Capital structure as an investment decision*

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Abstract

Building on the motivations for the creation and expansion of a firm, this paper treats the firm as a coordinated investment vehicle to take advantage of some unique investment opportunities and to benefit from easier access to cheaper financing that cannot be achieved directly by its individual investors. The firm's optimal capital structure decision becomes part of its coordinated investment process and is fundamentally an optimal risk taking decision given its equity level and the risk-return tradeoff prospect of its investment. Applying classic mean-variance analysis shows that the optimal leverage target of a firm is primarily determined by the forecast of the company's mean-variance ratio on its investment. We construct mean-variance ratio forecasts based on a company's return on asset history and show that the forecasts can explain a large proportion of the cross-sectional leverage variation. We also construct a relative company size measure to proxy a company's pricing power and show that companies with higher pricing powers enjoy lower financing cost and can accordingly have a higher leverage target. We show that cross-industry leverage variations are mostly driven by the cross-industry mean-variance ratio variations. Once we control for the mean-variance ratio effect, the contributions from other commonly identified explanatory variables become small, and some of the additional explained variations do not constitute optimal leverage target variations, but rather variations away from the target.

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1. Introduction

The ideal of an efficient market as defined by Fama (1970), in which prices provide accurate signals for firms to make production-investment decisions and for investors to choose among securities, represents not only the foundation for modern asset pricing theories, but also the starting assumption for the revolutionary insight of Modigliani and Miller (1958) on corporate decisions. When the market is so idealistically efficient that no one has more insight than the other and prices accurately reflect the values of all contracts, there is no need left for investment analysis, nor relevance for corporate decisions. In fact, in such an idealistic world, all production activities can be efficiently coordinated through contracts on the market for the production factors, leaving no role for the existence of a corporation to begin with.

Since Coase (1937) and Williamson (1985), economists have been striving to answer the question on the existence and nature of firms from the perspective of practical frictions and limitations of the market place. They argue that the long-term contractual coordination established through a firm can reduce the need and cost of negotiating on the spot market or writing complex contingent contracts. The coordination, when done in a large enough scale, can also create better access and market pricing power for the firm, both for reducing the cost of its production factors and for increasing the market pricing of its own products to increase its profits. Because of these frictions, there is a natural tendency for a firm to be created and grow as a coalition and coordination of a production process, up to the point when the increased cost of managing a larger firm starts to offset the increased benefit of the coordination or when the firm size has reached the anti-trust regulatory limit. In fact, the existence of anti-trust regulations highlight the benefit of firm aggregation and expansion to the firm's investors, but possibly at the expense of customers and small competitors.

To make meaningful analysis on corporate decisions, one must first establish the basic tenants that can motivate the existence and growth of a firm. In this paper, we frame the corporate capital structure decision within the classic discussions on the nature of firms (e.g., Hart (1995)), but with a subtle but crucial difference. While classic theories treat the firm as a coordinated production process that strives to maximize its expected profits, often with the assumption of risk neutrality on the managers, we posit that a firm is, more broadly, a coordination of investors to make long-term coordinated investment decisions, with or without a physical production process involved. While the investment process of a manufacturing firm tends to involve some production, the investment process of a retail firm may only involve buying and selling finished products, and an investment firm may invest purely in financial securities. With or without production involved, all firms are making investment decisions, not to maximize profits as if they do not care about risk, but to maximize risk-return tradeoffs as posited in classic investment analysis (Markowitz (1952)).

As a coordinated investment vehicle, where individual investors can come in and out of the vehicle while the vehicle itself stays, the firm makes two major related investment decisions. One is to decide which types of risky projects to take on. The decision is analogous to the security selection process in classic investment analysis, but with the desire of generating better risk-return tradeoffs through the long-term contracting and coordination of a firm. The ideal of an efficient market where everyone should invest in the "market portfolio" would make this process irrelevant. If everyone should invest in the market portfolio, no one would have the incentive to create and invest in an idiosyncratic endeavor, much less with long-term contracting. Therefore, to create and growth a firm, the investors must believe that they are not just gaining exposures to the current market, but rather they can create value and expand the current investment frontier by forming such a long-term coordination process.

Once the particular project types are chosen, the second part of the investment decision is to decide how much risk to take on for the equity investors, analogous to the risk allocation determination in standard investment analysis. In classic mean-variance investment analysis, the allocation weight is proportional to the mean-variance ratio of the risky investment, with the proportionality coefficient reflecting the investor's risk attitude. When the mean-variance ratio is high and the optimal allocation weight is greater than one, the investor will take on leverage to invest more than the equity stake.

In addition to mean-variance considerations, practical investment decisions are also subject to other considerations and constraints such as the financing cost when applying leverage and trading cost when rebalancing either the risky investment or the financing capital. In general, a larger firm not only has higher pricing power on its production factors and products and accordingly higher profit prospects, but it also tends to have more negotiating power to obtain better access for cheaper financing, adding more incentives to traditional arguments for the creation and expansion of a firm. Furthermore, the financing access and cost difference between a corporation and its individual investors also motivate investors to take on appropriate leverages within the firm rather than outside the firm by its individual investors.

In our formulation of the firm as a coordinated investment vehicle, the corporate capital structure decision is effectively the optimal risk taking decision in the second component of the investment process. Classic investment theory dictates that its chief determinant is the risk-return tradeoff feature of the risky project, which can be captured by the expected mean-variance ratio on the company's return on asset.

To examine the empirical validity of the theoretical predictions, we measure the leverage of a company as the ratio of its total asset to equity, and we construct the mean-variance ratio forecast for a company based on the company's return on asset history. Analyzing historical data over the past 40 years on US publicly traded companies shows that our constructed mean-variance ratio forecasts can explain a large proportion of the cross-sectional leverage variation, and consistently so over time. A cross-sectional regression of the leverage ratio against the mean-variance ratio forecast estimates generates a strongly positive coefficient estimate. The regression R^2 estimates average at 68%, and vary within a narrow range over time from 54% to 81% within the 5-95th percentile range.

The literature often finds that industry dummies or industry averages can explain a large proportion of the cross-sectional leverage variation, but without a clear understanding of the source of this explanatory power (Welch (2012)). We show that the cross-industry variation in the average leverage ratio is almost completely driven by cross-industry variation in the mean-variance ratio forecasts. With the leverage ratio and the mean-variance ratio forecasts aggregated to the 4-digit GICS industry level, the cross-industry regressions produce extremely high R^2 estimates that average at 92% and vary within a narrow range from 88% to 95%.

Aggregating the leverage and mean-variance ratio forecasts to the 2-digit GICS sector level further increases the average regression R^2 to 95%. Different industries take on different types of business, which can show different risk-return tradeoff prospects and naturally ask for different optimal risk taking levels.

Even with the same risk-return tradeoff prospect, the optimal risk taking theory suggests that firms with different financing cost can have different optimal risk taking levels. We motivate the creation and expansion of a firm by hypothesizing that a firm has better access to cheaper financing than its individual investors and a larger firm can have higher market pricing power and better financing capabilities than its smaller competitors. To test this hypothesis, we construct a company relative size measure by scaling the total sales of a company by the average total sales of the corresponding sector, and we measure the average proportional financing cost of a company by the ratio of total interest expense to total outstanding debt. Via a cross-sectional regression of the financing cost measure against a risk-adjusted leverage measure and the company relative size measure, we show that after controlling for the risk-adjusted leverage level, the average financing cost indeed declines with the relative company size. When we regress the financial leverage ratio against the company relative size measure at each date, we obtain an average positive and statistically significant loading coefficient estimate on the relative size measure, with or without controlling for the mean-variance effect. In a standardized bivariate cross-sectional regression of the leverage ratio against the mean-variance ratio forecast and the relative size measure, the mean-variance ratio remains the principal contribution with an average contribution of 82%, whereas the relative size measure has a small but statistically significant average contribution of 8%.

The literature has identified a list of other firm characteristics that have been found to have explanatory power on the cross-sectional leverage variation, we construct similar measures, including the asset tangibility ratio, a profitability measure proxied by the return on asset of the most recent quarter, and the market-to-book equity ratio as a relative value measure. We examine their contributions via standardized univariate cross-sectional regressions of the leverage ratio on each variable, as well as standardized bivariate cross-sectional regressions on each variable while also controlling for the mean-variance ratio effect.

Different from the literature findings, we find that the average contribution from the asset tangibility is negative and very small. Similar to the literature findings, profitability and market-to-book ratios by themselves both contribute strongly negatively to the leverage ratio variations. Nevertheless, once controlled for the mean-variance ratio effect, the average contribution of the profitability becomes very small, and the average contribution from the market-to-book ratio turns positive. Above all, with or without controlling for these other explanatory variables, the mean-variance ratio forecast remains the dominating determinant of the cross-sectional leverage ratio variation. In a multivariate regression that includes all these variables, the regression adjusted R^2 estimates average at 70%, only 2 percentage points higher than the univariate regression on the mean-variance ratio forecast alone.

Not only that, while our optimal risk taking theory identifies the mean-variance ratio as the chief determinant of the optimal financial leverage target and identifies company relative size as having an auxiliary positive contribution to the optimal target variation due to its effect on the financing cost, the literature explanations on the contributions of other variables such as profitability and market-to-book ratios are not always toward the optimal target variation, but rather can be toward variations away from the market. We propose a cross-sectional error-correction model specification that can distinguish whether the contribution variation from a certain variable is for the optimal target variation or for temporary leverage variations away from the target. We start with a benchmark prediction on the cross-sectional leverage variation using our mean-variance ratio forecast, and also generate alternative predictions by adding other explanatory variables in the cross-sectional regression. From the prediction of each specification, we formulate a cross-sectional error-correction model that uses the leverage deviation from the specification's prediction to forecast future leverage ratio changes. A specification that generates better prediction of the optimal leverage target variation will have stronger forecasting powers on future leverage changes toward to the specification's predicted optimal level. On the other hand, if a variable strongly predicts leverage variations away from the target, the specification can have a high explanatory power on the cross-sectional leverage variation, but the leverage deviations from this specification's prediction will not forecast future leverage changes as strongly. As such, the error-correction specification serves as a test on whether a particular specification is enhancing the prediction of the optimal target variation or variations away from the target. Estimation shows that relative to the benchmark prediction with the mean-variance ratio forecast alone, the company relative size measure can indeed enhance the prediction of the leverage target variation. On the other hand, adding profitability and market-to-book ratio to the specification actually reduces the forecasting power of future leverage changes. Therefore, their contributions are less for the optimal leverage target variation, but more for the variations away from the optimal target.

When we map company relative valuation as measured by the Tobin (1969)'s Q to the leverage deviations from our benchmark prediction with the mean-variance ratio, we identify a clear hump shaped relation where the Tobin's Q is maximized at zero deviation and declines when the leverage ratio deviates from the benchmark prediction in either direction. The hump-shaped relation verifies that the leverage decision that we derive from the investment decision setting also maximizes the firm value. On the other hand, although adding the market-to-book ratio to the specification enhances the explanatory power of the relation, it not only reduces the forecasting power of future leverage changes, but also distorts the relation with firm valuation. As such, firm valuation is not a determinant of a firm's optimal financial leverage, but rather a result of it. Finally, we find that adding industry dummy variables can enhance the explanatory power of both the cross-sectional leverage variation and the future leverage adjustments, but it weakens the value maximizing relation, suggesting that while managers do follow industry peers in their leverage decisions, the herding behavior does not enhance firm value.

While we treat the leverage decision as a risk taking decision that is chiefly determined by the risk-return tradeoff of the risky investment, the long-established capital structure literature tends to focus on the cost-benefit tradeoff of the debt component (Kraus and Litzenberger (1973) and Scott (1976)), or the adverse selection costs of security issuance (Myers (1984) and Myers and Majluf (1984)). When the risk-return characteristic of the investment dictates that it is optimal to take on more risk than the equity level, the cost and benefit of debt and the cost of security issuance can definitely enter the optimal risk taking and dynamic rebalancing decision; nevertheless, such considerations are in general secondary to the risk-return tradeoff consideration. When a project is expected to have a very high level of risk to begin with, an average risk-averse investor is not going to further lever up the investment to make it even riskier, unless the expected returns are extremely high. The tax benefits or the potential of signaling effects are rarely good enough reasons for investors to take excessive risks. Any discussion of cost and benefit of using debt is largely moot. On the other hand, when a project is expected to have extremely low risk but good return prospect, it is optimal for an average risk-averse investor to lever up the investment. Adding financial leverage to such an investment does not expose the investor to excess risk, but only raises the low risk level of the project to a normal level that the investor feels comfortable with. In this case, the potential cost of using debt such as the prospect of bankruptcy and agency issues can indeed reduce the optimal risk taking level, but these concerns are in general not enough to prevent the investors from taking leverage all together.

Due to the large costs associated with capital structure rebalancing, the literature has long recognized that a company's capital structure can vary passively either due to market pricing variations (Welch (2004)) or cumulations of operating profits (Strebulaev (2007)). These passive movements are not necessarily toward the company's leverage target, adding difficulties to the empirical tests of optimal capital structure theories. In addition, the classic market timing arguments on capital structure changes (e.g., Fischer and Merton (1984), Lucas and McDonald (1990), and Baker and Wurgler (2000)) can create capital structure variations that proactively move away from the target to capture market pricing opportunities. Our error-correction specification provides a mechanism to distinguish long-run optimal leverage target variations from variations away from the target in between rebalancing actions.

Our theoretical work builds on the literature on the nature of firms. We rely on the same motivations identified in this literature for the creation and expansion of a firm to motivate the capital structure decision. While this strand of the literature (e.g., Hart (1995) and Hart and Moore (1998)) tends to consider the capital structure from the perspective of optimal contracting, we consider a much simpler mean-variance investment problem by treating the firm as a coordinated investment vehicle.

Also related is the strand of literature that strives to build in the optimal capital structure and dynamic rebalancing decisions within the classic structural model setting of Merton (1974).[1] These models tend to start with some risk-neutral price or value process, which is a valid market-clearing assumption under equilibrium, but nevertheless prevents researchers from directly examining the effect of firm-specific risk-return tradeoff behaviors. Instead of starting from the equilibrium pricing behavior, we build our model from a micro level and directly make normative inferences on the firm's optimal risk taking based on classic mean-variance investment analysis.

The remainder of the paper is organized as follows. Section 2 build a theoretical framework that treats a firm's optimal capital structure decision as part of the firm's investment decision in determining the firm's optimal risk taking level. Section 3 describes the data collection process, variable constructions, and summary behaviors. Section 4 tests the implications of our theoretical predictions and examines the main drivers of cross-sectional capital structure variation. Section 5 proposes an error-correction model to differentiate long-run optimal leverage target variations from variations away from the target in between the discrete rebalancing actions. Section 6 concludes.

2. The nature of a firm and optimal risk taking

Classic corporate capital structure theories tend to start with the ideal of an efficient market, under which all productions can be organized in the market, leaving no room for the creation and growth of a firm, and all investors can raise financing with equal ease, leaving no relevance for firm-level financing decisions. By contrast, the literatures on the nature of firms, e.g., Coase (1937), Alchian and Demsetz (1972), Benjamin Klein and Alchian (1978), Williamson (1985), and Hart (1995), strive to identify realistic features of the market that motivate the creation and expansion of a firm as a coordinated production process. The coordinated production process can create value via several mechanisms, from reducing negotiating,

[1] See, for example, Leland (1994), who endogenizes the capital structure decision by incorporating the tax benefit and bankruptcy cost of debt; Fischer, Hernkel, and Zechner (1989), who examine the dynamic capital structure choice in the presence of recapitalization costs; Goldstein, Ju, and Leland (2001), who consider the dynamic leverage adjustment decision under different operating profit regimes; Titman and Tsyplakov (2007), who consider the joint decision of making investments and capital structure adjustments; and Strebulaev (2007), who consider the refinancing cycles under different regimes.

transacting, contracting, and information costs to increasing market pricing powers.

In this section, we build a theory of optimal corporate capital structure decision from the same foundations that motivate the creation and expansion of a firm. Instead of treating the firm as a coordinated production process, we treat the firm more broadly as a coordinated investment process. The coordinated investment process can involve productions by investing in production factors and converting them into new products, but it can also be pure investments into private companies, properties, assets, or public shares without being directly involved in any production process. With or without involving production, the purpose of creating the coordinated investment process is to generate superior risk-return tradeoffs that can expand the set of the investment opportunities. The same reasons that have been listed in the literature for the creation and growth of a firm still apply. Whether the coordination reduces costs or increases pricing power, anything that makes the production process more stable and more profitable also enhances the investment's risk-return tradeoff.

2.1. Two premises that motivate the creation and expansion of a firm

Among the many different rationales that have been proposed to motivate the creation and expansion of a firm, we distill two main tenets as the starting assumptions of our model.

Assumption 1. A firm must be unique to be a worthy existence. A firm is created, not for merely gaining exposures to the currently existing market, but for generating superior firm-specific risk-return tradeoffs, so that the firm as a coordinated investment vehicle can expand the investment opportunity of the market and thus creates and adds value to the market.

This premise states one of the most fundamental motivations for the creation of a firm. If a firm could only expect to generate returns proportional to its exposure to the current market, as dictated by the classic capital asset pricing model built on the efficient market assumption, there would be no reason for the firm to be created to begin with. Investors could simply invest in the current market portfolio to obtain the same expected return, but without the additional idiosyncratic risk of the firm.

When a new firm makes presentations to investors, the emphasis is rarely on how close the firm is the average market portfolio, but mostly on how "uniquely" the firm is positioned to be different from, and more importantly better than, the average market portfolio. Investors are willing to invest in the firm only when they think the firm can add value and can expand the existing investment opportunity. In the classic mean-variance portfolio construction setting, the new firm must be expected to be able to expand the existing mean-variance frontier for it to be considered a worthy investment.

Assumption 2. Size matters for financing power. Everything else equal, the financing cost for a firm as a coordinated investment vehicle can be much lower than the financing cost faced by the individual investors of the firm. Furthermore, the financing cost tends to further decline as the firm size grows.

Market pricing power has long been identified as an important motivation for firm expansion. A large firm, once becoming dominant in a market, can gain pricing power not only for selling its products at higher market prices, but also for obtaining production factors at lower costs. Anti-trust laws have been put to place to check a firm's pricing power at the expense of smaller competitors and consumers. Cross-firm coordination, or collusion, has also been deemed illegal in most countries. Both types of regulations underpin the practical significance of such market pricing power. Financing cost can be regarded as the cost of a production factor and a firm's pricing power can also be extended to its power in securing cheap financing.

This second premise directly contradicts one of the key foundations of the irrelevance argument that whatever leverage an investor wants to achieve, the investor could achieve the same leverage with equal ease and cost either in the market place or in the firm, thus making the firm-level financing decision irrelevant. In reality, investors and their associated firms are not born equal with the same access to capital. At the very basic level, most banks create tiered pricing for customers who have different levels of wealth under their management. The customers at the higher tier with more wealth under management enjoy a higher saving rate, a lower financing rate, and easier access to capital and services. A firm, as a coordinated vehicle for its investors, becomes a larger business customer for the banks, and can enjoy much easier access to capital than the firm's individual investors by themselves. As a firm grows larger, not only does it gain pricing power on its production factors and final products, but it also gains more and cheaper access to financing. The larger pricing power on its inputs, outputs, and financing constitutes an important motivation for the creation and growth of a firm.

An implication of this second premise is that a firm should take on financial leverages through the firm's coordinated channel up to the level that its investors as a whole intend to take on, instead of leaving the leverage decision to its individual investors. Indeed, Asness, Frazzini, and Pedersen (2012) and Frazzini and Pedersen (2014) find that individual investors faced with financial constraints are forced to bias their investments toward stocks with higher risks, driving down the expected returns of these stocks. Achieving the appropriate risk level through financial leverage at the firm level increases the attractiveness of the firm to the individual investors who themselves face tighter financial constraints and higher financing costs.

2.2. Company capital structure as an optimal risk targeting decision

Building on the two premises that we distill from the long list of rationales motivating the creation and expansion of a firm, we regard the firm as a coordinated investment process. The coordinated investment process involves two major investment-related decisions: what projects or productions to invest in, and how much risk to take for the coordinated cohort of investors. The optimal risk targeting decision is essentially the classic optimal capital structure decision, as it decides on the optimal risk level a firm should target given its level of equity.

We measure a firm's leverage L as the ratio of its total asset to its common equity. A firm takes on financial leverage when it invests in more risky assets than its equity level, or when $L > 1$. Treating the firm as a coordinated investment process and regarding the firm's optimal leverage targeting decision as a decision on optimal risk taking, we can formulate the optimal risk taking decision in a classic mean-variance framework of Markowitz (1952),

$$\max_{L} \quad L(\mu - c(L)) - \frac{1}{2}\lambda L^2 \sigma^2, \tag{1}$$

where μ and σ^2 denote the expected mean and variance on the firm's return on asset, λ captures the average risk preference (relative risk aversion) of the investors in the firm, and $c(L)$ denotes the firm's financing cost, which can vary with the leverage level.

By classifying the total asset as the risky investment and measure the mean and variance on the firm's return on asset, the optimal risk taking decision L is naturally always no smaller than one. When a firm takes on overly risky projects, it can reduce the risk either via hedging practices or by hoarding cash or both. Total asset represents the portfolio of the firm's investments, hedging practices, and cash. The risk and return feature on the return on asset naturally fits into the firm investors's risk tolerance level by construction. On top of this level of risk, the equity level can only be the same or less.

Representing the financing cost as an implicit function of the financial leverage, we have the first-order condition for the optimal risk taking decision in (1) as,

$$\mu - c'(L)L - c(L) = \lambda L \sigma^2, \tag{2}$$

from which we can write the optimal leverage target as an implicit solution to the following equation,

$$\overline{L} = \lambda^{-1} \frac{\mu}{\sigma^2} - \frac{c(\overline{L}) + c'(\overline{L})\overline{L}}{\lambda \sigma^2}, \tag{3}$$

where we use $\overline{L}$ to denote the optimal risk taking target.

The following proposition summarizes the implication of this implicit solution.

Proposition 1. *Under the premise that a firm targets its optimal risk taking level to maximize its risk-return tradeoff on its investment as in (1), a major determinant of the optimal risk target is the firm's expected mean-variance ratio μ/σ^2 on its investment. Conditional on the same mean-variance ratio, the optimal risk* *target declines with both the level of the financing cost and the speed at which it increases with increasing financing.*

Our second assumption not only motivates the optimal risk targeting decision at the firm level (instead of at the individual investor level), but also identifies firm size as a differentiating factor in the financing cost function, on top and beyond the risk-return tradeoff consideration. If larger firms enjoy cheaper financing for the same type of investments, the financing cost function can differ across firms with different sizes in addition to its dependence on the project itself. To capture this additional layer of cross-sectional variation in the financing cost function, and to convert the implicit solution in (3) into an explicit solution, we posit the following simple proportional approximation of the financial cost function:

Assumption 3. Financing cost increases linearly with leverage and project risk. The financing cost of a firm is proportional to its leverage level and the return variance of the risky investment,

$$c(L) = \frac{1}{2}\xi L\sigma^2, \tag{4}$$

where proportionality coefficient can vary across firms, reflecting a firm's power in securing cheap financing.

Based on our second assumption, as the firm's financing power increases with firm size, we expect the proportionality coefficient ξ to be smaller for a firm than for an individual investor, and to decline with increasing firm size.

With the particular form of financing cost function assumption in (4), we can aggregate the impact of business risk and financing cost and derive the optimal risk target level explicitly.

Proposition 2. *Under the premise that a firm targets its optimal risk taking level to maximize its risk-return tradeoff on its investment as in (1), and with the assumption that the firm's financing cost is proportional to its leverage level and project risk level as in (4), the optimal risk taking target is proportional to the firm's* *expected mean-variance ratio on its return on asset,*

$$\overline{L} = \frac{1}{\lambda + \xi} \frac{\mu}{\sigma^2}, \tag{5}$$

where the proportionality coefficient is inversely proportional to the average risk aversion of the firm's investors, λ, and the firm's proportional cost in accessing financing capital, ξ.

A firm's optimal risk target increases with the firm's expected mean-variance ratio on its investment. In general, an investor at a given risk preference level is willing to take on a higher risk level if the project has good risk-return tradeoff and lower risk level when the tradeoff is not as good. In the mean-variance framework, we can measure the tradeoff feature of a project using the information ratio $\mathcal{S} = \mu/\sigma$ of the project. Then, under the assumption that the average risk preferences of investors across firms are similar, firms will take on the same level of levered risk, as measured by the levered volatility σL, if the information ratios of their projects are similar. Alternatively speaking, with the same information ratio, firms will make investments inversely proportional to the volatility level of the project, $L \sim 1/\sigma$, in line with the risk parity argument in the investment literature (Qian (2011)). Several empirical studies find indeed that financial leverages tend to vary inversely with various measures of the company's operating risk.[2] When the information ratios differ, the optimal leverage target becomes proportional to the information ratio, scaled by the volatility, $L \sim \mathcal{S}/\sigma$, or directly the mean-variance ratio, μ/σ^2.

For investments with similar mean-variance ratios, the optimal risk target can also vary with the firm's relative ease and cost in accessing financing. The easier and cheaper a firm can secure its financing, the larger can be its optimal risk target. Combining our second assumption with the optimal risk target in Proposition 2, we obtain the following corollary on the effect of firm size on the optimal risk target.

Corollary 1. *Under the premise that a firm's ease of access to financing capital increases with the firm's size, and that a firm optimizes its risk taking target to maximize its risk-return tradeoff as in (1), at the same*

[2] See, for example, Titman and Wessels (1988), Rajan and Zingales (1995), Fama and French (2002), Faulkender and Petersen (2005), Lemmon, Roberts, and Zender (2008), and Im, Kang, and Shon (2020).

level of mean-variance ratio for the risky project, a firm's optimal target on its financial leverage increases with the firm's size as a proxy of the firm's pricing power.

The corollary identifies another firm characteristic, in addition to mean-variance ratio, that can potentially explain the cross-sectional variation of firm financial leverage target. It also suggests that optimally, an investor can achieve higher level of leverage through the coordination of a firm.

2.3. Dynamic capital structure rebalancing

Just as optimal risk targeting in an investment decision, a firm's capital structure is a dynamic decision that necessitates constant dynamic rebalancing. First, as a firm has motivations to grow larger and become more dominant in an industry over time, this growth process needs constant injection of new capital. As new equity issuance and new debt issuance both incur significant transaction costs, the capital injection is very much a discrete decision. Each discrete capital injection action is likely to cause the capital structure to jump. Maintaining the capital structure at a constant level is practically infeasible. Furthermore, as market conditions change and as the firm's business evolve, the firm's expectation about its future prospect of risk and profitability can also change. The firm's optimal capital structure target shall change with the changing expectation. Because of all these variations, a firm's actual leverage is likely to deviate from its optimal target and the firm needs to make rebalancing decisions to keep its actual leverage from deviating too far from the optimal target level.

To capture this dynamic capital structure rebalancing process, we expand the setting in the previous section and extend the static decision in (1) to a dynamic setting. We consider the optimal capital structure decision at time t, given a starting capital structure level at time $t-1$. In particular, we choose the optimal leverage rebalancing amount $x_t = L_t - L_{t-1}$ to maximize the firm's risk-return tradeoff, subject to adjustment cost, $a(|x_t|)$, which tends to increase with the adjustment amount $|x_t|$. Formally,

$$\max_{x_t} \quad (L_{t-1}+x_t)(\mu_t - c_t(L_{t-1}+x_t)) - \frac{1}{2}\lambda_t(L_{t-1}+x_t)^2\sigma_t^2 - |x_t|a(|x_t|) \tag{6}$$

For an explicit solution, we maintain the linear approximation of the financing cost dependence on leverage in (4), and we further assume an approximate proportional adjustment cost structure,

$$a(|x_t|) = \frac{1}{2}\eta|x_t|, \tag{7}$$

with η captures the proportional unit cost of leverage adjustment.

With the above assumption, we can derive the optimal rebalancing decision as

$$x_t = \frac{1}{1 + \frac{\eta_t}{(\xi_t+\lambda_t)\sigma_t^2}} \left(\overline{L}_t - L_{t-1}\right), \tag{8}$$

with $\overline{L}_t$ denotes the optimal leverage target in the absence of adjustment cost as stated in Proposition 2,

$$\overline{L}_t = \frac{\mu_t}{(\xi_t + \lambda_t)\sigma_t^2}. \tag{9}$$

Proposition 3. *Large transaction cost dictates that a firm's financial leverage can persistently deviate from its optimal target level. As a firm strives to rebalance its leverage level toward its optimal target, the speed of adjustment declines with increasing proportional adjustment cost, but increases with increasing risk level of the investment project.*

The theoretical implication of our optimal dynamic rebalancing decision in (8) is in line with empirical findings in, e.g., Leary and Roberts (2005). In an investment decision, the leverage can be adjusted by altering the equity amount, the debt amount, or the investment itself. In a typical brokerage account, when the value of the invested securities drop so low that it triggers the margin call, the investor can either inject new capital (equity) to reduce the leverage, or sell some of the securities to reduce the level of the risky investment. On the other hand, when the invested securities are performing well, the leverage of the account declines, and the investor can choose to invest in more risky securities to raise the leverage to the target level, or withdraw some of the equity from the account. A corporation can in principle also adjust its leverage through all three channels, but with different adjustment costs for different channels at different situations.

The classic market timing arguments, e.g., Fischer and Merton (1984) and Lucas and McDonald (1990), bring another dimension to the rebalancing of the investment decision. When a firm identifies potential mispricing in its equity, the mispricing itself represents another investment opportunity for the firm, in addition to the long-term projects the firm is built for. The firm can make either long (stock buy back) or short (stock issuance) investment decisions to its own equity based on whether the equity is under- or over-valued. The firm can also identify mispricing opportunities in its own debt and make reversal-based market-timing investment decisions on its debt (Barry, Mann, Mihov, and Rodríguez (2008)). Warusawitharana and Whited (2016) build a dynamic investment model to show how capital structure decisions respond to misvaluation opportunities. These decisions do not rebalance the firm's leverage level to its long-run target based on the risk-return tradeoff of its long-term projects, but rather capture the short-term mispricing opportunities in its own equity or debt to create additional investment returns. Some mispricing-based investment activities can move a firm's leverage level away from its long-run target. By constructing a company valuation model and separating a company's value into a fair value component and a misvalue component, Hu, Sy, and Wu (2020) find that net equity and debt issuance changes are dominated by the dynamic rebalancing objective toward its long-run target when the market value variations are driven by the fair value component, but the net issuance activities are dominated by the market-timing objective toward the opposite direction when the market valuation variations are driven by temporary misvaluation.

2.4. A counter factual: When all firms are born equal in an efficient market ideal

To show the importance of the two premises that we start with in deriving our optimal risk taking decision, we consider the counter factual case where all firms are created to make expected excess returns proportional to their exposures to the current market portfolio. In this case, firms are created not to *expand* the investment opportunity, but to "fit in" with the current investment opportunity.

We can write the expected excess return on asset for a firm i as

$$\mu_i - r = \beta_{U,i}\left(\mu_m - r\right), \tag{10}$$

where $\beta_{U,i}$ denotes the unlevered beta of the company on the market portfolio. We can represent the market risk premium $(\mu_m - r)$ according to the classic capital pricing model of Merton (1973) as

$$\mu_m - r = \lambda\sigma_m^2, \tag{11}$$

with λ denoting the relative risk aversion of the representative investor.

Under this setting, since investors do not gain any expected returns from the idiosyncratic component of the return on asset, they must strive to diversify away this idiosyncratic component in the market place, so that their actual risk exposure to the firm is only the market risk component, as captured by $\beta_{U,i}^2\sigma_m^2$. Accordingly, the mean-variance optimal risk taking decision is to make the associated expected returns by taking on the systematic market exposure. We can write the optimal risk taking target as,

$$\overline{L}_i = \frac{\mu_i - r}{\lambda\beta_{U,i}^2\sigma_m^2} = \frac{1}{\beta_{U,i}}, \tag{12}$$

where the leverage of a firm becomes inversely proportional to its unlevered beta.

The levered beta of the company's equity becomes

$$\beta_i = L\beta_{U,i} = 1. \tag{13}$$

Under this hypothetical world, stocks across names would all have the same beta of unity, the same as the market portfolio. Since the idiosyncratic risk makes no contribution, one should diversify away the idiosyncratic risk. Without idiosyncratic risk, each firm is just the same as the other firm or the market portfolio, there is no motivation for one firm to take more or less risk than the other firm or the average. This implication forms a sharp contrast with the observed large cross-sectional variation in stock betas.

3. Data collection and summary behaviors

To examine the implications of our optimal risk taking theory, we collect data on US publicly traded companies and examine the linkage between the cross-sectional variation of company financial leverages and their risk-return tradeoff behaviors.

We retrieve quarterly financial reporting information and the Global Industry Classification Standard (GICS) classification for each company from Compustat. We sample the data monthly at the end of each month. At each sampling date, we select our universe of companies based on the following filtering criteria: (i) The company is public traded with common shares listed on one of the three main US stock exchanges, AMEX, NYSE, or NASDAQ, with valid GICS classification information. (ii) The company has strictly positive market capitalization, common book equity, total book asset, and total sales, with the ratio of market capitalization to book equity ratio no larger than 10. (iii) The company has a minimum of 12 quarters of recent history in income statements.

We measure the relative risk taking level of each company as the ratio of total book asset to common equity, and we use relative size derived from total sales to proxy a company's market pricing power. The strict positivity filter on common equity, total asset, and total sales guarantees that our leverage and relative size measures are well-defined. We match the book equity value with the market capitalization at the end of the corresponding quarter. The filter on the upper limit of the market-to-book ratio, as in Baker and Wurgler (2002), further guarantees that the company's book common equity is not extremely small relative to its market valuation. Finally, as we forecast a company's expected mean-variance ratio on its return on asset based on the company's historical realizations, we require a minimum of 3 years (12 quarters) of recent history in the return on asset metric to generate the mean-variance ratio forecasts. We use the Global Industry Classification Standard (GICS) industry classification information to examine the cross-industry variation in company risk-return tradeoff behaviors and their average financial leverages.

We start the data collection in March 1965 when Compustat starts to have quarterly financial data. The number of companies satisfying our filtering criteria, especially the return history requirement, is small in the early years. We perform our cross-sectional analysis using data from January 1981 to December 2020, for a total of 480 months spanning 40 years. Figure 1 plots the number of selected companies per month over the 40 years span. The size of the cross section on each sampling date ranges from 1,069 names (in August 1981) to 2,934 names (in August 2003), with an average of 2,273 names per sampling date.

[Fig. 1 about here.]

3.1. Financial leverage as a measure of relative risk taking

Our optimal risk taking theory treats the capital structure decision as an integral part of an investment decision and represents the leverage decision in terms of how much risk to take given the company's equity level. Following this perspective, we measure the time-t financial leverage of a company i, $L_{t,i}$, as the ratio of the company's total book asset (AT) to its book common equity (CE).

By defining the leverage as the ratio of total asset to common equity, we avoid the issue of mistreating non-financial liabilities as equity in the commonly-used financial-debt-to-asset measures (Welch (2011)). The issue remains on whether we should treat preferred equity as equity or liability. For robustness check, we have repeated the analysis with the leverage defined as the ratio of total asset to total equity. The results are similar.

We choose to use book value to define the leverage to avoid temporary distortions induced by market pricing variations. Due to high adjustment costs, Welch (2004) show that capital structure rebalancing decisions do not actively respond to the effect of stock price fluctuations on the market value based financial leverages. Such passive market value fluctuations can move in the opposite direction of the active rebalancing target, adding noise to the empirical tests of optimal risk taking targets.

Table 1 reports the time-serial averages of the cross-sectional summary statistics on the financial leverage measure in the first row of statistics. On the average, the leverage ratio varies from 1.19 at the 5th percentile to 13.39 at the 95th percentile. To mitigate the impact of extreme observations, we winsorize the data cross-sectionally at the 5-95% level. The mean and standard deviation statistics are computed on the winsorized sample at each date. The winsorized mean leverage is 3.56. The winsorized cross-sectional standard deviation is at a similar level at 3.35. The cross sectional leverage distribution shows moderately positive skewness and excess kurtosis on average.

[Table 1 about here.]

3.2. Return on asset behaviors

Our optimal risk taking theory identifies the expected mean-variance ratio of the investment return as the chief determinant of a company's optimal risk taking level relative to its equity. To construct the mean-variance ratio forecast and examine this theoretical implication, we measure the investment return of a company using the company's return on asset, constructed as the ratio of the company's reported quarterly operating income after depreciation (OIADP) to the company's total book asset at the beginning of the quarter.

At each date t and for each company i, we construct the historical mean and volatility estimators on the company's return on asset history over the past five years. We generate the historical estimators when there are 12 or more quarters of recent history. Table 1 reports the time-series averages of the cross-sectional statistics on the historical mean ("Mean") and volatility ("Volatility") estimators. The mean estimators are constructed simply as the sample averages of the quarterly return on asset series over the past five years, reported in annualized percentage points. Although all companies are created in anticipation of making a positive return on average, any single company can have losses over any period of time. High growth companies may choose to expand their sales and market share aggressively at the expense of having losses over a number of years. Some companies may have simply performed below their expectations and have been struggling to make a profit. The statistics show that while the return on asset in our sampled universe averages around 8% per year, the average value at the 5th percentile is negative at -8.18%. The cross-sectional distributions of the mean estimators are reasonably symmetric, with small average skewness and excess kurtosis estimates.

Potentially due to accounting smoothing, some companies report extremely smooth quarterly return on asset numbers. To avoid degeneration in our mean-variance ratio forecasts, we construct the volatility estimators without demeaning the quarterly return series. The estimates are reported in annualized percentage points. On average, the volatility estimates vary from a low of 1.09% at the 5th percentile to 15.09% at the 95th percentile. The cross-sectional distributions of the volatility estimates show positive skewness but little excess kurtosis.

We use the annualized information ratio ("IR"), i.e., the ratio of mean to volatility of the return on asset, to capture the risk-adjusted profitability. The estimates vary from an average of -0.91 at the 5th percentile to an average of 1.99 at the 95th percentile. The information ratio estimates can become negative due to the negative mean return on asset estimates. On the other hand, by using the raw second moment of the quarterly return series to define the volatility estimator, the annualized information ratio estimates are capped at a maximum of two even if the quarterly returns are identical over the past five years. The average cross-sectional distribution of the information ratio estimates show negative skewness and positive excess kurtosis.

To generate a robust mean-variance ratio forecast from the historical estimates, we assume that companies within the same industry group share similar risk-return characteristics. With this assumption, we start with the historical information ratio estimate, and perform cross-sectional smooth averaging within each industry group at the 4-digit GICS level. We treat the industry-smoothed information ratio estimate as our information ratio forecast ("IRF"). Table 1 shows that, through the industry-smoothing, the average information ratio forecast at the 5th percentile becomes positive at 0.69. As no companies are created to lose money, it makes sense to generate a positive information ratio forecast, even for companies with a negative average return on asset over the past five years.

To construct the mean-variance ratio forecasts ("MVF"), we set a lower bound on the information ratio forecast to be no lower than 0.5, and we divide the truncated information ratio by the volatility estimate in percentage points. The last row in Table 1 reports the summary cross-sectional behaviors of the mean-variance ratio forecasts. The mean-variance ratio forecast varies from an average of 0.08 at the 5th percentile to an average of 1.62 at the 95th percentile. The cross-sectional distribution of the mean-variance forecasts show positive skewness and excess kurtosis, similar to the distributional behavior of the leverage ratio.

3.3. Commonly identified leverage determinants

To put in perspective the significance of the mean-variance ratio forecast in explaining the cross-sectional variation of company financial leverage, we also construct commonly identified capital structure determinants as control variables. Through a comprehensive examination, Frank and Goyal (2009) conclude that the most reliable explanatory variables for firm's financial leverage include the industry average, the market-to-book ratio, asset tangibility, firm profits, and size. They find that firms with larger size, more tangible assets, but lower profits and lower market-to-book ratios tend to have higher leverage. We construct similar measures as control variables and examine the relative contribution of each variable to the cross-sectional capital structure variation.

Specifically, we use total sales to represent the company size. Furthermore, we scale the total sales of a company by the corresponding industry average to capture the relative pricing power of the company relative to its industry peers. We construct the industry average on the broad 2-digit GICS sector level. We measure the asset tangibility as the ratio of net property, plant, and equipment to total assets; we measure the profitability of a company with its return on asset in the last quarter; and we construct the market-to-book ratio as the ratio of market capitalization to book common equity.

Table 2 reports the time-series averages of the cross-sectional summary statistics of these control variables. The relative size varies from an average of 1% of the industry average at the 5th percentile to 4.1 times the industry average at the 95th percentile. The tangibility measure averages at 0.51, and varies within a narrow range from 0.27 at the 5th percentile to 0.73 at the 95th percentile. The return on asset as a profitability proxy has an annualized average of 7.4%, and varies from -12.32% at the 5th percentile to 25.16% at the 95th percentile. Compared to the statistics on the 5-year average return reported in Table 1, the quarterly return on asset is much more volatile and varies over a much wider range. Finally, the market-to-book ratio has an average of 2.13 and a median of 1.7, suggesting that the market capitalization tends to be higher than the book common equity value on average. Nevertheless, at the 5th percentile, the average market-to-book ratio is below one at 0.66, suggesting that on average at least 5% of the companies have market capitalizations lower than their corresponding book value. Among the four variables, the cross-sectional distributions of size and market-to-book ratio show positive skewness and excess kurtosis, but the skewness and excess kurtosis estimates are small for the asset tangibility and profitability measures.

[Table 2 about here.]

4. Explaining the cross-sectional financial leverage variation

In this section, we analyze the cross-sectional financial leverage variation for US publicly traded companies over the past 40 years. First, we examine the empirical validity of our theoretical prediction on the mean-variance ratio forecast being the primary determinant of the financial leverage target variation. Second, we discuss our theory's implication on the well-documented cross-industry leverage variation. Third, we test the empirical validity of our assumption that larger firms have better access to cheaper financing, and we examine the empirical implication of this assumption on the optimal financial leverage variation. Finally, we compare the relative contributions of other explanatory variables to the cross-sectional leverage ratio variation, with and without controlling for the mean-variance ratio effect.

4.1. Mean-variance ratio as the primary determinant of leverage target

To examine the cross-sectional relation between financial leverage and the company's risk-return trade-off prospect, at each date, we perform a cross-sectional regression of the financial leverage measure $L_{t,i}$ against the mean-variance ratio forecast $\mathrm{MVF}_{t,i}$,

$$L_{t,i} = a_t + b_t \mathrm{MVF}_{t,i} + e_{t,i}. \tag{14}$$

As we have done in the summary statistics, we winsorize both the target leverage variables and the explanatory variable between the 5-95th percentile range. According to Proposition 2, the slope coefficient b_t from this regression represents the reciprocal of the summation of average investor relative risk aversion and proportional financing cost coefficient. The intercept estimate would be close to zero under the linear financing cost approximation in (4) and the proportional optimal risk taking solution in (5). When the financing cost does not increase proportionally with financial leverage, the intercept term a_t can capture some of its effects via the implicit relation in (3).

Panel A of Table 3 summarizes the results from the firm-level cross-sectional regression. The statistics include the time-series averages ("Average"), the Newey and West (1987) t-statistics ("NW") on the time-series average, and the percentile values of the regression coefficient estimates (a and b), their t-values (τ_a and τ_b), and the R^2 estimates of the regressions. The average t-value of the coefficient measures the average statistical significance of the estimate from the cross-sectional regressions and accordingly the average strength of the relation. The Newey-West t-statistics on the time-series average reflects the intertemporal stability of the estimates over time.

[Table 3 about here.]

The time-series averages of the t-values are highly positive for both the intercept and the slope coefficient; nevertheless, the t-values on the slope estimates are much larger. The univariate cross-sectional regressions generate very high R^2 estimates, ranging from 54% at the 5th percentile to 81% at the 95th percentile, and with a sample average of 68%.

To visualize the details of the cross-sectional relation, at each date, we sort the mean-variance ratio forecasts into percentile groups. For each percentile group, we compute the average mean-variance ratio forecasts and the average leverage ratio. Figure 2 plots the percentile-grouped scatter points of the time-series averages of the average leverage levels in each percentile group against the average mean-variance ratio forecasts in that percentile.

[Fig. 2 about here.]

The grouped scatter plot shows that on average, the financial leverage increases strongly with the mean-variance ratio forecast, with a nearly linear dependence structure. The dash-dotted line represents a linear fit of the scatter plots. The scatter points fall closely to the fitted line. Both the cross-sectional regression results and the average scatter plots show that the cross-sectional variation of company financial leverage can be very well explained by the cross-sectional variation in their average mean-variance ratio forecasts. While the scatter plots do not fall on an exact linear line, the overall deviations are small, contributing to the high average R^2 estimates from the cross-sectional regressions.

4.2. Explaining the industry effect with cross-industry mean-variance ratio variation

Industry or peer average has been found to be a strong explanatory variable for the cross-sectional variation of financial leverage (e.g., Leary and Roberts (2014) and Frank and Goyal (2009)), but for reasons not well understood (Welch (2012)). In this section, we show that the cross-industry variation in financial leverage is mainly driven by the corresponding cross-industry variation in the mean-variance ratio forecasts. Different industries take on different types of businesses, which can naturally have different risk-return characteristics. Our optimal risk-taking theory dictates that these different risk-return characteristics lead to different average financial leverage levels across industries.

We use the GICS information to classify industries and we consider both the broad 2-digit sector classification and the more refined 4-digit industry group classification. As each date, for each sector and industry group, we compute its average leverage level and its average mean-variance ratio forecast by aggregating the firm-level measures with common equity as weights. The GICS classification includes 11 sectors and 26 industry groups. The number of names varies greatly across groups. The Industrials, Financials, and Information Technology sectors all have more than 400 selected names per date on average, whereas the newly reclassified real estate sector only has an average of 19 selected names per date. Some 4-digit level classifications can have zero observations at a given date.

To examine how the cross-industry variations in financial leverages are related to the corresponding cross-industry variation in their mean-variance forecasts, we repeat the cross-sectional regressions at both the industry level and the sector level. The regressions exclude industry groups with fewer than 10 companies. The results are summarized in panels B and C of Table 3, respectively. By aggregating the firm-level estimates to the industry and the sector level, the average intercept estimates become smaller, but the slope estimates become larger, potentially because the averaging further reduces the measurement errors in the individual mean-variance ratio forecasts. With a much smaller cross section, the average t-values of the cross-sectional regression slope estimates become smaller, but the Newey and West (1987) t-statistics on the average slope coefficient estimates remain at about the same level to that from the firm-level regression.

With the aggregation, the regression R^2 estimates become even larger. At the 4-digit GICS industry level, the regression R^2 estimates have an average of 92%. Over time, the R^2 estimates of the cross-industry regressions vary within a vary narrow range between 88% at the 5th percentile to 95% at the 95th percentile. At the 2-digit sector level, the average R^2 becomes even higher at 95%, and the R^2 estimates vary over time within a similarly narrow range. Therefore, cross-industry or cross-sector average financial leverage variation can almost completely be explained by the corresponding cross-industry or cross-sector variation in the mean-variance ratio forecasts.

Figure 3 plots the scatter points of the time-series averages of the average leverage levels in each industry or sector group against the average mean-variance ratio forecasts in that group, with panel A representing average cross-industry variation and panel B representing the average cross-sector variation. The dash-dotted line in each panel represents the linear fitted line. The average scatter points fall closely onto the fitted linear line.

[Fig. 3 about here.]

The sector with the largest average leverage is financials. Some empirical studies exclude financials because they are "special" relative to other industries. The scatter plots show that they may indeed look special based on the much larger leverage they take relative to other industries, but this "specialness" disappears from the perspective of optimal risk taking. Their high leverage levels are supported by their high mean-variance ratio forecasts.

4.3. Expanding firm size to gain pricing power and cheaper financing

Company size has been found to be an important factor in explaining the cross-sectional variation of financial leverage, but without a very clear theoretical interpretation (Welch (2012)). Some researchers argue that large companies tend to have lower operational risks and can accordingly afford a higher level of leverage. Since our mean-variance ratio forecasts are specifically constructed to capture the risk-return tradeoff behavior and its contribution to the optimal risk taking decision, once controlled for the mean-variance ratio forecasts, any remaining size effect must come from some other sources.

In deriving our optimal risk taking theory, we argue that a firm as a coordinated investment vehicle can enjoy easier access to cheaper financing than can its individual investors. Furthermore, the larger a firm expands relative to its peers, the more market pricing power the firm enjoys. That pricing power can reduce the cost of its production factors and increase the selling price of its products. It can also include the power to negotiate better financing terms and enjoy better access to cheaper financing. Everything else equal, the optimal risk taking theory suggests that easier access to cheaper financing allow firms to target a higher optimal leverage level.

To examine our premise that larger firms can enjoy better access to cheaper financing, we construct a relative company size measure (RS) based on the company's total sales to proxy a company's pricing power, and we also construct a proportional financing cost measure (FC) as the ratio of total interest expense to total debt. For a given company, the proportional financing cost can increase with financial leverage due to the increased risk. Our hypothesis is that across different companies, conditional on the risk-adjusted leverage level, the financing cost should become lower for companies with higher pricing power as proxied by the company relative size measure. To test this hypothesis, we perform the following cross-sectional regression at each date,

$$\mathrm{FC}_{t,i} = \alpha_t + \beta_t L_{t,i}\sigma^2_{t,i} + \gamma_t \mathrm{RS}_{t,i} + e_{t,i}, \tag{15}$$

where we multiply the financial leverage ratio $L_{t,i}$ with the variance estimator on the return on asset ($\sigma^2_{t,i}$) to create a risk-adjusted leverage measure as the first explanatory variable, and we use $\mathrm{RS}_{t,i}$ to denote the relative size measure we have constructed on total sales. Under our hypothesis, we expect that the regressions generate on average a positive slope estimate on the risk-adjusted leverage measure and a negative slope on the relative size measure.

Panel A of Table 4 reports the summary statistics of this cross-sectional regression, including the time-series averages of coefficients and the R^2 estimates, and the Newey and West (1987) t-statistics on the average coefficients. Consistent with our hypothesis, the time-series average of the loading coefficients β_t is positive and strongly statistically significant, whereas the time-series average of the loading coefficient γ_t is negative and also statistically significant, consistent with our starting assumption that larger firms can benefit from better access to cheaper financing.

[Table 4 about here.]

Under our optimal risk taking theory, a firm with access to cheaper financing can target a higher financial leverage. To test the validity of this theoretical prediction and gauge the relative contribution of the company relative size measure to the cross-sectional financial leverage variation, we cross-sectionally regress the financial leverage ratio at each date on the relative size measure, both with and without the mean-variance ratio as a control variable. We also perform similar univariate and bivariate regressions on other commonly identified explanatory variables for comparison.

To make the regression coefficients more comparable relative to one another, we cross-sectionally standardize both the leverage variable and the explanatory variables by removing the cross-sectional sample average and dividing the de-meaned observations by the sample standard deviation. All variables are cross-sectionally winsorized before the standardization operation. With the standardization, the slope of the univariate regression reflects the cross-sectional correlation between the leverage level and the explanatory variable, and the squared of the coefficient is just the regression R^2. For the standardized bivariate regression, the two slope coefficients reflect the relative contribution and direction of the two explanatory variables to the variation of the leverage ratio.

Table 5 summarizes the regression results, with panel A for the univariate regressions and panel B for the bivariate regressions. For each coefficient, we report the time-series averages of the coefficient and its t-value, as well as the Newey and West (1987) t-statistics (NW) on the average coefficient. The last column in panel B reports the average adjusted R^2 estimates of the bivariate regressions. The average t-value of the coefficient measures the average statistical significance of the estimate from the cross-sectional regressions and accordingly the average strength of the relation. The Newey-West t-statistics on the time-series average of the coefficient reflects more of the intertemporal stability of the relation over time.

[Table 5 about here.]

In the first row of the table, we repeat the univariate regression on the mean-variance ratio forecast, this time standardized, and use it as a benchmark reference for other regressions. The average cross-sectional correlation between the mean-variance ratio forecast and the leverage ratio is at 82%, creating a very high watermark for other explanatory variables.

The second row of the statistics summarizes the contribution of the relative company size measure. From the univariate regression, the relative size measure shows a positive average cross-sectional correlation with the leverage ratio at an average of 8%. The average correlation estimate is magnitudes lower than the 82% average estimate with the mean-variance ratio forecast; nevertheless, both the average t-value and the Newey-West t-statistics are reasonably large, suggesting that the contribution of the relative size measure is statistically significant. The positive contribution remains after we control for the mean-variance ratio forecast in the bivariate regression. The slope estimate in the bivariate regression also averages at 8%, with high statistical significance. Because of its much smaller contribution relative to the mean-variance ratio forecast, the bivariate regression does not visibly increase the average adjusted R^2 estimate relative to the benchmark univariate regression. The average R^2 estimate remains around 68%.

To visualize the average relation between the leverage ratio and the relative size measure, at each date, we perform local linear regressions of the leverage ratio on the relative size measure. In addition, to control for the mean-variance ratio effect, we also regress the relative size measure against the mean-variance ratio forecast, and then perform the local linear regression on the regression residual. Figure 4 plots the time-series averages of the estimated relations in Panel A, where the circle-solid line represents the time-series averages of the fitted relation between the leverage ratio and the relative size measure, and the diamond-dashed line represents the time-series averages of the fitted relation between the leverage ratio and the regression residual of the size measure against the mean-variance ratio forecast. We cross-sectionally standardize the size variable and its regression residual so that we can put the two estimated relations in one graph. The circles and diamonds represent the estimated leverage ratio levels at each percentile values of the standardized variable and its standardized residual, respectively.

[Fig. 4 about here.]

On average, the leverage ratio goes up monotonically with the company relative size, with or without controlling for the mean-variance ratio effect. The slopes of the estimated relations are steeper at the lower percentiles of the size measure and become somewhat flatter at the higher percentiles, potentially reflecting the declining marginal benefit for further size increase once the company size is already larger than most of its peers.

4.4. Contributions from other commonly identified financial leverage determinants

The literature has identified several other variables that show positive explanatory power on the cross-sectional financial leverage variation, including asset tangibility, profitability, and market-to-book ratios. To examine their relative contribution to the financial leverage variation, we perform similar standardized univariate and bivariate cross-sectional regressions on these variables. The remaining rows of Table 5 summarize the regression results on these variables. We have also estimated their average local linear relations with the leverage ratio. Figure 4 plots the average estimated relations in panels B to D.

4.4.1. Asset tangibility ratio

Frank and Goyal (2003), Frank and Goyal (2009), and DeAngelo and Roll (2015), among others, find that the asset tangibility ratio can positively explain the cross-sectional capital structure variation. In our sample, however, its contribution is small and negative. The slope estimates average around -2% and are barely significant under both the univariate and bivariate specifications. The general argument is that more tangible assets can increase the value of collateral and reduce the financing cost. We do not find this effect to be significant in our sample.

Figure 4 plots the average estimated relations between the leverage ratio and the asset tangibility measure in panel B. On average, the cross-sectional variation of the leverage ratio does not have a clear dependence on the asset tangibility ratio, with or without controlling for the mean-variance ratio effect. The estimated relation is flat and non-monotonic. The small average slope estimates in Table 5 partially reflect this instability of the relation.

4.4.2. Profitability

By itself, the profitability measure contributes strongly negatively to the capital structure variation. The correlation estimates average at -21%, with strong statistical significance. The literature has documented similarly negative relations between profitability and the leverage ratio, e.g., Hovakimian, Opler, and Titman (2001), Flannery and Rangan (2006), Frank and Goyal (2009), and Graham and Leary (2011). In principle, holding everything else equal, a high average return on asset should contribute positively to the mean-variance ratio and accordingly positively to the optimal leverage target. Chen, Harford, and Kamara (2018) attribute the negative relation to the positive connection between profitability and operating leverage and hence operating risk. Over our sample, we indeed find that the profitability measure has an average positive cross-sectional correlation at 28% with the return on asset volatility estimate, and an average negative correlation at -26% with our mean-variance ratio forecast. Once we control for the mean-variance ratio forecast in the bivariate specification, the average contribution of the profitability measure becomes very close to zero and loses its statistical significance.

Due to large adjustment costs, the active leverage rebalancing decision can only be discrete (Strebulaev (2007)). In between the rebalancing actions, a company's financial leverage can deviate from its target level. One channel that can move a company's financial leverage away from its target level is through the cumulation of wealth via operating profits. When a company has been making more money than it distributes, its retained earnings account increases, which increases its total asset and common equity, reducing the leverage ratio. Therefore, in between active capital structure rebalancing actions, the wealth cumulation effect of operating profits can generate a negative contribution to the cross-sectional financial leverage variation. Danis, Rettl, and Whited (2014) find that the contributions of profitability can indeed become positive when the firms are at or close to their optimal leverage level, but otherwise can become negative due to variations away from the target. Once controlling for the mean-variance effect, we obtain a near-zero loading on the profitability measure, potentially due to the cancelling effects of the positive informational effect of profitability on future mean-variance prospects on the one hand and the negative wealth cumulation effect on the other.

Figure 4 plots the average estimated relations between the leverage ratio and the profitability measure in panel C. Without controlling for the mean-variance ratio effect, the average estimated relation in the circle-solid line is mostly downward sloping except at the lower percentiles of the profitability measure. After controlling for the mean-variance ratio effect, the average estimated relation becomes more symmetrically hump shaped. When the overall profitability level is low, the wealth cumulation effect is small, its effect on leverage is potentially dominated by its informational effect on the company's future risk-return prospect. A more positive realization raises the prospect whereas a negative realization reduces this prospect. On the other hand, for companies that are highly profitable, the cumulation of wealth effect can become more significant, turning the relation from positive to negative, and driving the leverage level away from the long-run target in between active leverage rebalancing actions.

4.4.3. Market-to-book ratio

By itself, the market-to-book equity ratio contributes negatively to the capital structure variation. The cross-sectional correlation estimates average at -14%, with strong statistical significance. Nevertheless, the market-to-book ratio also shows a strongly negative cross-sectional correlation with our mean-variance ratio forecast at an average of -32%. Once we control for the mean-variance ratio forecast, the bivariate regression generates an average positive slope on the market-to-book ratio at 15%, with high statistical significance.

Adding the market-to-book ratio to the regression increases the contribution from the mean-variance ratio forecast to an average of 87%. The bivariate regression with the mean-variance ratio and the market-to-book ratio also generates the highest average R^2 estimate at 70%, 2 percentage points higher than from the benchmark regressions with the mean-variance ratio forecast alone.

The literature uses the market-to-book ratio mainly as a relative value measure. The classic market timing arguments (e.g., Fischer and Merton (1984) and Lucas and McDonald (1990)) suggest that when a company is overvalued, the company tends to increase its net stock issuance to benefit from the temporary mispricing opportunity. The stock overvaluation can also have a spillover effect to the debt market, allowing the company to also raise more debt at a cheaper cost (Hu, Sy, and Wu (2020)). Meanwhile, the catering theory suggests that optimistic market valuations can encourage firms to take actions to confirm such expectations by raising more capital and making more investments (Polk and Sapienza (2009)). As our cross-sectional regressions are on the leverage levels instead of the net debt or equity issuances, the net contributions of these different considerations to the leverage level variations are not always clear. Over our sample, once controlled for the mean-variance ratio forecast, the market-to-book ratio on average has a net positive contribution to the cross-sectional leverage level variation.

Figure 4 plots the average estimated relations between the leverage ratio and the market-to-book ratio in panel D. Without controlling for the mean-variance ratio effect, the estimated relation in the circle-solid line is largely downward sloping, matching the strongly negative average slope estimate from the univariate regressions. Once we control for the mean-variance ratio effect, however, the average estimated relation in the diamond-dash-dotted line turns into a hump shape. The relation is upward sloping over a large range of the residual market-to-book ratio, and turns downward sloping only when the ratio becomes extremely large. As the dependence of market-to-book ratio on the mean-variance ratio forecast reflects more of systematic equity relative value variation, the regression residual can be regarded as a better measure of equity mispricing. The estimated relation seems to suggest that over a large range of the mispricing measure, the catering effect dominates the contribution to the leverage level variation: Market under-valuation of its equity lowers the expectation of the management on the investment opportunities and as a result lowers the firm's risk of financial leverage and risk taking. Nevertheless, when the equity is extremely overvalued, the market-timing incentive of issuing more equity starts to dominate the contribution and lowers the leverage level again.

To capture the joint contributions from all the identified determinants, we also perform a standardized multivariate cross-sectional regression at each date that includes both the mean-variance ratio forecast and the four other explanatory variables. Table 6 reports the time-series averages of the slope coefficient estimates and their t-values, the Newey and West (1987) t-statistics on the coefficient average, and percentile values of the coefficient estimates. The multivariate regression has an average adjusted R^2 estimate of 70%, close to that from the bivariate regressions with the mean-variance ratio and the market-to-book ratio.

[Table 6 about here.]

Under the multivariate setting, the relative company size contributes an average of 6% with strong statistical significance. The average contribution from asset tangibility remains small at merely -2% with marginal significance. The average contribution from the profitability measure is negative at -6% with strong statistical significance, while the average contribution from the market-to-book ratio is strongly positive at 15%. Above all, the contribution from the mean-variance ratio forecast remains magnitudes larger than the contributions from the other variables. The slope coefficient estimates on the mean-variance ratio forecasts average at 86%, and vary within a narrow range from 78% at the 5th percentile to 91% at the 95th percentile. The average t-value and Newey-West t-statistic are also multiples larger than those on any other variables. With or without controlling for the other explanatory variables, the mean-variance ratio forecast remains the principal determinants of the cross-sectional financial leverage variation.

5. Differentiate target and non-target leverage variations

Regressing the observed cross-sectional variation of financial leverage on a list of firm characteristics can identify the sources of the leverage variation, but the regression cannot differentiate whether these characteristics explain the cross-sectional variation of the optimal financial leverage *target*, or the variations *away* from the target. While our optimal risk taking theory identifies the mean-variance ratio as the chief determinant of the optimal financial leverage target, profitability can contribute to the leverage variation away from the target via the cumulation of operating profits, and potential mispricings on a company's equity or debt can trigger market-timing decisions on the company's net equity and debt issuance that can also move the company's leverage level temporarily away from its long-run target. Therefore, although these different variables can all explain the cross-sectional leverage variation to some extent, they are not necessarily determinants of the optimal financial leverage target.

In this section, we explore two approaches that can potentially differentiate the variation of the optimal financial leverage target from variations that are actually moving away from the target.

5.1. An error-correction model to differentiate target and non-target variations

We first propose to use a cross-sectional error-correction model as an out-of-sample test to differentiate the target and non-target variations. Our hypothesis is that if a specification better explains the financial leverage target variation, future leverage adjustments are more likely to move toward the specification's predicted leverage target level; on the other hand, if a variable explains more of the financial leverage variations away from the target, say due to cumulation of wealth or market-timing decisions, future leverage adjustments are less likely to move toward its predicted leverage level.

The error-correction model involves a two-step procedure. In the first step, we use a series of contemporaneous cross-sectional regression specifications to predict the financial leverage variation,

$$L_{t,i} = a_t + b_t \mathrm{MVF}_{t,i} + c_t^k X_{t,i}^k + e_{t,i}^k. \tag{16}$$

We start with the mean-variance ratio forecast (MVF) as the benchmark explanatory variable, and generate a benchmark prediction by itself. Then, we add each of the other explanatory variables $X_{t,i}^j$ into the regression together with MVF as the joint predictor of the leverage variations. Estimating each specification k at time t generates a forecast on the leverage level of each company i at that time,

$$\widehat{L}_{t,i}^k = \widehat{a}_t + \widehat{b}_t \mathrm{MVF}_{t,i} + \widehat{c}_t^k X_{t,i}^k. \tag{17}$$

In the second step, we propose the following cross-sectional error-correction model as an out-of-sample test on each specification k,

$$L_{t+h,i} - L_{t,i} = \rho^k_{t,h} \left(\widehat{L}^k_{t,i} - L_{t,i} \right) + \varepsilon^k_{t+h,i}, \tag{18}$$

where we predict future leverage changes $(L_{t+h,i} - L_{t,i})$ with the deviation of the current leverage level from the predicted leverage level from the above cross-sectional regression $\left(\widehat{L}^k_{t,i} - L_{t,i}\right)$. The deviation is essentially the negative of the regression residual, $-e^k_{t,i}$ from the contemporaneous cross-sectional regression specification in (16). The slope coefficient $\rho^k_{t,h}$ measures the speed of the future leverage adjustment toward the predicted leverage level over the next h years. To compare the relative predictive power of different specifications, we cross-sectionally standardize both the leverage change $(L_{t+h,i} - L_{t,i})$ and the predicted deviation $\left(\widehat{L}^k_{t,i} - L_{t,i}\right)$, so that the slope coefficient from the standardized regression captures the forecasting correlation between the deviation and the future leverage change. Under our hypothesis, a better leverage target estimate $\widehat{L}^k_{t,i}$ would generate a higher forecasting correlation estimate on future leverage changes.

We have estimated a long list of specifications in the previous section to explain the cross-sectional leverage ratio variation in cross-sectionally standardized regressions. We directly take the residuals from the negative of these standardized regressions as the regressor in the error-correction regression in (18), with further cross-sectional standardization on both the leverage change and the residual. In the previous section, we have also estimated univariate regressions on each of the other explanatory variables; nevertheless, as their stand-alone explanatory powers are magnitudes lower than that from the mean-variance ratio forecast, none of them are close to be the major determinant of the leverage target variation. Therefore, for the error-correction test in this section, we only consider their additional contributions on top of the mean-variance ratio forecast as the principal determinant in the joint specifications in (16).

In this two-step procedure, the R^2 estimate from the contemporaneous regression in (16) in the first step captures how much the specification can explain the cross-sectional variation of the observed financial leverage, whereas the R^2 estimate, or equivalently the slope estimate ρ, from the standardized error-correction forecasting regression in (18) in the second step determines whether the specification in (16) captures the true variation of the optimal leverage target that future leverages will adjust to. A higher explanatory R^2 estimate from the first regression does not necessarily lead to a higher error-correction forecasting R^2 in the second regression if the explained variations do not represent true optimal financial leverage target.

We consider leverage changes over the next $h = 1$ to 5 years. Table 7 reports in panel A on the left side the time-series averages of the forecasting correlation estimates across different forecasting horizons and different leverage prediction specifications. On the right side, panel B of the table reports the Newey and West (1987) t-statistics on the average differences in the forecasting correlation estimates between each specification and the benchmark specification. A positive t-statistic on a particular specification suggests that this specification on average generates higher forecasting correlations with future leverage adjustments and accordingly outperforms the benchmark specification in explaining the optimal leverage target variation. A negative t-statistic, on the other hand, would suggest that the specification does not explain more of the leverage target variation than the benchmark specification, even if the average R^2 of the specification is higher in explaining the cross-sectional leverage variation.

[Table 7 about here.]

The first row of statistics show that deviations from the benchmark prediction with the mean-variance ratio alone can strongly predict future leverage ratio changes from one to five years. The average forecasting correlation increases with the forecasting horizon from 15.2% at 1-year horizon to 34.5% at the 5-year horizon.

When we add the relative company size measure to the specification in a bivariate regression, the size variable contributes positively not only to the cross-sectional variation of the leverage ratio, but also helps enhance the forecasting relation with future leverage changes. The average forecasting correlation estimates are higher across all horizons. Although the average increases in the forecasting correlation estimates are small, the Newey-West t-statistics in panel B suggest that they are statistically significant, especially over longer horizons.

We have found that the asset tangibility ratio has a slightly negative contribution on average to the leverage variation, and the average adjusted R^2 estimate from the bivariate specification is no higher than that from the benchmark specification. Table 7 shows that its small contribution is nevertheless contributing to a better leverage target prediction and accordingly slightly higher error-correction forecasting correlation estimates. The enhancement is statistically significant at short forecasting horizons, but becomes less significant at longer horizons.

Once controlled for the mean-variance ratio forecast, the contribution of profitability to the leverage variation becomes very small. The error-correction estimation shows that this very small contribution is not toward a better leverage target prediction. Instead, deviations from the prediction show lower forecasting powers than that from the benchmark specification. The Newey-West t-statistics on the forecasting correlation differences are negatively across all forecasting horizons, but more strongly significant at longer horizons. This negative contribution to the forecasting power supports the literature explanation of the wealth cumulation effect, which can move the leverage away from the optimal target in between rebalancing actions.

The analysis in the previous section shows that adding the market-to-book ratio to the bivariate specification generates the largest R^2 increase; yet, deviations from this specification prediction actually generates the lowest forecasting correlation estimates. The Newey-West t-statistics on the forecasting correlation differences from the benchmark specification are strongly negatively across all forecasting horizons. Therefore, although the relative value variable can explain the market timing actions and its effects on the leverage level variation, these explained variations are mostly away from the long-run optimal leverage target. As such, future leverage rebalancing decisions do not adjust the leverage level toward these predicted levels, but away from them.

In the last row of the table, we consider a new specification where we add industry dummy variables to the mean-variance ratio forecast to explain the cross-sectional leverage variation. We construct the industry dummy variables based on the 2-digit GICS sector classification. Our early analysis has shown that on average 95% of the cross-sector leverage variation can be explained by the corresponding cross-sector variation in the mean-variance ratio. What this specification captures is the additional contribution of the remaining cross-sector leverage variation not explained by the mean-variance ratio forecast. Adding the industry dummy can indeed increase the average adjusted R^2 of the regression from 68% to 70%. The last row of Table 7 shows that the specification also generates higher average forecasting correlation estimates with future leverage adjustments. The Newey and West (1987) t-statistics are strongly positive across all forecasting horizons, suggesting that even after controlling for the mean-variance ratio forecast, future leverage adjustments still respond to deviations from the peer industry average, either because the industry average captures part of the optimal financial leverage variation not fully captured by the mean-variance ratio forecast, or because management has the tendency to lean on the peer average in making their own capital structure decisions (Leary and Roberts (2014)).

A variable that can explain the current capital structure variation does not necessarily determine the leverage target that the firm rebalances to in the long run. In testing capital structure theories, one must carefully distinguish the leverage target variation from variations away from the optimal target. The error-correction specification that we propose provide a mechanism to differentiate these two types of variations.

Taken together, our analysis shows that the risk-return tradeoff prospect, as captured by our mean-variance ratio forecast, represents the principal determinant of a company's optimal leverage target. Once we control for the mean-variance ratio effect, the contributions from the other commonly identified variables are either small or move the leverage levels away from the optimal target.

5.2. Identify leverage targets that maximize firm value

The literature often sets up the problem of optimal capital structure decision from the perspective of minimizing the weighted average cost of capital or equivalently maximizing the firm valuation; nevertheless, there is scant empirical evidence on the linkage between the leverage variation and firm value maximization, potentially because most of the explanatory variables identified in the literature do not fully capture the true determinant of the optimal leverage target variation. Given the much higher explanatory power of the mean-variance ratio forecast in explaining the cross-sectional leverage ratio variation and in predicting future leverage adjustments, we examine in this subsection whether the leverage ratio predicted by the mean-variance ratio forecast maximizes firm value and whether other explanatory variables contribute to the value-maximizing optimal leverage variation.

For this purpose, we start with the same set of specifications in (16) to explain the cross-sectional financial leverage variation. Then, we link the regression residual, i.e., the deviations of the leverage ratio from the predicted level, to firm valuation. We measure the relative value of a company using a simple construct of the Tobin (1969)'s Q ratio, constructed as the ratio of total book asset minus common book equity plus market capitalization to total book asset. If a specification k determines the optimal leverage ratio that maximizes the firm value, the Q ratio would have a hump-shaped relation with the regression residual from the specification $e^k_{t,i}$, where the Q ratio is maximized at zero residual and declines with increasing magnitude of the residual in either direction. To identify this potential hump-shaped relation, we perform local linear regressions of the Q ratio against the regression residual from each specification k at each date t. The local linear regression uses standard Gaussian kernel with 3 times the default bandwidth choice for a smooth estimated relation. To make the different specifications comparable to each other, we cross-sectionally standardize the regression residuals as we have done in the error-correction model estimation. We also cross-sectional standardize the Tobin's Q ratio before we estimate the relation.

Figure 5 plots the time-series averages of the estimated relations for each specification. We group the estimated relations in two panels. In each panel, the solid line denotes the benchmark specification that predicts the leverage variation with the mean-variance ratio (MVF) alone, and other lines denote specifications that include other variables. The first panel compares the benchmark specification with specifications that include the relative company size, asset tangibility, and the profitability measure, respectively. The second panel compares the benchmark specifications with specifications that include the market-to-book ratio and the industry dummy variable, respectively.

[Fig. 5 about here.]

The solid line from the benchmark prediction shows a clear hump-shaped average relation, where the hump peaks around zero deviation from the predicted leverage level. The estimated relation verifies that the optimal leverage ratio that we determine from the perspective of a mean-variance investment decision does match the objective of firm value maximization.

The other lines in the first panel show similar hump-shaped relations when we include size, tangibility, or profitability to the specifications. The specifications with size and profitability generate the average value relations indistinguishable from the benchmark relations. The specification with asset tangibility (the dash-dotted line) seems to enhance the value maximizing relation, even though it does not add much to the average explanatory power of the relation.

The second panel highlights the contribution from the market-to-book ratio in the dashed line. The dashed line deviates strongly from the benchmark hump shape. With the market-to-book ratio in the specification, the firm value is no longer maximized at zero deviation from the specification. This relation highlights the complex nature of the interaction between market valuation and the leverage decision. On the one hand, managers can try to time the market based on the relative valuation of its equity and/or debt, or try to reformulate its expectation to confirm with market valuation. On the other hand, the leverage decision the management takes also has a direct impact on market valuation of the company as investors value a company more when the firm's leverage is closer to the market's perceived optimal leverage level. In a sense, the market-to-book ratio is less a determinant of the optimal leverage target, but more a reflection of the optimality of the leverage decision.

The dash-dotted line in the second panel shows the contribution of the industry dummy variable in the leverage variation prediction. We have found earlier that adding the industry dummy variable increases both the explanatory power of the specification for the cross-sectional leverage variation and the forecasting power of future leverage adjustments. Nevertheless, the dash-dotted line is flatter than the benchmark solid line, suggesting that even though management may follow industry peers in their leverage decision, the herding behavior itself does not necessarily maximize firm value.

To formally test the relative strength of each specification in generating the value-maximizing leverage target, at each date, we perform a series of standardized cross-sectional regressions of the Tobin's Q ratio, $Q_{t,i}$, against the negative of the absolute magnitude of the predicted leverage variations from each specification, $\left|e_{t,i}^{k}\right|$,

$$Q_{t,i} = -\kappa_{t,h}^{k}\left|e_{t,i}^{k}\right| + \varepsilon_{t+h,i}^{k}, \tag{19}$$

where we cross-sectional standardize both the Q ratio $Q_{t,i}$ and the absolute leverage deviation $\left|e_{t,i}^{k}\right|$ so that the slope estimate $\kappa_{t,h}$ measures the negative of the cross-sectional correlation between the absolute deviation from the predicted leverage target and the relative company valuation. Under the value maximizing hypothesis, company relative value should decline with the absolute deviation, and the cross-sectional correlation estimate should be positive. The better the specification is at identifying the value-maximizing leverage target, the stronger the correlation estimate should become.

Table 8 reports the time-series averages of the slope coefficient estimates and its t-values, as well as the Newey and West (1987) t-statistics on the average coefficient estimates for each specification k. As in Table 7, we start with the benchmark specification that predicts the leverage target with the mean-variance ratio forecast (MVF) alone, and then consider specifications that also include other variables in bivariate or multivariate settings. The last column of the table reports the. Newey-West t-statistics on the average slope coefficient difference between each specification and the benchmark. A positive average slope difference would indicate that the specification outperforms the benchmark in identifying value-maximizing leverage targets.

[Table 8 about here.]

Similar to our observations from the local linear regression plots in Figure 5, adding company relative size, tangibility, or profitability to the specification does not generate significance performance differences.

The t-statistics on the average slope difference is weakly negative for size and profitability, and weakly positive for asset tangibility, but none with statistical significance. On the other hand, adding the market-to-book ratio or the industry dummy variable generates significantly lower average coefficient estimates, suggesting that neither helps identifying the value-maximizing leverage target.

6. Concluding remarks

Building on the motivations for the creation and expansion of a firm, this paper treats the firm as a coordinated investment vehicle and proposes a new optimal risk taking theory that solves the optimal leverage ratio as a mean-variance risk allocation problem, given the equity level of the firm and the risk-return tradeoff prospect of the firm's investment. The theory is built on two key premises. The first is that a firm is created not to take exposures on the existing market portfolio, but to provide unique investment opportunities to the investors to expand the current investment frontier. The second premise is that a firm can have better access to cheaper financing than its individual investors. Obtaining better access and higher pricing power is one the chief motivations for creating a firm instead of directly operating on the market. The first premise motivates us to examine the investment risk and return of the firm, instead of its exposure to the market. The second premise directly motivates the importance and relevance of an optimal firm-level leverage decision: Since investors do not have as easy access to financing, it is optimal for the firm as a coordinated investment vehicle to take on the appropriate leverage and risk level for its investors, rather than leaving the firm unlevered and leaving the financing burden to its individual investors.

Applying classic mean-variance risk allocation theory, we derive the optimal leverage ratio, i.e., the ratio of total asset investment to equity, as primarily proportional to the expected mean-variance ratio of the investment return, adjusted for the financing cost level and its speed of variation on risk-adjusted leverage. When the financing cost increases linearly with the risk-adjusted leverage level, we can solve the optimal leverage target explicitly and proportional to the mean-variance ratio, where the proportionality coefficient is inversely related to the average relative risk aversion of the investors and the proportionality coefficient of the financing cost.

To examine the empirical validity of the theoretical prediction, we measure the leverage ratio as the ratio of total asset to equity, and we construct the mean-variance ratio forecasts based on a company's return on asset history. Analyzing historical data over the past 40 years on US publicly traded companies shows that our constructed mean-variance ratio forecasts can explain a large proportion of the cross-sectional leverage ratio variation, and consistently so over time. We also find that a company's size relative to its industry peers can be a predictor of the company's market pricing power and its access to cheap financing. In addition to the dominant contribution from mean-variance ratio forecast, the relative company size measure also makes a small but statistically significant positive contribution to the leverage variation.

For comparison, we also examine the contribution of other explanatory variables identified in the literature. Similar to literature findings, we find that by themselves, both profitability and market-to-book ratios contribute negatively to the cross-sectional leverage variation. Nevertheless, once we control for the mean-variance ratio effect, the average contribution from the profitability measure becomes very small, and the average contribution from the market-to-book ratio turns positive. Above all, an estimation of an error-correction model specification shows that the contributions from these two variables are less for the optimal leverage target variation, but more for variations away from the target in between the discrete leverage rebalancing actions.

Our analysis shows that to analyze a firm's corporate decision, it can be useful to start from a micro level and build on the original motivations for the creation and expansion of a firm. While the market efficiency hypothesis is a great starting point for summarizing the aggregate behaviors of the market, it is not a good starting point to analyze the details of corporate decisions. One cannot build a relevant corporate theory based on a hypothesis that leaves no role for the existence of a corporation to begin with. For future research, one can potentially gain more insights by applying the coordinated investment perspective to different elements of corporate decisions.

References

Alchian, A. A., Demsetz, H., 1972. Production, information costs, and economic organization. American Economic Review 62, 777–795.

Asness, C. S., Frazzini, A., Pedersen, L. H., 2012. Leverage aversion and risk parity. Financial Analysts Journal 68, 47–59.

Baker, M., Wurgler, J., 2000. The equity share in new issues and aggregate stock returns. Journal of Finance 55, 2219–2257.

Baker, M., Wurgler, J., 2002. Market timing and capital structure. Journal of Finance 57, 1–32.

Barry, C. B., Mann, S. C., Mihov, V. T., Rodríguez, M., 2008. Corporate debt issuance and the historical level of interest rates. Financial Management 37, 413–430.

Benjamin Klein, R. G. C., Alchian, A. A., 1978. Vertical integration, appropriable rents, and the competitive contracting process. Journal of Law and Economics 21, 297–326.

Chen, Z., Harford, J., Kamara, A., 2018. Operating leverage, profitability, and capital structure. Journal of Financial and Quantitative Analysis 54, 369–392.

Coase, R. H., 1937. The nature of the firm. Economica 4, 396–405.

Danis, A., Rettl, D. A., Whited, T. M., 2014. Refinancing, profitability, and capital structure. Journal of Financial Economics 114, 424–443.

DeAngelo, H., Roll, R., 2015. How stable are corporate capital structures?. Journal of Finance 70, 373–418.

Fama, E. F., 1970. Efficient capital markets: A review of theory and empirical work. Journal of Finance 11, 404–419.

Fama, E. F., French, K. R., 2002. The equity premium. Journal of Finance 57, 637–659.

Faulkender, M., Petersen, M. A., 2005. Does the source of capital affect capital structure?. Review of Financial Studies 19, 45–79.

Fischer, E. O., Hernkel, R., Zechner, J., 1989. Dynamic capital structure choice: Theory and tests. Journal of Finance 44, 19–40.

Fischer, S., Merton, R. C., 1984. Macroeconomics and finance: The role of the stock market. Carnegie-Rochester Conference Series on Public Policy 21, 57–108.

Flannery, M. J., Rangan, K. P., 2006. Partial adjustment toward target capital structures. Journal of Financial Economics 79, 469–506.

Frank, M. Z., Goyal, V. K., 2003. Testing the pecking order theory of capital structure. Journal of Financial Economics 67, 217–248.

Frank, M. Z., Goyal, V. K., 2009. Capital structure decisions: Which factors are reliably important?. Financial Management 38, 1–37.

Frazzini, A., Pedersen, L. H., 2014. Betting against beta. Journal of Financial Economics 111, 1–25.

Goldstein, R., Ju, N., Leland, H., 2001. An EBIT-based model of dynamic capital structure. Journal of Business 74, 483–512.

Graham, J. R., Leary, M. T., 2011. A review of empirical capital structure research and directions for the future. Annual Review of Financial Economics 3, 309–345.

Hart, O., 1995. Firms, Contracts, and Financial Structure. Clarendon Press, Oxford.

Hart, O., Moore, J., 1998. Default and renegotiation: A dynamic model of debt. Quarterly Journal of Economics 113, 1–41.

Hovakimian, A., Opler, T., Titman, S., 2001. The debt-equity choice. Journal of Financial and Quantitative Analysis 36, 1–24.

Hu, X., Sy, M., Wu, L., 2020. A factor model of company valuation. Working paper. RMIT and Baruch College.

Im, H. J., Kang, Y., Shon, J., 2020. How does uncertainty influence target capital structure. Journal of Corporate Finance 64, 1–24.

Kraus, A., Litzenberger, R. H., 1973. A state-preference model of optimal financial leverage. Journal of Finance 28, 911–922.

Leary, M. T., Roberts, M. R., 2005. Do firms rebalance their capital structures?. Journal of Finance 60, 2575–2619.

Leary, M. T., Roberts, M. R., 2014. Do peer firms affect corporate financial policy?. Journal of Finance 69, 139–178.

Leland, H. E., 1994. Risky debt, bond covenants and optimal capital structure. Journal of Finance 49, 1213–1252.

Lemmon, M. L., Roberts, M. R., Zender, J. F., 2008. Back to the beginning: Persistence and the cross-section of corporate capital structure. Journal of Finance 63, 1575–1608.

Lucas, D. J., McDonald, R. L., 1990. Equity issues and stock price dynamics. Journal of Finance 45, 1019–1043.

Markowitz, H. M., 1952. Portfolio selection. Journal of Finance 7, 77–91.

Merton, R. C., 1973. Theory of rational option pricing. Bell Journal of Economics and Management Science 4, 141–183.

Merton, R. C., 1974. On the pricing of corporate debt: The risk structure of interest rates. Journal of Finance 29, 449–470.

Modigliani, F., Miller, M. H., 1958. The cost of capital, corporation finance and the theory of investment. American Economic Review 48, 261–297.

Myers, S. C., 1984. The capital structure puzzle. Journal of Finance 39, 574–592.

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

Newey, W. K., West, K. D., 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55, 703–708.

Polk, C., Sapienza, P., 2009. The stock market and corporate investment: A test of catering theory. Review of Financial Studies 22, 187–217.

Qian, E., 2011. Risk parity and diversification. Journal of Investing 20, 119–127.

Rajan, R. G., Zingales, L., 1995. What do we know about capital structure? some evidence from international data. Journal of Finance 50, 1421–1460.

Scott, J. H., 1976. A theory of optimal capital structure. The Bell Journal of Economics 7, 33–54.

Strebulaev, I. A., 2007. Do tests of capital structure theory mean what they say?. Journal of Finance 62, 1747–1787.

Titman, S., Tsyplakov, S., 2007. A dynamic model of optimal capital structure. Review of Finance 11, 401–451.

Titman, S., Wessels, R., 1988. The determinants of capital structure choice. Journal of Finance 43, 1–19.

Tobin, J., 1969. A general equilibrium approach to monetary theory. Journal of Money, Credit and Banking, 1, 15–29.

Warusawitharana, M., Whited, T. M., 2016. Equity market misvaluation, financing, and investment. Review of Financial Studies 29, 603–654.

Welch, I., 2004. Capital structure and stock returns. Journal of Political Economy 112, 106–131.

Welch, I., 2011. Two common problems in capital structure research: The financial-debt-to-asset ratio and issuing activity versus leverage changes. International Review of Finance 11, 1–17.

Welch, I., 2012. A critique of recent quantitative and deep-structure modeling in capital structure research and beyond. Critical Finance Review 2, 131–172.

Williamson, O. E., 1985. The Economic Institutions of Capitalism: Firms, Markets, and Relational Contracting. The Free Press, New York.

Table 1

Summary statistics of financial leverage and return on asset behaviors

Entries report the time-series averages of the cross-sectional summary statistics on company financial leverage (total asset to common equity) and their historical return-on-asset behaviors over the past five years, including the annualized percentage mean return ("Mean"), annualized percentage return volatility ("Volatility"), the annualized mean-volatility information ratio ("IR"), its cross-sectionally smoothed forecast ("IRF"), and the mean-variance ratio forecast ("MVF") constructed as the ratio of the information ratio forecast scaled by the volatility estimate. The summary statistics include the mean, standard deviation ('‘stdev"), percentile values, skewness ("skew") and excess kurtosis ("kurt"), all computed on samples winsorized at 5th-95th percentiles.

			Percentiles					Tails	
	mean	stdev	5	25	50	75	95	skew	kurt
Leverage	3.56	3.35	1.19	1.58	2.24	3.62	13.39	1.99	2.91
Mean	8.00	7.73	-8.18	3.24	7.83	12.86	23.04	-0.05	-0.07
Volatility	6.35	3.76	1.09	3.65	5.68	8.41	15.09	0.71	-0.08
IR	1.36	0.85	-0.91	1.16	1.77	1.93	1.99	-1.61	1.44
IRF	1.36	0.35	0.69	1.14	1.45	1.59	1.82	-0.94	1.26
MVF	0.40	0.43	0.08	0.15	0.24	0.40	1.62	2.11	3.55

Table 2

Summary statistics of commonly identified capital structure determinants

Entries report the time-series averages of the cross-sectional summary statistics on commonly identified capital structure determinants, including (i) a company relative size measure ("Size"), constructed as the total sales of the company divided by the corresponding industry average, (ii)asset tangibility ("Tangibility"), constructed as the ratio of net property, plant, and equipment to total assets, (iii) profitability measured by the return on asset of the most recent quarter in annualized percentages, and (iv) the market-to-book ("MB") ratio, constructed as the ratio of market capitalization to book common equity. The summary statistics include the mean, standard deviation ('stdev"), percentile values, skewness ("skew") and excess kurtosis ("kurt"), all computed on samples winsorized at 5-95%.

			Percentiles					Tails	
	mean	stdev	5	25	50	75	95	skew	kurt
Size	0.63	1.06	0.01	0.05	0.17	0.62	4.10	2.29	4.30
Tangibility	0.51	0.12	0.27	0.44	0.52	0.59	0.73	-0.17	-0.40
Profitability	7.40	9.12	-12.32	2.25	7.07	13.07	25.16	-0.11	0.00
MB ratio	2.13	1.32	0.66	1.15	1.70	2.72	5.51	1.18	0.57

Table 3

Cross-sectional linkage between financial leverage and mean-variance ratio forecasts

Entries report the summary statistics of coefficient estimates (*a* and *b*), their *t*-values (τ_a and τ_b), and the R^2 from the cross-sectional regressions of the leverage ratio against the mean-variance ratio forecasts. The statistics include the time-series sample average, the Newey-West *t*-value (NW) on the time-series average, and time-series percentile values. The three panels perform the regressions on the firm level (A), 4-digit GICS industry level (B), and 2-digit GICS sector level (C), respectively.

	Average	NW	Percentiles 5	25	50	75	95
A. Firm-level							
a	0.97	6.44	0.33	0.60	1.02	1.24	1.65
τ_a	18.81	5.71	5.09	9.57	20.78	25.24	32.32
b	6.77	10.83	3.90	5.57	6.58	8.52	9.15
τ_b	69.76	24.85	52.31	62.10	68.69	75.69	85.06
R^2	0.68	31.58	0.54	0.64	0.67	0.72	0.81
B. Industry-level							
a	0.79	4.69	0.07	0.34	0.84	1.13	1.48
τ_a	5.07	4.06	0.26	1.71	5.19	7.28	10.85
b	7.40	10.19	4.08	5.98	7.06	9.37	10.06
τ_b	18.21	26.58	13.86	16.17	17.80	19.92	22.52
R^2	0.92	140.72	0.88	0.91	0.92	0.94	0.95
C. Sector-level							
a	0.70	4.39	-0.02	0.29	0.72	1.04	1.47
τ_a	4.28	4.31	-0.14	1.40	4.44	6.93	8.36
b	7.51	10.37	4.01	6.13	7.25	9.39	10.12
τ_b	21.15	8.29	8.07	13.31	18.08	27.62	37.32
R^2	0.95	85.10	0.84	0.93	0.96	0.98	0.99

Table 4
Size effect on company financing cost
At each date, we perform a cross-sectional regression of a proportional financing cost measure (FC) on the risk-adjusted leverage level and the relative company size measure. Entries report the time-series average ("Average") of the regression coefficient estimates and the regression R^2 estimates (in percentages), the time-series average of the t-values of the coefficient estimates, and the Newey-West t-statistics on the time-series average of the coefficient estimates. The financing cost measure is constructed as the ratio of total interest expense to total debt in panel A, and as the ratio of interest expense to long-term debt in panel B, both in percentage points.

	α_t	β_t	γ_t	R^2
		A. FC = Interest Expense/(Total Debt)		
Average	7.78	12.67	-0.05	1.52
t-value	72.44	2.58	-2.91	—
NW	11.63	6.52	-2.24	3.66
		B. FC = Interest Expense/(Long-term Debt)		
Average	11.35	50.19	-0.10	1.20
t-value	34.32	3.00	-2.05	—
NW	11.83	7.10	-2.27	5.12

Table 5
Marginal contributions to the cross-sectional capital structure variation
At each date, we perform a standardized univariate cross-sectional regression of the leverage ratio against each of the explanatory variables, and we also perform a standardized bivariate cross-sectional regression with the mean-variance ratio forecast (MVF) as the common variable. Entries report the time-series averages of the slope coefficient estimates and the t-values, as well as the Newey-West t-statistics (NW) on the average slope. The last column reports the average adjusted R^2 from the bivariate regressions.

	A. Univariate regression			*B. Bivariate regression*						
				MVF			Other			
	slope	t-value	NW	slope	t-value	NW	slope	t-value	NW	R^2
MVF	0.82	69.76	64.03	0.82	69.76	64.03	0.82	69.76	64.03	0.68
Size	0.08	3.92	3.95	0.82	70.44	61.25	0.08	6.64	5.39	0.68
Tangibility	-0.02	-1.02	-0.51	0.82	66.40	63.67	-0.02	-1.74	-2.98	0.67
Profitability	-0.21	-10.19	-8.55	0.82	67.00	60.64	0.00	0.04	0.27	0.68
MB ratio	-0.14	-6.38	-7.96	0.87	71.85	90.60	0.15	11.92	14.28	0.70

Table 6

Explaining the cross-sectional capital structure variation in a multivariate setting

At each date, we perform a standardized cross-sectional regression of financial leverage against the mean-variance ratio forecast (MVF), relative company size, asset tangibility, profitability, and market-to-book (MB) ratio. Entries reports the time-series averages of the coefficient estimates and their t-values, the Newey-West t-values (NW) on the coefficient average, and percentile values of the coefficient estimates.

	Average	Average	NW	Percentiles				
	slope	t-value	slope	5	25	50	75	95
MVF	0.86	67.55	70.94	0.78	0.83	0.86	0.88	0.91
Size	0.06	5.35	5.28	-0.00	0.03	0.07	0.09	0.11
Tangibility	-0.02	-1.61	-3.42	-0.05	-0.03	-0.02	-0.01	0.02
Profitability	-0.06	-4.49	-11.03	-0.09	-0.07	-0.06	-0.05	-0.03
MB ratio	0.15	12.14	16.07	0.07	0.13	0.16	0.18	0.20

Table 7

Average error-correction forecasting correlation on future leverage changes

At each date, we perform a series of standardized cross-sectional forecasting regressions of future leverage ratio changes over horizons from one to five years against the current deviations of the leverage ratio from its predicted levels. We predict the leverage level first with the mean-variance ratio forecast (MVF) alone as a benchmark, and then with a list of other variables together with the MVF in a bivariate or multivariate regression. Entries on the left side report the time-series averages of the cross-sectional forecasting correlation estimates obtained from the error-correction forecasting regressions. Entries on the right side report the Newey-West (NW) t-statistics on the average forecasting correlation difference between the benchmark univariate specification with the mean-variance ratio alone and the other bivariate and multivariate specifications.

	A. Average forecasting correlations					*B. NW t-statistics on outperformance*				
h	1	2	3	4	5	1	2	3	4	5
Benchmark	Explain leverage variation with MVF									
MVF	0.152	0.239	0.291	0.319	0.345					
X_k	Explain leverage variation with MVF + X_k									
Size	0.154	0.243	0.296	0.325	0.352	1.71	2.39	2.62	2.88	3.15
Tangibility	0.158	0.244	0.296	0.323	0.347	2.09	1.57	1.34	1.00	0.29
Profitability	0.151	0.239	0.291	0.319	0.345	-0.67	-1.21	-2.15	-2.39	-2.19
MB ratio	0.141	0.228	0.280	0.309	0.336	-4.19	-4.70	-5.54	-5.47	-4.92
Industry	0.158	0.248	0.301	0.330	0.355	3.82	4.41	4.96	5.86	5.71

Table 8

Link company relative value to deviations from optimal leverage targets

At each date, we perform a series of standardized cross-sectional regressions of company relative value (Tobin's Q) against the negative of the absolute deviations of the leverage ratio from its predicted levels. We predict the leverage level first with the mean-variance ratio forecast (MVF) alone as a benchmark, and then with a list of other variables together with the MVF in a bivariate or multivariate regression. Entries report the time-series averages of the cross-sectional regression slope coefficient estimate and its t-values, and the Newey-West (NW) t-statistics on the time-series averages of the slope coefficients. The last column reports the Newey-West (NW) t-statistics on the average slope coefficient difference between each specification and the benchmark. A positive estimate represents an outperformance of the benchmark model in generating company value maximizing leverage target predictions.

	Average slope	Average t-value	NW slope	NW outperformance
Benchmark	Explain leverage variation with MVF			
MVF	0.232	11.44	26.05	
X_k	Explain leverage variation with MVF + X_k			
Size	0.231	11.39	28.65	-0.37
Tangibility	0.234	11.18	24.84	1.00
Profitability	0.232	11.44	24.11	-0.36
MB ratio	0.112	5.35	11.33	-15.32
Industry	0.211	10.38	23.12	-12.02

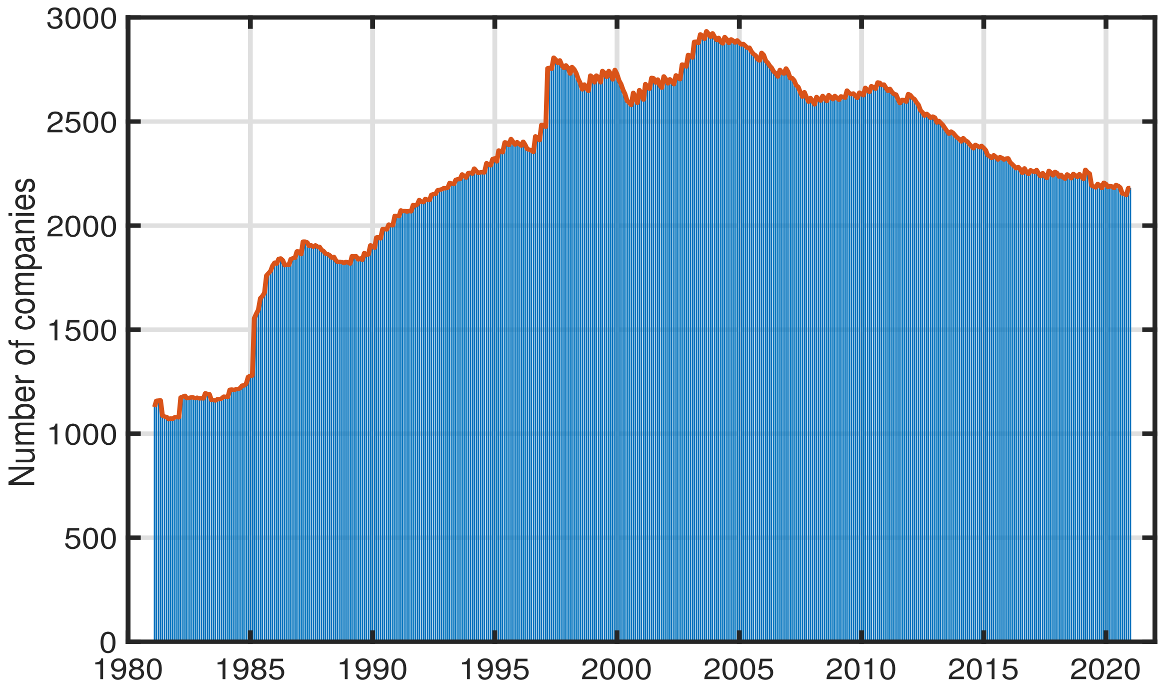

Fig. 1. Number of selected companies per month

The bar chart shows the number of selected companies per month from January 1981 to December 2020 for a total of 480 months.

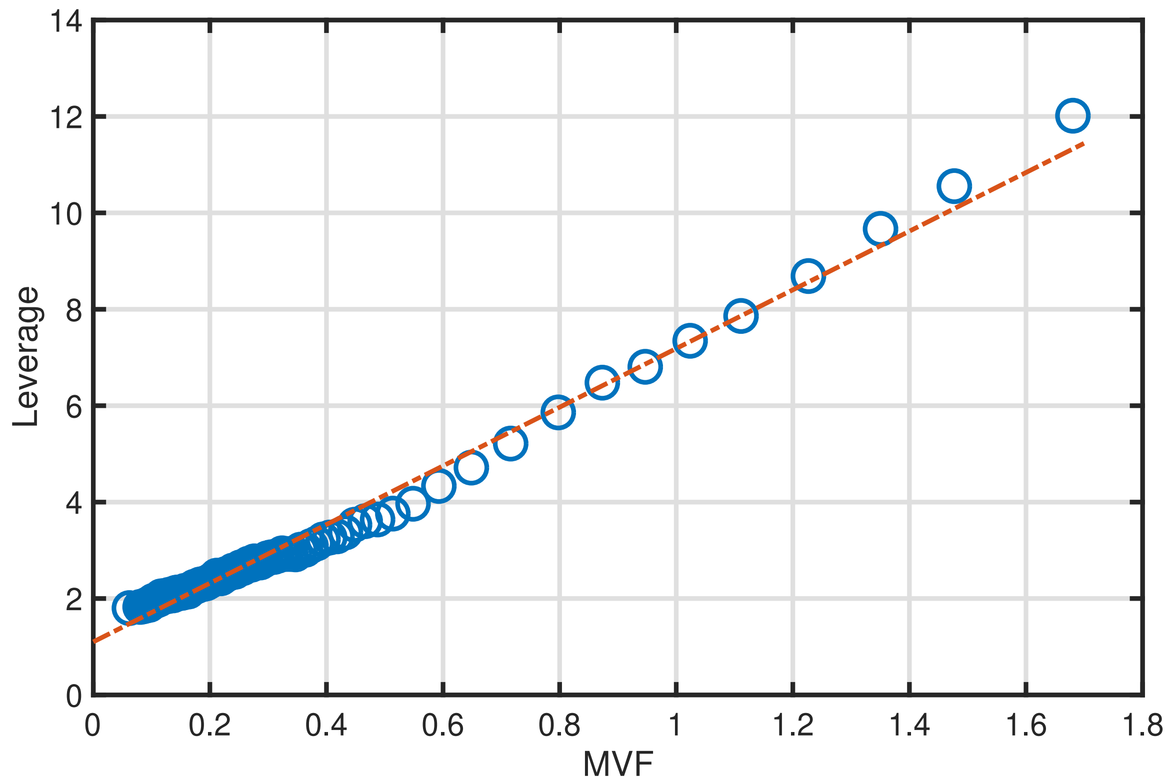

Fig. 2. Percentile grouped scatter plot of financial leverage versus mean-variance ratio forecasts
The scatter plot shows the relation between the average financial leverage level and the corresponding average mean-variance ratio forecasts at each percentile group. At each date, we sort the mean-variance ratio forecast into percentiles and compute the average leverage level and the average mean-variance ratio forecasts within each percentile group. The scatter plot represents the time-series averages of cross-group variation in financial leverage and mean-variance ratio forecasts. The dash-dotted line represents a linear fit of the scatter points.

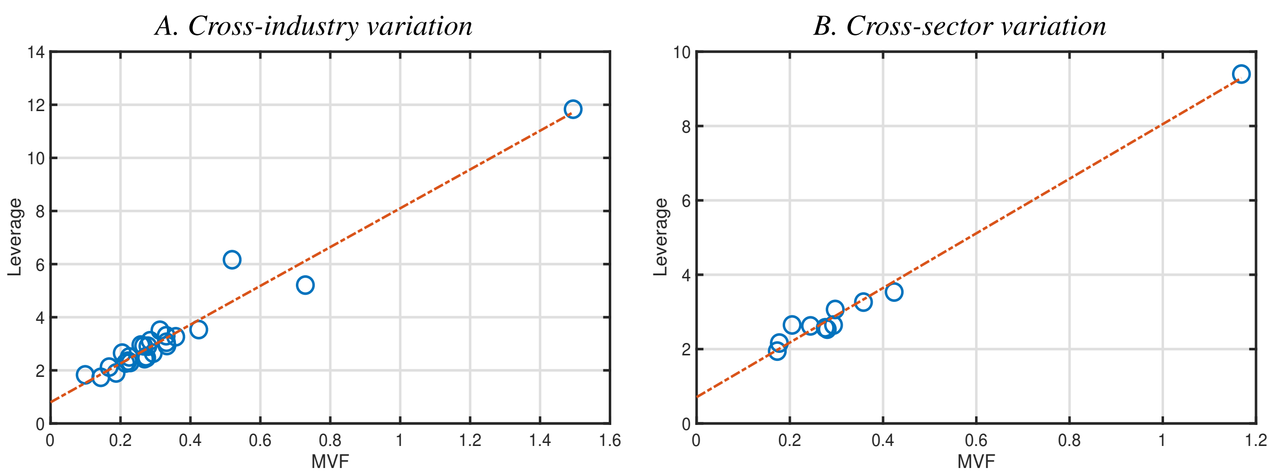

Fig. 3. Average cross-industry and cross-sector variation in financial leverage and mean-variance ratio forecasts
At each date, we compute the average financial leverage level and mean-variance ratio forecasts within each industry (panel A) and each sector (panel B). The scatter plots represent the time-series averages of cross-industry and cross-sector variations. The dash-dotted line in each panel represents a linear regression fit of the scatter plot.

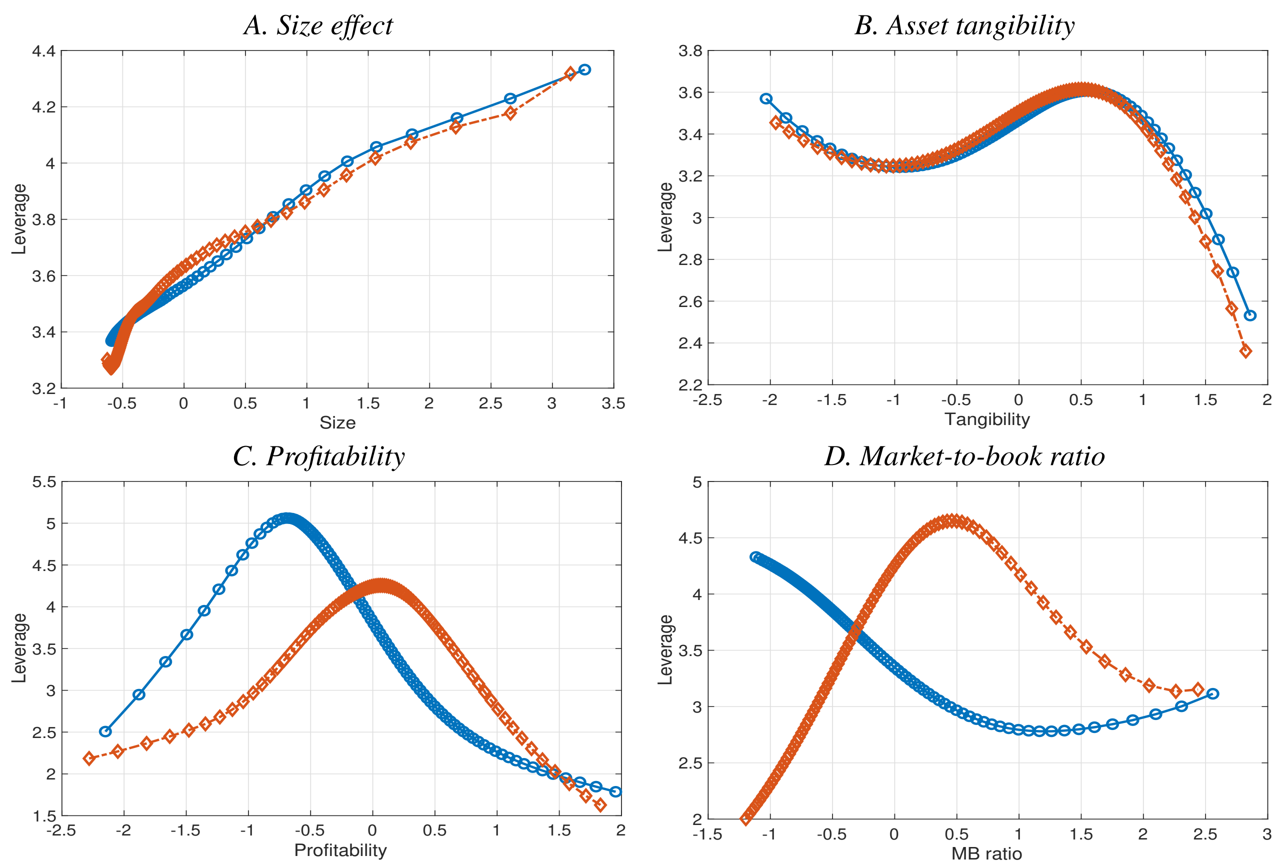

Fig. 4. Average cross-sectional leverage variation dependence on commonly identified determinants
At each date, we perform the cross-sectional local linear regression of the leverage ratio against each of the four explanatory variables: (A) relative company size, (B) asset tangibility, (C) profitability, and (D) market-to-book ratio. The circle-solid lines denote the time-series averages of the estimated relation. Furthermore, to control for the mean-variance ratio effect, we also regress each variable against the mean-variance ratio forecast, and estimate the local linear relation between the leverage ratio and the regression residual. The diamond-dashed lines capture the time-series averages of this estimated relation. Each panel is for the relations with one explanatory variable. We cross-sectionally standardize each variable and its regression residual. The circles and diamonds in each panel represent the estimated leverage levels at the percentile values of the standardized variable and the standardized residual, respectively.

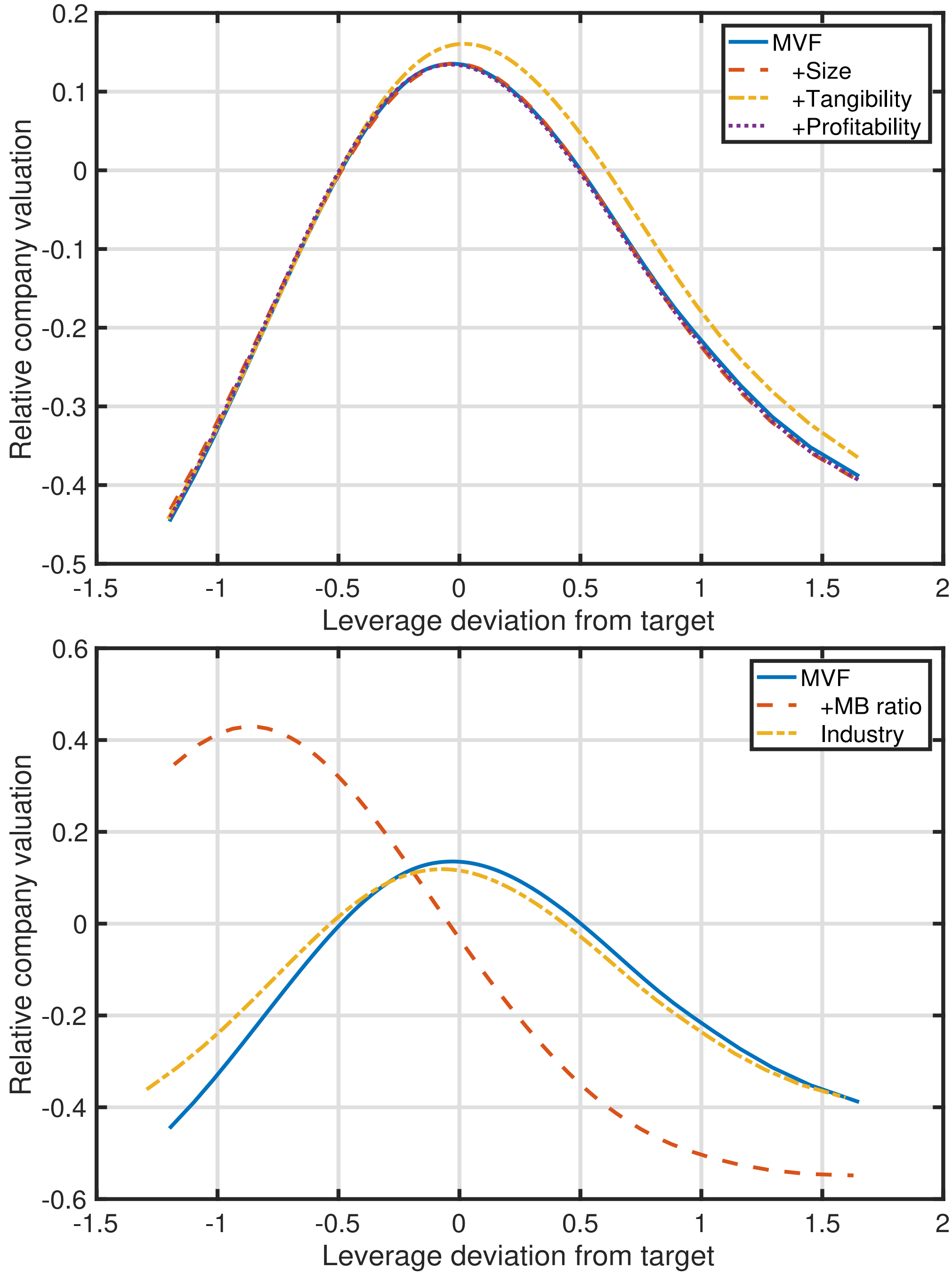

Fig. 5. Deviations from optimal financial leverage target and relative company valuation

Lines denote the time-series averages of the local linear relation between the Tobin's Q ratio and the deviations of financial leverage ratio from each specification. In group the specifications in two panels. In each panel, the solid line denotes the benchmark specification that predicts the leverage variation with the mean-variance ratio (MVF) alone, and other lines denote specifications that include other variables.