The Sensitivity of Investment to Cash Flow:

An Explanation Based on the Growth-type-aligned Financing Hierarchy

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Abstract

We show that the investment-cash-flow-sensitivity (ICFS) decreases significantly with a firm's asymmetric informational imperfection about growth (AI). In effect, firms' relatively high and low annual values of AI are highly persistent over time. Firms with distinctly initial AI values have distinct future investment styles and financing patterns. Higher initial AI predicts an investment style with more R&D intensity and a financing pattern with more equity than debt issues. Interestingly, the cross-section of AI captures types of asymmetric information (about growth vs. assets in place) which affect external finance differently so that growth uncertainty appears to facilitate rather than suppress equity financing. These findings are consistent with a growth-type explanation for ICFS and do not support the proposition that informational imperfection, especially about growth, must impose financial constraints.

Keywords: Investment, Growth type, Informational imperfection, Agency Conflict, Financing Hierarchy

JEL classification: G30, G31, G32, D92

1. Introduction

In their influential paper, Fazzari, Hubbard and Petersen (1988) proposed investment-cash-flow-sensitivity (ICFS) as a measure for the degree of financial constraint in a firm. Underlying their work is the belief that market imperfection generally imposes financial constraints on corporate investment and impedes firm growth. Fazzari, Hubbard and Petersen (1988) hypothesized that ICFS increases with the wedge between the costs of internal and external finance. As a result, they suggest that ICFS captures the degree of financial constraint, consistent especially with Myers' (1984) pecking order in financing based on Myers and Majluf (1984). Their paper was well received, but later Kaplan and Zingales (1997) questioned the validity of ICFS as a measure for financial constraint.

The literature then focused on formulating alternative measures for financial constraints. However, these proposed measures may also be questionable when applied to an extended sample of firms. Farre-Mensa and Ljungqvist (2015) recently show that popular measures of financial constraints—such as the KZ, WW and SA indexes proposed by Lamont, Polk and Saa-Reguejo (2001), Whited and Wu (2006), and Hadlock and Pierce (2010), respectively—may all measure something other than financial constraints.[1]

The controversy in the literature is not simply about the question of how to reliably measure financial constraints. A deeper issue already emerged in the famous Kaplan-Zingales vs Fazzari-Hubbard-Petersen debates. Kaplan and Zngales (1997) argued that firm specific variations in investment opportunities intricately affect corporate financing, undermining the financial-constraint interpretation of ICFS. Fazzari, Hubbard and Petersen (2000) provided a follow-up rebuttal to Kaplan and Zingales' (1997) validity critique of ICFS. In response to the

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[1] Financial constraint is closely related to impaired access to capital, a concept which has gained popularity in the literature recently. This view holds that shocks to financing affects investment. However, Kahle and Stulz (2013) find that the economic significance of such a causal link (deemed to be pronounced in the 2008 financial crisis) is tenuous. They argue that an economy-wide demand shock is likely to affect both investment and financing, without a causal link between the two. Consistent with the neoclassical intuition, a demand shock simply forces an equilibrium adjustment for both investment and financing.

rebuttal, Kaplan and Zingles (2000) pointed out that: "Fazzari, Hubbard and Petersen's (2000) defense of investment-cash flow sensitivities as measures of financial constraints, distracts attention from the more important question: what causes this sensitivity?" However, few studies since have directly answered this question.

Our paper attempts to provide an answer. The analysis in this paper will not only provide a new explanation for ICFS but also potentially free corporate finance research in general from depending on the largely normative concept of financial constraint (or impaired access to capital), for which many researchers have blamed informational imperfection (see Kahle and Stulz, 2013, for questioning popular theories of impaired access to capital). A more fruitful approach to corporate finance research is perhaps to start with recognizing corporate investment and financing as a kind of matching equilibrium, where the market is smart enough to mitigate market imperfection substantially through appropriate financing arrangements to facilitate valuable investments.

Using CRSP and Compustat data for 1971-2012 on U.S. nonfinancial firms, we start by computing the volatility of a firm's monthly market-to-book (M/B) ratios or growth uncertainty. This variable, new to the literature, measures the firms' asymmetric informational imperfection about growth (AI). AI varies in a spectrum between two distinct types of asymmetric information theoretically, one purely about investment opportunities (growth) and the other about assets in place: the higher is AI, the more likely asymmetric information arises from investment opportunities (growth) rather than assets-in-place. As we find that high and low annual AI values are highly persistent, we can study the relation between ICFS and AI to understand how corporate financing interacts with informational imperfection, which many believe gives rise to financial constraints generally. Surprisingly, we find that even after controlling for the KZ, WW and SA indexes, ICFS significantly decreases with AI.[2] This means that investments at firms with more asymmetric information about growth are less tied with internal cash flows.

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[2] Chen, Goldstein and Jiang (2007) find that the investment sensitivity to stock price *increases* with their private information variables, price non-synchronicity and PIN, as well as KZ. While it is not the focus of this paper, we will later show that the investment sensitivity to stock price *decreases* with AI. We will argue later that this contrast

One may argue that AI contains information on market-to-book ratio and may be confounded by concurrent market sentiments or mispricing. To mitigate endogeneity problems, we use Initial AI as our main explanatory variable. Initial AI is defined as the within-firm time-series average of annual AI over year 0, 1 and 2 (where year 0 is a firm's earliest data reporting year in the whole sample).

More precisely, we use Initial AI as our main independent variable to explain ICFS in standard investment regressions with annual panel data (see Zingales, 1998, for example, on using long-lagged variable as an identification strategy). We also use within-firm time-series KZ, WW and SA index medians, commonly used in the literature, as control variables for financial constraints that they may measure. The regression results show that ICFS decreases significantly with Initial AI. Replacing AI with investment style, measured by Investyle defined as R&D/[R&D+Capex], as a robustness check, ICFS also decreases with initial Investyle.

More revealing, we also find that annual External Financing Differential, EFD (i.e., equity minus debt issues), is positively related to lagged annual AI as well as Investyle. EFD positively responds to lagged market-to-book ratio (a proxy for investment opportunities and/or market conditions) in the same regressions. For an interaction effect, the sensitivity of EFD to lagged market-to-book ratio significantly increases with AI and Investyle. This pecking order in financing aligned with AI describes a much richer financing hierarchy than what is described by Myers' (1984) pecking order (see also Leary and Roberts, 2010, with a call for a richer financing hierarchy). This potentially provides a new interpretation for ICFS, different from the financial-constraint explanation based on the logic of the classic pecking order in financing.

We show that high and low AI values are persistent over time. Given this persistence, we argue that distinct AI values reflect persistently distinct specifications of market imperfection in terms of types of asymmetric information (about growth vs. assets-in-place). A higher AI tells that there is more asymmetric information on growth opportunities rather than assets-in-place, implying less managerial agency problems related to information asymmetries. This is because AI also tells the severity of incentive conflicts.

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suggests that AI is mainly related to managerial insider information rather than private information contained in stock prices that is new to managers, although both can matter to corporate investment.

In the literature, as a kind of agency conflict, tensions between existing shareholders (with whom the managers are assumed to be fully incentive-aligned) and new investors under asymmetric information typically produce the adverse selection effect of new equity issues if asymmetric information on assets-in-place dominates (Myers and Majluf, 1984), but not if asymmetric information on growth dominates (Myers, 2003; Wu and Wang, 2005). Controlling for private benefits, Wu and Wang (2005) show theoretically that an increase in asymmetric information on growth—more pronounced than an increase in expected growth—can improve the announcement effect of new equity issues. They argue that growth uncertainty seems to facilitate new equity issues because tensions between old and new shareholders under asymmetric information in this situation fail to produce the adverse selection effect that would be pronounced when asymmetric information on assets-in-place dominates.

There is another kind of agency conflict based on managerial private benefits, which give rise to the managerial empire-building motive and free cash flow problem in Jensen (1986) and Stulz (1990). It is worth mentioning that AI has no direct implication on this managerial agency conflict but the first moment variable M/B ratio as a proxy for Tobin's q (or Q) does. Commonly accepted in the literature, a higher Q implies that this managerial agency conflict is less likely to occur (McConnell and Servaes, 1995). But Q says nothing directly about the tensions between old and new shareholders under information asymmetries (Myers and Majluf, 1984). However, it is empirically true that AI and M/B ratio are positively correlated across firms. Thus AI also conveys information on this managerial agency conflict and helps specify at the same time the severity of two kinds of popular agency conflicts in the literature.

More precisely, low AI indicates strong agency conflicts in terms of both kinds: tensions between old and new shareholders which produce the adverse selection effect and, via the positive correlation with M/B ratio, also managerial rent extraction. In contrast, high AI implies that these two kinds of agency conflict are weak. Myers (2003) argues that the agency conflict due to Jensen and Meckling's (1976) managerial private benefits or rent extraction can also spawn a pecking order in financing (see Leary and Roberts, 2010). This is, however, more likely to occur when asymmetric information on assets in place dominates.

Consistent with our argument above, we can simply interpret a firm's AI as reflecting a firm's growth type, as conceptually described in Wu and Au Yeung (2012). They show that low growth type firms have firm valuation based mainly on assets-in-place. These firms rely on internal funds and debt to finance mainly tangible investments; they grow slowly and steadily. In contrast, high growth type firms have firm valuation based largely on investment opportunities; many are expected to be merged into other high growth type firms on their high growth path. These firms typically rely much more on new equity (rather than internal funds or debt) to finance relentless investment and sustain high growth. Intangible investments, especially through R&D, are pronounced in their total investment. Wu and Au Yeung (2012) show that firms remain high growth type firms for a surprisingly long time such that high and low growth paths typically do not converge over time.

In this paper, we suggest that a higher AI identifies a higher growth type firm. The AI measure is a continuous variable and enables a finer classification on firm growth type than just the three discrete growth types in Wu and Au Yeung (2012).[3] Thus an AI-aligned pecking order in financing as documented in this paper can be viewed as a growth-type-aligned financing hierarchy.

The growth type explanation in this paper suggests that firms with high ICFS tend to be of low growth type whereas firms with low ICFS tend to be of high growth type, following a unified AI-aligned pecking order in financing. This contradicts the financial-constraint interpretation of ICFS. In particular, high growth type firms in the sample typically stay on a high growth path with access to new equity financing despite high growth uncertainty.[4] Thus ICFS simply picks up on a firm's financing pattern that has little implication on financial constraints.

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[3] While M/B ratio is the first moment variable, AI is a second moment variable. In contrast to Bloom (2009) who studies the impact of the time-varying second moment (macroeconomic uncertainty) on important macroeconomic variables, we examine persistent, cross sectional impacts of firm-specific asymmetric informational imperfection (AI) on corporate investment and financing.

[4] The phenomenon that growth uncertainty fails to suppress new equity issues and hinder high growth occurs in normal times which predominate in the sample. During a financial crisis, however, uncertainty drastically increases and adversely affects investment and financing for most firms (Kahle and Stulz, 2013). Although rare, such a panic is associated with a sharp decrease in growth prospects.

The remainder of the paper proceeds as follows. Section 2 reviews the literature in detail. Section 3 describes data and regression explanatory variables. Section 4 shows the main results on ICFS. Section 5 provides further evidence to support a growth-type explanation for ICFS. Section 6 concludes.

2. Previous Research on Related Issues

2.1. Financial Constraints and Investment

It is a long-held belief that market imperfection imposes financial constraints on corporate investment (see the review in Hubbard, 1998). However, empirical results from corporate finance research on listed firms contradict this belief. Rajan and Zingales (1995) and Fama and French (2002, 2005) document the findings that informational imperfection generally does not hinder a listed firm's financing. Unlike private firms, for example, studied in Gao, Harford and Li (2013), listed firms in well-functioning capital markets have access to external finance, especially new equity, albeit not in a homogenous manner. The debates between Fazzari-Hubbard-Petersen and Kaplan-Zingales, which centered on whether the investment-cash-flow-sensitivity (ICFS) measures financial constraints, highlight the need for rethinking theoretical foundations of corporate finance (Zingales, 2000).

Based on the premise that external finance has a cost disadvantage over internal finance in imperfect capital markets, Fazzari, Hubbard and Petersen (1988) introduced ICFS as a measure for the degree of financial constraints. They argued that ICFS increases with the cost wedge between external and internal funds (the wedge or "lemons premium" that is deemed to increase with the degree of informational imperfection). After almost a decade, during which many studies adopted this ICFS measure, Kaplan and Zingales (1997) contended that ICFS does not measure financial constraints. They reasoned that firm specific variations in investment opportunities intricately affect corporate financing, creating a non-monotonic relation between ICFS and the size of the cost wedge (see the discussion following equation (6) in Kaplan and Zingales, 1997).

It follows from their argument that monotonicity is an important issue in empirical research on ICFS. Most researchers rely on some kind of sorting to classify firms as financially constrained or unconstrained—usually, a cut on some proxy or across a set of proxies for the believed cost wedge—and then show differential ICFS estimates between the sorted firm groups.

For example, Fazzari, Hubbard and Petersen (1988) classified financially constrained firms as those that persistently pay small or no dividends and unconstrained firms as those that pay large dividends. This Fazzari-Hubbard-Petersen (FHP) sorting shows that constrained firms have a high ICFS, whereas unconstrained firms display a low ICFS. Questioning this interpretation, Kaplan and Zingales (1997, 2000) pointed out that such a FHP sorting approach only works if the relationship between the ICFS and the degree of financial constraints is generally monotonic.

They argued that if the relationship is non-monotonic, ICFS may not necessarily measure financial constraints correctly, because other factors related to investment opportunities (but possibly unrelated to financial constraints) are likely to have an influence. Conversely, a sorting based on some exogenously determined degree of financial constraints may not necessarily produce the ICFS estimates as expected by Fazzari, Hubbard and Petersen (1988). In other words, ICFS may reflect a more comprehensive effect than that of financial constraints alone. To back up their argument, Kaplan and Zingales (1997) showed that some obviously unconstrained firms such as those with high interest coverage ratios display a high ICFS estimate, contradicting the claim that ICFS reliably measures the degree of financial constraints. Cleary (1999) subsequently used a large sample and a detailed classification system for firm financial status, and his findings support the argument of Kaplan and Zingales (1997).

Fazzari, Hubbard and Petersen (2000) disagreed and argued that the empirical classification system used by Kaplan and Zingales (1997) is likely to be flawed and fails to identify financial constraints appropriately. In response to this rebuttal, Kaplan and Zingales (2000) contended that their sorting system serves the identification purpose well and reveals the existence of general non-monotonicity that renders using ICFS as a reliable indicator of financial constraints questionable.

This famous debate has generated further intensive research on ICFS and financial constraints. Almeida and Campello (2007) acknowledge the non-linear relationship between ICFS and the degree of financial constraints posited by Kaplan and Zingales (1997), and find that ICFS increases with the tangibility of a firm’s assets (as pledgeability) only among their identified financially constrained firms. This is consistent with the claim that debt capacity is linked to tangibility (Myers, 1977; Gan, 2007). While this role of tangibility cannot address why many firms with primarily human capital or intangible assets (including growth opportunities) can invest and grow rapidly despite high uncertainty, it does provide a sense of firm segmentation in terms of financing choice.

Other studies have cast further doubt on whether ICFS measures the degree of financial constraints. Alti (2003) argues that cash flow contains valuable information about a firm's investment opportunities, and that the cross-sectional pattern of ICFS is consistent with the predictions of a model with no financing friction. Gomes (2001) concludes that a significant ICFS is likely due to a combination of measurement error in Q and identification problems. Using GMM estimation with a structural model in an attempt to minimize measurement error in Q, Erickson and Whited (2000) find that ICFS is not significant. They point out that the average Q—which is commonly used to replace the hard-to-measure marginal Q—is so noisy that it cannot appropriately capture investment opportunities. This suggests that a significant ICFS estimate obtained from standard (reduced-from) investment regressions may simply compensate for the measurement error in Q. In this sense, ICFS is expected to pick up some information on firm growth instead of financial constraints. Chen and Chen (2012) further show that ICFS decreases over time and conclude that ICFS cannot be a good measure of financial constraints.

These findings raise the question of what can reliably measure the degree of financial constraints, if ICFS cannot do so. Building on the work of Kaplan and Zingales (1997), Lamont, Polk and Saa-Requejo (2001) suggested the KZ index to measure the degree of financial constraints, but in an asset pricing context. Based on a small sample of selected firms that plausibly have various degrees of financial constraints in Kaplan and Zingales (1997), the KZ index is extrapolated for an extended sample of firms. The index incorporates several firm characteristics and can be time varying. The higher the KZ index, the greater is the degree of financial constraints.

Almeida, Campello and Weisbach (2004) examined corporate demand for funding liquidity to create an alternative measure for financial constraints. They argue that precautionary saving reflects a high cost of external finance, and suggest that a firm's propensity to save cash out of cash flow (the cash flow sensitivity of cash) can effectively capture the effect of financial constraints. However, an important study by McLean (2011) reveals that high cash holdings can come from issuing shares. In fact, many firms issue new equity too frequently to be reconciled with the classic pecking order in financing (Fama and French, 2005). Wu and Au Yeung (2012,

2015) find that persistently high levels of cash holdings, especially in high growth type firms, typically come from new equity issues. On the other hand, high cash holdings do not necessarily indicate free cash flow because they do not seem to hinder corporate investment and performance (Mikkelson and Partch, 2003). Thus the cash flow sensitivity of cash seems to work best for certain firms, perhaps similar to how the adverse selection argument of Myers and Majluf (1984) applies to firms mainly with asymmetric information on assets-in-place.

In studying financial constraint risk in the context of asset pricing, Whited and Wu (2006) construct a new financial constraint index, the WW index, based on their structural investment model. The WW index is supposed to proxy for the shadow price of external finance under an assumption of exogenous constraints on debt and new equity financing. Like most structural investment models in the literature, their model assumes new equity financing as a last resort as in Myers (1984) and basically focuses on the costs and benefits of debt. The WW index includes new firm characteristics such as a firm's sales growth relative to its industry. The higher the WW index, the greater is the degree of financial constraints.

The KZ and WW indexes represent two popular and comprehensive approaches to measuring financial constraints for an extended sample of firms. The KZ index approach relies on an extrapolation from a small sample of selected firms that are deemed in the first place to be financially constrained (or not). The WW index approach resorts to a structural model estimation with some exogenous assumptions on high costs of equity financing. Interestingly, the correlation of the KZ and WW indexes is only 0.13 in our sample, despite much overlap in their components.

Despite extensive research on financial constraints, the estimation of financial constraints remains somewhat difficult (Moyen, 2004)—perhaps because of the endogenous nature of most corporate finance variables. As a result, researchers have often reinterpreted the various financial constraint measures that have been proposed.

Baker, Stein and Wurgler (2003) interpret the KZ index instead as an index of equity dependence. The KZ-index-based equity dependent firms typically have a high leverage and low cash holdings, and they regard these firms as being prone to non-fundamental movements in stock prices in the firms' favor to relax the equity-financing constraint. By gauging the cost of external finance using a structural estimation, Hennessy and Whited (2007) suggest that the KZ and WW indexes are better understood as proxies for "external financing need" than for the cost of external finance. In contrast, Hennessy, Levy and Whited (2007) retain the original meaning and treat the WW index as a proxy for financial constraints.

Farre-Mensa and Ljungqvist (2015) point out that popular measures of financial constraints such as the KZ index and WW index may all measure something other than financial constraints. The difficulty that academics have encountered in identifying expected financial constraints directs our attention back to the neoclassical claim that the importance of investment opportunities overrides any impeding effect of market imperfection. This claim can make sense if financing choice turns out to be able to help circumvent adverse effects of market imperfection on investment.

New equity is important in financing investments. The notion of new equity as a last resort is not generally true—a shocking reality highlighted in Fama and French (2002, 2005); see the next section for details. Many firms are able to finance through new equity issues more easily than traditionally believed. Unlike budget constraints which can be endogenously optimal, financial constraints, almost by definition, must hinder valuable investment. Of course, firms can be financially constrained for various reasons. But there may not be an overarching relation between financial constraints and informational imperfection for listed firms in general, even though this relation is commonly reflected in the literature. As a result, it is ambiguous whether financial constraints tie down listed firms simply due to asymmetric informational imperfection. Unless we understand how optimal financing arrangements respond to informational imperfection, we cannot be sure whether or not the neoclassical intuition is valid.

2.2. Types of Asymmetric Information and the Severity of Incentive Conflicts

It is well known in the literature that asymmetric information causes underinvestment due to the adverse selection effect in new equity issues (Myers and Majluf, 1984). This gives rise to Myers' (1984) pecking order in financing (in which firms tend to use internal fund first, then debt, and as a last resort, the most averse selection sensitive new equity) and predicts that new equity can be so costly that firms have to skip profitable projects and underinvest. As a result, valuable internal fund and costly new equity go hand in hand in the classic pecking order in financing. In this traditional view, information asymmetry is an important form of market imperfection that impedes investment and affects firm valuation.

But Fama and French (2002) highlight the fact that small high-growth firms, fraught with asymmetric information, do not seem to suffer from the adverse selection effect in their new equity issues. Fama and French (2005) point out that many listed firms issue new equity more frequently than previously believed in the literature. They conclude that firms in general do not obey the classic pecking order in financing (see also Frank and Goyal, 2003). Asymmetric information seems to fail to spawn an overarching pecking order in financing.

The literature seems to turn attention away from asymmetric information to incentive conflicts. Consistent with Zingales' (2000) call for new foundations for corporate finance, Myers (2003) emphasizes the need for a deeper understanding of incentives of managers. Incentive conflicts and information asymmetries are two typical forms of market imperfection and often interact in specific ways although individual theories and hypotheses have their own emphasis on either incentive conflicts or information asymmetries. For example, Jensen's (1986) free cash flow problem is mainly based on the assumption of selfish mangers seeking private benefits at the expenses of shareholders. This affects financing choice under uncertainty (Stulz, 1990).

In effect, the classic information-asymmetry-driven pecking order in financing also has an incentive conflict imbedded. The information asymmetry in Myers and Majluf (1984) gives rise to a different kind of incentive conflict: tensions between existing shareholders and new investors especially at new equity issues. Myers and Majluf (1984) assume a full incentive-alignment between managers and existing shareholders, a condition that rules out Jensen' (1986) free cash flow problem. As a result, the two distinct kinds of incentive conflict in Myers and Majluf (1984) and Jensen (1986) produce opposite predictions on internal funds to affect financing and investment (see the discussion in Wu and Wang, 2005).

The classic pecking order is driven by tensions between old and new stockholders under asymmetric information. But Myers (2003) suggests that concerns on the entrepreneur managers' private benefits in Jensen and Meckling's (1976) can also spawn a similar pecking order in financing. The managerial rent extraction underlies a tradeoff: more outside equity lowers the costs of private benefits (as outside stockholders share the costs but not the private benefits) whereas more debt is more likely to internalize the costs of private benefits but increases default risk. In this managerial-rent-extraction-driven pecking order, as described in Myers (2003), "the firm prefers internal to external finance, and prefers debt to outside equity until debt becomes so risky and costly that managers turn to outside equity as a last resort." Since a pecking order under incentive conflicts can be richer than the classic adverse-selection-driven pecking order, Leary and Roberts (2010) conclude that financing behavior in reality reflects more incentive conflicts than information asymmetry.

The literature, however, remains largely unclear about how growth uncertainty or asymmetric information about growth affects financing and why. Research on debt suggests that firms with growth opportunities have a hard time using debt, for example, along the line of debt overhang argument of Myers (1977) or simply due to lack of collateral. But the lack of debt capacity does not really explain why such growth firms with a lot of uncertainty are able to issue new equity not as a last resort, as pointed out by Fama and French (2002, 2005). Metaphonically speaking, one cannot use the argument that fish cannot survive on land to explain why fish live in water. The fact that firms starting apparently without much debt capacity continue to issue new equity to finance high growth over time, as shown in Wu and Au Yeung (2012), does not necessarily mean that these firms preserve, or even need, debt capacity in the future. Low leveraged firms persist as long as 20 years (Lemmon, Roberts and Zender, 2008). One may argue that strong growth or high valuation can facilitate overvaluation. But Hertzel, Huson and Parrino (2012) show that sequential equity financing can provide screening and mitigate overinvestment especially for firms with high R&D intensity.

There is a need for a deep understanding of what incentive conflicts are really like under high growth uncertainty. Knowing what type of asymmetric information here actually matters. Unlike Cooney and Kalay (1993) without imposing an incentive structure, the generalized Myers and Majluf model of Wu and Wang (2005) incorporates both private benefits and the Myers and Majluf kind of asymmetric information on assets-in-place and growth opportunities. Controlling for private benefits, Wu and Wang (2005) show theoretically that an increase in asymmetric information on growth, more pronounced than an increase in expected growth, can improve the announcement effect of new equity financing. Growth uncertainty seems to facilitate new equity issues because tensions between old and new shareholders under asymmetric information fail to produce the adverse selection effect that would be pronounced when asymmetric information on assets-in-place dominates. This means that equity as a last resort occurs only under asymmetric information largely about assets-in-place (see also Harris and Raviv, 1991; Myers, 2003). Truth is that asymmetric information on growth does not typically produce the adverse selection effect to impede risk sharing. This gives rise to an overarching pecking order aligned with asymmetric information types which specify the severity of at least two kinds of incentive conflict at the same time, because of a positive correlation of growth uncertainty and expected growth empirically (Wu and Au Yeung, 2015).

More precisely, if firms have dominant asymmetric information on assets-in-place, a situation that may facilitate Jensen's (1986) empire-building as well (Jung, Kim and Stulz, 1996), firms prefer debt to minimize adverse selection (Myers, 1984) and private benefits (Jensen, 1986; Stulz, 1990). This is because under asymmetric information largely about assets-in-place, the two distinct kinds of agency conflict can be severe. If firms have dominant asymmetric information on growth a situation where tensions between old and new shareholders do not necessarily give rise to the adverse selection effect (Cooney and Kalay, 1993; Wu and Wang, 2005) and, at the same time, the debt capacity is limited due to lack of collateral and debt overhang (Myers, 1977), firms can use outside equity despite high uncertainty on growth. Under asymmetric information largely about growth, the two kinds of incentive conflict do not seem to be a threat at all.

Notice that there is no theory saying that high growth uncertainty directly indicates the lack of managerial agency problem. For one thing, the empire-building motive is an issue under uncertainty (Stulz, 1990). Thus the lack of agency conflict due to the empire-building motive in Jensen (1986) and Stulz (1990) should not be a direct reason for why growth uncertainty can facilitate new equity issues for risk sharing. The lack of this kind of agency conflict, however, occurs at the same time, largely due to a positive cross-sectional correlation between the first and second moments of growth.

Nobody questions that strong growth (via Q) generates a high need for external finance. But the rapid growth is typically accompanied by high growth uncertainty. Why is there no overarching pattern for market imperfection to hinder investment and especially inhibit new equity financing? The generalized Myers-Majluf model is able to help us understand why new equity provides financing flexibility in favor of certain firms despite their limited debt capacity.[5]

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[5] Financial flexibility is related to cash holdings which can be considered as financial slack, consistent with the classic pecking order logic. However, such financial flexibility may cause the concern about Jensen's (1986) free

2.3. Firm Growth Type versus Growth Opportunities

In his presidential address on "The Corporation in Finance", Rajan (2012) noted that the nature of corporations and finance are intimately linked. This means that the market can sort out different firm types and provide appropriate financing arrangements to facilitate investments. Wu and Au Yeung (2012, 2015) find that distinct firm growth types predict persistently different financing arrangements over time. In other words, firms invest and seek financing in a persistent manner compatible with their growth type. This pattern reflects a cross-sectional equilibrium with persistently distinct specifications of market imperfection. Growth type contains rich information on how market imperfection interacts with investment and financing, beyond what growth opportunities alone indicate.

The literature has shown that expected growth does affect financing patterns. However, the effect shown is reflected mainly in implications of debt financing. Measuring firm growth by Q, McConnell and Servaes (1995) find that debt is positively related to firm valuation for low growth firms (consistent with the debt disciplining role in agency problems of Jensen, 1986, and Stulz, 1990), and negatively related to firm valuation for high growth firms (consistent with the debt overhang argument of Myers, 1977).[6]

Growth opportunities, for example, measured by market-to-book ratio (as a proxy for Q), vary through time. Wu and Au Yeung (2012, 2015) find that firm growth type, initially identified,

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cash flow agency problem (see the two-edged-sword analysis on financial slack in Wu and Wang, 2005). Nevertheless, managers surveyed by Graham and Harvey (2001) tell that financial flexibility is important in capital structure policy to the benefit of firms. Recent literature has also shown many ways in which financial flexibility is desirable through internal retention and/or external finance (e.g., DeAngelo and DeAngelo, 2007; Gamba and Triantis, 2008; Denis, 2011; Denis and McKeon, 2012; Chen, Harford and Lin, 2014). While there is evidence that the classic precautionary saving motive forces managers to make a tradeoff between debt and cash, many firms with large cash holdings actually stockpile their cash through new equity financing (McLean, 2011). Most previous studies, however, did not explain why new equity investors under asymmetric information are willing in the first place to rationally provide financial flexibility to these firms.

[6] In this argument, debt overhang causes underinvestment for firms with growth potentials and hence incur firm value losses. Myers (1977) predicts an empirically negative relation between leverage ratio and market-to-book ratio. But in Myers (1977), one cannot infer whether firms with high growth opportunities face high or low costs of new equity.

predicts persistent financing behavior which responds to time-varying growth opportunities. More precisely, there is a growth-type-aligned pattern in external finance. Low growth type firms are typically profitable and have persistently low growth and low growth uncertainty, where low Q suggests a high likelihood of Jensen's (1986) free cash flow problem and, at the same time, asymmetric information on firm valuation is largely about assets-in-place rather than growth opportunities. Only these low growth type firms can be considered as obeying the classic pecking order in financing of Myers (1984), as emphasized in Myers (2003). In contrast, high growth type firms typically are able to maintain high growth with relentless R&D investment, despite limited debt capacity and high growth uncertainty. Interestingly, consistent with the generalized Myers and Majluf model, high growth uncertainty, which gives rise to asymmetric information about growth, appears to facilitate rather than suppress new equity financing.

In sum, the market has the ability to sort out firm types for optimal financing arrangements to facilitate investment. The resulting growth-type-aligned financing hierarchy simply reflects a matching equilibrium between investment and financing according to asymmetric information types that underlie firm growth types.

3. Data and Explanatory Regression Variables

In this section, we first describe the data (Section 3.1), define our main variables AI and Initial AI (Section 3.2), exhibit popular financial constraint indexes (Section 3.3), and then report correlation matrix for explanatory regression variables in investment regressions (Section 3.4).

3.1. The Data

We use a sample of U.S. firms from the Compustat and CRSP databases for 1971-2012. Similar to Fama and French (2001) and Baker, Stein and Wurgler (2003), we pre-process the data as follows. (1) We exclude financials (SIC 6000 – 6999). (2) For each firm, we define event year 0 as the first year in which Compustat reports its market equity value: fiscal year end closing price (PRCC_F) times common shares used to calculate earnings per share (CSHPRI). (3) We intersect the Compustat firms in year *t* with CRSP (NYSE, AMEX and NASDAQ) firms that have share codes of 10 and 11 and have market equity data for December of year *t* to be in the CRSP sample of that year. (4) We exclude firms that have annual market equity data for less than three consecutive years. (5) Each year, we exclude firms with assets below $10 million, and we also restrict book leverage ratio to be no greater than unity.

Finally, we winsorize firm-year observations by the top and bottom one percent for each of these variables: AI (defined later), market-to-book ratio, M/B, collateral, Tangibility, profitability, E/A, log of assets, LnA, asset growth, ΔA/A, sales growth, ΔS/S, cash holdings, Cash/A, cash flows, CF/A, tangible investment, Capex/A, intangible investment, R&D/A, change in retained earnings, ΔRE/A, net debt issue, ΔDebt/A, and net equity issue, ΔEquity/A, investment style, Investyle, and Tobin's q, Q. We also winsorize the ingredients for the KZ, WW and SA indexes in the same way. Except initial AI and the financial constraint indexes which we detail below, the detailed construction of other variables we use in this paper is reported in Appendix.

3.2. Asymmetric Informational Imperfection about Growth (AI)

Following the decomposition that dates back to Miller and Modigliani (1961), firm valuation comprises two components: the present value of assets-in-place and the net present value (NPV) of future investment or growth opportunities. Firm market-to-book ratio (M/B) is available monthly. Each year, we calculate a firm's standard deviation of monthly M/B's. Theoretically, M/B equals $(B+NPV_A+NPV_F)/B$ where B is the book value of assets-in-place, NPV_A is the net present value of the assets-in-place or $(B+NPV_A)$ is the total market value of assets-in-place, and NPV_F is the net present value of the firm's future investments. A firm's market value is $M = B + NPV_A + NPV_F$.

Thus we have $\sigma^2(M/B) = \sigma^2(NPV_A/B) + \sigma^2(NPV_F/B) + 2\rho\sigma(NPV_A/B)\sigma(NPV_F/B)$ where ρ is the correlation coefficient between NPV_A/B and NPV_F/B. Since it is difficult to separate out $E[NPV_A]$, let alone $E[NPV_F]$ in the first moment of M/B, the empirical literature commonly uses M/B as a proxy for expected growth opportunities $E[NPV_F/B]$. Likewise, we can use the second moment of M/B or $\sigma(M/B)$ as a proxy for the expected uncertainty over investment opportunities (or growth) that implies asymmetric informational imperfection about growth (AI).

AI varies in an informational imperfection type spectrum. The higher is AI (which equals $\sigma(M/B)$), the more that the asymmetric information arises from growth rather than assets-in-place. To limit the possibility of reverse causality that runs from current corporate policies to the informational imperfection type, AI, we mainly use Initial AI as our explanatory variable. A firm's Initial AI is its average AI over the first three years after the firm enters the data set.

3.3. The KZ Index, the WW Index and the SA Index

In the literature, there have been three popular and comprehensive measures for financial constraints: the KZ index, the WW index, and the SA index.

Based on the work in Kaplan and Zingales (1997), Lamont, Polk and Saa-Requejo (2001) constructed the KZ index. To study financial constraint risk in asset pricing, they propose the following KZ index as a measure of the degree of financial constraints:

$$KZ_{i,t} = -1.002\frac{CF_{i,t}}{A_{i,t-1}} - 39.368\frac{Div_{i,t}}{A_{i,t-1}} - 1.315\frac{C_{i,t}}{A_{i,t-1}} + 3.139Lev_{i,t} + 0.283Q_{i,t} \tag{1}$$

The KZ index cuts across several firm characteristics. The coefficients must be estimated with panel data, but component firm characteristics are allowed to vary to obtain a time-varying firm-specific index of financial constraints. For firm *i* in year *t*, the lower the cash flow, the lower the dividends, the lower the cash holdings, the higher the leverage ratio, or the better the growth prospects, the higher the KZ index, and hence the higher the degree of financial constraints.

Whited and Wu (2006) propose the WW index, which derives from their structural investment model to study financial constraint risk for asset pricing purposes. The WW index for firm *i* in year *t* is

$$WW_{i,t} = -0.091CF_{i,t} - 0.062DIVPOS_{i,t} + 0.021TLTD_{i,t} - 0.044LNTA_{i,t} + 0.102ISG_{i,t} - 0.035SG_{i,t} \tag{2}$$

Like the KZ index, the WW index also contains information on cash flows, dividends, leverage and firm size (the first four variables). But it also includes information on firm growth, such as the firm's sales growth relative to its industry. The higher the WW index, the greater is the degree of financial constraints.

Hadlock and Pierce (2010) have recently put forward another new measure for financial constraints, the Size-Age or SA index:

$$SA_{i,t} = -0.737Size_{i,t} + 0.043Size_{i,t}^2 - 0.040Age_{i,t} \tag{3}$$

Size is the natural log of inflation-adjusted (to 2004) book assets in dollars, and Age is the number of years the firm has been on Compustat with non-missing stock prices. In calculating the SA index, values of size larger than log of \$4.5 billion and ages greater than 37 years are replaced with those thresholds.

Like the KZ index, calculating the SA index requires qualitative information from annual corporate statements to infer the degree of financial constraints in the first place, but the estimation in (3) covers more years and uses a much larger sample than the estimation in (1) for the KZ index. The correlation between the SA index and the KZ index is mildly negative (–0.11), but its correlation with the WW index is highly positive (0.80), as reported in Hadlock and Pierce (2010). Conceptually, the construction of the SA index is close to that of the KZ index, but empirically the parsimonious SA index is tightly correlated with the WW index which is based on structural model estimation.

3.4. Correlation Matrix for ICFS-related Explanatory Regression Variables

AI is the main explanatory variable used to explain ICFS. Investment style regarding intangible vs. tangible investments reflects growth fundamentals. We define investment style using Investyle or R&D/(R&D+Capex). A higher Investyle implies a more R&D intensive investment style. Both AI and Investyle contain information about growth. We also use Initial Investyle (an initial value of Investyle), calculated in the same way as for Initial AI, as a robustness check to stand in for Initial AI in explaining ICFS as well as external finance.

Since both AI and Investyle are variables new to the literature, we will show their correlations and how closely they correlate with the financial constraints indexes, respectively.

Panel A of Table 1 shows that the correlation of Initial AI with future annual AI is 0.52, highly positive. Likewise, the correlation of Initial Investyle with annual Investyle is also highly positive, 0.86. This highest correlation result in Panel A is largely due to the fact that more than half of the firms in our sample report zero R&D. This implies that firms are better dispersed by Initial AI instead of Initial Investyle. But clearly Initial AI is positively correlated with investment style. As shown in Panel A, its correlation with Investyle is 0.29 and with Initial Investyle is similar, 0.30. Thus AI is correlated with investment style in the correct direction.

Panel A of Table 1 further shows that the annual average correlation of Initial AI with the KZ index is −0.24; and it is 0.17 with the WW index and 0.27 with the SA index. If we use time-varying AI instead of Initial AI, the average correlation numbers increase slightly in magnitude to –0.28, 0.18, and 0.31, respectively (the second column in Panel A). The average correlation in Panel A is the time-series average of the annual cross-sectional correlations. Additionally, there can be different computation methods: for example, one grand cross-sectional correlation of within-firm medians over the whole sample period (Panel B) and one grand cross-sectional rank correlation of within-firm median ranks (Panel C). Each method in Table 1 yields modest correlations between the measures for asymmetric informational imperfection and financial constraints, and between those for investment style and financial constraints. So we need to control for these financial constraint indexes in the investment regressions for ICFS.

4. Main Investment Regression Results for ICFS

In standard investment regressions, we first examine ICFS for individual firm quintiles based on a particular sort (Section 4.1). Then we investigate how Initial AI affects ICFS controlling for popular financing-constraint indexes (Section 4.2).

4.1. ICFS by Firm Quintile

We sort by Initial AI into quintiles, our sample of U.S. firms for 1971-2012. This produces five portfolios from low Initial-AI quintile 1 to high Initial-AI quintile 5. We also form different sets of firm quintiles by replacing Initial AI with the median KZ, WW and SA indexes, respectively.

As shown in Panel A of Table 2, the slope estimate for CF/A, *b*, is ICFS. It turns out that ICFS decreases across Initial-AI quartiles. As shown in Panel A1, firms in the lowest Initial-AI quintile (Low) have the highest ICFS (0.351) and firms in the highest Initial-AI quintile (High) have the lowest (0.040). As shown in Panel A2, the monotonic negative relation still holds when firm fixed effects are included (ICFS of 0.231 for quintile 1 and 0.011 for quintile 5). To the extent that Initial AI measures the asymmetric informational imperfection about growth early on, the differences in the ICFS estimates suggest that firms starting with low informational imperfection about growth have a high ICFS and firms with high informational imperfection about growth have a low ICFS. If one believes that informational imperfection necessarily gives rise to financial constraints which are measured by ICFS, our evidence here must be shocking.

Note the drastic increase in R^2 with firm fixed effects for all quintiles, for example, from 0.12 (Panel A1) to 0.52 (Panel A2) for quintile 1. This increased regression goodness-of-fit indicates a great deal of cross-sectional variation in capital investment (the Y variable).

The KZ, WW and SA indexes—often used in the literature for measuring financial constraints—summarize firm characteristics that are important for corporate finance. We also report the relationship between ICFS and each index. For each index, firm quintiles are sorted according to the within-firm, time-series medians of the index. This exercise (with a large panel dataset) is intended to give some sense of whether and how robustly ICFS estimates are related to what those previous studies interpret as financial constraints.

Panel B1 of Table 2 shows that the ICFS estimates monotonically increase from KZ quintile 1 (0.057) to 5 (0.192); the regression with firm fixed effects in Panel B2 also shows a similar pattern. This positive relationship would be consistent with a KZ-index-based financial constraint explanation for ICFS. Note that Lamont, Polk and Saa-Requejo (2001), and not Kaplan and Zingales (1997, 2000), constructed the KZ index. Perhaps because the latter's original work actually challenges the financial constraint interpretation of ICFS, Baker, Stein and Wurgler (2003) later play down the financial constraints interpretation of the KZ index even though they find a positive relation between the ICFS and the KZ index. Instead, they interpret the KZ index as "equity dependence" and focus on the KZ index and the slope estimates for Q in standard investment regressions.

Panel B of Table 2 shows that slope estimate for Q, *c*, varies with the KZ quintiles in a clear monotonic order, with or without firm fixed effects. For example, as shown in Panel B2, with firm fixed effect, *c* increases from KZ quintile 1 (0.009) to 5 (0.049). These results are consistent with the findings in Baker, Stein and Wurgler (2003) to the effect that corporate investment by high KZ index firms is more sensitive to stock prices than that by low KZ index firms. According to an earlier study by Barro (1990), financial variables that imbed market prices play a positive role in facilitating investment. Baker, Stein and Wurgler (2003) suggest that this stock market channel helps the equity dependent firms (which are high leveraged and lack of cash) solve the underinvestment problem because of non-fundamental movements in stock prices in the firms' favor.

Panel C1 of Table 2 shows that ICFS estimates monotonically decrease from WW quintile 1 (0.178) to 5 (0.053). The firm-fixed effect results show a similarly clear pattern (Panel C2). So greater financial constraint in terms of a higher WW index predicts a lower ICFS estimate—a pattern inconsistent with the interpretation of ICFS as a measure of financial constraints.

Since the SA index is closely correlated with the WW index (with a correlation coefficient of as high as 0.87 as shown in Table 1), the monotonic patterns in Panel D of Table 2 resemble those for WW in Panel C. In view of fundamental differences in the construction of the two indexes, their strong statistical similarity is surprising. The WW index comes from structural model estimation, but the SA index, like the KZ index, requires qualitative interpretation of financial constraints based on annual corporate financial statements in a much smaller sample than that used in the index-generating regression.

The KZ index, the WW index and the SA index, each with its own index construction, all significantly affect ICFS and hence jointly provide a comprehensive set of control variables for the main investment regressions that follow.

4.2. Initial AI to Explain ICFS Controlling for Financial Constraint Indexes

In standard regressions of capital investment on lagged cash flow, CF/A, and Q, we add time-invariant variables, Initial AI, the within-firm median KZ index, the median WW index, and the median SA index. These time-invariant variables also enter as interaction terms with lagged CF/A, as well as with lagged Q. Firm dynamic investment and financing behavior can be better judged with respect to within-firm financing patterns. We use eight regression specifications, all with firm-fixed effects to highlight time variation in firm behavior. In the first four we include, one by one, the time-invariant variables. In the next three, we include Initial AI and, one by one, the financial constraints indexes. Regression (8) includes all the variables together. We also standardize these variables before the regressions to facilitate economic interpretation of their slope estimates.

As shown in Panel A of Table 3, the slope estimates for CF/A are significantly positive in all eight regressions. For example, this baseline ICFS is 0.268 (t-value=53.01) in regression (8). The slope estimate of 0.268 means that a one standard deviation increase in CF/A, *ceteris paribus*, leads to an increase in investment (scaled by assets) by 0.268. A positive ICFS means that more internal cash flows facilitate capital investment. But the key question, as asked by Kaplan and Zingles (2000), is what causes this positive relation. So the slope estimates for the interaction terms are our main focus.

In Panel A of Table 3, the slope estimates for Initial AI interacted with cash flow are significantly negative. For example, the slope estimate for CF/A*Initial AI is −0.047 (*t*-value=−19.58) in regression (8). While the positive baseline ICFS is consistent with the findings of previous studies using standard investment regressions, the interaction term can show that ICFS either increases or decreases with other factors.

The decrease of ICFS with Initial AI suggests that capital investment, Capex/A, by firms starting with low growth uncertainty is highly sensitive to internal cash flows whereas capital investment by firms starting with high growth uncertainty is less sensitive. In other words, internal cash flows are significantly less important for capital investment in firms starting with higher informational imperfection on growth.

Consider now the KZ control. As shown in Panel A of Table 3, the slope estimates for $CF/A*KZ_{med}$ are positive and significant, for example, it is 0.049 (*t*-value=11.60) in regression (8). The positive slope for $CF/A*KZ_{med}$ indicates that capital investment is more sensitive to cash flows in high KZ firms than those in low KZ firms. Like Initial AI, the KZ index seems to capture the fact that internal fund is more important for capital investment by certain firms. But the interpretation of the KZ index is ambiguous in the literature.

The KZ index has a leverage ratio explicitly imbedded. High leverage, likely as an outcome, not only reflects a firm's heavy reliance on debt and perhaps internal cash flow but also can indicate a debt overhang. Complicating its interpretation, the KZ index can be also interpreted as indicating "equity dependence" instead of financial constraint (Baker, Stein and Wurgler, 2003). Departing from the traditional focus on ICFS, they use the sensitivity of corporate investment to stock prices or Q in standard investment regressions to measure equity dependence.

Panel A of Table 3 shows the slope estimates for Q which are positive and significant in all regressions. For example, the baseline Q sensitivity is 0.292 in regression (8). This slope estimate means that a one standard deviation increase in Q leads to an increase in investment by 0.292. The positive Q sensitivity is consistent with the essence of Q theory that an increase in investment opportunities induces more investment, even though researchers often use market-to-book ratio as a noisy proxy for Q. Most researchers have no problem with this baseline intuition, but some are concerned about the overvaluation implication of a high Q sensitivity especially if Q is considered to reflect mispricing as well.

Panel A of Table 3 shows that the Q sensitivity decreases with Initial AI in every regression. For example, the slope estimate for Q*Initial AI is −0.014 (*t*-value = −8.42) in regression (8). This means that capital investment by firms starting with low growth uncertainty has a high sensitivity to Q whereas capital investment by firms starting with high growth uncertainty has a low sensitivity to Q. This indicates that firms starting with high asymmetric informational imperfection on growth can somehow smooth their capital investment over dynamic market conditions (to which annual capital investments are less sensitive).

In contrast, a greater KZ index predicts a significantly greater Q sensitivity. For example, the slope estimate for Q*KZ_{med} is 0.105 (*t*-value = 31.85) in regression (8). This means that capital investments by high and low KZ firms have high and low sensitivities to Q, respectively. To the extent that KZ measures equity dependence, these relations would predict that high equity dependent firms have high levels of capital investment when investment opportunities increase or market conditions improve whereas less equity dependent firms should be less responsive to such conditions. Baker, Stein and Wurgler (2003) interpret high Q sensitivity as an indication of being sensitive to non-fundamental movements in stock prices. Since the Initial AI and the KZ show opposite results here, the equity dependence interpretation would suggest that capital investment by firms starting with high informational imperfection about growth is less influenced by non-fundamental movements.

It is worth noting that AI is unlikely to be related to private information contained in stock prices that is new to managers. Chen, Goldstein and Jiang (2007) show that the investment sensitivity to Q increases with their private information variables price non-synchronicity and PIN, like the case of KZ. Note that KZ is positively correlated with these private information variables as reported in Chen, Goldstein and Jiang (2007), but becomes negatively correlated with Initial AI as shown in Table 1 in this paper. In view of our evidence that the Q sensitivity decreases with Initial AI, the asymmetric informational imperfection about growth should be understood in a Myers and Majluf framework. This means the asymmetric information we refer to in this paper is mainly based on managerial insider-favored information rather than private information contained in stock prices that is new to managers, although both can matter to corporate investment.

The original ICFS literature focuses mainly on capital investment. We can consider total investment that includes both Capex (tangible) and R&D (intangible). As shown in Panel B of Table 3, the slope estimates for CF/A to explain (Capex+R&D)/A are also positive and significant in all eight regressions. Interestingly, this baseline ICFS drops from Panel A to Panel B in every regression. For example, in regression (8), ICFS is 0.268 in Panel A and 0.100 in Panel B. This is not surprising because when we examine a large cross section of listed firms, internal funds (cash flow) are not typically a major source of funding for R&D investment.

The slope estimates for CF/A*Initial AI remain significantly negative in Panel B in all eight regressions, even quantitatively similar to the results in Panel A. For example, in regression (8) in which all controlling explanatory variables are present, the slope estimate for CF/A*Initial AI is –0.046 (t-value = –23.37) in Panel B versus –0.047 (t-value = –19.58) in Panel A.

Total investment also positively responds to Q. The baseline Q sensitivities are significantly positive in all eight regressions in Panel B. For example, the slope estimate for Q is 0.278 (t-value =76.79) in regression (8). But Initial AI again weakens this positive relationship. For example, the slope estimate or Q*Initial AI is –0.004 (t-value = –3.12) in regression (8). So the main results still hold for total investment: firms starting with low informational imperfection about growth have high ICFS and Q sensitivities, whereas firms starting with high informational imperfection about growth have low ICFS and Q sensitivities. This evidence is hardly consistent with a financial-constraint interpretation for ICFS if one believes a higher informational imperfection tightens financial constraints which are measured by ICFS.

The WW and SA controls also indicate that ICFS is unlikely due to financial constraints. As already shown in Table 1, the two indexes each have a modestly positive correlation with Initial AI. They may therefore also contain similar information that is contained in Initial AI. As shown in both Panel A and B of Table 3, like Initial AI, both the WW and SA indexes negatively predict the ICFS. For example, the slope estimate for CF/A*WW_{med} in regression (6) is –0.118 (t-value = –25.49) in Panel A and –0.081 (t-value = –21.14) in Panel B. Similarly, the slope estimate for CF/A*SA_{med} in regression (7) is –0.118 (t-value = –27.56) in Panel A and –0.099 (t-value = –27.85) in Panel B. These findings would suggest that firms with high and low degrees of financial constraints have instead low and high ICFS, respectively. To the extent that WW and

SA reliably measure financial constraints, the ICFS patterns here are contradictory and hence ICFS does not seem to measure the degree of financial constraints.

The indexes each are presented as a basket of corporate variables and the inclusion of the indexes in regressions may attenuate the relevant information in Initial AI. The significant ICFS patterns for the KZ, WW and SA indexes suggest that all of them contain robust information that may not obviously mean financial constraints (Farre-Mensa and Ljungqvist, 2015). Our concern, however, is whether these indexes contain sufficient information to potentially wash out any predictive power of Initial AI given its moderately negative correlation with KZ and positive correlations with WW and SA as shown in Table 1. It turns out that the controlled tests reported in Table 3 show they do not. The main results here are similar to those in Table 2. In short, whatever these indexes measure, Initial AI contains unique and robust information on ICFS.

5. A Growth-type Explanation for ICFS

This single variable, AI, is fundamentally linked to many other variables in corporate finance. We believe that AI provides the best lens through which we can identify firm growth type, which dictates early on how corporate investment and financing adjust when future shocks arrive. Section 5.1 shows how initial AI is related to important corporate finance variables. Section 5.2 provides evidence that AI, like Investyle, is largely persistent over time. More revealing, there is a growth-type-aligned pattern in financing. Section 5.3 uses initial Investyle as a robustness check on our growth-type explanation for ICFS.

5.1. Fundamental Patterns Sorted by Initial AI

On important feature of initial AI is that it meaningfully predicts future investment style and financing behavior. Panel A of Table 4 shows that those Initial-AI quintiles predict the same order of future annual AI values (from 0.07 to 0.66) over the entire sample period of 1971-2012. Importantly, as AI is persistent, initial AI identifies persistent firm growth type.

What exactly is firm growth type? Wu and Au Yeung (2012) propose a two-way independent sort on initial market-to-book ratio and asset tangibility with median breakpoints across all firms. For each firm, an initial value is the annual average over the first three years after the firm enters the data set. Wu and Au Yeung (2012) sort out three firm growth types: low-growth type (G1) refers firms with low market-to-book ratios and high tangibility, high-growth type (G3) refers to firms with high market-to-book ratio and low tangibility, and mixed-growth type (G2) includes the other firms with less lopsided market-to-book and tangibility.

Wu and Au Yeung (2012) argue that in a world with asymmetric information that favors managers, low-growth firms (G1) are likely to have more asymmetric information about assets-in-place rather than about investment opportunities; conversely, high-growth firms (G3) are likely to have more asymmetric information about growth opportunities rather than about assets-in-place. The G3 firms likely correspond to Zingales' (2000) 'New Firm', which is human capital intensive and has uncertain intangibles including growth opportunities. As it is unclear which type of asymmetric information predominates in the other cases, these firms are of mixed-growth type (G2). They find that the three growth types are persistent.[7]

As shown in Panel A of Table 4, like the three growth types of Wu and Au Yeung (2012), Initial AI captures distinct firm growth type characteristics. To start, there is a good match between the G1, G2 and G3 firms and the Initial-AI quintiles. For example, 76.8% of the lowest Initial-AI firms (Low) are the low-growth type G1 firms and 74.8% of the highest Initial-AI firms (High) are the high-growth type G3 firms. Like the G1-G3 sort, an Initial-AI sort produces similar combinations of future M/B and asset tangibility. For example, the group means of annual M/B and tangibility for the lowest quintile (Low) are 0.84 and 0.58, respectively, whereas those for the highest quintile (High) are 2.92 and 0.35. With a clear pattern future M/B ratios line up well (from 0.84 to 2.92 monotonically) with Initial AI (from Low to High) and future asset tangibility in reverse order (from 0.58 to 0.35 monotonically) with Initial AI. This suggests that Initial AI contains information that can reveal firm growth type early on. The higher is Initial AI, the higher the growth type.

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[7] Such persistence is consistent with the common belief that many corporate variables are endogenously correlated. Perhaps growth type best describes sustainable corporate finance equilibria. One may wonder whether a sorting directly on any of these corporate variables can produce a similar cross section of firm fundamentals. Our observation is that AI is the best single variable, surely better than the level of market-to-book ratio (which is much noisy), in producing a well dispersed and largely persistent cross section of other corporate variables over time (results are available on request; see also Wu and Au Yeung, 2015).

Panel B of Table 4 shows that monotonic Initial-AI-sorted patterns are evident for the KZ index, the WW index, and the SA index as well. The KZ index (from 0.66 to −0.76) lines up negatively with Initial AI (from Low to High), and both the WW index (from −0.93 to −0.85) and the SA index (from −3.41 to −2.74) line up positively with Initial AI. All this is consistent with the correlation results in Table 1. Additionally, Initial-AI sorts also produce monotonic patterns for firm characteristics—that are important components of one or more measures of financial constraints—leverage ratio, likelihood that a firm pays dividends, firm size and firm age. More precisely, from the lowest quintile (Low) to the highest quintile (High), the future annual group means are from 0.32 to 0.13 for leverage, from 64.6 to 26.0% for likelihood of paying dividends, from $20.07 to 18.22 million for the logarithm of assets (LnA), and from 13.92 to 6.69 years for firm age, all progressing monotonically. The relations between these variables and between the relevant components and the financial constraint indexes are largely consistent with the findings of prior studies. The focus of this paper on growth type, however, sheds a new light.

High growth type firms are expected to show growth or investment fundamentals. Panel C of Table 4 shows that although firms with high Initial AI have notably lower Capex/A, this tangible or capital investment does not show a monotonic pattern across the Initial-AI quintiles. But intangible investment, R&D/A, lines up well. Firms in the lowest Initial-AI quintile 1 (Low) invest a paltry amount of R&D annually (0.8% of total assets), whereas firms in the highest Initial-AI quintile 5 (High) invest an annual average of 8.2% of total assets.

Because of a significant tilt toward R&D in their investment, firms with high Initial AI have high annual rates of growth in assets and sales, but produce low earnings compared with firms with low Initial AI. As shown in Panel C, firms in Initial-AI quintile 1 grow at an annual rate of 10.4% in terms of total assets and 10.9% in terms of sales. Firms in Initial-AI quintile 5 on average grow at 48.2% in total assets and 43.5% in sales (a much higher rate). In reverse order, the slowest growing firms (Low) generate, on average, a profitability (E/A) of 12.0%, while the fastest growing firms (High) have a lower profitability of 6.7%. Notice that the within-quintile *ex post* dispersion in profitability is smallest for the quintile 1 firms, swinging from −6.3% for loss-making firms to 12.8% for profitable firms. The dispersion becomes largest for quintile 5 firms, from −21.8% to 19.3%. Cao, Simin and Zhao (2008) show a positive relationship between firm growth options and future return volatility. Wu and Au Yeung (2012, 2015) point out that higher uncertainty about growth prospects and higher growth rates actually go hand in hand.

The next question is how firms finance their growth. Growth type can dictate financing behavior. Panel D of Table 4 shows that firms in quintile 5 (High) on average generate the lowest cash flows (CF/A, at 0.6% of total assets), but they do enjoy the largest cash holdings (30.7% of total assets). By contrast, firms in quintile 1 (Low) have relatively high cash flows (7.0%) but low cash holdings (6.7%). A scrutiny on all the three funding sources reveals what is going on.

Looking at financing mix from the three funding sources as flow variables, quintile 1 (Low) firms rely on all of them—retained earnings (ΔRE/A at 0.8% of total assets), net debt (ΔDebt/A at 1.1%) and net equity (ΔEquity/A at 0.5%). If we interpret it roughly as an order of importance in financing mix, this pattern is consistent with Myer's (1984) pecking order in financing. But this classic pecking order is clearly reversed for the two highest Initial-AI quintiles. Quintile 5 (High) firms on average have a negative change in retained earnings (−5.5%), a positive net debt (1.4%) and net equity (a startling 10.0%) annually. Quintile 4 shows a similar pattern.

The negative change in retained earnings does not really suggest internal funding. Rather it reflects aggressive R&D investments which are expensed in the current year but are expected to pay off in the long run. Nevertheless, high growth firms on average do enjoy persistently high market-to-book ratios (Panel A). It is also clear that large cash holdings (30.7% of total assets for the fastest growing firms) are stockpiled through years of heavy issuance of new equity (at 10.0% of total assets annually). It seems that the equity market enables high growth firms to invest relentlessly in R&D perhaps with multi-year investment plans and hence allows them to hold cash (see also Wu and Au Yeung, 2012).

The results shown in Panel C and D of Table 4 contain important information about Initial-AI-aligned investment style and financing behavior. The Initial-AI quintile sorts are able to produce monotonic patterns in matched investment style and financing behavior. Column "(3)-(2)" of Panel D shows that the external financing differential, EFD, defined as net equity minus net debt, increases on average from −0.5% to 8.70% annually, and at the same time, the proportion of R&D in total investment, R&D/(R&D+Capex), or Investyle, which we use as a measure for investment style, increases from 9.6% to 40.7%. In short, more intangible investment induces more equity rather than debt financing in external finance.

These results provide *prima facie* evidence for growth type compatibility in corporate finance. The patterns are similar to those shown with the three growth types in Wu and Au Yeung (2012). The new variable AI, however, allows finer distinctions among growth types. Thus we can simply use AI to proxy for firm growth type, which can be identified early on using Initial AI. The higher is Initial AI, the higher the firm's growth type. The rank correlation of AI with Investyle is as high as 0.49, as shown in Panel C of Table 1. Our evidence points to the existence of growth-type-aligned patterns in corporate finance.

5.2. Persistence in Investment Style and Financing Behavior

The central thesis of this paper is that ICFS is better interpreted as a result of growth-type-aligned financing choice. Simply put, ICFS reflects firm growth type rather than the degree of financial constraints. The finance literature seldom highlights persistence in corporate finance perhaps because the evidence potentially limits a plausible set of explanations (Lemmon, Roberts and Zender, 2008). But persistence facilitates a firm type story. In this section we investigate to what extent AI and Investyle are persistent and how financing choices arise in a manner compatible with firm growth type.

Table 5 shows a transition matrix for AI and Investyle, respectively. As shown in Panel A, firms in extreme Initial-AI quintiles have a high probability of staying in those same quintiles over time. For example, when re-sorting firms each calendar year using annual AI, 49% of the firms in the lowest initial quintile (Low) stay in the lowest quintile, 28% move up to the next quintile, but only 15%, 6% and 1% move up further. Firms in the highest initial quintile (High) show even stronger persistence: 58% stay and 23% move down to the next AI quintile, but only 12%, 6% and 2% move down further. Because of this persistence in AI, Initial AI is able to capture distinct growth types early on.

On the other hand, as shown in Panel B of Table 5, although we cannot sort firms by Investyle directly into quintiles because the median R&D is zero in the total sample of firms, we form five Investyle firms as follows. Group 1 (Low) contains the zero-R&D firms, and the remaining firms are sorted by non-zero Investyle into quartiles (group 2 – group 5). As a result, Investyle also shows strong persistence. For example, 94% of firms in the lowest Initial-Investyle group (Low) remain with no R&D and 69% of firms in the highest Initial group (High) continue to be most R&D intensive. The overall persistence can be summarized by a strong diagonal effect in the Investyle transition matrix of Investyle, with much higher probabilities of staying than migrating from where firms start.

Table 6 reports how growth type, via AI or Investyle, affects external finance year by year. As already shown in column "(3)-(2)" of Panel D of Table 4, External Finance Differential (EFD) lines up well with Initial AI. In this section, using firm-level panel data, we are regressing EFD on lagged AI or Investyle along with a host of other corporate variables. The main variables are a growth type variable (AI or Investyle) and market-to-book ratio (as a proxy for investment opportunities and/or market conditions). We also examine their interaction term. Other control variables are Tangibility, E/A (profitability), LnA (firm size), and Cash/A (cash holdings), along with their interaction terms with a growth-type variable.

We start with AI and use three regression specifications. The first regression (1) is just a pooled OLS. The second (2) is also a pooled OLS but we replace AI with Initial AI. If the main results of the two regressions are qualitatively similar, reverse causation (where growth type responds to opportunistic market timing) is unlikely. We use the two-way cluster correction for standard errors as suggested by Petersen (2009) for the panel regressions (1) and (2). The third regression (3) includes firm fixed effects and evaluates within-firm behavior.

As shown in Panel A of Table 6, the slope estimates for lagged AI are significantly positive, being greater than 0.343 for regression (1) and (3). Although dropping slightly to 0.209 (t-value=6.99) in regression (2) when we replace AI with Initial AI, the slope estimate is still significantly positive. The positive relation between EFD and AI as a firm-level regression result confirms the growth-type-aligned external finance pattern. A pecking order with more equity than debt financing goes with higher growth type which is initially identified.

Firms step up external finance when market conditions become favorable. As shown in Panel A, the slope estimates for lagged M/B are reliably positive in all three regressions. This means when investment opportunities arise, and/or market conditions improve, the preference for more equity rather than debt becomes more pronounced. But this is unlikely to be due to the opportunistic market timing of Stein (1992) and Baker and Wurgler (2003), because Initial AI dictates EFD early on, as shown by the result in regression (2).

The interaction term M/B*AI can capture whether the sensitivity of EFD to M/B depends on growth type. While the slope estimates for regressions (1) and (2) are not significant, the slope estimate with firm fixed effect in (3) is significantly positive (0.002, t-value=3.70). To the extent that the sensitivity of EFD to growth type is best understood to be a within-firm financing behavior, the significant result for M/B*AI in regression (3) means that growth type can matter to financing behavior reinforced by dynamic market conditions year by year.

To tie down financing choice to explicit growth-type fundamentals, we replace AI with investment style which is a clearly fundamental characteristic of growth type. As shown in Panel B of Table 6, the slope estimates for investment style to explain EFD are resoundingly positive in all three regressions. The significant slope estimate for Initial Investyle in regression (2) is 0.222 with a t-value of 6.61, confirming that investment style dictates EFD early on.

As shown in Panel B, annual EFD also increases significantly with M/B. Additionally, the interaction term M/B*Investyle are significantly positive, being around 0.021 with *t*-values greater than 6.68, in all three regressions. This means that the sensitivity of EFD to M/B increases with investment style—direct evidence for a growth fundamental determination of financing behavior year by year. This suggests that when investment opportunities increase and/or market conditions improve, investment style with higher R&D intensity tilt firms towards more equity rather than debt financing.

How do we know reverse causation is unlikely? Regression (2) uses time-invariant Initial Investyle instead of the time-varying annual Investyle. As shown in Panel B, the slope estimate for M/B*Initial Investyle in regression (2) is quantitatively similar to those in regressions (1) and (3). This is not surprising because, as shown in the transition matrix in Panel B of Table 5, Investyle is strongly persistent. This finding has a profound implication: financing behavior in the future is fundamentally determined early on (see also Lemmon, Roberts and Zender, 2008, and Wu and Au Yeung, 2012, for initial determination of persistent and significant differences in capital structure).

Brown, Fazzari and Petersen (2009) suggest that shifts in the supply of equity financing drive much of the 1990s R&D boom and imply that non-fundamentals may cause the supply shifts. Fama and French (2004) also acknowledge a downward shift in the equity supply curve since the late 1970s, but point out fundamental changes at the same time—changes in firm characteristics of new lists skewed toward high growth. Perhaps behind the seemingly non-fundamental phenomenon described by many researchers are economic fundamentals at work after all. In this regard, our findings point to an important managerial decision rule, namely, appropriate financing behavior in response to specific investment style is a first-order concern.

The results for control variables in Table 6 are largely significant as well. Notably, EFD significantly decreases with profitability, E/A. Growth type especially via investment style also matters here. For example, as shown in Panel B, the slope estimates are -0.239, -0.251 and -0.135 (t-values of -9.53, -10.31, and -11.78) in regressions (1), (2) and (3), respectively, for the interaction of E/A with investment style. Wu and Au Yeung (2012) argue that profitability can be a direct short-term outcome due to investment behavior. The regression results for investment style and E/A along with their interaction to explain EFD are consistent with a growth-type determination story: relentless R&D investment attracts heavy new equity financing and subsequently lowers profitability because R&D are currently expensed and won't pay off in the near future.

The results for other control variables in Table 6 are often significant in various regression specifications. Thus they are useful control variables, although they may also contain information about growth type and would tend to weaken our main results about growth-type-aligned financing choice.

Financing behavior under dynamic market conditions means within-firm variation. Persistence in a firm's financing behavior is likely to reflect a firm-type determination and is consistent with growth-type-compatible investment and financing based on firm fundamentals. It is one thing that firms with many growth options tend to avoid debt financing because of debt overhang concerns (Myers, 1977). Yet it is another whether these growth firms can get new equity as a natural choice, best for risk sharing. As the generalized Myers-Majluf model explains, high growth type firms can use new equity without the adverse selection problem despite high growth uncertainty.[8] While this does not mean that financial constraints do not exist, the notion that informational imperfection generally gives rise to financial constraints is questionable.

5.3. Using Investment Style instead of Initial AI in Explaining ICFS

We have used Initial AI as a main explanatory variable to explain ICFS in investment regressions, as previously reported in Table 3. Replacing Initial AI with investment style (measured by Investyle) can provide a clear sense of growth-type-related firm fundamentals. Note that unlike AI, Investyle is not well dispersed across firms because at least half of the firms in our sample (commonly employed in the literature) report zero R&D. Nevertheless, the results concerning ICFS and growth type still hold in this robustness check.

As shown in Panel A of Table 7 where we replace Initial AI with Initial Investyle, firms starting with investment style tilting towards more R&D have significantly lower ICFS and Q sensitivities. For example, in regression (8), the slope estimate for CF/A*Initial Investyle is –0.087 (*t*-value = –24.66), and for Q*Initial Investyle it is –0.079 (*t*-value = –27.41). At the same time, the results for the three index control variables also remain qualitatively similar to those in Panel A of Table 3.

We next use time-varying Investyle and also let the KZ, WW and SA indexes vary with time (all being lagged explanatory variables). If ICFS simply reflects growth-type-determined financing behavior, a persistent variable like Investyle, despite some time variation, is also able to capture a genuine relation between growth type and ICFS.

As shown in Panel B of Table 7, the main results are also qualitatively the same as before. For example, again in regression (8), the slope estimate for CF/A*Investyle is –0.071 (*t*-value = –22.86), and for Q*Investyle it is –0.080 (*t*-value = –29.90). The similar results for both Initial AI and Investyle are not surprising because both inform about firm growth type.

As our main results hold for investment style as well, we can clearly link ICFS and Q sensitivity to growth-type-related fundamentals. For example, alternative to a mispricing

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[8] One implication is that despite big information gaps, high growth firms can use new equity as a natural curb on banks' rent extraction, about which the information production argument for monitored debt in debt mix has been silent (Wu, Sercu and Yao, 2009).

interpretation of Q sensitivity, our finding that high-growth-type firms with relentless R&D investment typically have low Q sensitivities suggests that the equity market rationally allows these firms to use new equity raised in a lump sum to smooth their investment across volatile market conditions to maintain high growth.

Taken together, our results show that the ICFS decreases with firm growth type identified by Initial AI (or Investyle) early on. One may argue that Initial AI may measure financial constraints in reverse order: high-growth-type firms are less financially constrained and low-growth-type firms are more financially constrained. But such an explanation for financial constraints is apparently inconsistent with the concept of informational-imperfection-driven financial constraints. For one thing, it cannot explain why high-growth-type firms as a whole are able to sustain high growth by getting access to sufficient new equity despite their high growth uncertainty which is likely to give rise to informational imperfection.

6. Conclusion

This paper documents a significant negative relation between investment-cash-flow-sensitivity (ICFS) and asymmetric information imperfection about growth (AI). We suggest that interpreting AI as firm growth type can help explain this finding. AI varies in an informational imperfection spectrum between two types of asymmetric information about growth vs. assets in place. A higher AI or firm growth type means more asymmetric information about firm valuation arises from growth than assets in place. In effect, firm growth type can be identified by initial AI early on, facilitating our inference that growth type affects ICFS.

Previous research has shown that firms invest and seek financing in a persistent manner compatible with their distinct growth types. This pattern reflects a matching equilibrium between investment and financing according to asymmetric information type. The effect of asymmetric informational imperfection on financing choice hinges on types of asymmetric information (about growth vs. assets-in-place) rather than a general notion of information asymmetry. As a result, this paper argues that there is an overarching financing pattern spanned by the two distinct types of asymmetric information which dictate the severity of incentive conflicts. This AI-aligned overarching financing pattern, as shown in this paper, explains more than does the classic pecking order in financing and contradicts the financial-constraint-interpretation of ICFS.

Financial constraint, almost by definition, hinders valuable investment, but budget constraints can be an optimal equilibrium outcome in an economy. High-growth-type firms, which typically have high growth uncertainly, typically have access to capital via new equity issues for multi-year investment plans to maintain high growth. Even low-growth-type firms do not appear to be financial constrained despite showing high ICFS, as they typically have access to all three financing sources (internal, debt and, perhaps as a last resort, equity) and are solid dividend payers. Thus, such predictable financing arrangements that match investment styles seem to be largely a market equilibrium result with no financial constraint implication.

This is not to suggest that financial constraints do not exist. One can confidently identify financial constraints for some firms, especially in the sense of financial distress. Many also agree that a macroeconomic credit crunch can impose financial constraints on many firms. But one should wonder why researchers have had difficulty identifying a straightforward measure for financial constraints across listed firms—and difficulty in coming up with a meaningful overarching pattern of financial constraints due to informational market imperfection. Consistent with neoclassical intuition, the results of this study suggest that for firms listed on well-functioning capital markets, which are able to use predictable financing arrangements to mitigate market imperfection, corporate investment is surprisingly resilient to informational imperfection.

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Appendix: Definition of Annual Variables

Variable	Definition
Market Equity	CRSP's Closing Price (*PRC_t*) × Shares Outstanding (*$SHROUT_t$*) Note: unlike annual book variables, market equity has monthly data.
M/B_t	[Market Equity + Total Debt (*DLC_t+$DLTT_t$*) + Preferred Stock (*$PSTKL_t$*) – Deferred Tax (*$TXDITC_t$*)] / Asset (*AT_t*)
AI_t	Within-firm monthly standard deviation of M/B (monthly data)
$Tangibility_t$	[Inventories (*$INVT_t$*) + Property, Plant & Equipment (*$PPENT_t$*)] / Asset (*AT_t*)
$Leverage_t$	[Short-term Debt (*DLC_t*) + Long-term Debt(*$DLTT_t$*)] / Asset (*AT_t*)
$DivPayer_t$	Dividend payer status in year *t*, where a payer dummy takes 1 if dividends per share by the ex-date (*$DVPSX\_F_t$*) are non-zero; otherwise, it takes 0.
LnA_t	Log of Asset (*AT_t*)
AGE_t	The number of years since a firm was listed.
$Capex/A_t$	Capital Expenditure (*$CAPX_t$*) / Asset (*AT_t*)
$R\&D/A_t$	R&D (*XRD_t*) / Asset (*AT_t*)
$\Delta A/A_{t-1}$	Change in Asset (*AT*) from year *t* – 1 to year *t* / Asset (*AT_{t-1}*)
$\Delta S/S_{t-1}$	Change in Sales (SALE) from year *t* – 1 to year *t* / Sales (*$SALE_{t-1}$*)
E/A_t	Operating Income Before Depreciation (*$OIBDP_t$*) / Asset (*AT_t*)
CF/A_t	[Depreciation and Amortization (*DP_t*) + Earnings Before Extraordinary Items (*IB_t*)] / Asset (*AT_t*)
$Cash/A_t$	Cash (*CHE_t*) / Asset (*AT_t*)
$\Delta RE/A_t$	Change in Retained Earnings (*RE*) from year *t* – 1 to year *t* / Asset (*AT_t*)
$\Delta Debt/A_t$	Net Debt Issue (*$DLTIS_t$ – $DLTR_t$*) / Asset (*AT_t*)
$\Delta Equity/A_t$	Net Equity Issue (*$SSTK_t$ – $PRSTKC_t$*) / Asset (*AT_t*)
EFD_t	External Finance Differential ($\Delta Equity/A_t$ – $\Delta Debt/A_t$)
$Investyle_t$	R&D (*XRDt*) / [R&D + Capital Expenditure (*$CAPX_t$*)]
Q_t	[Market Equity + Asset (*AT_t*) – Common Equity (*CEQ_t*) – Deferred Tax (*$TXDB_t$*)] / Asset (*AT_t*)

Table 1: Correlation Matrix of Main Regression Variables

This table reports the correlation matrix for Initial AI, Initial Investyle, and annual values of AI, Investyle, the KZ, WW and SA index. Initial AI is the time-series average of AI over year 0, 1 and 2, where year 0 is the first year of a firm's data report in the total sample. $Investyle_t$ refers to $R\&D/(Capex+R\&D)_t$, a proxy for investment style. Initial Investyle is similarly defined as Initial AI. For each pair of variables (e.g., AI and KZ), three ways of calculating the correlation coefficient are shown in Panels A, B and C, respectively. The sample period is from 1971 to 2012.

	Initial AI	AI_t	Initial Investyle	$Investyle_t$	KZ_t	WW_t	SA_t
Panel A: Cross-firm Correlation Calculated Each Year, Then Time-series Averaged							
AI_t	0.52	1.00					
Initial Investyle	0.30	0.31	1.00				
$Investyle_t$	0.29	0.28	0.86	1.00			
KZ_t	-0.24	-0.28	-0.22	-0.20	1.00		
WW_t	0.17	0.18	0.11	0.11	0.13	1.00	
SA_t	0.27	0.31	0.21	0.19	-0.03	0.72	1.00
Panel B: Within-firm Median, Then Cross-firm Correlation of Medians							
AI_t	0.62	1.00					
Initial Investyle	0.42	0.52	1.00				
$Investyle_t$	0.43	0.52	0.91	1.00			
KZ_t	-0.26	-0.31	-0.31	-0.32	1.00		
WW_t	0.18	0.24	0.17	0.17	0.13	1.00	
SA_t	0.24	0.35	0.24	0.24	0.03	0.87	1.00
Panel C: Within-firm Medians Ranked, Then Cross-firm Correlation of Ranks							
AI_t	0.80	1.00					
Initial Investyle	0.44	0.51	1.00				
$Investyle_t$	0.42	0.49	0.87	1.00			
KZ_t	-0.35	-0.43	-0.36	-0.36	1.00		
WW_t	0.27	0.27	0.15	0.13	0.13	1.00	
SA_t	0.33	0.36	0.22	0.19	-0.01	0.84	1.00

Table 2: Investment-Cash-Flow-Sensitivity (ICFS) for Each Initial-AI Quintile

This table reports the results of standard investment regressions where the dependent variable is Capex/A_t (corporate capital investment in year *t*) and the explanatory variables are CF/A_{t-1} (cash flow in year *t*-1) and Q_{t-1} (Tobin's q in year *t*-1, which has a correlation of 0.98 with market-to-book ratio, M/B_{t-1}). Firm quintiles are sorted based on Initial AI (Panel A), the KZ index time-series median, KZ_{med} (Panel B), the WW index time-series median, WW_{med} (Panel C), or the SA index time-series median, SA_{med} (Panel D). The left half of the table shows the results from a pooled OLS panel regression for each firm quintile and the right half shows the results with firm-fixed effects. The slope, *b*, for CF/A_{t-1} measures the sensitivity of capital investment to cash flow, or ICFS. To save space, intercept results are not reported. The sample period is 1971-2012.

Panel A	Panel A1: Panel Regression for Each Initial AI Quintile						Panel A2: With Firm-fixed Effects				
		CF/A_{t-1}		Q_{t-1}			CF/A_{t-1}		Q_{t-1}		
Initial AI	Firm Year	*b*	*t-stat*	*c*	*t-stat*	R^2	*b*	*t-stat*	*c*	*t-stat*	R^2
1 Low	32,632	0.351	60.49	0.002	2.16	0.12	0.231	41.62	0.009	9.29	0.52
2	25,833	0.258	39.79	0.009	9.30	0.08	0.191	31.34	0.020	21.84	0.55
3	22,144	0.161	30.94	0.015	18.56	0.07	0.115	21.93	0.025	32.58	0.56
4	19,622	0.075	22.52	0.012	24.51	0.06	0.042	11.00	0.018	38.39	0.52
5 High	15,084	0.040	14.92	0.011	33.29	0.08	0.011	3.54	0.014	44.26	0.53

Table 2 Cont'd

Panel B	Panel B1: Panel Regression for Each KZ Index Quintile						Panel B2: With Firm-fixed Effects				
		CF/A_{t-1}		Q_{t-1}			CF/A_{t-1}		Q_{t-1}		
KZ_{med}	Firm Year	*b*	*t-stat*	*c*	*t-stat*	R^2	*b*	*t-stat*	*c*	*t-stat*	R^2
1 Low	22,279	0.057	26.65	0.007	26.58	0.06	0.025	9.70	0.009	34.76	0.52
2	24,354	0.098	37.31	0.012	34.72	0.09	0.048	16.13	0.015	43.69	0.53
3	27,983	0.148	42.37	0.020	40.50	0.10	0.088	22.90	0.023	46.11	0.52
4	23,732	0.196	38.39	0.027	36.11	0.10	0.130	25.03	0.031	41.20	0.55
5 High	16,967	0.192	26.16	0.041	35.24	0.10	0.114	14.40	0.049	37.43	0.56
Panel C	Panel C1: Panel Regression for Each WW Index Quintile						Panel C2: With Firm-fixed Effects				
		CF/A_{t-1}		Q_{t-1}			CF/A_{t-1}		Q_{t-1}		
WW_{med}	Firm Year	*b*	*t-stat*	*c*	*t-stat*	R^2	*b*	*t-stat*	*c*	*t-stat*	R^2
1 Low	38,345	0.178	46.31	0.003	10.33	0.06	0.154	38.23	0.012	31.77	0.53
2	24,721	0.148	36.97	0.009	20.39	0.07	0.100	23.71	0.016	36.18	0.55
3	21,125	0.138	34.25	0.011	22.95	0.07	0.080	19.02	0.018	34.75	0.55
4	18,476	0.104	26.35	0.014	25.28	0.06	0.042	10.20	0.018	33.26	0.53
5 High	12,648	0.053	12.51	0.016	24.18	0.05	0.020	4.02	0.021	29.00	0.51
Panel D	Panel D1: Panel Regression for Each SA Index Quintile						Panel D2: With Firm-fixed Effects				
		CF/A_{t-1}		Q_{t-1}			CF/A_{t-1}		Q_{t-1}		
SA_{med}	Firm Year	*b*	*t-stat*	*c*	*t-stat*	R^2	*b*	*t-stat*	*c*	*t-stat*	R^2
1 Low	46,204	0.267	61.05	0.001	4.12	0.09	0.204	51.11	0.012	32.26	0.51
2	23,675	0.146	31.15	0.012	24.59	0.07	0.087	19.66	0.018	37.98	0.56
3	19,416	0.111	26.94	0.011	21.85	0.06	0.057	13.39	0.018	35.43	0.54
4	15,935	0.083	23.03	0.011	21.19	0.05	0.028	6.80	0.016	30.44	0.53
5 High	10,085	0.059	13.21	0.011	16.41	0.04	0.014	2.72	0.016	20.96	0.59

Table 3: ICFS Interacted with Initial AI and Financial Constraint Index

This table reports the results of investment regressions where the dependent variable is $Capex/A_t$ (corporate capital investment in year *t*) in Panel A and $(Capex + R\&D)/A_t$ (total capital and R&D investment) in Panel B, respectively. The main explanatory variables are CF/A_{t-1} (cash flow in year *t*-1), Q_{t-1} (Tobin's q in year *t*-1) and their interaction terms with Initial AI and time series medians for the KZ, WW, and SA indexes, respectively. The index variables enter in interaction terms with various combinations to generate eight different regression specifications. We control for firm-fixed effects to highlight within-firm financing behavior. All variables are standardized. The sample period is 1971-2012.

Panel A: Capital Investment as Dependent Variable

$Y = Capex/A_t$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CF/A_{t-1}	0.197	0.159	0.222	0.230	0.197	0.265	0.263	0.268
	(44.93)	(40.86)	(47.98)	(49.99)	(45.18)	(52.54)	(53.34)	(53.01)
CF/A_{t-1}*Initial AI	-0.062				-0.052	-0.061	-0.055	-0.047
	(-26.44)				(-22.12)	(-26.05)	(-23.32)	(-19.58)
$CF/A_{t-1}*KZ_{med}$		0.060			0.043			0.049
		(14.73)			(10.36)			(11.60)
$CF/A_{t-1}*WW_{med}$			-0.124			-0.118		-0.058
			(-26.81)			(-25.49)		(-7.14)
$CF/A_{t-1}*SA_{med}$				-0.133			-0.118	-0.073
				(-31.08)			(-27.56)	(-9.77)
Q_{t-1}	0.261	0.271	0.216	0.214	0.316	0.237	0.237	0.292
	(65.63)	(83.59)	(66.24)	(63.84)	(75.07)	(58.55)	(58.17)	(66.77)
Q_{t-1}*Initial AI	-0.022				-0.017	-0.021	-0.022	-0.014
	(-13.60)				(-10.50)	(-12.70)	(-13.08)	(-8.42)
$Q_{t-1}*KZ_{med}$		0.111			0.112			0.105
		(36.80)			(35.54)			(31.85)
$Q_{t-1}*WW_{med}$			0.057			0.059		0.028
			(17.34)			(18.01)		(4.35)
$Q_{t-1}*SA_{med}$				0.039			0.045	-0.003
				(11.48)			(13.01)	(-0.54)
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Years	92,552	92,552	92,552	92,552	92,552	92,552	92,552	92,552
R^2	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.56

Table 3 Cont'd

Panel B: Total Capital and R&D Investment as Dependent Variable								
$Y=(Capex+R\&D)/A_t$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CF/A_{t-1}	0.044	0.005	0.042	0.060	0.046	0.091	0.100	0.100
	(12.19)	(1.70)	(10.90)	(15.77)	(12.83)	(21.84)	(24.43)	(23.92)
CF/A_{t-1}*Initial AI	-0.063				-0.052	-0.062	-0.057	-0.046
	(-32.36)				(-26.40)	(-32.05)	(-29.23)	(-23.37)
$CF/A_{t-1}*KZ_{med}$		0.083			0.065			0.066
		(24.59)			(19.11)			(18.84)
$CF/A_{t-1}*WW_{med}$			-0.085			-0.081		-0.008
			(-22.11)			(-21.14)		(-1.25)
$CF/A_{t-1}*SA_{med}$				-0.112			-0.099	-0.091
				(-31.64)			(-27.85)	(-14.74)
Q_{t-1}	0.255	0.276	0.234	0.228	0.297	0.238	0.234	0.278
	(77.42)	(102.68)	(86.50)	(82.27)	(85.35)	(70.85)	(69.48)	(76.79)
Q_{t-1}*Initial AI	-0.010				-0.006	-0.009	-0.010	-0.004
	(-7.34)				(-4.49)	(-6.70)	(-7.06)	(-3.12)
$Q_{t-1}*KZ_{med}$		0.081			0.083			0.079
		(32.65)			(31.87)			(28.93)
$Q_{t-1}*WW_{med}$			0.045			0.045		0.007
			(16.36)			(16.71)		(1.36)
$Q_{t-1}*SA_{med}$				0.039			0.041	0.015
				(13.77)			(14.37)	(2.78)
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Years	92,552	92,552	92,552	92,552	92,552	92,552	92,552	92,552
R^2	0.58	0.58	0.58	0.58	0.59	0.58	0.58	0.59

Table 4: Firm Variables for Each Initial-AI Quintile

This table reports annual average values of corporate finance variables for each Initial-AI quintile. These reported variables stand for growth-type characteristics (Panel A), indexes for financial constraints and some component characteristics (Panel B), investment, growth in assets and sales, and profitability profile (Panel C), and cash flow, cash holdings, financing arrangement, and investment style (Panel D). Asymmetric informational imperfection on growth (AI) is defined as growth uncertainty or the standard deviation of 12 monthly firm market-to-book ratios in a year. Initial AI is the time-series average of AI over year 0, 1 and 2, where year 0 is the first year of a firm's data report in the total sample. A firm's AI reflects its growth-type. The initial growth-type quintiles are based on a single cross-firm sort on Initial AI in the full sample. Alternatively, a two-way sort on initial annual market-to-book ratio (M/B) and initial asset tangibility or collaterals (Tangibility) is used to generate three growth-type groups with low- (G1), mixed- (G2) and high-growth (G3). The annual average value for G1, G2 or G3 dummies means the percent of G1, G2 or G3 firms in each Initial-AI quintile. The annual average value for AI, the KZ, WW, SA index, and each of the other variables is calculated using the Fama-MacBeth method, namely, a cross-firm average within each Initial-AI quintile each year followed by a time-series average of the annual averages over the sample period. Investyle$_t$ is R&D/(Capex+R&D)$_t$, a proxy for investment style. The variables are defined in Appendix. The sample period is from 1971 to 2012.

	Panel A: Growth-type Characteristics						
Initial AI	N	AI$_t$	G1	G2	G3	M/B$_t$	Tangibility$_t$
1 Low	2163	0.07	76.8%	22.8%	0.4%	0.84	0.58
2	2163	0.13	50.1%	42.6%	7.3%	1.06	0.53
3	2163	0.21	16.1%	47.1%	36.8%	1.39	0.47
4	2163	0.36	1.6%	38.8%	59.6%	1.99	0.41
5 High	2163	0.66	0.0%	25.2%	74.8%	2.92	0.35
	Panel B: Indexes and Some Characteristics for Financial Constraints						
Initial AI	KZ$_t$	WW$_t$	SA$_t$	Leverage$_t$	DivPayer$_t$	LnA$_t$	AGE$_t$
1 Low	0.66	-0.93	-3.41	0.32	64.6%	20.07	13.92
2	0.45	-0.89	-3.13	0.28	47.8%	19.26	10.49
3	0.12	-0.86	-2.94	0.22	36.3%	18.71	8.88
4	-0.32	-0.86	-2.84	0.16	29.8%	18.54	7.50
5 High	-0.76	-0.85	-2.74	0.13	26.0%	18.22	6.69
	Panel C: Tangible & Intangible Investment, Asset & Sales Growth, and Profitability Profile						
Initial AI	Capex/A$_t$	R&D/A$_t$	ΔA/A$_{t-1}$	ΔS/S$_{t-1}$	E/A$_t$	E/A$_t$ <0	E/A$_t$ >0
1 Low	6.6%	0.8%	10.4%	10.9%	12.0%	-6.3%	12.8%
2	7.3%	1.4%	16.0%	15.1%	13.3%	-7.8%	14.8%
3	7.7%	3.1%	23.7%	21.5%	12.5%	-12.7%	15.9%
4	7.6%	6.6%	31.6%	28.7%	10.4%	-17.5%	17.5%
5 High	7.2%	8.2%	48.2%	43.5%	6.7%	-21.8%	19.3%
	Panel D: Cash Flow, Cash Holdings, Financing Mix, and Investment Style						
Initial AI	CF/A$_t$	Cash/A$_t$	(1)ΔRE/A$_t$	(2)ΔDebt/A$_t$	(3)ΔEquity/A$_t$	(3)–(2)	Investyle$_t$
1 Low	7.0%	6.7%	0.8%	1.1%	0.5%	-0.5%	9.6%
2	7.8%	9.1%	1.4%	1.3%	1.5%	0.3%	13.8%
3	6.9%	14.0%	0.6%	1.5%	3.3%	1.9%	21.9%
4	4.7%	22.6%	-1.7%	1.3%	6.1%	4.9%	34.5%
5 High	0.6%	30.7%	-5.5%	1.4%	10.0%	8.7%	40.7%

Table 5: Transition Matrix for Annual AI and Investyle

This table shows the total frequencies at which a firm in an initial firm group transits to the five annually updated firm groups over time. Panel A is the transition matrix for annual AI, which contains information about growth type. Firms are re-sorted into quintiles according to annual AI each calendar year. Panel B is the transition matrix for Investyle defined as R&D/(Capex+R&D) as a proxy for investment style or growth-type fundamental. Firms that report zero R&D initially account for 52% of the total sample. The zero-R&D firms are in Investyle group 1 (Low) and the remaining firms which report positive R&D are sorted into quartiles (group 2 – group 5, High) according to Investsyle. The five Investyle firm groups are re-sorted each calendar year. Total frequencies sum up to 100% (horizontally) across the five updated firm groups. The sample period is 1971-2012.

	Panel A: Annually Updated AI_t or Growth-type				
Initial	1 Low	2	3	4	5 High
1 Low	**49%**	28%	15%	6%	1%
2	21%	**27%**	27%	19%	6%
3	10%	19%	**25%**	28%	19%
4	5%	11%	18%	**28%**	39%
5 High	2%	6%	12%	23%	**58%**
	Panel B: Annually Updated $Investyle_t = R\&D_t/(Capex_t + R\&D_t)$				
Initial	1 Low	2	3	4	5 High
1 Low	**94%**	3%	1%	1%	0%
2	28%	**46%**	19%	6%	2%
3	7%	20%	**34%**	26%	12%
4	5%	4%	20%	**35%**	36%
5 High	1%	2%	6%	22%	**69%**

Table 6: A Growth-type-aligned Pattern in External Finance with Changing Market Condition

This table shows results of regressions in which the dependent variable, external financing differential (EFD), is $\Delta Equity/A_t - \Delta Debt/A_t$ which measures the extent to which equity dominates over debt in external finance. The one-year lagged explanatory variables include growth type in Panel A (AI for growth type) and growth-type fundamental in Panel B (Investyle for growth-type fundamental), market-to-book ratio, M/B, and other controls. We also include interactions terms with growth-type varibles. Regression (1) is a standard panel regression. Regression (2) replaces annual growth-type variable in regression (1) with initial value variable, namely, AI with Initial AI (Panel A), and Investyle with Initial Investyle (Panel B), where the initial value is a within-firm average over year 0, 1 and 2. We use the two-way cluster correction for standard errors as suggested by Petersen (2009) for the panel regressions (1) and (2). Regression (3) is the same as regression (1) but with firm fixed effects. The sample period is 1971-2012.

$Y=EFD_t=$	(1) Pooled OLS		(2) Initial Value		(3) Firm Fixed Effect	
$\Delta Equity/A_t - \Delta Debt/A_t$	*Coef.*	*t-stat*	*Coef.*	*t-stat*	*Coef.*	*t-stat*
	Panel A: Growth-type (AI) Effect					
Intercept	0.069	(4.95)	0.072	(4.61)		
AI_{t-1}	0.343	(6.54)	0.209	(6.99)	0.348	(18.90)
M/B_{t-1}	0.018	(7.51)	0.017	(8.87)	0.013	(16.66)
$M/B_{t-1}*AI_{t-1}$	-0.001	(-1.07)	0.000	(-0.22)	0.002	(3.70)
$Tangibility_{t-1}$	0.006	(1.08)	0.008	(1.65)	-0.005	(-0.86)
$Tangibility_{t-1}*AI_{t-1}$	0.001	(0.05)	0.000	(0.04)	-0.008	(-0.94)
E/A_{t-1}	-0.253	(-13.53)	-0.282	(-13.41)	-0.198	(-33.04)
$E/A_{t-1}*AI_{t-1}$	-0.041	(-3.51)	-0.025	(-1.57)	-0.025	(-5.25)
LnA_{t-1}	-0.003	(-4.07)	-0.003	(-4.00)	-0.009	(-14.50)
$LnA_{t-1}*AI_{t-1}$	-0.020	(-6.86)	-0.011	(-6.97)	-0.020	(-22.04)
$Cash/A_{t-1}$	-0.030	(-3.44)	-0.011	(-1.25)	-0.112	(-18.88)
$Cash/A_{t-1}*AI_{t-1}$	0.048	(2.75)	-0.003	(-0.29)	0.040	(5.52)
Firm-years		115,315		115,315		115,315
R^2		0.16		0.16		0.32
	Panel B: Investment Style (Investyle) or Growth-type Fundamental Effect					
Intercept	0.097	(6.10)	0.090	(5.87)		
$Investyle_{t-1}$	0.152	(5.26)	0.222	(6.61)	0.478	(14.58)
M/B_{t-1}	0.006	(2.91)	0.007	(3.12)	0.005	(7.19)
$M/B_{t-1}*Investyle_{t-1}$	0.021	(7.83)	0.021	(6.68)	0.021	(17.01)
$Tangibility_{t-1}$	-0.007	(-1.30)	-0.007	(-1.46)	-0.029	(-4.92)
$Tangibility_{t-1}*Investyle_{t-1}$	0.090	(5.14)	0.098	(4.88)	0.067	(4.40)
E/A_{t-1}	-0.161	(-8.43)	-0.168	(-8.74)	-0.153	(-21.20)
$E/A_{t-1}*Investyle_{t-1}$	-0.239	(-9.53)	-0.251	(-10.31)	-0.135	(-11.78)
LnA_{t-1}	-0.004	(-5.61)	-0.004	(-5.26)	-0.008	(-12.09)
$LnA_{t-1}*Investyle_{t-1}$	-0.010	(-6.16)	-0.014	(-7.39)	-0.027	(-16.67)
$Cash/A_{t-1}$	-0.036	(-3.80)	-0.033	(-3.50)	-0.082	(-11.64)
$Cash/A_{t-1}*Investyle_{t-1}$	0.008	(0.53)	0.005	(0.29)	-0.034	(-2.68)
Firm-years		115,315		115,315		115,315
R^2		0.17		0.17		0.32

Table 7: ICFS Interacted with Investment Style and Financial Constraint

This table reports the results of investment regressions where the dependent variable is Capex/A_t (corporate capital investment in year t) in both Panel A and B. The main explanatory variables are CF/A_{t-1} (cash flows in year t-1), Qt-1 (Tobin's q in year t-1) and their interaction terms with growth-type fundamental (investment style) and the KZ, WW and SA indexes (financial constraints), respectively. Panel A is exactly the same as Panel A of Table 3 except Initial AI is replaced with Initial Investyle where Investyle is annual R&D/(Capex+R&D) which measures investment style as growth-type fundamental. The initial value is a within-firm average over year 0, 1 and 2. Panel B allows time-varying Investyle as well as annual KZ, WW and SA indexes (financial constraints), all lagged one year. These index variables enter in interaction terms with various combinations to generate eight different regression specifications. All variables are standardized. To save space in Panel B, estimates for non-interaction terms except for CF/A_{t-1} and Q_{t-1} are not reported. The sample period is 1971-2012.

Panel A: Initial Investment Style

Y=Capex/A_t	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CF/A_{t-1}	0.212	0.159	0.222	0.230	0.211	0.268	0.264	0.269
	(46.88)	(40.86)	(47.98)	(49.99)	(47.09)	(52.84)	(53.47)	(53.16)
CF/A_{t-1}*Initial Investyle	-0.110				-0.102	-0.104	-0.094	-0.087
	(-33.84)				(-29.61)	(-32.05)	(-28.52)	(-24.66)
CF/A_{t-1}*KZ_{med}		0.060			0.019			0.029
		(14.73)			(4.34)			(6.65)
CF/A_{t-1}*WW_{med}			-0.124			-0.102		-0.052
			(-26.81)			(-22.29)		(-6.44)
CF/A_{t-1} *SA_{med}				-0.133			-0.102	-0.063
				(-31.08)			(-23.79)	(-8.42)
Q_{t-1}	0.293	0.271	0.216	0.214	0.339	0.272	0.271	0.317
	(77.42)	(83.59)	(66.24)	(63.84)	(84.95)	(70.89)	(70.57)	(76.83)
Q_{t-1}*Initial Investyle	-0.091				-0.076	-0.092	-0.096	-0.079
	(-32.58)				(-27.21)	(-32.95)	(-34.24)	(-27.41)
Q_{t-1}*KZ_{med}		0.111			0.103			0.094
		(36.80)			(32.77)			(28.31)
Q_{t-1}*WW_{med}			0.057			0.065		0.020
			(17.34)			(20.04)		(3.15)
Q_{t-1}*SA_{med}				0.039			0.058	0.018
				(11.48)			(16.86)	(2.77)
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Years	92,552	92,552	92,552	92,552	92,552	92,552	92,552	92,552
R^2	0.55	0.55	0.55	0.55	0.56	0.56	0.56	0.56

Table 7 Cont'd

Panel B: Time Varying Growth-type Fundamental and Financial-constraint Indexes								
$Y=Capex/A_t$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CF/A_{t-1}	0.211	0.137	0.144	0.172	0.190	0.201	0.206	0.185
	(47.17)	(34.97)	(35.72)	(37.85)	(42.46)	(44.17)	(42.29)	(37.88)
$CF/A_{t-1}*Investyle_{t-1}$	-0.111				-0.099	-0.108	-0.079	-0.071
	(-35.13)				(-31.48)	(-34.25)	(-25.37)	(-22.86)
$CF/A_{t-1}*KZ_{t-1}$		0.011			0.007			0.011
		(4.92)			(3.26)			(4.76)
$CF/A_{t-1}*WW_{t-1}$			0.010			0.010		0.008
			(4.49)			(4.51)		(3.43)
$CF/A_{t-1}*SA_{t-1}$				-0.055			-0.046	-0.041
				(-17.10)			(-14.16)	(-11.60)
Q_{t-1}	0.266	0.252	0.236	0.173	0.286	0.269	0.218	0.237
	(72.59)	(71.01)	(73.98)	(48.79)	(70.84)	(73.57)	(55.88)	(55.12)
$Q_{t-1}*Investyle_{t-1}$	-0.080				-0.072	-0.077	-0.086	-0.080
	(-28.89)				(-26.45)	(-28.14)	(-32.15)	(-29.90)
$Q_{t-1}*KZ_{t-1}$		0.041			0.052			0.044
		(31.72)			(27.68)			(23.55)
$Q_{t-1}*WW_{t-1}$			0.013			0.010		0.000
			(8.01)			(6.34)		(0.06)
$Q_{t-1}*SA_{t-1}$				0.038			0.044	0.045
				(13.30)			(15.64)	(14.86)
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Years	90,418	90,418	90,418	90,418	90,418	90,418	90,418	90,418
R^2	0.56	0.56	0.55	0.58	0.57	0.57	0.59	0.60