What Drives Negative Investment-Cash Flow Sensitivities? Revenue Effect Versus Corporate Life-Cycle Dynamics

Jochen Lawrenz [ORCID] · **Julia Oberndorfer**

Abstract In order to identify the economic driver of negative investment-cash flow sensitivities (ICFS), we derive testable predictions from extending a theoretical investment model with endogenous financing costs ("revenue effect") and contrast them with the corporate life-cycle hypothesis. We find that firms with (i) lower levels of long-term debt display stronger negative ICFS, and (ii) firms with more risky revenues invest more, which contradicts the predictions of the revenue effect. At the same time firms with strongly negative ICFS are (iii) smaller, (iv) younger and (v) have higher growth opportunities, which is consistent with the life-cycle hypothesis.

Keywords Investment-Cash Flow Sensitivity · Nonlinearities · Cost-Revenue Effect · Corporate Life-Cycle

MSC-Classification JEL classification · G31 · G32

✉ Jochen Lawrenz

Department of Banking and Finance, University of Innsbruck, Universitätsstraße 15, 6020 Innsbruck, Austria
E-Mail: jochen.lawrenz@uibk.ac.at

1 Introduction

Investment-cash flow sensitivities (ICFS) have attracted significant interest in the corporate finance literature and a growing number of contributions have documented empirical as well as theoretical evidence for non-linearities in the relationship between investment and cash flow (see e.g. Cleary et al. 2007; Guariglia 2008; Hovakimian 2009, or Lyandres 2007). In particular subsequent to the debate between Fazzari et al. (1988) and Kaplan and Zingales (1997), many contributions were putting their focus on the question *if* nonlinearities exist and if ICFS are useful for measuring financial constraints. In contrast, only little attention has been paid sofar to the question *why* nonlinearities occur and which economic mechanism is driving them.[1] We address this latter question by shedding new empirical as well as theoretical light in particular on the negative part of the investment-cash flow relationship. We do so by discriminating between two prominent explanations for a negative ICFS in the recent literature. On the one hand, Cleary et al. (2007) is a prominent contribution which put forward a model of a U-shaped investment curve where the negative ICFS is driven by the following economic mechanism: Firms with low internal funds prefer to invest more since their financing costs actually decrease due to the fact that creditors (as senior claimholders) are increasingly likely to capture the corresponding investment return in case of a default. This mechanism has been labeled the *revenue effect*. On the other hand, Hovakimian (2009) argues that the negative ICFS for low internal funds is likely to be the result of a corporate life-cycle pattern: In an early stage of the life-cycle, firms tend to display both, low (even negative) cash flows as well as high investments. A negative relationship between both variables then follows from their tendency to develop in opposite directions as the firm matures. Our empirical identification strategy to discriminate between both hypotheses builds upon the model of Cleary et al. (2007). While we adopt their basic model formulation, our innovation is to formulate and prove two empirically relevant extensions, which yield novel model predictions. Testing them on a comprehensive data sample – which covers in particular also small- and medium-sized enterprises – uncovers the following main result of our analysis: Although we do find a U-shaped investment curve similar to Cleary et al. (2007), we find no convincing evidence that supports the investment revenue effect, while we can largely confirm the life-cycle hypothesis of Hovakimian (2009).

More specifically, we contribute in the following ways to the existing literature. First, in order to derive testable predictions and to disentangle between the revenue effect and the corporate life-cycle effect, we extend the theoretical model by Cleary et al. (2007) along two dimensions: We show how ICFS vary with (i) the extent of a firm's senior debt financing, and (ii) the riskiness of firm's revenues. Both aspects are also directly related to the corporate life-cycle hypothesis, as smaller and younger firms with higher growth opportunities tend to display lower senior debt ratios and higher levels of revenue risk. We take both model predictions to the

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[1] As Kaplan and Zingales (2000) themselves note: "*FHP's [2000] defense of investment-cash flow sensitivities as measures of financial constraints distracts attention from the more important question: what causes this sensitivity? We do not pretend to have given an answer to this.*" Kaplan and Zingales (2000) p. 711.

data and find contradictory results regarding the cost-revenue effect. Second, testing the corporate life-cycle hypothesis necessitates a dataset which covers companies in their early stages. Therefore, relying on the standard Compustat universe, as it is done in many studies (see e.g. Cleary et al. 2007; Ağca and Mozumdar 2008), runs into severe limitations as it covers predominantly the segment of large mature US firms.[2] In contrast, to circumvent these limitations, we test our hypothesis on a comprehensive German dataset that explicitly covers the SME segment. We obtain a data sample of 75,692 firm year observations (after data cleansing) out of which approximately 65% can be classified as SME. We show that the evidence for non-linear ICFS is substantially stronger within the subset of SME companies. Thus, we find strong support for the arguments in Hovakimian (2009). By using a German dataset, we also add to the literature on international evidence on ICFS such as in Pawlina and Renneboog (2005) for UK data, Bertoni et al. (2010) for Italian evidence or Moshirian et al. (2017) for a global comparison. Third, by running spline regressions similar to Cleary et al. (2007), we confirm the nonlinear relationship of capital expenditures with internal funds more generally. Thereby we complement and strengthen the mounting evidence for negative ICFS as already documented in various papers (see e.g. Allayannis and Mozumdar 2004; Cleary et al. 2007; Ağca and Mozumdar 2008; Hovakimian 2009).

Since the Cleary et al. (2007) model has received significant attention and is used amongst others in Chowdhury et al. (2016), our results imply that their model setup has to be used cautiously. To be clear, our results by no means invalidate the consistency of their model. However, they strongly question the interpretation that the revenue effect is a first-order explanation for the negative ICFS in the real data.

There exists a large bunch of literature on ICFS with a focus on financial constraints which displays partly conflicting results. On the one hand there is evidence of a positive correlation between cash flow and investment among financially constrained companies. For instance, Fazzari et al. (1988) and many subsequent studies such as e.g. Carpenter et al. (1998); Guaraglia (1998), or Carpenter and Petersen (2002), find that firms with low-dividend payout ratios have positive investment-cash flow sensitivities. On the contrary, Kaplan and Zingales (1997) showed that the investment rates of financially *un*constrained firms exhibit a higher sensitivity to cash flow than the ones of financially constrained firms, thereby suggesting that ICFS should be used with caution when predicting financial constraints. Following the debate, one can easily ascertain that the dissimilarities in results can be attributed to the differences in the sub-samples used. While Fazzari et al. (1988) applied capital market imperfections to divide firms into sub-samples of financial constraints, Kaplan and Zingales (1997) used financial ratios that are highly correlated with internal funds. Subsequent to this debate, a prominent model by Cleary et al. (2007) proposes a theoretical model as well as empirical support which shows that investment is rather U-shaped in internal funds. With this model they are – amongst others – able to reconcile the conflicting results of Fazzari et al. (1988) and Kaplan and Zingales (1997).

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[2] As also mentioned by Cleary et al. (2007), it is challenging to define good proxies for capital market imperfections that have cross-sectional variability by using Compustat data.

It is important to recognize, that the economic mechanism which drives the U-shape is given by what they call the tradeoff between the cost and the revenue effects of investment. To put it simply, the negative ICFS for low level of internal funds derives from the fact that (within the model) the investor (i.e. creditor) will benefit to a larger extent from additional investments in the firm, the closer the firm gets to default because the creditor as senior claimholder will then capture the investment return. While Cleary et al.'s (2007) model setup follows a fairly standard textbook description of debt contracts, it is ultimately an empirical question if it describes a first-order effect in real-world decision-making.

An alternative explanation for a U-shaped investment curve has been put forward by Hovakimian (2009), who argues that the negative ICFS for low internal funds is caused by the corporate life-cycle pattern. At an early stage of the business life-cycle, firms tend to have both, low cash flows and high investment opportunities, which then tend to develop in opposite directions. The empirical results in Hovakimian (2009) as well as in Hovakimian and Hovakimian (2009) are strongly supporting her line of reasoning.

By considering these two competing rationales in the literature, the question arises which effect prevails and drives the nonlinearities in ICFS in a data sample containing both SMEs and large-sized firms. Our analysis attempts to contribute to the clarification of this particular question. Our focus is thereby on a cross-sectional perspective and does not address the temporal variation in ICFS, such as Ağca and Mozumdar (2008); Brown and Petersen (2009) and recently Christodoulou and Artem Prokhorov (2022) who discuss the apparently declining evidence for ICFS.

The remainder of the paper is structured as follows. Sect. 2 formulates the extensions of the theoretical model by Cleary et al. (2007) and derives testable predictions. Sect. 3 presents the empirical analysis, including the strategy, the summary statistics and the results. Finally, Sect. 4 concludes. Proofs and further methodological details are contained in the Appendices.

2 Testable model predictions

This section outlines the derivation of our empirical hypotheses. To clearly identify the economic mechanism and to derive testable predictions, we review briefly the Cleary et al. (2007) model.[3] We then develop and proof two extensions to the model, which are able to yield testable hypotheses which can discriminate between the cost-revenue and the life-cycle hypothesis. To fix notation, consider a firm with access to a scalable investment opportunity I, that yields a return of $F(I, \theta)$ which depends on the state variable θ (say, e.g. random demand) being distributed on $[\underline{\theta}, \bar{\theta}]$ with pdf (cdf) $\omega(\theta)$ ($\Omega(\theta)$). The firm has internal funds of W and finances the remaining $I - W$ through a debt contract.[4] The firm defaults if θ realizes below

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[3] We only provide a sketch. For details of the model, we refer the reader to Cleary et al. (2007) and to the working paper version Povel and Raith (2001).

[4] Cleary et al. (2007) provide a proof that the debt contract is the optimal financing arrangement in their setup.

a critical threshold $\widehat{\theta}$, which in turn is determined by the (nominal) amount of debt financing D. In case of default, the firm will be either liquidated at the current market value of assets L or is allowed to continue as going-concern with the former owners in which case the assets have a value of π_2, with $\pi_2 > L$. The difference $\pi_2 - L$ can be interpreted either as private benefits of owners which are lost in default or as bankruptcy costs. Investors' (break-even) participation constraint is therefore given by:

$$\int_{\underline{\theta}}^{\widehat{\theta}} \left(F(I, \theta) + \frac{D - F(I, \theta)}{\pi_2} L \right) \omega(\theta)\mathrm{d}\theta + \left((1 - \Omega(\widehat{\theta})) \right) D = I - W. \qquad (1)$$

The second term of the integrand represents the liquidation value L which is multiplied with the probability of liquidation which is $(D - F(I, \theta))/\pi_2$ and which follows from deriving the optimal debt contract for a situation of non-verifiable project returns such as in Diamond (1984) or Bolton and Scharfstein (1990). The LHS of (1) represents the expected payoff to investors which has to equal the provided investment amount $I - W$ in order to break-even. However, note that the liquidation value L is not crucial to results and may be set to zero without changing the qualitative implications of the model.[5] It is only important that $L < \pi_2$, which represents the threat for existing owners to loose their private benefits in the case of liquidation and which guarantees that owners repay creditors truthfully.

The payoff to owners in solvent states is simply the project returns plus their additional private benefits net of debt cost, i.e. $F(I, \theta) + \pi_2 - D$. In default states, the owners repay investors in full and retain their private benefits π_2 only in case of continuation, which happens with probability $1 - (D - F(I, \theta))/\pi_2$. The owners objective function is therefore

$$\int_{\underline{\theta}}^{\widehat{\theta}} \left(1 - \frac{D - F(I, \theta)}{\pi_2} \right) \pi_2 \omega(\theta)\mathrm{d}\theta + \int_{\widehat{\theta}}^{\bar{\theta}} (F(I, \theta) - D + \pi_2)\omega(\theta)\mathrm{d}\theta \qquad (2)$$
$$\Leftrightarrow \mathbb{E}(F(I, \theta)) + \pi_2 - D(I, W),$$

which is optimized over investment volume I and debt amount D (or equivalently the default threshold $\widehat{\theta}$) given its level of internal funds W.[6] The constraint maximization program in (1)-(2) yields the optimal pair $(I^*, \widehat{\theta}^*)$, which can be considered as a function of W and therefore plotted against the exogenous W. Cleary et al. (2007) show that under fairly general conditions the graph of I^* is convex, or more precisely U-shaped in W, which they term the U-shaped investment curve.

It is important to recognize from (1) that debt financing costs are directly affected by the investment decision of the firm. As the first term on the LHS shows, creditors capture the investment returns in distress states (plus an additional liquidation value

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[5] See Cleary et al. (2007), p. 12. Since the difference $\pi_2 - L$ can be considered as bankruptcy costs, this implies, that the model's prediction are robust to the level of bankruptcy costs.

[6] We use $\mathbb{E}$ as expectation operator, i.e. $\mathbb{E}(F(I, \theta)) = \int_{\underline{\theta}}^{\bar{\theta}} F(I, \theta)\omega(\theta)\mathrm{d}\theta$.

independent of investment). This dependence on the investment return is called the *revenue* effect. In the extreme case of imminent bankruptcy (i.e. as $\widehat{\theta} \to \bar{\theta}$), creditors are essentially the new entrepreneurs and thus optimal investment will be first-best. Therefore, the revenue effect essentially makes expected (marginal) debt financing costs, and thus also the optimal investment, non-monotonic in internal funds. In particular, it displays a negative ICFS for low or negative values of internal funds.

The Cleary et al. (2007) model is consistent with empirical evidence in the sense of being able to generate the U-shaped investment curve. However, other models such as Hovakimian (2009) or Lyandres (2007) are also consistent with the U-shape. So, to discriminate between explanatory hypotheses and to derive further testable predictions, we need to extend the Cleary et al. (2007) model. While we follow the basic model setup of Cleary et al. (2007), our innovation is to provide extensions in two directions. As we want to disentangle between the cost-revenue effect by Cleary et al. (2007) and the corporate life-cycle hypothesis by Hovakimian (2009), we implement testable predictions that are also relevant for the corporate life-cycle hypothesis. First, we allow for different degrees of riskiness of the investment return, and second, we introduce outstanding senior debt.[7] Firms at an earlier stage of their life-cycle tend to exhibit more risky revenues, while their long-term debt ratios tend to be lower.

Model extensions and predictions   With respect to the riskiness, it is natural to analyze the change in the ICFS given a change in the variance of θ by holding constant its mean; i.e. for a mean-preserving spread applied to $\omega(\theta)$. To be consistent with Cleary et al. (2007), we adopt the same parametric specification, where $F(I, \theta) = \theta \sqrt{I}$ and θ is uniformly distributed, i.e. $\theta \sim U[\underline{\theta}, \bar{\theta}]$. For the uniform distribution, it is obvious that variance is governed by the choice of $\underline{\theta}$ and $\bar{\theta}$, so we denote μ as its mean $E(\theta)$ and define $\underline{\theta} = \mu - \delta$ and $\bar{\theta} = \mu + \delta$, so δ represents the standard deviation of θ. As we prove in Appendix A.1, it can be shown that the default threshold $\widehat{\theta}$ increases with δ (i.e. $\mathrm{d}\widehat{\theta}/\mathrm{d}\delta > 0$), which makes the investor more sensitive to the investment return in the default states. The reasoning behind the relationship appears straightforward. Higher risk makes debt financing generally more expensive, i.e. investors demand a higher repayment for the additional risk in revenues thereby increasing the sensitivity of financing costs with respect to investment returns. More formally, we prove the following model prediction:

Prediction 1a: *As the riskiness of the state variable increases in the sense of a mean-preserving spread, the ICFS (I_W) always decreases, i.e.* $\frac{\mathrm{d}I_W}{\mathrm{d}\delta} < 0$.

Furthermore, from the property of prediction 1a, it directly follows that the average investment decreases with risk, i.e. for a given investment curve, an increase in risk

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[7] Cleary et al. (2007) extend their basic model by allowing for information asymmetry. We refrain from pursuing this direction, since it is notoriously difficult to identify clear empirical proxies for information asymmetry.
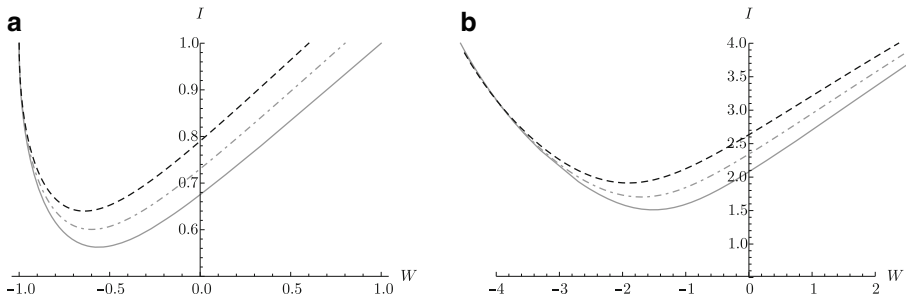
Fig. 1 Riskiness and the U-shaped investment curve. Notes: The graphs plot the investment curve $I(W)$ for different levels of risk. The left panel uses the parameter set of Cleary et al. (2007) with θ being uniformly distributed, i.e. $\theta \sim U[\underline{\theta}, \bar{\theta}]$, with $\underline{\theta} = \mu - \delta$ and $\bar{\theta} = \mu + \delta$, where $\mu = 2$ and $\delta = 2$ (solid line), $\delta = 1.8$ (gray dashed line), $\delta = 1.6$ (thick black line). The right panel uses an alternative parametric assumption with θ being lognormally distributed, i.e. $\theta \sim LogN(m, s^2)$ with $m = \{1; .895; .78\}$ and $s = \{1; 1.1; 1.2\}$ leading to a constant $E(\theta) = e^{(3/2)}$ for all three graphs but increasing variance. Again, the thick black line corresponds to the lowest level of risk

leads to an investment curve which always lies below the initial one. We summarize this as Prediction 1b:

Prediction 1b: *As the riskiness of the state variable increases in the sense of a mean-preserving spread, the investment curve always decreases, i.e. for $\delta' > \delta$, $I(W, \delta') < I(W, \delta), \forall W$.*

Proofs are in Appendix A.1. We illustrate the predictions numerically in Fig. 1 by using the same parameter set as Cleary et al. (2007) in the left panel (θ being uniformly distributed) and using an alternative specification (θ being lognormally distributed) in the right panel. In both panels of Fig. 1, the solid (gray) line displays the curve with the highest level of risk, while the bold dashed line represents the curve with the lowest level of risk. As implied by the proofs of our predictions, Fig. 1 clearly shows that a higher riskiness (i.e. higher δ or s) of the underlying state variable θ leads to a higher convexity of the investment curve, i.e. the curve is steeper when the investment-cash flow sensitivity is negative. Furthermore, the overall level of investment decreases with riskiness as well, in line with the intuition from the theoretical model. Note that in the left graph of Fig. 1, the solid line represents the benchmark case of Cleary et al. (2007).

Note further, that the life-cycle hypothesis relies on the idea that younger firms tend to invest (proportionally) more while being at the same time exposed to a larger extent of business risk. As they mature, they tend to be able to consolidate their revenue streams and thus become safer. Empirically, this tendency would manifest as a (cross-sectionally) positive relation between risk and investment level.

Next, we turn to the second model extension concerning the pre-existence of senior debt. We modify the Cleary et al. (2007) model in a straightforward way by assuming that the firm has already senior debt outstanding, denoted by D^s. The investment will be financed by junior debt, D^j, so that total nominal debt equals: $D = D^s + D^j$. We assume that strict seniority is enforced, so that from both, the
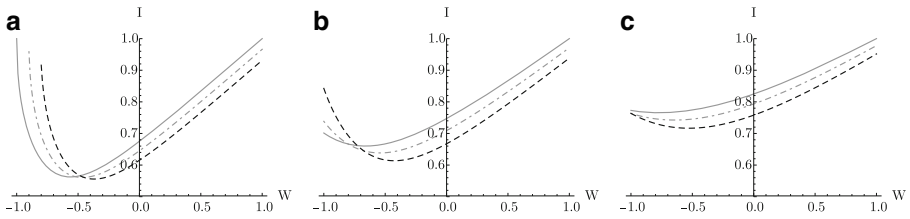
Fig. 2 Senior debt and the U-shaped investment curve. Notes: The graphs plot the investment curve $I(W)$ for different levels of existing senior debt, and by using the parameter set of Cleary et al. (2007) with θ being uniformly distributed, i.e. $\theta \sim U[0,4]$. In all three panels we display three levels of senior debt: $D^s = 0$ (gray solid line), $D^s = 0.1$ (gray dashed line), and $D^s = 0.2$ (thick black line). Across panels we vary the liquidation value L, with $L = 0$ (**a**), $L = 0.5$ (**b**), and $L = 1$ (**c**).

investment return $F(I, \theta)$ as well as the liquidation value L, junior lenders only obtain the residual, i.e. junior lenders' payoff is $\max(F(I, \theta) - D^s, 0)$ and $\max(L - D^s, 0)$ respectively. The junior investor's participation constraint is therefore:

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\int_{\underline{\theta}}^{\widehat{\theta}} \left(\max(F(I, \theta) - D^s, 0) + \frac{D - F(I, \theta)}{\pi_2} \max(L - D^s, 0)\omega(\theta) \right) d\theta \\
+ (1 - \Omega(\widehat{\theta}))D^j = I - W. \tag{3}
$$

Note that the critical (default) threshold $\widehat{\theta}$ follows from the condition that the firm is not able to meet total liabilities D out of their investment return, i.e. $\widehat{\theta}$ is implicitly defined from $D = F(I, \widehat{\theta})$.

In order to analyze the impact of senior debt D^s on the ICFS I_W, we again use the same specification as Cleary et al. (2007), with $F(I, \theta) = \theta\sqrt{I}$ and θ being uniform, i.e. $\theta \sim U[\underline{\theta}, \bar{\theta}]$. We provide a formal proof in Appendix A.2 and numerical illustrations in Fig. 2 of our second prediction.

Prediction 2: *A firm with a larger extent of existing senior debt displays a more negative ICFS (I_W).*

The proof in Appendix A.2 shows among others that the critical threshold $\widehat{\theta}$ always increases with D^s, thereby making investors more sensitive to the investment return. The formal proof relies on the simplified model where we set the liquidation value L equal to zero,[8] while the numerical result in Fig. 2 also includes the case of $L > 0$. In all three graphs, the solid line represents zero senior debt and the bold dashed line represents a senior debt level of $D^s = 0.2$. The qualitative prediction remains the same for different levels of L and is even more pronounced for the (more realistic) case of $L > 0$. The convexity of the investment curve increases with senior debt when internal funds are low, i.e. the ICFS is more negative as implied

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[8] Cleary et al. (2007) have already noted that setting $L = 0$ does not affect the qualitative results.

by Prediction 2.[9] Note that in the left graph of Fig. 2, the solid line represents the benchmark case of Cleary et al. (2007). Note further, that from the perspective of the life-cycle hypothesis, we should expect an opposite prediction. Young firms, which tend to display a stronger ICFS, are less likely to be financed with large amounts of debt. In contrast, young growth firms are known to be rather equity-financed.

We next turn to the empirical testing.

3 Empirical analysis

3.1 Empirical strategy

To test the different predictions of the theoretical model empirically, we have to estimate investment-cash flow sensitivities which we operationalize as follows. We assess capital expenditures by using an error-correction model according to Bond et al. (2003); Mizen and Vermeulen (2005); Mulier et al. (2016) and Buca and Vermeulen (2017). The error-correction model goes back to Bean (1981) and was later taken up by Bond et al. (2003). In principle, the error-correction model links a long-run equilibrium relation of the capital stock with flexible short-run investment dynamics by using a regression model (Bond et al. 2003).[10]

We assume that capital markets are not frictionless in the sense that firms' investment decisions are not independent of its status of financial constraints. To account for these frictions as well as the nonlinearities in ICFS, we include operating cash flow (OCF) to the investment equation derived in Appendix B. Following Cleary et al. (2007), we use spline regressions, i.e. we divide our sample into terciles of OCF. The regression equation to test the model predictions empirically is as follows:

$$\frac{CAPEX_{i,t}}{K_{i,t-1}} = \alpha_1 \frac{CAPEX_{i,t-1}}{K_{i,t-2}} + \alpha_2 \frac{OCFT1_{i,t}}{K_{i,t-1}} + \alpha_3 \frac{OCFT2_{i,t}}{K_{i,t-1}} + \alpha_4 \frac{OCFT3_{i,t}}{K_{i,t-1}} \quad (4)$$
$$+ \alpha_5 \Delta \ln S_{i,t} + \alpha_6 \Delta \ln S_{i,t-1} + \alpha_7 (\ln K_{i,t-2} - \ln S_{i,t-2}) + v_t + v_i + \epsilon_{i,t},$$

where *OCFT1-OCFT3* represent the different terciles of operating cash flow of equal size to measure investment as a piecewise linear and continuous function of operating cash flow. We focus on operating cash flow as it is supposed to be unaffected by investment decisions. At first glance, using a flow variable in the empirical test appears at odds with the interpretation of the theoretical model which uses a stock variable. However, within a one-period model, the distinction into flow and stock variable is rather pointless, and there are important empirical drawbacks of using

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[9] Note that the case of $L > 0$ is consistent with the general interpretation of the model. For high values of L, the investor already gets some fixed value in default and is therefore less sensitive to the (additional) investment return $F(I, \theta)$. The lower sensitivity to investment returns makes the investment curve less convex, in particular less negative.

[10] For the derivation of the error correction model, see Appendix B as well as Bond et al. (2003); Mizen and Vermeulen (2005); Mulier et al. (2016) and Buca and Vermeulen (2017).

cash holdings as stock variable as cash holdings suffer from endogeneity concerns. In line with Cleary et al. (2007) and much of the ICFS literature, we use the flow variable OCF for our empirical strategy.[11]

$CAPEX_{i,t}$ is depreciation in year t plus the change in tangible fixed assets from year $t-1$ to year t. The replacement value of the capital stock is computed as $K_{i,t} = K_{i,t-1} \times (1-\delta) + CAPEX_{i,t}$. The first value of K is quantified by the starting observation of tangible fixed assets. The depreciation rate δ is set at a constant rate of 4.5%.[12] $\Delta \ln S_{i,t}$ is the change in log sales. $(\ln K_{i,t-2} - \ln S_{i,t-2})$ denotes the error-correction parameter and assesses the long-run equilibrium between the natural logarithm of capital and its target value proxied by the natural logarithm of total sales.

We estimate the baseline model (Eq. (4)) with different approaches: (i) Simple OLS, (ii) the within estimator to control for time invariant and unobservable firm-specific characteristics and (iii) the two-step first-difference GMM estimator with lagged variables in levels as instruments for the first differences of the explanatory variables to control for autocorrelation and for endogeneity problems as developed by Arellano and Bond (1991). All further regressions are exclusively estimated with the GMM estimator.[13] Finally, to account for business cycle fluctuations and other life-cycle effects, we include year dummies.

3.2 Data

For our empirical analysis we use the Creditreform database provided by Creditreform AG, which is a comprehensive firm database containing annual balance sheet and income statement data of active companies registered in Germany.[14] The time frame we observe lasts from 2007 to 2015. To moderate misspecification, firm-year observations with negative values of total assets, total sales, tangible fixed assets and so on were deleted. We eliminate companies from the banking, finance, insurance and real estate sector as well as utilities because of their differences in balance sheets and income statements. We additionally exclude all firms that have switched in their size classification, which is defined below, i.e. from SME to large or vice versa. Finally, we only retain firms in our sample with leastwise four consecutive available observations to have at least two observations per firm. To control for outliers and potential measurement error in the capital ratio we trim dependent and independent variables at the third percentile in both tails.[15] After data cleansing and filters, we end up with an unbalanced sample containing 75,692 firm year observations on

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[11] As a robustness check, we report the relationship between mean and median investment ratios to cash holdings in Appendix D.

[12] In robustness checks, we also estimate the model with different depreciation rates. Our results remain stable.

[13] We consider the two-step first-difference GMM estimator to be superior because it controls for unobserved firm-specific effects and the endogeneity of independent variables δ dynamic regression models.

[14] Creditreform AG is one of Europe's leading providers of global business information with core services like business intelligence and receivables management.

[15] To make sure that the results are robust, we also trim the data at the one percentile and rerun the regressions. Results remain similar.

Table 1 Summary statistics

Panel A: Overall sample

	Mean	25th Pct.	Median	75th Pct.	Std.Dev.	N
$\frac{CAPEX_{i,t}}{K_{i,t-1}}$	0.156	0.048	0.101	0.187	0.208	75,692
$\frac{OCF_{i,t}}{K_{i,t-1}}$	0.494	0.116	0.233	0.505	1.011	75,692
$\frac{OCFT1_{i,t}}{K_{i,t-1}}$	0.112	0.116	0.169	0.169	0.175	75,692
$\frac{OCFT2_{i,t}}{K_{i,t-1}}$	0.121	0.000	0.063	0.298	0.128	75,692
$\frac{OCFT3_{i,t}}{K_{i,t-1}}$	0.261	0.000	0.000	0.037	0.916	75,692
$\ln K_{i,t-2} - \ln S_{i,t-2}$	−1.721	−2.573	−1.669	−0.845	1.274	75,692
$\Delta \ln S_{i,t}$	0.037	−0.034	0.031	0.104	0.161	75,692

Panel B: Sample split by size

	SME			Large		
	Mean	Std.Dev.	N	Mean	Std.Dev.	N
$\frac{CAPEX_{i,t}}{K_{i,t-1}}$	0.170	0.235	49,380	0.131	0.141	25,833
$\frac{OCF_{i,t}}{K_{i,t-1}}$	0.555	1.094	49,380	0.381	0.823	25,833
$\frac{OCFT1_{i,t}}{K_{i,t-1}}$	0.110	0.195	49,380	0.115	0.132	25,833
$\frac{OCFT2_{i,t}}{K_{i,t-1}}$	0.135	0.130	49,380	0.096	0.120	25,833
$\frac{OCFT3_{i,t}}{K_{i,t-1}}$	0.310	0.994	49,380	0.170	0.740	25,833
$\ln K_{i,t-2} - \ln S_{i,t-2}$	−1.902	1.277	49,380	−1.390	1.198	25,833
$\Delta \ln S_{i,t}$	0.035	0.177	49,380	0.042	0.124	25,833

Notes: This table reports summary statistics for the aggregate sample. We refer to Table 8 in Appendix C for details on the respective variables. Subscript $t - n$ means that the variable is lagged by n periods.

19,201 firms. Table 1 presents the summary statistics of the variables used in the regressions for the full sample. Fig. 3 represents mean and median of investment to capital and cash flow to capital ratios sorted by percentiles of cash flow to capital. It clearly shows that the investment ratio decreases both in mean and median with increasing cash flows as long as cash flows are low, but increases when cash flows become larger which is in line with a non-monotonic investment curve as advocated by Cleary et al. (2007); Allayannis and Mozumdar (2004); Ağca and Mozumdar (2008); Hovakimian (2009) and others.

3.3 Results

3.3.1 Baseline results

First, we start our analysis by estimating the baseline model of Eq. (4) for the aggregate sample. Panel A of Table 2 summarizes the results. While Columns 1–3 report standard results of ICFS, Columns 4–6 illustrate the results of the spline regressions when dividing the sample into terciles of cash flow ($\frac{OCFT1-3_{i,t}}{K_{i,t-1}}$) (see
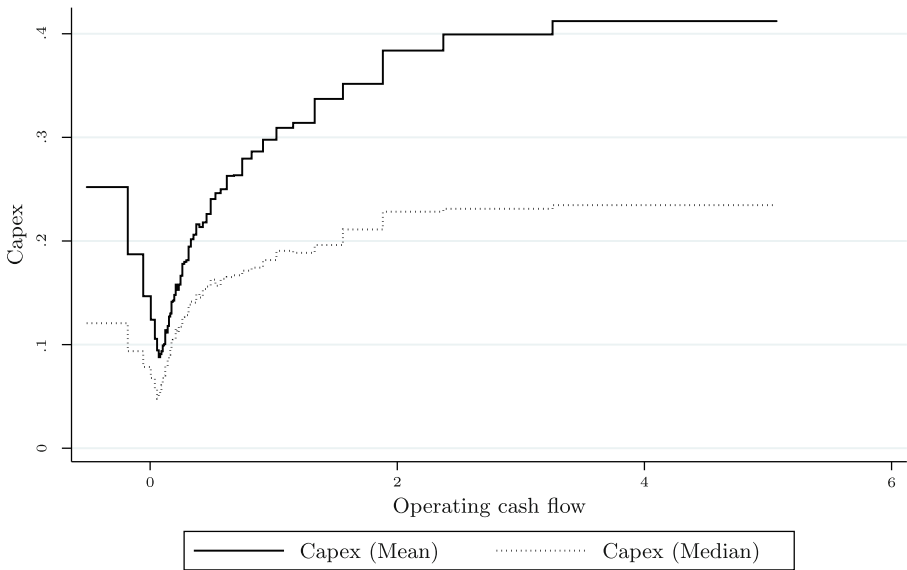
Fig. 3 Mean and median capex for percentiles of operating cash flow. Notes: This figure plots means and medians of $\frac{CAPEX_{i,t}}{K_{i,t-1}}$ for percentiles of $\frac{OCF_{i,t}}{K_{i,t-1}}$

e.g. Cleary et al. 2007). Columns 1–3 illustrate that the overall relation between cash flow and investment appears to be positive independent of which model has been chosen. However, having a closer look at cash flow, i.e. dividing it into terciles, exhibits a U-shaped investment-cash flow sensitivity in our data sample. All three models, OLS (Column 4), the within estimator (Column 5) as well as the GMM estimator (Column 6),[16] provide empirical evidence for a nonlinear relationship between cash flow and investment. Firms with cash flows being allocated in the first tercile show a significantly negative relation, i.e. investment is increasing with decreasing cash flows. In contrast, for firms in the second tercile the relation becomes significantly positive, thus increasing cash flows lead to increasing investments. The same holds true also for the third tercile, however the smaller coefficient implies that the positive relation decreases for high levels of internal liquidity. Thus, consistent with the model and results by Cleary et al. (2007), firms with low internal funds display a negative ICFS, while the relation is positive for firms with higher cash flows.[17]

Guariglia (2008) states in her work that testing the nonlinearities among a sample of unquoted firms has the advantage to be able to build proxies of capital market frictions that vary in the cross-section. We make use of this advantage and split

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[16] The first-difference GMM regressions are estimated in Stata using the command "xtabond2" by Roodman (2009).

[17] As a technical remark, note that the first difference GMM model appears to be correctly specified, as the lagged dependent variable lies between the OLS estimator and the within estimator.

Table 2 Baseline results

Panel A: Aggregate sample

	(1) OLS	(2) FE	(3) Diff GMM	(4) OLS	(5) FE	(6) Diff GMM
$\frac{CAPEX_{i,t-1}}{K_{i,t-2}}$	0.107***	−0.391***	−0.044***	0.108***	−0.387***	−0.021
	(0.006)	(0.009)	(0.016)	(0.006)	(0.009)	(0.018)
$\frac{OCF_{i,t}}{K_{i,t-1}}$	0.009***	0.005*	0.026**			
	(0.002)	(0.003)	(0.012)			
$\frac{OCFT1_{i,t}}{K_{i,t-1}}$				−0.020***	−0.039***	−0.133**
				(0.006)	(0.008)	(0.056)
$\frac{OCFT2_{i,t}}{K_{i,t-1}}$				0.171***	0.058***	0.549***
				(0.008)	(0.015)	(0.117)
$\frac{OCFT3_{i,t}}{K_{i,t-1}}$				0.003**	0.008***	0.038***
				(0.002)	(0.003)	(0.012)
$\ln K_{i,t-2} - \ln S_{i,t-2}$	−0.030***	−0.529***	−0.177***	−0.023***	−0.523***	−0.138***
	(0.001)	(0.011)	(0.021)	(0.001)	(0.011)	(0.025)
$\Delta \ln S_{i,t}$	0.154***	0.260***	0.080	0.139***	0.255***	0.056
	(0.006)	(0.007)	(0.104)	(0.006)	(0.007)	(0.097)
$\Delta \ln S_{i,t-1}$	0.127***	0.399***	0.183***	0.116***	0.394***	0.142***
	(0.005)	(0.009)	(0.026)	(0.005)	(0.009)	(0.029)
Industry FE	Yes	No	No	Yes	No	No
Firm FE	No	Yes	Yes	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.094	0.379		0.100	0.380	
N	75,692	75,692	75,692	75,692	75,692	75,692
AR(1)-test (p-value)			0.00			0.00
AR(2)-test (p-value)			0.20			0.38
H-test (p-value)			0.25			0.40

our sample into small- and medium-sized (SMEs) and large-sized firms.[18] Size is often used as a proxy for both measuring capital market frictions, i.e. information asymmetries, as well as growth opportunities. By splitting the sample into SMEs and large-sized firms, we want to test whether the U-shape of investment-cash flow sensitivities behaves similar within different size classes. Panel B of Table 2 shows that the nonlinear relationship between cash flow and investment is strongly significant for the sample of SMEs. However, for large-sized firms we find correct signs but no statistical significance. At first sight, this result may seem still consistent with results by Cleary et al. (2007) as size could be considered as proxy for information

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[18] We follow the legal definition of ğ267 of the German Commercial Code according to which firms are classified as *SME* if two of the three subsequent characteristics are fulfilled: Employees smaller or equal to 250, total assets smaller or equal to 19.25 M and total sales smaller or equal to 38.5 M.

Table 2 (Continued)

Panel B: SMEs vs. large-sized firms

	(1)	(2)
	SME	Large
$\frac{CAPEX_{i,t-1}}{K_{i,t-2}}$	−0.019	0.026
	(0.023)	(0.027)
$\frac{OCFT1_{i,t}}{K_{i,t-1}}$	−0.171**	−0.070
	(0.079)	(0.046)
$\frac{OCFT2_{i,t}}{K_{i,t-1}}$	0.729***	0.057
	(0.166)	(0.102)
$\frac{OCFT3_{i,t}}{K_{i,t-1}}$	0.043***	0.015
	(0.014)	(0.014)
$\ln K_{i,t-2} - \ln S_{i,t-2}$	−0.130***	−0.119***
	(0.032)	(0.032)
$\Delta \ln S_{i,t}$	−0.067	0.003
	(0.150)	(0.066)
$\Delta \ln S_{i,t-1}$	0.120***	0.122***
	(0.042)	(0.030)
Firm FE	Yes	Yes
Year FE	Yes	Yes
N	49,380	25,833
AR(1)-test (p-value)	0.00	0.00
AR(2)-test (p-value)	0.31	0.98
H-test (p-value)	0.60	0.02

Notes: This table reports regression estimates from OLS, firm fixed effects and two-step first-difference GMM regressions with robust standard errors in parentheses. Panel A reports the results for the aggregate sample. Columns 1–3 illustrate the estimates of investment as a linear function of operating cash flow. Columns 4–6 illustrate the estimates of spline regressions. We regress investment on a piecewise continuous function of operating cash flow with the knots being placed at terciles of operating cash flow. The regression model is given by the following investment error correction model: $\frac{CAPEX_{i,t}}{K_{i,t-1}} = \alpha_1 \frac{CAPEX_{i,t-1}}{K_{i,t-2}} + \alpha_2 \frac{OCFT1_{i,t}}{K_{i,t-1}} + \alpha_3 \frac{OCFT2_{i,t}}{K_{i,t-1}} + \alpha_4 \frac{OCFT3_{i,t}}{K_{i,t-1}} + \alpha_5 \Delta \ln S_{i,t} + \alpha_6 \Delta \ln S_{i,t-1} + \alpha_7 (\ln K_{i,t-2} - \ln S_{i,t-2}) + v_t + v_i + \epsilon_{i,t}$, where $OCFT1$–3 represents the different terciles. Panel B reports spline regression results for SMEs and large-sized firms using two-step first-difference GMM. Instruments set for Column 6 in Panel A and Columns 1–2 in Panel B: {$\frac{CAPEX_{i,t-j}}{K_{i,t-1-j}}$, $\frac{OCFT1_{i,t-j}}{K_{i,t-1-j}}$, $\frac{OCFT2_{i,t-j}}{K_{i,t-1-j}}$, $\frac{OCFT3_{i,t-j}}{K_{i,t-1-j}}$, $(\ln K_{i,t-1-j} - \ln S_{i,t-1-j})$, $\Delta \ln S_{i,t-j}$, with j being 2; time dummies}. We refer to Table 8 in Appendix C for details on the respective variables. * significant at 10%, ** significant at 5%, *** significant at 1%

asymmetries.[19] However, also the life-cycle hypothesis cannot be rejected, as SMEs are on average supposed to be at an earlier stage in their life-cycle compared to large-sized firms (see e.g. Hovakimian 2009). Thus, it is not yet clear whether the U-shape of investment-cash flow sensitivities is driven by the cost-revenue effect or by the life-cycle hypothesis.

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[19] Among others, Cleary et al. (2007) show that nonlinearities tend to be higher when information asymmetries are higher (see e.g. Cleary et al. 2007).

3.3.2 Testing the model predictions

In this subsection, we empirically test the different predictions of the theoretical model, which we derived in Sect. 2. Prediction 1a states that firms with more risky revenues should display a more pronounced negative ICFS. To operationalize different levels of risk, we build mutually exclusive subsamples based on sales

Table 3 Testing model predictions – Spline regressions

	Sales-risk		Long-term debt		Z-score	
	(1)	(2)	(3)	(4)	(5)	(6)
	High	Low	High	Low	High	Low
$\frac{CAPEX_{i,t-1}}{K_{i,t-2}}$	−0.032	−0.027	0.001	−0.020	−0.098***	0.002
	(0.025)	(0.029)	(0.030)	(0.028)	(0.034)	(0.030)
$\frac{OCFT1_{i,t}}{K_{i,t-1}}$	−0.137*	−0.089	−0.010	−0.174**	−0.294*	−0.032
	(0.080)	(0.075)	(0.090)	(0.071)	(0.158)	(0.078)
$\frac{OCFT2_{i,t}}{K_{i,t-1}}$	0.572***	0.373**	0.675***	0.513***	0.438**	0.474**
	(0.170)	(0.147)	(0.201)	(0.146)	(0.186)	(0.226)
$\frac{OCFT3_{i,t}}{K_{i,t-1}}$	0.030**	0.057***	0.051	0.005	0.025	0.061*
	(0.014)	(0.019)	(0.035)	(0.015)	(0.019)	(0.031)
$\ln K_{i,t-2} - \ln S_{i,t-2}$	−0.162***	−0.129***	−0.115***	−0.141***	−0.219***	−0.126***
	(0.036)	(0.036)	(0.043)	(0.035)	(0.047)	(0.041)
$\Delta\ln S_{i,t}$	0.005	0.238*	0.012	0.082	0.273	−0.054
	(0.141)	(0.128)	(0.103)	(0.119)	(0.177)	(0.162)
$\Delta\ln S_{i,t-1}$	0.151***	0.167***	0.103**	0.152***	0.222***	0.122***
	(0.042)	(0.041)	(0.044)	(0.038)	(0.055)	(0.046)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	37,063	38,478	27,138	27,486	21,552	21,875
AR(1)-test (p-value)	0.00	0.00	0.00	0.00	0.00	0.00
AR(2)-test (p-value)	0.70	0.32	0.25	0.19	0.48	0.25
H-test (p-value)	0.55	0.20	0.21	0.24	0.26	0.30

Notes: This table reports spline regression estimates from two-step first-difference GMM regressions with robust standard errors in parentheses. We regress investment on a piecewise continuous function of operating cash flow with the knots being placed at terciles of operating cash flow. The regression model is given by the following investment error correction model: $\frac{CAPEX_{i,t}}{K_{i,t-1}} = \alpha_1 \frac{CAPEX_{i,t-1}}{K_{i,t-2}} + \alpha_2 \frac{OCFT1_{i,t}}{K_{i,t-1}} + \alpha_3 \frac{OCFT2_{i,t}}{K_{i,t-1}} + \alpha_4 \frac{OCFT3_{i,t}}{K_{i,t-1}} + \alpha_5 \Delta\ln S_{i,t} + \alpha_6 \Delta\ln S_{i,t-1} + \alpha_7 (\ln K_{i,t-2} - \ln S_{i,t-2}) + v_t + v_i + \epsilon_{i,t}$, where *OCFT1–3* represents the different terciles. Instruments set: $\{\frac{CAPEX_{i,t-j}}{K_{i,t-1-j}}, \frac{OCFT1_{i,t-j}}{K_{i,t-1-j}}, \frac{OCFT2_{i,t-j}}{K_{i,t-1-j}}, \frac{OCFT3_{i,t-j}}{K_{i,t-1-j}}, (\ln K_{i,t-1-j} - \ln S_{i,t-1-j}), \Delta\ln S_{i,t-j}$, with j being 2; time dummies}. The first row indicates the various variables according to which we sort the different samples. In Columns 1–2, we sort according to sales risk, i.e. we generate a dummy variable which is 1 (*High*) if the firm's overall standard deviation of sales is above the two-digit industry sample median and 0 (*Low*) otherwise. In Columns 3–4, we sort according to long-term debt, i.e. we generate a dummy variable which is 1 (*High*) if the firm's average long-term debt is above the sample median and 0 (*Low*) otherwise. In Columns 5–6, we sort according to Altman's (2002) Z-score, i.e. we generate a dummy variable which is 1 (*High*) if the firm's average Z-score is above the sample median and 0 (*Low*) otherwise. We refer to Table 8 in Appendix C for details on the respective variables. * significant at 10%, ** significant at 5%, *** significant at 1%

Table 4 Means and medians of investment – High vs. low levels of sales risk

	High			Low			Test for equality in means	
	Mean	Median	N	Mean	Median	N	Δ	t-stat
$\frac{CAPEX_{i,t}}{K_{i,t-1}}$	0.175	0.108	37,063	0.138	0.097	38,478	0.038***	24.939
Age_t (in years)	28.437	20.000	37,063	37.297	23.000	38,478	−8.860***	−37.245
Total assets$_t$ (in Mio. €)	27.914	4.401	36,813	54.205	13.533	37,747	−26.290***	−43.201
Future sales growth$_t$	0.107	0.063	27,436	0.090	0.064	28,944	0.017***	8.071
Tangible assets$_t$	0.243	0.180	37,003	0.320	0.268	38,337	−0.077***	−45.228

Notes: This table reports means and medians for different levels (High vs. Low) of sales risk as well as differences in means applying a t-test. We sort according to sales risk, i.e. we generate a dummy variable which is 1 (*High*) if the firm's overall standard deviation of sales is above the two-digit industry sample median and 0 (*Low*) otherwise. We refer to Table 8 in Appendix C for details on the respective variables. * significant at 10%, ** significant at 5%, *** significant at 1%.

risk.[20] For sales risk, we generate a dummy variable which is one, if a firm's standard deviation of total sales to total assets is above the two-digit industry[21] sample median and zero otherwise, i.e. we estimate the standard deviation for each firm and then the median within the firm's two-digit industry. Columns 1–2 of Table 3 summarize the results of our estimations. The results show some tentative evidence that the negative relation between investment and cash flow when cash flows are low is only evident among firms with a high level of sales risk. The variable of particular interest is $\frac{OCFTI_{i,t}}{K_{i,t-1}}$, which has a negative sign in both subsamples but turns out significant (at 10%) only in the high-risk subsample. Taking it at face value, the ICFS is more negative among risky firms in line with Prediction 1a of the theoretical model. However, investigating the subset of more risky firms, we also identify them to be younger and smaller in size, while they exhibit lower asset tangibility, i.e. they tend to be at an earlier stage of their corporate life-cycle. In this sense, we cannot reject the revenue effect nor the life-cycle hypothesis at this stage.

To further analyze the impact of risk, we test Prediction 1b, which states that firms with more risky revenues should invest dominantly less than firms with less risky revenues. Again, to consider different levels of revenue risk, we build mutually exclusive subsamples based on sales risk as outlined above. Table 4 reports means and medians as well as differences in means of our main dependent variable (capital expenditures) and of variables that proxy for a firm's current status in its life-cycle within subsamples of high and low levels of sales risk. Results convincingly illustrate that both mean and median investments are significantly higher among firms with higher sales risk, which clearly contradicts Prediction 1b. A potential concern is that this result is caused by different levels of cash flow. However, if we plot investment

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[20] We also build mutually exclusive subsamples based on cash flow risk and find similar results. For endogeneity concerns, we consider cash flow risk to be less appropriate and refrain from reporting the corresponding results.

[21] We employ the NACE Rev. 2 code, which is the statistical classification of economic activities that is authorized by the European Union.

Fig. 4 Mean capex for percentiles of operating cash flow – High vs. low levels of sales risk. Notes: This figure plots means of $\frac{CAPEX_{i,t}}{K_{i,t-1}}$ for percentiles of $\frac{OCF_{i,t}}{K_{i,t-1}}$ for firms with high and low levels of sales risk. We sort according to sales risk, i.e. we generate a dummy variable which is 1 (*High*) if the firm's overall standard deviation of sales is above the two-digit industry sample median and 0 (*Low*) otherwise. We refer to Table 8 in Appendix C for details on the respective variables.
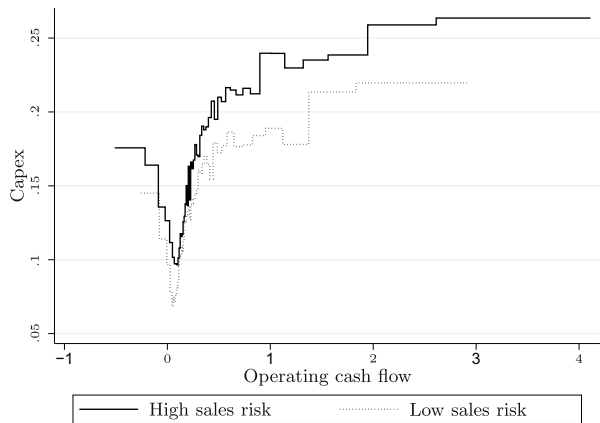
against operating cash flow ranked according to percentiles of cash flow levels for both high and low levels of sales risk, we find that the corresponding graph for high-risk firms is always above the graph of low risk firms. (see Fig. 4). This finding is a first indication that the predictions of the theoretical model are not in line with empirical evidence, while the results are still consistent with the corporate life-cycle theory. As outlined above, the results in Table 4 highlight, that firms with a higher level of sales risk tend to be at an earlier stage of their corporate life-cycle. Thus, the negative relation can be caused by the fact that investment opportunities are high, while internal funds are low at the same time.

In Prediction 2 we allow for senior debt in the theoretical model. We argue that firms with a higher senior debt ratio, should display a more convex investment curve when cash flows are low; in particular they should display a more negative ICFS compared to firms with a lower senior debt ratio. A simple explanation is given by the fact that allowing for senior debt increases the firm's probability of default, which is why investors will demand higher compensation for their provision of funds. In case of default, junior debt holders have to share revenues from investment with senior debt holders and thus become more sensitive to investment returns when internal funds are low. To test this model prediction empirically, we split the sample with respect to long-term debt, which should come closest to senior debt, as creditors usually demand collateral. We build mutually exclusive subsamples of firms with high and low long-term debt ratios, i.e. we generate a dummy variable being one if the firm's average long-term debt ratio lies above the sample median and zero otherwise.[22] Results are reported in Columns 3–4 of Table 3. Coefficients on the main variable of interest ($\frac{OCFTI_{i,t}}{K_{i,t-1}}$) are both negative, but while being far from significant in the subsample of high long-term debt firms, it is clearly significant (at 5%) for the low long-term debt firms. Therefore, the empirical evidence is opposite to the theoretical predictions and we have to reject Prediction 2. Investigating the

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[22] To rule out underinvestment due to debt overhang, we exclude the upper 5 percentiles of long-term debt firm-year observations from the sample in robustness checks. Qualitatively, our results remain the same and are therefore not affected by debt overhang problems.

firms in the low long-term debt sub-sample reveals that these firms tend to be younger, have higher sales growth and lower asset tangibility. Our findings are reminiscent of results such as e.g. Beck et al. (2006), who argue that obtaining external finance to fund investments is more difficult for young firms. Nevertheless, this limitation disappears when firms pass through the early stage of their life-cycle. Taken together, our empirical evidence again casts serious doubts that the cost-revenue effect is a first-order effect for the negative ICFS, while it provides support for the predictions of the corporate life-cycle hypothesis.

To strengthen our evidence and as robustness check, our final test focuses on direct test of the model's predictions. Cleary et al. (2007) claim that as the probability of default rises, the return originated by the company's investment becomes increasingly important to the investor who obtains the return in the event of default. An enhancement of investment, thus, reinforces the firm's solvency to meet its financial obligations and increases the investor's payoff in case of default. From this line of reasoning, we expect firms which are closer to default to increase their investments as cash flows are low. To account for default risk, we sort the sample according to Altman's (1968) Z-score which is a proxy for a firm's bankruptcy probability. We use the Altman (2002) Z-score for private firms which is considered to be more industry independent.[23] As higher Z-scores indicate lower insolvency risk (Altman 1968), we create a dummy variable which is one ($High$) if the firm's average Z-score is higher than the sample median and zero otherwise. Columns 5–6 of Table 3 report results and show a significant relationship only among the high Z-score firms. In particular, we can only find a significant negative coefficient on the first tercile, $\frac{OCFT1_{i,t}}{K_{i,t-1}}$ in the high Z-score sample, which is clearly a contradiction to the prediction. In line with our previous findings on long-term debt, the result implies that firms being closer to bankruptcy do not increase investments when internal funds are very low contradicting the theoretical predictions by Cleary et al. (2007). So far, our findings in this section can be interpreted as strong evidence that the revenue effect is not a first-order effect in the real data and thus unlikely to be driving the U-shaped investment curve.

3.3.3 Testing the corporate life-cycle hypothesis

The previous section has documented contradictions to the predictions of the (extended) theoretical model of Cleary et al. (2007), while at the same time, we indicated that the evidence appears consistent with the corporate life-cycle theory, as argued by Hovakimian (2009). We next turn to a more rigorous test of the latter hypothesis. To account for the different stages of firms' life-cycles and thus for their growth opportunities, we test whether the U-shaped ICFS are more pronounced among firms that are at an earlier stage of their life-cycle compared to those that are at a later stage. We assume that the former ones possess high growth opportunities, which demand large investments, while they are at the same time constrained in internal

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[23] The Altman Z-score is computed as follows: $Z_{i,t} = 6.56 \times \frac{Working\ Capital_{i,t}}{Assets_{i,t}} + 3.26 \times \frac{Retained\ Earnings_{i,t}}{Assets_{i,t}} + 6.72 \times \frac{EBIT_{i,t}}{Assets_{i,t}} + 1.05 \times \frac{Equity_{i,t}}{Debt_{i,t}}$. Working capital is measured as current assets net short-term liabilities.

funds. To account for the life-cycle, we estimate Eq. (4) on various mutually exclusive subsamples of firms sorted by different measures. We capture the stage of a firm's life-cycle by the firm's (i) size, (ii) age, (iii) size-age index, (iv) growth opportunities, and (v) industry asset specificity. First, size (*SME*) is defined as above and only reported for the sake of completeness. Second, we sort our sample with respect to *Age*. We generate a dummy variable which is one if the firm's year of foundation is larger than the sample median. According to evidence by e.g. Dickinson (2011), both the firm's size as well as its age are often related to the life-cycle. Third, we sort our sample according to Hadlock and Pierce (2010) and use the size-age index (*SA-index*) of German firms provided by Klepsch and Szabo (2016).[24] The dummy variable is one if the firm's average size-age index is higher than the sample median and zero otherwise, while a higher value accounts for firms being younger and smaller in asset size. Fourth, we sort the sample according to growth opportunities (*Growth*), which we measure by future sales growth: $SG_{i,t} = \frac{S_{i,t+1}-S_{i,t-1}}{S_{i,t-1}}$. We establish a dummy variable that is one if the firm's average future sales growth lies above its two-digit industry sample median and zero otherwise. Fourth, we use industry asset specificity to implement a more exogenous proxy for a firm's growth opportunities. We follow Acharya et al. (2007) and Garcia-Appendini (2018) and assign a dummy variable to be one if the two-digit industry median of tangible assets lies above the sample median and zero otherwise. The underlying reasoning is that, while this industry measure is more exogenous, growth opportunities tend to be lower in industries with highly specific assets and a high level of tangibility and vice versa.

Table 5 reports the results when we build mutually exclusive subsamples based on the life-cycle hypothesis and estimate Eq. (4). All five specifications confirm the assumptions of the corporate life-cycle theory. In particular, firms that are smaller in size, younger, have higher growth opportunities and belong to industries with low asset specificity exhibit negative investment-cash flow sensitivities when cash flows are low, while the relationship becomes positive when cash flows increase. In contrast, companies that are larger, older and have lower growth opportunities appear to be cash flow insensitive. According to the model of Cleary et al. (2007) the firms' set of growth opportunities is exogenous and does not vary and thus has no impact on the model. However, Table 5 shows that this cannot be confirmed empirically within our sample of SMEs and large-sized firms.

To further strengthen the empirical evidence of the corporate life-cycle theory, we also perform a sorting approach according to more than one of the above-mentioned measures, i.e. we sequentially sort according to size and age, according to size, age and the SA-index and finally according to size, age, the SA-index and growth opportunities. Table 6 illustrates distinct results. If we constrain the sample by additional measures to identify a firm's stage of life-cycle, we can see that the negative coefficient between investment and cash flow for low cash flow levels increases in absolute size, i.e. gets more negative. We again underline the fact that the nega-

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[24] The size-age index is computed pursuant to Klepsch and Szabo (2016): $SA_{i,t} = -1.181 \times \log(Assets_{i,t}) + 0.027 \times \log(Assets_{i,t}^2) - 0.008 \times Age_{i,t}$.

Table 5 Life-cycle – Spline regressions

	Size		Age		SA-index		Growth		Asset specificity	
	(1) SME	(2) Large	(3) Young	(4) Old	(5) High	(6) Low	(7) High	(8) Low	(9) High	(10) Low
$\frac{CAPEX_{i,t-1}}{K_{i,t-2}}$	−0.019	0.026	−0.053**	−0.022	−0.036	0.011	−0.039	−0.011	−0.008	−0.054**
	(0.023)	(0.027)	(0.027)	(0.024)	(0.030)	(0.023)	(0.024)	(0.024)	(0.026)	(0.025)
$\frac{OCFT1_{i,t}}{K_{i,t-1}}$	−0.171**	−0.070	−0.180*	−0.015	−0.203*	−0.049	−0.172*	−0.021	−0.063	−0.134
	(0.079)	(0.046)	(0.102)	(0.063)	(0.111)	(0.040)	(0.103)	(0.055)	(0.064)	(0.082)
$\frac{OCFT2_{i,t}}{K_{i,t-1}}$	0.729***	0.057	0.470**	0.503***	0.830***	0.265***	0.546***	0.406***	0.468***	0.575***
	(0.166)	(0.102)	(0.209)	(0.124)	(0.219)	(0.097)	(0.166)	(0.152)	(0.148)	(0.172)
$\frac{OCFT3_{i,t}}{K_{i,t-1}}$	0.043***	0.015	0.025*	0.039**	0.058***	0.003	0.034**	0.051***	0.035*	0.034**
	(0.014)	(0.014)	(0.015)	(0.017)	(0.018)	(0.011)	(0.015)	(0.018)	(0.021)	(0.014)
$\ln K_{i,t-2} - \ln S_{i,t-2}$	−0.130***	−0.119***	−0.175***	−0.143***	−0.142***	−0.130***	−0.165***	−0.119***	−0.136***	−0.172***
	(0.032)	(0.032)	(0.038)	(0.031)	(0.044)	(0.027)	(0.034)	(0.033)	(0.033)	(0.036)
$\Delta \ln S_{i,t}$	−0.067	0.003	0.286*	0.074	−0.091	0.075	0.107	0.128	0.158**	0.101
	(0.150)	(0.066)	(0.155)	(0.100)	(0.182)	(0.064)	(0.113)	(0.105)	(0.072)	(0.155)
$\Delta \ln S_{i,t-1}$	0.120***	0.122***	0.201***	0.145***	0.124**	0.129***	0.155***	0.140***	0.158***	0.169***
	(0.042)	(0.030)	(0.046)	(0.032)	(0.059)	(0.026)	(0.037)	(0.035)	(0.034)	(0.043)

Table 5 (Continued)

Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	49,380	25,833	34,270	41,422	33,075	42,617	42,008	33,684	35,529	40,163
AR(1)-test (p-value)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AR(2)-test (p-value)	0.31	0.98	0.42	0.98	0.29	0.87	0.88	0.06	0.44	0.77
H-test (p-value)	0.60	0.02	0.79	0.05	0.98	0.00	0.20	0.13	0.11	0.34

Notes: This table reports spline regression estimates from two-step first-difference GMM regressions with robust standard errors in parentheses. We regress investment on a piecewise continuous function of operating cash flow with the knots being placed at terciles of operating cash flow. The regression model is given by the following investment error correction model: $\frac{CAPEX_{i,t}}{K_{i,t-1}} = \alpha_1 \frac{CAPEX_{i,t-1}}{K_{i,t-2}} + \alpha_2 \frac{OCFT1_{i,t}}{K_{i,t-1}} + \alpha_3 \frac{OCFT2_{i,t}}{K_{i,t-1}} + \alpha_4 \frac{OCFT3_{i,t}}{K_{i,t-1}} + \alpha_5 \Delta \ln S_{i,t} + \alpha_6 \Delta \ln S_{i,t-1} + \alpha_7 (\ln K_{i,t-2} - \ln S_{i,t-2}) + \nu_t + \nu_i + \epsilon_{i,t}$, where $OCFT1$–3 represents the different terciles. Instruments set: $\{\frac{CAPEX_{i,t-1-j}}{K_{i,t-1-j}}, \frac{OCFT1_{i,t-j}}{K_{i,t-1-j}}, \frac{OCFT2_{i,t-j}}{K_{i,t-1-j}}, \frac{OCFT3_{i,t-j}}{K_{i,t-1-j}}, (\ln K_{i,t-1-j} - \ln S_{i,t-1-j}), \Delta \ln S_{i,t-j}\}$, with j being 2; time dummies}. The first row indicates the various variables according to which we sort the different samples. In Columns 1–2, we sort according to size, i.e. we generate a dummy variable which is 1 (*SME*) if the firm is classified as SME according to the legal definition of §267 of the German Commercial Code and 0 (*Large*) otherwise. In Columns 3–4, we sort according to a firm's founding year, i.e. we generate a dummy variable which is 1 (*Young*) if the firm's founding year lies above the sample median and 0 (*Old*) otherwise. In Columns 5–6, we sort according to a firm's size-age index, i.e. we generate a dummy variable which is 1 (*High*) if the firm's average size-age index is higher than the sample median and 0 (*Low*) otherwise. In Columns 7–8, we sort according to a firm's growth opportunities, i.e. we generate a dummy variable which is 1 (*High*) if a firm's average future sales growth lies above its two-digit industry sample median and 0 (*Low*) otherwise. In Columns 9–10, we sort according to a firm's industry asset specificity, i.e. we generate a dummy variable which is 1 (*Low*) if the two-digit industry median of tangible assets lies above the sample median and 0 (*High*) otherwise. We refer to Table 8 in Appendix C for details on the respective variables. * significant at 10%, ** significant at 5%, *** significant at 1%

Table 6 Life-cycle II – Spline regressions

	(1) Size	(2) Size & age	(3) Size, age & SA-index	(4) Size, age, SA-index & growth
$\frac{CAPEX_{i,t-1}}{K_{i,t-2}}$	−0.019	−0.054*	−0.080**	−0.103**
	(0.023)	(0.032)	(0.037)	(0.043)
$\frac{OCFT1_{i,t}}{K_{i,t-1}}$	−0.171**	−0.247**	−0.245*	−0.160
	(0.079)	(0.116)	(0.129)	(0.202)
$\frac{OCFT2_{i,t}}{K_{i,t-1}}$	0.729***	0.703***	0.699**	0.693**
	(0.166)	(0.265)	(0.306)	(0.352)
$\frac{OCFT3_{i,t}}{K_{i,t-1}}$	0.043***	0.028*	0.035*	0.027
	(0.014)	(0.017)	(0.021)	(0.025)
$\ln K_{i,t-2} - \ln S_{i,t-2}$	−0.130***	−0.173***	−0.206***	−0.247***
	(0.032)	(0.047)	(0.056)	(0.066)
$\Delta \ln S_{i,t}$	−0.067	0.188	0.203	0.250
	(0.150)	(0.190)	(0.196)	(0.218)
$\Delta \ln S_{i,t-1}$	0.120***	0.191***	0.222***	0.242***
	(0.042)	(0.060)	(0.070)	(0.079)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	49,380	25,048	19,667	11,912
AR(1)-test (p-value)	0.00	0.00	0.00	0.00
AR(2)-test (p-value)	0.31	0.34	0.31	0.43
H-test (p-value)	0.60	0.88	0.94	0.59

Notes: This table reports spline regression estimates from two-step first-difference GMM regressions with robust standard errors in parentheses. We regress investment on a piecewise continuous function of operating cash flow with the knots being placed at terciles of operating cash flow. The regression model is given by the following investment error correction model: $\frac{CAPEX_{i,t}}{K_{i,t-1}} = \alpha_1 \frac{CAPEX_{i,t-1}}{K_{i,t-2}} + \alpha_2 \frac{OCFT1_{i,t}}{K_{i,t-1}} + \alpha_3 \frac{OCFT2_{i,t}}{K_{i,t-1}} + \alpha_4 \frac{OCFT3_{i,t}}{K_{i,t-1}} + \alpha_5 \Delta \ln S_{i,t} + \alpha_6 \Delta \ln S_{i,t-1} + \alpha_7 (\ln K_{i,t-2} - \ln S_{i,t-2}) + v_t + v_i + \epsilon_{i,t}$, where *OCFT1–3* represents the different terciles. Instruments set: $\{\frac{CAPEX_{i,t-j}}{K_{i,t-1-j}}, \frac{OCFT1_{i,t-j}}{K_{i,t-1-j}}, \frac{OCFT2_{i,t-j}}{K_{i,t-1-j}}, \frac{OCFT3_{i,t-j}}{K_{i,t-1-j}}, (\ln K_{i,t-1-j} - \ln S_{i,t-1-j}), \Delta \ln S_{i,t-j}$, with j being 2; time dummies}. The first row indicates the various variables according to which we sort the different samples. In Column 1, we sort according to size, i.e. we include only firms that are classified as SME according to the legal definition of ğ267 of the German Commercial Code. In Column 2, we sort according to size and age, i.e. we include only firms that are classified as SMEs and if the founding year lies above the sample median. In Column 3, we sort according to size, age and a firm's size-age index, i.e. we include only firms that are classified as SMEs, if the founding year lies above the sample median and if their average size-age index is higher than the sample median. In Column 4, we sort according to size, age, size-age index and a firm's growth opportunities, i.e. we include only firms that are classified as SMEs, if the founding year lies above the sample median, if their average size-age index is higher than the sample median, and if their average future sales growth lies above the two-digit industry sample median. We refer to Table 8 in Appendix C for details on the respective variables. * significant at 10%, ** significant at 5%, *** significant at 1%

Table 7 Senior debt and size – Spline regressions

	SME		Large	
	(1)	(2)	(3)	(4)
	High	Low	High	Low
$\frac{CAPEX_{i,t-1}}{K_{i,t-2}}$	−0.018	−0.061*	−0.005	0.015
	(0.036)	(0.037)	(0.039)	(0.036)
$\frac{OCFT1_{i,t}}{K_{i,t-1}}$	−0.076	−0.189**	−0.038	−0.048
	(0.109)	(0.090)	(0.093)	(0.056)
$\frac{OCFT2_{i,t}}{K_{i,t-1}}$	0.810***	0.536**	0.056	0.007
	(0.288)	(0.239)	(0.144)	(0.128)
$\frac{OCFT3_{i,t}}{K_{i,t-1}}$	0.026	−0.004	0.003	−0.002
	(0.037)	(0.020)	(0.020)	(0.016)
$\ln K_{i,t-2} - \ln S_{i,t-2}$	−0.135**	−0.186***	−0.162***	−0.117***
	(0.053)	(0.048)	(0.045)	(0.044)
$\Delta \ln S_{i,t}$	0.044	0.278	0.123*	0.033
	(0.157)	(0.199)	(0.072)	(0.079)
$\Delta \ln S_{i,t-1}$	0.129**	0.222***	0.163***	0.128***
	(0.059)	(0.062)	(0.043)	(0.041)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	16,189	14,471	10,718	12,841
AR(1)-test (p-value)	0.00	0.00	0.00	0.00
AR(2)-test (p-value)	0.18	0.18	0.43	0.46
H-test (p-value)	0.10	0.10	0.06	0.26

Notes: This table reports spline regression estimates from two-step first-difference GMM regressions with robust standard errors in parentheses. We regress investment on a piecewise continuous function of operating cash flow with the knots being placed at terciles of operating cash flow. The regression model is given by the following investment error correction model: $\frac{CAPEX_{i,t}}{K_{i,t-1}} = \alpha_1 \frac{CAPEX_{i,t-1}}{K_{i,t-2}} + \alpha_2 \frac{OCFT1_{i,t}}{K_{i,t-1}} + \alpha_3 \frac{OCFT2_{i,t}}{K_{i,t-1}} + \alpha_4 \frac{OCFT3_{i,t}}{K_{i,t-1}} + \alpha_5 \Delta \ln S_{i,t} + \alpha_6 \Delta \ln S_{i,t-1} + \alpha_7 (\ln K_{i,t-2} - \ln S_{i,t-2}) + v_t + v_i + \epsilon_{i,t}$, where *OCFT1–3* represents the different terciles. Instruments set: $\{\frac{CAPEX_{i,t-j}}{K_{i,t-1-j}}, \frac{OCFT1_{i,t-j}}{K_{i,t-1-j}}, \frac{OCFT2_{i,t-j}}{K_{i,t-1-j}}, \frac{OCFT3_{i,t-j}}{K_{i,t-1-j}}, (\ln K_{i,t-1-j} - \ln S_{i,t-1-j}), \Delta \ln S_{i,t-j}$, with j being 2; time dummies}. The first row indicates the size of the firms that are included in the sample, i.e. we generate a dummy variable which is 1 (*SME*) if the firm is classified as SME according to the legal definition of ğ267 of the German Commercial Code and 0 (*Large*) otherwise. The second row indicates the level of long-term debt, i.e. we generate a dummy variable which is 1 (*High*) if the firm's average long-term debt is above the sample median and 0 (*Low*) otherwise. We refer to Table 8 in Appendix C for details on the respective variables. * significant at 10%, ** significant at 5%, *** significant at 1%

tive correlation between investment and cash flow is mainly determined by young companies with high growth opportunities and low internal financial resources.[25]

We finally sort the sample according to both size and long-term debt to control for the corporate life-cycle hypothesis and the theoretical model by Cleary et al. (2007) within one regression. According to Prediction 2, the negative sensitivity should be more pronounced among firms with a high level of long-term debt independent of

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[25] The disappearing effect in Column 4 is likely to be the result of the declining sample size.

their size. In contrast, the corporate life-cycle hypothesis implies, that the negative effect should be particularly evident among SMEs with low levels of long-term debt, as these firms are the ones that exhibit higher growth opportunities, are younger and have lower asset tangibility. Table 7 illustrates the results. Again, we can show that the nonlinearities are evident among SMEs but not among large-sized firms. Further, and even more important, the negative relation between investment and cash flow is statistically significant only among SMEs with low levels of long-term debt and not so among SMEs that have high debt ratios conflicting the derived predictions of the theoretical model by Cleary et al. (2007).[26]

Overall, our findings challenge the view that the revenue effect is a first-order effect for the negative ICFS in the real data, while we find strong support for the implications of the corporate life-cycle hypothesis.

4 Conclusion

This paper analyzes the nonlinearities of ICFS with a special focus on the negative part of the investment-cash flow relationship. In particular, we discriminate between two prominent explanations for a negative ICFS in the recent literature – the cost-revenue effect by Cleary et al. (2007) and the life-cycle hypothesis by Hovakimian (2009). The cost-revenue effect is derived from an investment model which assumes endogenous financing costs and relies on the idea that investors (creditors) capture the investment return in default states. The more investors' returns are sensitive to the investment return, the more pronounced is the negative ICFS. We use this insight to extend the Cleary et al. (2007) model in two directions and derive testable predictions considering the riskiness of revenues and the existence of senior debt. In the theoretical framework, we prove that higher revenue risk makes the negative relation between investment and cash flow steeper when cash flows are low, while the overall investment decreases with risk. For the existence of senior debt, we show theoretically that higher senior debt also increases the negative sensitivity between investment and cash flow, when cash flows are low, i.e. the curve gets steeper.

We take these model predictions to the data. We deliberately choose a rich German dataset covering explicitly the SME segment. Thereby we avoid the drawback of using a standard Compustat sample that only very limited inference can be made with respect to young and small companies – which is crucial for testing the life-cycle hypothesis.

From our empirical results, we are able to verify the steeper relation between investment and cash flow among risky firms. However, the level of investment is dominantly higher among firms with higher revenue risk, thereby contradicting the model. Overall, more risky firms tend to be younger, smaller in size, and have lower asset tangibility in line with the early stage of a firm's life-cycle.

With respect to the predictions concerning senior debt, we do not find evidence that the U-shape is more pronounced among firms with a high level of long-term

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[26] We also sort the sample according to long-term debt separately for SMEs and large sized firms. Our results remain stable.

debt. Quite to the contrary, firms with a low level of long-term debt exhibit a more pronounced nonlinear relation between investment and cash flow. Having a closer look at firms with low levels of long-term debt exhibits a negative correlation with age and asset tangibility and a positive one with growth opportunities providing an additional indication that rather the firm's life-cycle has an impact on the nonlinear relationship between investment and cash flow.

As final piece of evidence, we sort firms according to (a variant of) Altman's (1968) Z-score, i.e. bankruptcy risk. This test is directly addressing the implication of Cleary et al. (2007), since the revenue effect implies that the negative ICFS should be more pronounced among firms with high insolvency risk. Again, our results do not support the model's predictions, as we find that mainly firms with lower bankruptcy risk exhibit strong negative ICFS.

Overall, the contradictions between the theoretical model predictions and the empirical results lead us to the conclusion that the revenue effect – or in other terms, the endogenous financing cost effect – does not appear to be a first-order effect for the emergence of negative ICFS in our data.

In contrast, when checking our evidence against the implications of the corporate life-cycle hypothesis as advanced by Hovakimian (2009), we overall find neat consistency. In the early stage of a firm's life-cycle, firms tend to have limited cash flows, while investment opportunities are high inducing a negative relation between investment and cash flow. As the firm matures, cash flows increase as well as investments to ensure growth. At a later stage of their life-cycle, cash flows tend to be high, while investment opportunities are low and thus, investments tend to be insensitive to cash flows. Testing these arguments empirically, we find the nonlinear relationship to be more pronounced among firms that are younger, smaller in size, have higher growth opportunities and operate in industries with lower asset specificity.

In sum, our evidence strongly favors life-cycle dynamics as an explanation for negative ICFS, while we do not find support for the idea that they are driven by the endogenous financing cost, i.e. the revenue effect. In this sense, our results are a sign of caution for using the investment model with endogenous financing costs in related settings.

5 Appendix

5.1 Appendix A

In this appendix, we provide the rigorous theoretical derivation of the hypotheses described in Sect. 2. Sect. A.1 provides the proofs supporting Prediction 1a and 1b which states that a more risky cash flow yields a lower and "less convex" investment curve/stronger negative ICFS. Sect. A.2 constitutes the proof for Prediction 2 which claims that a higher level of senior debt results in a more negative ICFS.

5.1.1 Riskiness

As stated in the text, we consider θ' to be more risky than θ, if θ' follows from θ through a mean-preserving spread. Consistent with Cleary et al. (2007), we assume θ to be uniformly distributed on $[\underline{\theta}, \overline{\theta}]$, for which we label the mean as μ_θ or μ for short. Furthermore introduce δ as the distance from the mean to the upper and lower limit, i.e. define $\underline{\theta} = \mu - \delta$ and $\overline{\theta} = \mu + \delta$ respectively, meaning that δ represents the standard deviation. Then clearly, θ' is more risky than θ if $\delta' > \delta$, and we can analyse the model predictions from varying δ.

Again, following Cleary et al. (2007), use the investment function $F(I, \theta) = \sqrt{I}\,\theta$, then the break-even constraint of the investor is given by

$$\frac{\sqrt{I}}{4\delta}(\widehat{\theta}^2 - (\mu - \delta)^2) + \sqrt{I}\widehat{\theta}(1 + \frac{1}{2\delta}(\mu - \delta - \widehat{\theta})) = I - W,$$

which is quadratic in $\widehat{\theta}$ and can be solved for the two roots:

$$\widehat{\theta}_1 = \mu + \delta + 2\sqrt{\delta} \cdot C^{IW}, \qquad \widehat{\theta}_2 = \mu + \delta - 2\sqrt{\delta} \cdot C^{IW},$$

$$\text{with:} \quad C^{IW} = \frac{\sqrt{\sqrt{I}\mu - (I - W)}}{I^{1/4}} > 0$$

Note that for any meaningful solution, the numerator of C^{IW} implies that $\sqrt{I}\mu - (I - W)$ has to be positive, or $\sqrt{I}\mu > (I - W)$, which is an economically meaningful requirement as it states that the expected investment return $\mathbb{E}[F(I, \theta)] = \sqrt{I}\mu$ exceeds the amount raised $I - W$. Since $\widehat{\theta}$ can never be larger than $\overline{\theta} = \mu + \delta$, only the second solution $\widehat{\theta}_2$ is meaningful (to which we simply refer to $\widehat{\theta}$ in the following). As first step, we determine the derivative of $\widehat{\theta}$ with respect to δ:

$$\frac{\mathrm{d}\widehat{\theta}}{\mathrm{d}\delta} = 1 - \frac{C^{IW}}{\sqrt{\delta}}.$$

The sign of $\frac{\mathrm{d}\widehat{\theta}}{\mathrm{d}\delta}$ depends on the fact if $C^{IW} \gtrless \sqrt{\delta}$. Substituting back for C^{IW} shows that

$$\frac{C^{IW}}{\sqrt{\delta}} < 1 \quad \Leftrightarrow \quad \sqrt{I}(\mu - \delta) < (I - W) \quad \Leftrightarrow \quad F(I, \underline{\theta}) < I - W.$$

Thus, $\frac{\mathrm{d}\widehat{\theta}}{\mathrm{d}\delta}$ is positive if $F(I, \underline{\theta}) < I - W$. Since $F(I, \underline{\theta})$ is the investment return at the lower boundary of the support, this condition will be satisfied in particular for low (or negative) values of W. Thus, we find that $\widehat{\theta}$ increases with δ, which is economically meaningful as it simply states that for higher risk of the state variable, the firm will be more likely to default. In this sense, we have a first formal confirmation for the Hypothesis stated in the text, as it implies that with higher risk, the default threshold increases, which in turn means that the investor is more exposed

to the investment return and therefore the investment decision is more sensitive to available funds. To support this conclusion more rigorously, we analyse the first-order condition in the next step.

The objective function of the firm is $\mathbb{E}[F(I, \theta)] - F(I, \widehat{\theta})$, which under the above assumption is $\sqrt{I}(\mu - \widehat{\theta})$. Plugging in $\widehat{\theta}$ from above, the constrained objective function is

$$P = \sqrt{I}(2C^{IW}\sqrt{\delta} - \delta).$$

In order to get the first-order condition (FOC), plugging in for C^{IW} and simplifying yields

$$P = 2I^{1/4}\sqrt{\delta}\sqrt{\sqrt{I}\mu - (I - W)} - \sqrt{I}\delta.$$

Differentiating wrt I leads to the FOC

$$\frac{\mathrm{d}P}{\mathrm{d}I} = \frac{\sqrt{\delta}\left(2\sqrt{I}\mu - (3I - W) - I^{1/4}\sqrt{\delta}\sqrt{\sqrt{I}\mu - (I - W)}\right)}{2I^{3/4}\sqrt{\sqrt{I}\mu - (I - W)}}$$

Setting $\frac{\mathrm{d}P}{\mathrm{d}I}$ equal to zero, simplifies to

$$2\sqrt{I}\mu - (3I - W) - I^{1/4}\sqrt{\delta}\sqrt{\sqrt{I}\mu - (I - W)} = 0.$$

The FOC is increasing in δ as can be verified from differentiating

$$\frac{\mathrm{d}FOC}{\mathrm{d}\delta} = \frac{I^{1/4}(\sqrt{I}\mu - (I - W))}{2\sqrt{\delta}\sqrt{\sqrt{I}\mu - (I - W)}} > 0.$$

Thus, as δ increases I has to decrease to satisfy the FOC. For $\delta' > \delta$, the graph of (I, W) for δ' will lie below the graph for δ as illustrated in Fig. 1.

As final step, we formally determine the ICFS $\frac{\mathrm{d}I}{\mathrm{d}W}$. Since $I(W)$ cannot be determined explicitly,[27] we use implicit differentiation. Treating I as $I(W)$, differentiating wrt W and solving for I_W, yields

$$I_W = \frac{4C^{IW}\sqrt{I} - 2I\sqrt{\delta}}{4C^{IW}(3\sqrt{I} - \mu) + \sqrt{\delta}(2\sqrt{I}\mu - (3I - W))}.$$

To determine how I_W changes with δ, differentiating leads to:

$$\frac{\mathrm{d}I_W}{\mathrm{d}\delta} = I_{W,\delta} = -\frac{2C^{IW}\sqrt{I}(3I + W)}{\sqrt{\delta}\left(4C^{IW}(3\sqrt{I} - \mu) + \sqrt{\delta}(2\sqrt{I}\mu - 3I + W)\right)^2}.$$

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[27] To be precise, an explicit solution is feasible, but it is a highly complex polynomial which defeats further analytical discussion.

The denominator is always positive, so the sign depends on the term $3I + W$. Recall from above that we have the requirement $\sqrt{I}\mu - (I - W) > 0$. Note further that the highest possible I is the solution of the unconstrained (first-best) maximization problem $\mathbb{E}[F(I, \theta)] - I$, leading to $I^* = \frac{\mu^2}{4}$. Plugging in the maximal I^* in the constraint $\sqrt{I}\mu - (I - W) > 0$ and solving for W shows that W is bounded below by $-\frac{\mu^2}{4}$. Therefore, we get $W > -I$ for all I, verifying that $3I + W$ is always positive. In turn, this proves that $I_{W,\delta}$ is always negative and supports our Prediction 1a.

5.1.2 Senior debt

As stated in the text, a second extension of the model is related to the introduction of existing senior debt. We first show how the ICFS I_W is affected by the extent of existing senior debt under the parametric form already introduced in the previous section. We then show how it affects the general solution.

First, recall that the investor's participation constraint in the basic model is

$$\int_{\underline{\theta}}^{\widehat{\theta}} \left(F(I, \theta) + \frac{D - F(I, \theta)}{\pi_2} L \right) \omega(\theta)d\theta + (1 - \Omega(\widehat{\theta}))D = I - W.$$

As in Cleary et al. (2007), we argue that the crucial economic effect can be demonstrated by abstracting away from the (constant) liquidation value L, so to simplify the analytical exposition, we set $L = 0$.[28] We introduce D^s to denote the nominal amount of existing senior debt. Since investors of the new investment project are assumed to be junior, their participation constraint can be written as:

$$\int_{\underline{\theta}}^{\widehat{\theta}} \max(F(I, \theta) - D^s, 0)\omega(\theta)d\theta + (1 - \Omega(\widehat{\theta}))(D - D^s) = I - W, \qquad (5)$$

where the default threshold $\widehat{\theta}$ is determined by $F(I, \widehat{\theta}) = D$, i.e. by the total debt amount, and the max-function captures the seniority of existing debt. First note that the integral on the LHS has the representation

$$\int_{\underline{\theta}}^{\widehat{\theta}} \max(F(I, \theta) - D^s, 0)\omega(\theta)d\theta = \int_{\underline{\theta}^*}^{\widehat{\theta}} F(I, \theta) - D^s \omega(\theta)d\theta,$$

with a lower boundary $\underline{\theta}^* \geq \underline{\theta}$ determined by $F(I, \underline{\theta}^*) = D^s = 0$ or $\underline{\theta}^* = F^{-1}(I, D^s)$.

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[28] Note that we show numerical results for $L > 0$ in the main text.

Imposing the parametric assumptions of θ being uniformly distributed and $F(I, \theta) = \sqrt{I}\theta$, the above integral equals $(D^s - \sqrt{I}\widehat{\theta})^2 / 2\sqrt{I}(\bar{\theta} - \underline{\theta})$. Thus, the entire participation constraint is:

$$\frac{(D^s - \sqrt{I}\widehat{\theta})^2}{2\sqrt{I}(\bar{\theta} - \underline{\theta})} + \left(1 - \frac{\widehat{\theta} - \underline{\theta}}{\bar{\theta} - \underline{\theta}}\right)(\sqrt{I}\widehat{\theta} - D^s) = I - W.$$

Again, this is a quadratic equation in $\widehat{\theta}$, so it has the following two roots:

$$\widehat{\theta}_1 = \bar{\theta} + \frac{C^{DS}}{\sqrt{I}}, \quad \widehat{\theta}_2 = \bar{\theta} - \frac{C^{DS}}{\sqrt{I}},$$
$$C^{DS} = \sqrt{(D^s - \sqrt{I}\bar{\theta})^2 - 2\sqrt{I}(I - W)(\bar{\theta} - \underline{\theta})}.$$

Since $C^{DS} > 0$, only $\widehat{\theta}_2 < \bar{\theta}$ is a meaningful solution to which we refer in the following as simply $\widehat{\theta}$.

Taking the first derivative wrt D^s leads to:

$$\frac{\mathrm{d}\widehat{\theta}}{\mathrm{d}D^s} = \frac{\sqrt{I}\bar{\theta} - D^s}{\sqrt{I}C^{DS}}.$$

Thus, $\widehat{\theta}$ always increases with D^s, since we can rule out cases of $\sqrt{I}\bar{\theta} < D^s$, which would imply that the firm is already overlevered up to the point where even the best possible investment return $\sqrt{I}\bar{\theta}$ is insufficient to cover the senior debt. As discussed in the preceding section, this result is first evidence that the existence of senior debt implies an increased default threshold, which in turn makes investors more sensitive for investment returns and explains the more pronounced U-shape. To verify this more rigorously, we next show that I_W is more negative in the presence of senior debt.

Plugging in $\widehat{\theta}$ in the (constrained) objective function is

$$P = \frac{\sqrt{I}(\underline{\theta} - \bar{\theta})}{2} + C^{DS}.$$

The FOC is thus $P_I = \frac{\theta - \bar{\theta}}{4\sqrt{I}} + C_I^{DS} = 0$. Since C_I^{DS} is a higher-order polynomial in I, an explicit solution for I^* is analytically untractable. Thus, we resort to implicit differentiation, where we treat I as $I(W)$, writing the FOC as

$$\frac{\theta - \bar{\theta}}{4\sqrt{I(W)}} + C_I^{DS}(I(W), W) = 0$$

Note that C^{DS} is a function of $I(W)$ as well as W itself. Differentiating wrt W, leads to

$$\frac{(\overline{\theta} - \underline{\theta})I_W(W)}{8I(W)^{3/2}} + C^{DS}_{I,W}(I(W), W) + I_W(W)C^{DS}_{I,I}(I(W), W) = 0$$

which we can solve for I_W as:

$$I_W = \frac{8I(W)^{3/2}C^{DS}_{I,W}(I(W), W)}{(\underline{\theta} - \overline{\theta}) - 8I(W)^{3/2}C^{DS}_{I,I}(I(W), W)}.$$

Analyzing I_W in the minimum shows that $I_W = 0$ occurs at a value for W equal to

$$W_{I_W=0} = \frac{D^s\overline{\theta} - (D^s)^2/\sqrt{I} - I(\overline{\theta} - \underline{\theta})}{\overline{\theta} - \underline{\theta}}.$$

Importantly, the root $W_{I_W=0}$ increases in D^s for all D^s not too large, as can be verified from the derivative wrt D^s which is

$$\frac{\mathrm{d}W_{I_W=0}}{\mathrm{d}D^s} = \frac{\sqrt{I}\theta - 2D^s}{\sqrt{I}(\overline{\theta} - \underline{\theta})},$$

being positive as long as $\sqrt{I}\theta > 2D^s$.

5.2 Appendix B

Assuming a firm that maximizes its profits under constant returns to scale, a CES production function and no adjustment costs, the capital stock can be represented as log-transformation of output and the cost of capital:

$$k_{i,t} = a_i + y_{i,t} - \sigma j_{i,t}, \tag{6}$$

where the natural logarithm of the desired capital stock of firm i in year t is labelled as $k_{i,t}$, the natural logarithm of output as $y_{i,t}$, the natural log of the real user cost of capital as $j_{i,t}$, the elasticity of capital regarding the real user cost as σ and the firm specific intercept as a_i.

We use a dynamic regression model and take into account a slow adjustment process of the current capital stock to the desired capital stock by assuming the capital stock to pursue an ADL(2,2) model:

$$k_{i,t} = \gamma_1 k_{i,t-1} + \gamma_2 k_{i,t-2} + \delta_0 y_{i,t} + \delta_1 y_{i,t-1} + \delta_2 y_{i,t-2} + v_t + v_i + \epsilon_{i,t}, \tag{7}$$

where v_t and v_i are year and firm fixed effects and $\epsilon_{i,t}$ is the error term.

According to Bond et al. (2003), if we substitute $k_{i,t}$ and $y_{i,t}$ with $k_{i,t} = \Delta k_{i,t} + \Delta k_{i,t-1} + k_{i,t-2}$ and $y_{i,t} = \Delta y_{i,t} + \Delta y_{i,t-1} + y_{i,t-2}$ in Eq. (7), we get:

$$
\Delta k_{i,t} + \Delta k_{i,t-1} + k_{i,t-2} = \gamma_1 k_{i,t-1} + \gamma_2 k_{i,t-2} + \delta_0(\Delta y_{i,t} + \Delta y_{i,t-1} + y_{i,t-2}) \\
+ \delta_1 y_{i,t-1} + \delta_2 y_{i,t-2} + \nu_t + \nu_i + \epsilon_{i,t}. \tag{8}
$$

Solving for $\Delta k_{i,t}$, we get:

$$
\Delta k_{i,t} = (\gamma_1 - 1)\Delta k_{i,t-1} + \delta_0 \Delta y_{i,t} + (\delta_0 + \delta_1)\Delta y_{i,t-1} \\
- (1 - \gamma_1 - \gamma_2)k_{i,t-2} + (\delta_0 + \delta_1 + \delta_2)y_{i,t-2} + \nu_t + \nu_i + \epsilon_{i,t}. \tag{9}
$$

Demanding the restriction $\frac{(\delta_0 + \delta_1 + \delta_2)}{(1 - \gamma_1 - \gamma_2)} = 1$ to be consistent with the long-run unit elasticity of capital with respect to output, we can rewrite the ADL(2,2) model in Eq. (7) in error-correction form:

$$
\Delta k_{i,t} = (\gamma_1 - 1)\Delta k_{i,t-1} + \delta_0 \Delta y_{i,t} + (\delta_0 + \delta_1)\Delta y_{i,t-1} \\
- (1 - \gamma_1 - \gamma_2)(k_{i,t-2} - y_{i,t-2}) + \nu_t + \nu_i + \epsilon_{i,t}, \tag{10}
$$

Accordingly, capital expenditures over capital less depreciation can be implemented as proxy for the variation in capital stock $\Delta k_{i,t} \sim \frac{CAPEX_{i,t}}{K_{i,t-1}} - \delta i$ and the natural logarithm of sales as proxy for the natural logarithm of output $y_{i,t} \sim \ln S_{i,t}$. The natural logarithm of the replacement value of the capital stock $k_{i,t}$ is denoted as $\ln K_{i,t}$. Subsequently, the error-correction model can be written as follows:

$$
\frac{CAPEX_{i,t}}{K_{i,t-1}} = \alpha_1 \frac{CAPEX_{i,t-1}}{K_{i,t-2}} + \alpha_2 \Delta \ln S_{i,t} + \alpha_3 \Delta \ln S_{i,t-1} \\
+ \alpha_4(\ln K_{i,t-2} - \ln S_{i,t-2}) + \nu_t + \nu_i + \epsilon_{i,t}, \tag{11}
$$

where $CAPEX_{i,t}$ is depreciation in year t plus the change in tangible fixed assets from year $t-1$ to year t. The replacement value of the capital stock is computed as $K_{i,t} = K_{i,t-1} \times (1-\delta) + CAPEX_{i,t}$. The first value of K is quantified by the starting observation of tangible fixed assets. The depreciation rate δ is set at a constant rate of 4.5%. $\Delta \ln S_{i,t}$ is the change in log sales. $(\ln K_{i,t-2} - \ln S_{i,t-2})$ denotes the error-correction parameter and assesses the long-run equilibrium between capital and its target value proxied by the natural logarithm of total sales.[29]

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[29] See Bond et al. (2003); Mizen and Vermeulen (2005); Mulier et al. (2016) and Buca and Vermeulen (2017) for additional details on the model.

5.3 Appendix C

Table 8 Variable definitions

Variable	Formula	Description
$CAPEX_{i,t}$	($tangible\ fixed\ assets_{i,t}-$ $tangible\ fixed\ assets_{i,t-1})\ +$ $depreciation_{i,t}$	Capital expenditure
$K_{i,t=0}$	$tangible\ fixed\ assets_{i,t=0}$	Replacement value of the capital stock at $t=0$
$K_{i,t\neq0}$	$K_{i,t-1}*(1-\delta)+CAPEX_{i,t}$	Replacement value of the capital stock at $t\neq0$
$\ln K_{i,t}$	$\log(K_{i,t})$	Natural logarithm of the replacement value of the capital stock
$\Delta\ln S_{i,t}$	$\log(S_{i,t})-\log(S_{i,t-1})$	Change in log sales
$OCF_{i,t}$		Operating cash flow
$OCFSP1_{i,t}$-$OCFSP3_{i,t}$		See below
δ		Depreciation rate=0.045

If $OCF_{i,t}\leqslant 33^{\text{rd}}$ Pct. of OCF:	$OCFSP1_{i,t}=OCF_{i,t}$
$OCFSP2_{i,t}=0$	
$OCFSP3_{i,t}=0$	
If 33rd Pct. of $OCF<OCF_{i,t}\leqslant 66^{\text{th}}$ Pct. of OCF:	$OCFSP1_{i,t}=33^{\text{rd}}$ Pct.
$OCFSP2_{i,t}=OCF_{i,t}-33^{\text{rd}}$ Pct.	
$OCFSP3_{i,t}=0$	
If $OCF_{i,t}>66^{\text{th}}$ Pct. of OCF:	$OCFSP1_{i,t}=33^{\text{rd}}$ Pct.
$OCFSP2_{i,t}=66^{\text{th}}$ Pct.-33rd Pct.	
$OCFSP3_{i,t}=OCF_{i,t}-66^{\text{th}}$ Pct.	

5.4 Appendix D

This Appendix shows descriptive results for the relationship between investment and cash holdings. Analogous to Fig. 3, the Fig. 5 represents mean and median of investment to capital and cash holdings to capital ratios sorted by percentiles of cash hodlings to capital. We find that the increasing part displays a similar pattern for cash holdings and cash flow, but notably, when using the stock variable, the decreasing part is absent. As noted in the main body of the paper, cash holdings as stock variable suffer endogeneity problems with investment, which is the main reason why many papers refrain from using cash holdings in their empirical implementation. See also the discussion in Cleary et al. (2007).

The graphical representation is confirmed by running an analogous model to Eq. (4) with cash holdings (CS) as explanatory variable. We report results from spline regression with terciles of CS in the following Table 9.
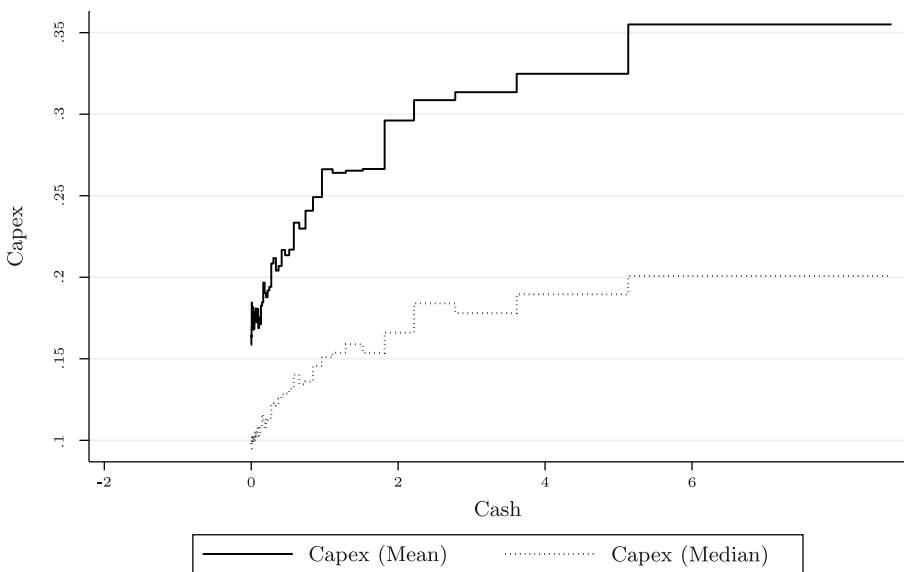
Fig. 5 Mean and median capex for percentiles of cash. Notes: This figure plots means and medians of $\frac{CAPEX_{i,t}}{K_{i,t-1}}$ for percentiles of $\frac{CS_{i,t}}{K_{i,t-1}}$

Table 9 Regression results with cash holdings CS

	(1) OLS	(2) FE	(3) Diff GMM	(4) OLS	(5) FE	(6) Diff GMM
$\frac{CAPEX_{i,t-1}}{K_{i,t-2}}$	0.103***	−0.401***	−0.059***	0.103***	−0.400***	−0.049***
	(0.006)	(0.009)	(0.015)	(0.006)	(0.009)	(0.015)
$\frac{CS_{i,t}}{K_{i,t-1}}$	−0.001	−0.004**	0.016***			
	(0.001)	(0.002)	(0.006)			
$\frac{CST1_{i,t}}{K_{i,t-1}}$				0.074**	0.107*	1.297***
				(0.034)	(0.059)	(0.480)
$\frac{CST2_{i,t}}{K_{i,t-1}}$				0.022***	−0.013	0.289***
				(0.007)	(0.014)	(0.089)
$\frac{CST3_{i,t}}{K_{i,t-1}}$				−0.002**	−0.004**	0.016***
				(0.001)	(0.002)	(0.006)
$\ln K_{i,t-2} - \ln S_{i,t-2}$	−0.035***	−0.539***	−0.188***	−0.033***	−0.539***	−0.170***
	(0.001)	(0.012)	(0.020)	(0.001)	(0.012)	(0.021)
$\Delta \ln S_{i,t}$	0.163***	0.263***	0.223**	0.161***	0.262***	0.226***
	(0.006)	(0.008)	(0.096)	(0.006)	(0.008)	(0.080)
$\Delta \ln S_{i,t-1}$	0.136***	0.408***	0.210***	0.134***	0.408***	0.193***
	(0.005)	(0.009)	(0.024)	(0.005)	(0.010)	(0.023)
Industry FE			No			No
Firm FE						Yes
Year FE						Yes
Adj. R²	0.090	0.381		0.091	0.380	
N	70,126	70,126	70,126	70,126	70,126	70,126
AR(1)-test (p-value)			0.00			0.00
AR(2)-test (p-value)			0.49			0.73
H-test (p-value)			0.03			0.02

Notes: This table reports regression estimates from OLS, firm fixed effects and two-step first-difference GMM regressions with robust standard errors in parentheses. Panel A reports the results for the aggregate sample. Columns 1–3 illustrate the estimates of investment as a linear function of cash holdings. Columns 4–6 illustrate the estimates of spline regressions. We regress investment on a piecewise continuous function of cash holdings with the knots being placed at terciles of cash holdings. The regression model is given by the following investment error correction model: $\frac{CAPEX_{i,t}}{K_{i,t-1}} = \alpha_1 \frac{CAPEX_{i,t-1}}{K_{i,t-2}} + \alpha_2 \frac{CST1_{i,t}}{K_{i,t-1}} + \alpha_3 \frac{CST2_{i,t}}{K_{i,t-1}} + \alpha_4 \frac{CST3_{i,t}}{K_{i,t-1}} + \alpha_5 \Delta \ln S_{i,t} + \alpha_6 \Delta \ln S_{i,t-1} + \alpha_7 (\ln K_{i,t-2} - \ln S_{i,t-2}) + \nu_t + \nu_i + \epsilon_{i,t}$, where $CST1$–3 represents the different terciles. Instruments set for Column 6: $\{ \frac{CAPEX_{i,t-j}}{K_{i,t-1-j}}, \frac{CST1_{i,t-j}}{K_{i,t-1-j}}, \frac{CST2_{i,t-j}}{K_{i,t-1-j}}, \frac{CST3_{i,t-j}}{K_{i,t-1-j}}, (\ln K_{i,t-1-j} - \ln S_{i,t-1-j}), \Delta \ln S_{i,t-j}$, with j being 2; time dummies$\}$. We refer to Table 8 in Appendix C for details on the respective variables. * significant at 10%, ** significant at 5%, *** significant at 1%.

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