
Panel A: Test Assets = 25 EP × CG Portfolios				
MKT	0.45***	0.00	0.38***	0.13
	(2.72)	(0.03)	(2.64)	(0.84)
Credit		0.39**		0.26*
		(2.34)		(1.75)
TFP			−0.57**	−0.49**
			(−2.10)	(−1.96)
J-statistic	22.21	17.44	15.61	16.84
J-test p-value	0.567	0.787	0.872	0.772
Panel B: Test Assets = 25 EP × NCG Portfolios				
MKT	0.49***	0.27**	0.36***	0.41***
	(3.31)	(2.09)	(3.03)	(2.97)
Credit		0.01		−0.05
		(0.19)		(−0.31)
TFP			−0.63	−0.52
			(−1.59)	(−1.43)
J-statistic	21.72	22.17	17.32	18.72
J-test p-value	0.596	0.510	0.793	0.662

Note: This table reports two-stage efficient GMM estimates of SDF coefficients. The Credit factor is the standardized innovation in the cyclical component of total RMB loan growth. The TFP factor is the standardized innovation in aggregate total factor productivity. Newey-West t-statistics with 6 lags are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

F Variable Definitions

Table F1 provides definitions and construction details for the variables used in the main text and appendix analyses. The table distinguishes the theoretical credit-state variable from its empirical proxy to avoid conflating the model object $\tilde{\theta}_t$ with the measured credit-cycle innovation used in the SDF tests.

Table F1: Variable Definitions

Variable	Mnemonic	Definition
Panel A: Return and Valuation Variables		
Stock return	$R_{i,t}$	Monthly individual stock return accounting for cash dividend reinvestment, sourced from CSMAR.
Excess return	$R_{i,t}^{exc}$	Monthly individual stock return minus the monthly risk-free rate converted from the annualized one-year time deposit rate.
Market return	$R_{m,t}$	Value-weighted average return of the filtered stock universe.
Market excess return	MKT	$R_{m,t} - r_{f,t}$, the value-weighted market return of the filtered A-share universe in excess of the risk-free rate.
Risk-free rate	r_f	Annualized one-year time deposit rate, converted to a monthly rate.

Continued on next page

Table F1: Variable Definitions (continued)

Variable	Mnemonic	Definition
Tradable market cap	ME	Total market capitalization of tradable shares, measured at the end of June in year t and used for size sorting. Firm size in return tests is $\log ME$.
Earnings-to-price ratio	EP	Net income divided by total market capitalization at fiscal year-end. $EP^{+} = \max(EP, 0)$ and $D(EP < 0) = 1$ if $EP < 0$.
Book-to-market ratio	BM	Book value of shareholders' equity divided by total market capitalization at fiscal year-end.
Panel B: Asset-Growth Variables		
Total assets	TA	Book value of total assets at fiscal year-end.
Annual change	$\Delta X_{i,t}$	$X_{i,t} - X_{i,t-1}$ for any balance-sheet item X.
Total asset growth	AG	$(TA_{i,t} - TA_{i,t-1})/TA_{i,t-1}$. Used as the aggregate asset-growth benchmark.
Collateralizable growth	CG	$(\Delta FA_{i,t} + \Delta CIP_{i,t} + \Delta AR_{i,t})/TA_{i,t-1}$. Baseline measure of collateralizable asset accumulation.
Non-collateralizable growth	NCG	$(\Delta Cash_{i,t} + \Delta RA_{i,t})/TA_{i,t-1}$. Measures growth in assets not classified as part of the core collateralizable borrowing base in the baseline classification.
Extended collateralizable growth	CG^{ext}	Baseline CG plus $\Delta INV_{i,t}$ and $\Delta IA_{i,t}$, scaled by $TA_{i,t-1}$. Used for robustness tests in Appendix D.
Panel C: Balance-Sheet and Financing Variables		

Continued on next page

Table F1: Variable Definitions (continued)

Variable	Mnemonic	Definition
Fixed assets	FA	Net fixed assets, excluding construction in progress unless stated separately.
Construction in progress	CIP	Construction in progress. Included in baseline CG because it represents physical capital in formation.
Accounts receivable	AR	Accounts and notes receivable, including receivables financing where available.
Cash holdings	$Cash$	Cash and cash equivalents.
Residual assets	RA	Total assets excluding fixed assets, construction in progress, accounts and notes receivable, inventory, intangible assets, and cash.
Inventory	INV	Inventory, including raw materials, work in process, and finished goods. Treated as a debated collateral item.
Intangible assets	IA	Intangible assets, including land use rights, patents, trademarks, and other intangible items. Treated as a debated collateral item.
FA and receivables ratio	–	$(FA + AR)/TA$. Used in the firm-profile validation table; construction in progress is included in CG but not reported separately in that descriptive table.

Continued on next page

Table F1: Variable Definitions (continued)

Variable	Mnemonic	Definition
Net interest-bearing debt issuance	$DebtFlow^{IB}$	Annual change in interest-bearing debt scaled by lagged total assets. Measures net debt inflow rather than gross issuance.
Bank-related debt flow	$DebtFlow^{Loan}$	Annual change in short-term loans, notes payable, current portion of non-current liabilities, and long-term loans, scaled by lagged total assets. Used in mechanism tests; bonds payable are excluded from the baseline measure.
Interest-bearing leverage	Lev	Interest-bearing debt divided by total assets.
Total leverage	–	Total liabilities divided by total assets.
Current ratio	–	Current assets divided by current liabilities.
Capital expenditures	Capex/Assets	Capital expenditures scaled by lagged total assets, used as an investment outcome in mechanism tests.
Fixed-asset growth outcome	FAGrowth	Growth of fixed assets used as an investment outcome in mechanism tests.
Panel D: Macroeconomic and Institutional Variables		
Aggregate credit state	$\tilde{\theta}_t$	Theoretical common credit-state variable governing how much debt financing is supported by a unit of collateralizable asset growth. It captures the macro credit environment, not a collateral-price shock or a firm-specific collateral haircut.

Continued on next page

Table F1: Variable Definitions (continued)

Variable	Mnemonic	Definition
Credit-cycle proxy	Credit	Standardized AR(1) innovation in the HP-filtered cyclical component of the year-over-year growth rate of total RMB loans of financial institutions. Positive values indicate credit expansions relative to trend.
TFP shock	TFP	Standardized AR(1) innovation in aggregate total factor productivity, computed at quarterly frequency and interpolated to monthly frequency. Used only in Appendix E.
Panel E: Asset Pricing Factors and SDF Coefficients		
Size factor	SMB	Average return of small portfolios minus the average return of large portfolios in the Liu et al. (2019) factor model.
Value factor	VMG	Average return of high-EP portfolios minus low-EP portfolios in the Liu et al. (2019) factor model.
Sentiment factor	PMO	Average return of low-turnover portfolios minus high-turnover portfolios in the Liu et al. (2019) factor model.
SDF coefficient	b_k	Coefficient on factor k in the empirical linear SDF. Used as a testing device for whether a candidate factor prices the relevant test assets.

Continued on next page

Table F1: Variable Definitions (continued)

Variable	Mnemonic	Definition
GMM moment	$g_T(b)$	Sample average of pricing-error moments used in two-stage efficient GMM estimation.
Hansen statistic	J	Overidentification statistic for the GMM SDF system.
Panel F: Theoretical and Appendix Objects		
Collateralizable asset growth	$\Delta CA_{i,t}$	Theoretical counterpart of CG: the flow of newly accumulated assets that expands collateral-based borrowing capacity.
Non-collateralizable asset growth	$\Delta NCA_{i,t}$	Theoretical counterpart of NCG: asset growth that does not support external borrowing.
Firm-specific collateral multiplier	κ_i	Optional firm-level multiplier in the generalized constraint $\Delta L_{i,t} \leq \kappa_i \tilde{\theta}_t \Delta CA_{i,t}$. Normalized in the baseline model and not estimated empirically.
Log-linearization constant	ρ	Discounting parameter in the Campbell–Shiller log-linear return decomposition, with $\rho < 1$.
Shadow price	μ_t	Lagrange multiplier on the financing constraint based on collateralizable assets in Appendix A. Represents the marginal value of relaxing borrowing frictions.
Adjustment cost	a_j	Quadratic adjustment-cost parameter for capital type $j \in \{C, N\}$ in Appendix A.