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Equity financing risk *

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Abstract

A risk factor linked to aggregate equity issuance conditions explains the empirical performance of investment factors based on the asset growth anomaly of Cooper, Gulen, and Schill (2008). This new risk factor, dubbed equity financing risk (*EFR*) factor, subsumes investment factors in leading linear factor models. Most importantly, when substituted for investment factors, the *EFR* factor improves the overall pricing performance of linear factor models, delivering a significant reduction in absolute pricing errors and their associated *t*-statistics for several anomalies, including the ones related to R&D expenditures and cash-based operating profitability.

Keywords: Equity returns, R&D, financing constraints, equity issuances, factor models

JEL Classification: G12, G31, G35

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1 Introduction

We show that a risk factor linked to aggregate equity issuance conditions explains the empirical performance of investment factors based on the asset growth anomaly of Cooper, Gulen, and Schill (2008). This new risk factor, dubbed equity financing risk (*EFR*) factor, subsumes the investment factors from the linear factor models of Fama and French (2015) and Hou, Xue, and Zhang (2015) in factor spanning tests. Most importantly, when the investment factors are replaced by the *EFR* factor, both mentioned factor models see a significant improvement in their overall pricing performance across a diverse set of anomalies.

Our analysis builds on the observation that, over time, U.S.publicly listed firms have displayed a stronger motive for precautionary savings due to the entry into public equity markets of low profitability (i.e., weaker) firms, as documented by Fama and French (2004) and Denis and McKeon (2017), among others. A direct consequence is a secular increase in the propensity to save cash out of equity issuance proceeds (e.g., McLean, 2011), especially when equity issuance costs are assumed to be low. Given that the level of equity issuance costs depends on aggregate economic conditions, a firm that relies on cash savings out of equity issuances to support its growth is exposed to an additional source of risk, namely, *equity financing risk*. This source of risk consists in having states of the world during which a firm needs to replenish its cash reserves via equity issuance but can only do so at a very high cost or not at all if, for example, liquidity dries up.

There is ample evidence that supports the systematic nature of equity issuance costs. Choe, Masulis, and Nanda (1993) show that adverse selection costs associated with the offering of equity shares are lower during economic expansions, while Eisfeldt and Muir (2016) show that the average cost per dollar of external financing raised displays a strong countercyclical behavior. Erel, Julio, Kim, and Weisbach (2012) show that macroeconomic conditions matter for capital raising, and especially so for lower rated, non-investment grade firms, which experience a reduction in capital raising during economic downturns. McLean and Zhao (2014) provide evidence that aggregate conditions affect the cost of issuing equity more than the cost of issuing debt. Covas and Den Haan (2012) show how the addition of a countercyclical equity issuance cost greatly improves the qualitative performance of a real business cycle model in describing the cyclical behavior of debt and equity. More recently, Belo, Lin, and Yang (2019) identify a proxy for an aggregate issuance cost shock and show that it is a priced source of risk in the cross section of equity returns.

Differently from the papers discussed above, we focus our attention on the subset of R&D-intensive firms to better identify the exposure to equity financing risk. Because of the high adjustment costs and the intangible nature that characterize the R&D process, R&D-intensive firms rely heavily on precautionary savings to avoid disruptions in their investment activities. However, because R&D-intensive firms are on average unable to generate internal financing, they have to rely on seasoned equity offerings to build liquidity reserves. Due to their intangibility and inability to service debt, R&D-intensive firms cannot readily substitute equity with debt and are thus more likely to be exposed to the time-varying nature of equity issuance costs[1].

To empirically capture firm-level concerns about equity issuance costs, we define a firm's *R&D coverage ratio* as its liquid assets relative to its R&D expenditures. The R&D coverage ratio tells us how many quarters of R&D expenditures a firm can sustain with current liquid assets assuming future R&D expenditures remain unchanged. A firm with a high R&D coverage ratio is unlikely to issue equity for cash savings purposes given high equity issuance costs in the near future. Conversely, this is much more likely for a firm with a low R&D coverage ratio.

Having a high or low R&D coverage ratio clearly affects a firm's exposure to *EFR*. However, this exposure can change quite dramatically depending on a firm's ability to engage in precautionary equity issuances. A firm with very little R&D coverage can suddenly reduce its exposure to *EFR* if it has the opportunity, in a given quarter, to perform a large equity issuance and save the proceeds. For this reason, we explore the interplay between R&D coverage and equity issuance activity to empirically identify firms with low or high exposure to *EFR*.[2]

We start our empirical analysis with Fama and MacBeth (1973) cross-sectional regressions of firms' returns on R&D coverage, equity issuance, and standard firm-level return predictors. To mitigate overinfluence of small stocks, we estimate the regressions using weighted least squares (WLS) with firms' market capitalizations as weights. We find that the R&D coverage ratio carries a negative and significant risk premium. At the same time, we find that higher equity issuances are associated with significantly lower future returns, which is consistent with the findings in previous literature. Importantly, we find that the predictive power of R&D coverage and equity issuance is

[1] Brown and Petersen (2011) study the link between cash balances and the high adjustment costs of the R&D process, while Falato, Kadyrzhanova, and Sim (2013) explore how the lack of tangibility of R&D investments increases a firm's precautionary saving motive. Passov (2003) provides anecdotal evidence on the importance of seasoned equity offerings to build cash reserves.

[2] In Appendix C, we show how exposure to equity financing risk naturally arises in a stylized model of a firm's optimal cash management in the presence of costly and risky external financing.

substantially weakened or completely disappears among firms with (i) high profitability and/or (ii) zero or missing R&D expenditures. These findings support the idea that equity issuance is particularly important in reducing the exposure to equity financing risk, and thus in lowering expected returns, for R&D-intensive firms which have little ability to internally finance R&D expenditures.

Next, we explore the interplay between R&D coverage and equity issuance for expected returns in greater detail using portfolios double sorted on the two characteristics. The use of double-sorted portfolios allows us to separate firms with a very low R&D coverage that are not able to issue equity in a given quarter and firms with a very high R&D coverage that are also able to issue equity in a given quarter. The former firms are naturally more sensitive to future equity issuance conditions (i.e., more exposed to *EFR*), while the latter, having plenty of liquid reserves relative to their R&D expenditures, can afford to wait a long time before tapping external financing again. All our portfolio sorts employ NYSE breakpoints and value-weighted returns in order to mitigate overinfluence of small stocks.

We find that firms more exposed to *EFR* (i.e., those with low R&D coverage ratio *and* no equity issuance) generate significantly higher average returns than firms less exposed to *EFR* (i.e., firms with a high R&D coverage ratio *and* high equity issuance), with an economically sizeable spread of about 1% per month. Moreover, when we include an additional control for size in our portfolio sorts, we find that the spread is particularly pronounced for small firms, where those more exposed to *EFR* generate significantly higher average returns with a spread of almost 2% per month. Among large firms, those more exposed to *EFR* also generate higher average returns with a significant spread of about 1% per month.

Motivated by these results, we construct an empirical asset pricing factor that plausibly captures the exposure to *EFR*. We construct our *EFR* factor using the same basic procedure employed by Fama and French (2015) and Hou, Xue, and Zhang (2015). Specifically, the *EFR* factor is an equal-weighted average of value-weighted large-cap and small-cap *EFR* strategies. The *EFR* factor generates a large and highly significant average return of 1.45% per month with a t-statistic of 4.80. Importantly, this return is neither explained by Fama and French's (2015) five-factor model, with or without the momentum factor, nor by Hou, Xue, and Zhang's (2015) q-factor model.

Consistent with our prior that the *EFR* factor should proxy for the exposure to aggregate equity issuance conditions, we show that this factor is highly correlated with three commonly employed proxies for aggregate equity issuance conditions: the implied volatility index (VIX), Pástor and

Stambaugh's (2003) aggregate liquidity measure, and the market excess return. Specifically, the *EFR* factor's excess returns tends to be high when implied volatility is high, or when the market excess return is low, or when aggregate liquidity is low. Moreover, we show that a linear combination of the three proxies of aggregate equity issuance conditions fully explain the *EFR* factor's average excess return and a substantial fraction of its volatility.

In the last part of the paper, we provide evidence in support of the inclusion of the *EFR* factor in the five-factor and *q*-factor models. First, we show in factor spanning tests that the *EFR* factor completely subsumes these models' investment factors (*CMA* and *I/A*): either model's investment factor is within the span of *EFR*, with or without controls for the other factors. The reason is that both *CMA* and *I/A* are highly correlated with aggregate equity issuance conditions. Specifically, we conduct a detailed analysis of the investment factors' underlying portfolio characteristics and show that the large increase in total assets that differentiates the investment factors' short portfolios from their long portfolios are predominantly driven by large equity issuances and increases in liquid assets rather than increases in physical assets. As such, our results suggest that these "investment" factors conflate variation in returns due to physical investments with variation in returns due to precautionary savings from equity issuance aimed at reducing the exposure to *EFR*.

Then, we conclude our empirical analysis by comparing the pricing power of the *EFR* factor with that of the investment factors. To this end, we borrow a set of test assets from the list of 46 strategies in Hou, Xue, and Zhang (2018) that generate a significant average return as well as a significant *q*-factor abnormal return. We find that when an investment factor is replaced by the *EFR* factor in the factor models of Fama and French (2015) and Hou, Xue, and Zhang (2015), there is a significant reduction in absolute pricing errors and their associated *t*-statistics for several anomalies, including the ones related to R&D expenditures and cash-based operating profitability.

Literature Review

Our paper belongs to a recent effort to understand the sources of risk (or mispricing) that drive the asset growth anomaly of Cooper et al. (2008). Cooper, Gulen, and Ion (2017) challenge the idea that firm-level investment is the main driver behind the explanatory power of the asset growth factors used in the multifactor models of Fama and French (2015) and Hou, Xue, and Zhang (2015). More recently, O'Donovan (2019) provides evidence that the asset growth anomaly was driven in the past by mispricing caused by earnings management. O'Donovan (2019) shows that in recent years this source of mispricing has greatly reduced, thus causing a weakening of the asset growth anomaly. We contribute to this effort by offering an alternative and complementary interpretation based on precautionary financing motives aimed at reducing exposure to equity financing risk[3].

We also provide a novel explanation for the observed negative relation between seasoned equity offerings (SEOs) and equity returns.[4] We show that when firms issue equity for precautionary savings, they reduce their exposure to equity financing risk and thus witness a reduction in expected equity returns. This channel complements explanations based on asymmetric information (e.g., Leland and Pyle 1977; Myers and Majluf 1984; Miller and Rock 1985; Lucas and McDonald 1990), exposure to inflation and default risk (e.g., Eckbo, Masulis, and Norli (2000)); heterogenous beliefs (e.g., Dittmar and Thakor, 2007), and investment activity (e.g., Carlson, Fisher, and Giammarino 2006 and Lyandres, Sun, and Zhang 2008).

Lastly, our paper contributes to a vast literature that tries to understand how firm-level characteristics shape the cross section of equity returns (e.g., Fama and French 1992 and more recently Hou, Xue, and Zhang 2018, among many others). We propose a new firm-level characteristic, the liquid assets-to-R&D ratio, that is linked to exposure to equity financing risk and is significantly priced in the cross section. In addition, we also contribute to the empirical asset pricing literature by introducing a new risk factor, namely, the equity financing risk (*EFR*) factor. This factor is (i) related to aggregate equity issuance conditions (ii) not subsumed by the multifactor models of Fama and French (2015) and Hou, Xue, and Zhang (2015); and (iii) produces significant improvements in pricing performance when used in place of these models' investment factors.

The paper is organized as follows. Section 2 provides a description of the data and sample used in the empirical analysis. In Section 3, we run Fama and MacBeth (1973) cross-sectional regressions of firms' returns on R&D coverage, equity issuances, and standard firm-level return predictors. Section 4 presents the portfolio analysis. Section 5 describes at length the equity financing risk (*EFR*) factor. We perform asset pricing tests using the *EFR* factor in Section 6. Section 7 concludes.

[3] Harford, Klasa, and Maxwell (2014) explore the role of cash holdings in mitigating debt refinancing risk. They find that the importance of cash holdings in lowering refinancing risk is much higher for firms with more debt. In this paper, we complement their study by focusing on how cash savings out of equity issuance proceeds affect equity returns by mitigating equity financing risk.

[4] The literature on the negative relation between SEOs and equity returns includes Asquith and Mullins (1986); Masulis and Korwar (1986); Spiess and Affleck-Graves (1995); Brav, Geczy, and Gompers (2000); Daniel and Titman (2006); Pontiff and Woodgate (2008); Fama and French (2008); and many others.

2 Data and sample

Our sample consists of firms for which we could obtain quarterly accounting data from the S&P Global's Compustat North America database (Compustat) and monthly security data from the Center for Research in Security Prices US Stock Database (CRSP) accessed via the Wharton Research Data Services (WRDS). We use quarterly accounting data in order to capture how within-year dynamics in R&D coverage and equity issuance affect subsequent returns. To be included in our main sample, firms must have ordinary common shares (SHRCD 10 and 11) traded on NYSE, Amex, or Nasdaq as well as strictly positive R&D expenditures (XRDQ).[5] Following Hou, Xue, and Zhang (2015, 2018), we exclude financial firms (SIC codes 6000-6999) and firms with negative book equity, and we employ quarterly earnings (IBQ) in the months immediately after earnings announcement dates (RDQ) but impose a 4-month lag between other accounting data and subsequent returns to ensure no look-ahead bias. Our sample covers January 1990 to December 2016, where the start date is determined by the availability of quarterly R&D data.[6]

Primary measures of R&D coverage and equity issuances

A firm's exposure to equity financing risk should depend on the amount of liquid assets relative to R&D expenditures (i.e., the R&D coverage ratio). Our primary measure of a firm's R&D coverage ratio in quarter t is its beginning-of-quarter near cash or "quick" assets relative to its end-of-quarter R&D expenditure, $QA_{t-1}/R\&D_t$. Quick assets are current assets minus inventory (ACTQ − INVTQ) or, equivalently, the sum of cash, marketable securities, and accounts receivable (CHEQ + RECTQ).[7] Quick assets are the most liquid current assets. They are typically convertible to cash at near book value and pledgeable as loan collateral.

Equity issuances are also important in shaping the exposure to equity financing risk. This is because a firm can radically increase its R&D coverage by issuing equity and savings the proceeds.

[5] R&D expenditures are subject to two accounting requirements. First, they must be expensed and deducted from earnings (IBQ) when incurred. Second, if the amount exceeds 1% of total revenue (REVTQ), it must be disclosed either as a separate line on the Income Statement or in the Notes to the Accounts. If not reported as a separate line on the Income Statement, R&D expenditures are typically included in selling, general, and administrative expenses (XSGAQ) and in very few cases in cost of goods sold (COGSQ). See Ball, Gerakos, Linnainmaa, and Nikolaev (2015).

[6] For the same reason, Hou, Xue, and Zhang (2015, 2018) also start their portfolio sorts involving quarterly R&D data in January 1990.

[7] We measure quick assets as ACTQ − INVTQ when available, or else as CHEQ + RECTQ. Compustat's CHEQ is also the sum of cash and short-term investments (CHQ + IVSTQ). Quick assets are commonly employed to measure liquidity balances in corporate finance, asset pricing, and credit risk studies (see, e.g., Almeida and Campello (2007); Hahn and Lee (2009); Acharya, Davydenko, and Strebulaev (2012); and the references therein).

To measure a firm's equity issuance proceeds, we start with Fama and French's (2005) market-based "dSM" variable, which gives the *net* dollars issued or repurchased over the latest year. At the end of month $m-1$ in quarter t (for predicting returns over month m), we measure *net* issuance proceeds over the latest year (4 quarters) as the monthly change in split-adjusted shares outstanding times the monthly average split-adjusted share price accumulated over the latest 12 months:

$$\mathrm{dSM}_{t-4,t} \equiv \sum_{n=0}^{11} \Delta(\mathrm{SHROUT}_{(m-1)-n}\,\mathrm{CFACSHR}_{(m-1)-n}) \times \tfrac{1}{2}\left(\frac{\mathrm{PRC}_{(m-1)-n}}{\mathrm{CFACPR}_{(m-1)-n}} + \frac{\mathrm{PRC}_{(m-1)-n-1}}{\mathrm{CFACPR}_{(m-1)-n-1}}\right). \quad (1)$$

The positive part, $\mathrm{dSM}^{+}_{t-4,t} = \max\{0, \mathrm{dSM}_{t-4,t}\}$, is then our measure of equity issuance proceeds over the latest year. Related measures are employed by Stephens and Weisbach (1998), Daniel and Titman (2006), Pontiff and Woodgate (2008), and Fama and French (2008). We accumulate monthly values because sampling prices at a higher frequency gives a more accurate estimate of issuance proceeds over time, although our results are insensitive to the sampling frequency. The one-year horizon is common and helps alleviate seasonalities in equity issuances. To alleviate the influence of outliers and errors in the split-adjustment factors, we trim them at the monthly 0.005 and 0.995 levels before computing dSM.[8] Note that dSM does not include IPO proceeds because it requires a firm's share price, but that it captures all other issuances, including those not publicized.

Summary statistics

Table 1 shows summary statistics for the main variable we employ in our tests as well as other key firm characteristics. When possible, the summary statistics are shown for the R&D sample (firm-quarters with strictly positive R&D expenditures) as well as the non-R&D sample (firm-quarters with zero or missing R&D expenditures). To avoid undue influence from outliers, the shown statistics are for variables trimmed at the samples' 1st and 99th percentiles.

Over our sample period, the R&D coverage ratio ($QA_{t-1}/R\&D_t$) has a mean of 30.78 and a median of 17.76. That is, the typical liquidity balance can cover R&D expenditures for a period of between 4.5 and 7.5 years. The mean quarterly R&D expenditure is 3% of assets. R&D-intensive firms have a mean quick assets-to-assets ratio of 47%, over 1.6 times higher than non-R&D firms.

Brown, Fazzari, and Petersen (2009) show that R&D-intensive firms tend to rely much more

[8]For the same reasons, Fama and French (2006) require that the split-adjustment factors from CRSP and Compustat match, while Pontiff and Woodgate (2008) correct firms' split-adjusted shares outstanding if they change by more than 20%, and subsequently 95% of the change is reversed within three months. Our approach is simpler but as effective.

Table 1. Summary statistics. This table shows summary statistics for the main variable we employ in our tests as well as other key firm characteristics. The "R&D" sample consists of firm-quarters with strictly positive R&D expenditures, while the "Non-R&D" sample consists of firm-quarters with zero or missing R&D expenditures. QA_t is quick assets in quarter t (ACTQ − INVTQ or else CHEQ + RECTQ), $R\&D_t$ is research and development expenditures (XRDQ), A_t is total assets (ATQ), $\mathrm{dSM}^+_{t-4,t}$ is the positive part of the monthly change in split-adjusted shares outstanding times the monthly average split-adjusted share price accumulated over the latest 12 months, $\mathrm{dD}^+_{t-4,t}$ is the positive part of the year-over-year change in interest-bearing debt (DLCQ + DLTTQ), COP_t is cash-based operating profits, ROE_t is return-on-equity (income before extraordinary items, IBQ, divided by lagged book equity, B_{t-1}), and M_t is market equity (PRCCQ × CSHOQ). The shown statistics are for variables trimmed at the sample's 1st and 99th percentiles. The sample excludes financial firms and firms with negative book equity. Data are quarterly and cover 1989 to 2016, where the start date is determined by the availability of quarterly data on R&D expenditures.

				Percentile				
Variable	Sample	Mean	Standard deviation	1st	25th	Median	75th	99th
R&D coverage								
R&D coverage ratio ($QA_{t-1}/R\&D_t$)	R&D	30.78	42.99	2.93	10.59	17.76	32.04	246.13
R&D expenditures ($R\&D_t/A_{t-1}$)	R&D	0.03	0.04	0.00	0.01	0.02	0.04	0.17
Quick assets (QA_{t-1}/A_{t-1})	R&D	0.47	0.22	0.09	0.29	0.44	0.64	0.93
	Non-R&D	0.29	0.19	0.03	0.14	0.25	0.39	0.85
Equity and debt issuance								
Equity issuance ($\mathrm{dSM}^+_{t-4,t}/A_{t-4}$)	R&D	0.24	0.56	0.00	0.00	0.02	0.16	3.03
	Non-R&D	0.09	0.34	0.00	0.00	0.00	0.03	1.84
Debt issuance ($\mathrm{dD}^+_{t-4,t}/A_{t-4}$)	R&D	0.04	0.11	0.00	0.00	0.00	0.02	0.60
	Non-R&D	0.06	0.13	0.00	0.00	0.00	0.06	0.69
Profitability								
Cash-based operating profitability net of R&D ($(COP_t - R\&D_t)/A_{t-1}$)	R&D	−0.01	0.08	−0.27	−0.04	0.01	0.04	0.14
	Non-R&D	0.02	0.06	−0.18	0.00	0.03	0.05	0.16
Return on equity (ROE_t)	R&D	−0.03	0.13	−0.57	−0.06	0.01	0.04	0.18
	Non-R&D	0.01	0.09	−0.42	0.00	0.02	0.04	0.19
Leverage								
Market leverage ($D_t/(D_t + M_t)$)	R&D	0.11	0.16	0.00	0.00	0.03	0.16	0.68
	Non-R&D	0.25	0.23	0.00	0.05	0.20	0.40	0.82
Book leverage (D_t/A_t)	R&D	0.13	0.16	0.00	0.00	0.06	0.22	0.61
	Non-R&D	0.24	0.19	0.00	0.07	0.23	0.37	0.68

heavily on equity issuances compared to debt issuances when tapping capital markets. The summary statistics confirm this. For R&D-intensive firms, equity issuance-to-assets ($\mathrm{dSM}^+_{t-4,t}/A_{t-4}$) has a mean of 24% and a median of 2%, while debt issuance-to-assets ($\mathrm{dD}^+_{t-4,t}/A_{t-4}$) has a mean of 4% and a median of zero. For non-R&D firms, equity issuance-to-assets has a mean of 9% and a median of zero, while debt issuance-to-assets has a mean of 6% and a median of zero. Hence, while equity and debt issuances are of about the same size for non-R&D firms, R&D intensive firms' equity issuances are typically much larger than their debt issuances.

The large liquidity balances and the preference for equity issuances are consistent with R&D-intensive firms' lower profitability and lower leverage. For instance, while cash-based operating profitability net of R&D ($(COP_t - R\&D_t)/A_{t-1}$) has a mean of -1% and a median of 1% for R&D-intensive firms, its mean and median are 2% and 3% for non-R&D firms.[9] Similar statistics hold for return on equity (ROE_t).[10] Our data show that R&D-intensive firms are also less levered, a fact in accordance with Hall and Lerner's (2009) view that leverage is a poor substitute for equity financing and delivers small benefits for this kind of firm. For instance, while market leverage ($D_t/(D_t + M_t)$) has a mean of 11% and a median of just 3% for R&D-intensive firms, it has a mean of 25% and a median of 20% for non-R&D firms. Similar statistics hold for book leverage (D_t/A_t).

3 Fama and MacBeth regressions

We start our exploration of the relation between the R&D coverage ratio and equity issuance on one hand and equity returns on the other hand using Fama and MacBeth (1973) cross-sectional predictive regressions. To mitigate the influence of small firms in OLS regressions, we estimate the coefficients via weighted least squares (WLS) with market capitalization as weight.

In addition to our primary measure of R&D coverage, $QA_{t-1}/R\&D_t$, we employ two other measures. The first replaces quick assets with just cash holdings (CHEQ). For the second measure, we replace R&D expenditures with total operating costs which, following Novy-Marx (2011), are costs of goods sold plus selling, general, and administrative expenses (COGSQ + XSGAQ).

In addition to our primary measure of equity issuance proceeds, $\text{dSM}^{+}_{t-4,t}$, which is over the latest year, we also employ two measures over the latest quarter: the monthly change in split-adjusted shares outstanding times the monthly average split-adjusted stock price accumulated over the latest 3 months, $\text{dSM}_{t-1,t}$ (see Eq. (1)), and the quarterly net sale of common and preferred stock from Compustat, NSS_t (defined as quarterly SSTKY minus quarterly PRSTKCY). We take

[9] We use a quarterly version of COP_t defined similarly to the annual version employed by Ball, Gerakos, Linnainmaa, and Nikolaev (2016). Specifically, it is total revenue minus the cost of goods sold minus selling, general, and administrative expenses plus R&D expenditures (zero if missing) minus accounting accruals adjustments (REVTQ − COGSQ − XSGAQ + XRDQ − ΔRECTQ − ΔINVTQ + Δ(DRCQ+DRLTQ) + ΔAPQ + ΔXACCQ). All changes are quarterly differences, and missing changes are set to zero. We subtract R&D expenditures from COP_t in Table 1 to make it comparable across the subsamples of R&D-intensive and non-R&D firms.

[10] We follow Hou, Xue, and Zhang (2015) and define quarterly return on equity, ROE_t, as the most recently available quarterly earnings (IBQ) divided by one-quarter lagged book equity, B_{t-1}. Quarterly book equity, B_t, is defined similar to the annual version employed by Fama and French (1993, 2015), Novy-Marx (2013), and others, and is shareholder's equity plus deferred taxes minus preferred stock. Shareholder's equity is SEQQ. If SEQQ is missing, we substitute it by common equity, CEQQ, plus preferred stock (defined below), or else by total assets minus total liabilities, ATQ − LTQ. Deferred taxes is deferred taxes and investment tax credits, TXDITCQ, or else deferred taxes, TXDBQ. Preferred stock is redemption value, PSTKRQ, or else carrying value, PSTKQ.

Table 2. Fama and MacBeth regressions of returns on R&D coverage and equity issuance. This table shows Fama and MacBeth cross-sectional predictive regressions of firms' monthly returns on measures of R&D coverage (Panel A) and equity issuance (Panel B). In Panel A, QA_{t-1} is one-quarter lagged quick assets (ACTQ − INVTQ or else CHEQ + RECTQ), $R\&D_t$ is research and development expenditure (XRDQ), C_{t-1} is one-quarter lagged cash and equivalents (CHEQ), and OC_t is operating costs (COGSQ + XSGAQ). In Panel B, $\mathrm{dSM}_{t-4,t}$ and $\mathrm{dSM}_{t-1,t}$ are the monthly changes in split-adjusted shares outstanding times the monthly average split-adjusted share price accumulated over the latest 12 and 3 months, respectively; NSS_t is the quarterly net sale of common and preferred stock (quarterly SSTKY minus quarterly PRSTKCY); A_t is total assets (ATQ), and $x^+ = \max\{0, x\}$ denotes the positive part of x. Regressions are estimated using WLS with marked capitalization as weight. Independent variables are trimmed at the monthly 1st and 99th percentiles and then standardized by their cross-sectional means and standard deviations. Controls are *Size* (log of market capitalization, M, for the previous month), book-to-market equity (B/M, where M is for the previous month), past performance over the previous month ($r_{1,0}$) and the previous 12 to 2 months ($r_{12,2}$), return on equity (*ROE*), asset growth ($\mathrm{dA}_{t-4,t}/A_{t-4}$), and repurchases ($\mathrm{dSM}^-_{t-4,t}/A_{t-4}$, where $\mathrm{dSM}^-_{t-4,t} = \max\{0, -\mathrm{dSM}_{t-4,t}\}$). The sample is restricted to firm-quarters with strictly positive R&D expenditures and excludes financial firms and firms with negative book equity. Data are monthly and cover January 1990 to December 2016.

	Slopes (×100) and test-statistics (in parentheses) from WLS cross-sectional regressions of the form $r_{it} = \boldsymbol{\beta}'\mathbf{X}_{it} + \epsilon_{it}$							
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: R&D coverage variables								
$\log(QA_{t-1}/R\&D_t)$	−0.23			−0.24	−0.23		−0.31	−0.25
	(−3.20)			(−2.07)	(−3.08)		(−2.75)	(−3.78)
$\log(C_{t-1}/R\&D_t)$		−0.09		0.06		−0.11	0.12	
		(−1.40)		(0.51)		(−1.66)	(1.19)	
$\log(QA_{t-1}/OC_t)$			0.02		0.00	0.07	−0.04	
			(0.22)		(−0.01)	(0.77)	(−0.54)	
ROE								0.37
								(3.43)
$\mathrm{dA}_{t-4,t}/A_{t-4}$								−0.14
								(−1.77)
$\mathrm{dSM}^-_{t-4,t}/A_{t-4}$								0.02
								(0.46)
$\log(B/M)$	0.11	0.05	0.00	0.09	0.05	0.01	0.06	0.20
	(1.11)	(0.47)	(0.01)	(0.94)	(0.54)	(0.14)	(0.56)	(1.93)
Size	−0.08	−0.09	−0.07	−0.08	−0.10	−0.09	−0.10	−0.14
	(−0.68)	(−0.82)	(−0.67)	(−0.72)	(−0.88)	(−0.83)	(−0.93)	(−1.29)
$r_{1,0}$	−0.26	−0.26	−0.23	−0.27	−0.25	−0.23	−0.26	−0.27
	(−2.15)	(−2.15)	(−1.90)	(−2.37)	(−2.13)	(−1.93)	(−2.25)	(−2.31)
$r_{12,2}$	0.27	0.27	0.21	0.25	0.24	0.22	0.23	0.31
	(1.72)	(1.70)	(1.31)	(1.66)	(1.54)	(1.41)	(1.52)	(2.02)
Avg. adj. R^2	8.6%	8.5%	9.3%	9.8%	10.2%	10.0%	11.0%	10.8%
Avg. N	1,146	1,157	998	1,132	983	978	970	1,099
Panel B: Equity issuance variables								
$\mathrm{dSM}^+_{t-4,t}/A_{t-4}$	−0.30			−0.29	−0.33		−0.30	−0.20
	(−3.76)			(−3.26)	(−3.94)		(−3.36)	(−2.55)
$\mathrm{dSM}^+_{t-1,t}/A_{t-4}$		−0.20		−0.10		−0.21	−0.11	
		(−3.23)		(−1.66)		(−3.48)	(−1.75)	
NSS^+_t/A_{t-1}			−0.04		0.04	−0.03	0.03	
			(−0.60)		(0.56)	(−0.48)	(0.42)	
ROE								0.25
								(2.22)
$\mathrm{dA}_{t-4,t}/A_{t-4}$								−0.12
								(−1.65)
$\mathrm{dSM}^-_{t-4,t}/A_{t-4}$								0.02
								(0.62)
$\log(B/M)$	0.03	0.03	0.06	0.02	0.02	0.02	0.02	0.08
	(0.25)	(0.26)	(0.59)	(0.20)	(0.20)	(0.19)	(0.16)	(0.77)
Size	−0.11	−0.09	−0.07	−0.12	−0.12	−0.09	−0.12	−0.15
	(−1.07)	(−0.78)	(−0.64)	(−1.09)	(−1.12)	(−0.85)	(−1.13)	(−1.42)
$r_{1,0}$	−0.28	−0.27	−0.26	−0.28	−0.28	−0.27	−0.28	−0.28
	(−2.32)	(−2.22)	(−2.08)	(−2.36)	(−2.34)	(−2.21)	(−2.36)	(−2.39)
$r_{12,2}$	0.32	0.30	0.26	0.33	0.31	0.29	0.32	0.30
	(2.02)	(1.91)	(1.64)	(2.12)	(1.95)	(1.84)	(2.05)	(1.94)
Avg. adj. R^2	8.6%	8.1%	8.0%	8.8%	8.7%	8.4%	9.0%	10.4%
Avg. N	1,171	1,172	1,170	1,164	1,161	1,162	1,155	1,125

the positive part of both variables and scale them by one-quarter lagged total assets, A_{t-1}.

The predictive power of R&D coverage ratio and equity issuance

Table 2 reports the results from Fama and MacBeth (1973) regressions employing the R&D coverage and equity issuance variables. Because R&D coverage has a highly right-skewed distribution, we use a log-transformed version in the regressions (similar to market capitalization and book-to-market equity), although the results are insensitive to this transformation. The regressions control for *Size*, book-to-market equity (*B/M*), past performance over the previous month ($r_{1,0}$) and the previous 12 to 2 months ($r_{12,2}$), return on equity (*ROE*), growth in total assets ($\mathrm{dA}_{t-4,t}/A_{t-4}$), and repurchases ($\mathrm{dSM}^{-}_{t-4,t}/A_{t-4}$, where $\mathrm{dSM}^{-}_{t-4,t} = \max\{0, -\mathrm{dSM}_{t-4,t}\}$).[11] To mitigate the influence outliers and aid interpretability, independent variables are trimmed at the monthly 1st and 99th percentiles and then standardized by their cross-sectional means and standard deviations.

Panel A shows the results for the regressions employing the R&D coverage variables. The first three specifications show that while quick assets relative to R&D expenditures has a negative and significant coefficient, neither cash relative to R&D expenditures nor quick assets relative to operating costs is significant. Specifications (4)-(7) show that the significance of the quick assets-to-R&D ratio does not disappear when we control for the two other measures, whether employed individually or together. The eighth specification shows that the effect of the quick assets-to-R&D ratio is only strengthened when controlling for profitability, asset growth, and repurchases.

Panel B shows the results for the regressions employing the equity issuance variables. The first three specifications show that only the market-based measures of equity issuance are significant, both with a negative coefficient. Specifications (4) to (7) show that $\mathrm{dSM}^{+}_{t-4,t}/A_{t-4}$ subsumes the two other equity issuance measures, whether employed individually or together. Finally, the eighth specification shows that while controlling for profitability and asset growth does reduce the predictive power of $\mathrm{dSM}^{+}_{t-4,t}/A_{t-4}$, it still remains significant. The fact that controlling for profitability and asset growth diminishes the predictive power of equity issuance is consistent with the results of Hou, Xue, and Zhang (2015) and Fama and French (2016).[12]

[11] We use quarterly versions of *Size*, *B/M*, and asset growth defined similar to the the annual versions employed by Fama and French (2015). *Size* is the log of equity market capitalization, M, for the previous month from CRSP. Asset growth is the year-over-year percentage change in total assets (i.e., $\mathrm{dA}_{t-4,t}/A_{t-4} \equiv \mathrm{ATQ}/\mathrm{ATQ}_{-4} - 1$). Book-to-market equity is quarterly book equity, B, divided by market capitalization, M, for the previous month from CRSP.

[12] In untabulated tests, we also control for firm-level financing constraints using Hadlock and Pierce's (2010) size-age index. We find that the size-age index has no predictive power in cross-sectional regressions of returns and that

Table 3. Fama and MacBeth regressions of returns on R&D coverage and equity issuance within subsamples. This table shows Fama and MacBeth cross-sectional predictive regressions of firms' monthly returns on R&D coverage and equity issuance. R&D coverage is one-quarter lagged quick assets relative to current R&D expenditures ($QA_{t-1}/R\&D_t$). Equity issuance is the positive part of the monthly change in split-adjusted shares outstanding times the monthly average split-adjusted share price accumulated over the latest 12 months and scaled by beginning-of-period total assets ($\mathrm{dSM}^{+}_{t-4,t}/A_{t-4}$). Regressions are estimated using WLS with marked capitalization as weight. Independent variables are trimmed at the monthly 1st and 99th percentiles and then standardized by their cross-sectional means and standard deviations. Controls are return on equity (ROE), asset growth ($\mathrm{dA}_{t-4,t}/A_{t-4}$), repurchases ($\mathrm{dSM}^{-}_{t-4,t}/A_{t-4}$), book-to-market equity (B/M), $Size$, and past performance ($r_{1,0}$ and $r_{12,2}$). In specifications (1)-(5), the the sample is restricted to firm-quarters with strictly positive R&D expenditures. In specifications (2)-(5), "low" and "high" are defined according to the monthly 20th and 80th percentiles for NYSE stocks. The splitting variable in specifications (2)-(3) is lagged return on equity (ROE_{t-1}) and in specifications (4)-(5) it is cash-based operating profits relative to R&D expenditures ($COP_t/R\&D_t$). In specification (6), the sample consists of firm-quarters with zero or missing R&D expenditures. All specifications exclude financial firms and firms with negative book equity. Data are monthly and cover January 1990 to December 2016.

	Slopes (×100) and test-statistics (in parentheses) from WLS cross-sectional regressions of the form $r_{it} = \boldsymbol{\beta}'\mathbf{X}_{it} + \epsilon_{it}$					
		R&D sample split into ROE_{t-1} quintiles		R&D sample split into $COP_t/R\&D_t$ quintiles		
Independent variable	Full R&D sample (1)	Low (2)	High (3)	Low (4)	High (5)	Zero or missing R&D (6)
$\log(QA_{t-1}/R\&D_t)$	−0.26	−0.54	−0.28	−0.44	−0.06	
	(−3.82)	(−4.57)	(−2.43)	(−4.16)	(−0.43)	
$\mathrm{dSM}^{+}_{t-4,t}/A_{t-4}$	−0.20	−0.24	−0.25	−0.46	−0.43	−0.08
	(−2.50)	(−2.12)	(−0.95)	(−3.01)	(−0.34)	(−1.46)
ROE	0.34	0.40	0.29	0.38	0.15	0.34
	(3.12)	(3.90)	(1.12)	(2.64)	(0.43)	(4.56)
$\mathrm{dA}_{t-4,t}/A_{t-4}$	−0.12	−0.23	0.09	−0.07	−0.26	−0.12
	(−1.65)	(−2.43)	(0.49)	(−0.61)	(−0.55)	(−2.35)
$\mathrm{dSM}^{-}_{t-4,t}/A_{t-4}$	0.01	−0.01	0.04	0.11	−0.05	0.03
	(0.18)	(−0.13)	(0.62)	(1.25)	(−0.58)	(1.11)
$\log(B/M)$	0.17	0.43	0.34	0.05	0.28	0.22
	(1.65)	(3.20)	(1.53)	(0.38)	(1.26)	(3.27)
$Size$	−0.16	−0.07	−0.06	−0.22	−0.11	−0.11
	(−1.51)	(−0.40)	(−0.29)	(−1.43)	(−0.62)	(−1.32)
$r_{1,0}$	−0.27	−0.54	−0.10	−0.22	−0.36	−0.22
	(−2.29)	(−4.47)	(−0.61)	(−1.90)	(−1.81)	(−2.28)
$r_{12,2}$	0.33	0.37	0.24	0.19	0.35	0.19
	(2.10)	(2.49)	(1.16)	(1.26)	(1.48)	(1.41)
Avg. adj. R^2	11.2%	11.3%	19.8%	13.7%	26.1%	8.9%
Avg. N	1,094	488	128	455	78	1,786

The exposure to equity financing risk crucially depends on a firm's ability to generate internal resources and to substitute equity financing with debt financing. For this reason, the power of R&D coverage and equity issuance in predicting returns should be stronger among firms with lower profitability, given their inability to generate internal financing. Similarly, the power of equity issuance in predicting returns should be stronger among R&D-intensive firms compared to non-R&D firms, given R&D-intensive firms' inability to substitute equity with debt.

In Table 3 we test these predictions using subsamples defined according to firms' profitability

controlling for it has no impact on the predictive power of R&D coverage or equity issuance.

and R&D intensity. All specifications control for profitability, asset growth, repurchases, book-to-market, size, and past performance. The first specification shows that, in our full sample of firm-quarters with positive R&D expenditures, R&D coverage ratio and equity issuance remain significant when employed together (t-statistics of -3.82 and -2.50, respectively). The second and third specifications repeat this regression within the subsamples of low and high lagged return on equity (ROE_{t-1}), defined according to the monthly 20th and 80th percentiles for NYSE stocks. They show that the power of the R&D coverage ratio is much stronger for the low-profitability group and that equity issuance is only significant within this group. The fourth and fifth specifications show that the same results hold when ROE_{t-1} is replaced by cash-based operating profits (which are before R&D expenditures) relative to R&D expenditures ($COP_t/R\&D_t$). The sixth and final specification shows that within the sample of firm-quarters with zero or missing R&D expenditures, the relation between equity issuance and returns is no longer significant.

These findings support our view of the R&D coverage ratio as a proxy for the exposure to equity financing risk. Unprofitable, R&D-intensive firms are unable to fund their R&D investments with internally generated cash flows. Hence, the ones with lower R&D coverage are more exposed to equity financing risk and have higher expected returns. At the same time, equity issuance activity seems to matter for future returns only for unprofitable R&D-intensive firms in virtue of its ability to increase precautionary savings and reduce the exposure to equity financing risk.

Overall, Tables 2 and 3 show that R&D coverage and equity issuances are important determinants of equity returns, especially for unprofitable firms. In the next section, we use a portfolio approach to study how these two characteristics jointly shape the cross section of equity returns.

4 Portfolio sorts

The exposure to equity financing risk should be affected by a firm's R&D coverage as well as its ability to engage in precautionary equity issuances. Fixing equity issuances, firms with higher R&D coverage should earn lower future returns. Conversely, fixing R&D coverage, firms that issue more equity should earn lower future returns. In this section, we provide evidence in support of these predictions using portfolios double sorted on R&D coverage ($QA_{t-1}/R\&D_t$) and equity issuance ($\mathrm{dSM}_{t-4,t}/A_{t-4}$). We only keep firms with nonnegative $\mathrm{dSM}_{t-4,t}$.

Table 4 shows the results. The portfolios are from independent 3×3 sorts, where the breakpoints

Table 4. Double-sorts on R&D coverage and equity issuances. This table shows results for portfolios double-sorted on R&D coverage ($QA_{t-1}/R\&D_t$) and equity issuance ($\mathrm{dSM}_{t-4,t}/A_{t-4}$). We only keep firms with nonnegative $\mathrm{dSM}_{t-4,t}$. The portfolios are from from independent 3×3 sorts where the breakpoints are the 30th and 70th percentiles for NYSE stocks and are value-weighted and rebalanced at the end of each month. Panel A shows the portfolios' average monthly excess returns above the T-bill rate as well as their abnormal returns relative to Fama and French's (2015) five-factor model, including the momentum factor, and Hou, Xue, and Zhang's (2015) q-factor model. It also shows time-series averages of the portfolios' value-weighted characteristics [ROE_t is current return on equity; $\mathrm{dA}_{t-4,t}$ is the year-over-year change in total assets; $\mathrm{dPI}_{t-4,t}$ is the year-over-year change in gross property, plant, and equipment plus inventory (PPEGTQ+INVTQ); $\mathrm{dQA}_{t-4,t}$ is the year-over-year change in quick assets; and B/M is the book-to-market equity ratio] as well as equal-weighted average market capitalization (M, in \$ millions) and number of firms (n). Panel B shows summary statistics and performance measures for equity financing risk (EFR) trading strategies that buy the low/low corner and short-sell the high/high corner from the double-sorts. Test statistics (in parentheses) are adjusted for heteroscedasticity and autocorrelation. R^2 is adjusted for degrees of freedom and given in %. The sample is restricted to firm-quarters with strictly positive R&D expenditures and excludes financial firms and firms with negative book equity. Data are monthly and cover January 1990 to December 2016.

Panel A: Portfolio excess returns, abnormal returns, and characteristics

	$\mathrm{dSM}_{t-4,t}/A_{t-4}$ tertiles			$\mathrm{dSM}_{t-4,t}/A_{t-4}$ tertiles			$\mathrm{dSM}_{t-4,t}/A_{t-4}$ tertiles		
	Low	2	High	Low	2	High	Low	2	High
$QA_{t-1}/R\&D_t$ tertiles									
		Excess return			*FF5+MOM* α			q-factor α	
Low	1.13	1.27	0.81	0.49	0.77	0.38	0.62	0.81	0.39
	(3.19)	(3.76)	(1.92)	(1.83)	(3.84)	(2.12)	(1.85)	(3.70)	(1.58)
2	0.61	1.06	0.49	0.07	0.57	0.28	0.19	0.59	0.31
	(1.73)	(3.47)	(1.19)	(0.35)	(3.09)	(1.32)	(0.83)	(3.13)	(1.32)
High	0.81	0.70	0.09	−0.08	−0.06	−0.44	−0.12	0.03	−0.46
	(2.35)	(2.06)	(0.20)	(−0.31)	(−0.30)	(−2.03)	(−0.51)	(0.13)	(−2.07)
		$QA_{t-1}/R\&D_t$			$\mathrm{dSM}_{t-4,t}/A_{t-4}$			ROE_t	
Low	12.61	12.62	11.81	0.00	0.02	0.96	0.04	0.04	−0.01
2	28.39	27.50	27.14	0.00	0.02	0.60	0.03	0.04	0.04
High	142.93	155.64	190.56	0.00	0.02	1.04	0.05	0.04	0.03
		$\mathrm{dA}_{t-4,t}/A_{t-4}$			$\mathrm{dPI}_{t-4,t}/A_{t-4}$			$\mathrm{dQA}_{t-4,t}/A_{t-4}$	
Low	0.09	0.13	0.59	0.03	0.06	0.11	0.02	0.04	0.24
2	0.07	0.13	0.53	0.03	0.04	0.10	0.03	0.05	0.30
High	0.06	0.13	0.90	0.03	0.06	0.15	0.02	0.05	0.38
		B/M			Average M			Average n	
Low	0.39	0.30	0.22	1,952	2,147	1,443	71	136	309
2	0.47	0.37	0.25	1,910	2,306	2,669	69	114	156
High	0.59	0.49	0.34	1,450	1,356	1,139	56	59	80

Panel B: Equity financing risk (*EFR*) strategy performance

	$\mathbb{E}[r^e]$	Volatility	Sharpe ratio	Skewness	Excess kurtosis			
Summary statistics	1.04	23.83	0.52	0.52	3.05			
	(2.79)							
	α	*MKT*	*SMB*	*HML*	*RMW*	*CMA*	*MOM*	R^2
FF5+MOM	0.93	−0.24	−0.41	−0.38	0.29	1.28	0.01	23.9%
	(2.55)	(−1.95)	(−2.20)	(−1.52)	(0.93)	(3.09)	(0.10)	
	α	*MKT*	*ME*		*ROE*	*I/A*		R^2
q-factor	1.08	−0.37	−0.36		0.09	0.84		21.1%
	(2.64)	(−2.69)	(−1.50)		(0.28)	(2.15)		

are the 30th and 70th percentiles for NYSE stocks, and are value-weighted and rebalanced at the end of each month. Panel A shows average monthly excess returns above the T-bill rate as well as abnormal returns relative to Fama and French's (2015) five-factor model augmented with the momentum factor (*FF5+MOM*) and Hou, Xue, and Zhang's (2015) q-factor model. Panel A also shows time-series averages of the portfolios' characteristics. Panel B shows the performance of a long-short equity finance risk (*EFR*) strategy that buys the low/low corner portfolio (high exposure to *EFR*) and short sells the high/high corner portfolio (low exposure to *EFR*).

The results are largely consistent with our predictions. Panel A shows that within a given R&D-coverage tertile, average returns decrease with equity issuances, and the same is true for abnormal returns. Similarly, within a given equity-issuance tertile, average returns and abnormal returns decrease with R&D coverage. Hence, both R&D coverage and equity issuances are negatively related to future returns when controlling for the other effect. However, the economic importance of R&D coverage for future returns depends crucially on how it is with coupled equity issuances, and vice versa. Indeed, as we move *diagonally* from the high-*EFR* portfolio (i.e., firms with a low R&D coverage ratio *and* low equity issuance) to the low-*EFR* portfolio (i.e., firms with a high R&D coverage ratio *and* high equity issuance), average excess returns decrease monotonically from a highly significant 1.13% per month ($t = 3.19$) to an insignificant 0.09% per month ($t = 0.20$). Similar relations hold for abnormal returns.

Panel B sheds more light on this return spread by studying the performance of the long-short *EFR* strategy. The strategy earns a significant average excess return of 1.04% per month with a t-statistic of 2.79. When we risk-adjust using the *FF5+MOM* or q-factor models, the spread is largely undiminished (0.93% and 1.08% per month with t-statistics of 2.55 and 2.64, respectively) despite the large and positive loadings on the asset growth factors (1.28 on *CMA* and 0.84 on *I/A*).

The *EFR* strategy's large, positive loadings on the investment factors are in line with the portfolio characteristics in Panel A. They show that the strategy—like the asset growth factors—indeed tends to be long firms with low asset growth (9% on average) and short ones with high asset growth (90% on average). However, the remaining portfolio characteristics show that the higher asset growth in the *EFR* strategy's short end (the low-*EFR* portfolio) is almost entirely driven by precautionary savings from equity issuances and *not* by physical investments. Firms in the low-*EFR* portfolio have large equity issuances (104% of book assets on average), but this is coupled with large increases in quick assets (38% of book assets on average) rather than gross property, plant, and equipment plus inventory (15% of book assets on average). We will later explore the connection between precautionary equity issuances and the asset growth factors in greater detail.

4.1 Portfolio sorts controlling for size

Despite being value-weighted and based on NYSE breakpoints, the double sorts in Table 4 do not explicitly control for size. This subsection alleviates concerns related to the large number of small-cap firms in our sample by using triple sorts on size (equity market capitalization from CRSP), R&D coverage ($QA_{t-1}/R\&D_t$), and equity issuance ($\text{dSM}_{t-4,t}/A_{t-4}$). The triple sorts show that our results also hold among large caps.

Table 5 shows the results. The portfolios are from 2×3×3 sorts based on NYSE breakpoints and are value-weighted and rebalanced at the end of each month. The breakpoint for size is the median, while the breakpoints for R&D coverage and equity issuance are the 30th and 70th percentiles. Because the three sorting variables are correlated, independent $2 \times 3 \times 3$ sorts based on NYSE breakpoints cause a highly uneven allocation of stocks across the portfolios. This, and the fact that we restrict the sample to firm-quarters with strictly positive R&D expenditures, results in some portfolios being extremely thin or even empty. To allocate stocks more evenly, we follow Fama and French (2015) and use separate NYSE breakpoints for small and large stocks when we sort on R&D coverage and equity issuance. Panel A of the table shows the portfolios' average excess returns, abnormal returns, and average characteristics. Panel B shows the performance of long-short equity finance risk (*EFR*) strategies within small and large firms.

Panel A shows that, for both small and large caps, average excess returns are monotonically decreasing as we move diagonally from the low-*EFR* to the high-*EFR* portfolio (from 2.01% to 0.11% per month for small firms and from 1.12% to 0.11% per month for large firms). Similar, monotonic relations hold for the abnormal returns.

Panel A also shows that small caps are on average less profitable, as measured by return on equity (ROE_t), compared to large caps in the same category. Nonetheless, among both small and large caps, the least profitable firms are in the highest equity-issuance tertile, as they are the ones that need liquid resources the most. The increase in quick assets for these firms following an equity issuance is five to ten times higher than their increase in physical assets. The average market capitalizations also reveal an interesting pattern. Among small caps, the high-*EFR* portfolio has

Table 5. Double-sorts on financial slack and equity issuance within small and large firms. This table shows results for portfolios double-sorted on financial slack ($QA_{t-1}/R\&D_t$) and equity issuance ($dSM_{t-4,t}/A_{t-4}$) within small and large firms. Firm size is equity market capitalization from CRSP. We only keep firms with nonnegative $dSM_{t-4,t}$. The portfolios are from $2 \times 3 \times 3$ sorts based on NYSE breakpoints and are value-weighted and rebalanced at the end of each month. The breakpoint for size is the median for NYSE stocks, while the breakpoints for financial slack equity issuance are the 30th and 70th percentiles for NYSE stocks. We use separate NYSE breakpoints for small and large stocks when sorting on slack and issuance. Panel A shows the portfolios' average monthly excess returns above the T-bill rate as well as their abnormal returns relative to Fama and French's (2015) five-factor model, including the momentum factor, and Hou, Xue, and Zhang's (2015) q-factor model. It also shows time-series averages of the portfolios' value-weighted characteristics [ROE_t is current return on equity; $dA_{t-4,t}$ is the year-over-year change in total assets; $dPI_{t-4,t}$ is the year-over-year change in gross property, plant, and equipment plus inventory (PPENTQ+INVTQ); $dQA_{t-4,t}$ is the year-over-year change in quick assets; and B/M is the book-to-market equity ratio] as well as equal-weighted average market capitalization (M, in \$ millions) and number of firms (n). Panel B shows summary statistics and performance measures for equity financing risk (EFR) trading strategies that buy the low/low corner and short sell the high/high corner from the double-sorts within small and large firms. Test statistics (in parentheses) are adjusted for heteroscedasticity and autocorrelation. R^2 is adjusted for degrees of freedom. The sample is restricted to firm-quarters with strictly positive R&D expenditures and excludes financial firms. Data are monthly and cover January 1990 to December 2016.

Panel A: Portfolio excess returns, abnormal returns, and characteristics

	Small									Large								
	$dSM_{t-4,t}/A_{t-4}$ tertiles			$dSM_{t-4,t}/A_{t-4}$ tertiles			$dSM_{t-4,t}/A_{t-4}$ tertiles			$dSM_{t-4,t}/A_{t-4}$ tertiles			$dSM_{t-4,t}/A_{t-4}$ tertiles			$dSM_{t-4,t}/A_{t-4}$ tertiles		
	Low	2	High	Low	2	High	Low	2	High	Low	2	High	Low	2	High	Low	2	High
$QA_{t-1}/R\&D_t$ tertiles																		
	Excess return			*FF5+MOM* α			q-factor α			Excess return			*FF5+MOM* α			q-factor α		
Low	2.01	1.59	0.90	1.34	0.89	0.45	1.52	1.05	0.62	1.12	1.37	0.85	0.58	1.03	0.46	0.66	1.04	0.46
	(3.29)	(2.92)	(1.52)	(4.12)	(3.90)	(2.34)	(4.09)	(4.09)	(2.34)	(3.54)	(3.98)	(2.00)	(2.23)	(4.33)	(2.22)	(2.26)	(3.97)	(1.67)
2	1.59	1.22	0.57	0.62	0.55	0.13	0.72	0.57	0.12	0.59	0.99	0.56	−0.20	0.56	0.43	−0.09	0.58	0.46
	(3.44)	(3.09)	(1.16)	(3.06)	(3.68)	(0.82)	(3.21)	(3.01)	(0.60)	(1.71)	(3.08)	(1.33)	(−0.88)	(2.82)	(1.86)	(−0.39)	(2.76)	(1.83)
High	0.96	0.93	0.11	0.08	0.04	−0.60	0.12	0.03	−0.56	0.46	0.95	0.11	−0.22	0.32	−0.40	−0.19	0.39	−0.36
	(2.32)	(2.32)	(0.22)	(0.35)	(0.22)	(−2.93)	(0.45)	(0.17)	(−2.57)	(1.27)	(2.60)	(0.26)	(−0.91)	(1.33)	(−1.56)	(−0.72)	(1.71)	(−1.40)
	$QA_{t-1}/R\&D_t$			$dSM_{t-4,t}/A_{t-4}$			ROE_t			$QA_{t-1}/R\&D_t$			$dSM_{t-4,t}/A_{t-4}$			ROE_t		
Low	12.61	12.60	11.04	0.00	0.02	1.11	−0.02	−0.01	−0.21	12.54	12.26	11.77	0.00	0.03	0.99	0.05	0.05	0.03
2	31.29	30.26	29.62	0.00	0.02	0.70	0.01	−0.02	0.01	26.04	25.43	25.60	0.00	0.03	0.63	0.04	0.05	0.04
High	235.12	224.47	276.28	0.00	0.02	0.83	0.02	0.02	0.02	116.20	111.90	147.93	0.00	0.03	0.95	0.05	0.04	0.04
	$dA_{t-4,t}/A_{t-4}$			$dPI_{t-4,t}/A_{t-4}$			$dQA_{t-4,t}/A_{t-4}$			$dA_{t-4,t}/A_{t-4}$			$dPI_{t-4,t}/A_{t-4}$			$dQA_{t-4,t}/A_{t-4}$		
Low	0.53	0.06	0.61	0.03	0.04	0.08	0.00	0.01	0.37	0.08	0.14	0.61	0.04	0.06	0.12	0.02	0.04	0.21
2	0.06	0.10	0.71	0.04	0.05	0.10	0.02	0.04	0.47	0.08	0.14	0.52	0.03	0.04	0.10	0.03	0.05	0.27
High	0.07	0.14	1.15	0.03	0.05	0.17	0.03	0.06	0.54	0.06	0.15	0.72	0.03	0.06	0.14	0.02	0.06	0.32
	B/M			Average *M*			Average *n*			*B/M*			Average *M*			Average *n*		
Low	0.74	0.55	0.28	139	223	258	63	118	302	0.34	0.27	0.21	16,794	12,961	9,656	7	18	32
2	0.79	0.56	0.35	200	291	337	53	86	134	0.39	0.33	0.23	10,773	11,561	10,401	11	20	27
High	0.85	0.64	0.42	206	269	284	39	41	62	0.50	0.43	0.29	8,192	5,966	6,034	11	12	14

(Continues)

(Continued)

Panel B: Equity financing risk (*EFR*) strategy performance

	EFR strategy within small stocks								*EFR* strategy within large stocks							
	$\mathbb{E}[r^e]$	Volatility	Sharpe ratio	Skewness	Excess kurtosis				$\mathbb{E}[r^e]$	Volatility	Sharpe ratio	Skewness	Excess kurtosis			
Summary statistics	1.90	22.82	1.00	1.56	8.54				1.01	24.28	0.50	0.12	0.87			
	(5.07)								(2.57)							
	α	*MKT*	*SMB*	*HML*	*RMW*	*CMA*	*MOM*	R^2	α	*MKT*	*SMB*	*HML*	*RMW*	*CMA*	*MOM*	R^2
FF5+MOM	1.94	−0.17	0.30	−0.24	−0.39	1.11	−0.17	14.2%	0.98	−0.30	−0.39	−0.25	0.39	0.82	0.01	20.2%
	(5.22)	(−1.71)	(1.63)	(−1.10)	(−1.14)	(3.56)	(−1.36)		(2.48)	(−2.78)	(−2.38)	(−1.38)	(1.63)	(2.71)	(0.10)	
	α	*MKT*	*ME*		*ROE*	*I/A*		R^2	α	*MKT*	*ME*		*ROE*	*I/A*		R^2
q-factor	2.08	−0.28	0.37		−0.60	0.62		12.7%	1.02	−0.37	−0.33		0.29	0.56		19.1%
	(5.08)	(−2.41)	(1.32)		(−2.71)	(2.13)			(2.49)	(−3.46)	(−2.01)		(1.60)	(2.35)		

the lowest average market capitalization (\$139 million). Among large caps, the opposite is true, as the high-*EFR* portfolio has the highest average market capitalization (\$16.8 billion). This also explains why there are relatively many small high-*EFR* firms but only a few large high-*EFR* firms.

The different ability to internally generate liquid resources is also reflected in the average return spreads between the low- and high *EFR*-portfolios among small and large caps. Among small caps, the spread reported in Panel B is a large 1.90% per month with a t-statistic of 5.07, and the corresponding abnormal returns are slightly larger with t-statistics exceeding 5.00. Among large caps, the spread is 1.01% per month with a t-statistic of 2.57, and the corresponding abnormal returns are about as large with t-statistics exceeding 2.40. At the same time, the strategy among small caps has a lower volatility that causes a twice as high Sharpe ratio (1.00 versus 0.50). Hence, while we get qualitatively similar results among small and large caps, the average return spread and corresponding abnormal returns are considerably stronger among smaller stocks.

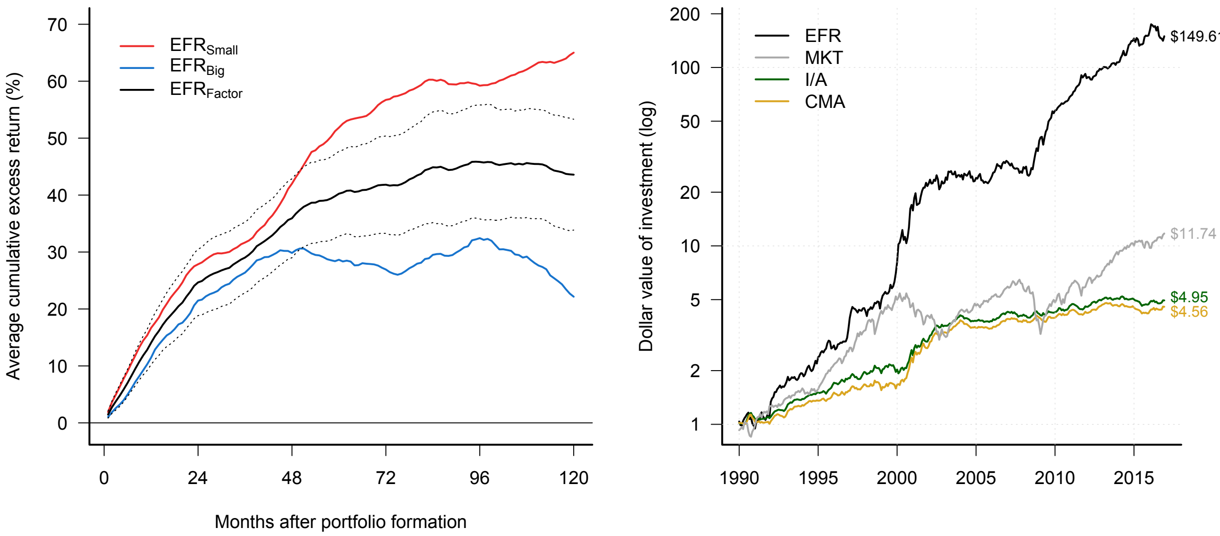
The portfolio analysis clearly shows that firms more likely to be exposed to equity financing risk earn a positive and significant excess return over firms less likely to be exposed to the same source of risk. In what follows, we use these two groups of firms to build a risk factor that proxies for exposure to equity financing risk.

5 Equity financing risk (*EFR*) factor

We construct an equity financing risk (*EFR*) factor as an equal-weighted average of the value-weighted small-cap and large-cap *EFR* strategies from Table 5. As such, the *EFR* factor is constructed using the same basic procedure employed by Fama and French (2015) and Hou, Xue, and Zhang (2015) to construct their factors (i.e., with a control for size). As we detail below, the *EFR* factor generates a large and highly significant average return of 1.45% per month with a t-statistic of 4.80 over our 1990-2016 sample period.

Figure 1 shows the *EFR* factor's post-formation and time-series performance. The left panel shows that the *EFR* factor's positive average returns persist for more than 7 years after formation. For the underlying small- and large-cap *EFR* strategies, the persistence is over 10 years and around 4 years, respectively. These findings show that the exposure to equity finance risk is a persistent phenomenon, especially for small caps, which, as we saw in Table 5, tend to be much less profitable. The right panel shows that the *EFR* factor has consistently delivered positive excess

Figure 1. *EFR* factor: Persistence and time-series performance.



This figure shows the persistence and time-series performance of the *EFR* factor. The left panel shows averages of cumulative sums of excess returns to the *EFR* factor as well as the underlying small- and large-cap *EFR* strategies, along with 95% confidence bands, as a function of months after portfolio formation. The right panel shows a time-series plot of the value of a $1 investment at the end of December 1989 in the *EFR* factor, the market (*MKT*), and the investment factors (*CMA* and *I/A*), calculated as in Daniel and Moskowitz (2016). Data are monthly and cover January 1990 to December 2016.

returns over time with no particular subsample driving its performance, and, moreover, that it has outperformed the asset growth factors (*CMA* and *I/A*) as well as the market over our sample period.

In the following subsections, we provide evidence that the *EFR* factor is linked to aggregate equity issuance conditions. In addition, we show that the *EFR* factor (i) generates a higher average return and a higher Sharpe ratio than the *FF5+MOM* factors and the *q*-factors; (ii) is highly non-redundant in either factor model, even by the higher significance threshold advocated by Harvey, Liu, and Zhu (2016), and (iii) completely subsumes these models' asset growth factors (*CMA* and *I/A*). The latter finding suggests that these 'investment' factors, at least over our sample period, conflate variation in returns due to physical investments with variation in returns due to precautionary savings from equity issuance aimed at reducing the exposure to equity financing risk.

5.1 *EFR* and aggregate equity issuance conditions

The *EFR* factor should, in principle, capture the exposure to aggregate corporate financing conditions and, specifically, aggregate equity issuance conditions. We consider three measures of aggregate equity issuance conditions: the CBOE implied volatility of the S&P 500 index (VIX), the one-month lagged Pástor and Stambaugh (2003) aggregate liquidity measure (AggLIQ_{-1}), and the excess return on the market factor (*MKT*). Higher values for the VIX indicate worsening equity

Table 6. Correlations between measures of financing conditions. This table shows pairwise correlations between measures of financing conditions. We consider three measures of equity issuance conditions: the CBOE implied volatility of the S&P 500 index (VIX), the one-month lagged Pástor and Stambaugh (2003) aggregate liquidity measure (AggLIQ_{-1}), and the excess return on the market factor (*MKT*). Panel A shows pairwise correlations at the monthly frequency between the three measures of equity market financing conditions and four financing conditions indexes: the Chicago Fed National Financial Conditions Index (NFCI), the Kansas City Financial Stress Index (KCFSI), the Goldman Sachs Financial Conditions Index (GSFCI), and the Bloomberg Financial Conditions Index (BFCI). Panel B shows pairwise correlations at the annual frequency between 12-month moving averages of the three equity issuance measures and Eisfeldt and Muir's (2016) estimated average cost paid per dollar of external financing (E&M, which is only available annually). Test statistics (in parentheses) are adjusted for heteroscedasticity and autocorrelation.

Panel A: Equity issuance conditions and aggregate financing conditions (monthly)

	AggLIQ_{-1}	*MKT*	NFCI	KCFSI	GSFCI	BFCI
VIX	−0.31	−0.38	0.76	0.81	0.41	−0.81
	(−3.94)	(−3.53)	(14.61)	(14.13)	(1.69)	(−13.03)
AggLIQ_{-1}		0.07	−0.26	−0.33	−0.13	0.34
		(0.90)	(−7.41)	(−8.06)	(−1.66)	(5.97)
MKT			−0.19	−0.19	−0.22	0.27
			(−1.78)	(−1.61)	(−2.53)	(3.16)
NFCI				0.93	0.52	−0.89
				(13.74)	(1.92)	(−9.43)
KCFSI					0.47	−0.89
					(1.56)	(−11.72)
GSFCI						−0.43
						(−2.98)

Panel B: Equity issuance conditions and estimated issuance costs (annual)

	AggLIQ_{-1}	*MKT*	E&M
VIX	−0.58	−0.33	0.44
	(−3.12)	(−1.92)	(1.73)
AggLIQ_{-1}		0.43	−0.22
		(3.10)	(−1.11)
MKT			−0.53
			(−2.78)

issuance conditions, while higher values for either AggLIQ_{-1} or *MKT* indicate improving equity financing conditions.[13]

In Panel A of Table 6, we report the pairwise correlation at a monthly frequency between the three measures of equity market financing conditions and four financing conditions indexes: the Chicago Fed National Financial Conditions Index (NFCI), the Kansas City Financial Stress Index (KCFSI), the Goldman Sachs Financial Conditions Index (GSFCI), and the Bloomberg Financial Conditions Index (BFCI).[14]

Market volatility is negatively correlated with the market return and (lagged) aggregate liq-

[13] Schill (2004) show that market volatility negatively affects firm-level equity issuance activity, especially for small or unseasoned firms. Butler, Grullon, and Weston (2005) and Hanselarr, Stulz, and Van Dijk (2019) document a positive correlation between aggregate market liquidity and the cost of issuing equity. Baker and Wurgler (2000), among others, show that firms time the market and tend to issue equity before periods of low market returns.

[14] In addition to these proxies, the St. Louis Fed also publishes a Financial Stress Index (STLFSI). However, because it is only available from January 1994, we exclude it from our main analysis to maximize the number of observations. In untabulated tests, we find very similar results when we include STLFSI in the analysis from 1994.

Table 7. *EFR* and aggregate equity issuance conditions. This table shows time-series regressions of the monthly excess return to the equity financing risk (*EFR*) factor. The explanatory variables are the three measures of aggregate equity issuance conditions considered in Table 6: the CBOE implied volatility of the S&P 500 index (VIX), the one-month lagged Pástor and Stambaugh (2003) aggregate liquidity measure (AggLIQ_{-1}), and the excess return on the market factor (*MKT*). In the fifth specification, we exclude the intercept but report the average residual $\overline{\epsilon_t}$ (in % per month). Test statistics (in parentheses) are adjusted for heteroscedasticity and autocorrelation. Data are monthly and cover January 1990 to December 2016.

	Intercepts, slopes, and test-statistics (in parantheses) from time-series regressions of the form $EFR_t = \boldsymbol{\beta}'\mathbf{X}_t + \epsilon_t$				
Independent variable	(1)	(2)	(3)	(4)	(5)
Intercept	1.68	−7.64	1.07	−1.33	
	(5.59)	(−2.90)	(3.53)	(−0.49)	
MKT	−0.37			−0.33	−0.34
	(−4.32)			(−3.78)	(−4.14)
VIX (log)		0.03		0.01	0.01
		(3.31)		(0.94)	(4.24)
AggLIQ_{-1}			−0.17	−0.14	−0.15
			(−2.53)	(−2.33)	(−2.57)
Adj. R^2	8.9%	3.7%	4.1%	12.2%	18.5%
$\overline{\epsilon_t}$ (%)					−0.01
					(−0.05)

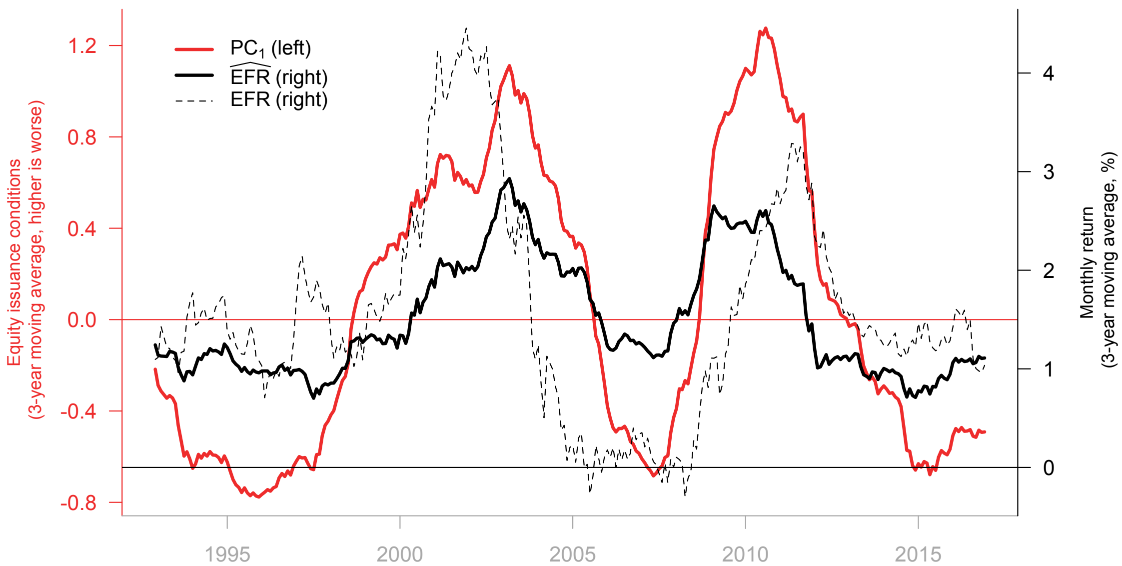
uidity. At the same time, this variable is very highly correlated with all the financing conditions indexes in Table 6, with the exception of GSFCI. This is not surprising since all the indexes but GSFCI include aggregate volatility among their components. The aggregate market excess return show no correlation with (lagged) aggregate liquidity, however both measures are correlated with all of the financing conditions indexes with a sign opposite to aggregate volatility.

In Panel B of Table 6, we report the pairwise correlations at an annual frequency between 12-month moving averages of the three equity issuance measures and Eisfeldt and Muir's (2016) estimated average cost paid per dollar of external financing (E&M, which is only available annually). This cost is significantly lower when aggregate market volatility is lower or when aggregate market return is higher. The correlation with aggregate liquidity is negative, as expected, but not significant[15]. Overall, the results in Table 6 make clear that the three measures of equity market financing conditions are correlated with widely used aggregate financing conditions indexes and with aggregate external financing costs.

Table 7 explores the connection between the monthly excess returns to the *EFR* factor and aggregate equity issuance conditions using time-series regressions. The first three specifications

[15]The lack of significance might be attributed to the fact that the estimated average cost of external financing in Eisfeldt and Muir (2016) takes into account both debt and equity issuance costs.

Figure 2. *EFR* and the first principle component of aggregate equity issuance conditions.



This figure shows a time-series plot of 3-year moving averages the first principal component of the three measures of equity market financing conditions (PC_1, red solid line, left axis), the predicted excess return to the *EFR* factor based on specification (5) in Table 7 ($\widehat{EFR}$, black solid line, right axis), and the realized excess return to the *EFR* factor (black dashed line, right axis). PC_1 is positively correlated with aggregate volatility but negatively correlated with the market return and aggregate liquidity. Hence, higher PC_1 values indicate *worse* aggregate equity issuance conditions. Data are monthly and cover January 1990 to December 2016.

show that *EFR* is significantly correlated with all three measures of equity market financing conditions. Specification (4) employs all three variables together. Here, the market return and aggregate liquidity remain significant with essentially unchanged coefficients, while both market volatility and the intercept become insignificant. Hence, in specification (5), we re-estimate the model with a zero intercept. The results in specifications (5) show that the average excess return to *EFR* and a substantial fraction of its volatility can be explained by a linear combinations of the three measures of aggregate equity issuance conditions.[16]

To conclude, Figure 2 shows 3-year moving averages of the first principal component of the three measures of equity market financing conditions (PC_1), the predicted excess return to the *EFR* factor based on specification (5) in Table 7 ($\widehat{EFR}$), and, finally, the realized excess return to the *EFR* factor. PC_1 is positively correlated with aggregate volatility but negatively correlated with the market return and aggregate liquidity. Hence, higher PC_1 values indicate *worse* aggre-

[16]It is worth noting that, over our sample period (January 1990 to December 2016), the *EFR* factor has an average excess return of 1.45% per month and a volatility of 5.37% per month, while the predicted factor from specification (5) in Table 7 has an average excess return of 1.44% per month and a volatility of 2.12% per month.

gate equity issuance conditions.[17] Both the predicted and the realized excess returns to the *EFR* factor closely follow the time-series behavior of PC_1. In particular, both the predicted and the realized *EFR* returns peak around the burst of dot-com bubble in the early 2000s and around the great financial crises of the late 2000s and early 2010s. These periods are characterized by very unfavorable aggregate equity issuance conditions, as captured by the corresponding peaks in PC_1. Conversely, both the predicted and the realized *EFR* returns dip in the intermediate periods, which are characterized by much more favorable equity financing conditions.[18]

5.2 Spanning tests relative to the *FF5+MOM* factors

Table 8 reports the performance of the *EFR* factor relative to the *FF5+MOM* factors. Panel A shows that over our 1990-2016 sample, *EFR* earned a highly significant average return of 1.45% per month with a t-statistic of 4.80 and a Sharpe ratio of 0.97, all of which are much higher than the ones for the *FF5+MOM* factors over our same period. It did so while exhibiting a slight positive skewness of 0.70 and an only moderate excess kurtosis of 3.37.

Panel B shows pairwise correlations between the factors. The *EFR* factor has a negative and significant correlation with the market (-0.30 with $t = -4.32$). This result suggests that increases in equity financing risk tend to coincide with market downturns. Not surprisingly, the *EFR* factor's correlation with *CMA* is positive and significant (0.37 with $t = 4.81$). The correlations with the remaining factors all are small and insignificant.

Panel C shows factor spanning tests, which are time-series regressions of one factor on a set of explanatory factors. A significant abnormal return suggests that the left-hand-side factor captures return variation not explained by the right-hand-side factors and is, as such, non-redundant in an asset pricing model that features the right-hand-side factors. An insignificant abnormal return, however, suggests that the left-hand-side factor is redundant relative to the right-hand-side factors. A redundant factor adds no additional explanatory power to that of the right-hand-side factors regardless of which assets one attempts to price with these factors.

The first specification shows that *EFR* is highly non-redundant in the *FF5+MOM* model, as

[17] The first principal component (PC_1) explains 47% of the volatility in the market return, 71% of the volatility in the VIX, and 35% of the volatility in aggregate liquidity.

[18] In untabulated tests, we find that the *EFR* factor's long leg is responsible for the bulk of the factor's co-movement with PC_1. Intuitively, the firms with low R&D coverage and low (past) equity issuance in the factor's long leg become riskier when aggregate equity issuance conditions are less favorable, while the firms with high R&D coverage and high (past) equity issuance in the factor's short leg are much less affected by aggregate equity issuance conditions.

Table 8. *EFR* factor spanning tests: Fama and French five-factor model. This table shows summary statistics (Panel A), pairwise correlations (Panel B), and time-series regressions (Panel C) for the equity financing risk (*EFR*) factor and the Fama and French (2015) factors, including the momentum factor. The *EFR* factor, based on the portfolios in Table 5, is defined as an equal-weighted average of value-weighted, monthly rebalanced, long-short strategies within small and large firms that buy firms in the low/low tertiles and sell firms in the high/high tertiles of financial slack and equity issuance. Test statistics (denoted by "*t*" in Panel A and given in parentheses in Panels B and C) are adjusted for heteroscedasticity and autocorrelation. R^2 is adjusted for degrees of freedom. Data are monthly and cover January 1990 to December 2016

Panel A: Factor summary statistics

	$\mathbb{E}[r^e]$	Volatility	t	Sharpe ratio	Skewness	Excess kurtosis
EFR	1.45	18.03	4.80	0.97	0.70	3.37
MKT	0.62	14.88	2.50	0.50	−0.65	1.17
SMB	0.20	10.73	1.17	0.22	0.47	5.11
HML	0.25	10.48	1.29	0.29	0.16	2.56
RMW	0.34	9.50	1.98	0.43	−0.45	10.90
CMA	0.26	7.25	2.04	0.43	0.57	2.27
MOM	0.52	16.86	1.84	0.37	−1.52	10.88

Panel B: Factor correlations

	MKT	*SMB*	*HML*	*RMW*	*CMA*	*MOM*
EFR	−0.30	−0.07	0.16	0.13	0.37	0.02
	(−4.32)	(−0.53)	(1.20)	(0.63)	(4.81)	(0.22)
MKT		0.21	−0.17	−0.43	−0.37	−0.25
		(3.01)	(−1.58)	(−3.61)	(−5.87)	(−3.07)
SMB			−0.13	−0.47	−0.04	0.02
			(−0.82)	(−3.41)	(−0.78)	(0.13)
HML				0.38	0.65	−0.19
				(3.32)	(11.77)	(−1.17)
RMW					0.23	0.08
					(1.84)	(0.41)
CMA						0.05
						(0.38)

Panel C: Spanning tests

			Independent factors							
	Dependent factor	α	*MKT*	*SMB*	*HML*	*RMW*	*CMA*	*MOM*	*EFR*	R^2
(1)	*EFR*	1.46	−0.23	−0.04	−0.24	0.00	0.97	−0.08		16.3%
		(4.74)	(−2.86)	(−0.31)	(−1.62)	(0.01)	(3.73)	(−0.81)		
(2)	*SMB*	0.30	0.04		0.05	−0.55	0.08	0.05		22.4%
		(1.78)	(0.69)		(0.51)	(−3.74)	(0.51)	(0.89)		
(3)	*SMB*	0.32	0.03		0.05	−0.55	0.09	0.05	−0.01	22.2%
		(1.82)	(0.65)		(0.48)	(−3.69)	(0.62)	(0.87)	(−0.29)	
(4)	*HML*	−0.11	0.11	0.03		0.36	0.93	−0.13		55.0%
		(−0.73)	(1.93)	(0.49)		(3.83)	(9.60)	(−4.09)		
(5)	*HML*	−0.05	0.09	0.03		0.36	0.97	−0.14	−0.04	55.4%
		(−0.33)	(1.82)	(0.47)		(4.19)	(9.86)	(−4.39)	(−1.46)	
(6)	*RMW*	0.47	−0.21	−0.32	0.38		−0.24	0.05		42.6%
		(3.76)	(−5.36)	(−3.32)	(3.14)		(−1.51)	(1.20)		
(7)	*RMW*	0.47	−0.21	−0.32	0.38		−0.24	0.05	0.00	42.4%
		(3.43)	(−5.24)	(−3.26)	(3.28)		(−1.75)	(1.17)	(0.01)	
(8)	*CMA*	0.24	−0.15	0.02	0.47	−0.12		0.05		52.2%
		(2.55)	(−4.74)	(0.53)	(9.04)	(−1.42)		(1.58)		
(9)	*CMA*	0.10	−0.11	0.02	0.46	−0.11		0.05	0.08	55.8%
		(1.07)	(−3.83)	(0.65)	(11.45)	(−1.75)		(1.96)	(3.51)	
(10)	*MOM*	0.58	−0.22	0.13	−0.66	0.25	0.51			14.0%
		(1.93)	(−2.16)	(0.91)	(−3.38)	(1.15)	(1.35)			
(11)	*MOM*	0.68	−0.24	0.13	−0.67	0.25	0.57		−0.07	14.2%
		(2.24)	(−2.34)	(0.89)	(−3.60)	(1.14)	(1.61)		(−0.76)	

its abnormal return is a highly significant 1.46% per month with a t-statistic of 4.74. The latter comfortably exceeds the higher t-statistic threshold of 3.00 advocated by Harvey et al. (2016). The *EFR* factor generates this large abnormal return despite garnering a large, positive, and highly significant loading on *CMA* (0.97 with $t = 3.73$). The adjusted R^2 of just 16.3% suggests that *EFR* captures return variation that is inherently distinct from that captured by the *FF5+MOM* factors.

The remainder of Panel C shows spanning tests for the other factors with and without *EFR* as an explanatory factor. Specifications 2 and 3 show that *SMB* is redundant in the *FF5+MOM* model and that adding the *EFR* has no effect on these results. Specifications 4 and 5 show that the same results hold for *HML*. The sixth specification shows that *RMW*'s abnormal return of 0.47% per month ($t = 3.76$) is larger and much stronger than its average return over the sample (0.34% with $t = 1.98$), mainly because of its negative loadings on *MKT* and *SMB*. The seventh specification shows that controlling for *EFR* slightly shrinks *RMW*'s abnormal return t-statistic to 3.43.

The eighth specification shows that *CMA*'s abnormal return of 0.24% per month ($t = 2.55$) is about as large as, but statistically stronger than, its average return over the sample (0.26% with $t = 2.04$). The ninth specification shows that this is no longer the case when controlling for *EFR*: With the addition of *EFR*, the abnormal return to *CMA* fades to an insignificant 0.10% per month ($t = 1.07$) because *CMA* garners a positive and highly significant loading on *EFR*. As a result, *CMA* is redundant relative to the model that includes *EFR*. In untabulated tests, we find that *CMA* is within the span of *EFR* even without controlling for the other factors (abnormal return of 0.04% per month with a t-statistic of 0.35), whereas *EFR* is not within the span of *CMA* (abnormal return of 1.10% per month with a t-statistic of 4.15). These results suggest that the redundancy of *CMA* is entirely driven by *EFR*, and not a combination of *EFR* and the other factors.

The last two specifications show that *MOM*'s abnormal return relative to the *FF5* factors is 0.58% per month with a t-statistic of 1.93, which is similar to its average return over the sample (0.52%, $t = 1.84$). The addition of *EFR* increases this abnormal return to 0.68% per month with a t-statistic of 2.24, mainly because *MOM* has a negative (albeit insignificant) loading on *EFR*.

5.3 Spanning tests relative to the q-factors

Table 8 shows that *EFR* is non-redundant in the *FF5+MOM* model and that it subsumes the model's asset growth factor. Table 9 shows that the same results hold relative to the q-factor model.

Before going into details, it is important to note that while this may seem unsurprising given the many similarities between the *FF5* and q-factor models, it is in fact remarkable given the subtle but important differences between the two. Specifically, while both models feature a profitability and an asset growth factor, the factor construction differs across the two models. The factors from the *FF5* model (*RMW* and *CMA*) are constructed from independent double sorts on size and either operating profitability or asset growth, where the sorts employ annual data and the portfolios are rebalanced annually. In contrast, the corresponding q-factors (*ROE* and *I/A*) are based on independent triple sorts on size, return on equity, and asset growth, where the *ROE* sorts employ quarterly data and monthly rebalancing, while the *I/A* sorts employ annual data and annual rebalancing. As such, *RMW* and *CMA* capture profitability and asset growth at a low (annual) frequency *without* controlling for the other effect. *ROE* and *I/A*, however, capture high-frequency (quarterly) profitability but low-frequency (annual) asset growth *with* a control for the other effect. As argued by Novy-Marx (2015a,b), these subtle but important differences matter for the q-factor model's ability to price strategies based on price momentum, earnings momentum, and gross profitability. Nonetheless, we show in the following that *EFR* (i) performs better over our sample than the q-factors, (ii) is non-redundant in the q-factor model, and (iii) subsumes the *I/A* factor despite the fact that *I/A* controls for high-frequency profitability.

Table 9's Panel A shows that *EFR* strongly outperforms the q-factors over our 1990-2016 sample in terms of its average return, the significance of its average return, and its Sharpe ratio. As expected, Panel B shows that *EFR* is positively correlated with *I/A* (0.30 with t = 3.46), but has otherwise insignificant correlations with *ROE* and the q-factor model's size factor, *ME*.

Panel C shows spanning tests employing the q-factors. The first specification shows that *EFR* is also non-redundant in the q-factor model, as it generates a large and highly significant abnormal return of 1.55% per month with a t-statistic of 4.59. The latter again satisfies Harvey et al.'s (2016) higher threshold of 3.00. *EFR* generates this abnormal return despite its positive and significant loading on *I/A* (0.59 with t = 2.54). The adjusted R^2 is just 13.3%, similar to *FF5+MOM*.

The remaining specifications in Panel C show spanning tests for the q-factors with and without *EFR* on the right-hand side. The second specification shows that *ME*, like its counterpart in the *FF5+MOM* model, is redundant. The third specification shows that controlling for *EFR* implies that *ME*'s abnormal return t-statistic increases to 2.03. Hence, controlling for the exposure to equity financing risk, the small-stock premium captured by the *ME* factor becomes significant

Table 9. *EFR* factor spanning tests: *q*-factor model. This table shows summary statistics (Panel A), pairwise correlations (Panel B), and time-series regressions (Panel C) for the equity financing risk (*EFR*) factor and the Hou, Xue, and Zhang (2015) factors. The *EFR* factor is based on the portfolios in Table 5 and is defined as an equal-weighted average of value-weighted, monthly rebalanced, long-short strategies within small and large firms that buy firms in the low/low tertiles and sell firms in the high/high tertiles of financial slack and equity issuance. Test-statistics (denoted by "t" in Panel A and given in parentheses in Panels B and C) are adjusted for heteroscedasticity and autocorrelation. R^2 is adjusted for degrees of freedom. Data are monthly and cover January 1990 to December 2016.

Panel A: Factor summary statistics

	$\mathbb{E}[r^e]$	Volatility	t	Sharpe ratio	Skewness	Excess kurtosis
EFR	1.45	18.03	4.80	0.97	0.70	3.37
MKT	0.60	14.91	2.41	0.49	−0.70	1.45
ME	0.26	11.02	1.49	0.28	0.81	7.33
ROE	0.48	9.61	2.96	0.60	−0.74	4.57
I/A	0.28	6.92	2.43	0.49	0.31	1.96

Panel B: Factor correlations

	MKT	*ME*	*ROE*	*I/A*
EFR	−0.31	−0.05	0.07	0.30
	(−4.45)	(−0.35)	(0.52)	(3.46)
MKT		0.23	−0.44	−0.34
		(3.00)	(−7.06)	(−5.29)
ME			−0.33	−0.13
			(−2.65)	(−1.46)
ROE				0.18
				(1.42)

Panel C: Spanning tests

			Independent factors					
	Dependent factor	α	*MKT*	*ME*	*ROE*	*I/A*	*EFR*	R^2
(1)	*EFR*	1.55	−0.33	0.02	−0.15	0.59		13.3%
		(4.59)	(−3.43)	(0.12)	(−0.86)	(2.54)		
(2)	*ME*	0.39	0.07		−0.33	−0.07		11.4%
		(1.68)	(0.90)		(−1.95)	(−0.35)		
(3)	*ME*	0.38	0.07		−0.32	−0.07	0.01	11.1%
		(2.03)	(1.16)		(−2.26)	(−0.37)	(0.12)	
(4)	*ROE*	0.67	−0.24	−0.21		0.04		24.0%
		(6.04)	(−3.88)	(−2.87)		(0.21)		
(5)	*ROE*	0.72	−0.25	−0.21		0.06	−0.04	24.2%
		(5.69)	(−3.96)	(−3.03)		(0.35)	(−0.82)	
(6)	*I/A*	0.37	−0.15	−0.03	0.02			11.1%
		(3.03)	(−3.92)	(−0.38)	(0.20)			
(7)	*I/A*	0.22	−0.11	−0.03	0.03		0.08	15.3%
		(1.56)	(−3.17)	(−0.40)	(0.37)		(2.08)	

at conventional levels, which is generally in line with our results from Table 5. The fourth specification shows that *ROE*'s abnormal return of 0.67% per month (t = 6.04) is considerably higher and twice as strong as its average return over our sample (0.48%, t = 2.96). The fifth specification shows that controlling for *EFR* reduces *ROE*'s abnormal return t-statistic to 5.69.

Turning to the spanning tests for *I/A*, the sixth specifications shows that it generates an abnormal return of 0.37% per month with a t-statistic of 3.04, which is only slightly higher but considerably stronger than its average return over our sample (0.28%, t = 2.43). The seventh and final specifi-

Table 10. Factor spanning tests using *EFR* projected on equity issuance conditions. This table shows time-series regressions of the monthly excess returns to the asset growth factors (*CMA* and *I/A*) from each of the Fama and French (2015) and Hou, Xue, and Zhang (2015) factor models. The explanatory variables are the predicted and residual components of the *EFR* factor ($\widehat{EFR}$ and $EFR^{\perp}$) based on the regression of *EFR* on the three measures of aggregate equity issuance conditions in specification (5) of Table 7. Test statistics (in parentheses) are adjusted for heteroscedasticity and autocorrelation. Data are monthly and cover January 1990 to December 2016.

	Intercepts, slopes, and test-statistics (in parantheses) from time-series regressions of the form $y_t = \alpha + \boldsymbol{\beta}'\mathbf{X}_t + \epsilon_t$					
	Dependent factor					
	CMA			*I/A*		
Independent factor	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.26	−0.35	−0.34	0.28	−0.26	−0.26
	(2.04)	(−1.95)	(−2.20)	(2.43)	(−1.42)	(−1.63)
$\widehat{EFR}$		0.41	0.41		0.37	0.37
		(3.25)	(4.23)		(2.91)	(3.74)
$EFR^{\perp}$			0.11			0.08
			(3.56)			(1.98)
Adj. R^2		13.0%	19.1%		11.4%	14.8%

cation shows that *I/A* is redundant in the *q*-factor model when controlling for *EFR*, as its abnormal return is reduced to an insignificant 0.22% per month with a *t*-statistic of 1.56. The reason is *I/A*'s positive and significant loading on *EFR*.

5.4 Why does the *EFR* factor subsume asset growth factors?

In this section, we shed more light on why the *EFR* factor subsumes asset growth factors. We do this using both a time series and a cross sectional approach.

Table 10 shows time-series regressions of the asset growth factors (*CMA* and *I/A*) on each of the predicted and residual components of the *EFR* factor ($\widehat{EFR}$ and $EFR^{\perp}$). The latter are based on the regression of *EFR* on the three measures of aggregate equity issuance conditions in specification (5) of Table 7. The table shows that regressing the asset growth factors on the predicted component ($\widehat{EFR}$) implies that their positive and significant average returns turn negative (marginally significant for CMA and insignificant for I/A) because both asset growth factors load positively and significantly on $\widehat{EFR}$. Furthermore, the regressions' R^2 values are 13% for *CMA* and 11% for *I/A*. In contrast, we do not find these result when we regress the asset growth factors on the residual component ($EFR^{\perp}$): both *CMA* and *I/A* have a positive and significant abnormal return relative to $EFR^{\perp}$ despite garnering positive and significant loadings on it. Furthermore, the regressions' R^2 values are at most 6%. That is, the ability of *EFR* to subsume the asset growth factors is entirely driven by the part of *EFR* directly linked to aggregate equity issuance conditions. Any residual variation in *EFR* cannot subsume the asset growth factors.

Table 11 shows portfolio characteristics for the long and short portfolios (within size groups) underlying each of *EFR* and *CMA*. We focus on *CMA* for simplicity and because its construction (being long and short a single portfolio within size groups) makes it easier to compare to *EFR*.[19]

Panel A shows the average overlap between the stocks held in the long and short portfolios underlying *EFR* and *CMA*. The two factors display substantial overlap in the stocks held in their long and short legs among both small- and large-caps. Among small-caps, the average overlap is over 50% for both legs, and the same is true for the short leg among large-caps. Only the long leg among large-caps displays a somewhat lower overlap, although it is still a considerable 24%.

Panel B shows time-series averages of the portfolios' monthly value-weighted characteristics together with each factor's long-short difference for each characteristic within size groups. Two results are worth highlighting. First, the two factors display a remarkable similarity across the six characteristics we consider: asset growth; equity issuances from CRSP and from Compustat; growth in net property, plant and equipment; growth in quick assets; and book-to-market equity. Second, for both factors, the difference in asset growth is predominantly driven by large changes in quick asset. In particular, the higher asset growth that characterizes the *CMA* factor's short leg is also predominantly driven by higher savings from precautionary equity issuances, not from greater investment in physical assets.

Panel B of Table 11 also shows a significant long-short difference in physical capital among both small- and large-caps portfolios used to build the *EFR* factor. As a consequence, a concern might be whether the *EFR* factor it is merely an investment-based factor in disguise. To alleviate such a concern, we consider the relation between the *EFR* factor and what is plausibly a more 'pure' investment factor; namely, the Lyandres, Sun, and Zhang (2008) factor (*LSZ*). We construct

[19] To construct the *CMA* portfolios, we follow Fama and French (2015) and use NYSE breakpoints to sort all common shares on NYSE, Amex, and Nasdaq into 6 portfolios from 2×3 independent sorts on size and asset growth. The breakpoint for size is the median while the breakpoints for asset growth are the 30th and 70th percentiles. The portfolios are value-weighted and rebalanced annually at the end of June. Size is equity market capitalization at the end of June from CRSP while asset growth is the year-over-year percentage change in total book assets ($\mathrm{AT}/\mathrm{AT}_{-1} - 1$) from the annual Compustat file. Annual accounting data for a given fiscal year is employed starting at the end of June of the following calendar year. We exclude financial firms and firms with negative book equity. *CMA* is the equal-weighted average of the value-weighted large-cap and small-cap strategies that buy the low-asset-growth portfolio and short the high-asset-growth portfolio. Over our sample period (January 1990 to December 2016) the original *CMA* (from Ken French's website) yields an average excess return of 0.26% per month with a *t*-statistic of 2.04. The *CMA* we build yields an average excess return of 0.26% per month with a *t*-statistic of 2.28. Their correlation is over 95%.

Table 11. Portfolio characteristics for *EFR* and *CMA*. This table shows portfolio characteristics for the long and short portfolios within size groups underlying each of *EFR* and *CMA*. Panel A shows time-series averages of the monthly overlap between stocks in the portfolios, where the 'overlap' between two sets, X and Y, is measured as $|X \cap Y|/\min\{|X|, |Y|\}$. Panel B shows time-series averages of the portfolios' monthly value-weighted characteristics as well as the difference in averages. Test-statistics (in parentheses) are adjusted for heteroscedasticity and autocorrelation. A_t is total assets; "$\mathrm{dSM}_{t-4,t}$ from CRSP" is the monthly change in split-adjusted shares outstanding times the monthly average split-adjusted share price accumulated over the latest 12 months; "$\mathrm{dSM}_{t-4,t}$ from Compustat" is the year-over-year change in split-adjusted shares outstanding times the yearly average split-adjusted share price at the beginning and end of the year from Compustat (quarterly file for *EFR*, annual file for *CMA*); PI_t is gross property plant and equipment plus inventory; QA_t is quick assets (current assets minus inventories, or else cash and equivalents plus receivables); B/M is the book-to-market equity ratio. The sample excludes financial firms and firms with negative book equity. The sample used to construct *EFR* is restricted to firm-quarters with strictly positive R&D expenditures. Data are monthly and cover January 1990 to December 2016.

Panel A: Portfolio overlap

	Small		Big	
	Long	Short	Long	Short
Overlap between stocks	53.9%	56.2%	24.0%	59.0%
in *EFR* and *CMA* portfolios	(30.24)	(37.61)	(11.65)	(17.53)

Panel B: Portfolio characteristics

		Small			Big		
Characteristic	Factor	Long	Short	Diff	Long	Short	Diff
$\mathrm{dA}_{t-4,t}/A_{t-4}$	*CMA*	−0.06	1.08	−1.14	−0.04	0.46	−0.51
		(−6.81)	(3.88)	(−4.15)	(−6.84)	(5.04)	(−5.25)
	EFR	0.53	1.15	−0.62	0.08	0.72	−0.64
		(1.60)	(4.34)	(−1.44)	(7.86)	(4.80)	(−4.24)
$\mathrm{dSM}_{t-4,t}/A_{t-4}$	*CMA*	0.16	1.33	−1.16	0.03	0.57	−0.54
(from CRSP)		(3.38)	(2.81)	(−2.75)	(2.62)	(1.74)	(−1.67)
	EFR	0.002	0.83	−0.83	0.004	0.95	−0.95
		(6.52)	(4.03)	(−4.02)	(9.86)	(1.89)	(−1.89)
$\mathrm{dSM}_{t-4,t}/A_{t-4}$	*CMA*	0.06	0.39	−0.33	0.01	0.23	−0.22
(from Compustat)		(5.35)	(4.43)	(−4.38)	(4.85)	(2.80)	(−2.62)
	EFR	0.05	0.51	−0.46	0.01	0.52	−0.51
		(6.49)	(7.26)	(−6.63)	(5.57)	(2.53)	(−2.52)
$\mathrm{dQA}_{t-4,t}/A_{t-4}$	*CMA*	−0.03	0.58	−0.60	−0.01	0.16	−0.17
		(−6.34)	(3.80)	(−4.04)	(−4.25)	(3.42)	(−3.78)
	EFR	0.00	0.54	−0.53	0.02	0.32	−0.29
		(0.51)	(4.07)	(−4.13)	(4.28)	(4.46)	(−4.03)
$\mathrm{dPI}_{t-4,t}/A_{t-4}$	*CMA*	0.23	0.40	-0.17	0.28	0.33	-0.05
		(20.99)	(12.78)	(-5.69)	(10.51)	(20.84)	(-3.14)
	EFR	0.03	0.17	-0.14	0.04	0.14	-0.10
		(4.16)	(7.91)	(-8.05)	(4.93)	(10.25)	(-7.43)
B/M	*CMA*	0.79	0.51	0.28	0.46	0.32	0.14
		(14.07)	(17.49)	(8.94)	(14.57)	(14.70)	(7.09)
	EFR	0.74	0.42	0.32	0.34	0.29	0.05
		(17.12)	(14.61)	(11.78)	(20.03)	(13.00)	(2.54)

LSZ from 3 × 3 × 3 independent triple sorts on size, book-to-market equity, and the year-over-year change in the sum of gross property, plant and equipment (PPEG) and inventories (INVT) divided by one-year lagged total assets. We use the 30th and 70th percentiles for NYSE stocks as breakpoints. The resulting 27 portfolios are value-weighted and rebalanced annually in June. The *LSZ* factor is the equal-weighted average of the 9 low-investment portfolios minus the equal-weighted average of the 9 high-investment portfolios. In untabulated tests, we find that *LSZ* yields a significant average excess return of 0.32% per month (t = 3.16) over our sample period. However, its time-series correlation with the *EFR* factor is a relatively modest 19%. As such, neither factor subsumes the other in univariate spanning tests. Finally, in contrast to the *EFR* factor, the *LSZ* factor is redundant in both the *FF5+MOM* and q-factor models. In short, it is unlikely that the *EFR* factor is driven by firm-level optimal investment decisions.

Overall, the cross-sectional analysis reveals that *CMA*, like the *EFR* factor, separates firms with large positive changes in liquid assets driven by equity issuances from firms that experience no equity issuances and no change in liquid assets. The former firms, by reducing their exposure to equity financing risk via cash savings out of equity issuance proceeds, carry a lower risk premium.

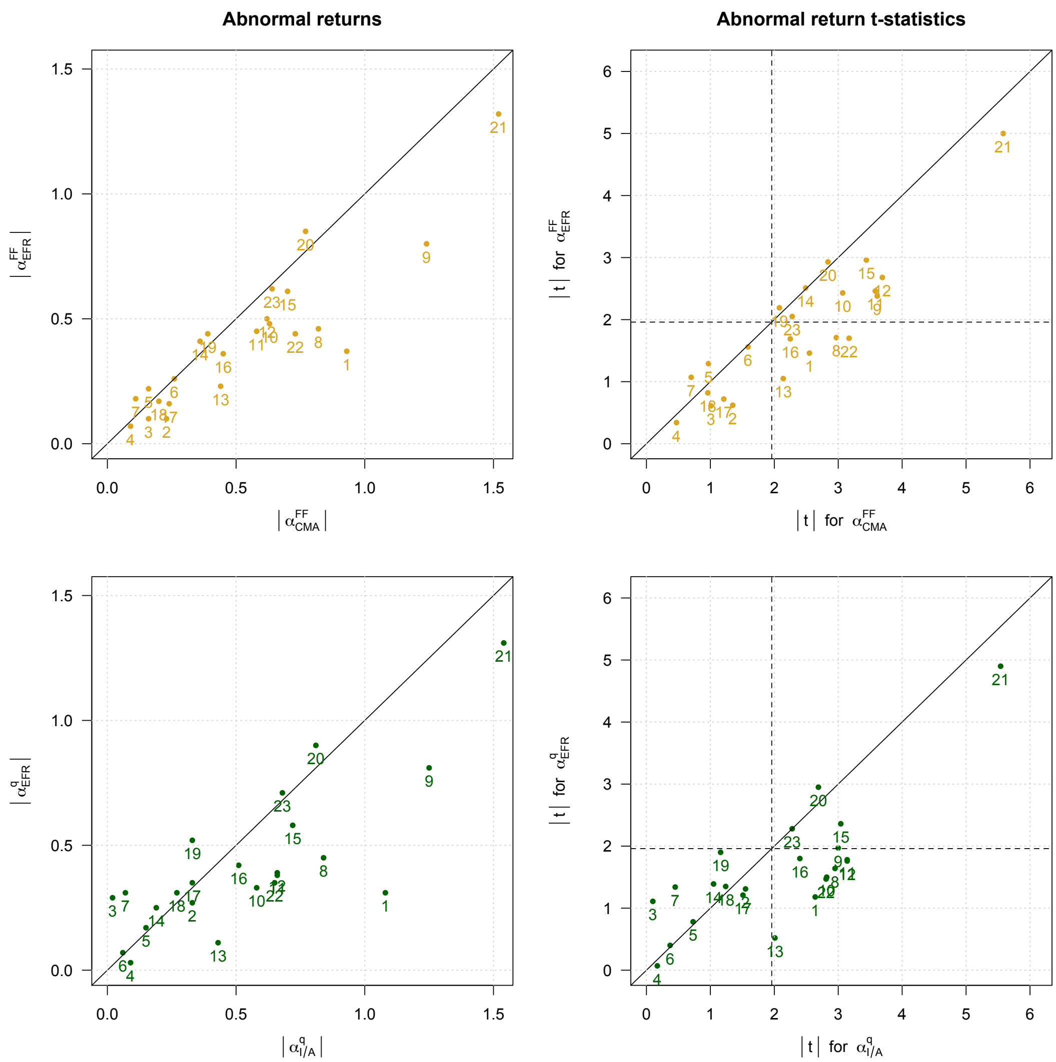
6 Explaining significant anomalies using the *EFR* factor

We conclude our analysis by comparing the pricing power of the *EFR* factor with that of the investment factors (*CMA* and *I/A*). The test assets are always zero-cost, long-short strategies that trade value-weighted portfolios from sorts based on NYSE breakpoints. We consider the equity financing risk strategy from Table 4 as well as 22 additional strategies that trade the extreme portfolios from univariate sorts. Appendix A gives the detailed strategy construction. The sample excludes financial firms and firms with negative book equity. Asset pricing tests cover January 1990 to December 2016, where the start date is determined by the availability of the *EFR* factor.

Our pricing tests center around comparing each strategy's abnormal return (α) relative to four different factor models: The standard *FF5+MOM* model that includes *CMA* (α^{FF}_{CMA}), the standard q-factor model that includes *I/A* ($\alpha^{FF}_{I/A}$), and alternative versions of these models with the investment factors replaced by *EFR* (α^{FF}_{EFR} and α^{q}_{EFR}).

Before going into detail, we provide a graphical summary in Figure 3. It plots the performance of the alternative factor models against that of the standard factor models, both in terms of abnor-

Figure 3. Comparing the pricing power of the *EFR* factor with that of the asset growth factors.



This figure illustrates the pricing tests in Table 12 by plotting the performance of the alternative factor models against that of the standard factor models for the 23 test assets. The left panels show the absolute abnormal returns of the alternative factor models (α^{FF}_{EFR} and α^{q}_{EFR}) plotted against the absolute abnormal returns of the standard factor models (α^{FF}_{CMA} and $\alpha^{q}_{I/A}$) along with a 45-degree line. The right panels show the absolute abnormal return t-statistics for the alternative models plotted against the absolute abnormal return t-statistics for the standard models along with a 45-degree line and an indication of 1.96 on the two axes (dashed lines). In either panel, a point below the 45-degree line means that the alternative factor model brings an abnormal return closer to zero. Data are monthly and cover January 1990 to December 2016.

mal returns (left-most panels) as well as abnormal return t-statistics (right-most panels). The two left-most panels show that, compared with the standard models, the alternative models produce abnormal returns that are closer to zero (i.e., tend to lie below the 45-degree line). For the few strategies where this is not the case, the abnormal returns are similar in terms of magnitude and significance for either set of models. The two right-most panels show that the alternative factor models are able to generate insignificant pricing errors (absolute t-statistics below 1.96) when the corresponding standard models deliver significant pricing errors (absolute t-statistics above 1.96).

Looking at the two right-most panels' bottom-right quadrants, we see that this is the case for five strategies relative to the *FF5+MOM* model and seven strategies relative to the q-factor model. At the same time, the two right-most panels' top-left quadrants are, in fact, empty. That is, there are no insignificant pricing errors obtained using the standard factor models that become significant when using the alternative factor models.

Table 12 provides the details of the pricing tests. The first seven test assets are baseline strategies directly related to the factors. The table's first line shows, not surprisingly, that replacing the investment factors with *EFR* implies that both models can price the equity financing risk strategy from Table 4. The next six lines show that employing *EFR* does not hurt the pricing of strategies based on market capitalization, book-to-market equity, momentum, operating profitability, return on equity, and asset growth.

Our starting point for the remaining test assets is the list of 46 strategies in Hou, Xue, and Zhang (2018) that generate a significant average return as well as a significant q-factor abnormal return (see their Tables 8 and 9). We further restrict attention to

1) strategies that can be constructed using only the primary Compustat quarterly/annual data files and the CRSP monthly data file (i.e., we do not consider strategies that require CRSP daily data, Compustat segment data, or I/B/E/S analysts' forecasts data);

2) strategies that do not require estimation of the sorting variable through time-series or cross-sectional regressions;

3) strategies that are either rebalanced monthly and have a one-month holding period or annually and have a one-year holding period; and

4) strategies that generate a statistically significant average return ($|t| > 1.96$) over our sample period (January 1990 to December 2016).

The first three restrictions are for simplicity. The fourth restriction excludes a total of seven strategies, suggesting that the significant performance of these strategies documented by Hou, Xue, and Zhang (2018) is driven by the pre-1990 period.[20] These restrictions leave us with the

[20]The seven insignificant strategies are those based on cash-flow-to-price (0.56% per month, t = 1.81), operating cash-flow-to-price (0.53% per month, t = 1.78), inventory changes (−0.36% per month, t = −1.94), operating accruals (−0.15% per month, t = −0.76), the change in net non-cash working capital (−0.29% per month, t = −1.43), the change in net financial assets (0.31% per month, t = 1.84), and 12-month return seasonality (0.46% per month,

remaining 16 strategies considered in Table 12, which we group into the following categories: R&D, profitability, asset composition, payout and financing policy, valuation, and seasonality.

The R&D category consists of the R&D-to-market strategy with annual and monthly updating (lines 8-9). Both generate average returns above 0.90% per month with t-statistics of at least 2.70. The abnormal returns relative to the two standard factor models are about as large as the strategies' average returns and statistically even stronger. Replacing the investment factors with *EFR* implies that both alternative models fully explain the annually updated strategy. For the monthly updated strategy, the abnormal return relative to the alternative q-factor model has a t-statistic of 1.97.

The first four strategies in the profitability category (lines 10-13) are related to operating profitability. All four strategies generate significant abnormal returns relative to the standard factor models. Replacing the investment factors with the *EFR* factor implies that the alternative q-factor model can price all four strategies. The final strategy in the profitability category (line 14) is based on the change in return on equity. It is not explained by the standard Fama-French model, but is explained by the standard q-factor model. Replacing the investment factors with the *EFR* factor does not alter these conclusions.

In the asset composition category (lines 15-16), replacing the investment factors with *EFR* (i) shrinks the abnormal returns of the strategy based on net operating assets to less than three standard errors from zero and (ii) completely explains the returns to the strategy based on the industry-adjusted real estate ratio.

The two strategies in the payout and financing policy category (lines 17-18) are both explained by the two standard models. The single strategy in the valuation category (line 19) is not explained by the standard Fama-French model but is explained by the standard q-factor model. Replacing the investment factors with *EFR* does not alter these conclusions.

The final category considers four strategies related to return seasonality (lines 20-23). Here, the standard and alternative models have the same difficulties in explaining the strategies' returns, with the exception of the strategy based on the average 11-15 year return seasonality (line 22). For this strategy, replacing the investment factors with *EFR* shrinks the abnormal returns from around three standard errors above zero to insignificance.

t = 1.68). For completeness, Appendix A also gives the detailed construction of these strategies. In general, the insignificant strategies do not cause problems for either set of factor models (untabulated).

Table 12. *EFR* factor pricing tests. This table compares the pricing power of the *EFR* factor with those of the investment factors (*CMA* and *I/A*). It shows each strategy's average excess return as well as its abnormal return (α) relative to four different factor models: the standard *FF5+MOM* model that includes *CMA* (α^{FF}_{CMA}), the standard *q*-factor model that includes *I/A* ($\alpha^{FF}_{I/A}$), and alternative versions of these models with the investment factors replaced by *EFR* (α^{FF}_{EFR} and α^{q}_{EFR}). The test assets are zero-cost, long-short strategies that trade in value-weighted portfolios from sorts based on NYSE breakpoints. The equity financing risk strategy is the one considered in Table 4. All other strategies are from univariate decile sorts. Appendix A gives the detailed strategy construction. Annual strategies are rebalanced at the end of June, while monthly strategies are rebalanced at the end of each month. Financial firms and firms with negative book equity are excluded. Test statistics (in parentheses) are adjusted for heteroscedasticity and autocorrelation. Data are monthly and cover January 1990 to December 2016, where the start date is determined by the availability of the *EFR* factor.

			Abnormal return (α) relative to different factor models			
			Baseline factors: *MKT, SMB, HML, RMW,* and *MOM*		Baseline factors: *MKT, ME,* and *ROE*	
	Strategy	$\mathbb{E}[r^e]$	α^{FF}_{CMA}	α^{FF}_{EFR}	$\alpha^{q}_{I/A}$	α^{q}_{EFR}
	I. Baseline					
(1)	Equity financing risk	1.04 (2.79)	0.93 (2.55)	−0.37 (−1.46)	1.08 (2.64)	−0.31 (−1.18)
(2)	Market equity (annual)	−0.31 (−0.96)	−0.23 (−1.35)	−0.10 (−0.62)	−0.33 (−1.55)	−0.27 (−1.31)
(3)	Book-to-market equity (annual)	0.16 (0.60)	−0.16 (−1.01)	−0.10 (−0.61)	−0.02 (−0.10)	0.29 (1.11)
(4)	Momentum	0.82 (2.06)	0.09 (0.47)	0.07 (0.34)	0.09 (0.17)	0.03 (0.07)
(5)	Operating profitability (OP_{FF}/B, annual)	0.29 (0.90)	−0.16 (−0.97)	−0.22 (−1.29)	−0.15 (−0.73)	−0.17 (−0.78)
(6)	Return-on-equity (monthly)	0.59 (1.85)	0.26 (1.59)	0.26 (1.56)	0.06 (0.37)	0.07 (0.40)
(7)	Asset growth (annual)	−0.47 (−2.03)	−0.11 (−0.70)	−0.18 (−1.07)	−0.07 (−0.45)	−0.31 (−1.34)
	II. R&D					
(8)	R&D-to-market (annual)	0.91 (2.78)	0.82 (2.97)	0.46 (1.71)	0.84 (2.95)	0.45 (1.64)
(9)	R&D-to-market (monthly)	0.98 (2.70)	1.24 (3.61)	0.80 (2.38)	1.25 (3.00)	0.81 (1.97)
	III. Profitability					
(10)	Operating profits before R&D relative to lagged assets ($OP_{\mathrm{BGLN}}/A_{-1}$, monthly)	0.87 (3.06)	0.63 (3.07)	0.48 (2.43)	0.58 (2.82)	0.33 (1.50)
(11)	Cash-based operating profits relative to assets (COP/A, annual)	0.74 (2.64)	0.58 (3.58)	0.45 (2.46)	0.66 (3.14)	0.38 (1.78)
(12)	Cash-based operating profits relative to lagged assets (COP/A_{-1}, annual)	0.66 (2.62)	0.62 (3.69)	0.50 (2.68)	0.66 (3.14)	0.39 (1.76)
(13)	Cash-based operating profits relative to lagged assets (COP/A_{-1}, monthly)	0.49 (2.16)	0.44 (2.14)	0.23 (1.05)	0.43 (2.01)	0.11 (0.52)
(14)	Change in ROE (monthly)	0.51 (2.88)	0.36 (2.49)	0.41 (2.51)	0.19 (1.05)	0.25 (1.39)

(Continues)

(Continued)

	Strategy	$\mathbb{E}[r^e]$	Abnormal return (α) relative to different factor models — Baseline factors: *MKT, SMB, HML, RMW,* and *MOM* α^{FF}_{CMA}	α^{FF}_{EFR}	Baseline factors: *MKT, ME,* and *ROE* $\alpha^{q}_{I/A}$	α^{q}_{EFR}
	IV. Asset composition					
(15)	Net operating assets (annual)	−0.83 (−4.06)	−0.70 (−3.44)	−0.61 (−2.96)	−0.72 (−3.04)	−0.58 (−2.36)
(16)	Industry-adjusted real estate ratio (annual)	0.46 (2.21)	0.45 (2.25)	0.36 (1.69)	0.51 (2.40)	0.42 (1.80)
	V. Payout and financing policy					
(17)	Net payout yield (annual)	0.71 (3.32)	0.24 (1.21)	0.16 (0.72)	0.33 (1.51)	0.35 (1.21)
(18)	Net stock issuance (annual)	−0.61 (−2.31)	−0.20 (−0.96)	−0.17 (−0.82)	−0.27 (−1.24)	−0.31 (−1.35)
	VI. Valuation					
(19)	Enterprise multiple (monthly)	−0.58 (−2.09)	−0.39 (−2.08)	−0.44 (−2.19)	−0.33 (−1.16)	−0.52 (−1.90)
	VII. Seasonality					
(20)	Average 2-5 year return seasonality	0.79 (3.19)	0.77 (2.84)	0.85 (2.93)	0.81 (2.69)	0.90 (2.95)
(21)	Average 6-10 year return seasonality	1.27 (5.44)	1.52 (5.58)	1.32 (5.00)	1.54 (5.54)	1.31 (4.90)
(22)	Average 11-15 year return seasonality	0.60 (2.95)	0.73 (3.17)	0.44 (1.70)	0.65 (2.81)	0.35 (1.47)
(23)	Average 16-20 year return seasonality	0.53 (1.97)	0.64 (2.28)	0.62 (2.05)	0.68 (2.28)	0.71 (2.28)

Table 13. Average model performance across all and non-baseline strategies. This table reports the average absolute pricing errors (α) and average absolute t-statistics for the abnormal returns in Table 12 calculated using four different factor models: The standard *FF5+MOM* model that includes *CMA* (α^{FF}_{CMA}), the standard q-factor model that includes *I/A* ($\alpha^{FF}_{I/A}$), and alternative versions of these models with the investment factors replaced by *EFR* (α^{FF}_{EFR} and α^{q}_{EFR}). The table also shows, for each quantity, the difference between the one implied by the standard factor models and the one implied by the alternative model (Δ) as well as the two-sided p-value for the null hypotheses of a zero difference based on a normal distribution approximation. Data are monthly and cover January 1990 to December 2016, where the start date is determined by the availability of the *EFR* factor.

	All strategies (1 to 23)	Non-baseline strategies (8 to 23)
Panel A: Standard and alternative *FF5+MOM* models		
Abnormal returns		
$\lvert\alpha^{FF}_{CMA}\rvert$	0.53	0.65
$\lvert\alpha^{FF}_{EFR}\rvert$	0.42	0.52
$\Delta\lvert\alpha\rvert$	−0.11	−0.13
p-value for $H_0 : \Delta\lvert\alpha\rvert = 0$	0.00	0.00
Abnormal return t-statistics		
$\lvert t\rvert$ for α^{FF}_{CMA}	2.35	2.84
$\lvert t\rvert$ for α^{FF}_{EFR}	1.84	2.21
$\Delta\lvert t\rvert$	−0.51	−0.63
p-value for $H_0 : \Delta\lvert t\rvert = 0$	0.00	0.00
Panel B: Standard and alternative q-factor models		
Abnormal returns		
$\lvert\alpha^{q}_{I/A}\rvert$	0.53	0.65
$\lvert\alpha^{q}_{EFR}\rvert$	0.42	0.51
$\Delta\lvert\alpha\rvert$	−0.11	−0.14
p-value for $H_0 : \Delta\lvert\alpha\rvert = 0$	0.04	0.01
Abnormal return t-statistics		
$\lvert t\rvert$ for $\alpha^{q}_{I/A}$	2.03	2.55
$\lvert t\rvert$ for α^{q}_{EFR}	1.61	1.92
$\Delta\lvert t\rvert$	−0.42	−0.63
p-value for $H_0 : \Delta\lvert t\rvert = 0$	0.00	0.00

We summarize the different models' performance in Table 13. For each standard model, we report the mean absolute return and mean absolute t-statistic and compare these quantities with the ones generated with the alternative models. The latter clearly outperform the standard ones by delivering consistently lower mean absolute returns and mean absolute t-statistics. These differences are also statistically significant. As an example, across the 16 non-baseline strategies, the standard q-factor model's mean absolute return is 0.65% per month and its mean absolute t-statistic is 2.55. Replacing *I/A* with *EFR* implies a significant reduction in the mean absolute return of about 20% and a significant reduction in the mean absolute t-statistic of about 25%.

7 Conclusion

Exposure to equity financing risk is an important dimension of a firm's expected equity returns. Using a measure of liquid assets relative to R&D expenditures (i.e., R&D coverage ratio) and a measure of equity issuance activity, we identify firms more or less exposed to equity financing risk. We find that firms more exposed to *EFR* (i.e., those with low R&D coverage ratio *and* no equity issuance) generate significantly higher average returns than firms less exposed to *EFR* (i.e., firms with a high R&D coverage ratio *and* high equity issuance). In addition, we construct a factor that captures exposure to equity financing risk. This factor is linked to aggregate equity issuance conditions and generates large and highly significant average excess returns that cannot be explained by leading empirical asset pricing models.

We find that the equity financing risk factor (i) completely subsumes the asset-growth factors from both the Fama and French five-factor model and the Hou, Xue, and Zhang (2015) q-factor model and (ii) improves the pricing performance of standard linear factor models when it replaces the asset-growth factor. These results suggest that factors based on asset growth conflate variations in expected returns due to physical investments (as noted by Lyandres et al., 2008) with variations due to precautionary cash savings aimed at reducing the exposure to equity financing risk. Accounting for the exposure to equity financing risk thus seems to be important for the broad cross section of returns, not only the returns of firms that are R&D-intensive.

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Appendix A

All strategies trade in value-weighted portfolios from sorts based on NYSE breakpoints. Quarterly earnings (IBQ) are employed in the months immediately after earnings announcement dates (RDQ). Other quarterly accounting data are lagged 4 months relative to subsequent returns to ensure no look-ahead bias. Annual accounting data for a given fiscal year is employed starting at the end of June of the following calendar year. The sample excludes financial firms (SIC codes 6000-6999) and firms with negative book equity. Asset pricing tests cover January 1990 to December 2016, where the start date is determined by the availability of quarterly data on R&D expenditures for the construction of the *EFR* factor.

A.1 Baseline strategies

A.1.1 Equity financing risk

At the end of month $m-1$, we form 9 portfolios from independent 3×3 sorts on R&D coverage ratio and equity issuance, where the breakpoints are the 30th and 70 percentiles for NYSE stocks. Financial slack is 1-quarter lagged quick assets (ACTQ − INVTQ or else CHEQ + RECTQ) relative to R&D expenditures (XRDQ) from the latest fiscal quarter ending at least 4 months ago. Equity issuance is the cumulative monthly change in split-adjusted shares outstanding (change in SHROUT × CFACSHR) times the monthly average split-adjusted share price (average of PRC / CFACPR) for the latest 12 months (i.e., months $m-12, \ldots, m-1$) scaled by beginning-of-period total assets (4-quarter lagged ATQ). We only keep firms with strictly positive R&D expenditures and nonnegative equity issuance. We calculate value-weighted returns for month m and rebalance the portfolios at the end of month m. The equity financing risk strategy buys the low/low corner portfolio (high exposure to equity financing risk) and short sells the high/high corner portfolio (low exposure to equity financing risk). The first sort is at the end of December 1989. See also Table 4.

A.1.2 Market equity (annual)

At the end of June of year t, we form portfolios from a decile sort on market equity using NYSE breakpoints. Market equity is share price times number of shares outstanding from CRSP (PRC × SHROUT) at the end of June of year t. We calculate monthly value-weighted returns from July of year t to June of year $t+1$ and rebalance the portfolios at the end of June of year $t+1$. The first sort is at the end of June 1989.

A.1.3 Book-to-market equity (annual)

At the end of June of year t, we form portfolios from a decile sort on book-to-market equity, B/M, using NYSE breakpoints. Here, B is book equity for the fiscal year ending in calendar year $t-1$ and M is market equity from CRSP at the end of December of year $t-1$. Book is shareholder's equity plus deferred taxes minus preferred stock. Shareholder's equity is SEQ. If SEQ is missing, we substitute it by common equity, CEQ, plus preferred stock (defined below), or else by total assets minus total liabilities, AT − LT. Deferred taxes is deferred taxes and investment tax credits, TXDITC, or else deferred taxes and/or investment tax credit, TXDB and/or ITCB. Preferred stock is redemption value, PSTKRV or else PSTKR, or else liquidating value, PSTKL, or else carrying value, PSTK. We calculate monthly value-weighted returns from July of year t to June of year $t+1$ and rebalance the portfolios at the end of June of year $t+1$. The first sort is at the end of June 1989.

A.1.4 Momentum

At the end of month $m-1$, we form portfolios from a decile sort on prior 11-month returns using NYSE breakpoints. Prior 11-month returns is the cumulative return from month $m-12$ to month $m-2$, skipping the return over month $m-1$ (at the end of which the portfolios are formed). We calculate value-weighted returns for month m and rebalance the portfolios at the end of month m. For instance, at the end of June 2016, we sort on cumulative returns from July 2015 to May 2016; calculate value-weighted returns for July 2016, and rebalance the portfolios at the end of July 2016. The first sort is at the end of December 1989.

A.1.5 Operating profitability (OP_{FF}/B, annual)

At the end of June of year t, we form portfolios from a decile sort on operating profitability, OP_{FF}/B, using NYSE breakpoints. Here, OP_{FF} is Fama and French's (2015) definition of annual operating profits for the fiscal year ending in calendar year $t-1$ and B is contemporaneous (not lagged) book equity (see Appendix A.1.3). Annual operating profits is total revenue (REVT) minus cost of goods sold (COGS, zero if missing) minus selling, general, and administrative expenses (XSGA, zero if missing) minus interest expenses (XINT, zero if missing). We require at least one of the three expense items to be non-missing. We calculate monthly value-weighted returns from July of year t to June of year $t+1$ and rebalance the portfolios at the end of June of year $t+1$. The first sort is at the end of June 1989.

A.1.6 Return on equity (monthly)

At the end of month $m-1$, we form portfolios from a decile sort on Hou, Xue, and Zhang's (2015) return on equity using NYSE breakpoints. return on equity is total earnings from the latest earnings announcement date scaled by 1-quarter lagged book equity (IBQ/B_{-1}). Quarterly book equity, B, is shareholder's equity plus deferred taxes minus preferred stock. Shareholder's equity is SEQQ. If SEQQ is missing, we substitute it by common equity, CEQQ, plus preferred stock (defined below), or else by total assets minus total liabilities, ATQ − LTQ. Deferred taxes is deferred taxes and investment tax credits, TXDITCQ, or else deferred taxes, TXDBQ. Preferred stock is redemption value, PSTKRQ, or else carrying value, PSTKQ. We calculate value-weighted returns for month m and rebalance the portfolios at the end of month m. The first sort is at the end of December 1989.

A.1.7 Asset growth (annual)

At the end of June of year t, we form portfolios from a decile sort on the percentage growth in total book assets (AT), over the fiscal years ending in calendar years $t-2$ and $t-1$, using NYSE breakpoints. We calculate monthly value-weighted returns from July of year t to June of year $t+1$ and rebalance the portfolios at the end of June of year $t+1$. The first sort is at the end of June 1989.

A.2 Research and developement

A.2.1 R&D-to-market (annual)

At the end of June of year t, we form portfolios form a decile sort on R&D-to-market using NYSE breakpoints. R&D expenditures (XRD) are for the fiscal year ending in calendar year $t-1$ and market equity is from CRSP at the end of December of year $t-1$. We only keep firms with strictly positive R&D expenditures. We calculate monthly value-weighted returns from July of year t to June of year $t+1$ and rebalance the portfolios at the end of June of year $t+1$. The first sort is at the end of June 1989.

A.2.2 R&D-to-market (monthly)

At the end of month $m-1$, we form portfolios form a decile sort on R&D-to-market using NYSE breakpoints. R&D expenditures (XRDQ) are from the latest fiscal quarter ending at least 4 months ago and market equity is from CRSP at the end of month $m-1$. We only keep firms with strictly positive R&D expenditures. We calculate monthly value-weighted returns for month m and rebalance the portfolios at the end of month m. The first sort is at the end of December 1989.

A.3 Profitability

A.3.1 Operating profits before R&D relative to lagged assets (OP_{BGLN}/A_{-1}, monthly)

At the end of month $m-1$, we form portfolios from a decile sort on operating profits before R&D relative to lagged assets, OP_{BGLN}/A_{-1}, using NYSE breakpoints. Here, OP_{BGLN} is similar to Ball, Gerakos, Linnainmaa, and Nikolaev's (2015) definition of annual operating profits before R&D but for the latest fiscal quarter ending at least 4 months ago and A_{-1} is 1-quarter lagged total assets (ATQ). Operating profits before R&D expenditures is quarterly total revenue (REVTQ) minus cost of goods sold (COGSQ) minus selling, general, and administrative expenses (XSGAQ) plus R&D expenditures (XRDQ, zero if missing). We calculate monthly value-weighted returns for month m and rebalance the portfolios at the end of month m. The first sort is at the end of December 1989.

A.3.2 Cash-based operating profits relative to assets (COP/A, annual)

At the end of June of year t, we form portfolios from a decile sort on cash-based operating profits relative to assets, COP/A, using NYSE breakpoints. Here, COP is Ball, Gerakos, Linnainmaa, and Nikolaev's (2016) definition of cash-based operating profits for the fiscal year ending in calendar year $t-1$ and A is contemporaneous (not lagged) total assets (AT). Cash-based operating profits is annual total revenue (REVT) minus cost of goods sold (COGS), minus selling, general, and administrative expenses (XSGA), plus R&D expenditures (XRD, zero if missing), minus the change in accounts receivable (RECT), minus the change in inventory (INVT), minus the change in prepaid expenses (XPP), plus the change in deferred revenue (DRC + DRLT), plus the change in trade accounts payable (AP), plus the change in accrued expenses (XACC). All changes are annual changes and missing changes are set to zero. We calculate monthly value-weighted returns from July of year t to June of year $t+1$ and rebalance the portfolios at the end of June of year $t+1$. The first sort is at the end of June 1989.

A.3.3 Cash-based operating profits relative to lagged assets (COP/A_{-1}, annual)

At the end of June of year t, we form portfolios from a decile sort on cash-based operating profits relative to lagged assets, COP/A_{-1}, using NYSE breakpoints. Here, COP is Ball, Gerakos, Linnainmaa, and Nikolaev's (2016) definition of cash-based operating profits for the fiscal year ending in calendar year $t-1$ (see Appendix A.3.2) and A_{-1} is total assets (AT) for the fiscal year ending in calendar year $t-2$. We calculate monthly value-weighted returns from July of year t to June of year $t+1$ and rebalance the portfolios at the end of June of year $t+1$. The first sort is at the end of June 1989.

A.3.4 Cash-based operating profits relative to lagged assets (COP/A_{-1}, monthly)

At the end of month $m-1$, we form portfolios from a decile sort on cash-based operating profits relative to lagged assets, COP/A_{-1}, using NYSE breakpoints. Here, COP is similar to Ball, Gerakos, Linnainmaa, and Nikolaev's (2016) definition of annual cash-based operating profits but for the fiscal quarter ending at least 4 months ago and A_{-1} is 1-quarter lagged total assets (ATQ). Cash-based operating profits is quarterly total revenue (REVTQ) minus cost of goods sold (COGSQ), minus selling, general, and administrative expenses (XSGAQ), plus R&D expenditures (XRDQ, zero if missing), minus the change in accounts receivable (RECTQ), minus the change in inventory (INVTQ), plus the change in deferred revenue (DRCQ + DRLTQ), plus the change in trade accounts payable (APQ), plus the change in accrued expenses (XACCQ). All changes are quarterly changes and missing changes are set to zero. We calculate monthly value-weighted returns for month m and rebalance the portfolios at the end of month m. The first sort is at the end of December 1989.

A.3.5 Change in ROE (monthly)

At the end of month $m-1$, we form portfolios from a decile sort on the change in return on equity (ROE) using NYSE breakpoints. The change in ROE is the most recent ROE (see Appendix A.1.6) minus its value from 4 quarters ago. We calculate monthly value-weighted returns for month m and rebalance the portfolios at the end of month m. The first sort is at the end of December 1989.

A.4 Asset composition

A.4.1 Net operating assets (annual)

At the end of June of year t, we form portfolios from a decile sort on net operating assets relative to lagged assets, NOA/A_{-1}, using NYSE breakpoints. Here, NOA is operating assets minus operating liabilities for the fiscal year ending in calendar year $t-1$ and A_{-1} is total assets (AT) for the fiscal year ending in calendar year $t-2$. Operating assets are total assets minus cash and marketable securities (AT − CHE). Operating liabilities are total assets (AT) minus debt included in current liabilities (DLC, zero if missing), minus long-term debt (DLTT, zero if missing), minus minority interests (MIB, zero if missing), minus preferred stocks (PSTK, zero if missing), minus common equity (CEQ). We calculate monthly value-weighted returns from July of year t to June of year $t+1$ and rebalance the portfolios at the end of June of year $t+1$. The first sort is at the end of June 1989.

A.4.2 Industry-adjusted real estate ratio (annual)

At the end of June of year t, we form portfolios from a decile sort on industry-adjusted real estate ratio using NYSE breakpoints. A firm's real estate ratio for the fiscal year ending in calendar year $t-1$ is the sum of buildings at cost (FATB) and leases at cost (FATL) relative to gross property, plant, and equipment (PPEGT). The industry-adjusted real estate ratio is a firm's real estate ratio minus its industry average. Industries are defined by two-digit SIC codes. To alleviate the influence of outliers, we trim firms' real estate ratios at the yearly 1st and 99th percentiles before computing the industry average. We exclude industries with fewer than five firms. We calculate monthly value-weighted returns from July of year t to June of year $t+1$ and rebalance the portfolios at the end of June of year $t+1$. The first sort is at the end of June 1989.

A.5 Payout and financing policy

A.5.1 Net payout yield (annual)

At the end of June of year t, we form portfolios from a decile sort on net payout yield, NPO/M, using NYSE breakpoints. Here, NPO is net payouts for the fiscal year ending in calendar year $t-1$ and M is market equity from CRSP at the end of December of year $t-1$. Net payouts are total payouts minus equity issuances from the cash-flow statement. Total payouts are dividends on common stock (DVC) plus total expenditure on the purchase of common and preferred stocks (PRSTKC) plus any reduction (negative yearly change) in the value of the net number of preferred stocks outstanding (item PSTKRV). Equity issuances from the cash-flow statement are the sale of common and preferred stock (SSTK) minus any increase (positive yearly change) in the value of the net number of preferred stocks outstanding (PSTKRV). We exclude firms with non-positive total payouts and firms with zero net payouts. We calculate monthly value-weighted returns from July of year t to June of year $t+1$ and rebalance the portfolios at the end of June of year $t+1$. The first sort is at the end of June 1989.

A.5.2 Net stock issuance (annual)

At the end of June of year t, we form 10 portfolios on net stock issuance, NSI, using NYSE breakpoints: Firms with negative NSI are sorted into two portfolios (1 and 2); firms with zero NSI are in a single portfolio (3), and firms with positive NSI are sorted into 7 portfolios (4 to 10). Here, NSI is the yearly change in the log of split-adjusted shares outstanding from the annual statement, i.e., $\log\left(\frac{\text{CSHO}\times\text{AJEX}}{\text{CSHO}_{-1}\times\text{AJEX}_{-1}}\right)$. We calculate monthly value-weighted returns from July of year t to June of year $t+1$ and rebalance the portfolios at the end of June of year $t+1$. The net stock issuance strategy buys the extreme net-issuers (portfolio 10) and short sells the extreme net-repurchasers (portfolio 1). The first sort is at the end of June 1989.

A.6 Valuation

A.6.1 Enterprise multiple (monthly)

At the end of month $m-1$, we form portfolios from a decile sort on enterprise multiple, EM, using NYSE breakpoints. Here, EM is enterprise value relative to quarterly operating income before depreciation (OIBDPQ) for the fiscal quarter ending at least 4 months ago. Enterprise value is market equity from CRSP at the end of month $m-1$ plus total debt (DLCQ + DLTTQ) plus the book value of preferred stock (PSTKQ) minus cash and marketable securities (CHEQ). We exclude firms with negative enterprise value or negative operating income before depreciation. We calculate monthly value-weighted returns for month m and rebalance the portfolios at the end of month m. The first sort is at the end of December 1989.

A.7 Seasonality

A.7.1 Average x-y year return seasonality

At the end of month $m-1$, we form portfolios from a decile sort on average x-y year return seasonality using NYSE breakpoints.

1. Average 2-5 year return seasonality is the average return across months $m-24, m-36, m-48$, and $m-60$.

2. Average 6-10 year return seasonality is the average return across months $m-72, m-84, m-96, m-108$, and $m-120$.

3. Average 11-15 year return seasonality is the average return across months $m-132, m-144, m-156, m-168$, and $m-180$.

4. Average 16-20 year return seasonality is the average return across months $m-192, m-204, m-216, m-228$, and $m-240$.

We calculate monthly value-weighted returns for month m and rebalance the portfolios at the end of month m. For instance, for the 2-5 year return seasonality sort at the end of June 2016, we sort on average returns for {July 2014, July 2013, July 2012, July 2011}; calculate value-weighted returns for July 2016, and rebalance the portfolios at the end of July 2016. The first sort is at the end of December 1989.

A.8 Insignificant strategies

A.8.1 Cash flow-to-price (monthly)

At the end of month $m - 1$, we form portfolios from a decile sort on quarterly cash flow-to-price, CF/M, using NYSE breakpoints. Here, CF is quarterly total cash flows and M is market equity at the end of month $m - 1$ from CRSP. Quarterly total cash flows are income before extraordinary items (IBQ) plus depreciation (DPQ), both for the latest fiscal quarter ending at least 4 months ago. We do not employ the IBQ from the latest earnings announcement date to be consistent with the 4-month lag imposed for DPQ. We calculate monthly value-weighted returns for month m and rebalance the portfolios at the end of month m. The first sort is at the end of December 1989.

A.8.2 Operating cash flow-to-price (annual)

At the end of June of year t, we form portfolios from a decile sort on annual operating cash flow-to-price, OCF/M, using NYSE breakpoints. Here, OCF is annual cash flows from operating activities (OANCF) for the fiscal year ending in calendar year $t - 1$ and M is market equity from CRSP at the end of December of year $t - 1$. We only keep firms with positive operating cash flows. We calculate monthly value-weighted returns from July of year t to June of year $t + 1$ and rebalance the portfolios at the end of June of year $t + 1$. The first sort is at the end of June 1989.

A.8.3 Inventory change (annual)

At the end of June of year t, we form portfolios from a decile sort on inventory change using NYSE breakpoints. Inventory change is the change in inventory (INVT) over the fiscal years ending in calendar years $t - 2$ and $t - 1$ relative to the average of total assets (AT) for the fiscal years ending in calendar years $t - 2$ and $t - 1$. We exclude firms that have zero inventory for both fiscal years ending in calendar years $t - 2$ and $t - 1$. We calculate monthly value-weighted returns from July of year t to June of year $t + 1$ and rebalance the portfolios at the end of June of year $t + 1$. The first sort is at the end of June 1989.

A.8.4 Operating accruals (annual)

At the end of June of year t, we form portfolios from a decile sort on operating accruals using NYSE breakpoints. Operating accruals are net income (NI) minus cash flows from operating activities (OANCF) for the fiscal year ending in calendar year $t - 1$ relative to total assets (AT) for the fiscal year ending in calendar year $t - 2$. We calculate monthly value-weighted returns from July of year t to June of year $t + 1$ and rebalance the portfolios at the end of June of year $t + 1$. The first sort is at the end of June 1989.

A.8.5 Change in net non-cash working capital (annual)

At the end of June of year t, we form portfolios from a decile sort on the change in net non-cash working capital relative to lagged assets, dWc/A_{-1}, using NYSE breakpoints. Here, dWc is the change in current operating assets minus the change in current operating liabilities over the fiscal years ending in calendar years $t-2$ and $t-1$, while A_{-1} is total assets (AT) for the fiscal year ending in calendar year $t-1$. Current operating assets are total current assets minus cash and marketable securities (ACT − CHE) and current operating liabilities are total current liabilities minus debt in current liabilities (LCT − DLC). Missing changes in debt in current liabilities are set to zero. We calculate monthly value-weighted returns from July of year t to June of year $t+1$ and rebalance the portfolios at the end of June of year $t+1$. The first sort is at the end of June 1989.

A.8.6 Change in net financial assets (annual)

At the end of June of year t, we form portfolios from a decile sort on the change in net financial assets relative to lagged assets, dFA/A_{-1}, using NYSE breakpoints. Here, dFA is the change in financial assets minus the change in financial liabilities over the fiscal years ending in calendar years $t-2$ and $t-1$, while A_{-1} is total assets (AT) for the fiscal year ending in calendar year $t-1$. Financial assets are short-term investments plus long-term investments (IVST + IVAO) while financial liabilities are long-term debt plus debt in current liabilities plus preferred stock (DLTT + DLC + PSTK). Missing changes in debt in current liabilities, long-term investments, long-term debt, short-term investments, and preferred stock are set to zero, but we require least one change to be non-missing when constructing each of the change in financial assets and the change in financial liabilities. We calculate monthly value-weighted returns from July of year t to June of year $t+1$ and rebalance the portfolios at the end of June of year $t+1$. The first sort is at the end of June 1989.

A.8.7 12 month return seasonality

At the end of month $m-1$, we form portfolios from a decile sort on the return in month $m-12$ using NYSE breakpoints. We calculate monthly value-weighted returns for month m and rebalance the portfolios at the end of month m. For instance, at the end of June 2016, we sort on returns for July 2015; calculate value-weighted returns for July 2016, and rebalance the portfolios at the end of July 2016. The first sort is at the end of December 1989.

Appendix B

B.1 Model

This section presents a stylized model of a firm's cash balances and equity returns in the presence of risky external financing. Our main goal is to illustrate how cash balances affect the fraction of a firm's value tied to risky external financing and, consequently, equity returns. We introduce risky external financing by assuming a cost of issuing equity that is dependent on the aggregate state of the economy. To emphasize the role of precautionary savings via equity issues, we also assume that the firm cannot rely on internally generated cash flows or on debt financing. The latter two assumptions better describe firms that are unable to finance their investment activities with internally generated cash flows and have a low ability to substitute equity with debt.

B.1 Model setup

Our model setup is based on Palazzo (2012), but features stochastic external financing costs and no internally generated cash flows. We consider an all-equity firm in a three-period economy with time periods indexed by $t = 0, 1, 2$. At $t = 0$, the firm is endowed with an initial cash balance of c_0. At $t = 1$, after the realization of the external financing cost, the firm has an investment opportunity consisting of an option to install an asset that produces a deterministic cash flow of c_2 at $t = 2$. The investment bears a fixed cost I, which is known at $t = 0$. We assume a fixed investment cost to capture the smoothness (i.e., low volatility and low cyclicality) of R&D expenditures (e.g. Brown and Petersen (2011)). To further simplify the analysis, we assume that c_2 is a risk-less cash flow proportional to the investment cost and equal to RIe^{μ}, where μ is a positive constant and R is the gross risk-free rate. We also assume that the firm has no intermediate cash flows in periods 0 and 1. The firm can transfer cash from one period to the next at a gross accumulation rate of $\widehat{R} \geq 0$, assumed to be lower than the gross risk-free rate to prevent an unbounded accumulation of cash.

Equity financing is costly. We follow Belo et al. (2019) and assume that the cost paid to issue an amount E_t is $e^{\lambda_t} Q(E_t)$, where $Q(E_t) = \left(\phi_1 E_t + \frac{\phi_2}{I} E_t^2\right)$ is the issuance cost's quadratic component (with ϕ_1 and ϕ_2 both positive constants) and e^{λ_t} is a time-varying scaling factor.[21] We assume

$$e^{\lambda_t} = e^{\lambda - \frac{1}{2}\sigma_x^2 - \sigma_x \varepsilon_{x,t}}, \tag{C.1}$$

[21] For analytical convenience, we scale the quadratic component of the equity issuance cost by the investment amount. This assumption is consistent with Hennessy and Whited (2007) and allows us to generate equity returns that are independent of the investment scale.

where λ and σ_x are positive parameters and where $\varepsilon_{x,t} \sim \mathcal{N}(0,1)$ for each t is an equity issuance shock. We also assume that λ_t cannot exceed a maximum value of $\lambda^* > 0$, which is equivalent to assuming a truncated normal distribution for the equity issuance shock: $-\sigma_x\varepsilon_{x,t} < \varepsilon_x^* = \lambda^* - \lambda + \frac{1}{2}\sigma_x^2$. In addition, $\varepsilon_{x,t}$ is correlated with an aggregate shock, $\varepsilon_{z,t}$, thus making the issuance decision risky. In the following, we assume $\varepsilon_{z,t} \sim \mathcal{N}(0,1)$ and $\mathbb{COV}(\varepsilon_{x,t}, \varepsilon_{z,t}) = \sigma_{x,z} \geq 0$ for each t. Note that because $\varepsilon_{x,t}$ and $\varepsilon_{z,t}$ have unit variance, $\sigma_{x,z}$ is also their correlation, and we must also have $\sigma_{x,z} \leq 1$.

Cash flows in period t are discounted back to $t-1$ using the stochastic discount factor (SDF)

$$M_t = e^{m_t} = e^{-r-\frac{1}{2}\sigma_z^2-\sigma_z\varepsilon_{z,t}}, \tag{C.2}$$

where r and σ_z are positive parameters. This in particular implies that the period 0 expected value of the period 1 SDF is given by $E_0[M_1] = e^{-r} = 1/R$–i.e., the inverse of the gross risk-free rate.

For a given E_t, our assumptions imply (i) a non-negative issuance cost that is bounded above; (ii) an issuance cost decreasing in the external financing shock; and (iii) that a firm with an external financing shock more correlated with the aggregate state has a larger reduction (increase) in expected issuance cost in booms (recessions) than a firm with a less cyclical financing cost.

B.2 The firm's problem

Given the initial cash balance, c_0, and the (log) external financing cost, λ_0, the firm decides how much cash to save for period 1, c_1, so as to maximize the market value of equity. At $t = 0$, if the firm chooses $c_1 \leq \widehat{R}c_0$, it distributes any excess cash as a dividend. If, however, the firm chooses $c_1 > \widehat{R}c_0$, it issues equity to meet its cash needs. The firm's dividend at $t = 0$ is thus

$$d_0 = \left(c_0 - \frac{c_1}{\widehat{R}}\right) + \Delta_0 e^{\lambda_0} Q\left(c_0 - \frac{c_1}{\widehat{R}}\right), \tag{C.3}$$

where Δ_0 is an indicator function that takes the value 1 if $c_1 > \widehat{R}c_0$ (i.e., if the firm issues equity). Note that even though the fixed investment cost is known at $t = 0$, the firm may optimally choose $c_1 < 1$ because the stochastic issuance cost implies that it may be optimal to smooth issuances across periods 0 and 1.

In what follows, we assume that the return on investment is greater than the maximal total issuance cost: $e^{\mu} > 1 + e^{\lambda^*}(\phi_1 + \phi_2)$. Under this assumption, the firm always invests at $t = 1$. If, at $t = 1$, $c_1 \geq I$, the firm distributes any excess cash as a dividend, whereas if $c_1 < I$, the firm issues additional equity to cover the remaining investment cost. The firm's dividend at $t = 1$ is thus

$$d_1 = \left(c_1 - I\right) + \Delta_1 e^{\lambda_1} Q\left(c_1 - I\right), \tag{C.4}$$

where Δ_1 is an indicator variable that takes the value 1 if $c_1 < I$. Because the investment generates a deterministic cash-flow of c_2 at $t = 2$, the corresponding dividend is $d_2 = c_2$.

Given the initial cash balance, c_0, and the (log) issuance shock, λ_0, the firm's cum-dividend equity value at $t = 0$ is determined by the saving policy, c_1, that maximizes the present discounted value of current and future dividends. Because m_1 and λ_1 are normally distributed with $\mathbb{COV}(m_1, \lambda_1) = \sigma_x \sigma_z \sigma_{xz} \equiv \beta$, it follows from the properties of the truncated log-normal distribution (Lemma 1 in Appendix A) that we can write the firm's problem as

$$v_0(c_0, \lambda_0) = \max_{c_1 \geq 0} \; d_0 + e^{-r}(c_1 - I + e^{\mu} I) - e^{-r} \Delta_1 Q\big(c_1 - I\big) e^{\lambda + \beta} \Gamma, \tag{C.5}$$

where $\Gamma = \Phi\left(\frac{\varepsilon_x^* - \sigma_x^2 - \beta}{\sigma_x}\right) / \Phi\left(\frac{\varepsilon_x^*}{\sigma_x}\right)$ and where Φ is the standard normal cumulative distribution function. Here, the first term is the period 0 dividend, the second term is the present discounted value of the net payoff from investment, and the third term is the present discounted value of the expected period 1 total issuance cost. The latter quantity has two components. The first one, $Q\big(c_1 - I\big)$, is the deterministic quadratic part. The second one, $e^{\lambda+\beta}\Gamma$, is the expected value of the issuance cost's scaling factor at $t = 1$, which depends on the cyclicality of the external financing shock (β). In what follows, we assume the following necessary and sufficient condition for $e^{\lambda+\beta}\Gamma$ to be increasing in β:

Condition 1. $\Phi\left(\frac{\varepsilon_x^* - \sigma_x^2 - \beta}{\sigma_x}\right) > \frac{1}{\sigma_x} \varphi\left(\frac{\varepsilon_x^* - \sigma_x^2 - \beta}{\sigma_x}\right)$.

Condition 1 is satisfied for a wide range of plausible values for the model's parameters. It ensures that the expected issuance cost is increasing in β, implying that riskier firms are less valuable.

B.3 Optimal savings policy

When studying the optimal choice of cash balances in period 1, it is important to distinguish between the financially constrained and the financially unconstrained cases. In the latter case, cash balances are high enough to fully cover the investment cost, i.e. $\widehat{R} c_0 \geq I$, and the firm never issues equity ($\Delta_0 = \Delta_1 = 0$). In this case, it is always optimal for the firm to save internal resources up to $c_1 = I$ and distribute a dividend at $t = 0$ equal to $c_0 - I/\widehat{R} > 0$.

The interesting case is therefore when the firm is constrained, i.e. when $\widehat{R} c_0 < I$. To better illustrate the firm's trade-off, we write down the Euler equation implied by Eq. (C.5):

$$\frac{1}{\widehat{R}}\left[1 + \Delta_0 e^{\lambda_0}\left(\phi_1 + 2\widehat{\phi}_2\left(\frac{c_1}{\widehat{R}} - c_0\right)\right)\right] \leq \frac{1 + \Delta_1 e^{\lambda+\beta}\Gamma\left(\phi_1 + 2\widehat{\phi}_2\,(I - c_1)\right)}{R}, \tag{C.6}$$

where $\widehat{\phi_2} = \phi_2/I$. The left-hand side is the present value of the marginal cost of saving an extra dollar of cash. If the firm saves less than the available resources ($c_1 < \widehat{R}c_0$), then the marginal cost is constant and equal to $1/\widehat{R}$, otherwise the marginal cost jumps by an amount equal to $e^{\lambda_0}\phi_1/\widehat{R}$ when $c_1 = \widehat{R}c_0$ and then it increases linearly in the amount saved.

The right-hand side is the present value of the marginal benefit of saving an extra dollar of cash. The marginal benefit has two components. The first, $1/R$, is the present value of the extra dividend distributed at time 1, which is constant. The second, $\frac{\Delta_1 e^{\lambda+\beta}\Gamma\left(\phi_1+2\widehat{\phi_2}(I-c_1)\right)}{R}$, is the present value of the reduction in equity issuance cost, which is linearly decreasing in the amount saved.

From the above analysis, it follows that the marginal cost is non–decreasing in c_1, while the marginal benefit is strictly increasing in c_1. Then an optimal saving policy with strictly positive c_1 always exists if the marginal benefit is larger than the marginal cost when $c_1 = 0$–that is, $1 + e^{\lambda+\beta}\Gamma(\phi_1 + 2\phi_2) > R/\widehat{R}$. In what follows, we will always assume that a strictly positive saving policy exists by imposing the following condition:

Condition 2. $1 + e^{\lambda+\beta}\Gamma(\phi_1 + 2\phi_2) > R/\widehat{R}$.

When the solution is strictly positive, we can have different outcomes, depending on the parameters' values. First, the firm can set the optimal saving policy to I. This choice can happen if the marginal benefit is very high (e.g., very high β or very high λ) or the marginal cost is very low (e.g., very low λ_0 or very high $\widehat{R}$). Alternatively, the firm can set the optimal policy equal to $\widehat{R}c_0$. This choice happens when the marginal benefit is above the flat portion of the marginal cost when $c_1 \leq \widehat{R}c_0$ but always below the increasing portion when $c_1 > \widehat{R}c_0$.

Outside the two corner solutions described above, the Euler equation holds with equality and we can better appreciate the effect of equity financing risk on the optimal cash policy by taking the total differential w.r.t. β. In this case, the optimal saving policy is increasing in the cyclicality of the external financing shock and, as a consequence, riskier firms save more.[22] The reason being that high-β firms have a larger expected issuance cost (i.e., a higher $e^{\lambda+\beta}\Gamma$) and, as a consequence, a larger precautionary saving motive.

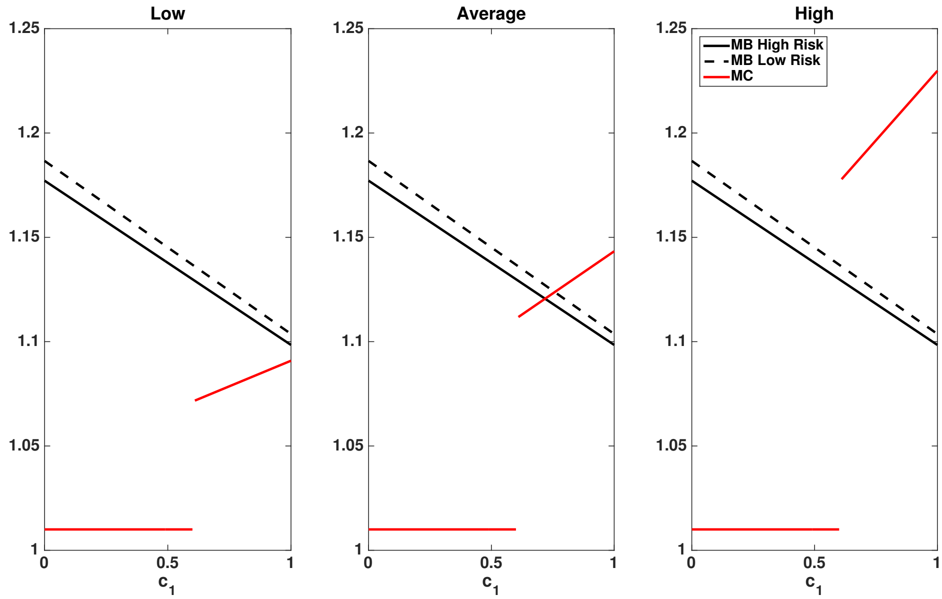
In Figure 4, we highlight the importance of the time 0 equity issuance cost in determining the optimal saving policy. We report the marginal cost (solid red line) and the marginal benefit for a low-risk firm (solid

[22]The closed form for the interior solution is

$$c_1^* = \frac{1 + e^{\lambda+\beta}\Gamma\left(\phi_1 + 2\widehat{\phi_2}I\right) - \frac{R}{\widehat{R}}\left(1 + \Delta_0 e^{\lambda_0}\left(\phi_1 - 2\widehat{\phi_2}c_0\right)\right)}{2\widehat{\phi_2}\left(\frac{\Delta_0 R e^{\lambda_0}}{\widehat{R}^2} + e^{\lambda+\beta}\Gamma\right)},$$

which depends on issuance activity at time 0, Δ_0. Condition 1 guarantees that $dc_1^*/d\beta > 0$.

Figure 4. Optimal Saving Policy



This figure reports the marginal cost (solid red line) and the marginal benefit for a low-risk firm (solid black line) and a high-risk firm (dashed black line) in Eq. (C.6). The three panels differ in their value of λ_0, namely for the cost of issuing equity at time 0. The left panel has a low value (-0.50), the middle panel an average value (0.00), and the right panel a high value (0.50). The correlation parameter σ_{xz} takes values 0.00 (low risk) and 0.9 (high risk). The other parameters' values are: {R=1.01; $\widehat{R}$=1.00; ϕ_1=0.10; ϕ_2=0.04; λ=0; σ_x=0.45; σ_z=0.15; c_0 = 0.60; I = 1}.

black line) and a high-risk firm (dashed black line) implied by our model. The three panels differ for their value of λ_0, namely for the cost of issuing equity at time 0. The left panel has a low value, the middle panel an average value, and the right panel a high value. As explained above, the marginal cost presents a discontinuity at $c_1 = \widehat{R}c_0$, while the marginal benefit is monotonically decreasing in c_1.

When issuing equity at time 0 is very cheap (left panel), the marginal benefit is always larger than the marginal cost and the firm decides to issue equity and save the full investment amount, thus completely avoiding equity issuance in the next period. When issuing equity at time 0 takes an average value (middle panel), then an interior solution exists as described in Equation C.7. In this case, both firms issue equity to save in excess of $\widehat{R}c_0$; however the riskier firm saves more, having a higher risk exposure (i.e., a higher marginal benefit). To conclude, when issuing equity at time 0 is too expensive (right panel), the optimal saving policy is dictated by the amount of available internal resources, and both firms save $\widehat{R}c_0$.

B.4 Cash balances and expected returns

We now investigate the model's implications for expected equity returns. To ensure that the firm transfers some cash between periods 0 and 1, we assume that Condition 2 holds.

The expected gross return on the firm's equity between periods 0 and 1, $R^e_{0,1}$, is the ratio of the expected future dividends at $t = 0$ and the ex-dividend equity value at $t = 0$,

$$R^e_{0,1} \;=\; \frac{\mathbb{E}_0\left[d_1 + \mathbb{E}_1[M_2 d_2] \mid \lambda_1 < \lambda^*\right]}{v_0(c_0, \lambda_0) - d_0}. \tag{C.7}$$

We can immediately verify that when the optimal policy c_1^* is equal to I, then the expected return is just the risk-free rate. This outcome happens when initial cash balances are large ($\widehat{R}c_0 > I$) or the time 0 equity issuance cost is low. Otherwise, it follows by the properties of the truncated log-normal distribution (Eq. (D.2) in Appendix A) that the expected return is given by

$$R^e_{0,1} \;=\; e^r \frac{c_1^* - I + Ie^{\mu} - e^{\lambda}\Gamma^* Q(I - c_1^*)}{c_1^* - I + Ie^{\mu} - e^{\lambda+\beta}\Gamma Q(I - c_1^*)} = e^r \frac{-E_1^* + e^{\mu} - e^{\lambda}\Gamma^* Q(E_1^*)}{-E_1^* + 1e^{\mu} - e^{\lambda+\beta}\Gamma Q(E_1^*)}, \tag{C.8}$$

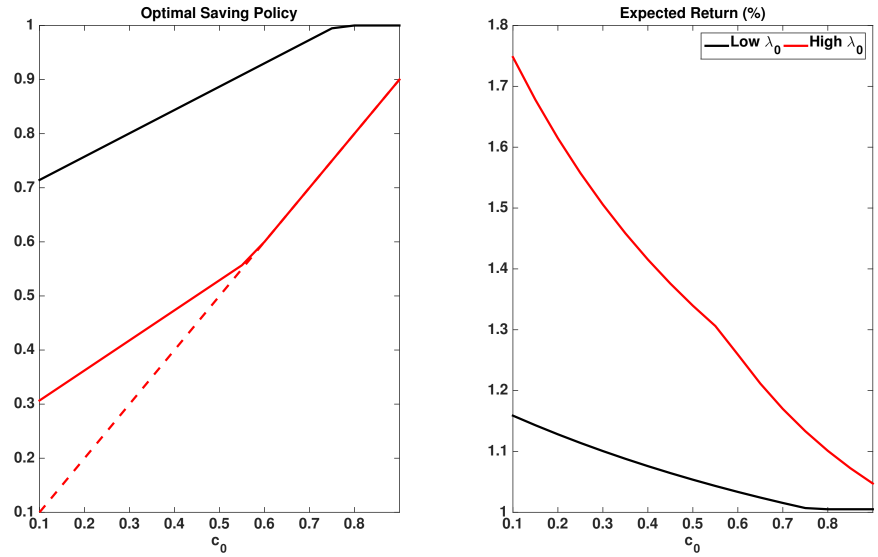
where $\Gamma^* = \Phi\left(\frac{\varepsilon_x^* - \sigma_x^2}{\sigma_x}\right)/\Phi\left(\frac{\varepsilon_x^*}{\sigma_x}\right)$ and $E_1^* = 1 - c_1^*/I$ is the fraction of time 1 investment that is equity financed. The quantity $e^{\lambda}\Gamma^*$ can be interpreted as the expected scaling factor when $\beta = 0$–that is, for a firm with an issuance cost that is uncorrelated with the SDF. Given the assumption $\widehat{\phi_2} = \phi_2/I$, expected equity returns are scale-independent. What drives the firm-level exposure to systematic risk is the fraction of cash relative to the investment expenditure. In what follows we show that the larger the fraction of the time 1 investment that is equity financed, the larger the exposure to equity financing risk (i.e., the larger expected equity returns).

We can immediately show that $R^e_{0,1}$ depends negatively on the initial cash balance c_0 if $e^{\beta}\Gamma > \Gamma^*$, namely if the expected value of the scaling factor is higher for a firm with a risky issuance cost ($\beta > 0$) compared with a firm with an issuance cost that is uncorrelated with the aggregate economy ($\beta = 0$). Condition 1, which guarantees optimal cash balances will be declining in β, implies $e^{\beta}\Gamma > \Gamma^*$, and hence it is also sufficient to guarantee that firms with higher cash balances relative to their investment cost command lower expected returns.

Our stylized model introduces heterogeneity in risk driven by heterogeneity in the amount of internal resources relative to the investment expenditures. Figure 5 provides an illustration. We report the optimal saving policy c_1^* (left panel) and expected equity returns (right panel) as a function of cash balances at time 0 (c_0) for two firms that are identical except for their cost of external financing at time 0. The right panel shows how firms with larger c_0 deliver a lower expected return, every thing else being equal. The reason being that the higher c_0, the higher the amount that can be saved, the lower the firm's value tied to costly equity issuance, and the lower the covariance of the firm's equity value with the aggregate shock.

At the same time, Figure 5 makes clear that the time 0 equity issuance cost plays a key role in shaping differences in equity returns. If two firms are identical except for their value of λ_0, then they can deliver different expected returns. A firm with a low cost of issuing equity (solid black line) can raise equity and save cash, thus lowering the exposure to the equity issuance shock. A firm with a high cost of issuing equity

Figure 5. Cash and Returns



This figure reports the optimal saving policy c_1^* (left panel) and expected equity returns (right panel) as a function cash balances at time $0(c_0)$. The solid black line refers to a firm with low time 0 issuance cost ($\lambda_0 = -0.25$), while the solid red line refers to a firm with high time 0 issuance cost ($\lambda_0 = 0.25$). The dashed red line in the left panel is the 45-degree line. The other parameter's values are: {R=1.01; $\widehat{R}$=1.00; ϕ_1=0.10; ϕ_2=0.04; λ=0; σ_x=0.45; σ_z=0.15; $\sigma_{xz} = 0.90$; $I = 1$}.

(solid red line) saves less and carries more risk, hence delivering a higher expected return. Not surprisingly, the differential in returns between the two firms shrinks as the amount of initial resources becomes bigger.

B.5 Empirical predictions

Our stylized model provides a number of novel predictions that link a firm's financial policy to its expected equity returns.

Prediction 1. A firm with high cash balances relative to its investment expenditures (i.e., a firm with a large investment coverage ratio) has a lower expected return than an otherwise identical firm with lower cash balances.

Prediction 2. Equity issuance lowers a firm's expected return by reducing the exposure to equity financing risk via an increase in the coverage ratio.

Prediction 3. The above predictions crucially depend on firms being financially fragile (e.g., low cash balances, low profitability, high equity issuance cost). If this is not the case, then there is low exposure to equity financing risk and, consequently, weaker effects of the coverage ratio and equity issuance activity on equity returns.

Appendix D

D.1 Properties of the truncated log-normal distribution

Lemma 1. *Suppose $X \sim \mathcal{N}(\mu_x, \sigma_x^2)$ and $Y \sim \mathcal{N}(\mu_y, \sigma_y^2)$ with $\mathbb{COV}(X, Y) = \sigma_{xy}$. Then*

$$\mathbb{E}\left[e^{X+Y} \,\middle|\, Y < y\right] = e^{\mu_x+\mu_y+\frac{1}{2}(\sigma_x^2+\sigma_y^2+2\sigma_{xy})} \frac{\Phi\left(\frac{y-\mu_y-\sigma_y^2-\sigma_{xy}}{\sigma_y}\right)}{\Phi\left(\frac{y-\mu_y}{\sigma_y}\right)}$$

for any $y \in \mathbb{R}$, where Φ is the standard normal cumulative distribution function.

Proof of Lemma 1. We start with three auxiliary results. In the following, let Z_1 and Z_2 be independent $\mathcal{N}(0, 1)$-distributed random variables, and let $a, b, c, z \in \mathbb{R}$ be real constants.

First, a fundamental property of the log-normal distribution is that

$$\mathbb{E}\left[e^{a+bZ_1}\right] = e^{a+\frac{1}{2}b^2}. \tag{D.1}$$

Second, direct computation gives that

$$\begin{aligned} \mathbb{E}\left[e^{cZ_2} \,\middle|\, Z_2 < z\right] &= \frac{\mathbb{E}\left[e^{cZ_2} 1_{(Z_2<z)}\right]}{\mathbb{P}(Z_2 < z)} \\ &= \frac{1}{\Phi(z)} \int_{-\infty}^{z} e^{cz'} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(z')^2} dz' \quad = \quad e^{\frac{1}{2}c^2} \frac{\Phi(z-c)}{\Phi(z)}. \end{aligned} \tag{D.2}$$

Third, using the independence of Z_1 and Z_2 and applying Eqs. (D.1) and (D.2), it follows that

$$\mathbb{E}\left[e^{a+bZ_1+cZ_2} \,\middle|\, Z_2 < z\right] = e^{a+\frac{1}{2}b^2+\frac{1}{2}c^2} \frac{\Phi(z-c)}{\Phi(z)}. \tag{D.3}$$

To prove the lemma, note that we can write X and Y in terms of the independent Z_1 and Z_2 as

$$X = \mu_x + \sigma_x \sqrt{1-\rho_{xy}^2} Z_1 + \sigma_x \rho_{xy} Z_2 \quad \text{and} \quad Y = \mu_y + \sigma_y Z_2 \quad \mathbb{P}\text{-almost surely},$$

where $\rho_{xy} = \frac{\sigma_{xy}}{\sigma_x \sigma_y}$ is the correlation between X and Y. The lemma then follows from Eq. (D.3) with

$$a = \mu_x + \mu_y, \quad b = \sigma_x \sqrt{1-\rho_{xy}^2}, \quad c = \sigma_x \rho_{xy} + \sigma_y, \quad \text{and} \quad z = \frac{y-\mu_y}{\sigma_y}.$$

□