Corporate Policies and Asset Prices

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I would like to dedicate this thesis to my family . . .

Declaration

I hereby declare that except where specific reference is made to the work of others, the contents of this dissertation are original and have not been submitted in whole or in part for consideration for any other degree or qualification in this, or any other university. This dissertation is my own work and contains nothing which is the outcome of work done in collaboration with others, except as specified in the text and Acknowledgements. This dissertation contains fewer than 65,000 words including appendices, bibliography, footnotes, tables and equations and has fewer than 150 figures.

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Abstract

This thesis analyzes the interconnections between corporate policies and asset prices that arise under imperfect capital markets. The magnitude of financial frictions and uncertainty about their future value affect optimal decisions regarding investment, cash savings, financing, payout, and ultimately, valuations. Recognising these effects can help our understanding of return behaviour deemed anomalous under standard asset pricing theory. In turn, we can utilize price data for precise measurement of the frictions. The thesis is based on three papers. The first paper sheds further light on the documented link between earnings and price momentum. I provide evidence that both permanent and transitory shocks contribute to fluctuations in the earnings of momentum firms. I show, theoretically and empirically, that financial constraints can explain the surprisingly large price impact of transitory shocks for momentum firms. The second paper provides a mechanism for value and momentum premia that is driven by the valuation effects of optimal corporate policies under uncertain financing conditions. Time-series variation in the cost of issuing equity leads to a procyclical momentum premium and a countercyclical value premium, consistent with the data. The model can also explain the performance of the two premia during market rebounds as well as the time-series behaviour of their correlation. Finally, the goal of the third paper is to estimate the variation of equity floatation costs, both over time and in the cross-section, at a high level of granularity. Equity issuance is measured based on the daily variation in shares outstanding. This measure identifies issuance events and allows us to exploit data moments related to the quantity issued, its timing and the price reaction, all of which are highly informative of the costs. The estimated model is useful for quantifying the importance of the market timing motive for financing policy.

Table of contents

List of figures

List of tables

Chapter 1

Permanent and Transitory Earnings Shocks and Stock Price Momentum

Abstract

Earnings surprises subsume the power of price momentum in predicting returns. Analysis of the time-series properties of earnings per share data shows that both permanent and transitory shocks contribute significantly to total variations in earnings. In this paper, I explore the relative importance of the two types of earnings shocks on price momentum. Different filtering techniques show that price momentum loads significantly on both permanent and transitory earnings surprise measures. While sentiment represents a possible driver of the importance of transitory earnings surprises, I provide evidence that financial constraints also play a role. Intuitively, transitory shocks do not affect future cash flows but they do increase the risk of liquidation if the firm is financially constrained. I employ several financial constraints indexes that indicate firms included in price momentum portfolios are the most constrained in the cross-section.

1.1 Introduction

The predictability of stock returns based on their recent past history, known as price momentum (Jegadeesh and Titman, 1993), and the predictability of stock returns based on previously-announced earnings, known as post-earnings-announcement-drift or earnings momentum (Ball and Brown, 1968), represent two of the most prominent regularities in the asset pricing literature. Evidence in Chordia and Shivakumar [2006] and Novy-Marx [2015] shows that the two are related: earnings surprises subsume the predictive power of price momentum on future returns.

In this paper I investigate whether the price impact of earnings surprises relates to news about the long-term or short-term prospects of the company and examine which of the two is responsible for subsuming price momentum. The motivation starts from a growing corporate finance literature that shows firm policies and valuation respond differently depending on whether cash-flow shocks are permanent or transitory. In frictionless markets, the effect of transitory shocks would be expected to be minimal since they affect only current cash-flows. Evidence of the contrary can be related to either market “fads" or financial frictions. Intuitively, a transitory shock can drive a firm out of business if it is financially constrained. I decompose earnings into permanent and transitory components using different filtering techniques and show that transitory shocks have significant explanatory power on price momentum. I then provide evidence of price momentum firms being the most financially constrained in the cross-section, supportive of financial frictions driving the importance of transitory shocks.

I start by examining the time-series behaviour of individual firm earnings. Unit root and variance ratio tests show that both permanent and transitory shocks contribute significantly to earnings fluctuations. This result is not confined to a specific subset of firms and also holds for stocks that end up in price momentum portfolios. Building on this evidence, I employ several filtering techniques in decomposing the earnings series into permanent and transitory components. I focus on three filters widely used in the empirical literature: the Hodrick and Prescott (HP) filter, the Beveridge and Nelson (BN) decomposition and an ideal bandpass filter (IF). I then compute the surprise measures related to each component, based on which I construct long-short portfolio strategies (factors). Regardless of the filtering method used, results show that both permanent and transitory earnings surprises predict future returns.

Cross-sectional regressions of future returns on past return performance and surprise measures related to permanent and transitory earnings shocks show that both earnings measures have power in subsuming the predictive ability of past performance. In time-series regressions of returns to price momentum strategies on the Fama and French [2015] five factors and the two measures of earnings surprises show that the performance of price momentum is fully captured and momentum loads positively on both components. These tests provide evidence that transitory earnings shocks play a key role in the link between earnings and price momentum.

Financial constraints represent a potential driver of the significant impact of transitory shocks. I show this theoretically by exploring the asset pricing implications of a simple liquidity management model based on Décamps, Gryglewicz, Morellec, and Villeneuve [2017], where firm cash-flows are subject to both permanent and transitory shocks. Expected returns in this set up are a function of the sensitivities to the two shocks, which vary over time depending on the financial position of the firm. Sensitivity to transitory shocks is low for well-capitalised firms, but becomes increasingly important as the firm runs out of capital. Any cash-flow shock realisations for financially constrained firms have a large price impact, implying large realised returns in absolute terms. These will be precisely the firms that end up in the extreme past performance portfolios in momentum sorts. Financial constraints would then explain the documented large sensitivity of price momentum firms to transitory earnings shocks.

To test the relationship between momentum and financing constraints empirically, I rely on three well-known financial constraints indexes proposed in the literature: the Whited-Wu (WW) index, the Kaplan and Zingales (KZ) index and the Hadlock and Pierce (SA) index. I compute the values of these indexes for the entire universe of firms over which price momentum strategies are constructed. While these measures are known to be inconsistent with one another, they consistently show that momentum winners and losers are both the most constrained firms in the cross-section. Double-sorted portfolios on the financial constraints indexes and past returns provide further supportive evidence. Price momentum strategies work only among the most financially constrained firms. This result is in line with Avramov, Chordia, Jostova, and Philipov [2007] showing that momentum firms have the lowest credit ratings.

This paper relates to the literature that studies the sources of momentum profits. The theoretical literature identifies two main competing explanations: sentiment-driven (e.g. Barberis, Shleifer, and Vishny, 1998, Daniel, Hirshleifer, and Subrahmanyam, 1998) and risk-based (e.g. Conrad and Kaul, 1998, Berk et al., 1999, Johnson, 2002). Despite the large body of work on both camps, there is still no consensus. The difficulty lies in providing a mechanism for price momentum and, at the same time, reproducing the magnitude and the specific formation and holding periods over which momentum strategies are profitable.

The key contribution of this paper is showing that permanent and transitory shocks to earnings are relevant both theoretically and empirically for predicting future returns and explaining price momentum. A large asset pricing literature examines the separate effects of permanent and transitory shocks (e.g. Cochrane, 1994, Bansal and Yaron, 2004, Garleanu, Panageas, and Yu, 2012), but the focus is typically on aggregate asset pricing puzzles from the standpoint of consumption-based theoretical models. I explore the distinct effects of the two shocks on expected returns and price momentum from a corporate financing perspective which, to the best of my knowledge, is new in the literature. Another important contribution of this paper stands in showing empirically that transitory shocks to earnings have a significant explanatory power for price momentum. The evidence on the variation of financing constraints indexes with past performance and the concentration of momentum profits only on the most financially constrained firms is also novel in the liteature.

The paper is organised as follows. In section 1.2 I present the empirical results related to the persistence of earnings per share data. I next describe the filters used to decompose earnings into permanent and transitory components and show how the two components of earnings relate to future returns and price momentum. Section 1.3 explores the relationship between financial constraints and price momentum. I first present a liquidity management model that accounts for both permanent and transitory shocks to cash-flows. Next, I empirically evaluate the degree of financial constraints for price momentum firms. Section 1.4 concludes.

1.2 Trend and cycle components of earnings

This section studies the time series properties of quarterly earnings per share data. The evidence presented here shows important contributions from both permanent and transitory shocks to fluctuations in the earnings series. Building on this, I then decompose earnings into the two components and examine their separate effects on price momentum. The overall results show that price momentum loads significantly on transitory shocks.

1.2.1 Persistence tests

Several studies examine the time-series behaviour of firm earnings (e.g., Watts, 1975, Foster, 1977, Griffin, 1977, Brown and Rozeff, 1979, Bathke and Lorek, 1984, Bernard and Thomas, 1990). The sample sizes used in this early literature are rather limited compared to the data available today [1]. The results reported here also make use of stationarity tests that were not available at the time these papers were published.

The sample covers the period from July 1971 to March 2020. The analysis excludes financial firms (SIC codes 6000 to 6999) and utility firms (SIC codes 4900 to 4999). Firm earnings per share data (EPSPXQ) are divided by the adjustment factor cumulative by ex date (AJEXQ) to account for splits. I winsorize the data at the 1st and 99th percentiles at the individual firm level.

I use two unit root tests on individual firm earnings data: the Augmented Dickey-Fuller (ADF) test and the Kwiatkowski, Phillips, Schmidt, and Shin [1992] (KPSS) test. I also employ variance ratio tests (Cochrane, 1998), which provide a measure of the relative importance of permanent and transitory shocks to the series. The ADF test considers the null hypothesis of the earnings per share series having a unit root and thus being non-stationary, while the KPSS test considers the null hypothesis of the earnings series being stationary. The variance ratio test considers the null that the earnings series

[1] For example, Foster [1977] examines a sample of 69 firms over the period 1946-1974, as opposed to approximately 20,000 firms studied here over the period 1971-2020.

is a random walk. The variance ratio in itself measures the contribution of the variance of the random walk component of the series to total variation.

Table 1.1 Unit root tests on individual firm earnings per share.
This table reports results of unit root tests on individual firm earnings per share. The columns referring to the KPSS test represent the percentage of times the null hypothesis of stationarity in this test cannot be rejected. Results are reported for three different confidence levels: 10%, 5 % and 1%. The columns referring to the ADF test report the percentage of time the null hypothesis of a unit root for this test is rejected. Results are presented using three different criteria regarding the minimum number of quarterly observations of earnings per share: 10, 20 and 40 quarters. The column referring to the variance ratio reports the average variance ratio for each sample. The period covers July 1971 to March 2020. The column referring to the number of firms reports the number of firms considered for the two tests at each of the three different levels of minimum number of quarterly observations allowed for the computations. The analysis excludes financial firms (SIC codes 6000 to 6999) and utility firms (SIC codes 4900 to 4999). Firm earnings per share data are divided by the adjustment factor, cumulative by ex date (AJEXQ) to account for splits. I winsorize the data at the 1st and 99th percentiles at the firm level.

KPSS			ADF			Variance	Min.	No. of
10%	5%	1%	10%	5%	1%	ratio	quarters	firms
52.6	52.6	71.7	63.8	63.8	50.3	64.8	10	19,004
45.0	45.0	63.6	74.2	74.2	63.2	62.0	20	13,249
34.9	34.9	52.1	85.5	85.5	77.7	59.6	40	6,597

Table 1.1 summarises the test results for the firms included in the Compustat quarterly database. The table reports the percentage of times the null hypothesis of stationarity in the KPSS test cannot be rejected and the percentage of times the null hypothesis of non-stationarity in the ADF test is rejected. I report the results for three different confidence levels: 10%, 5% and 1% and use three different minimum requirements on the number of consecutive quarterly observations available: 10, 20 and 40. For each case, I report the number of firms for which the tests are carried out and the average variance ratio. For robustness, I carry out the same tests using total firm earnings from Compustat (*IBQ*) scaled by the first available observation of total assets, so that any changes in the ratio are driven solely by changes in earnings. Appendix I contains

the results of the stationarity tests on *IBQ*, with the inference remaining unchanged from the tests that use earnings per share data.

The results of the KPSS or ADF tests are mixed. As the minimum required number of observations increases, the KPSS test indicates a smaller, although still substantial, proportion of firms for which stationarity cannot be rejected. The ADF test, however, indicates a larger proportion of firms for which the hypothesis of a unit root can be rejected. The variance ratio decreases slightly as the minimum sample size increases. The reported values of this test indicate that the random walk component of the average earnings series contributes around 60% to total earnings variability, with the remainder being due to the temporary component. Overall, these results show that transitory shocks to earnings provide an important contribution to fluctuations in total earnings. The mixed results from the KPSS and ADF tests and the average variance ratios provide evidence that the earnings series stand between the two extremes of a pure random walk and a stationary series.

The results in Table 1 refer to the average firm. They may be driven by a specific subsample of firms and not necessarily hold for the firms included in momentum portfolios [2]. I therefore next examine whether the behaviour of the earnings series of momentum firms differs from the average firm. Table 1.2 shows the results of KPSS and ADF tests using a significance level of 5% as well as the average variance ratio for each past performance decile.

[2] Note that the sample in the tests for momentum firms is smaller compared to the one that uses the entire Compustat universe. Examining the earnings of momentum portfolios requires the merging CRSP and Compustat databases, with the intersection being much smaller than the size of either database.

Table 1.2 Unit root tests for momentum firms.
This table presents the results of KPSS and ADF tests as well as the variance ratio in each past performance sorted portfolio. The row referring to the KPSS test reports the percentage of firms for which the null of stationarity cannot be rejected. The results referring to the ADF test report the percentage of firms for which the null of a unit root is rejected. Portfolio 1 contains the decile of firms with the highest past performance over the previous year (skipping the most recent month due to reversal) and Portfolio 10 contains the decile of firms with the lowest past performance over the previous year (skipping the most recent month due to reversal). Results are reported at two different confidence levels: 10% and 5%. Firm earnings per share (EPSPXQ) are divided by the adjustment factor, cumulative by ex date (AJEXQ) to account for splits. The sample period covers July 1971 to December 2019. The analysis excludes financial firms (SIC codes 6000 to 6999) and utility firms (SIC codes 4900 to 4999). I winsorize the data at the 1st and 99th percentiles at the firm level.

Portfolio	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
KPSS	37.3	37.2	37.0	37.0	37.1	37.6	38.2	39.3	41.2	42.2
ADF	64.3	63.6	63.2	62.5	62.8	63.7	64.9	66.5	68.4	69.3
Variance ratio	51.8	51.6	51.4	51.3	51.3	51.4	51.5	51.6	51.7	51.78
No. of firms	428	307	278	269	270	286	294	322	384	564

Portfolio (1) refers to the decile of firms with the highest past performance over the previous (the winners) year and portfolio (10) refers to the decile with the lowest past performance over the previous year (the losers). Momentum portfolios are rebalanced monthly. The table reports the time-series average of the tests for each past performance decile in each momentum portfolio constructed over the period July 1971 to December 2019. The table shows that the time-series behaviour of momentum firms does not differ significantly from the average firm. Both permanent and transitory earnings shocks are important drivers of fluctuations in the earnings series of price momentum firms.

1.2.2 Decomposing earnings into trend and cycle

The previous section presents evidence that firm earnings contain both a permanent and a transitory component. To explore the separate roles played by these components on price momentum, in this section I decompose earnings into permanent and transitory components employing several approaches. I use the Hodrick and Prescott [1997] (henceforth, HP) filter, the Beveridge and Nelson [1981] (henceforth, BN) decomposition, the Baxter and King [1999] (henceforth, BK) filter and an optimal finite sample approximation of an ideal bandpass filter (henceforth, IF). These filters are commonly used in the economics literature related to business cycles. Following a growing literature recognising transitory and permanent shocks having distinct effects on corporate policies, empirical implementations using these filters have become more common in corporate finance (e.g., Byun, Polkovnichenko, and Rebello, 2018). To the best of my knowledge, however, this is the first paper to examine the asset pricing implications of permanent and transitory shocks to earnings. Because of the limitations related to each filter, I use several for robustness purposes.

Before applying the filters, the earnings per share data is winsorized at the 1st and 99th percentile at the individual firm level. To ensure accuracy in the implementation of the filters, especially for the estimation of the trend component, I impose a requirement that firms need to have at least 10 years (40 quarters) of consecutive earnings-per-share data available.

To account for seasonality in the earnings data I deseasonalize earnings-per-share by applying a stable seasonal filter. The time series of (deseasonalized) firm earnings can be represented as the sum of a long-term (trend) component and short-term (cyclical) component:

$$EPS_{i,t} = \rho_{i,t} + \xi_{i,t}, \tag{1.1}$$

where $EPS_{i,t}$ denotes earnings of firm i in quarter t, $\rho_{i,t}$ denotes the trend component and $\xi_{i,t}$ denotes the cyclical component.

The HP filter separates the permanent (trend) component from the temporary (cyclical) component by solving the following optimization problem:

$$\underset{\{\rho_{i,t}\}_{t=-1}^{T}}{Min}\left\{\sum_{t=1}^{m}\xi_{i,t}^{2}+\lambda\sum_{t=2}^{m-1}[(\rho_{i,t+1}-\rho_{i,t})-(\rho_{i,t}-\rho_{i,t-1})]^{2}\right\}, \tag{1.2}$$

where the parameter λ serves to penalize variablity in the long-term component [3]. The first term in Equation (1.2) minimizes the difference between the time-series and its trend component. The second term minimizes the second-order difference of the trend component.

The BN filter identifies the trend component as the limiting forecast of the level of the series and the cycle is the difference between the level of the series and the trend component. The time-series is assumed to be an integrated process of order one ($I(1)$). I follow a similar approach to Chang, Dasgupta, Wong, and Yao [2014] by applying an ARMA (2, 2) model to the earnings series. In this decomposition, the trend component is a random walk with a drift and the cyclical component is a stationary zero-mean series.

The BK and IF filters are both band-pass filters that separate the trend component by choosing weights in a moving average process. For the BK filter I use the standard periodicities of 8 and 32 quarters as in the business cycle literature. This means that shocks within these periodicities refer to the trend while those of shorter periodicities are considered cyclical. The IF filter uses a fourier transformation to compute the moving average weights. The results from the two filters are similar, so in the following I only report those for the IF filter.

Although using the entire earnings per share series available for each firm when applying the filters would provide more accurate estimates, doing so runs the risk of incorporating information that is not available in real time. To ensure the accounting data is available, I filter earnings data using expanding-windows. More specifically, I apply the filter starting from ten non-missing consecutive earnings per share observations and extend the window of observations by one quarter and re-apply the filter on the new (longer) series. I only update the estimate for the last observation.

[3] The appropriate value of the smoothing parameter λ for quarterly data is 1600.

Having decomposed the earnings series into trend and cyclical components with each of these filters, I then compute the respective earnings surprise measures. The literature measures earnings surprises (referred to as standardized unexpected earnings, henceforth SUE) as the year-on-year change in earnings per share (to account for seasonality), divided by the standard deviation of the earnings surprises:

$$SUE_{i,t} = \frac{EPS_{i,t} - EPS_{i,t-4}}{\sigma_{i,t}},$$

where $\sigma_{i,t}$ is the standard deviation of the year-on-year changes in EPS over the past eight quarters. I follow a similar procedure in computing the earnings surprise component related to the trend ($SUE^T_{i,t}$) and the surprise component related to the cycle ($SUE^C_{i,t}$) [4]. Table 1.3 presents summary statistics for total earnings surprises and the trend and cycle components computed using the different filters [5].

[4]I compute year-on-year annual changes in earnings for comparison purposes in terms of magnitudes of earnings surprises with existing literature. In unreported results, I construct the earnings surprise measures using quarterly changes in earnings, once the earnings per share data is deseasonalized. Both qualitative and quantitative implications remain largely unchanged.

[5]I henceforth drop subscripts $\{i,t\}$.

Table 1.3 Summary statistics on permanent and transitory earnings shocks.
This table presents summary statistics for variables measuring earnings surprises calculated over the period July 1976 to March 2020. Each month I calculate the cross-sectional mean (*Mean*), standard deviation (*SD*), skewness (*Skew*), kurtosis (*Kurt*), minimum (*Min*), maximum (*Max*), median (*Med*). The table reports the time-series averages of these cross-sectional values. The column labeled *n* reports the average number of firms for which the variable is available each month. SUE is calculated as the year-on-year change in earnings per share, scaled by the standard deviation of year-on-year earnings innovations over the previous eight quarters. Earnings per share data is adjusted for splits by dividing by the cumulative adjustment factor by ex-date, Compustat item *AJEXQ*. The split-adjusted earnings data is decomposed into permanent and transitory components using three different filters: the Hodrick and Prescott filter (*HP*), the Beveridge Nelson decomposition (*BN*) and a filter that uses an optimal finite sample approximation of the ideal bandpass filter (*IF*). Variable indexed with the subscript T denote the trend (permanent) components, while those indexed by C denote the cyclical (transitory) components. The surprise variable based on each component of earnings is computed as the year-on-year change of the component (permanent earnings or transitory earnings) scaled by the standard deviation of the year-on-year innovations of the respective component over the previous eight quarters. The earnings data is winsorized at the 1st and 99th percentile at the individual firm level.

	Mean	Stdev	Skew	Kurt	Min	Max	Med	n
SUE	0.22	1.397	-0.01	1.307	-4.51	4.609	0.167	724
SUE^T_{HP}	0.367	1.775	0.055	-0.32	-3.92	4.566	0.373	568.6
SUE^T_{BN}	0.075	1.123	-0.10	0.67	-3.39	3.169	0.062	610.5
SUE^T_{IF}	0.227	1.222	0.049	0.647	-3.38	3.713	0.189	607.7
SUE^C_{HP}	-0.03	1.173	-0.15	0.596	-3.59	3.106	-0.02	609.8
SUE^C_{BN}	0.260	1.396	0.064	0.268	-3.55	4.069	0.223	602.3
SUE^C_{IF}	-0.05	1.323	-0.09	-0.06	-3.63	3.221	-0.04	613.2

1.2.3 Earnings surprise factors and momentum

Evidence in Chordia and Shivakumar [2006] and Novy-Marx [2015] shows that earnings surprises subsume the ability of momentum to predict returns. In this section I explore whether this result relates to permanent or transitory earnings surprises. Regardless of the filtering method used, the results show that both components are important.

Table 1.4 shows that surprises related to both trend and cycle components of earnings have predictive power on future returns. The results are consistent regardless of the type of filter used. I construct the factors based on double-sorted portfolios on size and the relevant measure of earnings surprises. The factor return in each instance is given as the difference between the average return of the small and large tercile of firms with the highest earnings surprises and the average return of the small and large tercile of firms with the lowest earnings surprises.

Table 1.4 Permanent and transitory shock factor performance.
This table shows the average return (*Avg. ret.*), test statistic (*t-stat*) and standard deviation (*SD*) of factors based on earnings surprise measures. Average returns are reported in percentage terms, based on a monthly frequency. The factors are formed using six value-weighted portfolios sorted on size and the earnings surprise measure. SUE is the average return on the two high SUE portfolios minus the average return on the low SUE portfolios. The other factors are based on earnings surprise measures that use decompositions of firm earnings into trend and cycle components using three different filters: the Hodrick and Prescott filter (*HP*), the Beveridge and Nelson filter(*BN*) and a filter that uses an optimal finite sample approximation of the ideal filter (*IF*). Construction of the factors follows the same procedure as that of the SUE factor. The sample period covers July 1976 to March 2020.

	SUE	SUE_{HP}^{T}	SUE_{HP}^{C}	SUE_{BN}^{T}	SUE_{BN}^{C}	SUE_{IF}^{T}	SUE_{IF}^{C}
Avg. ret.	0.797	0.446	0.728	0.722	0.721	0.252	0.750
t-stat	[6.256]	[3.206]	[6.686]	[6.489]	[6.598]	[2.156]	[5.78]
SD	2.788	3.046	2.386	2.437	2.394	2.558	2.842

Similar to the results related to the SUE factor, firms that receive the highest positive surprises related to the trend or the cycle components of earnings earn significantly higher returns than firms that receive the lowest surprises related to the trend or the cycle components of earnings. Appendix II shows that the time-series performance of both earnings surprise factors, cannot be fully explained by the Fama and French five factor model and price momentum.

I next examine the relationship between the different earnings surprise measures and price momentum. Table 1.5 shows the results of Fama and MacBeth regressions of stock returns on price momentum ($r_{12,2}$) and the most recent values of the different earnings surprise measures. The regressions include the other standard controls such as size ($ln(ME)$), the book-to-market ratio ($ln(B/M)$), gross profitability (GP/A) and short-term reversal ($r_{0,1}$). The variables are trimmed at the 1st and 99th percentiles for each cross-section. The sample covers the period from July 1976 to March 2020. Appendix III contains details on the construction of the control variables.

The first specification shows that the return over the previous year ($r_{12,2}$) is significantly positively correlated with expected returns. This is the well-known result that past performance over the intermediate-term has predictive power on returns. The second specification shows that this predictive power disappears once controlling for earnings surprises (SUE). The coefficient on past performance changes sign, with the positive correlation between momentum and expected returns breaking down. The third and fourth specifications show that surprises in both the trend and cycle components identified using the HP filter subsume the positive predictive power of momentum on expected returns. Similar results hold for earnings surprises constructed using the other decompositions (BN and IF filters).

Appendix IV presents the results of Fama and MacBeth regressions for different subsamples. Tables A.4 - A.6 show the results for three different subsamples of firms based on size: microcap, small and large. Microcap stocks belong to the first and second NYSE size deciles, small stocks belong to the third and fourth decile and large stocks have market capitalizations above the median NYSE breakpoint. Tables A.7 - A.8 show the results of these regressions separately for the first half of the sample period and the second. Results remain largely unchanged from those reported for the full sample in Table 1.5. Both trend and cycle earnings surprises are important in subsuming the power of price momentum to predict the cross-section of expected stock returns.

Table 1.6 shows the results of time-series regressions of returns to price momentum strategies on the Fama and French five factors as well as the factors formed on different earnings surprise measures. The first specification shows that the Fama and French five factor model cannot explain the profitability of the price momentum strategies given the positive and significant alpha in the regression. The second specification shows that the alpha on momentum becomes statistically insignificant when adding the SUE factor among the regressors. Specifications (3) to (5) show that, regardless of the decomposition method, the loading of momentum on the cycle (transitory) component of earnings is positive and significant. When using the BN and IF filters, the cycle component is, in fact, more important than the trend component.

Table 1.5 Fama and MacBeth regressions.
This table reports the Fama and MacBeth regressions of monthly expected excess stock returns on earnings surprises measured based on standardized unexpected earnings (SUE), its permanent component (SUE_T) as well as its temporary component SUE_C and past performance which is measured as the cumulative return over the previous year skipping the most recent month to avoid the effect of short-term reversal. The permanent and cyclical components of earnings are computed using three filters: the Hodrick and Prescott filter (*HP*), the Beveridge Nelson decomposition (*BNK*) and an ideal bandpass filter (*IF*). Controls include size (ln(ME)), book-to-market (ln(B/M)), profitability (GP/A) and short-term return reversal ($r_{1,0}$). The sample period covers July 1976 to March 2020.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$r_{2,12}$	0.39	-0.61	-0.58	-0.19	-0.33	-0.34	-0.49	-0.18
	[2.25]	[-2.98]	[-2.37]	[-0.90]	[-1.49]	[-1.64]	[-2.41]	[-0.87]
SUE		0.458						
		[14.85]						
SUE^T_{HP}			0.231					
			[3.32]					
SUE^C_{HP}				0.377				
				[10.47]				
SUE^T_{BN}					0.004			
					[12.55]			
SUE^C_{BN}						0.003		
						[9.33]		
SUE^T_{IF}							0.00	
							[1.16]	
SUE^C_{IF}								0.004
								[8.73]
ln(ME)	-0.11	-0.06	-0.07	-0.06	-0.07	-0.05	-0.08	-0.08
	[-3.32]	[-1.70]	[-1.87]	[-1.51]	[-1.75]	[-1.33]	[-1.99]	[-1.74]
$ln(BM)$	0.23	0.3]	0.41	-0.10	0.37	0.16	0.33	0.08
	[4.73]	[5.31]	[4.18]	[-0.34]	[3.07]	[1.76]	[4.75]	[0.52]
GP/A	0.66	0.57	1.00	0.07	0.63	0.24	0.77	0.83
	[4.23]	[2.90]	[1.74]	[0.13]	[2.16]	[0.57]	[1.83]	[2.47]
$r_{1,0}$	-4.90	-3.52	-2.91	-3.03	-3.24	-2.96	-3.18	-2.41
	[-12.8]	[-8.38]	[-5.76]	[-6.38]	[-7.12]	[-6.50]	[-6.75]	[-5.45]
Intercept	1.59	1.38	1.47	1.30	1.45	1.35	1.52	1.51
	[4.67]	[3.91]	[4.17]	[3.38]	[4.03]	[3.74]	[4.26]	[4.09]
R^2 (%)	3.50	5.90	6.70	6.70	6.70	6.60	6.80	6.50

Table 1.6 Spanning tests.
This table shows the results of regressions of the monthly returns of the momentum factor on different explanatory variables. The explanatory variables include the Fama and French five factors: the market factor (MKT), the size factor (SMB), the investment factor (CMA) and the profitability factor (RMW). The additional factors include: standardized unexpected earnings (SUE) and standardized unexpected trend and cycle components of earnings constructed using three filters: the Hodrick and Prescott filter (*HP*), the Beveridge Nelson decomposition (*BNK*) and an ideal bandpass filter (*IF*). The sample period covers May 1973 to December 2018. Newey and West test statistics are presented in parentheses.

	(1)	(2)	(3)	(4)	(5)
α	0.59	0.08	0.02	0.06	0.21
	[2.48]	[0.34]	[0.07]	[0.23]	[0.87]
β_{SUE}		0.76			
		[5.48]			
$\beta_{T_{HP}}$			0.68		
			[4.97]		
$\beta_{C_{HP}}$			0.39		
			[4.36]		
$\beta_{T_{BN}}$				0.31	
				[2.50]	
$\beta_{C_{BN}}$				0.56	
				[4.24]	
$\beta_{T_{IF}}$					0.36
					[2.95]
$\beta_{C_{IF}}$					0.47
					[4.55]
β_{mkt}	-0.11	-0.15	-0.09	-0.14	-0.14
	[-1.38]	[-2.06]	[-1.34]	[-1.90]	[-1.83]
β_{smb}	0.12	0.18	0.15	0.08	0.15
	[1.08]	[1.93]	[1.78]	[0.74]	[1.51]
β_{hml}	-0.65	-0.44	-0.40	-0.49	-0.49
	[-3.77]	[-3.66]	[-3.64]	[-3.62]	[-3.76]
β_{cma}	0.48	0.30	0.45	0.22	0.37
	[1.68]	[1.33]	[2.08]	[0.99]	[1.61]
β_{rmw}	0.33	0.08	0.11	0.21	0.15
	[1.65]	0[.47]	[0.70]	[1.13]	[0.79]
R^2 (%)	12.40	32.80	37.70	25.40	28.40

1.3 Financing constraints

The previous section shows that news about the short-term prospects of the company, as captured by transitory earnings shocks, help explain the performance of price momentum strategies. Financing constraints represent a potential driver of this result. In this section, I explore this conjecture both theoretically and empirically. I start by considering a liquidity management model, in the spirit of Décamps et al. [2017], that considers both permanent and transitory shocks to cash-flows. I focus on the asset pricing implications of a simplified version of the Décamps et al. [2017] model. This set up predicts that price momentum firms have high exposure to transitory shocks because they are financially constrained. Next, I empirically evaluate the degree of financial constraints for momentum firms. I refer to several financial constraints indexes, which confirm the link between price momentum and financial constraints.

1.3.1 A liquidity management model

Model setup

The setup of the model is that of Décamps et al. [2017]. Markets are complete and arbitrage-free. Time is continuous and the risk-free rate is constant at $r > 0$. The model considers an all equity-firm, with cash-flows exposed to both permanent and transitory shocks. Shocks of a permanent nature affect the productivity of the firm's assets in place. A_t denotes productivity which follows a geometric Brownian motion:

$$dA_t = \mu A_t dt + \sigma_P A_t dW_t^P$$

where μ and $\sigma_P > 0$ are constant and W^P is a standard Brownian motion under the physical measure, $\mathbb{P}$. The parameter μ represents the expected growth rate in productivity, while σ_P represents the volatility of the productivity process. The per-period cash-flow, denoted by dX_t, is uncertain and depends on the level of productivity in the previous period:

$$dX_t = \alpha A_t \, dt + \sigma_T A_t \, dW_t^T$$

where α and σ_T are positive constants and W^T is a standard Brownian motion under the physical measure, $\mathbb{P}$. The parameter α represents the expected growth rate in productivity-scaled cash flows, while σ_T denotes the volatility of the productivity-scaled cash-flow process. The short-term shock to scaled cash-flows, W^T, correlates to W^P with an instantaneous correlation coefficient $\rho \in [-1, 1]$:

$$dW_t^T \, dW_t^P = \rho \, dt$$

Given this correlation, the short-term shock to cash flows can be decomposed into a permanent and a transitory component:

$$dX_t = \alpha A_t \, dt + \sigma_T A_t \, \rho \, dW_t^P + \sigma_T A_t \sqrt{1-\rho^2} \, dW_t^Z \tag{1.3}$$

where W^Z is another Brownian motion which is uncorrelated to W^P. Absent short-term shocks ($\sigma_T = 0$), cash-flows are given by $\alpha A_t \, dt$. Because both α and A_t are positive, cash-flows in this set-up cannot turn negative. The presence of short-term shocks ($\sigma_T > 0$) means that cash-flows can become negative, exposing the firm to potential losses. Exposure to potential losses provides a precautionary motive for retaining earnings as cash reserves. Equation (2.4) highlights the fact that the size of the short-term shock scales with productivity. The higher the level of productivity of the firm, the larger the exposure to losses and the greater the precautionary motive for holding cash. Denoting the cost of carrying cash by $\lambda \in (0, r]$, the following describes the $\mathbb{P}$-dynamics of cash holdings, denoted by M_t:

$$dM_t = (r - \lambda) M_t \, dt + dX_t - dD_t$$

where D_t is the cumulative dividend paid to shareholders up to time t. Shareholders weigh the carry costs and precautionary benefits of holding cash to determine an optimal level of cash holdings. If the cash balance increases beyond this optimum, the excess is paid out as a dividend. If the cash balance reaches zero, liquidation becomes optimal. Given productivity, a, and cash, m, shareholders thus choose dividend and liquidation policies that maximise firm value, $V(a, m)$:

$$V(a,m) = \max_{(D_t)_t, \tau} \mathbb{E}^{\mathbb{Q}}_{a,m} \left[\int_0^{\tau} e^{-rt} \, dD_t + e^{-r\tau} \left(\frac{\omega \, \hat{\alpha} A_\tau}{r - \hat{\mu}} + M_\tau \right) \right] \tag{1.4}$$

where ω is the fraction of the unconstrained value of the assets that is recovered in the liquidation event, $\hat{\alpha}$ is the risk-adjusted expected growth rate in cash-flows and $\hat{\mu}$ is the risk-adjusted expected growth rate in productivity. To simplify the model solution, it is useful to note that equity value is homogenous of degree one in a and m, therefore:

$$V(a, m) = a V(1, \frac{m}{a}) \equiv a F(c)$$

where $c = \frac{m}{a}$ represents the productivity scaled cash holdings and $F(c)$ represents the productivity scaled value function. The solution to the ODE derived from the Hamilton-Jakobi-Bellman equation of the problem in (2.5) provides the firm value function. Appendix V contains a detailed description of the steps taken to solve the model.

Expected returns and risk premia

To obtain expected returns and risk premia, a representative agent is assumed to have a marginal utility process Λ_t, with dynamics given by:

$$\frac{d\Lambda_t}{\Lambda_t} = -r\,dt - \eta_T\,dZ_t^T - \eta_P\,dZ_t^P$$

where Z_t^T and Z_t^P are standard Brownian motions independent of one another. Z_t^T is correlated with the source of short-term risk to firm cash-flows, W_t^T, with a correlation coefficient of χ_T. Z_t^P is correlated with the source of permanent risk to firm cash-flows, W_t^P, with a correlation coefficient of χ_P. η_T and η_P represent the market prices of short-term and permanent cash-flow risks, respectively. This specification of the stochastic discount factor implies that the systematic components of both short-term and permanent sources of risks are priced.

The conditional risk premium on the firm can be obtained by comparing the coefficients of the ODE from the HJB equation for the scaled value function, $F(c)$, under the physical and risk-neutral measures. The conditional expected excess return on the equity, denoted as EER_t, is given by:

$$EER_t(c) = \chi_T\,\sigma_T\,\eta_T\,\frac{F'(c)}{F(c)} + \chi_P\,\sigma_P\,\eta_P\,(1 - \frac{c\,F'(c)}{F(c)}) \tag{1.5}$$

Equation (1.5) shows that the total risk premium is given by the sum of the risk premia associated with exposures to permanent and short-term systematic risks. The short-term shock premium is given by the first term on the right-hand side of Equation (1.5). This premium is determined by the market price of short-term cash-flow risk, η_T, and the firm's exposure to this risk. The exposure to short-term shock risk is given by the product of the correlation of the firm's cash-flows to systematic short-term cash-flow shocks, χ_T, the volatility of the firm's scaled cash-flows, σ_T, and the semi-elasticity of $F(c)$ with respect to c, $\frac{F'(c)}{F(c)}$.

The second term in Equation (1.5) gives the permanent shock premium. It is determined by the market price of permanent risk, η_P, and the firm's exposure to this risk. The exposure to permanent shock risk is given by the product of the correlation of the firm's cash-flows with permanent shocks to the pricing kernel, χ_P, the volatility of the productivity process, σ_P, and the semi-elasticity of $F(c)$ with respect to c, $1-\frac{cF'(c)}{F(c)}$.

The level of productivity-scaled cash drives the time-variation in conditional expected returns. Considering an alternative setting that prices only permanent shocks, temporary shocks would still affect firm risk by changing the cash-to-productivity ratio. Time-variation in expected returns in such a set up, however, would be limited.

A beta pricing model can be derived from this setting assuming that there is a traded asset (such as the market) whose returns follow a Brownian motion with a drift. It can be shown that the short-term beta can be expressed as:

$$\beta_t^T(c) = \frac{\chi_T \sigma_T}{\sigma_M^T} \frac{F'(c)}{F(c)}$$

The permanent-shocks beta can be expressed as:

$$\beta_t^P(c) = \frac{\chi_P \sigma_P}{\sigma_M^P} \left(1 - \frac{cF'(c)}{F(c)}\right)$$

Both betas vary over time and depend on the level of productivity-scaled cash holdings. $\frac{F'(c)}{F(c)}$ leads to time-variation in the short-term shock beta. The ratio is positive and decreasing (proof provided in Appendix VI), resulting in the transitory beta increasing as the cash balance is depleted. $\frac{cF'(c)}{F(c)}$ leads to time-variation in the permanent shocks beta. The sign of $\frac{cF'(c)}{F(c)}$ and the sign of its derivative are, on the other hand, unconstrained (proof provided in Appendix VI). $\frac{F'(c)}{F(c)}$ also represents the semi-elasticity of firm value with respect to scaled cash holdings in the cash retention region, $(o, c*)$. Similarly to the transitory beta, the sensitivity of firm value to cash rises with the distance of cash holdings to target. This sensitivity is greater than exponential. As argued by Johnson [2002], extreme sensitivity of firm value with respect to a risk factor may cause prices to behave in a fashion that seems bubble-like but is in fact rational. Figure 1.1 shows numerically how the permanent and transitory betas change with scaled cash holdings (when below target) for a firm that approaches liquidation.

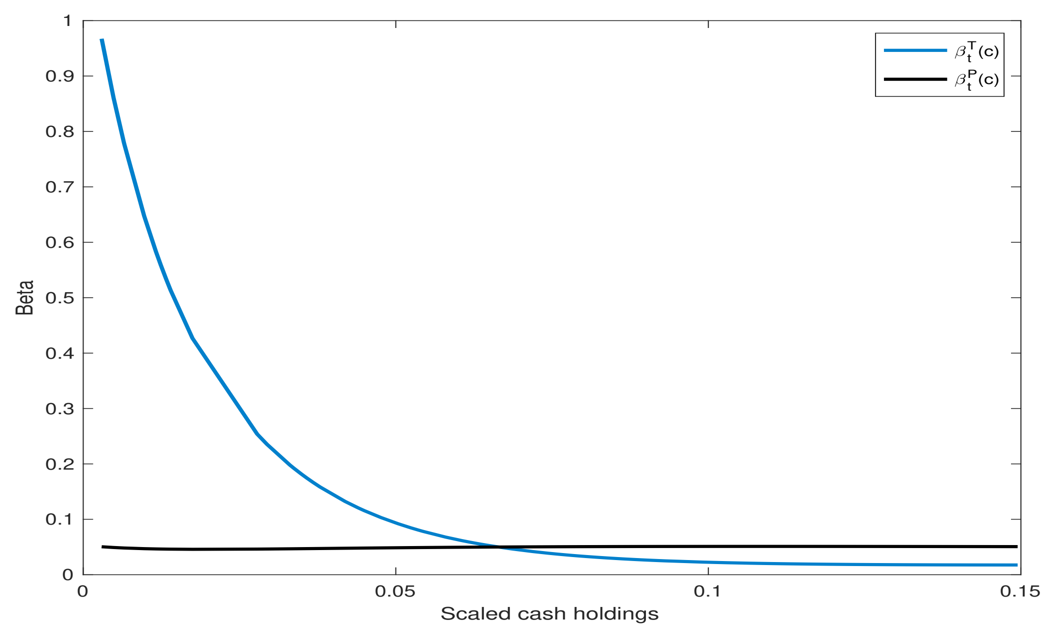

Fig. 1.1 Permanent and transitory shock betas.
The figure plots the permanent and transitory betas as a function of productivity-scaled cash-holdings. The parameter values are at the baseline level of Décamps et al. [2017], where: $\alpha = 0.18$, $\mu = 0.01$, $\sigma_P = 0.25$, $\sigma_T = 0.09$, $\rho = 0.5$, $r = 0.06$ and $\lambda = 0.02$. The market parameter values are set to: $\sigma_M^T = 0.09$ and $\sigma_P^T = 0.25$. The correlations between long-term and short-term shocks to the pricing kernel and long-term and short-term shocks to cash flows, denoted as χ_P and χ_T respectively, are both set to 0.8.

I set the parameters at the baseline levels of Decamps et al. (2016). The volatilities of short-term and permanent shocks of the market are set to: $\sigma_M^T = 0.09$ and $\sigma_P^T = 0.25$. To compare the two betas, β_t^T and β_t^P, only along their respective sensitivities to productivity scaled cash holdings the correlations of the firm's cash flows to short-term and permanent shocks to the pricing kernel are both set to be equal to 0.8. The number of months used in the simulation is 600.

Figure 1.1 shows that the permanent shock beta is more important at higher levels of scaled cash holdings. At low levels, the transitory beta increases at an increasing rate. Exposure to short-term risk becomes much more important than exposure to permanent cash-flow risk. Intuitively, firms close to liquidation are extremely sensitive to transitory cash-flow shocks as these can potentially lead to immediate liquidation, regardless of the long-term prospects of the company.

The key implication of this analysis is that price momentum firms are financially constrained and have high exposure to short-term cash-flow risk. A high-minus-low price momentum portfolio involves firms that in the recent past have experienced the largest returns in absolute terms (considering both winners and losers). In the theoretical set up presented here, the largest returns in absolute terms occur for the most financially constrained firms. For these firms, even small realizations of cash-flow shocks, especially transitory shocks, lead to large changes in value, and therefore, large realized returns in absolute terms.

Accounting for both permanent and transitory cash-flow shocks is important for price momentum. To see this, consider a set up where cash-flows are subject to only permanent shocks. As can be seen from Figure 1.1, firm risk would not change with its financial position since the permanent shock beta remains largely unchanged with the scaled cash balance. Heterogeneity in terms of the cash-flow parameters and correlations to aggregate shocks would, nevertheless, lead to cross-sectional dispersion in mean expected returns. Such dispersion, as argued in Conrad and Kaul [1998], would still potentially lead to momentum effects. Because of limited time-variation in risk, however, momentum effects would persist indefinitely, contrary to the empirical evidence. This highlights the importance of accounting for transitory shocks, the presence of which allows for larger time-variation in firm risk premia. The alternative set up that considers only transitory shocks is unrealistic as such a cash-flow structure would also be counterfactual, with the empirical evidence in Gryglewicz, Mancini, Morellec, Schroth, and Valta [2020] showing that firm cash-flows exhibit a significant degree of persistence.

Considering a richer set up that also allows for external financing and investment would provide greater insight on the relative risk exposures of winners and losers. This paper remains silent in this regard, being beyond its scope and given the overly simplified framework. This simple framework, however, does provide a theoretical link between permanent and transitory earnings shocks and price momentum that can help gain further insights on the empirical evidence presented in the previous section.

1.3.2 Financing constraints measures

In this subsection, I empirically investigate the degree of financial constraints for price momentum firms. To measure financing constraints, I compute three well-known financing constraints indexes for each firm in the merged CRSP-Compustat database: the Kaplan and Zingales (KZ) index (Kaplan and Zingales, 1997, Lamont, Polk, and Saá-Requejo, 2001), the Whited-Wu (WW) index (Whited and Wu, 2006) and the Hadlock and Pierce (SA) index (Hadlock and Pierce, 2006). All three indexes are calculated using observable firm characteristics and the implied relationships between these characteristics and financing constraints from the three studies.

The KZ index uses five accounting variables: cash flow to total assets, the market-to-book ratio, debt to total assets, dividends to total assets and cash holdings to total assets. The value of the KZ index is computed using the regression coefficients from Kaplan and Zingales [1997]. The KZ index value is higher for firms that are more financially constrained.

I construct the WW index in a similar spirit. I use the Euler-equation estimates from Whited and Wu [2006] and the values of six accounting variables: cash flows to total assets, a dividend dummy, long-term debt to total assets, the natural log of total assets, the firm's 3-digit industry sales growth and firm sales growth. The WW index value also increases with financing constraints.

Hadlock and Pierce [2006] argue that the above two indexes rely on endogenous financial choices such as leverage and cash holdings and may thus not necessarily represent reliable measures of financing constraints. The SA index that they propose instead is much more parsimonious in construction. It is uses only firm size and age. Appendix VII contains details on the accounting variables and the computations of the three indexes.

Figure 1.2 shows the time-series average of the median values of the three indexes for ten past performance sorted portfolios constructed over the period July 1975 to December 2018 [6]. Portfolio 1 represents the high past performance (winner) portfolio and portfolio 10 represents the low past performance (loser) portfolio. In all instances, the financing

[6] I refer to the median values for the portfolio statistics as opposed to value-weighted statistics given that the WW and SA indexes already rely on size.

constraints index values are highest for the extreme momentum portfolios, indicating both winners and losers are the most financially constrained firms in the cross-section. The three measures are also consistently higher for the loser portfolio. The profitability of momentum strategies that buy winners and sell losers, then indicates that the most financially constrained firms (the losers) have lower expected returns. While exploring why this is the case is beyond the scope of this paper, the result is in line with the findings in Lamont et al. [2001].

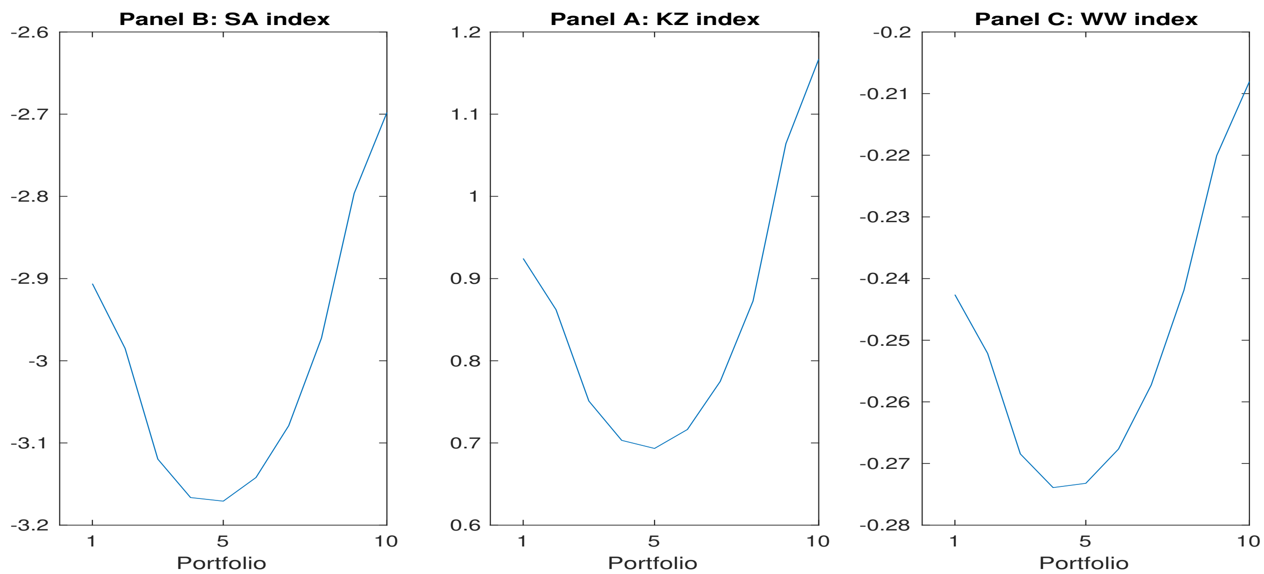

Fig. 1.2 Financing constraints and momentum portfolios.
The plots show the time-series average of the median value of the financing constraints indexes for each past performance sorted portfolio, for the period July 1975 to December 2018. Portfolio 1 represents the high past performance (winner) portfolio and portfolio 10 represents the low past performance (loser) portfolio. Panel A reports the statistics for the Kaplan and Zingales (KZ) index. Panel B presents the statistics for the Hadlock and Pierce (SA) index and Panel C reports the results for the Whited-Wu (WW) index.

Table 1.7 shows the average return of factors constructed using the three financial constraints indexes over the period of July 1975 to December 2018. The average return in all three cases is negative, although statistically significant only for the KZ index. This evidence is consistent with Figure 1.2 indicating that financially constrained firms earn lower expected returns. One would expect financing constraints to be associated with higher expected returns. Since the most financially constrained firms also belong to the loser portfolio, then the lower documented average returns in Table 8 link the surprising negative returns to financing constraints factors to momentum. Understanding the source of the lower returns of firms classified as more financially constrained by these indexes should help in the understanding of why losers earn lower returns compared to winners. Appendix VIII presents the results of time-series regressions of the returns to the three portfolios constructed based on the financial constraints indexes on the Fama and French five factors and momentum. The loadings on the factors are not always consistent, which is expected given the different criteria the indexes rely on. The loadings on momentum, however, are all negative. This is because a high-minus-low financial constraints index, as per Figure 1.2, buys the loser portfolio, which is the short leg of the momentum factor.

Table 1.7 Financing constraints factors.
This table shows the average return (*Avg. ret.*) and test statistic (*t-stat*) of factors based on financing constraints indexes. Average returns are reported in percentage terms, based on a monthly frequency. The factors are formed using six value-weighted portfolios sorted on size and three financial constraints indexes: Hadlock and Pierce [2006] (SA) index, the Kaplan and Zingales [1997] (KZ) index and the Whited and Wu [2006] (WW) index. The sample period covers July 1975 to December 2018.

	SA index	KZ index	WW index
Avg. ret	-0.19	-0.40	-0.30
t-stat	[-1.11]	[-3.33]	[-1.55]

I next conduct double-sorts on the financing constraints indexes and past performance. Table 1.8 shows the results for 25 portfolios sorted on the SA index and momentum. The average excess return of the high-minus-low past performance portfolios increases along the SA index quintiles. Only the high SA index momentum portfolios earn a significant Fama and French 5-factor alpha. The average excess return of the high-minus-low SA index portfolios is negative along all past performance quintiles, indicating that financially constrained firms earn lower expected returns. Such evidence is consistent with Lamont et al. [2001]. The average excess returns of the high-minus-low SA index portfolios is reliably different from zero and negative especially along the low past performance quintiles.

Table 1.8 Double sorts on price momentum and the SA index.
This table reports the performance of 25 portfolios constructed based on double sorts on price momentum and the Hadlock and Pierce [2006] (SA index), the excess returns on the high-low portfolios formed for each type of sort as well as the results of the regressions of the excess returns on the latter on the Fama-French five factors. The sample period covers July 1975 to December 2018.

	SA index quintiles					SA index strategies	
	Low	2	3	4	High	r^e	α^{FF5}
Momentum quintiles							
Low	0.88	1.12	0.73	0.59	0.60	-0.65	-0.19
						(-2.25)	(-0.80)
2	1.05	0.94	0.96	0.88	0.72	-0.71	-0.52
						(-3.17)	(-3.19)
3	1.10	1.13	1.07	1.05	0.78	-0.69	-0.49
						(-3.09)	(-3.21)
4	1.09	1.21	1.16	1.41	1.22	-0.24	-0.09
						(-1.10)	(-0.64)
High	1.33	1.63	1.70	1.82	1.68	-0.02	0.18
						(-0.08)	(1.14)
r^e	0.08	0.14	0.60	0.86	0.71		
	(0.24)	(0.40)	(2.01)	(2.94)	(2.71)		
α^{FF5}	0.25	0.31	0.49	0.83	0.62		
	(0.77)	(0.88)	(1.64)	(2.85)	(2.31)		

Table 1.9 presents the performance of portfolios double-sorted on the KZ index and momentum. The results are consistent with the SA index. Momentum strategies earn significant average excess returns and Fama and French 5-factor alphas only along the high KZ index quintiles. High-minus-low KZ index strategies also earn negative average excess returns that are significant mostly along the low past performance quintiles. Despite Hadlock and Pierce [2006] casting doubt on the validity of the KZ index, the relationship to momentum is consistent with the SA index they propose.

Table 1.9 Double sorts on price momentum and the KZ index.
This table reports the performance of 25 portfolios constructed based on double sorts on price momentum and the Kaplan and Zingales [1997] (KZ index), the excess returns on the high-low portfolios formed for each type of sort as well as the results of the regressions of the excess returns on the latter on the Fama-French five factors. The sample period covers July 1975 to December 2018.

	KZ index quintiles					KZ index strategies	
	Low	2	3	4	High	r^e	α^{FF5}
Momentum quintiles							
Low	1.27	1.12	1.01	0.81	0.30	-1.34	-1.21
						(-5.77)	(-5.37)
2	1.01	1.12	1.04	0.92	0.85	-0.53	-0.51
						(-2.91)	(-2.84)
3	1.18	1.18	1.07	1.04	0.94	-0.61	-0.53
						(-3.58)	(-3.28)
4	1.16	1.28	1.21	1.29	1.15	-0.38	-0.49
						(-2.27)	(-3.18)
High	1.33	1.62	1.47	1.63	1.64	-0.06	-0.07
						(-0.32)	(-0.43)
r^e	-0.32	0.13	0.09	0.45	0.97		
	(-0.99)	(0.42)	(0.29)	(1.52)	(3.16)		
α^{FF5}	-0.19	0.26	0.16	0.68	0.95		
	(-0.58)	(0.86)	(0.50)	(2.26)	(3.10)		

Finally, Table 1.10 presents the performance of portfolios double-sorted on the WW index and momentum. The relationship between momentum and this measure of financing constraints is not as clear as in the previous two cases. A potential reason could be related to the index relying on firm sales growth. The WW index is lower for firms with positive sales growth. Although both winners and losers appear to be constrained according to the SA index and KZ index, they differ in terms of sales growth before portfolio formation. Avramov et al. [2007] provides evidence that winners experience positive sales growth, while losers experience negative sales growth. Different sales trajectories would then lead to different categorisations in terms of financing constraints from the WW index.

Table 1.10 Double sorts on price momentum and the WW index.
This table reports the performance of 25 portfolios constructed based on double sorts on price momentum and the Whited and Wu [2006] (WW index), the excess returns on the high-low portfolios formed for each type of sort as well as the results of the regressions of the excess returns on the latter on the Fama-French five factors. The sample period covers July 1975 to December 2018.

	WW index quintiles					WW index strategies	
	Low	2	3	4	High	r^e	α^{FF5}
Momentum quintiles							
Low	0.89	0.83	0.84	1.20	0.77	-0.49	-0.11
						(-1.73)	(-0.45)
2	1.03	1.04	1.01	0.93	0.88	-0.52	-0.32
						(-2.22)	(-1.81)
3	1.05	1.11	0.92	0.99	1.08	-0.34	-0.32
						(-1.53)	(-2.05)
4	1.08	1.21	1.32	1.28	1.16	-0.30	-0.10
						(-1.28)	(-0.66)
High	1.32	1.70	1.50	1.55	1.55	-0.14	-0.00
						(-0.62)	(-0.02)
r^e	0.07	0.50	0.29	-0.02	0.41		
	(0.22)	(1.46)	(0.93)	(-0.06)	(1.59)		
α^{FF5}	0.14	0.62	0.25	-0.10	0.24		
	(0.44)	(1.79)	(0.78)	(-0.34)	(0.92)		

It is known that financing constraints indexes do not always provide the same rankings. The evidence from the double sorts on momentum and the three indexes overall seems largely supportive of the notion that both winners and losers are financially constrained firms.

1.4 Conclusion

The evidence presented in this paper sheds further light on the documented relationship between earnings and price momentum. Both permanent and transitory shocks to earnings contribute significantly to fluctuations in total earnings and to the power of earnings surprises in subsuming price momentum. The importance of transitory shocks is surprising when assuming a frictionless world. Two leading explanations for their effect include sentiment and the presence of financial constraints. I provide support for the latter, both theoretically and empirically. Notably, three widely used financial constraints indexes, known to be largely inconsistent with one another, agree on price momentum firms being the most constrained.

A limitation of this analysis stands in the theoretical framework being much simplified and silent on the relative riskiness of winners and losers in a price momentum sort. A richer set up that also accounts for investment and different forms of external financing would be promising in terms of pinning down a mechanism for momentum.

Chapter 2

The Value-Momentum Correlation: An Investment Explanation

Abstract

The correlation between the returns to value and momentum strategies varies over time. This paper shows that the time-variation of the correlation is related to the business cycle, aggregate investment and aggregate external financing. I provide an explanation for this evidence based on a theory of investment that incorporates uncertain financing conditions. In the model, the behaviour of the return premia is a response to a fundamental mechanism: the interaction between uncertain financing costs and earnings shocks. Changes in the cost of issuance over the business cycle lead to a procyclical momentum premium and a countercyclical value premium, consistent with the data. The model can also explain the performance of the two strategies during market rebounds as well as the time-series behaviour of their correlation. Several new testable predictions arise in this set up regarding the dynamics of the investment and external financing of firms included in value and momentum strategies. The empirical evidence is largely supportive.

2.1 Introduction

Extensive empirical evidence shows that firms with a high book-to-market equity ratio and high recent past performance relative to other firms earn higher average returns[1]. The question of why we observe these regularities in the data is still relatively unsettled, despite the vast literature devoted to this purpose. Existing explanations typically focus on either strategy in isolation, and those that consider both strategies cannot reproduce the documented negative correlation (e.g. Asness, Moskowitz, and Pedersen, 2013). While the sign of the correlation is surprising, its significance implies that value and momentum premia cannot be independent. A satisfactory explanation for these premia, therefore, needs to account for the co-movement.

This paper provides novel evidence that the correlation between the returns to value and momentum strategies, reflecting their common source of variation, is not always negative. The correlation changes significantly with the business cycle, and relates strongly to aggregate investment and external financing. This evidence indicates that firm investment and financing decisions, and their variation over the business cycle, may have important asset pricing implications that can help our understanding of the economic drivers of value and momentum premia.

I explore this conjecture by examining the links between the book-to-market ratio, past performance and expected returns in a model that considers optimal corporate policies under business cycle uncertainty. The model in Bolton, Chen, and Wang [2013] provides a flexible and tractable set up for studying these relationships. I show that the framework can produce both premia simultaneously, as well as the time-variation in their correlation. In the model, the behaviour of the premia is a response to a fundamental mechanism: the interaction between uncertain financing costs and earnings.

[1] Stattman [1980] and Rosenberg, Reid, and Lanstein [1985] provide the first evidence on the value premium in US equities. Fama and French [1992] show that, along with a size factor, book-to-market subsumes the ability of leverage and earnings-to-price ratio to predict returns. Chan, Hamao, and Lakonishok [1991] show that book-to-market predicts returns of Japanese equities as well. Fama and French [1998] document a strong value premium in global stock markets. Jegadeesh and Titman [1993] document positive and significant returns to momentum strategies. Rouwenhorst [1998] shows that there is persistence in returns over the medium-term horizon not only in the US, but also in international equity markets. Moskowitz and Grinblatt [1999] show that there is a strong momentum effect in industry portfolios.

The main idea is as follows. Take a neoclassical model in which the firm's cash flow is stochastic. Suppose issuing equity is costly [2]). With a financing pecking order, equity issuances will be used infrequently. The value of issuing equity becomes a delay option, whose value depends on the distance to issuance. Following negative cash-flow shocks, issuance becomes more likely and the risk premium of the firm increases. Firm value becomes more sensitive to productivity shocks as negative cash-flow realizations increase the possibility of having to resort to costly external financing or liquidation.

When the cost of issuing equity is random, firm value is exposed to an additional source of risk: financing shocks [3] . This risk also increases as the firm moves closer to issuance. Firms that are more financially constrained are more likely to have to pay the higher issuance costs in the event they materialize. The risk that the equity issuance cost becomes too high in the future, however, motivates the constrained firm to issue sooner than necessary. To do so, the firm draws down its cash reserves and credit line following negative cash-flow shocks, and at the same time, increases investment. The risk premium now decreases as issuance becomes more likely, because timing the equity markets effectively lowers the overall cost of financing for the firm.

The changes in the systematic risk of the equity around timed issuances imply a positive correlation between past returns, which reflect cash-flow shock realizations, and expected returns. Such changes occur only for the most constrained firms, as it is for these firms that the timing options are sufficiently into the money. The most constrained firms exhibit the most extreme price reactions to productivity and financing shocks as are the riskiest in the cross-section. As a result, these are the firms that end up in the extreme portfolios sorted on past performance. A positive correlation between past returns and expected returns for the firms with the most extreme past performance then implies a positive momentum premium. During periods of high issuance costs, the timing options are no longer valuable and the momentum premium disappears.

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[2]Equity issuance can be costly because of direct floatation costs (e.g.Smith, [1977], Altinkilic and Hansen, [2000], Eckbo and Masulis, [1992]) and indirect costs such as agency costs (Jensen and Meckling, 1976) and adverse selection costs (Myers and Majluf, 1984

[3]Choe and Nanda [1993] present evidence of firms issuing more equity during expansionary periods. Erel, Julio, Kim, and Weisbach [2012] show that changes in macroeconomic conditions affect the ability of firms to obtain external equity financing. Kahle and Stulz [2013] show that the decrease in equity issuance during the Great Recession was greater than the decrease in debt issuance. McLean and Zhao [2014] also provide evidence supportive of time-variation in the costs of equity issuance and show that this variation has real effects on firm investment and employment.

The value premium in the model captures the risk differential between financially con- strained and unconstrained firms. Financially constrained firms invest less because they face a higher marginal cost of financing. Low investment implies low future profitability and greater exposure to systematic risks. This is reflected in a lower valuation relative to capital, i.e. a higher book-to-market ratio. When financing costs are low, the risk differential between constrained and unconstrained firms is positive but small due to the timing options reducing risk. The value premium is amplified during periods of high financing costs, as the financially constrained firms face an even greater liquidation risk and may even engage in asset sales to avoid the high equity issuance costs.

Eisfeldt and Muir [2016] provide time-series estimates of the cost of external financing and show that the cost is higher during recessions. Given higher issuance costs in these periods, the model predicts a procyclical momentum premium and a countercyclical value premium. Such behaviour can simultaneously explain the presence of unconditional value and momentum premia and an overall negative correlation between the two.

Several new testable predictions arise in this setting that link the two premia to funda- mentals. First, the model predicts a lower level of external financing for winners compared to losers. To test this prediction, I construct two factors based on external financing: a low-minus-high debt factor and a low-minus-high equity issuance factor. The alpha on momentum disappears once the two external financing factors are added to the Fama and French three and five factor models. Portfolio statistics reveal that the differences in external financing levels appear starting from one year before formation and reverse the year after, consistent with the temporary nature of momentum profits. Along with changes in external financing levels, the model also predicts accompanying changes in in- vestment: (i) decreasing investment for winners and (ii) increasing investment for losers. I therefore look at the evolution of investment before and after portfolio formation in the data. Confirming the hypothesis, the investment of the winner portfolio declines during the year before formation, while the investment of the loser portfolio increases. This pat- tern is no longer present during periods of recessions and down markets, which serve as indicators of times of high issuance costs, and reverses in the following year.

The difference in investment levels between winners and losers justifies the positive loading of momentum on a low-minus-high investment factor. The investment factor, however, does not price momentum. The reason lies in both winners and losers having high levels of investment compared to the cross-section. This is predicted in the model and confirmed in the data. Comparative statics suggest stronger momentum for more procyclical firms. Stronger momentum for these firms results from the equity market timing options being even more valuable. The prospect of worse investment and financing opportunities induces greater investment in periods of low issuance costs and high expected cash-flow growth rates. The model then predicts high investment for both winners and losers. To test this prediction, I conduct a double-sort on investment and past performance. The results show that momentum strategies work only among high investment firms. These results are robust to using different sorting methods.

The model also predicts a larger difference in investment levels between value and growth firms during periods of high equity issuance costs. Portfolio statistics are affirmative. Investment monotonically decreases with book-to-market during recessions and down markets. The monotonicity is not observed in other periods and the difference in investment levels is smaller. These results explain why the alpha on value strategies dis- appears once an investment factor is added among the regressors. Combining the results on both strategies, the alpha of the 50/50 value-momentum combination strategy is no longer significant after accounting for investment and external financing factors.

Finally, the evidence on the time-variation of the correlation between the returns to value and momentum strategies can be used to obtain optimal exposures to each. I construct a dynamic value-momentum strategy, in essence representing factor timing, where the weights on each strategy change so as to maximise the Sharpe ratio of the combination. The approach is similar to Daniel and Moskowitz [2016], but instead of one, I have two correlated assets. The Sharpe ratio of the dynamic value-momentum strategy exceeds that of a simple 50/50 combination in the US as well as other markets.

The paper is organised as follows. Section 2 documents stylized facts regarding the dependence of value and momentum premia and their correlation on market states as well as firm fundamentals. Section 3 describes the model, develops the testable hypotheses and shows the results of the cross-sectional simulations. Section 4 presents the empirical results. Section

5 describes the construction of the dynamic value-momentum strategy and documents its performance in international markets. Section 6 discusses the related literature. Section 7 concludes.

2.2 Stylized facts

The main data sources include CRSP and Compustat, merged using 6-digit CUSIP identifiers. The sample covers the period July 1967 to December 2018. Momentum strategies buy firms with the highest cumulative returns over the previous year and sell firms with the lowest. Because of reversal, momentum does not include the performance of the most recent month in the computation of cumulative returns. Value strategies buy stocks with the highest book-to-market ratio and sell the ones with the lowest. I follow the same methodology as [43] in calculating and lagging the book-to-market ratio. Value and momentum portfolios use decile sorts, NYSE breakpoints and value-weighted returns. The data library of Kenneth French[4] provides the returns to value and momentum strategies formed on Japanese, European and Global stocks.

Table 2.1 shows the performance of value, momentum and a 50/50 combination of the two in different market states. Given the evidence in Daniel and Moskowitz [2016] on momentum crashes that occur following down markets, I identify market states using an ex-ante bear market indicator. The indicator equals one when the cumulative return on the market over the previous year is negative, and zero otherwise [5].

[4]http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[5]The ex-ante bear market indicator in Daniel and Moskowitz [2016] is based on the cumulative returns on the market over the previous two years as opposed to the previous year. I use both, but the results based on the indicator build on the previous year are much stronger. In unreported results, a similar pattern of the performance of value and momentum conditional on market states emerges when identifying the market state based on NBER recessions.

Table 2.1 Value and momentum performance conditional on market states.
This table presents the average returns and Sharpe ratios based on monthly returns of four strategies over the 1968:06 - 2018:12 time period. MOM is the winner-minus-loser momentum strategy. B/M is the high book-to-market minus low book-to-market value strategy. 50/50 VM is an equally-weighted portfolio of value and momentum. All strategies are based on quintile sorts. The distinction between good and bad times is based on a bear market indicator. The indicator is equal to 1 if the cumulative market return over the previous year is negative and zero otherwise. Test statistics are presented in parentheses.

Strategy	Full sample	Up markets	Down markets	Full sample	Up markets	Down markets
	United States			Japan		
MOM	1.23	1.50	0.55	0.22	0.30	0.13
	[3.70]	**[4.37]**	**[0.71]**	**[0.81]**	**[0.84]**	**[0.32]**
B/M	0.40	0.16	1.01	0.30	0.10	0.52
	[2.00]	**[0.74]**	**[2.23]**	**[1.68]**	**[0.36]**	**[2.16]**
50/50 VM	0.82	0.83	0.78	0.26	0.20	0.33
	[4.48]	**[4.34]**	**[1.84]**	**[1.94]**	**[1.44]**	**[1.38]**
	Europe			Global		
MOM	0.91	1.00	0.75	0.60	0.82	0.04
	[3.68]	**[4.84]**	**[1.25]**	**[2.44]**	**[3.70]**	**[0.06]**
B/M	0.34	0.18	0.64	0.27	0.10	0.71
	[2.24]	**[1.08]**	**[2.11]**	**[1.87]**	**[0.66]**	**[2.08]**
50/50 VM	0.63	0.59	0.69	0.44	0.46	0.38
	[4.99]	**[5.82]**	**[2.26**	**[3.49]**	**[5.51]**	**[0.96]**

Momentum strategies deliver higher unconditional returns and Sharpe ratios than value strategies in all markets, except for Japan. Following up markets, momentum performance strengthens, while the return on value becomes statistically indistinguishable from zero. Following down markets, the return on momentum becomes statistically indistinguishable from zero, while value strengthens. The pattern holds in all markets, including Japan. It confirms the result in the literature of pro-cyclical momentum and counter-cyclical value [6]. The performance pattern also explains the average negative correlation between value and momentum, one of the main results in [3].

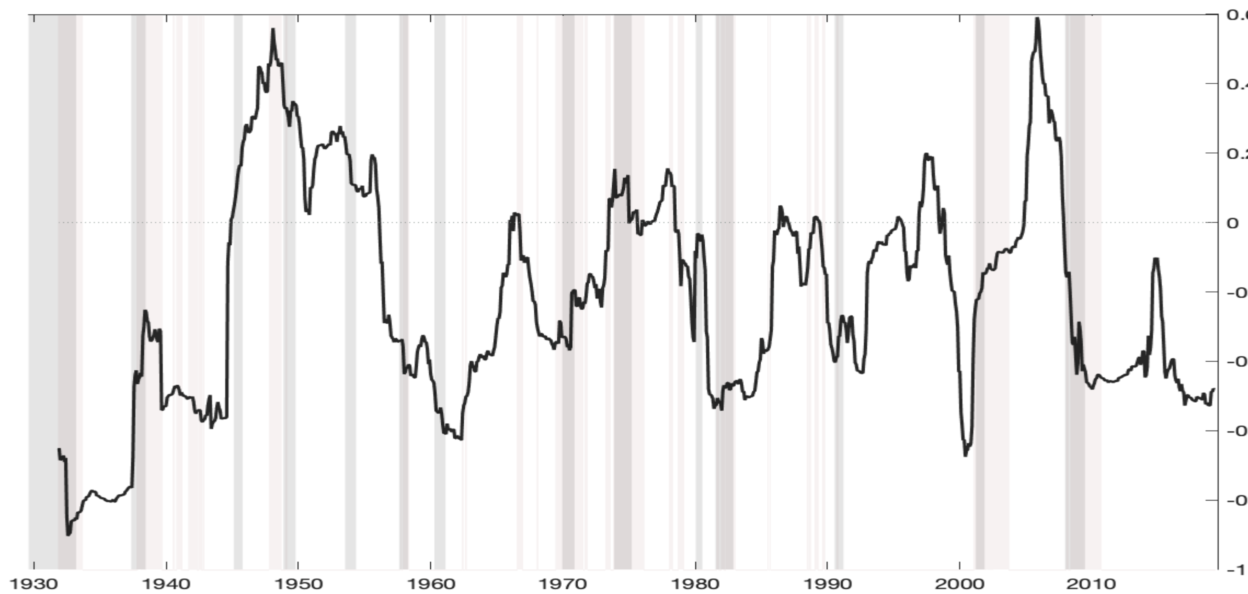


Fig. 2.1 The time-series of the value-momentum correlation.
This figure shows the 5-year rolling correlation between value and momentum returns in the US from December 1931 to December 2018. The light shaded bars indicate months where the return on the market has been negative over the previous year. The dark shaded bars indicate NBER recession months.

The negative correlation, however, is an average result. Figure 2.1 presents a 5-year rolling correlation between value and momentum in US equities. The light shaded bars indicate months where the return on the market has been negative over the previous year. The dark shaded bars indicate NBER recession months. Although negative on average, the correlation turns positive during favourable market conditions. It becomes negative during recessions, reaching some of its lowest values towards the end of the Great Depression and the Great Recession. These represent periods of market rebounds and coincide with momentum crashes. The time-series behaviour of the correlation between value and momentum returns shown in Figure 2.1 for the US is observed in other markets as well. Appendix A. 1 shows the time-series of a 5-year rolling window correlation between the returns to value and momentum strategies constructed using Japanese, European and Global stocks. Similar to the results for the US, the correlations are negative on average in all markets and vary with

[6][25] show that momentum strategies yield positive returns only during expansionary periods. [90] show that the value premium exhibits a countercyclial pattern of risk.

the market state. The correlations also obtain the largest positive values during the expansion of the mid-2000s and turn negative during the recent financial crisis.

Table 2.2 Momentum crashes.
This table shows the 13 worst monthly returns to momentum for the period July 1966 to December 2018 in the US. BM_t refers to the returns to value during the momentum crash months. Both value and momentum strategies use decile sorts, NYSE breakpoints and value-weighted returns. MKT−1y represents the cumulative return on the market over the twelve months preceding the current month and MKT_t represents the contemporaneous market return.

Rank	Month	WML_t	BM_t	MKT-1y_t	MKT_t
1	2001:01	-44.06	7.43	-11.71	3.67
2	2009:04	-43.58	-3.01	-37.00	10.20
3	2016:04	-24.22	11.60	-0.83	0.93
4	2002:11	-22.99	8.97	-13.62	6.08
5	1973:07	-22.49	2.13	-7.82	5.69
6	1974:01	-21.70	11.74	-19.25	0.46
7	1970:09	-20.79	-4.51	-14.68	4.72
8	2015:04	-20.09	8.90	11.78	0.59
9	2016:03	-19.79	7.38	-8.33	6.98
10	1980:03	-19.28	-6.26	28.25	-11.69
11	2009:05	-19.08	2.85	-33.74	5.21
12	1999:04	-18.90	10.37	13.64	4.70
13	1991:02	-18.56	0.50	6.51	7.67
Average		-24.27	4.47	-6.68	3.48

The stronger negative correlation between value and momentum strategy returns in down markets is reflected in large positive returns to value strategies during these periods. Table 2.2 confirms the result in Daniel and Moskowitz [2016]. Momentum experiences its largest losses when the market starts to rebound: the past return on the market is negative, while the current return on the market is positive. The return on value strategies during momentum crash months is high and positive. In the US, value delivers on average 4.47% over the thirteen worst months of momentum performance. This is much higher than the unconditional value premium and the average value premium conditional on down markets. The value premium disappears when excluding momentum crash months. Appendix A. 2 shows similar results for Japanese, European and Global stocks.

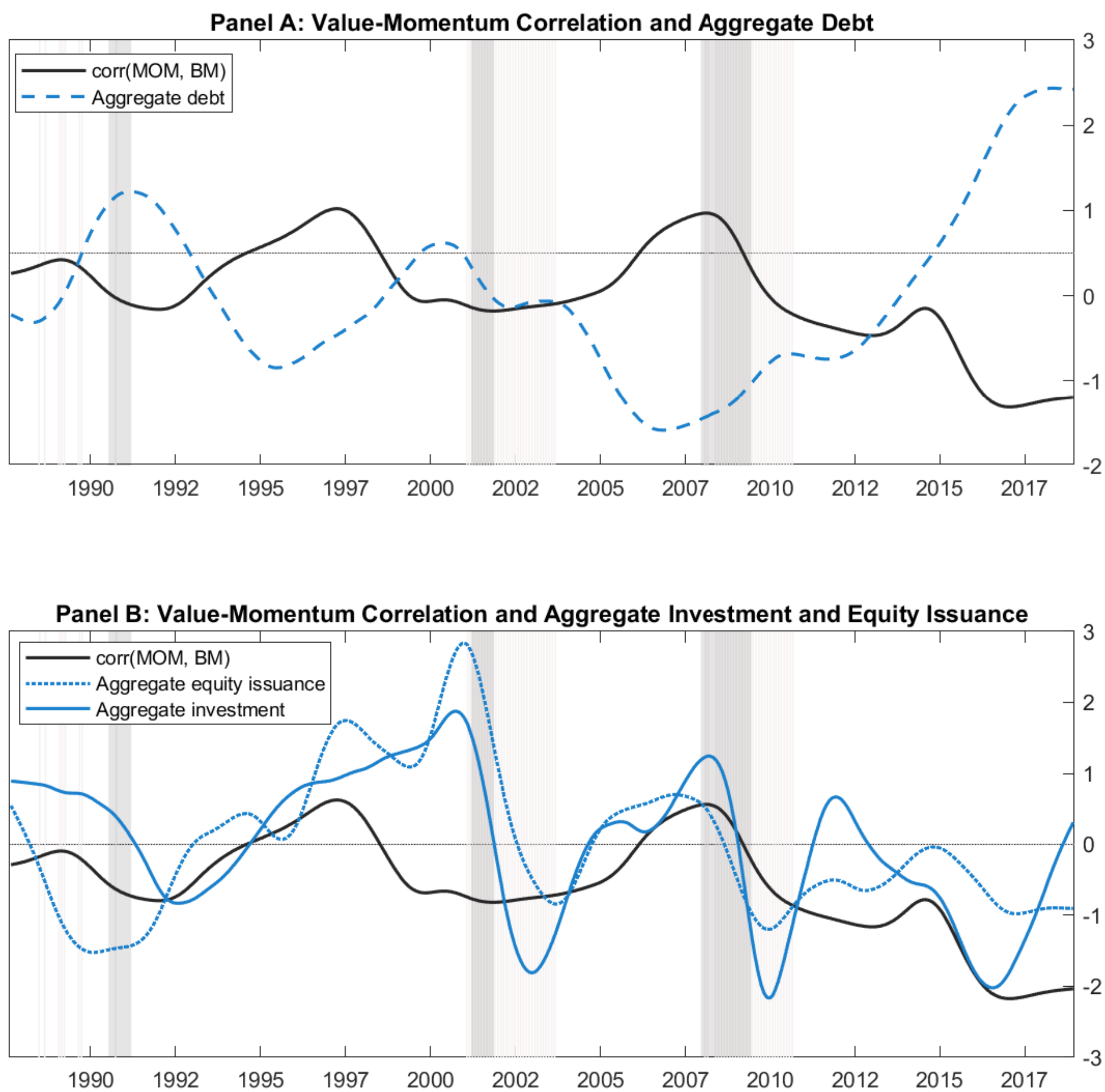


Fig. 2.2 Correlation between value and momentum strategies, aggregate investment and aggregate external finance. This figure shows the time-series of the 5-year correlation between the returns to value and momentum factors, aggregate investment, aggregate debt and aggregate equity issuance in the merged CRSP-Compustat universe. The investment and external financing series are scaled by lagged total assets, HP-filtered and normalized to have mean zero and unit variance. The time series of the correlation between value and momentum strategy returns is also HP-filtered. External financing is the sum of cash proceeds from equity issuance (Compustat variable SSTKQ) and the sum of long term debt and debt in current liabilities (Compustat variables DLCQ and DLTTQ respectively). The shaded bars indicate NBER recession periods.

While investor psychology could play a role in the sensitivity of the value and momentum performance to market states, Figure 2.2 shows that fundamentals are also important. Panel A shows the time-series of the rolling correlation between value and momentum and aggregate debt in the US. Panel B shows aggregate investment and aggregate equity issuance. Aggregate investment is the year-on-year change in total assets in the CRSP universe that serves to form momentum and value strategies. Aggregate equity issuance is the total cash proceeds from issuance of common and preferred equity (Compustat quarterly variable SSTK). Debt represents the sum of long term debt and debt in current liabilities (Compustat quarterly variables DLTT and DLC respectively). To obtain stationarity, all Compustat variables are scaled by lagged total assets. To ensure data availability, the Compustat variables are lagged using the Fama and French [1992] methodology. All four series are HP-filtered, to remove noise and high frequency trends. Finally, the Compustat series are standardized to have mean zero and unit variance.

Panel A shows a strong negative relationship between the correlation in the strategy returns and aggregate debt. Panel B shows a clear positive relationship between the correlation in the two strategy returns and aggregate investment and equity issuance. All pairwise correlations with the time series of the correlation between returns to value and momentum are statistically significant, the one with debt being the strongest. A univariate regression of the 5-year rolling correlation between value and momentum returns on aggregate debt has an R^2 of 28%. The coefficient on aggregate debt is -0.17. The dependence of the correlation on market states seems to be driven by the dependence of debt levels on market states. The evidence in Figure 1 points towards debt being counter-cyclical, consistent with Halling, Yu, and Zechner [2016]. Based on this, a model that incorporates stochastic investment and financing opportunities seems suitable in studying value and momentum premia and their correlation.

2.3 The model

This section focuses on the asset pricing implications of a dynamic corporate financing model based on Bolton et al. [2013]. I add credit lines as an alternative source of external financing, following the extension to Bolton, Chen, and Wang [2011]. The purpose is to show that accounting for optimal corporate policies under different market conditions is crucial for understanding value and momentum premia and their interaction. Appendix B.2 contains a detailed description of the model set up and the solution. The following section provides a brief overview.

2.3.1 Overview of the model

The model considers a financially constrained firm that faces stochastic financing opportunities. The firm can be in one of two possible states of the world, denoted by $s_t = G, B$. Investment and external financing opportunities are better in the good state, G, and worse in the bad state, B. There is a constant probability, ζ_s, that the economy switches from the current state s to state s^-, where s^- denotes a state different from s.

Production requires two inputs, cash W, and capital K. The firm buys and sells capital at the price of one. The following accounting identity applies to the capital stock of the firm:

$$dK_t = (I_t - \delta K_t)\,dt, \quad t \geq 0, \tag{2.1}$$

where I denotes investment and $\delta \geq 0$ the rate of capital depreciation.

The firm faces a productivity shock, dA_t, that follows an arithmetic Brownian motion:

$$dA_t = \mu_s\,dt + \sigma_s\,dZ_t^A, \tag{2.2}$$

where Z_t^A is a standard Brownian motion, and μ_s and σ_s represent the drift and volatility of the productivity process in state s. Firm revenues are given by $K_t\, dA_t$, thus assumed to be proportional to the capital stock K_t. This specification of the cash-flow process means the firm faces potential losses. Potential losses coupled with costly external financing provide a motive for saving cash. Cash within the firm earns a lower rate of return compared to the risk-free rate r_s, making it costly. The firm can also use external financing to cover potential losses and finance investment. External financing involves credit lines and new equity issues [7]. Only a fixed portion of the capital of the firm, $c_s > 0$, is posted as collateral for the credit line. This limits of the credit line draw-down to an amount of $c_s K$. Credit line access involves a cost in the form of a spread, α_s, over the risk-free rate on the amount borrowed. Equity issuance is also costly. The costs include a fixed component, $\phi_s K$, where ϕ_s is the fixed cost parameter in state s, and a proportional component $\gamma_s > 0$, where γ_s is the marginal cost parameter in state s.

In each state of the economy s, there are two state variables in the firm's optimization problem: firm size K and the cash balance W. Management chooses investment, external financing, cash savings, payout policies and liquidation time that maximize shareholder value. Optimal policies result in the cash balance evolving between two barriers: an upper payout boundary $\overline{W_s}$ in each state s and a lower boundary $\underline{W_s}$ in each state s, where the firm issues equity. To solve the model, it is useful to note that firm value is homogeneous of degree one in capital K and cash W in each state s. This allows to define the problem as a function of only one state variable based on the ratio of cash-to-capital: $w = W/K$. Let $P(K,W,s)$ denote the state-dependent firm value function. The homogeneity property allows the value function to be written as $P(K,W,s) = p_s(w)K$, where $p_s(w)$ represents the scaled value function in state s. This makes it possible to write the Hamilton-Jakobi-Bellman equation of the shareholders' maximisation problem in $(\underline{w}_s, \overline{w}_s)$ as:

[7] The relative costs of the credit line and equity issuance will determine which source of funding is used first. Throughout this analysis, the cost of issuing equity is assumed to be higher. The model thus generates a pecking order between the three sources of financing: the firm issues equity only after exhausting its cash balance, and then drawing down its credit line.

$$\begin{aligned} r_s p_s(w) = \max_{i_s} \; & [(r_s + \Phi_s) w + \hat{\mu}_s - i_s - g_s(i_s)] \, p_s'(w) + \frac{\sigma_s^2}{2} p_s''(w) \\ & + (i_s - \delta) \left(p_s(w) - w \, p_s'(w) \right) + \hat{\zeta}_s \left(p_{s^-}(w) - p_s(w) \right) \end{aligned} \tag{2.3}$$

where

$$\Phi_s = \begin{cases} +\alpha_s, & \text{if } w \leq 0. \\ -\lambda_s, & \text{if } w > 0. \end{cases}$$

where i_s is the investment-to-capital ratio, I/K, and $g_s(i_s)$ represents the investment adjustment cost function, which is increasing and convex [8].

The left-hand side of equation (2.3) represents the required rate of return for investing in the firm. Under the risk-neutral measure, $\mathbb{Q}$, this is the risk-free rate. The first and the second term on the right-hand side of (2.3) represent the effects of productivity shocks on firm value. In the region $(0, \overline{w}_s)$ the firm funds investment using cash reserves that earn interest lower than the risk-free rate, $(r_s - \lambda_s)$. In $(\underline{w}_s, 0)$ the firm uses the credit line. Firm value decreases following a negative productivity shock, with the decrease reflecting the additional interest it needs to pay on the credit line $(r_s + \alpha_s)$. The third term captures the marginal effects of investment. The last term represents the expected change in firm value when the state changes from s to s^-.

The ODE in (2.3) is solved using value matching and smooth pasting conditions at the boundaries as well as continuity and smoothness conditions at zero.

[8]The detailed specification of the investment adjust cost function is given in Appendix B.2.

2.3.2 Risk premia

The model incorporates two types of priced shocks: shocks to productivity and shocks to the state of the economy. Productivity shocks, dZ_t^A, affect firm risk by changing its *level* of financial slack, as measured by the cash-to-capital ratio, w. Shocks to the state of the economy, s, affect firm risk by changing the *value* of financial slack. During bad times, the marginal value of cash is higher, making financial slack more valuable and the firm riskier. The existence of two sources of aggregate uncertainty implies the CAPM no longer applies. Let $\mu_s^R(w)$ denote the expected excess return on the firm. Matching terms in the Hamilton-Jakobi-Bellman equations under the risk-neutral probability measure $\mathbb{Q}$ and the physical probability measure $\mathbb{P}$, the following obtains for the expected excess return, $\mu_s^R(w)$:

$$\mu_s^R(w) = -(e^{\kappa_s} - 1)\,\zeta_s\,\frac{p_{s^-}(w) - p_s(w)}{p_s(w)} + \eta_s\,\rho_s\,\sigma_s\,\frac{p_s^{'}(w)}{p_s(w)}. \tag{2.4}$$

The first term in equation (2.4) represents the state risk premium. This is given by the market price of the risk of the economy switching states, κ_s, the probability of the economy switching states, ζ_s, and the percentage change in firm value, at the current cash-to-capital ratio, if the economy switches to a different state (from s to s^-). Firms whose prices drop more when the economy switches to a state of higher marginal utility require a greater risk premium in the current state. The second term in equation (2.4) represents the productivity risk premium. This is given by the market price of productivity risk, η_s, and the firm's exposure to this risk, $\rho_s\,\sigma_s\,p_s^{'}(w)/p_s(w)$. $p_s^{'}(w)$ represents the marginal cost of financing. The higher the marginal cost of financing faced by the firm, the greater the risk premium.

2.3.3 Calibration

I calibrate the theoretical model at the daily frequency. I first motivate the parameter set that reproduces the average firm. To introduce cross-sectional heterogeneity, I then choose reasonable ranges for some of the key parameters.

The parameters in the baseline case of Bolton et al. [2013] serve as a starting point for the calibration of the average firm. Recent empirical evidence motivates a few divergences. Glover [2016] estimates much higher expected bankruptcy costs compared to the previous literature, reconciling the empirical evidence on leverage and expected costs of default. He estimates the average firm loses 45% of its value in the event of liquidation. Glover [2016] does not provide separate estimates for the cost of default in different market states. Following a similar intuition to Bolton et al. [2013] who use the estimates in Hennessy and Whited [2007], I set the expected bankruptcy cost in the bad state higher than the one in the good state. The relative values in the two states are chosen in a similar proportion. The expected bankruptcy cost is set to 20% in the good state and 50% in the bad state. The chosen expected costs of bankruptcy imply a capital liquidation value of $l_G = 0.8$ in the good state and $l_B = 0.5$ in the bad state.

I use different values for the equity issuance cost parameters from Bolton et al. [2013] who rely on estimates from Eckbo et al. [2007] and Altinkilic and Hansen [2000]. These studies base their estimates on Seasoned Equity Offerings (SEOs), which are infrequent. Fama and French [2005] show that firms issue equity much more frequently and at smaller amounts compared to SEOs. The higher frequency implies a lower fixed cost of equity issuance compared to estimates based on SEO samples. The smaller size implies a higher marginal cost. Although the costs of equity issuance that take this evidence into account are yet to be estimated, I intuitively adjust the parameter values. I set the fixed cost of equity issuance at 0.1% in the good state and 30% in the bad state. I set the marginal cost of equity issuance at 10% in both states. Although both fixed and marginal costs increase in bad states of the world, I only change the fixed cost as that is what determines access to the external equity market. The size of the issue, mainly determined by the marginal cost, is not necessarily the central to the asset pricing implications of the model.

Assuming an average duration of good times of ten years, and an average duration of bad times of two years, the transition intensities are set to $\zeta_G = 0.1$ out of the good state and $\zeta_B = 0.5$ out of the bad state. Similar to Bolton et al. [2013], the model assumes exogenous risk adjustments. The spread paid for the credit line is set to 1.5%, based on the estimates of Sufi [2007]. The remaining parameters in the baseline calibration, listed in Appendix B.3, are set at the same levels as in Bolton et al. [2013].

To be able to compare with the empirical evidence on value and momentum premia, I need to add heterogeneity to the simulated data. To do so, I vary some of the key parameters around the values for the average firm. The nature of the distribution of the parameters is unknown. I therefore draw them from a discrete set around the values for the average firm.

2.3.4 Value effects

In this subsection, I show that the model produces a positive unconditional value premium. Stochastic investment and financing opportunities produce a higher value premium in bad states of the economy. Changes in risk premia when the state switches from bad to good explain the documented large positive returns to value during market rebounds.

The ratio of capital-to-value serves as the model-equivalent of the book-to-market ratio. In the model, high book-to-market firms are more financially constrained and generally invest less. Figure 2.3 shows numerically how investment changes with book-to-market. Panel A shows that the relationship between investment and book-to-market is non-monotonic in good times. Investment, however, generally decreases with the book-to-market ratio. Panel B shows that investment is strictly decreasing in the book-to-market ratio in bad times. High book-to-market firms engage in asset sales, while low book-to-market firms continue to expand capital.

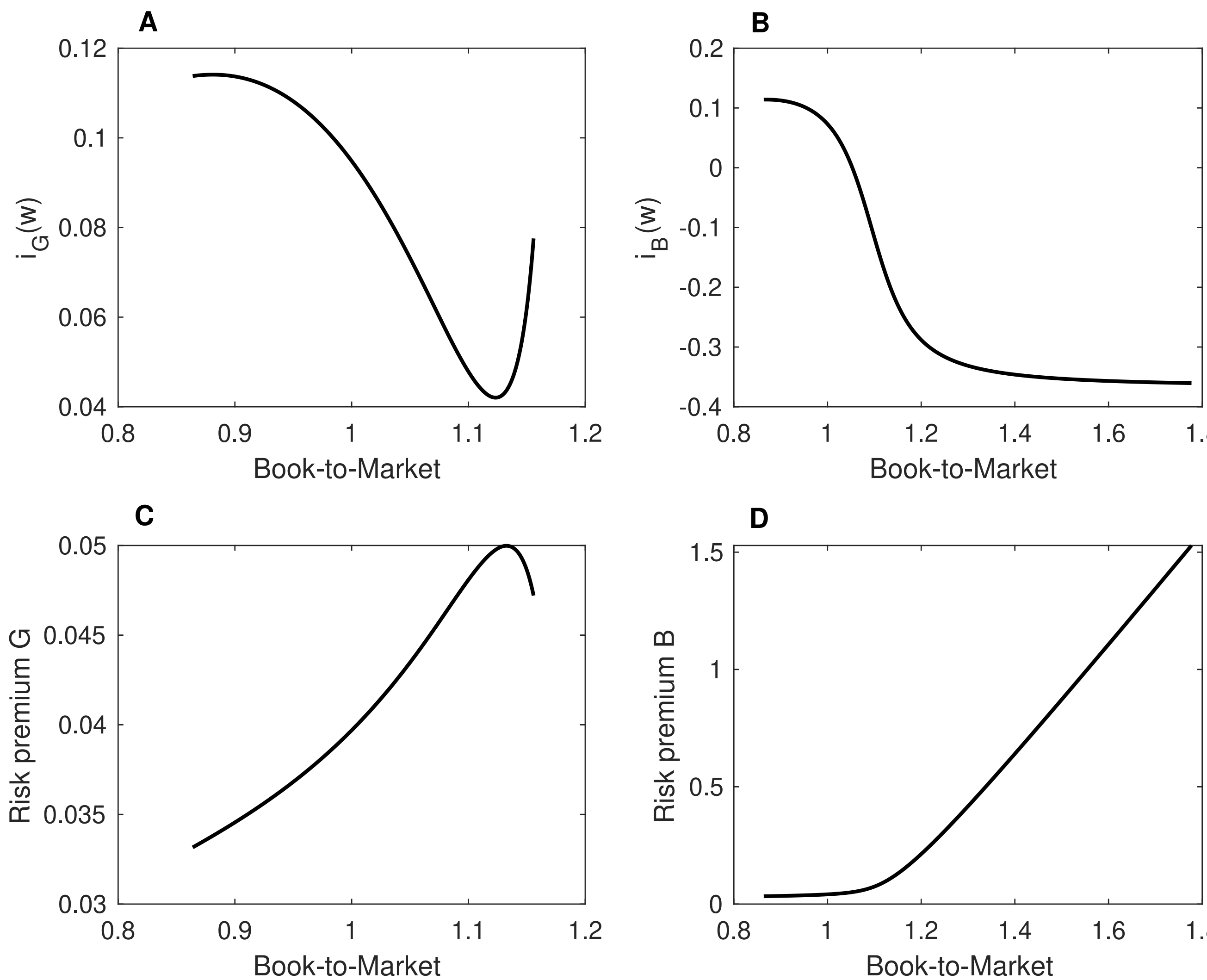


Fig. 2.3 Value effects.
The plots show how investment and the risk premium in the model change with the book to market ratio. Panels A and B show the relationship between investment and book-to-market during favourable market conditions and unfavourable market conditions, respectively. Panels C and D show the relationship between the total risk premium and book to market during favourable market conditions and unfavourable market conditions, respectively. Results are based on the numerical solution for the average firm.

Differences in the marginal cost of financing drive the differences in investment levels in the two states. High book-to-market firms in the model rely on external funds to finance investment, while low book-to-market firms rely on cash savings. The wedge in the marginal costs of financing between internal and external funds is positive but small in good times. The possibility to time the equity market lowers the overall effective costs of financing further for the financially constrained firm, allowing it to invest more. This makes the difference between the investment levels of high and low book-to-market firms even smaller. The difference in marginal costs is amplified in bad times because of the much higher external financing costs. Financially constrained firms (high book-to-market) engage in asset sales to avoid the large costs of external financing. Well-capitalised firms (low book-to-market) fare much better. The resulting difference in expected returns becomes much larger.

The inverse relationship between risk and investment can be seen analytically by re-arranging equation (2.4) in terms of investment $i_s(w)$:

$$\mu_s^R(w) = -(e^{\kappa_s} - 1)\,\zeta_s\,\frac{p_{s^-}(w) - p_s(w)}{p_s(w)} + \eta_s\,\rho_s\,\sigma_s\,\frac{1}{(i_s(w) - \nu_s)\,\theta + w + 1}. \tag{2.5}$$

Low levels of investment lead to a high productivity risk premium and a high overall risk premium. The generally negative relationship between investment and the book-to-market ratio and the negative relationship between the risk premium and investment imply a generally *positive* relationship between the total risk premium (the sum of the state premium and productivity premium) and the book-to-market ratio. Panels C and D in Figure 2.3 show numerically how the risk premium changes with book-to-market. In good times (Panel C) small differences in investment levels justify a small difference in the risk premium between high and low book-to-market firms. In bad times (Panel D) large differences in investment levels, driven by large differences in the marginal cost of financing, justify a large value premium. The model produces a positive value premium even without time-variation in investment and financing opportunities. Accounting for business cycles, however, brings the model closer to the data.

The model can also explain the observed large positive returns to value strategies during market rebounds. When the economy switches from a bad to a good state, Figure 2.3 shows that the risk premium on high book-to-market firms declines significantly, leading to large positive returns. Consistent with the stylized facts, when the market rebounds value strategies, being long the profitable high book-to-market firms, incur large profits.

2.3.5 Momentum effects

This subsection shows that stochastic financing opportunities give rise to a positive momentum premium. Consistent with the empirical evidence, momentum is present only in the good state of the market.

Following Johnson (2002), to study momentum effects, I look at the instantaneous covariance between cumulative excess returns and expected excess returns. The expected excess return, $\mu_s^R(w)$, given in equation (2.4), also represents the drift of the cumulative excess return process, labelled CER_t. In the region $(\underline{w}, \overline{w})$, the cumulative excess return process follows:

$$dCER_t = p_s(w)(i_s - \delta)\,dt + \frac{d\,p_s(w)}{p_s(w)} - r\,dt$$

Appendix B.4 provides details of the derivations of the cumulative and expected excess return processes and their covariance. Let $\mathscr{F}_t$ be the time t information set. Then, the instantaneous covariance between cumulative and expected excess returns is given by:

$$\mathbb{E}\left[(CER_{t+l} - \mathbb{E}\left[CER_{t+l} \mid \mathscr{F}_t\right]) \cdot (EER_{t+l} - \mathbb{E}\left[EER_{t+l} \mid \mathscr{F}_t\right]) \mid \mathscr{F}_t\right]$$

The sign of the covariance changes depending on the cash-to-capital ratio and the state of the market. I use a numerical example to show this dependence. Figure 2.4 shows how the instantaneous correlation between cumulative and expected excess returns associates with the cash-to-capital ratio w and the firm risk premium, $\mu_s^R(w)$, under the baseline calibration. Panels A and B show the relationship between the correlation and the firm financing position w in the good state and bad state, respectively. Cumulative and expected returns correlate positively only for the most financially constrained firms in good times. Panel C shows that, in good times, stronger momentum generally associates with a higher risk premium.

Panel D shows that, in the region where the correlation between cumulative and expected returns is positive, investment increases with the strength of the momentum effects.

The reasoning is as follows. In good times, in anticipation of the economy switching to a state of higher equity issuance costs, the firm has the option to issue costly equity sooner than absolutely necessary. Issuing new equity becomes necessary sooner for the financially constrained firm, making the option more in-the-money. As the financially constrained firm receives cash-flow shocks that affect its financing position, the moneyness of the option changes, affecting firm value. The constrained firm that receives negative shocks experiences negative cumulative returns, while the constrained firm that receives positive shocks experiences positive cumulative returns. Because of the overall higher level of risk, a sort on past performance concentrates on the constrained firms. Panel C in Figure 2.4 confirms this: firms with positive momentum generally earn the highest risk premia in the cross-section. Following negative shocks, the constrained firm draws down its credit line further as the cash-to-capital ratio w decreases. The equity market timing option is more likely to be exercised and becomes more in-the-money. To reach the issuance boundary sooner, the firm optimally chooses to increase investment, despite the negative cash-flow shocks. More formally, the investment-cash sensitivity is negative: $i'(w) < 0$. This allows the firm to reap the benefits of the equity market timing option and effectively lower its overall cost of financing. The expected returns on the losers decrease.

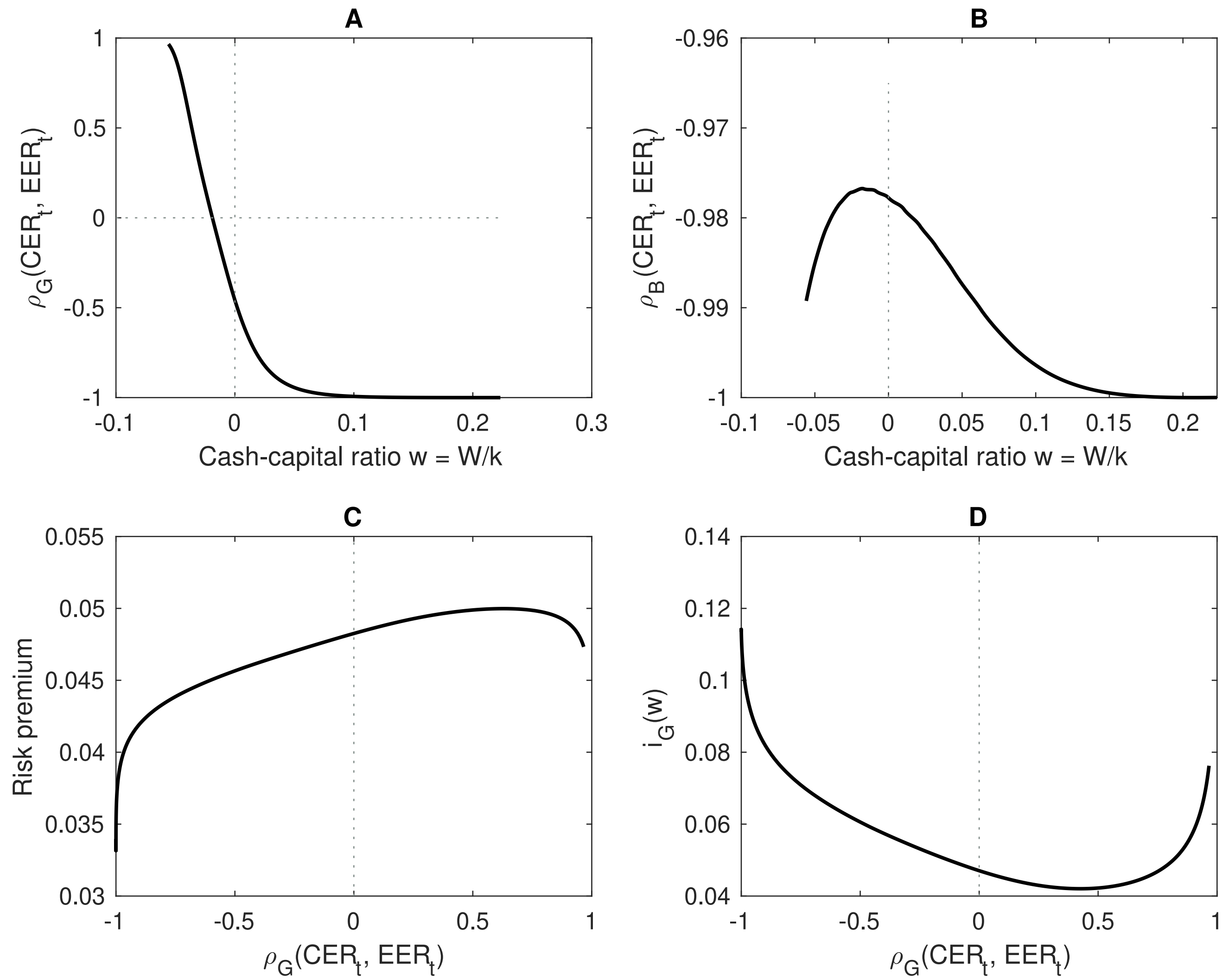


Fig. 2.4 Momentum effects.
Panels A and B show how the instantaneous covariance between cumulative past returns and expected excess returns, $\rho(CER_t, EER_t)$, changes with the cash-to-capital ratio, w. Panel A presents the relationship during favourable market conditions (good times). Panel B presents the relationship during unfavourable market conditions (bad times). The correlation is positive only in good times. Panel C shows how the risk premium relates to the instantaneous correlation in returns, $\rho(CER_t, EER_t)$, in good times. Panel D shows how investment relates to the instantaneous correlation in returns, $\rho(CER_t, EER_t)$, in good times.

The opposite occurs for the winners. The market timing option of the constrained firm that receives positive cash-flow shocks becomes more out-of-the money, and thus riskier. The firm optimally chooses to use to positive cash-flows to reduce credit. Lower likelihood of equity market timing causes the overall cost of financing for the firm to increase. Its investment declines as a result. Recent winners therefore have lower investment levels compared to recent losers. Based on Equation 2.5, low investment firms demand a higher risk premium, implying greater expected returns for winners compared to losers. Therefore, the largest positive cumulative returns generally imply ex post high levels of financing constraints and lower levels of investment. The largest negative cumulative returns generally imply ex post high levels of financing constraints and higher levels of investment.

Comparative statics exercises, presented in Appendix B.5 show stronger momentum effects for more procyclical firms. The correlation between cumulative and expected returns increases for firms that in bad times face lower expected growth rate in cash-flows and higher equity issuance costs. A higher cost of issuing equity during bad times makes the equity market timing option even more valuable in good times, justifying a stronger momentum effect. Timing the equity market also leads to higher investment compared to other financially constrained firms.

Consistent with the evidence of momentum crashes in the data Daniel and Moskowitz [2016], the model predicts large losses to momentum strategies when the state switches from bad to good. In bad states of the world, extreme past performance sorts still focus on the most financially constrained firms, being the subset of firms where productivity shocks have the largest price impact. Firms rely more on credit lines compared to good times and deter from issuing external equity. As a result, the relationship between capitalisation and risk is monotonic: firm risk always increases following negative cash-flow shocks and always declines following positive cash-flow shocks. Cumulative and expected returns therefore correlate negatively (as shown in Panel B). This means that in bad times, losers have higher risk premia than winners, resulting from both high productivity and high state betas. When the state switches to a good one, because of the higher betas, the prices of loser firms increase the most. This translates to large positive returns to the loser leg. Momentum strategies, being short the losers, incur large losses.

2.3.6 Cross-sectional simulations

The state of the market and differences in financing positions drive the profitability of value and momentum strategies in the model. Cross-sectional heterogeneity with respect to financing positions can be obtained even through simulations based on only one parameter set. To show the importance of financing positions on the two premia, I first conduct simulations using only the set of parameters for the average firm. I simulate 680 months at the daily frequency, dropping the first 200 months to obtain a steady state distribution. That leaves 40 years of simulated data. To conduct the simulations, I discretise the model. Using the same parameter set, I repeat the simulation 3,000 times. The size of the panel is chosen to match the size of the datasets used in the empirical studies. In the simulated dataset, I construct value and momentum portfolios. Value portfolios buy the decile with the highest capital-to-price ratio, $K/P(W,K,s)$, and sell the decile with the lowest. Momentum buys the decile with the highest cumulative returns over the previous year, skipping the most recent month, and sells the decile with the lowest cumulative returns. To observe the timing of the profitability of momentum strategies, I construct the portfolios using holding periods from one month to 5 years.

The results show that, even with only one parameter set, the model produces significant positive returns to value and momentum strategies and a negative correlation between the two. The model produces a momentum premium of 0.26%, with a test statistic of 1.98. A sort on book-to-market also yields a positive premium of 0.28%, with a test statistic of 2.36. The correlation between the simulated value and momentum returns is -0.03, negative but much smaller compared to the data.

To bring the model closer to the data, I introduce additional cross-sectional heterogeneity by changing some of the key technology and external financing parameters. These include the expected cash-flow growth rate μ, investment adjustment costs θ, the fixed cost of equity issuance ϕ and the capital liquidation value l. I draw the parameter values from a discrete set around the values for the average firm presented in Appendix B.3, as opposed to drawing them from specific distributions. Without estimating the model, the distributions of the parameters are unknown. Estimation of the model would provide valuable insights, but remains outside the scope of this paper.

The second set of simulations also involves panels of 3000 firms for 680 months. Similar to the previous simulations, I drop the first 200 months, leaving 40 years of monthly data. The additional heterogeneity does provide higher value and momentum premia. The average return to the momentum strategy is 0.69%, with a t-stat of 4.23, while the average return to the value strategy is 0.35%, with a t-stat of 2.8. Figure 2.5 shows the time-series of a 5-year rolling correlation between returns to one set of simulated value and momentum portfolios. The time-series behaviour of the correlation computed on simulated data resembles that of the correlation computed on real data, shown in Figure 2.1. The correlation is negative on average and changes significantly over time, exhibiting a similar market state dependence observed empirically. The model can thus reproduce the negative correlation between value and momentum strategies and the time-series behaviour of their co-movement.

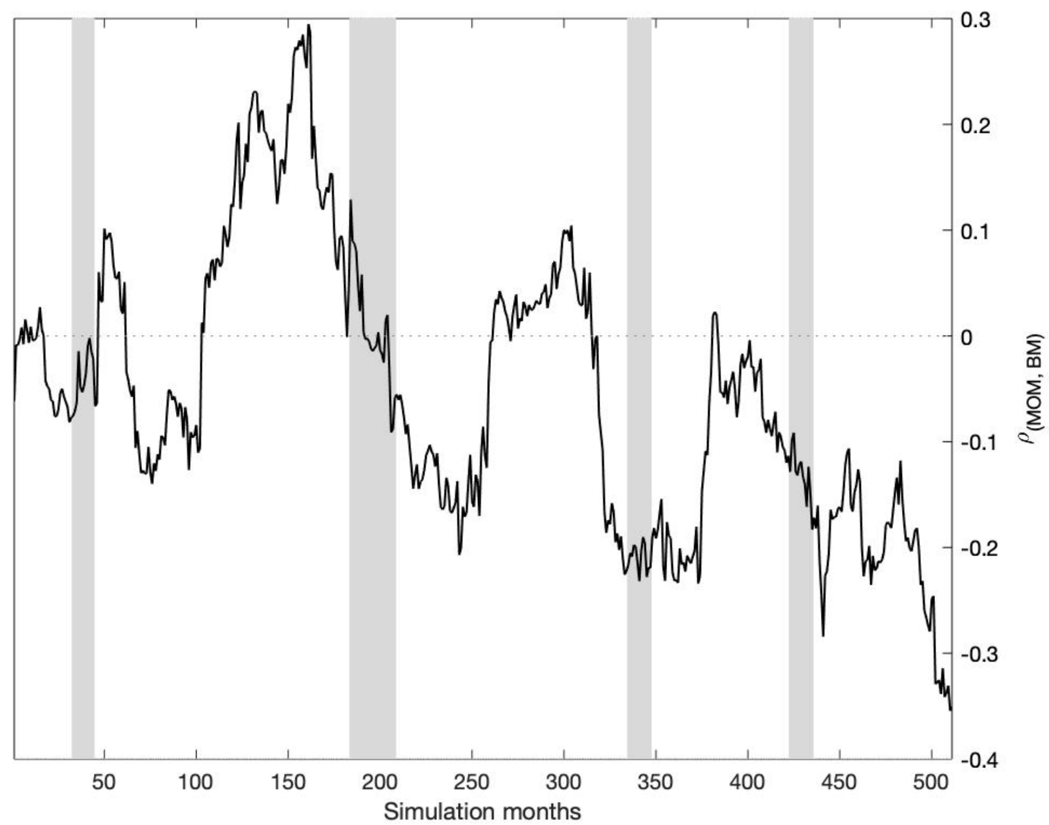


Fig. 2.5 Simulated value-momentum correlation.
The plot shows the correlation between returns to value and momentum strategies constructed on simulated data. Shaded bars indicate states of the market with unfavourable investment and financing conditions. Value and momentum strategies use decile sorts and monthly rebalancing.

An important limitation of the model is that the profitability of the momentum strategy disappears after one month. Empirically, momentum profits persist up to one year after portfolio formation. The reason for the lower persistence in the model relates to the specification of the cash-flow process. The model set up considers Arithmetic Brownian shocks, implying no persistence in cash-flows. Empirical evidence shows such an assumption to be unrealistic. A specification with greater persistence in the cash-flow process provides a promising venue in this regard, but remains to be explored in future research.

2.3.7 Testable predictions

The model provides a unified framework that explains both value and momentum premia. For both anomalies, differences in investment and financing levels justify differences in risk. The dynamics in the model that give rise to value and momentum provide specific predictions regarding the levels and evolution of investment and external financing.

1. The model suggests that the levels of external financing between winners and losers differ significantly at the time of portfolio formation. Following positive cash-flow shocks, winners reduce debt and equity issuance. Following negative cash-flow shocks, losers increase debt and equity issuance. Empirical factors formed on cash-flow shocks and levels of debt and equity issuance should, as a result, correlate with momentum. Novy-Marx [2015] shows that measures of earnings surprises do price momentum. This still leaves open the question of whether firm policies change in response to these shocks.

2. The model predicts investment growth of opposite signs for winners and losers during the period of portfolio formation. Winners experience negative investment growth, and losers experience positive investment growth.

3. The model suggests that both winners and losers are high investment firms. Model simulations show that in the region where the equity market timing option is in-the-money, $p''_G(w) < 0$, investment increases with the correlation between cumulative and expected returns:

$$\frac{\partial i_G(w)}{\partial \rho(CER_t, EER_t)} > 0. \tag{2.6}$$

Momentum strategies, as a result, have high levels of investment. This also implies that a sort on investment does not capture the returns to momentum strategies. The reason is that an investment factor buys low investment firms and sells high investment firms, thus being short both winners and losers.

4. The model predicts a positive difference between the investment levels of low book-to-market and high book-to-market firms. The difference is predicted to increase during down markets.

2.4 Empirical results

This section provides the results of the empirical tests of the hypotheses developed in the previous section. The investment and external financing of value and momentum firms generally conform with the model predictions.

2.4.1 Momentum and external financing

To test the relation between external financing and momentum proposed in the first hypothesis I construct two factors, one based on debt and one on equity issuance. I follow a similar methodology to Fama and French [1992], using 2×3 sorts on each factor and size. The long debt portfolio return represents the (simple) average of the returns to small and large firms in the low debt tercile. The short debt portfolio return represents the (simple) average of the returns to small and large firms in the high debt tercile. I construct the equity issuance factor similarly. Portfolios use value-weights and NYSE breakpoints. Similar to the previous computations, debt is the sum of long term debt and debt in current liabilities (Compustat quarterly variables DLTTQ and DLCQ respectively). I use quarterly data and lag debt by one quarter. Equity issuance is measured by cash proceeds from the issuance of common and preferred stock (Compustat item SSTK from the Statement of Cash Flows). I obtain cash proceeds from equity issuance from the annual statement, as opposed to the quarterly statements. Because they represent a flow variable, observing the flows over a longer time frame provides a better picture of relative firm issuance activity and financial position over the formation period of the momentum strategy.

The debt factor delivers a positive premium of 0.18% per month, with a t-statistic of 2.61. Unreported regressions of the debt factor on the Fama and French three and five factors show that neither of the models can explain its returns. The intercepts of the regressions are around 0.40% per month, with t-statistics greater than 5.40. Notably, exposures of the debt factor on the Fama and French factors have similar signs to those of momentum. The equity issuance factor also delivers a positive premium, averaging 0.19% per month, with a t-statistic of 1.89. The equity issuance factor, however, is completely subsumed by the Fama and French factors. Neither of the two premia achieves the threshold of Harvey, Liu, and Zhu [2016] of 3 on the test statistic. The purpose here is not to propose new asset pricing factors, but to show the presence of a relationship between value and momentum and underlying firm fundamentals.

Table 2.3 presents spanning tests on momentum, value and a 50/50 combination of the two. Value and momentum factors are constructed using the 2×3 factor formation methodology as well. The regressors include the Fama and French five factors: the market factor (MKT), the size factor (SMB), the investment factor (CMA) and the profitability factor (RMW), as well as two additional external financing factors, DEBT and SSTK (equity issuance). Over the period May 1973 to December 2018 the momentum factor earns an unconditional risk premium of 62 basis points, with a test statistic of 3.32. May 1973 serves as the starting point for the regressions due to limited data availability on external financing prior to this period. The second and third specifications regress returns to momentum on the Fama and French three and five factors. The alpha on momentum is high and significant against the Fama and French three factors. It is lower but still positive and significant against the Fama and French five factors.

The alpha on momentum disappears when adding the two additional external financing factors. It declines from 0.65 to 0.25, a value statistically indistinguishable from zero. Momentum loads positively on debt and equity issuance, consistent with the prediction that winners rely less on external financing compared to losers. The fifth specification adds the value factor to the specification in (4). Because of the negative correlation between value and momentum, including value among the regressors makes the alpha on momentum higher. The alpha remains statistically insignificant. The final specification for momentum considers only the Fama and French three factors and the external financing factors. The alpha is still low

Table 2.3 Spanning tests.
This table shows the results of regressions of the monthly returns of the Fama and French value, momentum factors and an equally-weighted combination of the two on different explanatory variables. These include the Fama and French five factors: the market factor (MKT), the size factor (SMB), the investment factor (CMA) and the profitability factor (RMW). The additional factors include a factor constructed sorting on the debt to assets ratio (Debt), cash proceeds from equity issuance scaled by assets (SSTK) and a proxy for the relative distance from target cash (DTC). The sample period covers May 1973 to December 2018. Newey and West test statistics are presented in paretheses.

	Momentum						Value			50/50 Combination			
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(1)	(2)	(3)	(4)
α	0.62	0.84	0.65	0.25	0.33	0.29	0.31	0.42	0.00	0.46	0.55	0.31	0.21
	[3.32]	[4.83]	[2.91]	[1.05]	[1.38]	[1.40]	[2.53]	[2.96]	[-0.02]	[4.59]	[5.54]	[2.75]	[1.72]
β_{MKT}		-0.19	-0.13	-0.07	-0.07	-0.07		-0.18	0.00		-0.15	-0.06	-0.04
		[-1.83]	[-1.72]	[-1.09]	[-1.18]	[-1.23]		[-3.95]	[0.05]		[-4.11]	[-1.61]	[-1.22]
β_{SMB}		0.02	0.06	0.16	0.16	0.14		0.01	-0.02		0.01	0.03	0.08
		[0.14]	[0.56]	[1.52]	[1.20]	[1.26]		[0.10]	[-0.28]		[0.23]	[0.64]	[1.63]
β_{HML}		-0.37	-0.59		-0.46								
		[-2.64]	[-3.70]		[-3.26]								
β_{CMA}			0.49	0.02	0.30				1.02			-0.46	0.31
			[1.85]	[0.09]	[1.20]				[14.60]			[-4.19]	[2.64]
β_{RMW}			0.23	0.13	0.08							0.14	0.01
			[1.17]	[0.73]	[0.49]							[1.49]	[0.16]
β_{Debt}				1.01	0.82	1.01							0.31
				[4.41]	[3.35]	[4.54]							[2.56]
β_{SSTK}				0.45	0.62	0.51							0.41
				[2.42]	[3.17]	[2.61]							[4.38]
$R^2\,(\%)$		7.32	10.40	17.68	21.06	17.38		7.51	47.81		1.78	21.61	29.87

and statistically insignificant. These results confirm the model prediction that momentum winners and losers differ in terms of their use of external financing. A SUE factor alone, as shown in Novy-Marx [2015], has a larger effect on momentum, causing the alpha to become negative. This implies that behavioural biases, slow information diffusion or other potential explanations also play a role. The results in Table 6 show that changes in fundamentals play the most important role.

The second panel in Table 2.3 provides spanning tests on the value factor. Specification (1) shows that value earns an unconditional premium of 31 basis points with a test statistic of 2.53. Value earns a positive and significant alpha relative to a specification that includes a market and a size factor (specification (2)). The third specification shows that the investment factor alone is able to capture the returns to the value premium. This is consistent with the model, where low average q (market-to-book ratio) firms invest less compared to high average q firms.

The third panel in Table 2.3 provides spanning tests on the equal-weighted combination of value and momentum. Asness et al. [2013] argue that the high Sharpe ratio of the combination represents an even greater challenge for rational explanations. The value-momentum combination earns an unconditional premium of 46 basis points with a test statistic of 4.59. It has a positive and significant alpha relative to both the Fama and French two and four factors (I exclude value from the regressors) . The final specification includes the Fama and French four factors as well as the debt and equity issuance factors. The alpha becomes statistically insignificant, with the external financing factors pricing the momentum exposure and the investment factor pricing the value exposure. These results show that insights from a dynamic investment model that incorporates external financing are useful in explaining the value and momentum premia as well as their co-movement.

The differences in debt and equity issuance between winners and losers have a temporary nature, consistent with the temporary nature of momentum profits. Figure 2.6 presents the dynamics of average debt separately for good times (up markets) and bad times (down markets) [9]. The sample period covers May 1973 to December 2018. The strategy uses monthly rebalancing, leading to 540 cross-sections of firms sorted on past performance over this period. I compute the

[9] I define market states based on the ex-ante bear market indicator, that equals one when the cumulative return on the market over the previous year has been negative and zero otherwise. Because this indicator strongly differentiates times when the strategies work and times when they do not, I refer to it to see how fundamentals change when the strategies work and when they do not. The Appendix contains the evolution of the statistics when defining market states based on NBER recession months. The results do not differ.

value-weighted average debt for each decile in each cross-section, starting from 24 months before the respective portfolio formation up to 24 months after. The plots show the time-series average of the debt level for a given month relative to formation for each past performance decile over the 540 portfolios. Portfolio 1 represents the winners and portfolio 10 represents the losers.

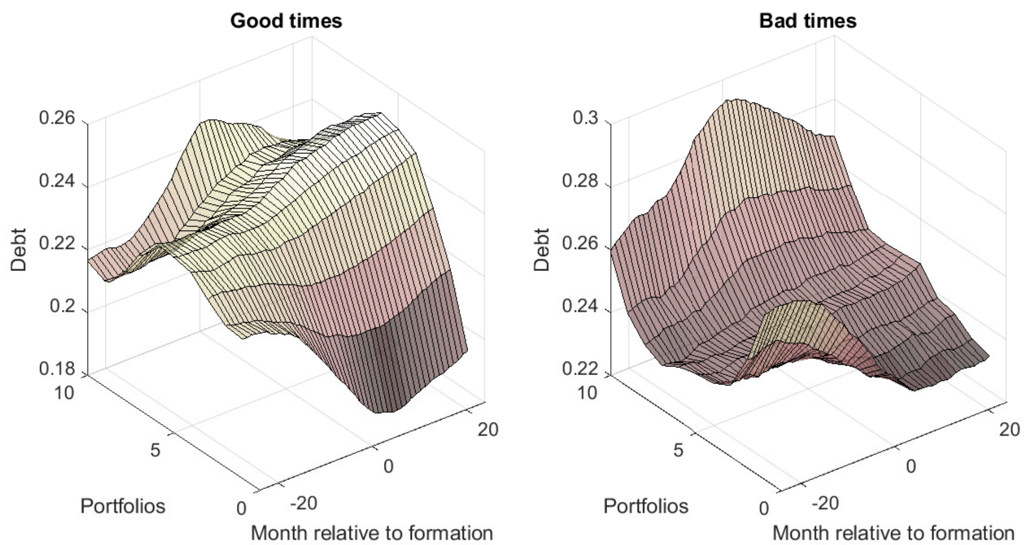


Fig. 2.6 Evolution of debt for past performance portfolios.
The plots show how average portfolio debt changes around momentum portfolio formation. Average debt is the value-weighted average of the debt-to-assets ratio for each of the ten past performance portfolios. The statistics are computed starting from two years before formation, up to two years after. Panel A shows the average evolution of investment in periods when the cumulative return on the market over the previous year has been positive. Panel B shows the average evolution of investment when the cumulative return on the market over the previous year has been negative. The sample period covers May 1973 to December 2018.

Both panels show similar debt levels of winner and loser portfolios up to a year before formation. Compared to the intermediate portfolios, debt levels of winners and losers are lower in good times and higher in bad times. These results conform with the model suggesting that firms with the higher market timing motive issue equity sooner and rely less on debt. The market timing motive is strong for both winners and losers, explaining the low debt levels in the cross section for the two portfolios in good times. In bad times, it is these firms that rely more on debt, explaining the higher debt levels of winner and loser portfolios in these periods. Consistent with the model prediction, starting from one year before formation the debt level of the winner portfolio declines, while the debt level of the loser portfolio increases. The timing of the change in the debt coincides with the timing of the computation of cumulative returns in a momentum sort. In month zero the difference in debt levels between winners and losers reaches its maximum. This holds for both good and bad times, with the difference in debt levels being highest in good times. In unreported results, changes in long term debt rather than in current liabilities drive the changes in total debt, indicating that winners use the positive cash-flow shocks to reduce their reliance on long-term debt. Appendix B.6 presents the evolution of equity issuance for winners and losers. Consistent with the model prediction, losers issue more equity than winners during portfolio formation. The temporary nature of these dynamics is consistent with the temporary nature of momentum profits. These results explain why the debt and equity issuance factors can capture momentum profits as shown in Table 2.3.

2.4.2 Momentum and Investment

The results in Table 2.3 also show that the investment factor, CMA, long low investment firms and short high investment firms, does not play a significant role in pricing momentum. The loading is positive, consistent with Chen and Zhang (2008). The positive loading indicates a lower level of investment for winners compared to losers. Compared to the entire cross-section, however, the model predicts a relatively high level of investment for both legs of the momentum strategy. An investment factor, thefore, would be short both winners and losers.

Table 2.4 Conditional double-sorts.
This table shows the performance of momentum portfolios constructed using dependent double sorts on investment, equity issuance and debt. Investment is the year-on-year change in total assets. Equity issuance refers to the cash proceeds from issuing equity obtained from the cash-flow statement (Compustat variable SSTK). Debt is the sum of long-term debt and debt in current liabilities (Compustat variables DLT and DLC). Equity issuance and debt are scaled by lagged total assets. Portfolio (1) represents the tercile with the high values of the conditional sorting variables. Average returns are presented in percentage terms (× 100). The sample period covers July 1963 to December 2018.

Portfolio	Mean return		
	Investment	SSTK	Debt
High	0.54	0.29	0.30
	[3.08]	[1.93]	[2.01]
(2)	0.09	0.24	0.12
	[0.70]	[1.76]	[0.83]
Low	-0.07	0.07	0.42
	[-0.40]	[0.39]	[2.48]

Table 2.4 presents the results of conditional double sorts on investment and momentum. Firms are first sorted in three portfolios based on their investment levels (investment is measured as the year-on-year change in total assets, lagged using the Fama and French, 1992, methodology). Within each of the three portfolios, firms are sorted into quintiles based on past performance. The returns to the three momentum portfolios along the investment terciles increase monotonically with investment. A momentum strategy is profitable only among high investment firms, earning 54 basis points per month, with a test statistic close to 3, a result that is close to the returns to unconditional momentum strategies. This shows that unconditional momentum strategies concentrate on high investment firms. Table X in the Appendix shows the performance of independent double sorts on momentum and investment. The results confirm the positive relationship

between momentum and investment. High minus low past performance portfolios yield positive and significant returns only among the high investment firms.

Table 2.4 also presents the results of conditional double sorts on equity issuance and debt levels and momentum. Because both momentum winners and losers are close to their equity issuance boundaries, in the cross-section they represent the firms that issue equity more often. That is why momentum strategies earn positive and significant premia along the two high SSTK terciles. The returns are marginally significant, however, and this is expected given the differences in equity issuance between winners and losers. The last column shows that the relationship to debt is U-shaped. Momentum strategies are most profitable among the two extreme debt portfolios. This is also expected given the differences in debt levels between winners and losers.

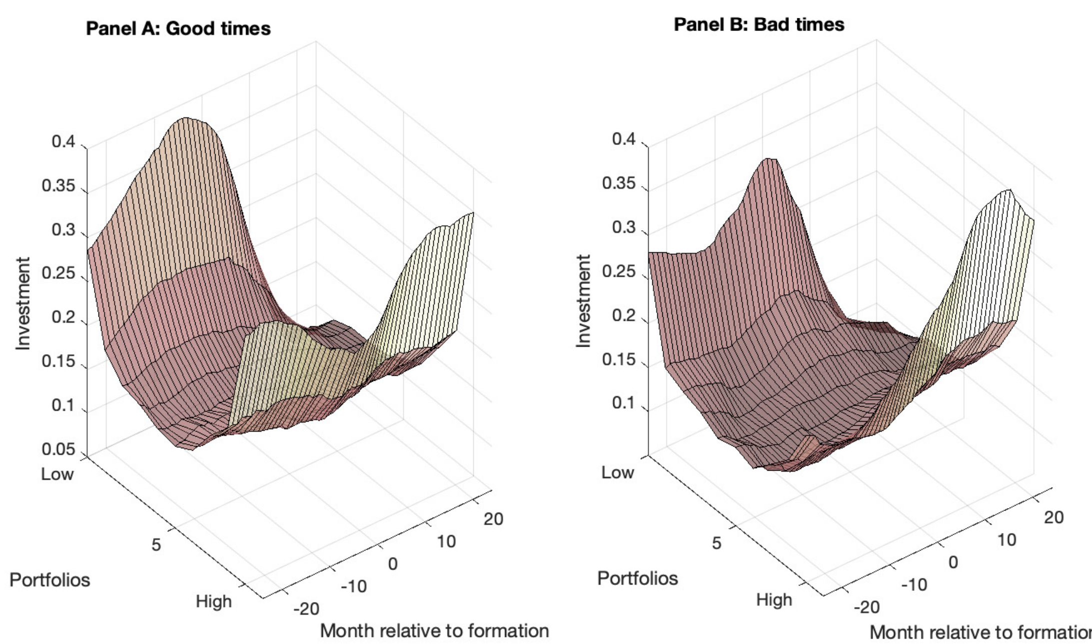


Fig. 2.7 Evolution of investment for past performance portfolios.
The plots show how average portfolio investment changes around momentum portfolio formation. Average investment is the value-weighted average of the year-on-year change in total assets for each of the ten past performance portfolios. The statistics are computed starting from two years before formation, up to two years after. Panel A shows the average evolution of investment in periods when the cumulative return on the market over the previous year has been positive. Panel B shows the average evolution of investment when the cumulative return on the market over the previous year has been negative. The sample period covers May 1973 to December 2018.

What differentiates momentum winners and losers the most in terms of investment is the direction of the changes in investment, that is investment growth. Following positive cash-flow shocks winners decrease investment. Following negative cash-flow shocks, losers increase investment. Figure 2.7 shows the evolution of investment for portfolios sorted on past performance during good and bad times. Both panels show that momentum winners and losers have the highest investment levels in the cross-section. The left panel shows that in good times, the investment of winners and losers changes rapidly. During portfolio formation, winners decrease their investment while losers increase their investment, consistent with the model prediction. The difference in investment levels between winners and losers is highest in month zero. This difference explains the positive loading of momentum on the low-minus-high investment factor. The direction of investment changes reverses during the holding period. The investment of winners increases while the investment of losers declines. A year after portfolio formation, the investment level of winners is much higher compared to that of losers. The reversal in investment growth explains the temporary nature of momentum profits. The dynamics in investment growth are present only in good times, justifying the presence of a momentum premium only during these periods. The right panel shows that the investment of winners and losers does not change much during portfolio formation and that levels of investment in month zero are almost identical.

2.4.3 Value and Investment

Figure 2.8 shows the evolution of investment for portfolios sorted on the book-to-market ratio in good and bad times. In good times, investment generally decreases with the book-to-market ratio, but the relationship is non-monotonic. The difference in investment levels between value and growth firms is small. In bad times, investment monotonically decreases with the book-to-market ratio and there is a large difference in investment levels between value and growth firms. The larger difference in investment justifies the much larger value premium during these periods. In contrast to the evolution of investment for the past performance portfolios, there are no important dynamics over the formation and holding period. This also explains why the returns to value strategies are more persistent compared to those on momentum.

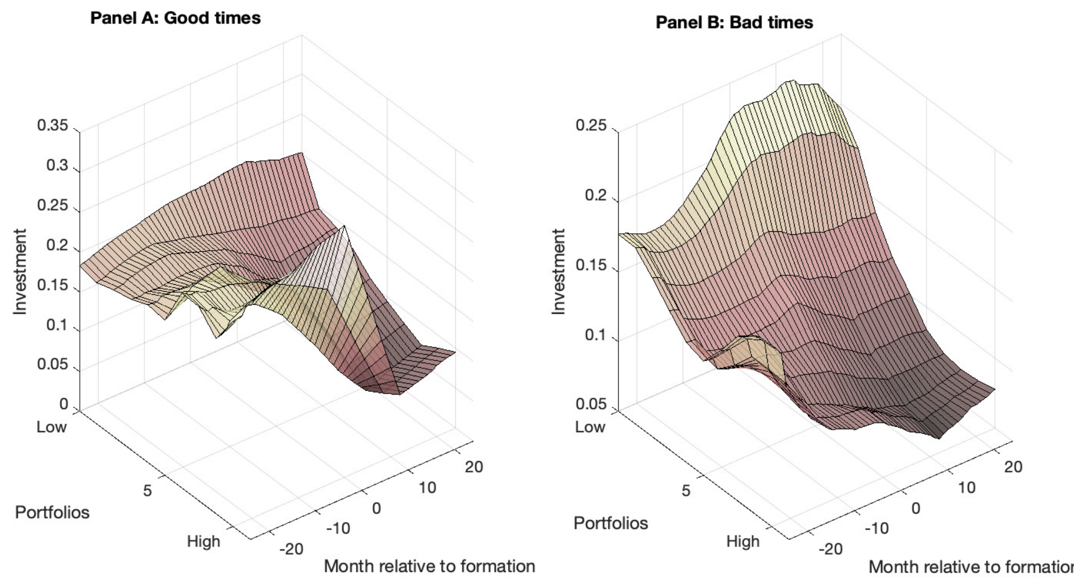


Fig. 2.8 Evolution of investment for book-to-market portfolios.
The plots show how average portfolio investment changes around value portfolio formation. Average investment is the value-weighted average of the year-on-year change in total assets for each of the ten book-to-market portfolios. The statistics are computed starting from two years before formation, up to two years after. Panel A shows the average evolution of investment in periods when the cumulative return on the market over the previous year has been positive. Panel B shows the average evolution of investment when the cumulative return on the market over the previous year has been negative.The sample period covers May 1973 to December 2018.

2.4.4 Investment-adjusted returns

Table 2.5 shows that adjusting returns to investment fully explains both the momentum and value premia, in both good and bad times. The left panel shows the raw returns to the two strategies over the full sample as well as during up and down markets separately. The right panel shows the investment adjusted returns over the full sample as well as during up and down markets. Adjusted returns are computed using the unexplained portion (intercept and residual) of the model: $R_t = \alpha + \beta \,\mathrm{Inv}_t + \varepsilon_t$, where Inv_t represents investment measured as the year-on-year change in total assets (Compustat item AT). The model parameters are estimated using data from month $t-1$ to month $t-60$. Portfolio sorts are based on cumulative past raw returns in both cases. The strategy investment-adjusted return is the difference between the value-weighted adjusted return of the high characteristic portfolio (past performance or book-to-market) and the value-weighted adjusted return of the low characteristic portfolio (past performance or book-to-market). The performace of the portfolios is shown over the full sample, over up-market periods and down-market periods. Up-market periods are defined as years where the cumulative return on the CRSP-value weighted index are positive and down-markets are defined as years where the cumulative return on the CRSP-value weighted index has been negative. The sample period covers July 1963 to December 2018.

Table 2.5 Investment-adjusted returns.
This table shows the performance of momentum and value strategies using raw returns and returns adjusted for investment. Adjusted returns are computed using the unexplained portion (intercept and residual) of the model: $R_t = \alpha + \beta \,\mathrm{Inv}_t + \varepsilon_t$, where Inv_t represents investment measures as the annual change in total assets (Compustat item AT). The model parameters are estimated using data from month $t-1$ to month $t-60$. The performace of the portfolios is shown over the full sample, over up-market periods and down-market periods. Up-market periods are defined as years where the cumulative return on the CRSP-value weighted index are positive and down-markets are defined as years where the cumulative return on the CRSP-value weighted index has been negative. The sample period covers July 1963 to December 2018.

	Raw returns			Adjusted returns		
	Overall	Up-markets	Down-markets	Overall	Up-markets	Down-markets
MOM	1.33	1.62	0.56	-0.16	0.30	-1.37
	[4.25]	[5.06]	[0.74]	[-0.52]	[0.96]	[-1.80]
BM	0.36	0.14	0.93	0.08	-0.21	0.83
	[1.92]	[0.71]	[2.15]	[0.41]	[-1.08]	[1.90]

The results in Table 2.5 show that the investment-adjusted returns of both value and momentum strategies are no longer statistically significant.The model predicts that the sensitivity of returns to investment is highest for the most financially constrained firms. These would include momentum winners and losers as well as value firms in a book-to-market sort. The results confirm the model prediction that investment changes account for the momentum premium. The premium disappears not only unconditionally, but also in good times when it is highest and most significant. The results for value are not particularly strong in bad times. This is still consistent with the model, as it is differences in investment levels rather than investment growth that explain the value premium.

2.5 Dynamic momentum and value strategy

The average negative correlation between value and momentum results in a high Sharpe ratio for a 50/50 combined portfolio. An even higher Sharpe ratio can be obtained by dynamically adjusting the weights on value and momentum using the forecastability of the performance of the two strategies and their correlation by market states. In constructing a dynamic value-momentum combination strategy, I follow a similar methodology to Daniel and Moskowitz [2016]. I obtain the optimal weights by solving a constrained maximisation problem that has the objective of maximizing the combined portfolio expected return subject to the unconditional portfolio volatility being equal to the in-sample volatility of the market. The optimal weight on the momentum strategy is given by:

$$w_{t-1}^{M} = \frac{\mu_{t-1}^{M} - \mu_{t-1}^{V} + \lambda\left(2\sigma_{V,t-1}^{2} - 2\rho_{t-1}\sigma_{M,t-1}\sigma_{V,t-1}\right)}{2\lambda\left(\sigma_{M,t-1}^{2} + \sigma_{V,t-1}^{2}\right)}$$

where w_{t-1}^{M} is the optimal weight on momentum, μ_{t-1}^{M} and μ_{t-1}^{V} represent the conditional expected returns on momentum and value respectively, $\sigma_{M,t-1}^{2}$ and $\sigma_{V,t-1}^{2}$ represent the conditional variances of the momentum and value strategies, ρ_{t-1} is the conditional correlation between the returns to the two strategies and λ is a constant that serves to match the unconditional risk and return of the two strategies. The weight placed on momentum increases when its conditional expected return is higher compared to that of value, when the conditional expected volatility on value is high and the forecasted volatility on momentum is low. The weight on value is computed in a similar manner.

I estimate the conditional means of value and momentum for each month t from the fitted values of regressions of the returns of each strategy on the interaction between an ex-ante bear market indicator and the variance of the daily returns on the market over the preceding six months. The ex-ante bear market indicator is equal to one in months where the return on the market over the previous year has been negative, and zero otherwise. To estimate the covariance, I use a dynamic conditional correlation (DCC) multivariate GJR-GARCH. The parameters of the model are estimated over the full time series using maximum likelihood. The estimates of the variances of each of the strategies are based on a combination of the fitted DCC GJR-GARCH and the strategy realised variance over the 126 days preceding the current month t. I construct the dynamic value-momentum strategy using US data as well as data from other markets such as Japan, Europe and Global stocks. The scaling parameter λ in each market is chosen so as to match the in-sample volatility of the dynamic strategy to the annualized volatility of the respective market portfolio.

Table 2.6 Dynamic value-momentum strategy.
This table shows the performance of a dynamic value-momentum strategy and an equally-weighted value-momentum strategy, during up and down markets in the US, Japan, Europe and Global stocks. Up-markets are defined as periods when the cumulative return on the market over the previous year has been positive. In down-markets the cumulative return of the respective market over the previous year has been negative. The optimal weights in the dynamic value-momentum strategy are computed by solving a constrained maximisation problem that has the objective of maximizing the expected return of a portfolio that combines value and momentum portfolios subject to the unconditional this portfolio volatility being equal to the in-sample volatility of the market. The sample period for the US covers June 1968 to December 2018, while the sample period for the other countries covers January 1991 to December 2018.

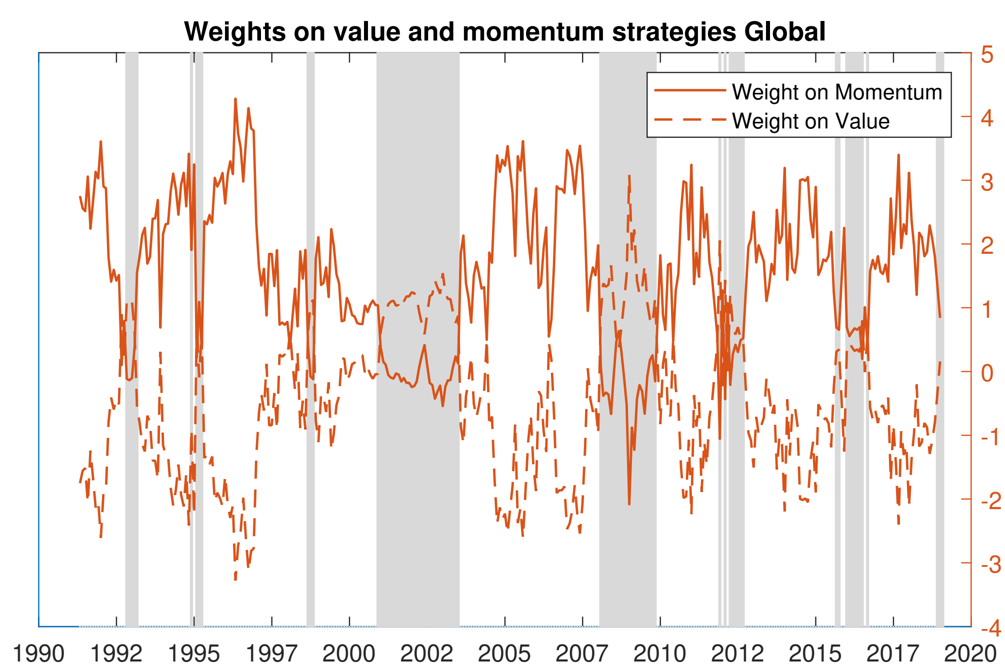
Strategy	Full sample	Good times	Bad times	Sharpe ratio	Full sample	Good times	Bad times	Sharpe ratio
	United States				Japan			
50/50 VM	0.82	0.83	0.78	0.63	0.26	0.20	0.33	0.40
	[4.48]	[4.34]	[1.84]		[1.94]	[1.44]	[1.38]	
Dyn VM	1.22	1.23	1.21	0.75	0.55	0.27	0.90	0.61
	[5.60]	[5.16]	[2.49]		[3.21]	[1.26]	[3.22]	
	Europe				Global			
50/50 VM	0.63	0.59	0.69	1.03	0.44	0.46	0.38	0.72
	[4.99]	[5.82]	[2.26]		[3.49]	[5.51]	[0.96]	
Dyn VM	2.16	2.64	1.16	1.29	1.42	1.44	1.36	0.92
	[6.79]	[6.24]	[2.77]		[4.87]	[4.33]	[2.24]	

Table 2.5 shows the performance of the dynamic strategy versus an equal-weighted combination of value and momentum. The top panel on the left presents performance in the US, over both good and bad times. The other panels show the

performance of the two combination strategies in international markets. In all markets, the dynamic value-momentum strategy achieves higher returns than the equal-weighted combination and a higher Sharpe ratio.

Implementing the dynamic strategy, however, entails considerable transaction costs. Figure 2.9 shows the weights that the dynamic strategy places on value and momentum when considering Global stocks. Given the dependence on market states, the strategy is long momentum in good times and short value. The opposite positions, although at lower scales, are taken in bad times. The weights on each strategy vary substantially, with extremes ranging from 4.1 to -3.2. The results in other markets are similar. It could be the case that the high returns from the dynamic value-momentum strategy may not survive transaction costs. Another source of concern with the results of the dynamic combination strategy is the fact that the weights are determined using parameters estimated over the full available sample. To address this concern, an out-of-sample dynamic value-momentum strategy can be constructed following the same procedure but estimating the parameters using only available data as of time $t-1$.

Fig. 2.9 Dynamic value-momentum strategy weights
This figure shows the dynamic weights on value and momentum obtained from a maximum Sharpe ratio strategy that uses global stocks. The optimal weights in the dynamic value-momentum strategy are computed by solving a constrained maximisation problem that has the objective of maximizing the expected return of a portfolio that combines value and momentum portfolios subject to the unconditional this portfolio volatility being equal to the in-sample volatility of the market. The sample period covers January 1991 to December 2018.



2.6 Related literature

A large volume of empirical work documents the presence of value and momentum premia in the US and international markets. This paper contributes to the empirical literature on both anomalies by showing the dependence of their co-movement on market states. Asness et al. [2013] show that liquidity risk provides a partial explanation for the negative correlation between value and momentum. This paper argues that the negative correlation is generally confined to periods of recessions and especially times when the market starts to rebound. The prediciton of momentum crashes occuring because of the large betas of losers in down markets is consistent with the empirical findings of Daniel and Moskowitz [2016]. The model prediction of value firms being high beta stocks in recessions is consistent with the empirical findings of Petkova and Zhang [2005]. A natural extension is the predicion of large positive returns to value strategies during momentum crash months (market rebounds). The empirical evidence is supportive. The average returns to value strategies when excluding the ten worst months of momentum performance are no longer statistically significant.

A number of theoretical papers are devoted to explaining value and momentum premia, typically by focusing on each strategy in isolation. This paper is one of the few that provide a theoretical basis for both. The framework in Zhang [2005] can provide an explanation for the value premium, but the empirical equivalent of the asset pricing model would be a conditional CAPM. Petkova and Zhang [2005] show time-varying risk goes in the right direction in explaining the value premium, but the beta differentials between value and growth are not sufficient to explain its observed magnitude. This paper specifies two sources of priced risk, thus the model does not collapse to the conditional CAPM. In a similar spirit to Berk, Green, and Naik [1999] and Johnson [2002], this paper proposes an explanation for the momentum premium in a theoretical framework that incorporates systematic risk that is time-varying. The model in Berk et al. [1999] is silent on the relationship between value and momentum as well as momentum crashes. Johnson [2002] is solely focused on momentum, being also silent on value premia and the co-movement.

The framework in this paper predicts that momentum relates to both macroeconomic variables and firm characteristics, consistent with the empirical evidence. Liu and Zhang [2008] show that the growth rate in industrial production is a priced risk factor that accounts for more than half of momentum profits. Chordia and Shivakumar [2002] link momentum to common macroeconomic variables related to the business cycle. Sagi and Seasholes [2007] link firm characteristics, such as revenues, costs and growth options to price momentum. This paper reconciles this evidence by arguing that firm characteristics imply different sensitivities to macroeconomic variables in different states of the economy, and it is these differences that explain the time-series behaviour of value and momentum strategies.

A series of papers link momentum and value to behavioural biases. Lakonishok, Shleifer, and Vishny [1994] and Haugen and Baker [1996] believe that value strategies work because investors systematically make errors in their forecasts or because investors are uncomfortable holding value stocks. Barberis, Shleifer, and Vishny [1998] combine conservatism bias and representative heuristic to explain the timing of the profitability of the momentum strategy. Daniel, Hirshleifer, and Subrahmanyam [1998] link momentum to traders exhibiting a self-attribution bias. This paper proposes a partial equilibrium model. The intuition relies on firm fundamentals, but the exogenous specification of the stochastic discount factor does not rule out the SDF representing the discounting process of a biased investor.

This paper contributes to the investment asset pricing literature, focusing on how the producer's value maximizing decisions on capital transformation affect stock returns. As Cochrane [1991] argues, by fixing the return process in the producer's first order condition, the restriction on the joint stochastic process of investment and asset returns becomes a version of the q-theory of investment. Peters and Taylor [2017] show that q-theory works best for firms that invest heavily in R&D. Winners and losers in a momentum sort, as well as growth firms in a book-to-market sort, have the highest R&D-to-capital ratios in the cross-section. Fixing investment in the restriction on the joint stochastic process of investment and asset returns derives a production based asset pricing model. Given their equivalence, q-theory being well-suited to explaining the investment of high R&D firms implies production based asset pricing models being well-suited to explaining the returns to high R&D firms. This implies that production based asset pricing models would be well-suited for explaining the returns of the firms included in value and momentum portfolios.

Liu and Zhang [2014] represents a closely related paper that builds on the neoclassical theory of investment to explain returns to momentum strategies. They show that the investment model can capture several features of the returns to momentum strategies. However, the model fails to reproduce the procyclicality of momentum as well as its negative interaction with value. I propose a similar framework in continuous time, that incorporates stochastic macroeconomic conditions as well as cash accumulation. These are necessary to reproduce a value premium and a value-momentum correlation consistent with the data.

This paper builds on Bolton et al. [2013], where financing opportunities are stochastic. Incorporating business cycles into a q-theoretic framework as in Bolton et al. [2013] introduces time-varying financing constriants. Time-variation in the cost of financing has two effects: (i) the wedge between the costs of internal and external financing increases during adverse economic conditions and (ii) firms time the equity markets during favourable economic conditions. Both features of this model play a key role in capturing value and momentum. Although several papers explore the effects of financing constraints on stock returns (Lamont, Polk, and Saá-Requejo, 2001, Whited and Wu, 2006, and Livdan, Sapriza, and Zhang, 2009), the evidence is inconclusive. Different definitions of financing constraints as well as the implicit assumption of a monotonic relationship between returns and constraints explain the conflicting evidence. Equity market timing in this model leads to a non-monotonic relationship between risk and financing constraints in good times. This proves essential for producing a momentum premium and the negative correlation with value.

2.7 Conclusion

This paper shows that financing frictions and market timing play a key role in explaning value and momentum premia in stock returns and their co-movement. I first document a new set of stylized facts. The negative correlation between the returns to value and momentum strategies mainly relates to their opposite performance in times when the market rebounds: momentum experiences crashes while value delivers some of its highest returns. In other periods the correlation is weaker and may even turn positive. The time-series of the correlation strongly relates to real variables like aggregate investment and aggregate debt and equity issuance. Motivated by this, I focus on the asset pricing implications of a q-theoretical set up based on Bolton et al. [2013] that accounts for time-variation in external financing opportunities. In this set up, firms that are more procyclical and have low levels of investment require higher expected returns. The model reproduces the profitability of value and momentum strategies as well as the dependence of their correlation on market states. The model predicts large betas for momentum losers and value firms during down markets. This explains their large positive returns when the market rebounds and the resulting negative returns to momentum and positive returns to value.

A series of new testable hypotheses arise. The model predicts that momentum winners and losers differ in terms of their levels of external financing and investment growth. The empirical evidence is largely supportive, showing that factors constructed based on levels of external financing explain the alpha of momentum strategies. Portfolio statistics show negative investment growth for winners and positive investment growth for losers, consistent with the dynamics implied by the model. Also consistent with the model predictions, the difference in investment levels between value and growth firms increases during recessions and down markets, justifying the higher value premium. In light of this evidence, investment and external financing factors explain the returns to a value-momentum $50/50$ combination, which represents a puzzle on its own.

The theoretical set up in this paper considers a partial equilibrium model where the stochastic discount factor is specified exogenously. The exogenous specification cannot distinguish between the effects of rational pricing, learning or sentiment. The empirical evidence provided in this paper, however, being based on firm fundamentals, hints towards a rational story. A general equilibrium set up that also models consumer preferences would be able to answer the question of whether value and momentum do indeed reflect rational pricing. Because the model would not collapse to the conditional CAPM given two sources of aggregate risk, such a set up would be promising.

Chapter 3

Market-Implied Equity Issuance Costs

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Abstract

We estimate time and cross-sectional variation in equity issuance costs using a dynamic model of the firm that considers investment, financing and cash saving policies in the presence of uncertain financing costs. We measure equity issuance based on the daily variation in shares outstanding. This measure identifies issuance events and allows us to exploit data moments related to the quantity issued, its timing and the price reaction, all of which are highly informative of the costs. We estimate the model with a high level of granularity and use it to quantify the importance of the market timing motive for financing policy.

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3.1 Introduction

The costs of equity issuance are an important determinant of financing frictions that constrain investment, external financing and capital structure. Precise measurement is useful to understand whether theories hold (e.g., are firms optimally levered given the costs?) or to gauge aggregate frictions in the economy. Altinkilic and Hansen [2000] show that the underwriting spread changes with issuer quality, implying important cross-sectional variation. Evidence in Eisfeldt and Muir [2016] and McLean [2011] suggests that time-series variation in the costs plays a key role in corporate policies: firms issue more and save the proceeds when the cost of issuance is low, to avoid having to raise large amounts when future costs may be higher.

Equity issuance costs have been measured by looking directly at the reported costs of doing a seasoned equity offering (SEO) (e.g., Altinkilic and Hansen, 2000). Estimates of the average costs based on reports are likely biased downwards because firms expecting higher fixed costs, such as more opaque firms expecting to mount bigger roadshows, will issue less frequently. Model-implied estimates (e.g., Hennessy and Whited, 2007, Eisfeldt and Muir, 2016) are free of this problem. However, existing studies infer the costs from annual data which aggregates issuances and repurchases within a year. Our evidence shows that equity can be frequently issued and retired in the same year and for smaller amounts each time.

The goal of this paper is to estimate the variation in equity issuance costs, cross-sectionally and over time, with as much granularity as feasible. We apply the simulated method of moments (SMM) to a dynamic model that considers optimal firm investment, financing and liquidity management policies in the presence of uncertain financing costs. We estimate the model for 2,370 groups of firms, that we form based on industry classification and market capitalization. The estimated model allows us to quantify the importance of market timing, time-series variation in costs and determine any changes in the behaviour of firms over time regarding their issuance and savings policies.

An important departure from existing literature is measuring equity issues based on the daily change in the number of (split-adjusted) shares shares outstanding. This measure has several advantages. First, due to the high frequency of observation, it pinpoints every issuance event. Therefore, every issuance can be associated to its price reaction. This allows us to exploit moments related to the quantity, timing and price reaction at the issuance event, which is perhaps an event more informative of the value of issuance cost parameters. Second, unless there is an unlikely issuance and repurchase on the same day, this measure provides a clear distinction between issuances and repurchases. Third, dS/S includes all items that generate cash. The measure will, however, also include issues of stock that may not be driven by firm liquidity management policy. We exclude observations that we identify as related to mergers through the SDC Mergers and Acquisitions database. We also impose a minimum issue size of 0.2% of outstanding equity to ensure we do not account for issues related to the exercise of employee stock options, as these may not be costly.

For comparison, we calculate the total amounts issued implied by our measure by dS/S multiplying the average (split-adjusted) share price around the issuance event. Annual issuance proceeds based on dS/S events have a correlation of 0.95 with total annual proceeds in Compustat item SSTK (Sale of Common and Preferred Stock), which accounts for the annual cash proceeds from equity issuance. Issue proceeds from our measure also closely match those from SDC for the SEO universe. Our measure performs similar to SSTK in regressions based on McLean [2011]: cash savings are sensitive to dS/S, with loadings increasing over time as for SSTK.

We estimate a model that builds on Bolton, Chen, and Wang [2013]. This framework provides the tight link between cash savings and external financing policies that has been documented empirically by Kim and Weisbach [2008] and McLean [2011]. This model is best suited to assess the effects of equity market timing behaviour on prices, issuance timing and amounts. But the cash-flow model in Bolton et al. [2013] is not fully realistic. We adopt a cash-flow structure that accounts for permanent and transitory shocks, motivated by evidence in Gryglewicz, Mancini, Morellec, Schroth, and Valta [2020] (GMMSV) showing that policy choices related to cash holdings and equity issuance depend on the nature of these shocks. To achieve maximium possible granularity in the estimates, we estimate the model for 2,370 groups of firms. We group firms ex-ante on their three-digit SIC industry classification and market capitalization, given our evidence of substantial differences in the frequency and amounts issued by firm size.

We calibrate most of our parameters directly from the data. Given the high level of granularity of the cash-flow parameter estimates in GMMSV, we use those values in our simulations, so that we can focus on the costs. We set the values of the market prices of permanent and short-term cash-flow risk equal to the Sharpe ratios of two portfolios that we form based on short-term and permanent cash-flow shocks identified in GMMSV. These portfolios buy the firms with the highest correlation of short-term (permanent) shocks to average market short-term (permanent) shocks and sell firms with the lowest shock correlations. Notably, exposure to permanent cash-flow risk earns higher returns compared to short-term cash-flow risk. This evidence is consistent with the long-run risk literature, arguing asset prices are driven by concerns regarding long-term growth.

To estimate the equity issuance cost parameters we target several moments. The first set of moments relate to firm issuance activity. The frequency of issues is informative of the fixed cost, while the mean, volatility and skewness of the issue size are informative of the variable costs. Next, we target moments from regressions that relate to the probability of issuance based on the current level of the cash balance, using two different forecasting horizons. The intercept of these regressions is informative of both issuance cost parameters, as well as liquidation values. All these parameters are also sensitive to the mean and volatility of cumulative abnormal returns (CAR) measured around the issuance event. Finally, we match policy moments such as the average cash-to-assets ratio, the mean and variance of investment, the covariance between cash and investment as well as the covariance between equity issuance and investments. These moments are informative of the issuance, liquidation and investment adjustment costs.

We cannot yet report the final results of the estimation, but we next discuss the expected outcome and possible uses of the estimated model. Our average estimate of the fixed issuance cost should be lower compared to Hennessy and Whited [2007], given the higher frequency observed from dS/S. The smaller amounts per issue that we identify, in contrast, imply higher average estimates of the variable costs compared to Hennessy and Whited [2007]. An interesting exercise is to exclude data related to SEOs, as identified by SDC, and observe whether estimates of the issuance costs change. Repeating this analysis by decade would allow us to observe the time-series variation of the costs and thus determine whether firm issuance behaviour has changed. If estimates do change significantly over time, it could be that the SEO concept has disappeared. This would imply that firms do not raise money for specific projects, but they raise money when it is cheap to do so, in case opportunities arise.

Another important use of the estimated model is to quantify the effect of market timing on Tobin's Q and cash policy by conducting counterfactual analysis, where we estimate the change in cash target and Tobin's Q in an alternative model where equity issuance costs are constant. This exercise allows us to determine the relative importance of dynamic trade-off models and market timing motives in capital structure decisions. Rather than arguing one is true and the other false, we can use a model nesting both drivers.

The paper is organised as follows. Section 3.2 reviews the related literature. In Section 3.3 we present the model. We discuss the construction of our equity issuance measure, how it compares to existing measures and present statistics on the market price reaction around the identified issuance events in Section 3.4. Section 3.5 describes our empirical strategy and in Section 3.6 we discuss alternative uses of the model.

3.2 Literature review

Our work relates to the large literature that focuses on measuring equity floatation costs. A series of papers rely on underwriting fees from SEO data (e.g. Smith, 1977, Eckbo and Masulis, 1992, Altinkilic and Hansen, 2000)[1]. Estimates range between 4% and 5% of the issuance proceeds, with Kim et al. [2010] reporting a clustering of SEO underwriting spreads at 5%. Our work differs in two important ways. First, we use a large dataset that is not confined only to SEOs. Second, we do not look at underwriter spreads directly, but obtain model-implied estimates of the total cost of issuance. Importantly, this total cost estimate also accounts for indirect issuance costs, such as underpricing, announcement effects as well as any potential costs associated with changes in the capital structure of the firm.

[1]Other related papers include: Hansen and Pinkerton [1982]; Drucker and Puri [2005]; Hansen and Torregrosa [1992]; Denis [1993]; Bøhren, Eckbo, and Michalsen [1997]; Gajewski and Ginglinger [2002]; Kim, Palia, and Saunders [2010]; Butler, Grullon, and Weston [2005]; Lee and Masulis [2009].

We follow a structural estimation approach to identify of both direct and indirect costs of issuance. In fact, model-implied estimates in Hennessy and Whited [2007] are larger than the ones reported in studies that focus on direct costs only, showing that indirect costs can be substantial[2]. In a closely related work, Eisfeldt and Muir [2016] consider the dynamic interaction between firm external financing and liquidity policies and estimate the time-series variation of financing costs. However, they refer to the total cost of external financing, thus considering the average cost of debt and equity issuance[3]. Belo, Lin, and Yang [2019] focus explicitly on the cost of issuing equity and the effect of time-variation in this cost on asset prices. They employ a framework that, similar to ours, is closely related to Bolton et al. [2013]. A key difference in our paper is the use of moments around the issuance event, which are highly informative about the issuance cost parameters and cannot be computed from Compustat data. Additionally, we can provide estimates of cross-sectional variation of the costs at a much higher level of granularity.

Our paper also relates to the large literature that analyzes stock price behaviour around equity issuance. Return data is especially informative of indirect costs such as underpricing. Most of the existing literature focuses on the price reaction to SEO announcements (e.g. Asquith and Mullins [1986]; Korajczyk, Lucas, and McDonald [1990]; Jegadeesh, Weinstein, and Welch [1993]; Altinkilic and Hansen [2003])[4]. These studies consistently find negative announcement returns that average around -2%. In contrast, we find a positive price reaction, with an average of 0.19% in our expanded dataset.

Finally, our paper also belongs to the corporate finance literature that analyzes the effects of permanent and transitory shocks on corporate policies (e.g. Gorbenko and Strebulaev [2010]; DeMarzo, M. Fishman, and Wang [2012]; Décamps et al. [2017]; Gryglewicz et al. [2020]). We use the more realistic cash-flow process specified in Décamps et al. [2017] and

[2]For example, Hennessy and Whited [2007] estimate a fixed cost of 8.3% of the gross issuance proceeds and a marginal cost with a slope of \$616 per million. In contrast, Altinkilic and Hansen [2000] estimate a fixed cost of 5.1%, and a marginal cost with a slope of \$299 per million.

[3]Distinguishing between debt and equity is important because potentially different cyclical behaviour of the two series makes it difficult to examine time-variation of equity issuance costs based on the aggregate external financing cost index in Eisfeldt and Muir [2016]. The evidence on the cyclical behaviour of debt and equity is mixed. For example, Jermann and Quadrini [2012] find that debt is procyclical and equity issuance is countercyclical, while Korajczyk and Levy [2003] find the opposite results: countercyclical debt issuance and procyclical equity issuance. This means that, while the aggregate may be procyclical, either debt or equity issuance could be countercyclical due to substitution between the two.

[4]Related papers also include: Hansen and Crutchley [1990]; Eckbo and Masulis [1992]; Masulis and Korwar [1986]; Mikkelson and Partch [1986]; Kalay and Shimrat [1987]; Slovin, Sushka, and Bendeck [1994]; Denis [1994]

Gryglewicz et al. [2020]. Our contribution stands in examining the asset pricing implications of permanent and transitory shocks around equity issuance events.

3.3 The model

In this section we present the model set up, building on the framework in Bolton et al. [2013] that considers optimal cash savings, financing and investment decisions of a firm facing stochastic equity issuance costs. We adopt the cash-flow structure in Décamps et al. [2017] that incorporates correlated permanent productivity shocks and short-term cash-flow shocks. Given this set up, we describe the risk-adjustments and the model solution. In the last subsection we derive an expression for the stock return around the equity issuance event, that explicitly links the price reaction to the equity issuance cost parameters and the issue size.

3.3.1 Set up

There are two possible states of the macroeconomy, denoted by $s = 1,2$, with different financing opportunities. In each state, there is a constant probability ζ_s that the state switches to the other.

The firm employs physical capital K for production, which evolves according to:

$$dK_t = (I_t - \delta K_t)\,dt, \tag{3.1}$$

where $\delta \geq 0$ is the capital depreciation rate and I_t is investment at time t.

Operating revenues are proportional to capital K (constant returns to scale). Revenues are subject to both permanent and transitory shocks. Permanent shocks affect the productivity of assets, denoted by P, which follows a geometric Brownian motion:

$$dP_t = \mu\, P_t\, dt + \sigma_P\, P_t\, dW_t^P \tag{3.2}$$

where μ and σ_P denote the drift and volatility of the productivity process. $W^P = \left(W_t^P\right)_{t\geq 0}$ is a standard Brownian motion. Revenues are also subject to transitory shocks that do not affect productivity, P. Denoting cash-flows per period by dA_t, produced by each unit of installed capital K_t, the per period cash-flow is given by:

$$dA_t = \alpha\, P_t\, dt + \sigma_A\, P_t\, dW_t^A, \tag{3.3}$$

where α and σ_A denote the drift and volatility parameters of the cash-flow process, and $W^A = \left(W_t^A\right)_{t\geq 0}$ is a standard Brownian motion. W^P and W^A can be correlated:

$$dW_t^P\, dW_t^A = \rho\, dt,\ \text{with}\ \rho \in [-1, 1], \tag{3.4}$$

where ρ denotes the correlation coefficient between short-term and productivity shocks. Operating revenues can then be re-written as:

$$K_t\, dA_t = K_t\left[\alpha\, P_t\, dt + \sigma_A\, P_t\left(\rho\, dW_t^P + \sqrt{1-\rho^2}\, dW_t^T\right)\right],\ t \geq 0, \tag{3.5}$$

where $W^T = \left(W_t^T\right)_{t\geq 0}$ is another Brownian motion that is independent of W^P.

The firm can adjust its capital stock over time. The price of capital K is assumed to be proportional to productivity, P, so that the firm does not grow out of this cost. There are adjustment costs to investment, denoted as $G(I,K,P)$. The adjustment cost function is smooth in all three parameters, proportional to productivity P and homogeneous of degree one in investment I and capital K (as in Hayashi (1982)). One can then re-write the total cost of investment as:

$$I_t P_t + G(I_t, K_t, P_t) = g(i_t) P_t K_t, \tag{3.6}$$

where $i_t \equiv I_t / K_t$ is the investment-capital ratio and $g(i_t)$ is given by:

$$g(i_t) = i_t + \theta i_t^2 / 2 \tag{3.7}$$

where $\theta > 0$ is a constant parameter that measures the degree of investment adjustment costs [5]. The operating profit of the firm is then given by:

$$K_t dA_t - g(i_t) P_t K_t dt \equiv \left[(\alpha - g(i_t)) dt + \sigma_A \left(\rho dW_t^P + \sqrt{1-\rho^2} dW_t^T \right) \right] P_t K_t. \tag{3.8}$$

[5] Proof:

$$\begin{aligned} I_t P_t + G(I_t, K_t, P_t) &= I_t P_t \frac{K_t}{K_t} + G(I_t, K_t, P_t) \frac{K_t}{K_t} \\ &= \frac{I_t}{K_t} P_t K_t + \frac{f_1(I_t, K_t) P_t K_t}{K_t} \\ &= i_t P_t K_t + f_2(i_t) P_t K_t \\ &= (i_t + \theta i_t^2 / 2) P_t K_t \\ &= g(i_t) P_t K_t, \end{aligned}$$

where $G(I_t, K_t, P_t) = f_1(I_t, K_t) P_t$ by the fact that the investment adjustment costs are proportional to productivity, P, $\frac{f_1(I_t, K_t)}{K_t} = \frac{K_t f_1(I_t/K_t, 1)}{K_t} = f_2(i_t)$ by the homogeneity property of the investment adjustment cost function and $f_2(i_t) = \theta i_t^2 / 2$, the standard assumption of a quadratic functional form.

The presence of transitory shocks exposes the firm to potential losses. These can be covered by the firm accessing the external financing markets. When external financing is costly, the firm has a motive to build up cash reserves, denoted as M. Cash reserves are assumed to earn an interest rate of $r-\lambda$, where $\lambda > 0$ represents the carrying cost of cash. The following describes the dynamics of the cash holdings of the firm:

$$dM_t = (r-\lambda)\,M_t\,dt + \left[(\alpha - g\,(i_t))\,dt + \sigma_A\left(\rho\,dW_t^P + \sqrt{1-\rho^2}\,dW_t^T\right)\right]P_t\,K_t - dL_t + dE_t, \tag{3.9}$$

where L_t and E_t are a non-decreasing processes that represent the cumulative (endogenous) dividend paid to shareholders and the cumulative net external financing obtained up to time $t \geq 0$, respectively. The cost of raising net proceeds dE_t is given by:

$$\phi_{s_t}\,K_t\,P_t\,1_{(dE_t>0)} + \gamma_{s_t}\,dE_t, \tag{3.10}$$

where ϕ_{s_t} denotes the fixed cost of equity issuance in state s_t, γ_{s_t} denotes the marginal cost of equity issuance in state s_t.

The firm can be liquidated if its cash buffer has reached zero and it is too costly to obtain external financing. In the event of liquidation shareholders recover a value of $l_s < 1$, which is a fraction of firm value at the time of liquidation.

Management chooses optimal policies so as to maximize shareholder value. Profitability P_t, capital K_t and cash savings M_t represent the three state variables in the optimisation. The firm maximizes expected discounted proceeds to shareholders:

$$\mathbb{E}_0^{\mathbb{Q}}\left[\int_0^{\tau_0} e^{-rt}dL_t + e^{-r\,\tau_0}\,(l\,P_{\tau_0}\,K_{\tau_0} + M_{\tau_o})\right] \tag{3.11}$$

3.3.2 Risk adjustments

There are three types of shocks in this economy: (1) permanent productivity shocks, (2) short-term cash-flow shocks and (3) financing shocks. Each type of shock can have both idiosynchratic and systematic components. Permanent productivity shocks and short-term cash-flow shocks are standard Brownian. Financing shocks come from movements in the state variable s_t, which here is assumed to follow a two-state Markov chain with a generator matrix: $\zeta = \left[\zeta_{ij}\right]$. Intuitively, ζ_{ij} represents the probability of the state s_t of switching from i to j per unit of time interval.

The stochastic discount factor (SDF) Λ_t has the following dynamics:

$$\frac{d\Lambda_t}{\Lambda_{t^-}} = -r_{s_{t^-}} - \eta^P \, dW_t^{M_P} - \eta^A \, dW_t^{M_A} + \sum_{s_t \neq s_{t^-}} \left(e^{\left(\kappa(s_{t^-}, s_t)\right)} - 1 \right) dM_t^{\left(s_{t^-}, s_t\right)}, \tag{3.12}$$

where η^P is the market price of systematic permanent productivity shocks $W_t^{M_P}$, η^A is the market price of systematic short-term cash-flow shocks $W_t^{M_A}$ that are independent of $W_t^{M_P}$, $\kappa(s_{t^-}, s_t)$ is the relative jump size of the discount factor when the Markov chain switches from state s_{t^-} to state s_t, and $M_t^{\left(s_{t^-}, s_t\right)}$ is a compensated Poisson process with intensity $\zeta_{s_{t^-} s_t}$,

$$dM_t^{\left(s_{t^-}, s_t\right)} = dN_t^{\left(s_{t^-}, s_t\right)} - \zeta_{s_{t^-} s_t} \, dt, \;\; s_{t^-} \neq s_t. \tag{3.13}$$

Given (3.12), the following describe the risk adjustments for the expected productivity growth rate and mean cash-flow rate under the risk-neutral measure $\mathbb{Q}$:

$$\hat{\mu} = \mu - \chi^P \eta^P \sigma_P, \tag{3.14}$$

$$\hat{\alpha} = \alpha - \chi^A \eta^A \sigma_A, \tag{3.15}$$

where χ^P denotes the correlation between productivity risk W_t^P and systematic productivity risk $W_t^{M_P}$, χ^A denotes the correlation between short-term cash-flow risk W_t^A and systematic short-term cash-flow risk $W_t^{M_A}$.

Risk-averse investors will also require a risk premium as a compensation for the risk of the state of the economy switching. Similar to Bolton, Chen and Wang (2013) this risk is captured through the wedge between the transition intensity under the physical probability measure ζ_s and the transition intensity under the risk-neutral probability measure $\mathbb{Q}$, $\hat{\zeta}_s$. The following relationship holds between the two:

$$\hat{\zeta}_s = e^{\kappa_s} \zeta_s, \tag{3.16}$$

where κ_s captures the risk premium required by the risk-averse investor for exposure to the risk of state switching.

3.3.3 Model solution

Let $V(P_t, K_t, M_t, s)$ denote the value of the firm in state s. The benefits of cash holdings relative to the carrying costs determine an optimal payout policy that is characterized by a profitability- and size-dependent target cash level, denoted as $\overline{M}_s(P_t, K_t)$. This will represent the upper boundary for the cash balance of the firm, beyond which it starts paying out dividends. In a similar vein, there is a lower boundary for cash holdings determined by the optimal external financing policy. The lower boundary, denoted by $\underline{M}_s(P_t, K_t)$, represents the point where the firm decides to issue new equity.

The interior regions: $M \in \left(\underline{M}_s, \overline{M}_s\right)$ **for** $s = 1, 2$**.** In this region, firm value, $V(P, K, M, s)$, satisfies the following system of HJB equations (under the risk-neutral measure $\mathbb{Q}$):

$$
\begin{aligned}
rV(P,K,M,s) = \max_{I}\, &[P\,\hat{\mu}\,V_P(P,K,M,s) + ((\hat{\alpha} - g(i_t))PK \\
&+ (r-\lambda)M)V_M(P,K,M,s) + (I - \delta K)V_K(P,K,M,s) \\
&+ \frac{1}{2}P^2(\sigma_P^2 V_{PP}(P,K,M,s) + 2K\sigma_P\sigma_A\rho V_{PM}(P,K,M,s) \\
&+ K^2\sigma_A^2 V_{MM}(P,K,M,s)) + \hat{\zeta}_s(V(P,K,M,s^-) - V(P,K,M,s))]
\end{aligned}
\tag{3.17}
$$

The first term on the right side of the HJB equation, $\hat{\mu}\,P$, represents the effect of a change in profitability on expected firm value (under the risk-neutral measure); the terms $\hat{\alpha} - g(i_t))PK + (r-\lambda)M$ represent the effect of changes in the cash balance of the firm; the term $(I - \delta K)$ captures the marginal effect of investment; the terms $\frac{1}{2}P^2\,(\sigma_P^2\,V_{PP}(P,K,M,s) + 2\,K\,\sigma_P\,\sigma_A\,\rho\,V_{PM}(P,K,M,s) + K^2\,\sigma_A^2\,V_{MM}(P,K,M,s))$ capture the effects of volatility in cash balances and profitability. The last term represents the expected change in the value of the firm from a change of state from s to s^-.

In each state of the world s, there are three state variables in the optimization problem of the firm. The problem is homogeneous of degree one in PK and M, which allows to express firm value as:

$$V(P,K,M,s) = P\,K\,F_s(c), \tag{3.18}$$

where $c \equiv \frac{M}{PK}$ represents cash holdings scaled by the product of profitability and capital, and $F_s(c)$ is the scaled value function. The derivatives of the scaled firm value function can be derived using Equation (3.18): $V_P(P,K,M,s) = K\,F_s(c) - K\,c\,F_s^{'}(c)$, $V_M(P,K,M,s) = F_s^{'}(c)$, $V_K(P,K,M,s) = -P\,c\,F_s^{'}(c) + P\,F_s(c)$, $V_{PP}(P,K,M,s) = K\,\frac{c^2}{P}\,F_s^{''}(c)$, $V_{PM}(P,K,M,s) = -\frac{c}{P}\,F_s^{''}(c)$, $V_{MM}(P,K,M,s) = \frac{1}{PK}F_s^{''}(c)$.

The ODE in Equation (3.17) can be re-written using these expressions and simplifying as:

$$
\begin{aligned}
(r-\hat{\mu}+\delta)\,F_s(c) = \max_i \Big\{ & i\,F_s(c) + [\hat{\alpha} - g(i) + (r+\delta-i-\lambda-\hat{\mu})\,c]\,F_s^{'}(c) \\
& + \frac{1}{2}F_s^{"}(c)\,\left[\sigma_P^2 c^2 - 2\,\sigma_P\,\sigma_A\,\rho\,c + \sigma_A^2\right] + \hat{\zeta}_s\,[F_{s^-}(c) - F_s(c)] \Big\}
\end{aligned}
\tag{3.19}
$$

Maximizing over i, Equation (3.19) becomes:

$$
\begin{aligned}
(r-\hat{\mu}+\delta-i^*)\,F_s(c) = {} & [\hat{\alpha} - g(i^*) + (r+\delta-i^*-\lambda-\hat{\mu})\,c]\,F_s^{'}(c) \\
& + \frac{1}{2}F_s^{"}(c)\,\left[\sigma_P^2 c^2 - 2\,\sigma_P\,\sigma_A\,\rho\,c + \sigma_A^2\right] + \hat{\zeta}_s\,[F_{s^-}(c) - F_s(c)]\,,
\end{aligned}
\tag{3.20}
$$

where i^* represents the optimal investment-capital ratio, which is given by:

$$
i^* = \frac{1}{\theta}\left[\frac{F_s(c)}{F_s^{'}(c)} - c - 1\right] \tag{3.21}
$$

Equation (3.20) is subject to the following boundary conditions. The productivity- and capital-scaled cash balance of the firm will move between two boundaries: an upper payout boundary $\overline{c}_s$, and a lower equity issuance boundary $\underline{c}_s$.

In the payout region, the marginal value of cash to shareholders is larger than the marginal value of cash to the firm because of the excessive cash carrying costs. When $c > \overline{c}_s$, we therefore have:

$$
F_s(c) = F_s(\overline{c}_s) + c - \overline{c}_s \tag{3.22}
$$

Subtracting $F_s(\overline{c}_s)$ from both sides of the above equation, and dividing by $c - \overline{c}_s$ and taking the limit as c tends to $\overline{c}_s$ shows that $F_s(c)$ satisfies:

$$F_s^{'}(\overline{c}_s) = 1, \tag{3.23}$$

$$F_s^{"}(\overline{c}_s) = 0. \tag{3.24}$$

Equation (3.23) shows that payout optimality means the marginal value of cash at the payout boundary $\overline{c}_s$, is equal to unity. Equation (3.24) denotes the super contact condition (Dumas, 1991).

When the scaled cash balance of the firm c falls below the equity issuance boundary $\underline{c}_s$, firm value satisfies:

$$F_s(c) = F_s(m_s) - \phi_s - (1+\gamma_s)(m_s - c), \ \ c \leq \underline{c}_s, \tag{3.25}$$

where ϕ_s denotes the fixed cost of equity issuance in state s, γ_s denotes the marginal cost of equity issuance in state s and m_s represents the scaled cash balance of the firm after issuance.

At $\underline{c}_s$ the following value-matching and smooth-pasting conditions apply:

$$F_s(\underline{c}_s) = F_s(m_s) - \phi_s - (1+\gamma_s)(m_s - \underline{c}_s), \tag{3.26}$$

$$F_s^{'}(m_s) = 1 + \gamma_s \tag{3.27}$$

Condition (3.26) states that the scaled firm value function in continuous around the equity issuance boundary. Condition (3.27) states that the target cash return level m_s is chosen optimally, so that the marginal benefit of issuance is equal to the marginal cost of issuance $1+\gamma_s$.

At the lower boundary $\underline{c}_s$, optimality implies:

$$F_s^{'}(\underline{c}_s) = 1+\gamma_s. \tag{3.28}$$

The marginal value of cash must be equal to the marginal cost of issuing equity at this lower boundary. If the marginal value of cash is lower, the firm continues to draw down its cash balance. When the cash balance is depleted, if the marginal value of cash is still lower than the marginal cost of issuing equity, the firm considers liquidation. In that event, firm value is given by:

$$F_s(0) = l_s. \tag{3.29}$$

where l_s is the value of the firm in the liquidation event.

3.3.4 Expected returns

Denoting the conditional expected return on the firm by $\mu_j^R(c)$, the system of HJB equations for the scaled firm value function $F_s(c)$ under the physical measure $\mathbb{P}$ is given by:

$$\left(\mu^R(c)-\mu+\delta-i^*\right)F_s(c)=\left[\alpha-g(i^*)+(r+\delta-i^*-\lambda-\mu)\,c\right]F_s^{'}(c)$$
$$+\frac{1}{2}F_s^{"}(c)\,\left[\sigma_P^2c^2-2\,\sigma_P\,\sigma_A\,\rho\,c+\sigma_A^2\right]+\zeta_s\left[F_{s^-}(c)-F_s(c)\right], \tag{3.30}$$

where $\mu_j^R(c)$ represents the expected return on the firm under the physical measure. Subtracting Equation (3.19) from Equation (3.30) gives the expression for the expected excess return $\mu^R(c)-r$:

$$\mu^R(c)-r=\chi^A\,\sigma_A\,\eta^A\,\frac{F_s^{'}(c)}{F_s(c)}+\chi^P\,\sigma_P\,\eta^P\left(\frac{F_s(c)-c\,F_s^{'}(c)}{F_s(c)}\right)-\left(e^{\kappa_s}-1\right)\zeta_s\,\frac{F_{s^-}(c)-F_s(c)}{F_s(c)}, \tag{3.31}$$

where the first term on the RHS represents the risk premium associated with exposure to short-term cash-flow shocks, the second term on the RHS represents the risk premium that compensates for exposure to permanent productivity shocks and the third term is the risk premium that investors require as a compensation for exposure to the possibility of the state switching to one with different financing conditions. Exposure to the three types of shocks changes over time given changes in the scaled cash balance of the firm c and changes in the state of the macroeconomy, s.

Return upon equity issuance

Let RI_t denote the stock return upon issuance. Using Equation (3.25), AN_t is given by:

$$\begin{aligned} RI_t &= \frac{F_s(m_s)-F_s(c)}{F_s(c)} \\ &= \frac{\phi_s+(1+\gamma_s)(m_s-c)}{F_s(m_s)-\phi_s-(1+\gamma_s)(m_s-c)}>0 \end{aligned} \tag{3.32}$$

The return around the issuance barrier is positive and depends on the magnitude of the issuance cost parameters as well as how far below target the firm's cash holdings are before issuance.

3.4 Measuring equity issuance

In this section we describe our proposed measure of equity issuance which relies on changes in the number of shares outstanding from the daily CRSP file. Its key advantages over the existing measures are the greater coverage and identification of the timing of the issuance event.

3.4.1 Review of existing measures

The common source for SEO data is the Thomson One SDC New Issues database. This data set provides information on the announcement date for secondary equity offerings, which is useful for measuring the announcement return. But its coverage is limited. Between January 1970 and December 2018, SDC includes 11,217 deals that can be matched to price data from CRSP. These largely relate to seasoned equity offerings (SEOs), which are relatively infrequent and nowadays an outmoded way of raising cash. The low frequency and large amounts involved in SEOs may not be representative of the average firm issuance activity. Fama and French [2005] show that firms in fact issue new equity much more frequently and in smaller amounts through means other than SEOs. The large fixed costs and small marginal costs inferred from SEO data may there be misleading of the population. The cash raised in SEOs is also typically earmarked for specific projects and therefore, not necessarily related to liquidity management and equity market timing.

Compustat provides an alternative source of information of the amounts of new equity issued, through the item SSTK (Sale of Common and Preferred Stock) from the cash-flow statement. Compustat has a much greater coverage than the

SDC database. However, Compustat reports total annual net issuance and does not include the dates of each issuance event in the year [6].

Fama and French [2005] propose another measure of equity issuance that also relies on Compustat data. They look at the product of the year-on-year change in the number of (split adjusted) shares outstanding with the average (split adjusted) stock price at the beginning and end of the year. The inherent assumption in the construction of this measure is that the average stock price at the beginning and at the end of a fiscal year is a good approximation of the price at which the new equity was issued, which may be a rather strong assumption. Further, this measure represents a net figure between issuances and repurchases within the same year, which means it cannot separately identify new equity issues. Additionally, the reliance on Compustat data implies that the highest frequency at which new issues are measured is quarterly. This makes identification of the timing of the issuance difficult.

3.4.2 An alternative measure

We follow an approach similar in spirit to Fama and French [2005] in measuring new equity issues, but rely on daily data from the CRSP files. We look at the daily (split adjusted) change in the number of shares outstanding. This variable, denoted as dS/S, is given by:

$$dS/S = \frac{Shares_t \times Adjust_t - Shares_{t-1} \times Adjust_{t-1}}{Shares_{t-1} \times Adjust_{t-1}}, \tag{3.33}$$

[6] One problematic feature of SSTK relates to its inconsistent definition. The SSTK variable contains instances where the figure represents the difference between cash inflows from new issues of common and preferred equity and cash outflows from stock repurchases. The SSTK variable represents a net amount also when the new issues are made from the sale of treasury stock. In these cases, SSTK is the difference between the amount issued and the historical cost of the purchase of shares held in the treasury account. In the instances where SSTK represents a net figure, the item underestimates the amount issued. The lower the frequency of the data, the greater the underestimation.

where Shares_t and Adjust_t are the CRSP shares outstanding and adjustment factor for splits in day t. This measure has a number of advantages. First, by looking at the percentage change in the number of shares outstanding we do not need to make any assumptions regarding the sale price of the new equity issued. Second, the daily measurement frequency allows us to identify the timing of the issuance event and therefore measure the market price reaction on that day. Third, unless there is an unlikely issuance and repurchase on the same day, positive changes in shares outstanding can distinguish sales of stock from repurchases, which are negative. Fourth, the number of issues is much larger based on this measure than in other databases.

The larger coverage comes with some concerns. First, dS/S may capture changes in shares outstanding related to mergers and acquisitions. To address this, we exclude observations matched with Thomson One SDC Mergers and Acquisitions. We also impose an upper limit of 100% on the remaining dS/S observations. The second concern is that some issues may include sales of equity that may not be costly or not generate cash, such as the exercise of executive and employee stock options and conversions of debt. Such instances are beyond the scope of the liquidity management theoretical framework we use.

We use the Executive Compensation Database (ExecuComp) to obtain information on the exercise of executive stock options. The reported frequency is annual and does not allow us to match obervations to dS/S. We can, however, use this data as guidance for determining a lower bound. We measure dS/S based on the number of options exercised per year and the associated proceeds based on the average stock price at the beginning and end of the year, as in Fama and French [2005]. In Table 3.1 we report statistics on these measures both at the executive and firm level. Values for dS/S are reported in percentage terms. Average annual proceeds from the exercise of executive options are considerable: \$4.42 million at the executive level and \$ 11.32 million at the firm level. Relative to firm market capitalization, however, the values are small, indicating option exercises are particularly important for large firms. The average change in shares outstanding from the exercise of executive options is 0.07% per year at the executive level, and 0.49% per year at the firm level.

Table 3.1 ExecuComp data
This table shows the average annual proceeds ($m) from the exercise of executive stock options and the associated percentage change in shares outstanding, dS/S (%), at both the executive and firm level, using option data from the ExecuComp database. The product of the number of options exercised per executive per year with the average (split-adjusted) share price for the year serves as the estimate of the option exercise proceeds. The sample covers 47,028 executives from 3,635 firms for the period 1992 to 2016.

Variable	Mean	Std. Dev.	25%	50%	75%
Exec option proceeds ($m)	4.42	22.02	0.37	1.16	3.52
Firm year proceeds ($m)	11.32	47.79	0	1.41	8.39
Exec option dS/S (%)	0.07	0.12	0.01	0.03	0.07
Firm year dS/S (%)	0.49	11.62	0	0.09	0.42

Exercises of employee stock options from non-executives are also substantial. Babenko, Lemmon, and Tserlukevich [2011] report that approximately 82% of option exercise proceeds relate to exercises from nonexecutives (their sample uses hand collected data for the period 2000 to 2005). Taking this into account, we can infer an average of total option exercise relative proceeds of 2.72% per annum at the firm level. Considering that this value is a total over all executives and employees that exercised throughout the year, even a level of 0.3% (a tenth of the annual total) may be a conservative lower bound for dS/S.

We next examine how the distributions of the number and the size of issues per firm, as identified by dS/S, change with firm market capitalization and different lower thresholds. Table 3.2 shows the mean, median and standard deviation of the number and size of issues at four different lower thresholds: 0, 0.2%, 0.5% and 1%, along five firm size portfolios. Issuance behaviour changes significantly with market capitalization. Large firms issue more frequently, but the amounts issued as a percentage of total capitalization are smaller. Increasing the lower threshold has a considerable impact on the number and size of issues by large firms, indicating that a substantial proportion of these issues may relate to the exercise of employee stock options.

Table 3.2 Summary statistics. This table presents summary statistics for the number and size of equity issues per firm. The statistics are shown separately for different size buckets, the first representing small firms, the fifth representing large firms. The last panel sorts firms by book-to-market, with growth representing low book-to-market firms and value representing high book-to-market firms. The CRSP sample covers the period January 1961 to December 2018. The total number of issues identified by the change in shares outstanding is 526,374 (dS variable, excluding instances where it is greater than 1). Excluding issues smaller than 0.2% of shares outstanding, the total number of issues identified is 305,739; excluding issues smaller than 0.5% of shares outstanding, the total number of issues identified is 211,354; when issues smaller than 1% of shares outstanding are excluded, the total number of issues identified is 148,971. When excluding issues smaller than 5% of shares outstanding, the total number of issues identified by dS is 64,027. The SDC database covers 11,217 deals for the period January 1970 to December 2018. The issue proceeds from the SDC database are scaled by the market value of equity in the month preceding the announcement.

	$\Delta S/S > 0$							$\Delta S/S > 0.2\%$					
	No. of issues			Size of issue (%)				No. of issues			Size of issue (%)		
	Mean	Med	SD	Mean	Med	SD		Mean	Med	SD	Mean	Med	SD
Small	2.80	1	4.72	6.39	1.03	13.56	Small	2.12	1	3.76	8.44	2.30	15.05
2	4.89	2	7.56	4.24	0.50	10.72	2	3.26	1	5.09	6.33	1.39	12.63
3	7.62	4	10.75	3.19	0.35	8.99	3	4.63	2	6.45	5.20	1.03	11.08
4	12.49	6	16.23	2.42	0.28	7.47	4	7.04	4	8.86	4.24	0.87	9.56
Large	23.36	11	29.57	1.67	0.21	6.20	Large	11.91	6	15.00	3.21	0.68	8.39

	$\Delta S/S > 0.5\%$							$\Delta S/S > 1\%$					
	No. of issues			Size of issue (%)				No. of issues			Size of issue (%)		
	Mean	Med	SD	Mean	Med	SD		Mean	Med	SD	Mean	Med	SD
Small	1.73	0	3.15	10.23	3.67	16.05	Small	1.41	0	2.65	12.38	5.40	17.09
2	2.46	1	3.87	8.30	2.61	14.00	2	1.88	1	3.05	10.65	4.41	15.28
3	3.28	2	4.62	7.21	2.01	12.63	3	2.34	1	3.38	9.80	3.87	14.13
4	4.76	3	5.98	6.12	1.72	11.15	4	3.24	2	4.17	8.64	3.39	12.73
Large	7.28	4	9.22	5.04	1.38	10.33	Large	4.54	2	5.96	7.65	2.89	12.36

	SDC/ME							$\Delta S/S > 0$					
	No. of issues			Size of issue (%)				No. of issues			Size of issue (%)		
	Mean	Med	SD	Mean	Med	SD		Mean	Med	SD	Mean	Med	SD
Small	1.14	1	0.94	35.99	26.54	40.54	Growth	10.00	4	14.95	2.78	0.33	7.96
2	1.19	1	0.70	24.59	20.77	17.74	2	7.96	4	11.30	2.09	0.24	7.08
3	1.32	1	0.79	19.01	17.07	12.89	3	6.92	3	10.45	1.94	0.22	6.78
4	1.45	1	0.94	14.86	13.02	10.52	4	5.91	3	9.72	2.10	0.25	7.14
Large	2.04	1	1.88	9.54	8.18	6.98	Value	4.44	2	6.72	3.44	0.37	9.81

The effect of an increase from a lower threshold of zero to 0.2% is much larger compared to changes along the higher thresholds. This, coupled with the evidence from Table 3.1, motivates setting the lower threshold to 0.2%. It ensures we exclude option-related issues, while still having a large number of issues per firm that enables estimation of issuance costs at a high level of granularity.

Table 3.2 also reports statistics on issuances measured using SEO data from Thomson One SDC. For comparison purposes, we scale the issuance proceeds from SDC by the market capitalization of the firm at the time of issuance. The frequencies are evidently lower, and the amounts issued larger. The very different statistics and the small sample size of 11,217 (compared to 148,971 for dS/S at the higher threshold of 1%) show that this sample is not representative of average issuance activity.

The last panel in Table 3.2 reports the statistics for $dS/S > 0$ along book-to-market quintiles, where growth firms have lowest book-to-market ratios and value firms the highest. Book-to-market is usually considered a proxy for investment opportunities, but the frequency and size of issues do not change as starkly as compared to firm size, largely used as an indicator of financing constraints. This evidence supports our approach of examining issuance behaviour from the perspective of a liquidity management model.

Given a lower threshold of 0.2%, our final sample covers 305,739 observations for the period January 1963 to December 2018. Table 3.3 reports summary statistics on dS/S, issuance proceeds inferred from the product of dS/S with the average (split-adjusted) share price the day before and the day of the issuance, dSM, the cumulative returns over the three days surrounding the issuance, $CAR_{[-1,+1]}$ as well as statistics on the book-to-market ratio (B/M) and market capitalization of issuing firms (ME). The change in outstanding equity is 4.9% and the issuance proceeds are \$37 million for the average firm. The distributions are skewed, indicating a large proportion of small issues unlikely to be SEOs.

Table 3.3 Summary statistics for issuing firms
This table presents summary statistics on the daily percentage change in the (split-adjusted) number of shares outstanding, dS/S, the issuance proceeds ($\$m$) inferred from the product of dS/S with the average (split-adjusted) share price the day before and the day of the issuance, dSM, the cumulative abnormal return for the three days surrounding the issuance, $CAR_{\{-1,+1\}}$, the book-to-market ratio (B/M) and market capitalization of issuing firms (ME). Cumulative abnormal returns,$CAR_{[-1,+1]}$, are computed as excess returns over the market over the same measurement period. The statistics are computed conditional on issuing firms. All variables, including the adjustment factors for shares and prices, are trimmed at the top and bottom 0.5%. The equity issuance measure, dS/S, excludes values identified as mergers from the Thomson One SDC Mergers and Acquisitions, any remaining observation greater than one as well as observations smaller than 0.2%. The sample period covers January 1963 to December 2018.

	Mean	Stev	Min	25^{th}	50^{th}	75^{th}	Max	No. obs
dS/S (%)	4.90	10.89	0.20	0.42	0.95	3.62	100.00	305,739
dSM ($\$m$)	37.01	530.70	0.00	0.52	2.35	10.88	113,210.00	304,886
$CAR_{-1,+1}$ (%)	0.19	5.95	-23.2	-2.57	-0.10	2.55	32.33	301,300
B/M	0.78	1.573	0	0.221	0.45	0.85	27.67	210,938
ME	1,638.00	9,558.00	0.014	45.01	187.9	773.5	8.957	305,473

Appendix 2 shows how the aggregate issuance proceeds estimated from our measure, dSM, compare to proceeds based on SDC and Compustat data. Figure C.1 compares the proceeds for the sample of firms covered in the SDC database, showing dSM follows the other two measures very closely. Figure C.2 compares dSM with cash proceeds measured by SSTK in Compustat. The left panel compares values when aggregating at the quarterly frequency and the right panel refers to the annual frequency. The correlation of the aggregate annual proceeds from dSM and SSTK is 0.95. The level of dSM is, however, higher. This relates to the fact that dSM uses the average price around the issuance to approximate the issue price, when in reality secondary issues are typically underpriced. For this reason, we refer to dS/S in our empirical implementation, which does not require any assumptions on the issue price. The comparisons of dSM with the other measures, nevertheless, indicate that we are capturing the same issues (in total) while identifying also the time each issue was made.

3.4.3 Market reaction

Table 3.3 shows that the average issuance return is positive at 0.19%. [7].This result stands in contrast to the SEO literature reporting large negative returns associated with new equity issues. The average $CAR_{[-1,+1]}$ surrounding the announcement in the SDC database is -2.40%, consistent with previously reported values. A direct comparison between the two figures may, however, be imprecise because we do know the announcement date for all issues identified by dS/S. To obtain an estimate of the average time between announcement and issuance, we look at the distance between these two dates in the SDC database, which is approximately 9 days. Average returns are still positive even when extending the window of measurement to 20 days before the issuance.

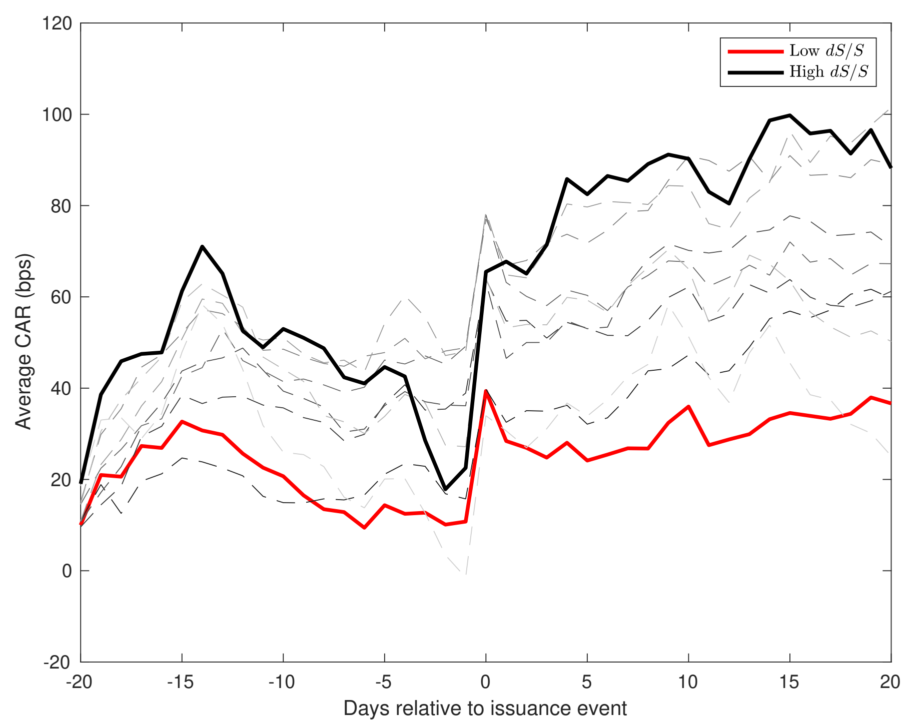

Fig. 3.1 CAR$_{[-20,+20]}$ in event time.
This figure plots the average cumulative abnormal return over a window of $[-20,+20]$ days around issuance as identified by the daily change in shares outstanding, dS/S, for 10 portfolios sorted on dS/S. Dashed lines represent the cumulative returns for intermediate portfolios. The equity issuance measure, dS/S, excludes values identified as mergers from the Thomson One SDC Mergers and Acquisitions, any remaining observation greater than one, as well as observations smaller than 0.2%. The sample period covers January 1963 to December 2018.

[7]CAR around issuance would reflect underpricing and therefore be a better measure of the indirect costs of issuance as compared to the price reaction on the announcement day, which as argued in Altinkilic and Hansen (2000) ague that the price reaction on announcement is not a cost, except for investors who had planned to sell their shares earlier. Further, numerous studies document a lack of relationship between issuance size and price reaction on announcement.

Figure 3.1 shows the cumulative abnormal return, $CAR_{[-20,+20]}$, computed starting from 20 days before the issuance event to 20 days after. The returns are computed for ten portfolios constructed based on dS/S deciles. There is a significant spike in returns on the issuance day for all issue size portfolios. Larger issues are associated with larger returns, but the relationship is not monotonic.

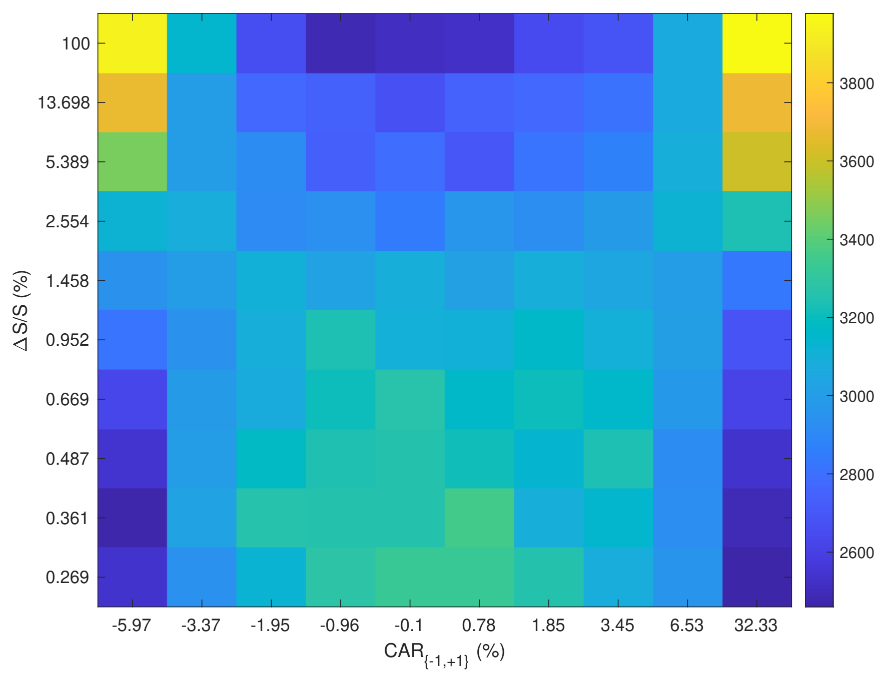

Fig. 3.2 Heatmap of $\mathbf{CAR_{[-1,+1]}}$ and dS/S.
The figure shows a heatmap based on deciles of the percentage changes in shares outstanding, dS/S, and deciles of the 3-day cumulative returns around issuance, $CAR_{[-1,+1]}$. The equity issuance measure, dS/S, excludes values identified as mergers from the Thomson One SDC Mergers and Acquisitions, any remaining observation greater than one, as well as observations smaller than 0.2%. The sample period covers January 1963 to December 2018.

To observe how the return upon issuance changes with issuance size, as measured by dS/S, we construct a heatmap between issue size and $CAR_{[-1,+1]}$, shown in Figure 3.2. The return upon issuance, in absolute terms, increases with issue size. Large issues are either associated with large negative returns or large positive returns. The large issues associated with negative returns may relate to SEOs. This different price reaction at the right tail of the issuance distribution may relate to large issues undertaken by the firm for different motives. Issues such as SEOs related to investment projects may provide a negative signal to the market, as argued in the SEO literature. On the other hand, liquidity related large issues may constitute good news about company fundamentals: the decision to undertake a liquidity motivated issuance reveals firm going concern value is greater than liquidation.

3.5 Empirical strategy

This section describes our sample selection, identification strategy and estimation procedure. We calibrate most of our parameters directly from the data and existing estimates in previous studies. To estimate the equity issuance cost function and other unknown parameters we use the Simulated Method of Moments (SMM).

3.5.1 Data

Our dataset combines accounting information from Compustat and stock price data from Center for Research in Security Prices (CRSP).

The theoretical set up in our paper considers a similar cash-flow environment to Décamps et al. [2017], that more realistically accounts for both permanent shocks to productivity and short-term shocks to cash-flows. GMMSV use a novel Kalman filering technique that identifies the permanent and transitory shocks in a discrete time version of the Décamps et al. [2017] model. They provide estimates of the cash-flow parameters: μ, σ^A, α, σ^P and ρ, which we use in our simulations. This restricts our sample to the one covered in GMMSV.

We refer to the extended GMMSV sample of 15,891 firms, representing 73.38% of all the 21,657 unique gvkey IDs in Compustat. The sample covers the period 1975 to 2016 and excludes financial firms (SIC codes 6000 to 6999), utility firms (SIC codes 4900 to 4999), other regulated firms (SIC codes 8000 to 9999), and firms with asset growth rates above

500% [8]. We match this sample to the daily CRSP file to obtain data on our measure of equity issuances, dS/S, and the market price reactions upon issuance, $CAR_{-1,1}$.

3.5.2 Calibrated parameters

In this subsection we explain our choice of calibration. Table C.4 in Appendix 2 lists the parameters used in the model, distinguishing between aggregate and group-level calibrated parameters, as well as aggregate and group-level parameters to be estimated.

We set the risk-free rate to $r = 5\%$, its average value for the period 1975 to 2015. Based on the average value of the depreciation to total assets in our sample, we set the rate of capital depreciation to $\delta = 15\%$. We set the carry cost of cash to $\lambda = 1.5\%$, similar to [17]. These are all aggregate parameters, with values expressed in annual terms. We also follow Bolton et al. [2013] in setting the market prices of risk for financing shocks to $\kappa_H = \ln 3$ and $\kappa_L = -\ln 3$. These risk adjustments are substantial and affect the wedge between the transition intensities out of each state under the physical and risk-neutral measures.

We use estimates from GMMSV for the cash-flow parameters (μ, σ^A, α, σ^P and ρ), that vary with the estimation groups, indexed here by j. GMMSV split the sample into 794 groups. The classification procedure produces a high degree of heterogeneity across groups along many dimensions, and, at the same time, a low degree of heterogeneity regarding cash flow dynamics within groups. The groups are formed by first identifying firms within the same three-digit SIC industry. Next, each three-digit SIC group is split into groups of at least 10 firms, conditioning on similar average cash flow growth rates.

[8] Estimates in GMMSV rely on a sample of 9,232 firms, given a constraint of a minimum of 10 years of non-consecutive years of data. An additional 6,659 firms can be matched to the estimation groups based on average annual growth rates being within the bounds of any of the groups. GMMSV examine possible selection issues and conclude that there are no important differences between the sampled and excluded firms regarding the parameter point estimates.

The separate identification of permanent and transitory shocks in GMMSV ($dW^A_{j,t}$ and $dW^P_{j,t}$) also allows us to measure directly how individual firm shocks correlate with the aggregate market shocks, and therefore obtain χ^A_j and χ^P_j [9]. We construct the permanent and transitory shocks to cash-flows at the aggregate market level (denoted as $dW^{M_A}_t$ and $dW^{M_P}_t$) by computing the market-value-weighted averages of the short-term cash-flow shocks, $dW^A_{j,t}$ and permanent productivity shocks $dW^P_{j,t}$, respectively. Figure 3.3 shows the time-series variation of the two aggregate shocks. Shaded bars indicate NBER recessions. Both types of shocks decrease during recession periods, confirming a link between the identified shocks and investment opportunities. The two aggregate series also strongly correlate with one another, with a correlation coefficient of 0.56. We impose this value for the correlation between $dW^{M_A}_t$ and $dW^{M_P}_t$ in the simulation of our panel datasets.

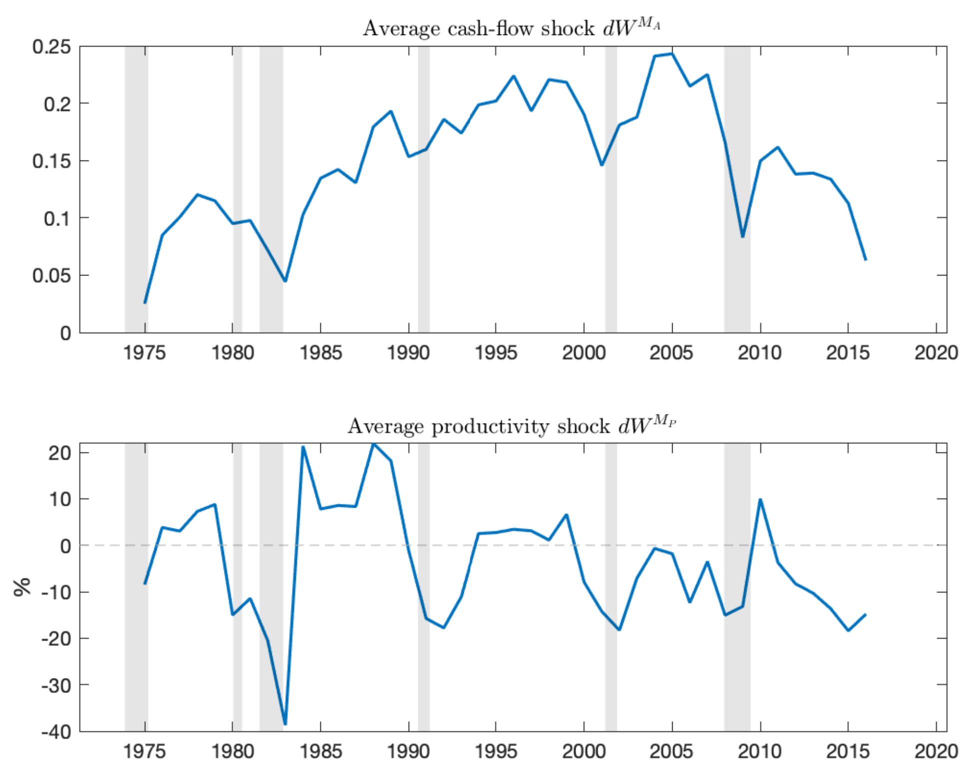

Fig. 3.3 Aggregate permanent and short-term shocks.
This figure shows the time-series of the the equity-market-value-weighted short-term shocks, dW^{M_A}, in the top panel and the equity-market-value-weighted productivity shocks, dW^{M_P}, in the bottom panel. The series are computed based on the individual shocks of the 15,891 firms in the GMMSV sample. Shaded bars indicate NBER recessions. The data is winsorized at the 1st and 99th percentiles. The time period covers 1975 to 2016.

[9]The identifying assumption in GMMSV is that short-term cash-flow shocks are firm specific, while permanent productivity shocks are common to all firms within the same group j. This then implies that the short-term shock correlations χ^A_j differ within the group but the permanent productivity shock correlations χ^P_j do not.

The correlations χ_j^A and χ_j^P are also informative about the market prices of the two types of shocks, η^A and η^P. Intuitively, higher levels of these correlations imply greater exposure to the two sources of cash-flow risk. The Sharpe ratio of a portfolio that buys the high χ_j^A stocks and sells the low χ_j^A stocks identifies the market price of short-term shock risk, η^A. Similarly, the Sharpe ratio of a portfolio that buys the high χ_j^P stocks and sells the low χ_j^P stocks identifies the market price of permanent shock risk, η^P. We follow the Fama and French [1992] procedure when constructing these portfolios, by conducting double-sorts on size, measured by market equity, and the respective correlations χ_j^A and χ_j^P. We estimate the correlations χ_j^A and χ_j^P using 10-year rolling windows for two reasons. First, using correlations calculated over the entire time-series to predict returns induces look-ahead bias. Second, the use of rolling windows provides time-series variation of the sorting variable, which allows for greater variability in the factor performance.

Table 3.4 Portfolio performance
This table shows the average monthly return (*Mean*), test statistic (*t-stat*) and Sharpe ratio (*Sharpe*) of factors based on the operating cash-flow shocks identified in GMMSV. Average returns are reported in percentage terms. The factors are formed using six value-weighted portfolios sorted on size and the two operating cash-flow shock measures: total short-term shock, dW^A and permanent shock, dW^P, and the individual firm 10-year rolling correlations of these shocks with aggregate short-term shocks, dW^{M_A}, (χ^A) and average productivity shocks, dW^{M_P} (χ^P). The rolling correlations are computed using a minimum requirement of 5 data points. Panel A reports the performance of the factors constructed using the raw values of the shocks and correlations. Panel B reports the results for portfolios constructed using industry-adjusted values, where we subtract the three-digit SIC median value. The data is trimmed for each individual firm at the 1st and 99th percentiles. The sample covers 15,891 firms over the period 1975 to 2016.

	Shocks		Correlations	
	dW^A	dW^P	χ^A	χ^P
Panel A: Raw values				
Mean	-0.06	-0.05	0.09	0.11
(t-stat)	(-0.88)	(-0.71)	(1.19)	(1.57)
Sharpe	-0.04	-0.04	0.06	0.08
Panel B: Industry-adjusted values				
Mean	-0.06	0.08	0.01	0.14
(t-stat)	(-0.07)	(1.52)	(0.13)	(2.55)
Sharpe	-0.003	0.08	0.01	0.13

Table 3.4 presents the average monthly return, test statistic and Sharpe ratio for the high-minus-low factors constructed sorting on the correlations, χ_j^A and χ_j^P. For robustness, we also report the performance of two additional portfolios constructed using the values of the shocks, dW^A and dW^P. Panel A refers to portfolios that use raw values of the sorting variables. Panel B refers to portfolios that use industry-adjusted values, where the adjustment subtracts the industry median from each observation [10]. The results in Table 3.4 indicate that exposure to permanent productivity shocks is priced, with the Sharpe ratio ranging between 0.08 to 0.13. The portfolio that uses industry-adjusted values of the productivity shocks, dW^P, also earns a Sharpe ratio of 0.08. The mean returns of portfolios that sort on the short-term operating cash-flow shocks and the short-term shock correlations are not statistically significant in any of the specifications. This evidence is consistent with the long-run risk literature, arguing that asset prices are driven by concerns related to long-term growth. Based on these results, we set the market price of permanent productivity risk to $\eta^P = 0.13$ and the market price of short-term cash-flow risk to $\eta^A = 0.01$.

To estimate the remaining model parameters we use SMM. The procedure chooses the parameters that minimize the distance between model-generated moments and their sample analogs. In the next subsection we describe the algorithm for the model simulations.

3.5.3 Algorithm

To estimate the equity cost parameters at a level that is as granular and precise as possible, we group firms following a procedure that is similar in principle to GMMSV. We start by grouping based the on three-digit SIC industry classification. Next, within each three-digit SIC group, we sort firms based on their equity market capitalization. The rationale for this sort relates to the evidence presented in Section 3.4, showing large variation of both frequency and amounts issued with size.

[10]In unreported results, we also conduct the industry adjustment using the value-weighted industry mean, with no significant differences in the portfolio performance from the industry adjustment that uses the industry median.

Table C.5 in Appendix 2 reports group statistics on the number of firms and number of issuances identified from our new measure dS/S, using a lower threshold of 0.2% to ensure we are not capturing changes in our variable related to exercises of employee and executive stock options. We report the results for both sorting based on quintiles and sorting based on deciles. To ensure our sorts do not overweigh the smallest firms, we also construct the size portfolios using NYSE breakpoints. This does not alter the results in a significant manner. It is not surprising because the GMMSV sample excludes the most short-lived firms, which would be precisely the microcaps that affect the size breakpoints. Table C.5 shows that even a finer sort that uses deciles provides groups with an average of 7 firms and an average number of issuances of 87, allowing for a large degree of precision in estimation. Our primary estimation, therefore, relies on groups of firms based on three-digit SIC industries and size deciles. This procedure identifies 2,370 groups. Each of these groups is indexed here by f.

For each group f, we estimate the vector of parameters Θ_f, where

$$\Theta_f = (\theta_f, l_f^H, l_f^L, \phi_f^H, \phi_f^L, \gamma_f^H, \gamma_f^L). \tag{3.34}$$

The simulated method of moments chooses the vector of parameters Θ_f that minimizes the distance between the group f moments in the data and the corresponding model-generated moments. To obtain moments related to stock returns around equity issuance days, we simulate the model at the daily frequency.

We have two nested optimization problems: one at the aggregate level and one at the firm level. The unknown parameters at the aggregate level include the Markov transition intensitites, ζ_H and ζ_L. We set their starting values to those in Bolton et al. [2013], where $\zeta_H = 0.1$ and $\zeta_L = 0.5$. Given these values of the Markov transition intensities, ζ_H and ζ_L, we simulate N^S series of model states $s = H, L$, for T days. We fix the series of simulated model states for each simulated panel. Given the model state series, we start by generating N^M series of aggregate permanent productivity shocks, dW^{M_P} and short-term cash-flow shocks, dW^{M_A}, for each $m = \{1, ..., N^S\}$ and $j \in \{1, ..., J\}$, where $J = 794$. The grouping at this stage refers to the one used in GMMSV.

Next, for each group j we draw a shock, $d\widetilde{W}_{j,t}^{P,m}$ that has a correlation of χ_j^P with the aggregate productivity shock, $dW_t^{M_A,m}$. The permanent productivity shock is given by:

$$d\widetilde{W}_{j,t}^{P,m} = \chi_j^P \, dW_t^{M_P,m} + \sqrt{1-\chi_j^{P2}} \, dW_{j,t}^{Z_P,m}, \tag{3.35}$$

where $dW_{j,t}^{Z_P,m}$ is another standard normal shock that is uncorrelated with $dW_t^{M_P,m}$. We then use the correlation χ_j^A with the aggregate short-term shock, $dW_t^{M_A,m}$, to draw a component of the group j short term shock, denoted as $d\widetilde{W}_{j,t}^{A,m}$:

$$d\widetilde{W}_{j,t}^{A,m} = \chi_j^A \, dW_t^{M_A,m} + \sqrt{1-\chi_j^{A2}} \, dW_{j,t}^{Z_A,m}, \tag{3.36}$$

where $dW_{j,t}^{Z_A,m}$ is another standard normal shock that is uncorrelated with $dW_t^{M_A,m}$. So far the procedure only imposes a correlation structure between each the group j shocks and the respective aggregate shock. To ensure that the correlation between the group j permanent shocks, $dW_{j,t}^{P,m}$, and short-term shocks, $dW_{j,t}^{A,m}$, is equal to the estimated correlation of ρ_j in GMMSV, we proceed as follows. We set the group j permanent productivity shock equal to $d\widetilde{W}_{j,t}^{P,m}$:

$$dW_{j,t}^{P,m} = d\widetilde{W}_{j,t}^{P,m}. \tag{3.37}$$

The group j short-term cash-flow shock is given by the component previously drawn, $d\widetilde{W}_{j,t}^{A,m}$, that imposes the correlation of χ_j^A with the aggregate short-term shock, $dW_t^{M_A,m}$, plus another standard normal shock that imparts the correlation between permanent and short-term shocks at both the aggregate and group j level, denoted as $\widetilde{\rho}_j$:

$$dW_{j,t}^{A,m} = d\widetilde{W}_{j,t}^{A,m} + \widetilde{\rho}_j \, dW_t^{P,m} + \sqrt{1-\widetilde{\rho}_j^{\,2}} \, dW_{j,t}^{Z,m}, \tag{3.38}$$

where $dW_{j,t}^{Z,m}$ is a standard normal shock uncorrelated with $dW_t^{M_P,m}$. The correlation $\widetilde{\rho}_j$ in Equation (3.38) is such that the correlation between the group j permanent and short-term shocks is equal to ρ_j. To solve for $\widetilde{\rho}_j$ we also need the correlation between the aggregate shocks, $dW_t^{M_P,m}$ and $dW_t^{M_A m}$. We set this to the same level that we find in the aggregated shocks in GMMSV, which is equal to 0.56 [11].

We then simulate the time-series of T days of the productivity process, $P_{j,t}$ and the cash-flow process, $A_{j,t}$ for each group j and simulation m using the cash-flow parameters α_j, μ_j, σ_j^P *and* σ_j^A from GMMSV and the simulated cash-flow shocks, $dW_{j,t}^{A,m}$ and $dW_{j,t}^{P,m}$.

Next, we form groups $f = \{1,...,F\}$ based on our double sorting procedure that uses three-digit SIC groups split into size deciles. Each firm in group f also belongs to a group j in the GMMSV sample. This means we can obtain its cash-flow series from the previous step in the simulation. We then compute group f policies taking the parameter vector $\Theta_f = (\theta_f, l_f^H, l_f^L, \phi_f^H, \phi_f^L, \gamma_f^H, \gamma_f^L)$ as given.

The group-level GMM represents the first step. In the second step, we estimate the aggregate-level parameters by searching for the values that minimize the distance between the simulated panels from the first step and actual data.

3.5.4 Selection of moments

This subsection describes our choice of moments that should be informative about the seven unknown parameters in Θ and how they help in identification. Because our measure of issuance, dS/S, identifies the issuance event, it allows us to elect moments that are original compared to existing structural estimation studies of equity issuance costs.

Our key moments are based on three endogenous variables related to equity issuance: (1) quantity, (2) timing and (3) price reaction, in one adjustment point: the lower issuance threshold, $\underline{c}_s$. These moments should be much more sensitive to

[11] To find the correlation $\widetilde{\rho}_j$ we solve the following: $corr(dW_{j,t}^{A,m}, dW_{j,t}^{P,m}) = \rho_j$, where we substitute $dW_{j,t}^{A,m}$ with the expression in Equation 3.38.

the parameters in Θ compared to, for example, moments related to the cash balance of the firm where there is considerable inaction, and therefore, considerable noise in estimation.

Issuance activity

Fixed costs of issuance, ϕ_f^H and ϕ_f^L, affect issuance frequency and average amounts issued. Intuitively, firms facing a high fixed cost will issue infrequent, large amounts. Conversely, firms facing low fixed costs, will issue frequent, small amounts. The mean, variance and skewness of amounts issued should be informative of the marginal costs of issuance, γ_f^H and γ_f^L. In the model, the lower issuance threshold, $\underline{c}_s$, decreases with issuance costs, as the firm optimally delays issuance to avoid incurring the high costs. Additionally, the return cash balance after issuance, m_s, is high in order to reduce the probability of the firm having to issue again and pay the issuance costs. This then implies a large distance $(m_s - \underline{c}_s)$, which largely determines the average amount issued. The variance and skewness of the amounts issued depends on cash-flow volatility, because cash-flow volatility determines by how much the cash balance goes below the lower threshold, $\underline{c}_s$, namely the difference $(\underline{c}_s - c)$. Given a large distance $(m_s - \underline{c}_s)$ for firms facing large costs of issuance, the effects of cash-flow volatility on $(\underline{c}_s - c)$ and therefore the amount issued, $(m_s - c)$, are small. As a consequence, the variance and skewness of amounts issued should decrease with marginal issuance costs.

Issuance probabilities

We match additional moments from two regressions that forecast future issuance using the current level of the cash balance. We use two forecasting horizons of $\tau = 6, \text{and}\, 12$ months. For each horizon, we calculate the cash balance of the firm scaled by a lower bound proxy and check if the firm has issued equity at any time within the next six or twelve months. We then estimate the following regression:

$$\mathbf{1}_{\{\text{issuance within } \tau \text{ months of } c_{it}\}} = \lambda_{0\tau} + \lambda_{1\tau} \frac{c_{it}}{\min c_i} + \varepsilon_{it}, \tag{3.39}$$

where $\min c_i$ proxies for the lower issuance bound, $\underline{c}$, of firm i. The lower the fraction $c_{it}/\underline{c}_i$, the higher the probability of crossing the lower threshold is and the closer the firm is to issuing. The minimum observed cash balance over the full available time series for a firm that issues equity serves as a proxy for the lower issuance bound, $\underline{c}_i$. For firms that never issue equity, we use the lower of the firm's minimum observed cash balance and the average of $\min c_i$ for equity issuing firms within the same group f. The four estimates of $\lambda_{0\tau}$ and $\lambda_{1\tau}$ from these regressions provide four additional moments.

The moment $\lambda_{0\tau}$ represents the probability of issuing equity when the cash balance is almost depleted. This probability increases as the cash balance approaches the lower threshold, $\underline{c}_i$. In the model, it is unlikely that the cash balance reaches zero for firms that have a high lower threshold, $\underline{c}_i$, but much more likely for firms with $\underline{c}_i$ close to zero. All model parameters affect the optimal lower boundary, $\underline{c}_i$, but the liquidation values, l_f^H and l_f^L, and equity issuance costs play a key role. The moment $\lambda_{0\tau}$ should, therefore, be especially informative of these parameters.

Price reaction moments

The mean and volatility of $CAR_{-1,1}$ upon issuance is also informative of the issuance cost function parameters. This is evident in Equation 32, showing that the announcement return relates directly to both costs. The announcement return effectively captures the ratio of total issuance costs to firm value. The greater the issuance costs are, the larger the announcement return. Observing ex post that the firm has issued equity, it must be the case that the going concern value of the firm, after incurring the issuance costs, is greater than the liquidation value, l_s. This implies that, liquidation values, l_f^H and l_f^L, also affect moments related to $CAR_{-1,1}$.

Policy moments

Next, we consider five policy moments. The average cash-to-assets ratio should be sensitive to liquidation values, l_f^H and l_f^L. Intuitively, the precautionary motive is high for firms with low liquidation values, resulting in a high average cash-to-assets ratio as firms try to maintain their cash balance close to target in the steady state. The mean and variance of the investment to assets ratio is informative of the investment adjustment cost parameter, θ_f. High investment adjustment costs result in low investment rates and low variability of investment. It follows that the covariance between the investment to assets ratio and changes in cash savings should be sensitive to both investment adjustment costs, θ_f and the liquidation parameters in the two states. Further, investment adjustment costs and liquidation values will also affect the covariance between the investment to assets ratio and equity issuance.

We consider additional moments related to the cash-flow sensitivity of cash and cash-flow sensitivity of investment. The cash-flow sensitivity of cash savings should be informative of all model parameters. The cash-flow sensitivities of savings and investment should also help in the separate identification of the equity issuance costs between states. To see this, consider the expression for the cash-sensitivity of investment:

$$i_s'(c) = -\frac{1}{\theta}\frac{F_s(c)F_s''(c)}{F'(c)^2}. \tag{3.40}$$

The market timing motive is high for a firm that faces low issuance costs in the high state $s = H$, and large issuance costs in the low state, $s = L$. The firm value function becomes locally convex when close to the issuance threshold in the high state, implying the second derivative, $F_s''(c)$, is positive. Firm value is globally concave in the low state. As a consequence, the investment-cash sensitivity is negative only in the high state when close to the issuance boundary. The greater the market timing motive, the more negative the investment-cash sensitivity is. The average sensitivity of investment to cash-flow conditional on the sensitivity being negative, $i_s'(c) < 0$, should therefore be informative of all equity issuance cost parameters, but more so for the ones in the low state, ϕ_f^L and γ_f^L,.

3.6 Discussion

The higher frequency of issues and the smaller amounts issued based on dS/S suggest that our average estimates of the fixed costs should be lower compared to those reported in the existing literature (e.g. Hennessy and Whited, 2007), while our average estimates of the marginal costs should be higher. We can observe how these costs differ in the cross-section and identify commonalities in the characteristics of firms facing higher costs. We also expect firms to face much higher costs during 'cold' equity issuance markets, motivating the documented market timing behaviour.

Because most of the existing literature refers to SEO data, we can exclude SEOs, as identified by SDC, and observe whether our estimates of the costs change. We can test if the importance of SEOs has changed over time, by repeating the analysis by decade. If the costs change significantly, then it could be that the SEO concept has disappeared: firms do not raise cash earmarked for specific projects but tap the external equity markets when it is cheap to do so, in case opportunities arise.

Another important use our estimated model is to quantify the effect of market timing on Tobin's Q and cash policy. We can do so by conducting a counterfactual analysis where equity issuance costs are constant, and estimate how investment and cash policy change. Such an exercise allows us to compare the relative importance of dynamic trade-off models and market timing motives in capital structure decisions. The two motives do not need to be mutually exclusive: we can use a model that nests both drivers.

Finally, estimation of the Markov transition intensities, ζ_H and ζ_L, would allow us to observe 'hot' and 'cold' equity markets that do not necessarily equate to economic expansions and recessions. We can determine how the identified equity market states relate to observable variables that are currently used as proxies in the literature, such as the VIX, proxies for investor sentiment and indexes of macroeconomic uncertainty (e.g. Jurado, Ludvigson, and Ng, 2015), and assess their usefulness.

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Appendix A

Permanent and Transitory Earnings Surprises and Stock Price Momentum

A.1 Earnings persistence

I Persistence tests on *IBQ*

Table A.1 Persistence tests on *IBQ*.
This table reports results of unit root tests on individual firm earnings scaled by beginning-of-period total assets. The columns referring to the KPSS test represent the percentage of times the null hypothesis of stationarity in this test cannot be rejected. Results are reported for three different confidence levels: 10%, 5 % and 1%. The columns referring to the ADF test report the percentage of time the null hypothesis of a unit root for this test is rejected. Results are presented using three different criteria regarding the minimum number of quarterly observations of earnings per share: 10, 20 and 40 quarters. The column referring to the variance ratio reports the average variance ratio for each sample. The period covers July 1971 to March 2020. The column referring to the number of firms reports the number of firms considered for the two tests at each of the three different levels of minimum number of quarterly observations allowed for the computations. The analysis excludes financial firms (SIC codes 6000 to 6999) and utility firms (SIC codes 4900 to 4999). Firm earnings data is obtained from Compustat item *IBQ*, a scaled by the first available observation of total assets per individual firm. I winsorize the data at the 1st and 99th percentiles at the firm level.

KPSS			ADF			Variance	Min.	No. of
10%	5%	1%	10%	5%	1%	ratio	quarters	firms
53.5	53.5	72.2	63.1	63.1	49.8	64.1	10	20,813
46.5	46.5	64.5	74.6	74.6	63.5	61.1	20	14,601
37.1	37.1	54.2	84.5	84.5	76.9	59.0	40	7,768

II SUE portfolio performance

Table A.2 Spanning tests.
This table shows the results of regressions of the monthly returns of the earnings surprise factors on different explanatory variables. The explanatory variables include the momentum factor (MOM) and Fama and French five factors: the market factor (MKT), the size factor (SMB), the value factor (HML), the investment factor (CMA) and the profitability factor (RMW). The additional factors include: standardized unexpected earnings (SUE), standardized unexpected trend components of earnings constructed using two different filters: the Hodrick and Prescott filter (*HP*) and the Baxter and King filter(*BK*) and the standardized unexpected cycle component of earnings constructed using the three different filters. The sample period covers May 1973 to December 2018. Newey and West test statistics are presented in parentheses.

	SUE	SUE^T_{HP}	SUE^C_{HP}	SUE^T_{BN}	SUE^C_{BN}	SUE^T_{IF}	SUE^C_{IF}
α	0.484	0.289	0.529	0.551	0.482	0.098	0.494
	[4.225]	[2.412]	[4.943]	[4.849]	[4.266]	[0.846]	[3.914]
β_{mkt}	0.083	-0.02	0.081	0.045	0.058	0.052	0.059
	[2.271]	[-0.64]	[2.618]	[1.167]	[2.056]	[1.392]	[1.458]
β_{smb}	-0.10	-0.12	0.045	0.001	0.052	-0.04	-0.08
	[-2.43]	[-2.43]	[1.109]	[0.045]	[1.188]	[-0.86]	[-1.77]
β_{hml}	-0.07	-0.09	0.025	-0.05	-0.08	-0.10	0.007
	[-1.24]	[-1.39]	[0.430]	[-0.58]	[-1.40]	[-1.49]	[0.105]
β_{cma}	0.090	-0.24	0.164	0.077	0.293	0.131	-0.05
	[1.036]	[-2.31]	[1.782]	[0.755]	[3.134]	[1.332]	[-0.57]
β_{rmw}	0.225	0.208	-0.03	0.143	0.057	0.005	0.255
	[3.827]	[2.912]	[-0.57]	[2.323]	[0.877]	[0.079]	[3.716]
β_{mom}	0.306	0.331	0.166	0.135	0.191	0.187	0.245
	[7.866]	[7.249]	[5.193]	[3.83]	[6.488]	[5.452]	[7.383]
R^2 (%)	31.40	36.40	11.60	8.70	17.20	12.90	21.40

III Sample and control variables

Constructing the variables used in the empirical analysis requires the merger of data from the daily and monthly stock files from the Center for Research in Security Prices (CRSP) with quarterly as well as annual accounting fundamentals from Compustat. Data on Fama-French factors, NYSE breakpoints and industry SIC codes is obtained from Kenneth French's website. The sample, starting in July 1967 and ending in December 2018, excludes financial firms (SIC codes 6010- 6799) and utility firms (SIC codes 4900-4999).

To ensure that the accounting data is available before the time period over which returns are measured, I use the methodology employed in Fama and French (1992, 1993). Namely, the returns from July in year t to June in year $t+1$ are matched with the values of the accounting data in the fiscal year end in year $t-1$. Size is calculated as the absolute value of the product of market value, PRC, in June of year t, with shares outstanding, SHROUT, in June of year t (divided by 1000 since the SHROUT field in CRSP is recorded in thousands). The market value of equity at the end of December of year $t-1$ is used to compute the book-to-market variable. Book equity, BE, is given by shareholder's equity, SEQ in Compustat, adjusted for tax effects by adding deferred taxes, TXDB, and investment tax credits, ITCB, and subtracting the book value of preferred stock. For the latter, its redemption value is used, PSTKRV, if available, or else its liquidating value, PSTKL, or else its par value, PSTK. Book equity is not calculated if SEQ or TXDB are unavailable. It is taken to be zero if there is no available value for preferred stock or investment tax credit. All independent variables are trimmed at the 1% and 99% levels. Table C.6 presents summary statistics (equal-weighted) for the control variables used in the Fama and MacBeth regressions. These statistics are time-series averages of their respective cross-sectional values in each month.

Table A.3 Summary Statistics
This table presents summary statistics for independent variables used in Fama-MacBeth regressions, measured in the period from January 1975 to December 2015. The sample includes U.S.-based common stocks in the merged CRSP and Compustat database, excluding financials. For each month, the mean, standard deviation, skewness, kurtosis, minimum, median and maximum value of each of the variables are calculated. The table provides the time-series average for each cross-sectional value of the respective statistic. The last column labelled *n* shows the average number of stocks for which the variable is available. *Size* is the natural logarithm of the market capitalization of the stock calculated at the end of June in the previous year. *BM* is the ratio of the book value of equity to the market value of equity. *GP/A* represents profitability, calculated as the ratio of gross profits to total assets of the company. $r_{1,0}$ is the short-term reversal, which is the stock return during month *t*. $r_{12,2}$ represents the stock's momentum, measured as the cumulative return of the stock during the 11-month period starting from 12 months before the measurement date and ending a month before the measurement date. The statistics on the return variables are expressed in percentage terms.

	Mean	Stdev	Skewness	Kurtosis	Min	Max	Median	n
$r_{12,2}$	14.04	57.64	4.10	63.83	-84.73	994.794	5.32	3391
ln(ME)	4.80	1.88	0.30	-0.13	-1.13	11.53	4.68	4541
ln(B/M)	-0.40	0.93	0.67	5.44	-4.67	6.19	-0.39	3213
GP/A	0.36	0.63	7.35	530.14	-3.99	24.48	0.32	3415
$r_{1,0}$	1.17	14.87	2.87	56.77	-60.63	238.56	0.09	3695

IV Fama and MacBeth regressions

Table A.4 Fama and MacBeth regressions conducted using microcap stocks.
This table reports the Fama and MacBeth regressions of monthly expected excess stock returns on earnings surprises measured based on standardized unexpected earnings (SUE), its permanent component (SUE_T) as well as its temporary component SUE_C and past performance which is measured as the cumulative return over the previous year skipping the most recent month to avoid the effect of short-term reversal. The permanent and cyclical components of earnings are computed using three filters: the Hodrick and Prescott filter (*HP*), the Beveridge Nelson decomposition (*BNK*) and an ideal bandpass filter (*IF*). Controls include size (ln(ME)), book-to-market (ln(B/M)), profitability (GP/A) and short-term return reversal ($r_{1,0}$). The sample includes microcap stocks over period July 1976 to March 2020. Microcap stocks belong to the first and second NYSE size deciles.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$r_{2,12}$	0.29	-0.79	5.46	-0.36	-0.14	-0.51	-0.46	-0.19
	[1.80]	[-3.38]	[0.91]	[-1.34]	[-0.62]	[-2.00]	[-1.92]	[-0.80]
SUE		0.90						
		[3.66]						
SUE_{HP}^{T}			0.01					
			[0.06]					
SUE_{HP}^{C}				0.51				
				[10.70]				
SUE_{BN}^{T}					0.01			
					[3.46]			
SUE_{BN}^{C}						0.01		
						[12.51]		
SUE_{IF}^{T}							0.01	
							[3.41]	
SUE_{IF}^{C}								0.001
								[4.47]
ln(ME)	-0.28	-0.24	1.18	-0.13	-0.43	0.07	-0.01	-0.16
	[-5.15]	[-1.37]	[0.92]	[-1.57]	[-1.30]	[0.37]	[-0.14]	-[1.40]
$ln(B/M)$	0.22	0.16	0.33	0.48	0.63	0.21	0.31	0.27
	[4.56]	[0.87]	[1.25]	[1.36]	[1.69]	[2.24]	[3.65]	[2.33]
GP/A	0.48	1.17	-1.02	0.47	0.42	0.69	0.31	4.47
	[3.03]	[1.68]	[-0.86]	[1.45]	[1.55]	[2.51]	[0.97]	[1.14]
$r_{1,0}$	-5.31	-3.90	6.89	-3.45	-3.39	-3.03	-3.63	-2.55
	[-13.20]	[-7.77]	[0.72]	[-6.64]	[-6.49]	[-5.83]	[-6.91]	[-4.84]
Intercept	2.21	1.475	-2.13	1.59	1.64	1.63	1.63	1.64
	[6.40]	[3.68]	[-0.58]	[3.77]	[3.95]	[3.89]	[3.97]	[3.91]
R^2 (%)	3.00	6.60	7.90	7.80	7.80	7.80	7.80	7.50

Table A.5 Fama and MacBeth regressions conducted using small stocks.
This table reports the Fama and MacBeth regressions of monthly expected excess stock returns on earnings surprises measured based on standardized unexpected earnings (SUE), its permanent component (SUE_T) as well as its temporary component SUE_C and past performance which is measured as the cumulative return over the previous year skipping the most recent month to avoid the effect of short-term reversal. The permanent and cyclical components of earnings are computed using three filters: the Hodrick and Prescott filter (*HP*), the Beveridge Nelson decomposition (*BNK*) and an ideal bandpass filter (*IF*). Controls include size (ln(ME)), book-to-market (ln(B/M)), profitability (GP/A) and short-term return reversal ($r_{1,0}$). The sample includes small stocks over the period July 1976 to March 2020. Small stocks belong to the third and fourth NYSE size decile.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$r_{2,12}$	0.74	-0.72	-0.43	-0.19	-0.20	-0.27	-0.54	-0.26
	[3.28]	[-1.80]	[-0.91]	[-0.38]	[-0.47]	[-0.54]	[-1.02]	[-0.53]
SUE		0.33						
		[3.23]						
SUE_{HP}^{T}			0.26					
			[2.33]					
SUE_{HP}^{C}				0.43				
				[5.45]				
SUE_{BN}^{T}					0.004			
					[5.26]			
SUE_{BN}^{C}						0.003		
						[5.20]		
SUE_{IF}^{T}							0.002	
							[3.17]	
SUE_{IF}^{C}								0.003
								[4.27]
ln(ME)	-0.10	-0.53	-0.72	-0.80	-0.63	-1.01	-0.63	-1.01
	[-0.65]	[-1.35]	[-1.59]	[-1.59]	[-1.40]	[-2.13]	[-1.26]	[-2.11]
$ln(B/M)$	0.21	0.47	0.30	0.65	-0.13	0.28	0.31	0.61
	[3.16]	[1.65]	[1.32]	[1.17]	[-0.30]	[1.38]	[1.69]	[1.30]
GP/A	0.60	0.36	0.27	0.41	0.40	0.65	0.30	0.24
	[2.62]	[0.86]	[0.62]	[0.86]	[0.89]	[1.38]	[0.63]	[0.54]
$r_{1,0}$	-4.67	-3.47	-3.09	-3.47	-4.1	-3.25	-4.06	-2.52
	[-8.82]	[-4.10]	[-3.06]	[-3.48]	[-4.29]	[-3.21]	[-3.75]	[-2.65]
Intercept	1.31	3.64	5.46	5.30	4.09	6.27	4.68	6.73
	[1.35]	[1.57]	[2.14]	[1.97]	[1.65]	[2.39]	[1.78]	[2.49]
R^2 (%)	6.50	19.90	23.90	23.80	23.80	23.70	24.00	23.70

Table A.6 Fama and MacBeth regressions conducted using large stocks.
This table reports the Fama and MacBeth regressions of monthly expected excess stock returns on earnings surprises measured based on standardized unexpected earnings (SUE), its permanent component (SUE_T) as well as its temporary component SUE_C and past performance which is measured as the cumulative return over the previous year skipping the most recent month to avoid the effect of short-term reversal. The permanent and cyclical components of earnings are computed using three filters: the Hodrick and Prescott filter (*HP*), the Beveridge Nelson decomposition (*BNK*) and an ideal bandpass filter (*IF*). Controls include size (ln(ME)), book-to-market (ln(B/M)), profitability (GP/A) and short-term return reversal ($r_{1,0}$). The sample includes large stocks over the period July 1976 to March 2020. Large stocks have market capitalizations above the median NYSE breakpoint.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$r_{2,12}$	0.54	-0.43	0.05	-0.25	0.03	-0.14	-0.08	-0.15
	[2.12]	[-1.31]	[0.13]	[-0.70]	[0.09]	[-0.42]	[-0.24]	[-0.43]
SUE		0.17						
		[4.35]						
SUE_{HP}^{T}			0.02					
			[0.77]					
SUE_{HP}^{C}				0.20				
				[3.75]				
SUE_{BN}^{T}					0.001			
					[2.44]			
SUE_{BN}^{C}						0.001		
						[2.90]		
SUE_{IF}^{T}							0.001	
							[2.39]	
SUE_{IF}^{C}								0.001
								[2.23]
ln(ME)	-0.02	-0.00	0.10	0.14	0.16	0.12	0.12	0.15
	[-0.59]	[-0.12]	[1.19]	[2.04]	[2.20]	[1.62]	[1.70]	[1.86]
$ln(B/M)$	0.24	0.37	0.29	0.31	0.31	0.38	0.35	0.28
	[4.17]	[3.68]	[2.41]	[2.86]	[2.87]	[3.57]	[3.19]	[2.53]
GP/A	0.92	0.48	0.94	0.86	0.43	0.88	0.54	0.81
	[4.58]	[1.57]	[2.91]	[2.73]	[1.10]	[2.77]	[1.53]	[2.40]
$r_{1,0}$	-3.17	-1.86	-1.54	-2.29	-2.04	-1.64	-1.69	-1.57
	[-5.81]	[-2.49]	[-1.83]	[-2.71]	[-2.35]	[-2.05]	[-1.97]	[-1.85]
Intercept	0.88	0.90	-0.05	-0.17	-0.19	0.10	0.01	-0.17
	[1.99]	[1.50]	[-0.08]	[-0.27]	[-0.29]	[0.15]	[0.02]	[-0.25]
R^2 (%)	8.20	17.60	21.30	20.50	20.30	19.70	20.70	20.70

Table A.7 Fama and MacBeth regressions conducted using all stocks for the first half of the sample.
This table reports the Fama and MacBeth regressions of monthly expected excess stock returns on earnings surprises measured based on standardized unexpected earnings (SUE), its permanent component (SUE_T) as well as its temporary component SUE_C and past performance which is measured as the cumulative return over the previous year skipping the most recent month to avoid the effect of short-term reversal. The permanent and cyclical components of earnings are computed using three filters: the Hodrick and Prescott filter (*HP*), the Beveridge Nelson decomposition (*BNK*) and an ideal bandpass filter (*IF*). Controls include size (ln(ME)), book-to-market (ln(B/M)), profitability (GP/A) and short-term return reversal ($r_{1,0}$). The sample period covers July 1976 to January 1994.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$r_{2,12}$	0.55	-0.62	-0.73	0.023	-0.31	-0.28	-0.47	-0.09
	[2.39]	[-2.10]	[-1.73]	[0.07]	[-0.90]	[-1.01]	[-1.68]	[-0.30]
SUE		0.53						
		[11.30]						
SUE^T_{HP}			0.35					
			[2.27]					
SUE^C_{HP}				0.41				
				[6.49]				
SUE^T_{BN}					0.01			
					[10.06]			
SUE^C_{BN}						0.003		
						[4.90]		
SUE^T_{IF}							8.52	
							[0.06]	
SUE^C_{IF}								0.01
								[5.54]
ln(ME)	-0.15	-0.07	-0.09	-0.08	-0.09	-0.07	-0.09	-0.13
	[-3.12]	[-1.18]	[-1.43]	[-1.25]	[-1.41]	[-1.08]	[-1.47]	[-1.46]
$ln(B/M)$	0.32	0.49	0.64	-0.42	0.60	0.14	0.44	-0.02
	[4.04]	[4.57]	[3.35]	[-0.64]	[2.34]	[0.79]	[3.90]	[-0.07]
GP/A	0.62	0.54	1.76	-0.53	0.86	-0.18	1.16	1.15
	[2.90]	[1.75]	[1.39]	[-0.45]	[1.52]	[-0.19]	[1.30]	[1.68]
$r_{1,0}$	-7.19	-5.47	-4.54	-4.32	-4.74	-4.38	-4.61	-3.67
	[-13.60]	[-8.42]	[-5.11]	[-5.50]	[-6.63]	[-5.97]	[-5.96]	[-5.24]
Intercept	2.18	1.82	1.79	1.54	1.81	1.68	1.89	2.06
	[4.55]	[3.25]	[3.17]	[2.30]	[3.12]	[2.85]	[3.28]	[3.34]
R^2 (%)	3.40	6.70	7.70	7.60	7.50	7.60	7.80	7.40

Table A.8 Fama and MacBeth regressions conducted using all stocks for the second half of the sample.
This table reports the Fama and MacBeth regressions of monthly expected excess stock returns on earnings surprises measured based on standardized unexpected earnings (SUE), its permanent component (SUE_T) as well as its temporary component SUE_C and past performance which is measured as the cumulative return over the previous year skipping the most recent month to avoid the effect of short-term reversal. The permanent and cyclical components of earnings are computed using three filters: the Hodrick and Prescott filter (*HP*), the Beveridge Nelson decomposition (*BNK*) and an ideal bandpass filter (*IF*). Controls include size (ln(ME)), book-to-market (ln(B/M)), profitability (GP/A) and short-term return reversal ($r_{1,0}$). The sample period covers February 1994 to December 2018.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$r_{2,12}$	0.27	-0.61	-0.47	-0.35	-0.34	-0.38	-0.51	-0.25
	[1.06]	[-2.13]	[-1.62]	[-1.24]	[-1.19]	[-1.29]	[-1.75]	[-0.87]
SUE		0.41						
		[9.90]						
SUE^T_{HP}			0.14					
			[4.94]					
SUE^C_{HP}				0.35				
				[8.51]				
SUE^T_{BN}					0.003			
					[8.02]			
SUE^C_{BN}						0.003		
						[9.25]		
SUE^T_{IF}							0.001	
							[3.45]	
SUE^C_{HP}								0.003
								[8.00]
ln(ME)	-0.08	-0.06	-0.06	-0.04	-0.05	-0.04	-0.06	-0.04
	-[1.76]	[-1.22]	[-1.20]	[-0.87]	[-1.06]	[-0.80]	[-1.34]	[-0.93]
$ln(B/M)$	0.16	0.23	0.23	0.15	0.20	0.17	0.25	0.16
	[2.67]	[2.95]	[2.54]	[1.70]	[2.28]	[1.99]	[2.83]	[1.89]
GP/A	0.69	0.60	0.42	0.53	0.46	0.56	0.47	0.58
	[3.12]	[2.33]	[1.50]	[1.94]	[1.64]	[2.00]	[1.65]	[2.09]
$r_{1,0}$	-3.14	-2.03	-1.66	-2.05	-2.1	-1.87	-2.08	-1.45
	[-6.09]	[-3.79]	[-2.92]	[-3.52]	[-3.60]	[-3.30]	[-3.60]	[-2.57]
Intercept	1.13	1.04	1.23	1.12	1.17	1.10	1.23	1.08
	[2.36]	[2.31]	[2.74]	[2.51]	[2.58]	[2.44]	[2.74]	[2.43]
$R^2\,(\%)$	3.60	5.40	5.90	6.00	6.00	5.90	5.90	5.70

V Model solution

In the region where it is optimal to retain earnings, $M \in (0, \bar{M})$, the equity value function $V(a,m)$ satisfies the following ODE:

$$rV = \hat{\mu}\, a V_a + (\hat{\alpha}\, a + (r-\lambda)\, m) V_m + \frac{1}{2} a^2 \left(\sigma_P^2 V_{aa} + 2\rho\, \sigma_P\, \sigma_T\, V_{a,m} + \sigma_T^2 V_{mm} \right) \tag{A.1}$$

The LHS of the above equation represents the required return on the equity of the firm. The first two terms on the RHS represent the effects of changes in profitability μa and cash savings $\alpha\, a + (r-\lambda)\, m$. The last term represents the effects of the volatilities in profitability and cash flows. $V_{a,m} \neq 0$ in this model, meaning that changes in productivity affect firm value as well as cash reserves.

To simplify the model solution, it is useful to note that equity value is homogenous of degree one in A and M, therefore:

$$V(a,m) = a V(1, \frac{m}{a}) \equiv a F(c)$$

where $c = \frac{m}{a}$ represents the productivity scaled cash holdings. The first and second order derivatives of the equity value with respect to productivity and cash holdings can be expressed as: $V_a = F(c) - c F'(c)$, $V_{aa} = \frac{c^2}{a} F''(c)$, $V_m = F'(c)$, $V_{mm} = \frac{1}{a} F''(c)$ and $V_{am} = -\frac{c}{a} F''(c)$. The ODE in (A.1) can then be re-written as:

$$(r-\mu) F(c) = (\hat{\alpha} + (r - \lambda - \hat{\mu})\, c) F'(c) + \frac{1}{2} \left(\sigma_P^2 c^2 - 2\rho\, \sigma_P\, \sigma_T\, c + \sigma_T^2 \right) F''(c) \tag{A.2}$$

subject to boundary conditions

$$F(0) = \frac{\omega \hat{\alpha}}{r - \hat{\mu}},$$

$$F'(c*) = 1, \; F''(c*) = 0,$$

$$F(c) = F(c*) + c - c*, \; for \; c > c*$$

.

VI Proof

Proofs: Given that $F'(c) > 1$ when $c \in (o, c*)$ and $F(c) > 0$, their ratio $\frac{F'(c)}{F(c)} > 0$. This is equivalent to short-term risk exposure having a positive price. To see that this is a decreasing function, one can look at the sign of the first derivative of the transitory beta:

$$\left(\frac{F'(c)}{F(c)}\right)' = \frac{F(c)F''(c) - [F'(c)]^2}{[F(c)]^2}$$

Since $F(c)$ is increasing and concave, $F''(c)$ will be negative, making the above ratio negative as well. The sign of the permanent beta is not constrained, although it is most likely to be positive (since the average level of scaled cash holdings is typically below 0.2, and the short term beta is unlikely to be greater than 5, thus making the permanent beta more likely to be positive but less than 1. The sign of its first derivative with respect to scaled cash holdings is also unconstrained.

VII Financial constraints indexes

Kaplan and Zingales [1997] estimate an ordered logit model to classify firms in to categories of financial constraints based on observable firm characteristics. I use the same regression estimates as in Lamont et al. [2001] of the Kaplan and Zingales [1997] regressions. The value of the KZ index at time t is given by:

$$\begin{aligned} &-1.001909 \times CF_{it} + 0.2826389 \times Q_{it} + 3.139193 \times D_{it} \\ &\qquad - 39.3678 \times DIV_{it} - 1.314759 \times CASH_{it}, \end{aligned} \tag{A.3}$$

where CF represents cash flow to total assets, Q is the market-to-book ratio, D is debt to total assets, DIV is cash dividends to total assets and $CASH$ is the ratio of cash and cash equivalents to total assets. Cash is cash and cash equivalents (cheq) when available or when greater than cash (chq), otherwise cash is equal to chq. Cash flow is computed as net income plus depreciation and amortization.

Whited and Wu [2006] construct their index of financing constraints by estimating the shadow value of scarce external funds. The estimation is based on Generalised method of moments (GMM) of a structural investment model. In their estimation, they express the shadow value of external financing, which is unobservable, as a function of several observable firm characteristics. Some of these characteristics overlap with Kaplan and Zingales [1997], although the correlation between the two indexes is virtually zero. The time t value of the Whited-Wu (WW) index is computed based on:

$$\begin{aligned} &-0.091 \times CF_{it} - 0.062 \times DIVPOS_{it} + 0.021 \times TLTD_{it} \\ &\qquad - 0.044 \times LNTA_{it} + 0.102 \times ISG_{it} - 0.035 \times SG_{it}, \end{aligned} \tag{A.4}$$

where CF is cash-flow to total assets, $DIVPOS$ is a dummy equal to one for firms paying cash dividends, $TLTD$ is long-term debt to total assets, $LNTA$ is the natural log of total assets, ISG is the 3-digit SIC industry sales growth and SG is individual firm sales growth.

I compute the SA index using the expression in Hadlock and Pierce [2006]:

$$-0.737 \times Size + 0.043 \times Size^2 - 0.040 \times Age, \tag{A.5}$$

where $Size$ is the logarithm of total book assets and Age is the number of years the stock has been on Compustat with a non-missing stock price. I impose similar restrictions to Hadlock and Pierce [2006] to account for the documented flat regions in the relationship between financing constraints and the variables used in the construction of the index. Size is replaced with log($4.5 billion) and age is replaced with thirty-seven years for firms where the actual values exceed these thresholds.

VIII Financial constraints index portfolio performance

Table A.9 Spanning tests.
This table shows the results of regressions of the monthly returns of the momentum factor on different explanatory variables. The explanatory variables include the Fama and French five factors: the market factor (MKT), the size factor (SMB), the investment factor (CMA) and the profitability factor (RMW). The additional factors include: standardized unexpected earnings (SUE), standardized unexpected trend components of earnings constructed using two different filters: the Hodrick and Prescott filter (*HP*) and the Baxter and King filter(*BK*) and the standardized unexpected cycle component of earnings constructed using the three different filters. The sample period covers May 1973 to December 2018. Newey and West test statistics are presented in parentheses.

	KZ index	WW index	SA index
α	-0.19	0.176	0.275
	[-2.78]	[1.35]	[2.63]
β_{mkt}	0.163	-0.02	0.049
	[8.03]	[-0.59]	[1.79]
β_{smb}	0.175	0.550	0.306
	[4.98]	[8.95]	[7.16]
β_{hml}	-0.24	-0.44	-0.47
	[-6.03]	[-5.62]	[-9.10]
β_{cma}	-0.30	-0.34	-0.35
	[-4.83]	[-3.02]	[-4.31]
β_{rmw}	-0.28	-0.57	-0.64
	[-5.52]	[-7.16]	[-12.3]
β_{mom}	-0.15	-0.22	-0.16
	[-6.64]	[-5.02]	[-4.80]
R^2 (%)	70.0 0	63.20	73.60

Appendix B

The Value-Momentum Correlation: An Investment Explanation

B.1 International evidence

I Time-varying correlation between value and momentum strategy returns

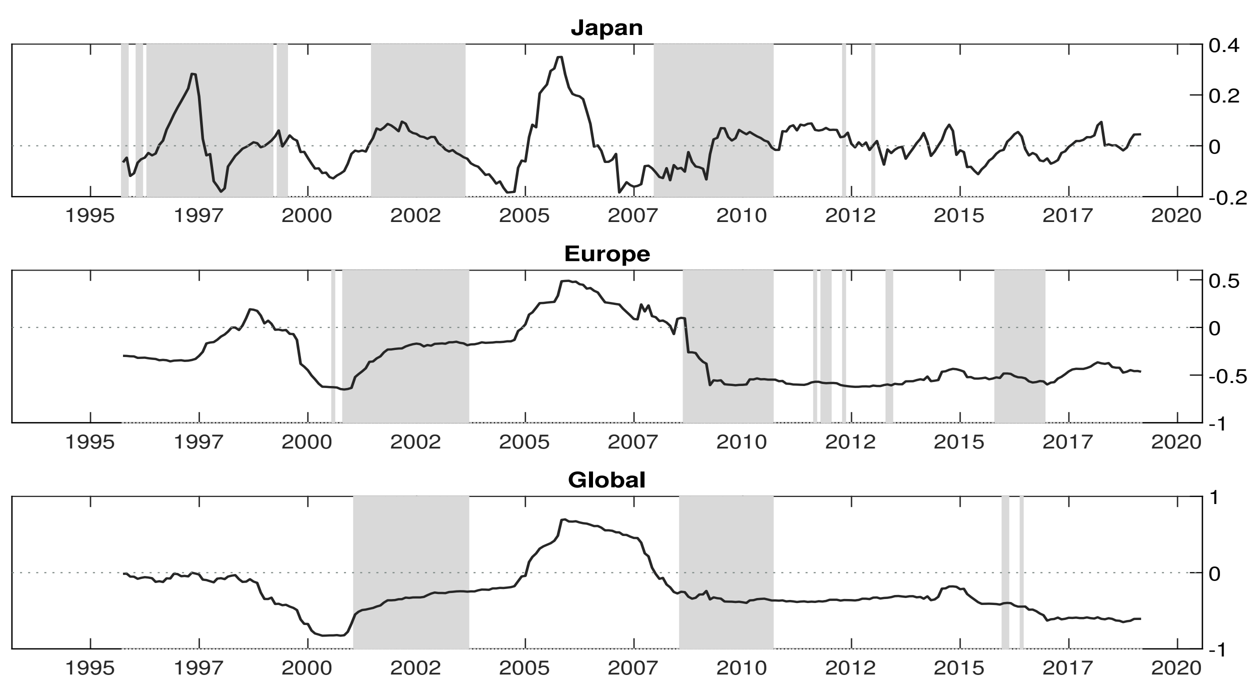


Fig. B.1 International evidence on the value-momentum correlation.
The plots show the 5-year rolling correlation between value and momentum strategy returns in Japan, Europe and Global stocks. Shaded areas represent months where the cumulative return on the (respective) market over the previous year has been negative. The time period covers November 1991 to March 2019.

II Momentum crash periods

Table B.1 Performance during momentum crashes.
This table shows the average performance of value and momentum portfolios over the months where momentum had the worst 2% performances in each market. MKT−2y represents the cumulative return on the market over the 24 months preceding the current month and MKT_t represents the contemporaneous market return.

	US	Europe	Japan	Global
MOM_t	-28.55	-12.94	-14.26	-13.31
BM_t	4.91	3.44	1.88	2.23
MKT-2y_t	-10.70	-17.96	1.88	-6.41
MKT_t	4.54	5.52	7.04	3.43

B.2 The model

The basic model setup is similar to Bolton et al. [2011], DeMarzo, M. Fishman, and Wang [2012] and Bolton et al. [2013]. The model considers a financially constrained firm that faces stochastic investment and financing opportunities. The firm can be in one of two possible states of the world, denoted by $s_t = G, B$. State G represents the good state of the world and state B represents the bad state of the world. Investment and external financing opportunities are better in the good state G and worse in the bad state B. States differ in terms of the growth rates in expected cash flows (investment opportunities) and the costs of external financing (financing opportunities). There is a constant probability, ζ_s, that the economy switches from the current state s to state s^-, where s^- denotes a state that is different form s. External financing opportunities involve new equity and credit lines.

Production requires two inputs, cash and capital. The firm buys and sells capital at a price of one. The following accounting identity applies to the firm's capital stock:

$$dK_t = (I_t - \delta K_t)\,dt, \quad t \geq 0, \tag{B.1}$$

where K denotes the capital stock, I denotes investment and $\delta \geq 0$ the rate of capital depreciation.

Firm cash flows are subject to shocks, dA_t, that follow an arithmetic Brownian motion:

$$dA_t = \mu(s_t)dt + \sigma(s_t)dZ_t^A, \tag{B.2}$$

where Z_t^A is a standard Brownian motion, and $\mu(s_t)$ and $\sigma(s_t)$ represent the drift and volatility in state s.

Operating revenues are proportional to capital and given by $K_t\,dA_t$ (AK production technology). The operating profit of the firm is also proportional to capital and given by:

$$dY_t = K_t dA_t - I_t dt - \Gamma(I_t, K_t, s_t)dt, \quad t \geq 0, \tag{B.3}$$

where I_t is investment over the time increment dt, $\Gamma(I_t, K_t, s_t)$ is the investment adjustment cost. The cost of adjusting investment can change depending on the state of the world. It is assumed to be homogeneous of degree one in I and K. Denoting the firm's investment to capital ratio as i ($i = I/K$), the investment adjustment cost can be expressed as:

$$\Gamma(I_t, K_t, s_t) = g_s(i)\,K,$$

where $g_s(i)$ is increasing and convex. $g_s(i)$ is given by:

$$g_s(i) = \frac{\theta_s(i - \nu_s)^2}{2}, \tag{B.4}$$

where θ_s is the investment adjustment cost parameter in state s and ν_s a constant.

At any time τ_0, shareholders can liquidate firm assets. A constant fraction $l > 0$ of the firm's capital stock determines the realized value upon liquidation L_t, given by:

$$L_t = l K_t.$$

The firm can use cash holdings to cover potential losses and finance investment. Let W_t denote the firm's cash holdings at time $t > 0$. Cash within the firm earns a lower rate of return compared to the risk-free rate, $r(s_t)$, making it costly. Let $\lambda > 0$ denote the carry cost of cash. The firm's optimal cash policy involves weighting the marginal cost of carrying cash against the marginal benefit of holding cash. When cash holdings exceed a certain level, the marginal value of cash outside the firm exceeds the marginal value of cash inside the firm. Distributing cash to shareholders at this point becomes optimal. Distributions can take the form of either dividends or share repurchases.

The firm can also use external financing to cover potential losses and finance investment. External financing involves credit lines and new equity issues. Only a fixed portion of the firm's capital, $c > 0$, is posted as collateral for the credit line. This limits the credit line draw down to an amount of cK. Credit line access involves a cost in the form of a spread of α_s over the risk-free rate on the amount borrowed.

External equity financing is also costly. As in Bolton et al. [2013], the costs of equity issuance involve a fixed component, $\phi_s K$, where ϕ_s is the fixed cost parameter in state s, and a proportional component, $\gamma_s > 0$, where γ_s is the marginal cost parameter in state s. The fixed cost of equity issuance scales with size to ensure that the firm does not grow out of this cost. This assumption also preserves the model's homogeneity in the capital stock K. Let dX_t denote the cost of issuing a net amount of equity of dH_t. The total cost of issuing new equity is given by $dX_t = \phi_{s_t} K_t 1_{dH_t > 0} + \gamma_{s_t} dH_t$.

The relative costs of holding cash, drawing down the credit line and issuing new equity determine the pecking order between internal funds, external borrowing and external equity financing. In the baseline calibration, the firm first exhausts its cash holdings, then accesses a credit line. When the optimal maximum credit line draw down is reached, the firm issues equity. With stochastic equity financing opportunities, the firm optimally chooses to tap the equity market sooner than it would if financing opportunities did not change. The optimal maximum credit line draw down in this set up is, as a result, smaller in good times.

Having specified production technology and financing, the dynamics of the firm's cash holdings can be expressed by:

$$dW_t = (r(s_t) - \lambda) W_t dt + dY_t + dF_t - dD_t \tag{B.5}$$

where dD_t is the dividend paid over the time increment dt and $dF_t = dH_t + cdK_t$ is the net external financing for the same time increment, including both equity and credit lines. Equation (5) is an accounting identity where distributions to shareholders and external financing are endogenously determined. Cash reserves increase with the interest earned on the existing cash balance (the first term), the firm's operating profit (the second term) as well as any external financing obtained over the period (the third term). Cash reserves decrease with any distributions to shareholders (the last term).

I Systematic risk and the pricing of risk

This model incorporates two sources of systematic risk: (1) a small diffusion shock to cash flows and (2) a large shock when the economy switches from one state to another. With risk-averse investors, the physical and risk-neutral probability measures are distinct. The diffusion shocks to productivity correlate with the aggregate market with a correlation coefficient of ρ_s. Each state of the economy assumes a constant market price of risk, denoted as η_s. Under the risk-neutral measure $\mathbb{Q}$, the firm's cash flow shocks are given by:

$$dA_t = \hat{\mu}_s + \sigma_s d\hat{Z}_t^A, \tag{B.6}$$

where $\hat{Z}_t^A$ is a standard Brownian motion under the risk-neutral measure $\mathbb{Q}$ and $\hat{\mu}_s$ is the risk-adjusted drift of the cash flow process in state s. This can be written as:

$$\hat{\mu}_s = \mu_s - \rho_s \eta_s \sigma_s. \tag{B.7}$$

Similar to Bolton, Chen and Wang (2013), the wedge between the transition intensity under the physical probability measure and the transition intensity under the risk-neutral measure represents the risk premium associated with the risk of the economy switching states. Let $\hat{\zeta}_G$ denote the transition intensity from the good state G to the bad state B and $\hat{\zeta}_B$ denote the transition intensity from the bad state G to the good state B, both under the risk-neutral measure. The risk-adjustments related to state switching are then given by:

$$\hat{\zeta}_G = e^{\kappa_G} \zeta_G \;\; and \;\; \hat{\zeta}_B = e^{\kappa_B}, \tag{B.8}$$

where κ_G and κ_G represent the risk adjustments associated with the change of state. The transition intensity out of state G (B) is higher (lower) under the risk-neutral measure compared to the physical measure. This implies $\kappa_G = -\kappa_B > 0$.

II Firm optimality

Management chooses investment, external financing, cash savings and payout policies and liquidation time to maximize shareholder value. In each state of the economy s, there are two state variables in the firm's optimization problem: firm size K_t and the cash balance W_t.

$$P(K,W,s) = \max_{L,I} \mathbb{E}_0^{\mathbb{Q}} \left[\int_0^{\tau_o} e^{-\int_0^t r_u du} dU_t + e^{-\int_0^{\tau_0} r_u du} (L_\tau + W_\tau) \right] \tag{B.9}$$

where $dU_t = dD_t - dF_t$ represents the net payouts to shareholders and r_u is the interest rate at time u. The first term in equation (B9) is the present discounted value of net payouts to incumbent shareholders until the liquidation time τ_0. The second term represents the present discounted value of the firm in the event of liquidation.

III Model solution

The solution to problem (B9) requires specification of the firm's optimal financing, payout and liquidation policies. Consider first financing and liquidation. The firm chooses to exhaust its cash holdings before accessing external markets. Cheaper internal funds make this an optimal decision. Only when the cash balance reaches zero does the firm consider external financing. At this point, the firm either obtains external funds or liquidates. If the cost of external financing is not too high, the firm starts to draw down a credit line. The firm draws down the credit line up to a limit $\underline{W}_s < 0$ that represents the lower boundary for the firm's cash to capital ratio. The lower boundary equals the credit line limit $-c_s$ in each state of the economy. Different investment and financing opportunities in each state determine different lower boundaries/credit line limits.

Consider next payout policy. The benefit of cash holdings is highest at low levels because of the need to delay costly external financing or avoid inefficient liquidation. This implies that at high levels of cash holdings their benefit is low and might become lower than the carry costs. Because shareholders can invest this cash at the risk-free rate, which is higher than the rate cash earns inside the firm, the marginal benefit of cash outside the firm becomes higher than the marginal benefit of cash inside the firm. At this point it becomes optimal to distribute excess cash to shareholders. Optimality then suggests that there is a target cash level $\overline{W}_s$ for each state s, where the marginal benefit of cash is equal to its marginal cost, with any excess cash over this level being distributed to shareholders.

To solve for firm value, consider first the interior region $(0, \overline{W}_s)$ for $s = G, B$. In this region, the firm does not distribute cash to shareholders nor obtain external financing. Firm value in this region satisfies the following ODE:

$$\begin{aligned} r_s P(K,W,s) = \max_I \, & [(r_s - \lambda)W + \hat{\mu}_s K - I - \Gamma(I,K,s)] P_W(K,W,s) \\ & + \frac{\sigma_s^2 K^2}{2} P_{WW}(K,W,s) + (I - \delta K) P_K(K,W,s) \\ & + \hat{\zeta}_s (P(K,W,s^-) - P(K,W,s)) \end{aligned} \tag{B.10}$$

where P_W denotes the first order derivative of the firm value function with respect to the cash balance W, P_K denotes the first order derivative of the firm value function with respect to capital K and P_{WW} denotes the second order partial derivative with respect to the cash balance. The left-hand side of (B10) represents the required rate of return for investing in the firm. Under the risk-neutral measure, $\mathbb{Q}$, this is the risk-free rate. The first and the second term on the right-hand side of equation (B10) represent the effects of changes in cash holdings and their volatility on firm value. The third term captures the marginal effects of investment. The last term represents the expected change in firm value when the state changes from s to s^-.

Firm value is homogeneous of degree one in capital K and cash W in each state. This allows to define the problem as a function of only one state variable based on the ratio of cash-to-capital $w = W/K$. Firm value can, therefore, be written as:

$$P(K,W,s) = p_s(w)K,$$

where $p_s(w)$ represents the scaled value function in state s. This makes it possible to rewrite the shareholders' optimization problem in $(0, \overline{w})$ as:

$$\begin{aligned} r_s p_s(w) = \max_{i_s} \, & [(r_s - \lambda)w + \hat{\mu}_s - i_s - g_s(i_s)]p_s'(w) + \frac{\sigma_s^2}{2} p_s''(w) \\ & + (i_s - \delta)(p_s(w) - w p_s'(w)) + \hat{\zeta}_s(p_{s^-}(w) - p_s(w)) \end{aligned} \tag{B.11}$$

The first-order condition for the investment-to-capital ratio $i_s(w)$ is:

$$i_s(w) = \frac{1}{\theta}\left(\frac{p_s(w)}{p_s'(w)} - w - 1\right) + \nu_s, \tag{B.12}$$

where $p_s'(w) = P_W(K,W,s)$ is the marginal value of cash in state s.

When the marginal source of financing is the credit line, that is the region $(\underline{W}_s, 0)$, firm value solves the following ODE:

$$\begin{aligned} r_s P(K,W,s) = \max_{I} \, & [(r_s + \alpha)W + \hat{\mu}_s K - I - \Gamma(I,K,s)]P_W(K,W,s) \\ & + \frac{\sigma_s^2 K^2}{2} P_{WW}(K,W,s) + (I - \delta K)P_K(K,W,s) \\ & + \hat{\zeta}_s(P(K,W,s^-) - P(K,W,s)), \end{aligned} \tag{B.13}$$

where α is the spread over the risk-free rate that the firm pays when the credit line is used. Similarly to the first region, the cash-to-capital ratio can be used as the one state variable in the optimisation problem. Equation (B13) can then be re-written as:

$$\begin{aligned} r_s p_s(w) = {} & [(r_s+\alpha)w + \hat{\mu}_s - i_s - g_s(i_s)]p_s'(w) + \frac{\sigma_s^2}{2}p_s''(w) \\ & + (i_s-\delta)(p_s(w) - wp_s'(w)) + \hat{\zeta}_s(p_{s^-}(w) - p_s(w)) \end{aligned} \tag{B.14}$$

When cash holdings exceed the upper payout boundary ($W \geq \overline{W}_s$), the firm starts to distribute cash to shareholders. For each state s, the payout boundary $\overline{w}_s = \overline{W}_s/K$ satisfies the following value matching condition:

$$p_s'(\overline{w}) = 1. \tag{B.15}$$

Optimality also requires the the super contact condition (Dumas, 1991):

$$p_s''(\overline{w}) = 0. \tag{B.16}$$

When cash holdings exceed the target, in each state s, the firm pays the excess over the target to current shareholders. This means that firm value above the payout boundary ($w > \overline{w}_s$) is given by:

$$p_s(w) = p_s(\overline{w}_s) + w - \overline{w}_s. \tag{B.17}$$

Cash distributions to shareholders occur following increases of the cash-to-capital ratio due to cash-flow shocks or when the state switches from s to s^- and the current cash balance is above $\overline{w}_{s^-}$.

The firm will issue equity only after it reaches its optimal maximum credit line draw down. This means that $-c$ equals the lower boundary for equity issuance, $\underline{w}_s$. This boundary can be crossed either due to declines in the cash-to-capital ratio related to diffusion shocks or when the economy switches from state s to state s^- and the current cash-to-capital ratio is below the new credit line limit ($w < -c_{s-}$). In each state s, when the cash balance is below $-c_s$, firm value satisfies:

$$p_s(w) = p_s(m_s) - \phi_s - (1+\gamma_s)(m_s - w). \tag{B.18}$$

At the external equity financing boundary $-c_s$, the following value matching and smooth pasting conditions apply:

$$p_s(-c_s) = p_s(m_s) - \phi_s - (1+\gamma_s)(m_s + c), \tag{B.19}$$

$$p_s^{'}(-c_s) = 1 + \gamma_s. \tag{B.20}$$

The firm value function is continuous and smooth everywhere, and therefore two additional boundary conditions are needed when the cash balance reaches zero. At each point, the firm compares continuation value to liquidation value. If the liquidation value is higher, shareholders choose to liquidate. Because the firm's capital is always productive, the firm never voluntarily liquidates before it runs out of cash. In the case of liquidation, firm value is given by:

$$p_s(0) = l_s. \tag{B.21}$$

Enterprise value represents firm value net of the value of short-term illiquid assets. In the model, it is then defined as $P(K,W,s) - W$. Average q is defined as the ratio between enterprise value and the capital stock,

$$q_s(w) = \frac{P(K,W,s) - W}{K} = p_s(w) - w. \tag{B.22}$$

The sensitivity of average q relative to changes in the cash-to-capital ratio measures how much enterprise value changes with an extra dollar of cash inside the firm. It is given by:

$$q_s^{'}(w) = p'_s(w) - 1. \tag{B.23}$$

This represents the marginal value of cash.

IV Quantitative results

Using the baseline parameter set, the average firm has a target cash-to-capital ratio of 0.20 in good times. The optimal credit line draw down in good times, c_1, is 4.52% of capital. Once the equity issuance boundary is reached, the firm issues equity at the amount of $c_1 + m_1 = 0.09$, where m_1 represents the level of the cash-to-capital ratio the firm returns to after issuance. At this point, the marginal value of cash is equal to the marginal cost of equity. The average amount of equity issued of 9% of capital is smaller compared to the size of SEOs, but more in line with the evidence in Fama and French (2005) of smaller but more frequent equity issues.

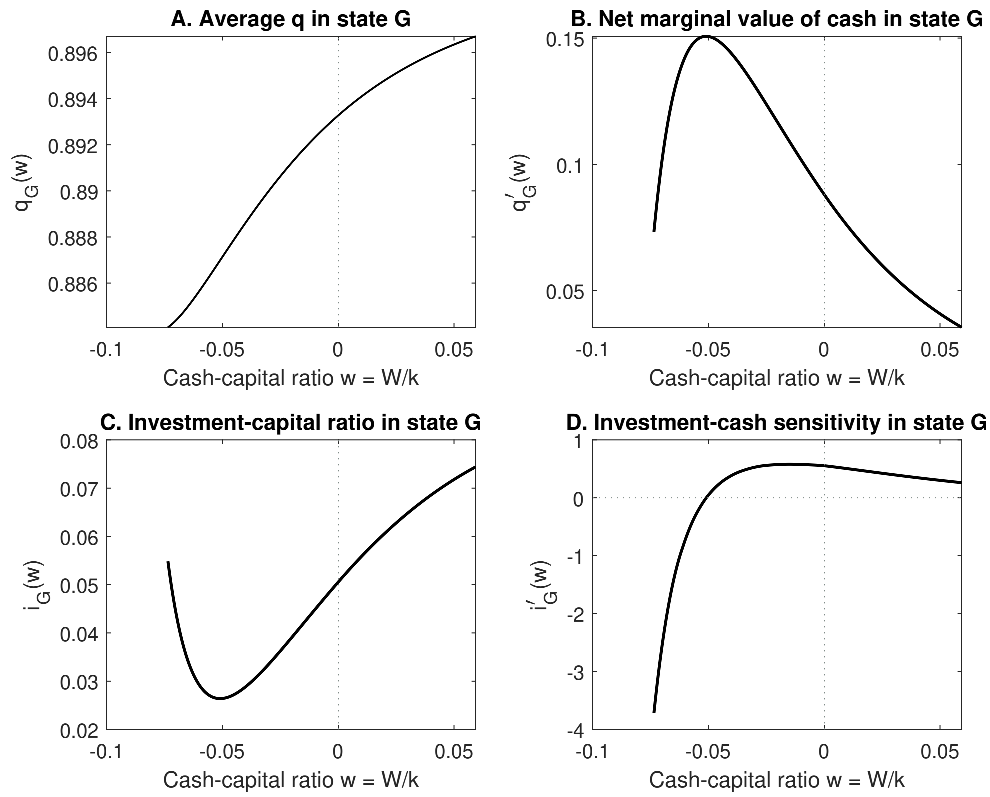


Fig. B.2 Credit line and market timing in state G. The figure shows how firm value and investment change with the cash-to-capital ratio in the good state G when the firm can access a credit line. Panel A shows average q, $q_G(w)$, Panel B shows the net marginal value of cash, $q'_G(w)$, Panel C shows the investment-to-capital ratio, $i_G(w)$ and Panel D shows the investment-to-cash sensitivity, $i'_G(w)$.

Figure 11 shows how average q, investment and their sensitivities to cash change with the cash-to-capital ratio, w. A negative cash-to-capital ratio means the firm is drawing down its credit line. The higher cost of issuing equity in bad times makes issuing more equity in good times a valuable option. The equity market timing option is more valuable for firms close to their equity issuance boundaries. Because firms issue equity sooner than absolutely necessary, they rely less on bank borrowing in good times. In other words, the credit line drawn in good times is smaller compared to a model without stochastic financing opportunities. This is consistent with the empirical evidence of firms issuing more equity in good times and relying less on debt. Because of the option to time the equity market, the marginal value of cash is non-monotonic with respect to the firm's financing position. As the firm draws down its credit line and approaches its equity issuance boundary, it becomes more risk-loving. The marginal value of cash declines. The equity market timing option becomes more in-the-money, and therefore less risky. This motivates the firm to save less and invest more. As a result, the relationship between investment and cash is also non-monotonic and the investment-cash sensitivity switches signs. This has important implications for firm risk premia.

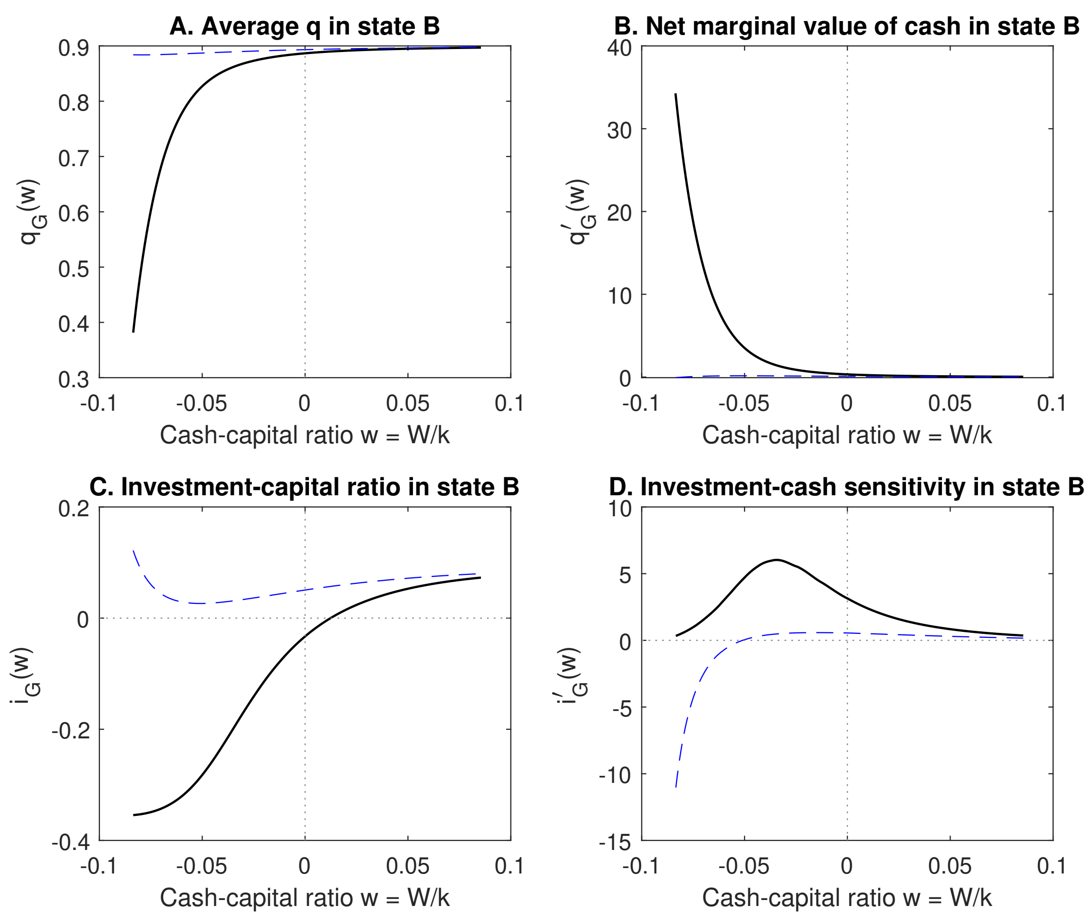


Fig. B.3 Credit line and market timing in state B. The figure shows how firm value and investment change with the cash-to-capital ratio, w, in the bad state B when the firm can access a credit line. Panel A shows average q, $q_B(w)$, Panel B shows the net marginal value of cash, $q'_B(w)$, Panel C shows the investment-to-capital ratio, $i_B(w)$ and Panel D shows the investment-to-cash sensitivity, $i'_B(w)$. The dashed blue lines show the respective values in the good state G.

Figure 12 shows how average q, investment and their sensitivities to cash change with the cash-to-capital ratio in bad times. The solid black lines represent values in the bad state, while the dashed blue lines represent values in the good state. The credit line limit is higher compared to the good state. The reason relates to firms having lost the equity market timing options . Lower average credit line limits in good times and higher limits in bad times are consistent with the evidence of countercyclical debt shown in Figure 2. Higher equity issuance in good times and lower equity issuance in bad times are consistent with the evidence of pro-cyclical equity issuance. Figure 12 also highlights the fact that average q and investment differ significantly in the two states. The average q for firms close to the credit line limit drops sharply. The marginal value of cash, in turn, reaches levels above 30, indicating severe distress. Financially constrained firms engage in asset sales up to 40% of capital. The firm prefers selling assets to incurring the high costs associated with equity issuance.

The absence of equity market timing options in bad times also implies that average q is strictly concave with respect to the cash-to-capital ratio. This in turn leads to the marginal value of cash monotonically decreasing with the cash-to-capital ratio and investment monotonically increasing with the cash-to-capital ratio. Investment-cash sensitivity is always positive in bad times.

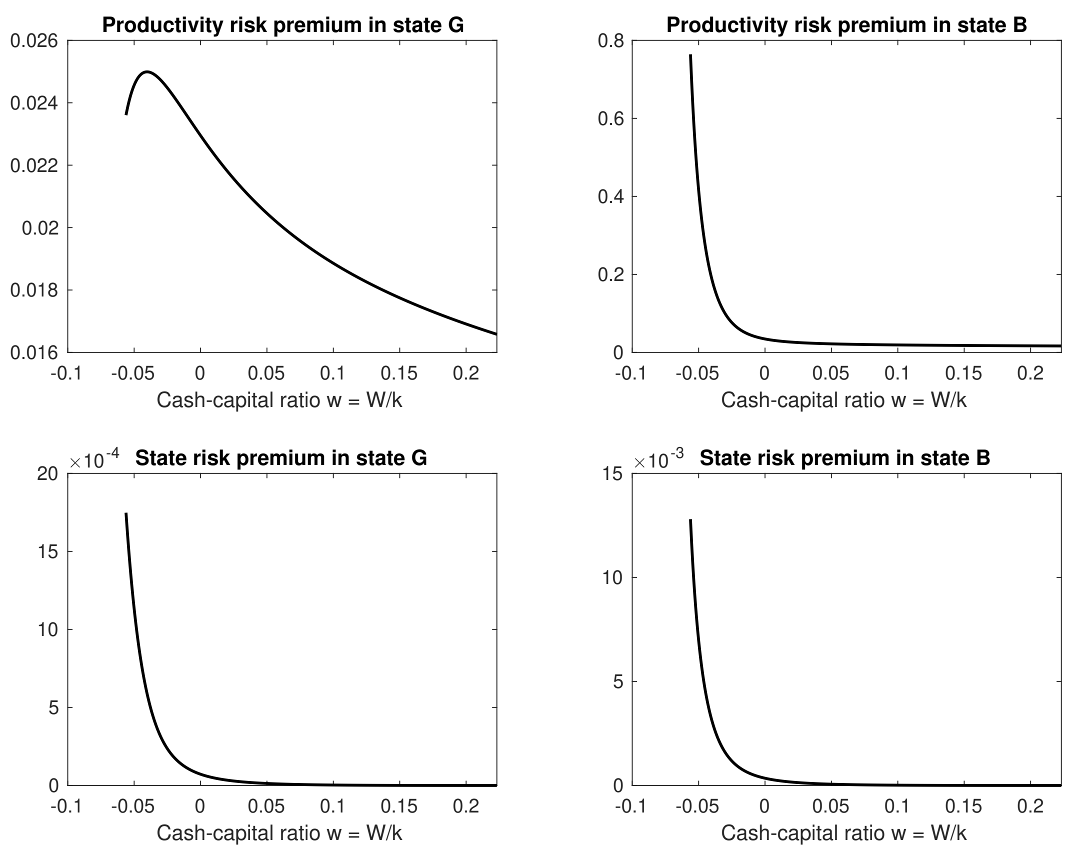


Fig. B.4 Risk premia.
The top panels show how the productivity risk premium changes with the cash-to-capital ratio, w. The left panel refers to the good state and the right panel refers to the bad state. The two panels at the bottom show how the state premium changes with the cash-to-capital ratio, w. The left panel refers to the good state and the right panel refers to the bad state.

Figure 13 shows how the productivity and state premia change with the cash to capital ratio. Panel 1 shows the productivity premium in the good state. The premium initially increases with the cash-to-capital ratio and then declines, reflecting the impact of the equity market timing option on firm value. Intuitively, a firm approaching its equity issuance boundary becomes less risky as the option to time the equity market becomes more in-the-money. Panel 2 shows the productivity premium in the bad state. Absent the equity market timing options, the premium declines monotonically with cash. It exceeds the level of the productivity premium in the good state by a large margin, especially so for low levels of w.

Panels 3 and 4 show the state premia in good and bad times. The benchmark values for the market price of state shocks imply lower state premia compared to the productivity premia. The state premium always decreases with cash, although more rapidly in state B. Firm value changes significantly from one state to another at low levels of the cash-to-capital ratio. This explains the higher levels of the sensitivity to shocks to the market state in this region. The difference in firm value between states is negligible when close to the payout boundary. The model thus predicts a positive premium between low w and high w firms, with a larger difference in bad times. This is equivalent to a positive premium between low average q (high book-to-market) and high average q (low book-to-market) firms, with a much larger premium in bad times. This evidence alone shows that the model can reproduce an unconditional value premium as well as a larger value premium in bad times.

B.3 Calibration

Table B.2 Benchmark parameter values.
This table lists the benchmark parameter values used to solve and simulate the model when allowing for credit lines. All parameters are presented in annualized form.

Parameter	Value state G	Value state B	Description
r	5%	5%	Risk-free rate
δ	15%	15%	Rate of capital depreciation
μ	22.7%	22.7%	Expected productivity shock
σ	12%	12%	Volatility of productivity shock
θ	1.8	1.8	Investment adjustment cost parameter
ν	15%	15%	Center of adjustment cost parameter
λ	1.5%	1.5%	Carry cost of cash
γ	6%	6%	Marginal cost of equity issuance
ρ	0.4	0.4	Correlation between Z_t^A and Z_t^M
η	0.4	0.4	Price of risk for technology shocks
ζ_s	0.1	0.5	State transition intensity
l_s	0.8	0.5	Liquidation value of capital
ϕ_s	0.1%	30%	Fixed cost of equity issuance
κ_s	ln(3)	-ln(3)	Price of risk for financing shocks

B.4 Covariance between cumulative and expected returns

The instantaneous covariance between cumulative excess returns and expected excess returns is given by:

$$\Gamma_t(w,s) = \mathbb{E}\left[(CER_{t+l} - \mathbb{E}\left[CER_{t+l} \mid \mathscr{F}_t\right]) \cdot (EER_{t+l} - \mathbb{E}\left[EER_{t+l} \mid \mathscr{F}_t\right]) \mid \mathscr{F}_t\right]$$

Based on the above, only the diffusion terms of the dCER$_t$ and dEER$_t$ processes are needed. In the cash retention region, $\left(\underline{W}, \overline{W}\right)$, the cumulative excess return process is given by:

$$d\,CER_t(K,W,s) = \frac{d\,P_t\,(K,W,s)}{P_t(K,W,s)} - r_s\,dt$$

The cumulative excess return process in terms of the scaled value function (using Ito's lemma) is given by:

$$\begin{aligned} d\,cer_t(w,s) &= \frac{p_t(w,s)\,d\,K_t + K_t\,d\,p_t(w,s)}{p_t(w,s)\,K_t} - r_s\,dt \\ &= (i_s(w) - \delta)\;p_t(w,s)dt + \frac{d\,p_t(w,s)}{p_t(w,s)} - r_s\,dt \end{aligned}$$

The percentage change in the scaled value function, $\frac{d\,p_t(w,s)}{p_t(w,s)}$, in the region $(0, \overline{w})$ is given by:

$$\frac{d\,p_t(w,s)}{p_t(w,s)} = \{[(r_s-\lambda)\,w+\mu_s-i_s(w)-g_s(i(w))]\,\frac{p_t^{'}(w,s)}{p_t(w,s)}+\frac{\sigma_s^2}{2}\frac{p_t^{''}(w,s)}{p_t(w,s)} + (i_s(w)-\delta)\left(1-\frac{p_t^{'}(w,s)}{p_t(w,s)}\right)+\frac{p_t(w,s^-)-p_t(w,s)}{p_t(w,s)}\zeta_s - r_s\}\,dt + \sigma_s\frac{p_t^{'}(w,s)}{p_t(w,s)}\,dZ_t^A+\frac{p_t(w,s)-p_{t-1}(w,s^-)}{p_{t-1}(w,s^-)}\,\varepsilon_t,$$

In the region ($\underline{w}$, 0), $\frac{d\,p_t(w,s)}{p_t(w,s)}$ is given by:

$$\frac{d\,p_t(w,s)}{p_t(w,s)} = \{[(r_s+\alpha)\,w+\mu_s-i_s(w)-g_s(i(w))]\,\frac{p_t^{'}(w,s)}{p_t(w,s)}+\frac{\sigma_s^2}{2}\frac{p_t^{''}(w,s)}{p_t(w,s)} + (i_s(w)-\delta)\left(1-\frac{p_t^{'}(w,s)}{p_t(w,s)}\right)+\frac{p_t(w,s^-)-p_t(w,s)}{p_t(w,s)}\zeta_s - r_s\}\,dt + \sigma_s\frac{p_t^{'}(w,s)}{p_t(w,s)}\,dZ_t^A+\frac{p_t(w,s)-p_{t-1}(w,s^-)}{p_{t-1}(w,s^-)}\,\varepsilon_t,$$

where ε_t is the realised

$$\varepsilon_t = \begin{cases} 0, & \text{if } s_{t-1}=s_t. \\ 1, & \text{otherwise.} \end{cases}$$

The drift of the cumulative excess return process is equal to the expected excess return. The expression for $d\,cer_t(w,s)$ can then be simplified to:

$$d\,cer_t(w,s) = EER_t\,dt + \sigma_s \frac{p_t^{'}(w,s)}{p_t(w,s)}\,dZ_t^A + \frac{p_t(w,s) - p_{t-1}(w,s^-)}{p_{t-1}(w,s^-)}\,\varepsilon_t. \tag{B.24}$$

Realised returns deviate from expectations due to cash flow shocks and shocks to the state of the economy. The second term in equation (D1) captures the portion of the return attributable to cash flow shocks. The third term captures the change in firm value resulting from a change in the state of the economy from time $t-1$ to time t. The state shock, ε_t, is a Poisson shock with expected value equal to the transition probability, ζ_s, under the physical measure.

The expected excess return, $eer_t(w,s)$ is given by:

$$eer_t(w,s) = -(e^{\kappa_s} - 1)\,\zeta_s\,\frac{p_{s^-}(w) - p_s(w)}{p_s(w)} + \eta_s\,\rho_s\,\sigma_s\,\frac{p_s^{'}(w)}{p_s(w)}.$$

Using Ito's lemma and assuming the changes in the state of the economy are uncorrelated to cash-flow shocks, the expected excess return process, $d\,eer_t(w,s)$, is given by:

$$d\,eer_t(w,s) = \frac{\partial\,eer_t}{\partial\,w_t}\,dw_t + \frac{1}{2}\frac{\partial^2\,eer_t}{\partial\,w_t^2}\,(dw_t)^2 + \frac{\partial\,eer_t}{\partial\,s}\,d\,\varepsilon_t + \frac{1}{2}\frac{\partial^2\,eer_t}{\partial\,s_t^2}\,(d\,\varepsilon_t)^2$$

The dynamics of the cash-to-capital ratio, w, are given by:

$$d\,w_t = [\mu_s - i_s(w) - g_s(i(w)) + w_t\,(r_s - \lambda + i_s(w) - \delta)]\,dt + \sigma_s d\,Z_t^A + \frac{dF_t}{K_t} - \frac{d\,D_t}{K_t}$$

The diffusion term of the expected excess return process, $d\,eer_t(w,s)$ is then given by:

$$A_t(w,s)\,\sigma_s\,dZ_t^A + B_t(w,s)\,\varepsilon_t \tag{B.25}$$

where

$$A_t(w,s) = \eta_s \rho_s \sigma_s \frac{p_t^{''}(w,s)p_t(w,s) - \left(p_t^{'}(w,s)\right)^2}{(p_t(w,s))^2} - (e^{\kappa_s}-1)\,\zeta_s \frac{p_t^{'}(w,s^-)p_t(w,s) - p_t(w,s^-)p_t^{'}(w,s)}{(p_t(w,s))^2} \tag{B.26}$$

and

$$B_t(w,s) = \eta_{s^-}\rho_{s^-}\sigma_{s^-}\frac{p_t^{'}(w,s^-)}{p_t(w,s^-)} - \eta_s\rho_s\sigma_s\frac{p_t^{'}(w,s)}{p_t(w,s)} - (e^{\kappa_{s^-}}-1)\,\zeta_{s^-}\frac{p_t(w,s)-p_t(w,s^-)}{p_t(w,s^-)} + (e^{\kappa_s}-1)\,\zeta_s\frac{p_t(w,s^-)-p_t(w,s)}{p_t(w,s)}$$

The instantaneous covariance between $d\,cer_t$ and $d\,eer_t$ is given by:

$$\Gamma_t(w,s) = A_t(w,s)\,\sigma_s^2\,\frac{p_t^{'}(w,s)}{p_t(w,s)} + B_t(w,s)\,\zeta_{s^-}\,\frac{p_t(w,s)-p_{t-1}(w,s^-)}{p_{t-1}(w,s^-)}$$

The instantaneous correlation coefficient, which is more easily interpretable, is given by:

$$\Upsilon_t(w,s) = \frac{\Gamma_t(w,s)}{\sqrt{A_t^2(w,s)\,\sigma_s^2 + B_t^2(w,s)} \times \sqrt{\sigma_s^2\left(\frac{p_t^{'}(w,s)}{p_t(w,s)}\right)^2 + \zeta_{s^-}^2\left(\frac{p_t(w,s)-p_{t-1}(w,s^-)}{p_{t-1}(w,s^-)}\right)^2}}$$

B.5 Comparative statics

Fig. B.5 Comparative statics: Expected cash-flow growth rate in bad times.
The plots show how the productivity risk premia, financing risk premia, investment, investment-cash sensitivities and the instantaneous covariance between cumulative past returns and expected excess returns change with the expected growth rate in cash flows during bad times, μ_2. Panels A and B refer to good times, with Panel A showing the results with respect to financially constrained firms and Panel B showing the results of financially unconstrained firms. Panels C and D refer to bad times, with Panel C referring to financially constrained firms and Panel D referring to financially unconstrained firms.

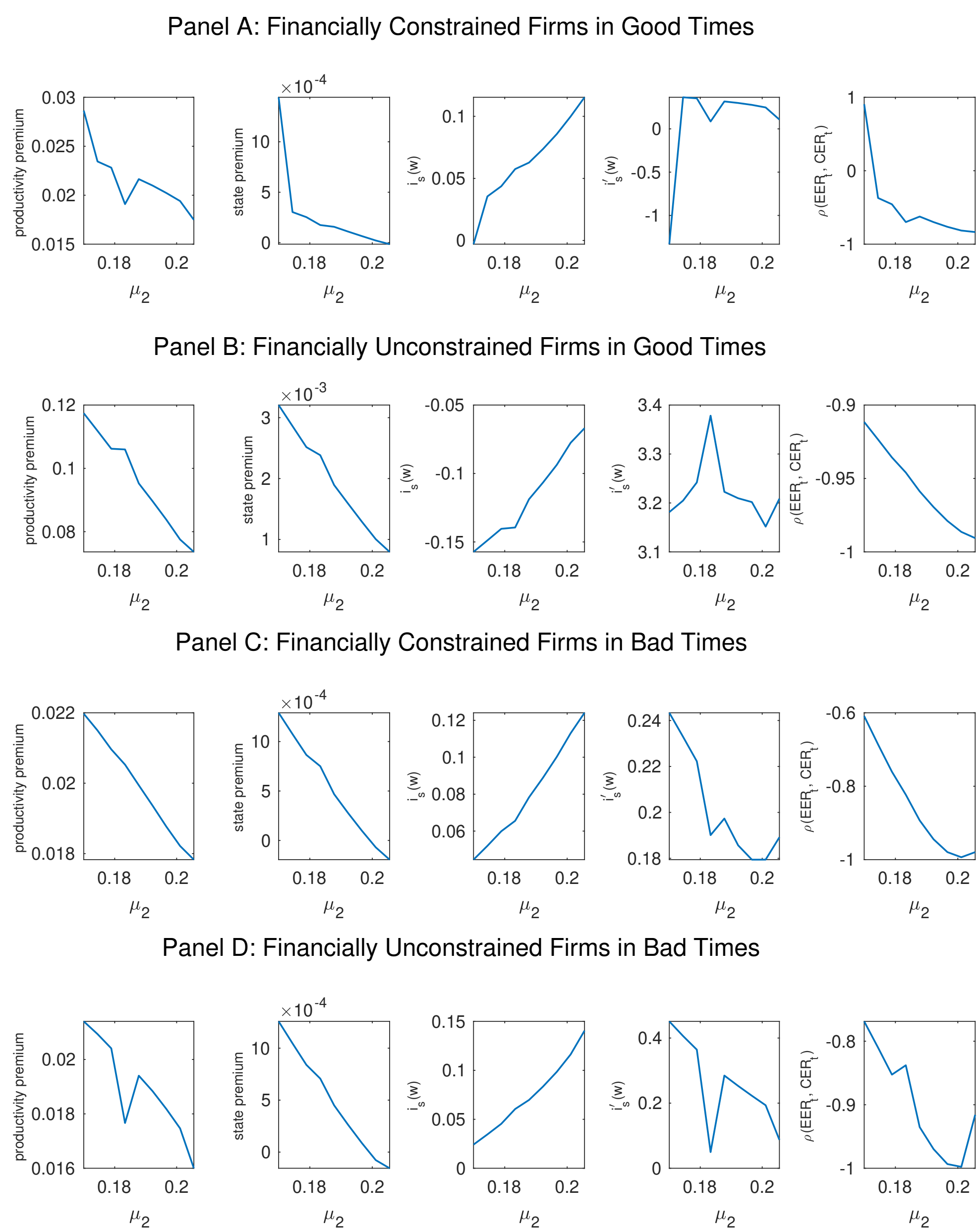


Fig. B.6 Comparative statics: Investment adjustment costs in bad times.
The plots show how the productivity risk premia, financing risk premia, investment and investment-cash sensitivities of financially constrained and unconstrained firms change with the investment adjustment cost parameter in bad times, θ_2. Panels A and B refer to good times, with Panel A showing the results with respect to financially constrained firms and Panel B showing the results of financially unconstrained firms. Panels C and D refer to bad times, with Panel C referring to financially constrained firms and Panel D referring to financially unconstrained firms.

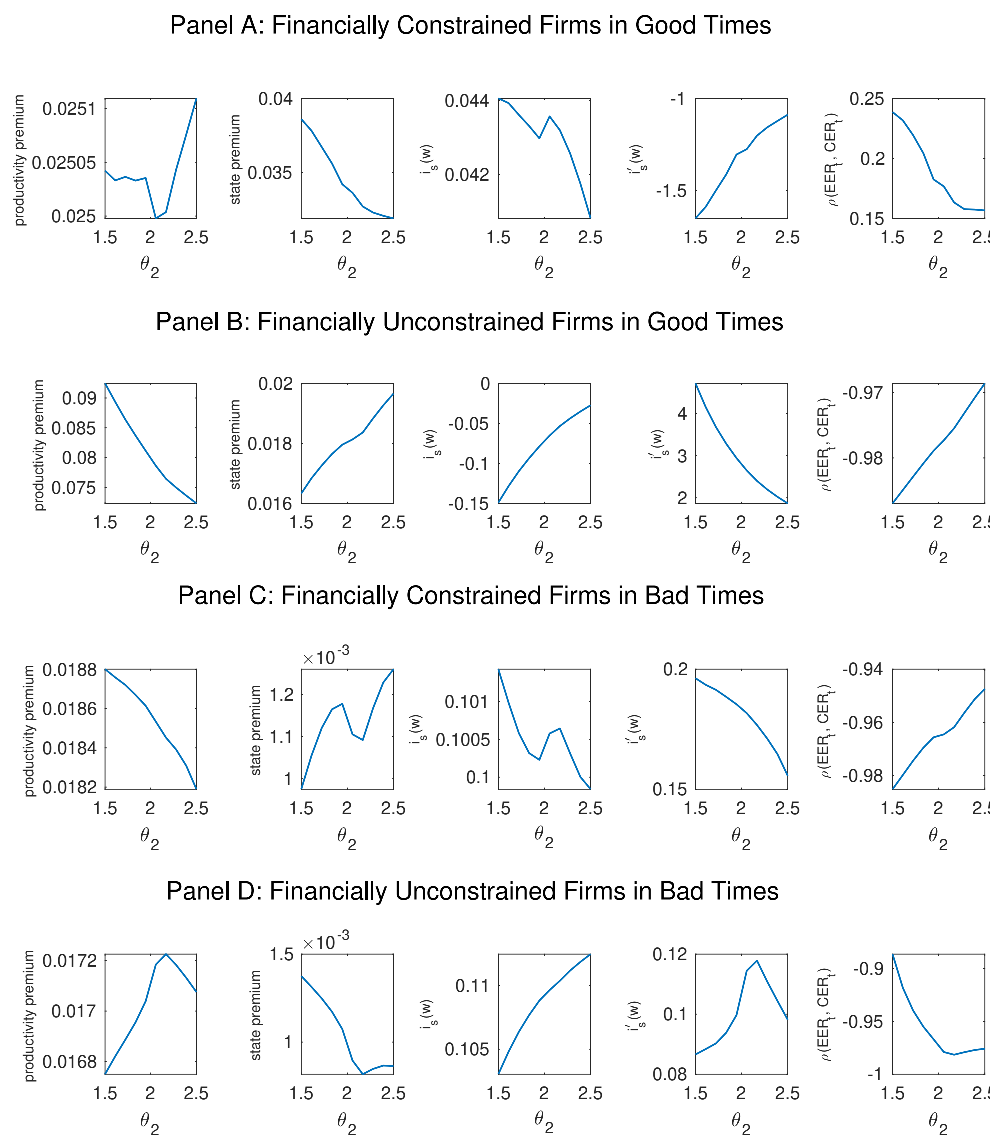


Fig. B.7 Comparative statics: Expected cash-flow growth rate.
The plots show how productivity risk premia, financing risk premia, investment and investment-cash sensitivities of financially constrained and unconstrained firms, change in good and bad times with the expected growth rate in cash flows, where $\mu = \mu_1 = \mu_2$. Panels A and B refer to good times, with Panel A showing the results with respect to financially constrained firms and Panel B showing the results of financially unconstrained firms. Panels C and D refer to bad times, with Panel C referring to financially constrained firms and Panel D referring to financially unconstrained firms.

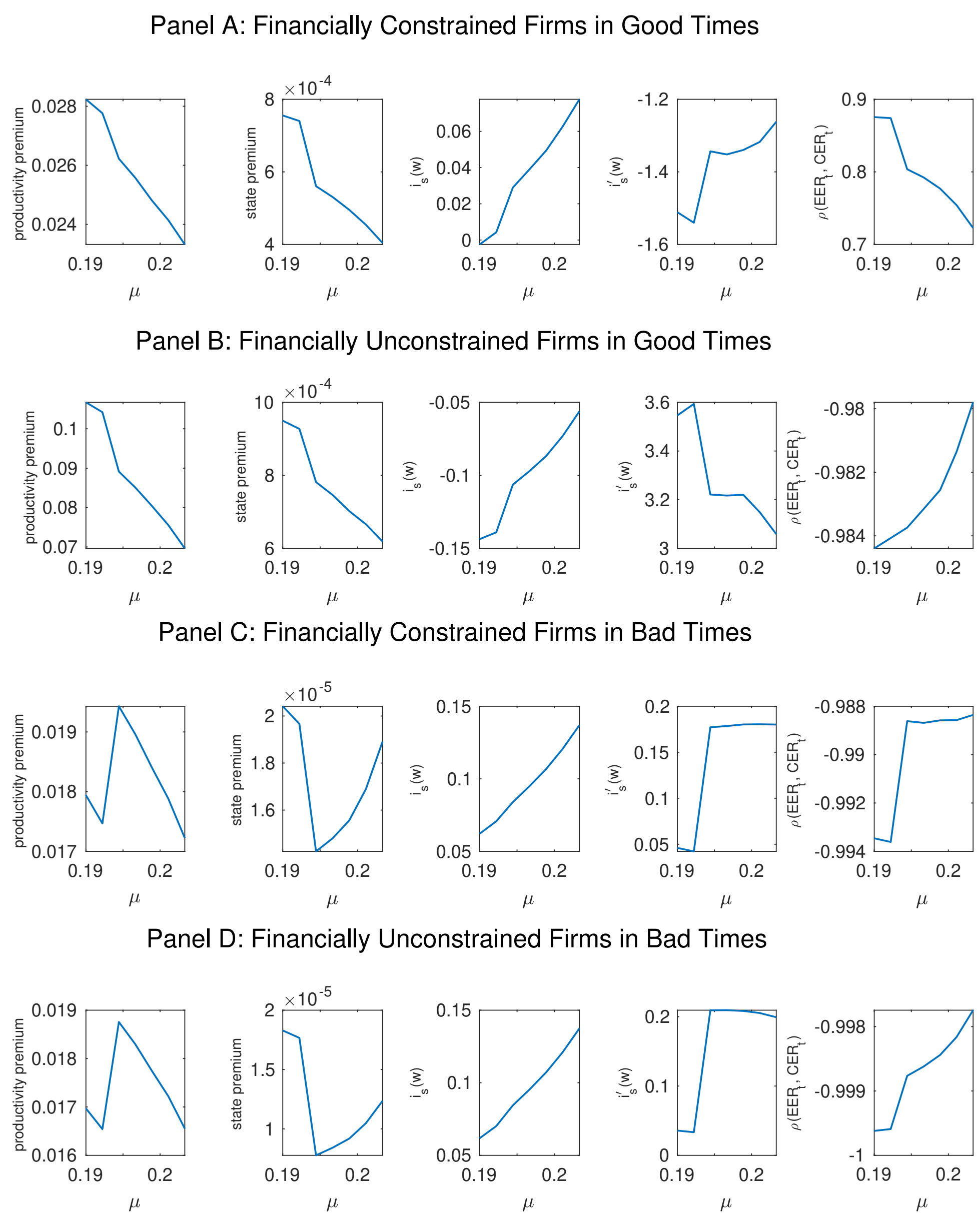


Fig. B.8 Comparative statics: Fixed cost of issuing equity in bad times.
The plots show how productivity risk premia, financing risk premia, investment and investment-cash sensitivities of financially constrained and unconstrained firms, change in good and bad times with the fixed cost of equity issuance in bad times ϕ_2. Panels A and B refer to good times, with Panel A showing the results with respect to financially constrained firms and Panel B showing the results of financially unconstrained firms. Panels C and D refer to bad times, with Panel C referring to financially constrained firms and Panel D referring to financially unconstrained firms.

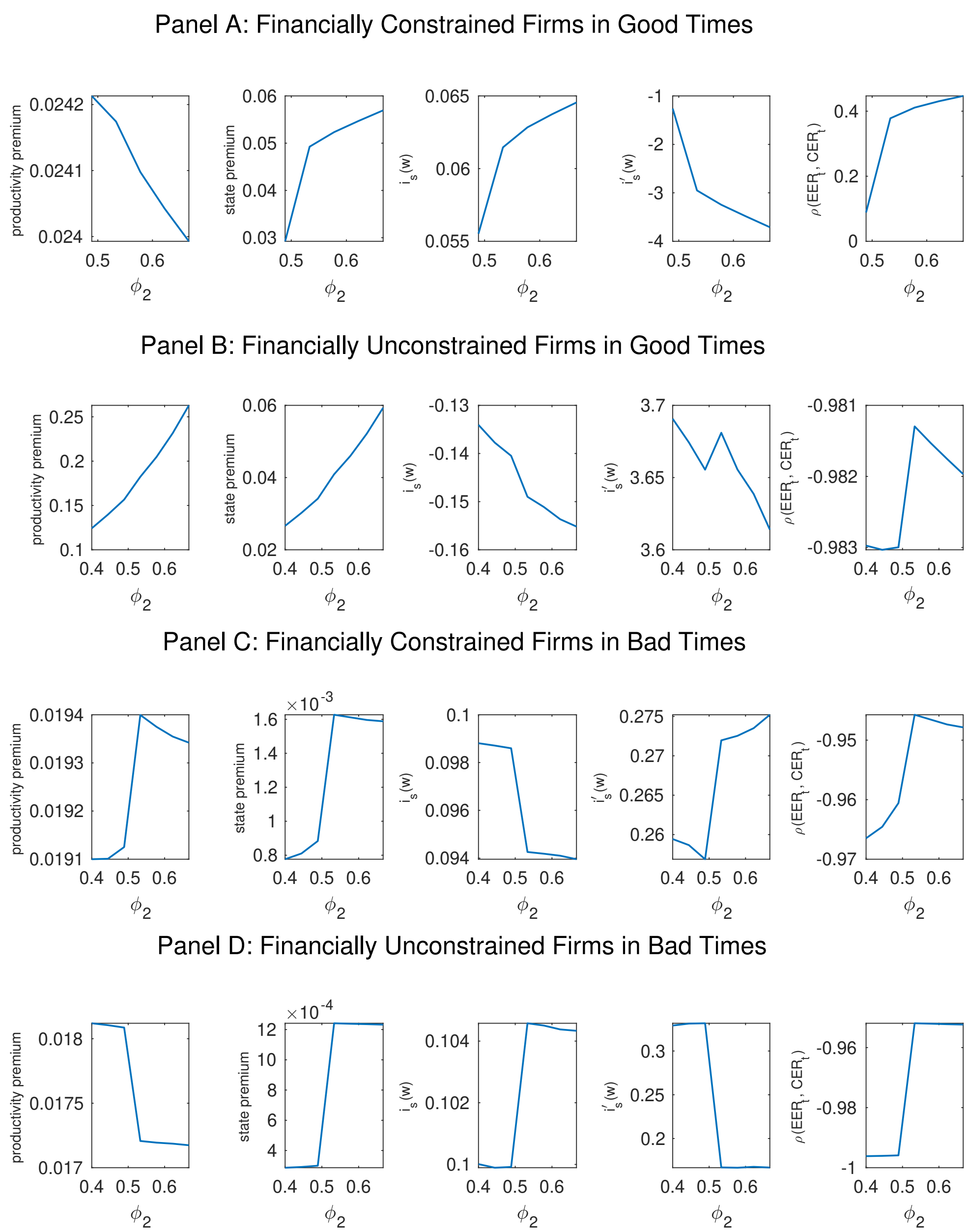
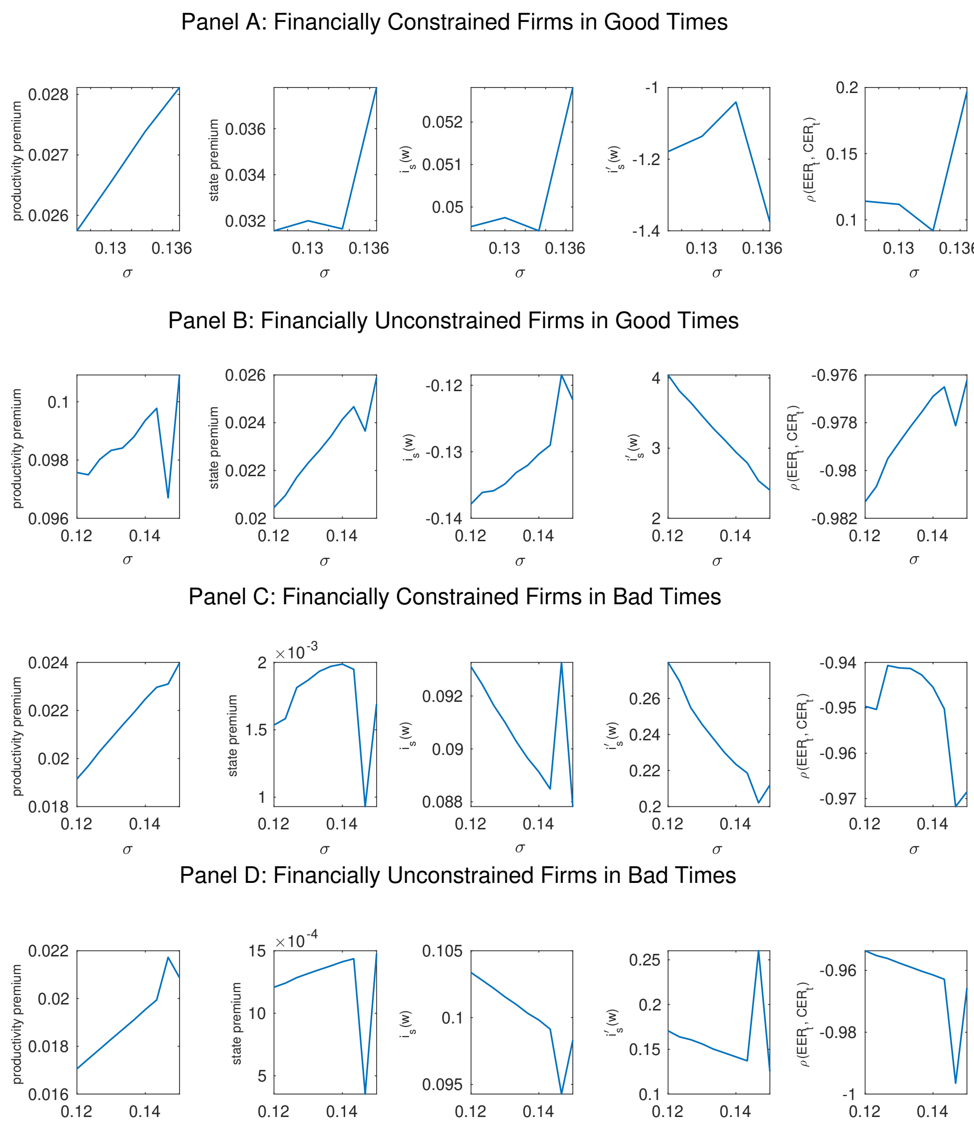


Fig. B.9 Comparative statics: Volatility of cash-flow shocks.
The plots show how productivity risk premia, financing risk premia, investment and investment-cash sensitivities of financially constrained and unconstrained firms, change in good and bad times with the volatility of cash-flow shocks σ. The volatility of cash-flow shocks is assumed to be equal in both good and bad times: $\sigma_1 = \sigma_2 = \sigma$. Panels A and B refer to good times, with Panel A showing the results with respect to financially constrained firms and Panel B showing the results of financially unconstrained firms. Panels C and D refer to bad times, with Panel C referring to financially constrained firms and Panel D referring to financially unconstrained firms.



B.6 Characteristics of value and momentum firms

Fig. B.10 Characteristics of momentum portfolios in event time.
For each portfolio formation month from January 1965 to December 2018, average portfolio statistics are computed starting from two years before formation up to two years after. The plots show the average characteristic for each month relative to formation based on all momentum portfolios constructed. Portfolio 1 contains firms with the highest past performance as of month 0 (the winners), while portfolio 10 contains firms with the lowest past performance as of month 0 (the losers). Past performance is measured as the cumulative return over the previous twelve months, skipping the most recent month due to reversal. Investment is the year-on-year change in Total Assets. Debt is measured as the sum of long term and short term debt (Compustat items DLCQ and DLTTQ respectively), scaled by total assets. Equity issuance is the cash proceeds from issuance of common and preferred shares (Compustat item SSTK). Cash is cash and cash equivalents. Distance from target cash is measured as the different between the current level of cash from the 5-year average of cash-to-assets for each firm. All variables are lagged, using the methodology from Fama and French [1992].

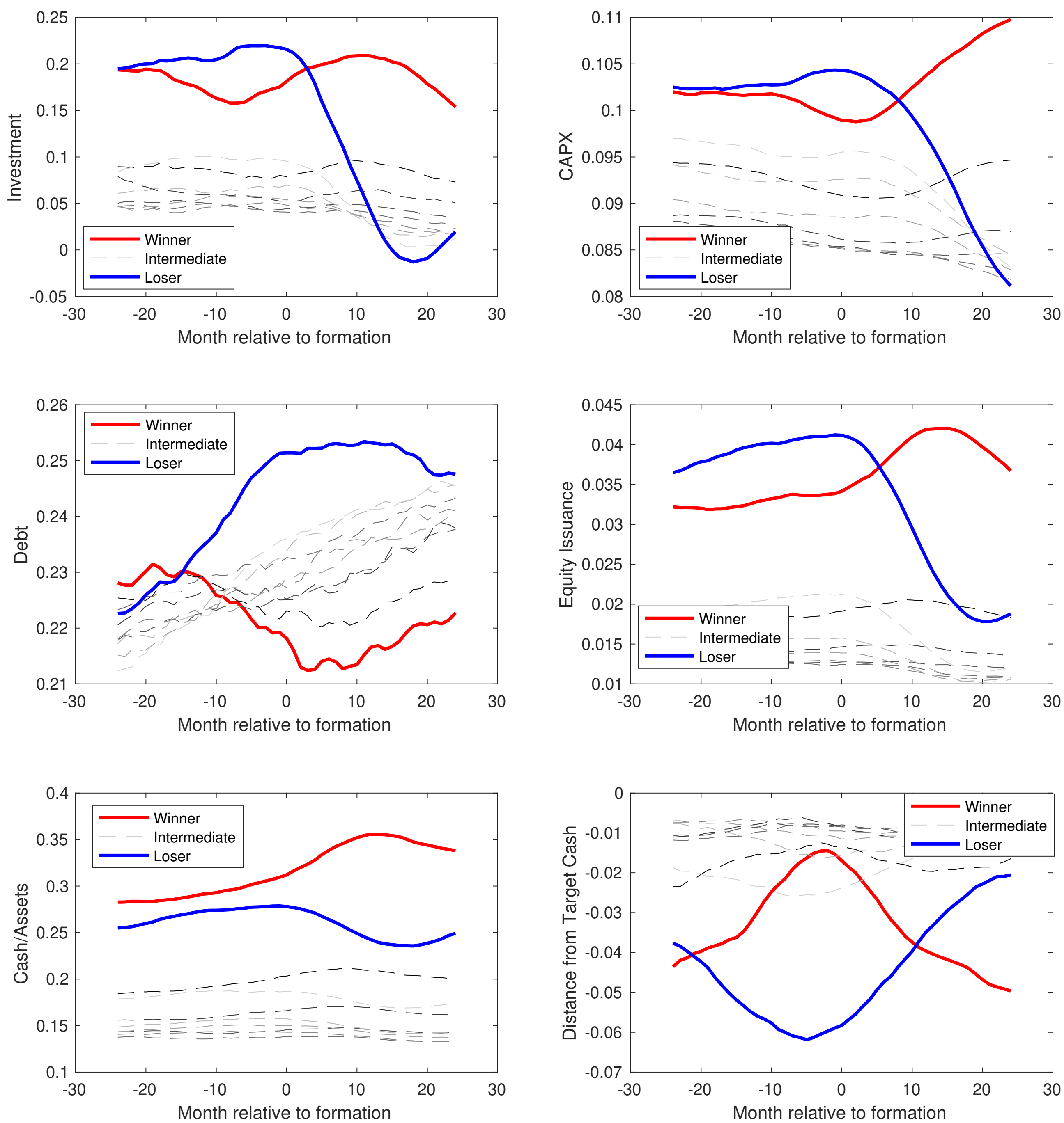


Fig. B.11 Characteristics of momentum portfolios in event time
For each portfolio formation month from January 1965 to December 2018, average portfolio statistics are computed starting from two years before formation up to two years after. The plots show the average characteristic for each month relative to formation based on all momentum portfolios constructed. Portfolio 1 contains firms with the highest past performance as of month 0 (the winners), while portfolio 10 contains firms with the lowest past performance as of month 0 (the losers). The operating margin is measured as the ratio of revenues minus cost of goods sold (Compustat variables REVT and COGS respectively) to revenues. Turnover is the ratio of revenues (REVT) to total assets (AT). R&D is the expense on research and development. Net Working Capital is given by the difference between current assets and current liabilities (Compustat variables ACT and LCT respectively), scaled by total assets. Cash flow is net income minus depreciation expense (Compustat variables NI and DP respectively).

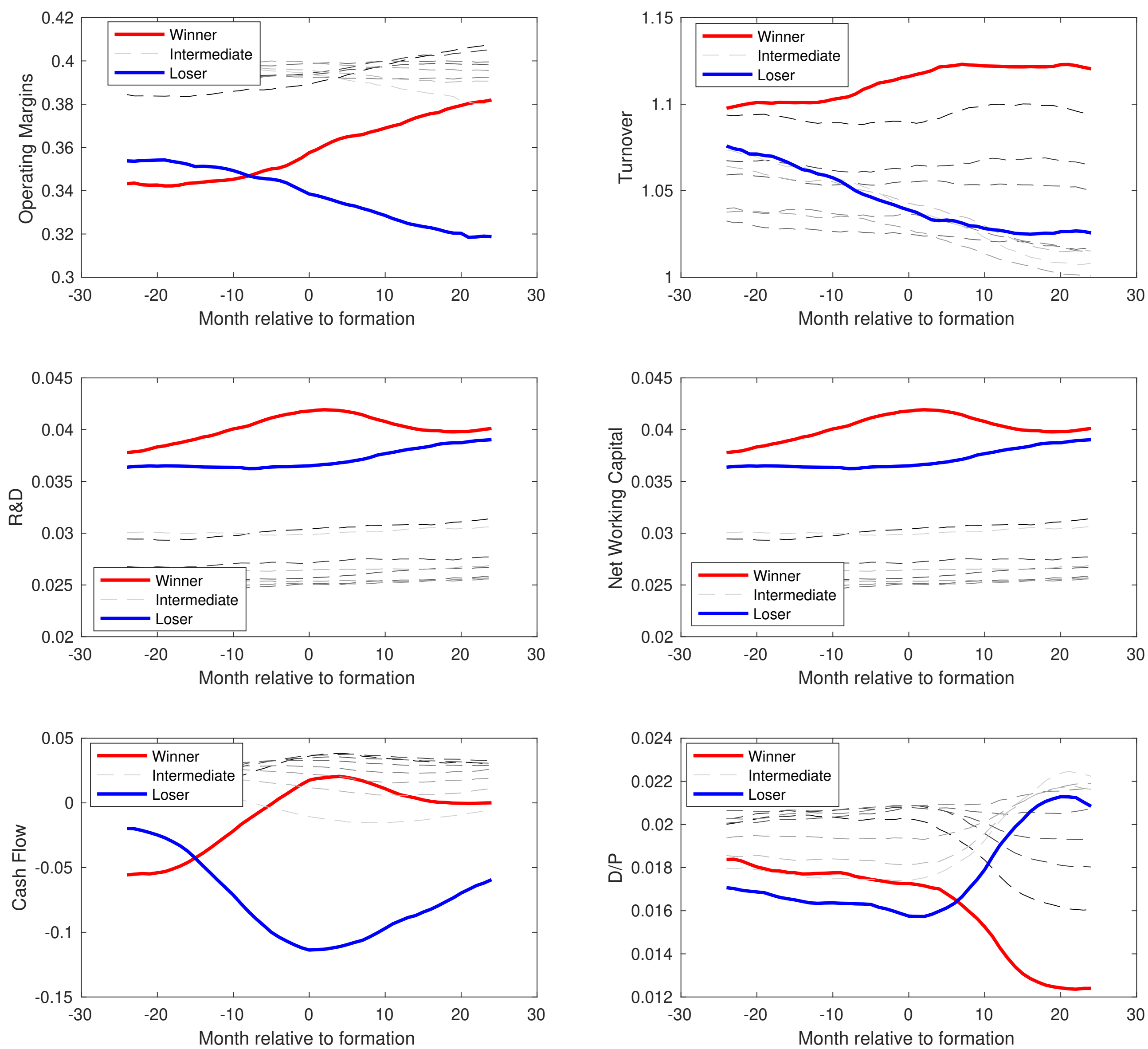


Fig. B.12 Characteristics of momentum portfolios in event time
For each portfolio formation month from January 1965 to December 2018, average portfolio statistics are computed starting from two years before formation up to two years after. The plots show the average characteristic for each month relative to formation based on all momentum portfolios constructed. Portfolio 1 contains firms with the highest past performance as of month 0 (the winners), while portfolio 10 contains firms with the lowest past performance as of month 0 (the losers). Past performance is measured as the cumulative return over the previous twelve months, skipping the most recent month due to reversal. The book-to-market ratio is calculated and lagged as in [43]. Gross profitability is revenues minus cost of goods sold (Compustat variables REVT and COGS), scaled by total assets. Size is measured as the market value of equity. SUE refers to standardized unexpected earnings, measured as the unexpected earnings based on a model of earnings assuming a seasonal random walk with drift. The drift for each firm in each quarter is measured as the average value of year-on-year changes in earnings over the previous eight quarters. The earnings forecast consists of the previous year's earnings per share plus the drift. Subtracting this forecast from the earnings announced for the quarter provides a measure of the earnings surprise. This measure is standardized by dividing by the standard deviation of the earnings surprises over the past eight quarters. CAR is the cumulative abnormal return over that of the market over three days surrounding the announcement. Earnings announcement dates are from Compustat's RDQ field.

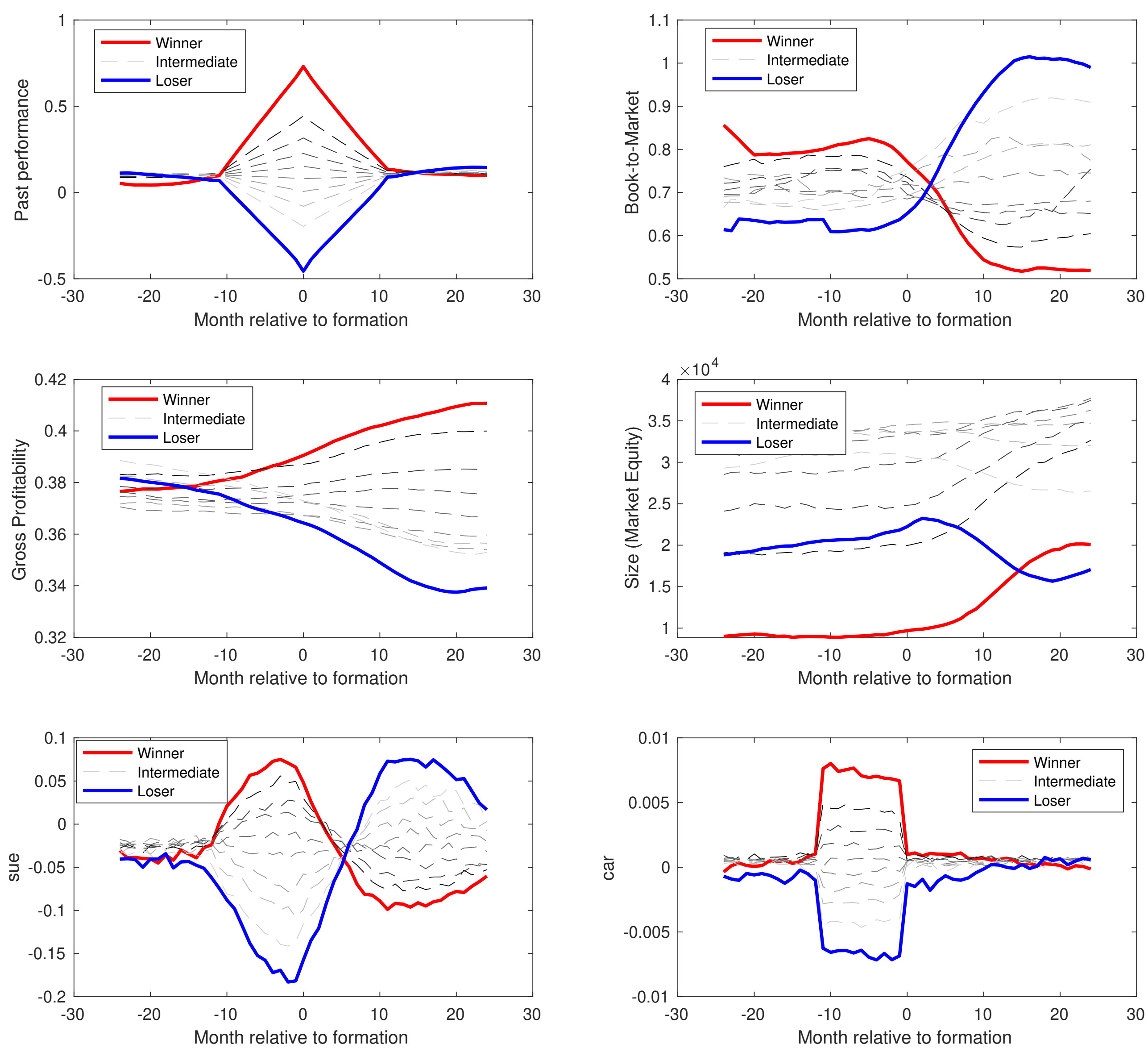


Fig. B.13 Characteristics of book-to-market portfolios in event time
For each portfolio formation month from January 1965 to December 2018, average portfolio statistics are computed starting from two years before formation up to two years after. The plots show the average characteristic for each month relative to formation based on all book-to-market portfolios constructed. Portfolio 1 contains firms with the highest book-to-market ratio as of month 0 (the winners), while portfolio 10 contains firms with the lowest book-to-market ratio as of month 0 (the losers). Book-to-market is measured as in Fama and French (1993). Book-to-market represents the ratio of book value of equity as of June in the most recent year to market value of equity as of December in the most recent year. Investment is the year-on-year change in Total Assets. Debt is measured as the sum of long term and short term debt (Compustat items DLTC and DLTS respectively), scaled by total assets. Equity issuance is the cash proceeds from issuance of common and preferred shares (Compustat item SSTK). Cash is cash and cash equivalents. Distance from target cash is measured as the different between the current level of cash from the 5-year average of cash-to-assets for each firm. All variables are lagged, using the methodology from Fama and French [1992].

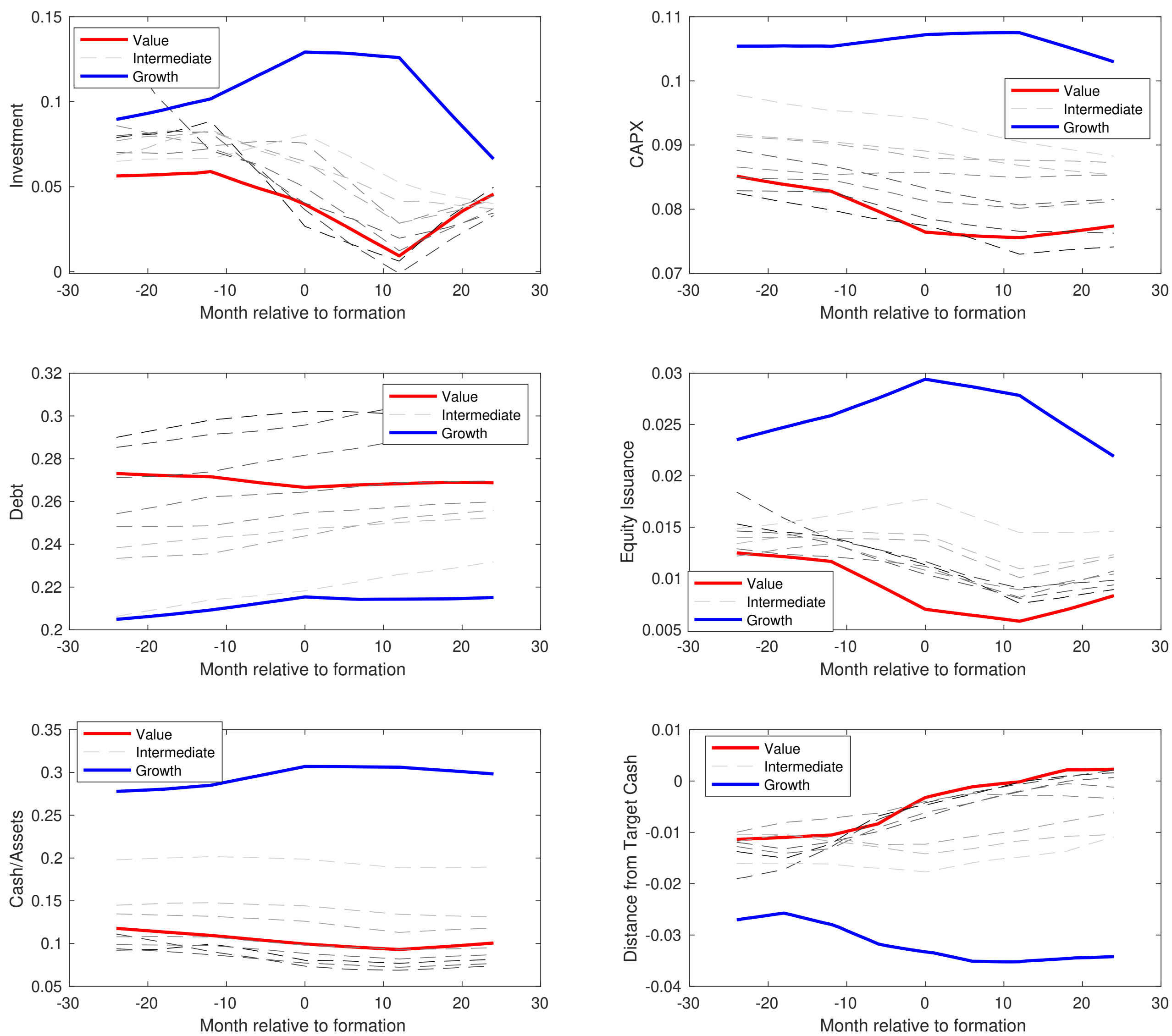


Fig. B.14 Characteristics of book-to-market portfolios in event time
For each portfolio formation month from January 1965 to December 2018, average portfolio statistics are computed starting from two years before formation up to two years after. The plots show the average characteristic for each month relative to formation based on all book-to-market portfolios constructed. Portfolio 1 contains firms with the highest book-to-market ratio as of month 0 (the winners), while portfolio 10 contains firms with the lowest book-to-market ratio as of month 0 (the losers). Book-to-market is measured as in Fama and French (1993). Book-to-market represents the ratio of book value of equity as of June in the most recent year to market value of equity as of December in the most recent year. The operating margin is measured as the ratio of revenues minus cost of goods sold (Compustat variables REVT and COGS respectively) to revenues. Turnover is the ratio of revenues (REVT) to total assets (AT). R&D is the expense on research and development. Net Working Capital is given by the difference between current assets and current liabilities (Compustat variables ACT and LCT respectively), scaled by total assets. Cash flow is net income minus depreciation expense (Compustat variables NI and DP respectively).

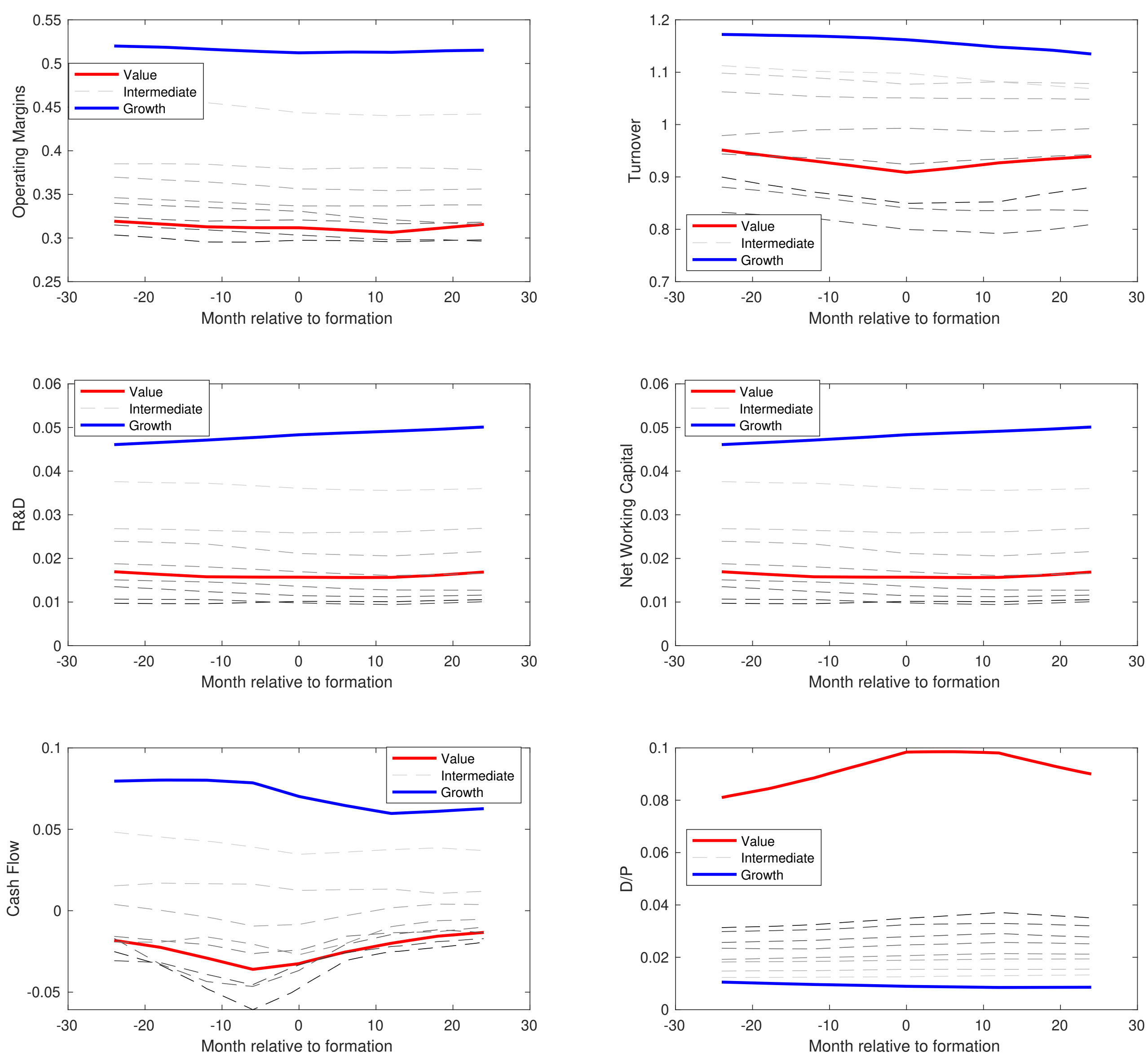
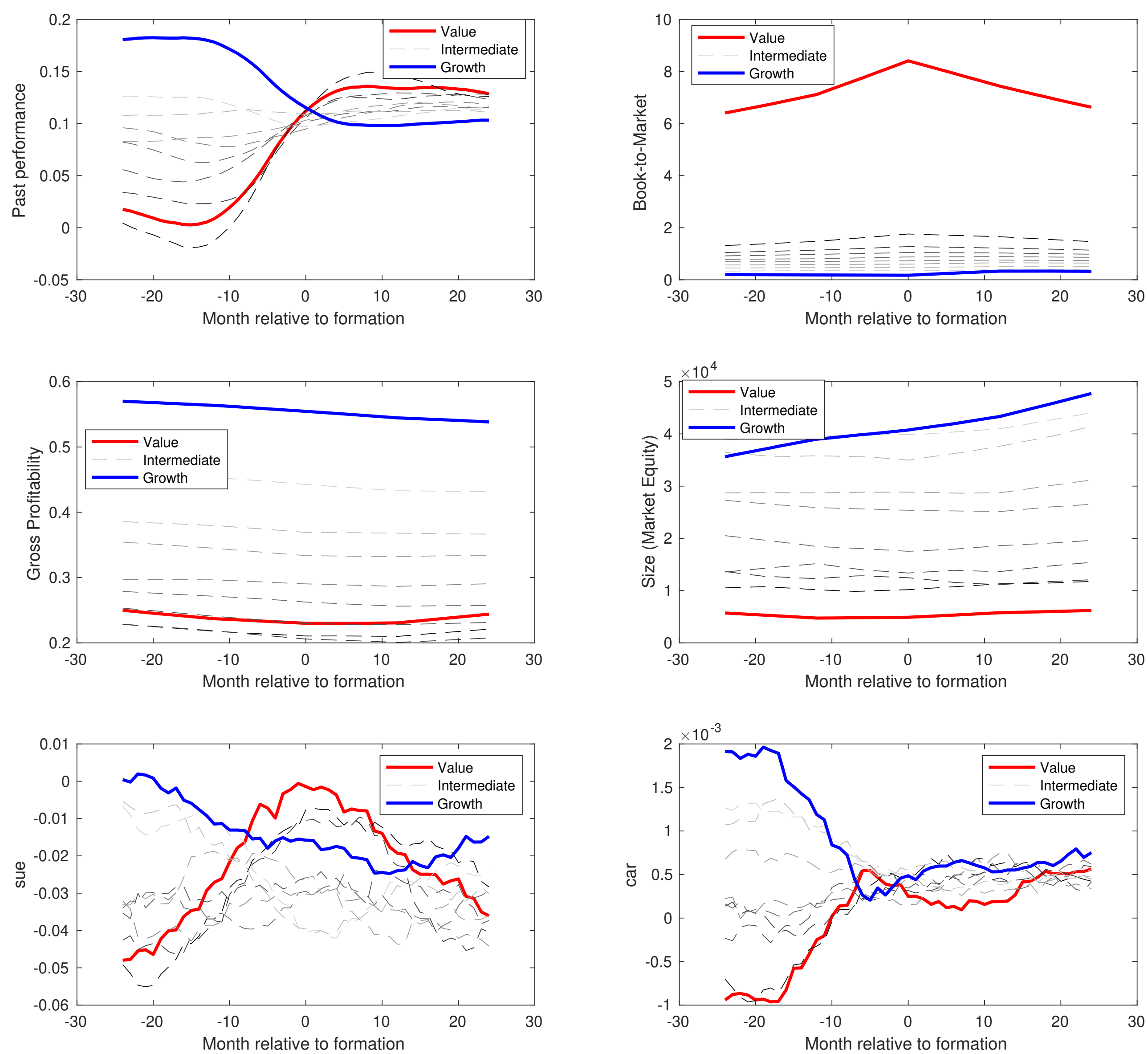


Fig. B.15 Characteristics of book-to-market portfolios in event time
For each portfolio formation month from January 1965 to December 2018, average portfolio statistics are computed starting from two years before formation up to two years after. The plots show the average characteristic for each month relative to formation based on all book-to-market portfolios constructed. Portfolio 1 contains firms with the highest book-to-market ratio as of month 0 (the winners), while portfolio 10 contains firms with the lowest book-to-market ratio as of month 0 (the losers). Book-to-market is measured as in Fama and French (1993). Book-to-market represents the ratio of book value of equity as of June in the most recent year to market value of equity as of December in the most recent year. Past performance is measured as the cumulative return over the previous twelve months, skipping the most recent month due to reversal. Gross profitability is revenues minus cost of goods sold (Compustat variables REVT and COGS), scaled by total assets. Size is measured as the market value of equity. SUE refers to standardized unexpected earnings, measured as the unexpected earnings based on a model of earnings assuming a seasonal random walk with drift. The drift for each firm in each quarter is measured as the average value of year-on-year changes in earnings over the previous eight quarters. The earnings forecast consists of the previous year's earnings per share plus the drift. Subtracting this forecast from the earnings announced for the quarter provides a measure of the earnings surprise. This measure is standardized by dividing by the standard deviation of the earnings surprises over the past eight quarters. CAR is the cumulative abnormal return over that of the market over three days surrounding the announcement. Earnings announcement dates are from Compustat's RDQ field.



B.7 Sorts on momentum and investment

Table B.3 [Double sorted portfolios on momentum and investment.
This table reports the performance of the 25 portfolios constructed based on double sorts on price momentum and investment, the excess returns on the high-low portfolios formed for each type of sort as well as the results of the regressions of the excess returns on the latter on the Fama-French five factors. Price momentum is measured as the cumulative return over the previous year, skipping the most recent month due to short-term reversal. Investment is computed as the year-on-year change in total assets. The sample period covers May 1973 to December 2018. Newey and West test statistics are presented in paretheses.

	Investment quintiles					Investment strategies						
	Low	2	3	4	High	r^e	α	β_{mkt}	β_{smb}	β_{hml}	β_{rmw}	β_{cma}
Momentum quintiles												
Low	1.00	1.16	0.81	0.49	0.13	0.49	-0.04	0.09	0.21	-0.10	0.17	1.30
						(1.96)	(-0.16)	(1.56)	(2.55)	(-0.89)	(1.53)	(7.61)
2	1.13	1.07	0.83	0.80	0.26	0.49	0.11	0.01	-0.09	0.28	0.08	0.92
						(2.29)	(0.57)	(0.13)	(-1.28)	(3.06)	(0.83)	(6.56)
3	1.20	1.12	0.98	0.77	0.72	0.10	-0.35	0.05	0.03	0.24	0.03	1.04
						(0.54)	(-2.01)	(1.24)	(0.49)	(3.12)	(0.38)	(8.60)
4	1.57	1.23	1.09	1.22	0.85	0.34	-0.06	0.04	-0.03	0.11	-0.07	1.17
						(1.75)	(-0.37)	(0.91)	(-0.58)	(1.49)	(-0.85)	(9.79)
High	1.44	1.51	1.35	1.50	1.22	-0.16	-0.58	0.05	0.16	-0.00	-0.22	1.31
						(-0.75)	(-3.02)	(1.09)	(2.46)	(-0.04)	(-2.44)	(9.70)
Momentum strategies												
r^e	0.06	-0.03	0.16	0.63	0.71							
	(0.17)	(-0.07)	(0.55)	(1.99)	(2.29)							
α	0.24	0.05	0.33	0.66	0.78							
	(0.69)	(0.13)	(1.07)	(2.00)	(2.48)							
β_{mkt}	-0.16	-0.24	-0.14	-0.14	-0.12							
	(-1.97)	(-2.87)	(-1.94)	(-1.73)	(-1.63)							
β_{smb}	0.03	0.13	0.21	0.22	0.08							
	(0.21)	(1.06)	(2.02)	(1.91)	(0.70)							
β_{hml}	-0.84	-0.91	-0.70	-0.70	-0.93							
	(-5.26)	(-5.62)	(-5.04)	(-4.66)	(-6.47)							
β_{rmw}	-0.13	0.26	-0.19	0.14	0.26							
	(-0.79)	(1.56)	(-1.33)	(0.92)	(1.79)							
β_{cma}	0.65	0.80	0.45	0.58	0.64							
	(2.65)	(3.21)	(2.08)	(2.50)	(2.88)							

Appendix C

Market-implied equity issuance costs

C.1 Measuring equity issuance

1 Repurchases

Table C.1 Summary statistics on repurchases.
This table presents summary statistics for the number and size of repurchases per firm. Repurchases are measured based on the percentage change in the number of (split-adjusted) shares outstanding, dS/S, conditional on the change being negative. The statistics are shown separately for five firm size buckets and four different lower thresholds for dS/S: 0, -0.2%, -0.5% and -1%. The sample covers the period January 1961 to December 2018.

	$dS/S < 0$														
	No. of repurchases					Size of repurchase (% $\lvert dS/S \rvert$)					Size of repurchase ($m)				
	Mean	SD	25^{th}	50^{th}	75^{th}	Mean	SD	25^{th}	50^{th}	75^{th}	Mean	SD	25^{th}	50^{th}	75^{th}
Small	1.37	2.98	0	0	1	5.12	12.51	0.17	0.93	3.98	2.68	77.75	0.01	0.05	0.21
2	1.57	3.49	0	0	2	3.36	8.60	0.11	0.63	2.64	3.49	123.90	0.03	0.16	0.68
3	1.97	4.40	0	0	2	2.83	7.79	0.10	0.54	2.15	7.83	343.53	0.08	0.44	1.83
4	3.02	6.18	0	1	3	2.26	6.07	0.09	0.53	1.96	12.34	147.75	0.28	1.70	6.70
Large	8.99	16.74	0	1	10	1.46	3.57	0.14	0.55	1.47	130.83	777.53	4.12	20.39	79.32
	$dS/S < -0.2\%$														
	No. of repurchases					Size of repurchase (% $\lvert dS/S \rvert$)					Size of repurchase ($m)				
	Mean	SD	25^{th}	50^{th}	75^{th}	Mean	SD	25^{th}	50^{th}	75^{th}	Mean	SD	25^{th}	50^{th}	75^{th}
Small	1	2.42	0	0	1	6.97	14.18	0.70	1.98	6.12	3.67	90.89	0.04	0.10	0.34
2	1.07	2.62	0	0	1	4.91	10.07	0.59	1.55	4.52	5.14	150.34	0.15	0.39	1.20
3	1.31	3.13	0	0	1	4.25	9.26	0.55	1.35	3.77	11.81	422.42	0.46	1.14	3.26
4	1.98	4.46	0	0	2	3.41	7.23	0.56	1.30	3.18	18.74	182.27	1.80	4.37	11.51
Large	6.31	12.47	0	1	6	2.06	4.12	0.49	0.99	2.07	181.87	923.21	14.54	41.27	126.45
	$\Delta S/S < -0.5\%$														
	No. of repurchases					Size of repurchase (% $\lvert dS/S \rvert$)					Size of repurchase ($m)				
	Mean	SD	25^{th}	50^{th}	75^{th}	Mean	SD	25^{th}	50^{th}	75^{th}	Mean	SD	25^{th}	50^{th}	75^{th}
Small	0.83	2.05	0	0	1	8.36	15.23	1.20	2.83	7.91	4.43	99.96	0.06	0.15	0.44
2	0.85	2.12	0	0	1	6.10	10.99	1.08	2.36	5.97	6.45	168.76	0.27	0.60	1.61
3	1.01	2.46	0	0	1	5.37	10.24	1	2.04	4.97	15.13	479.43	0.84	1.76	4.48
4	1.54	3.61	0	0	1	4.28	7.97	0.98	1.90	4.12	23.67	206.00	3.22	6.48	14.97
Large	4.70	9.28	0	0	5	2.65	4.62	0.84	1.41	2.65	224.78	1,063.02	21.92	55.74	162.50
	$\Delta S/S < -1\%$														
	No. of repurchases					Size of repurchase (% $\lvert dS/S \rvert$)					Size of repurchase ($m)				
	Mean	SD	25^{th}	50^{th}	75^{th}	Mean	SD	25^{th}	50^{th}	75^{th}	Mean	SD	25^{th}	50^{th}	75^{th}
Small	0.67	1.70	0	0	1	10.22	16.46	2	4.13	10.24	5.51	111.53	0.10	0.22	0.58
2	0.66	1.70	0	0	1	7.68	12.05	1.81	3.43	7.95	8.30	192.01	0.46	0.89	2.22
3	0.76	1.90	0	0	1	6.91	11.4	1.70	3.08	6.76	19.94	553.41	1.45	2.68	6.09
4	1.14	2.81	0	0	1	5.53	8.94	1.63	2.74	5.47	31.08	239.15	5.41	9.70	19.83
Large	3.12	6.18	0	0	3	3.62	5.42	1.42	2.09	3.66	280.71	1,280.98	32.32	75.31	208.88

2 Aggregate issuance activity

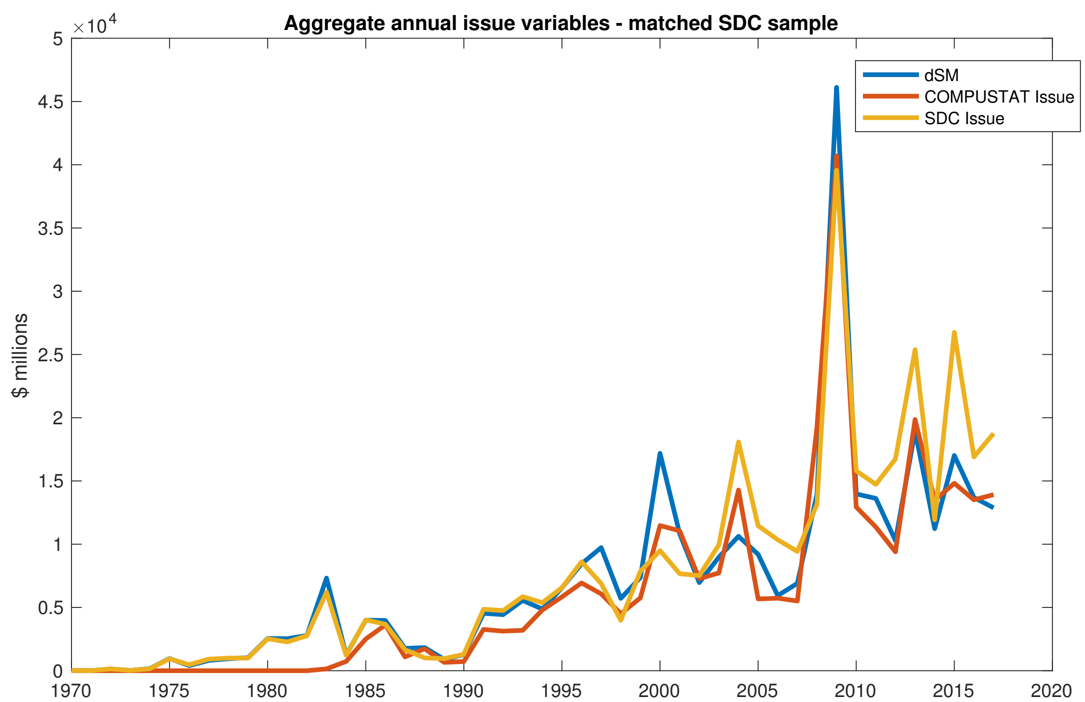


Fig. C.1 Aggregate annual equity issuance proceeds for the SDC sample.
This figure shows aggregate annual equity issuance proceeds (in millions of USD) for the SDC sample, using three measures: (1) SDC Issue, based on proceeds oversold data from Thomson SDC New Issues, (2) Compustat Issue, based on item SSTK (Sale of Common and Preferred Stock) from the annual Compustat files and (3) *dSM*, based on the proceeds inferred using daily data from the CRSP files. *dSM* is computed as the product of the daily change in the number of (split-adjusted) shares outstanding and the average (split-adjusted) stock price over the day before and the day of the issuance. Amounts obtained from *dSM* are cumulated over the fiscal year. The sample period covers 1970-2017.

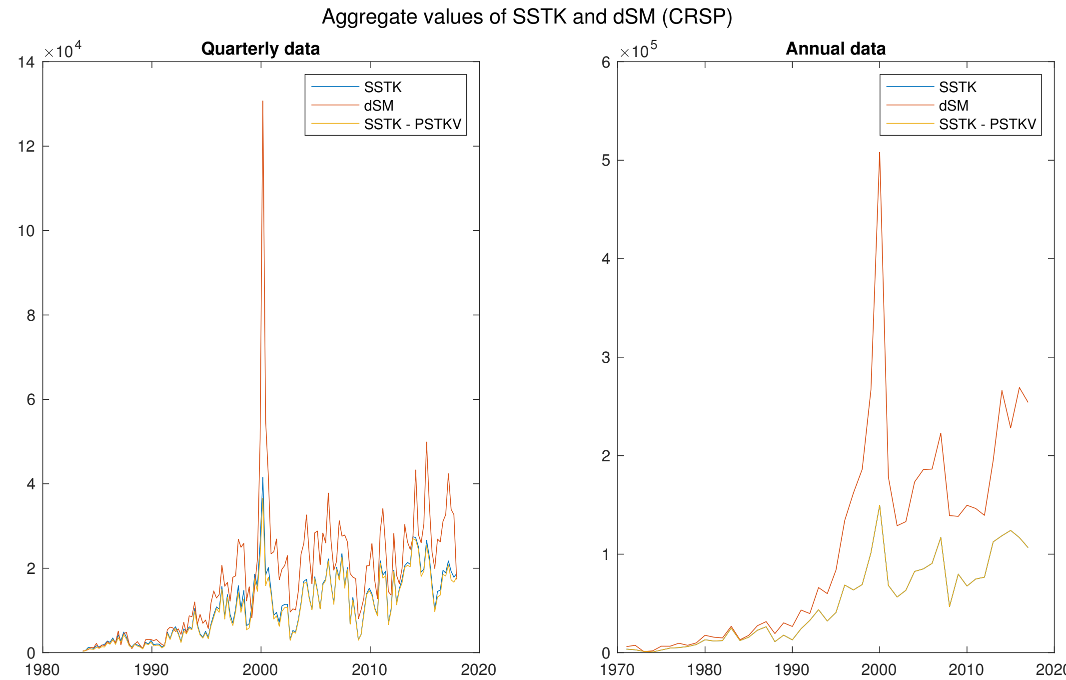


Fig. C.2 Aggregate values of *dSM* and SSTK.
The figures show the time-series of the aggregate issuance proceeds (in millions of USD) from Compustat item SSTK (Sale of Common and Preferred Stock) and proceeds measured using changes in shares outstanding from CRSP, *dSM*. The left panel shows aggregate quarterly amounts and the right panel aggregate annual amounts. *dSM* is computed as the product of the daily change in the number of (split-adjusted) shares outstanding and the average (split-adjusted) stock price over the day before and the day of the issuance. Amounts obtained from *dSM* are cumulated at the respective frequency (quarterly on the left panel and annual on the right panel). The amounts apply to the sample where data is available for both variables. The sample covers the intersection of CRSP and Compustat firms over the period 1985-2017.

3 McLean (2011) regressions

Table C.2 Average values for McLean regression coefficients (annual)
This table shows the average values of the coefficients from yearly regressions of changes in cash on sources of cash, conducted similar to McLean [2011]. The regression model is:

$$\Delta Cash_i = \alpha + \beta_1 Equity_i + \beta_2 Debt_i + \beta_3 Cash\,flow_i + \beta_4 Other_i + \beta_5 Assets_i + \varepsilon_i.$$

$\Delta Cash$ is the change in the cash balance over the fiscal year. *Equity* represents the cash proceeds from the sale of new shares, measured using two alternative measures: (1) Compustat item SSTK (Sale of common and preferred stock) and (2) proceeds measured using data from the daily CRSP files, based on product of the daily change in (split-adjusted) shares outstanding with the average (split-adjusted) share price over the day before and on the day of the issuance, *dSM*. Proceeds from the daily CRSP file are cumulated over the fiscal year. *dSM* excludes values identified as mergers from the Thomson One SDC Mergers and Acquisitions database, any remaining observations of the percentage change in shares outstanding greater than one or smaller than 0.2%. *Debt* is the cash proceeds from debt sales. *Cash flow* is cash flow from operations. *Other* represents all other cash sources. All variables are scaled by lagged total assets. *Assets* is the log of total assets. Panel A reports the results for the specification that uses SSTK as the measure of proceeds from equity issuance. The specification in Panel B uses *dSM* as the measure of equity issuance proceeds and Panel C uses both. Test statistics are presented in parentheses.

	R^2	Intercept	Issue	*dSM*	Debt	Cash Flow	Other
Panel A							
Coefficient	0.37	-0.04	0.39		0.03	0.21	0.05
		[-9.92]	[12.57]		[4.94]	[15.37]	[5.77]
Panel B							
Coefficient	0.24	-0.05		0.16	0.03	0.15	0.05
		[-9.77]		[9.79]	[5.36]	[12.68]	[5.39]
Panel C							
Coefficient	0.49	0.00	0.47	0.19	0.02	0.19	-0.05
		[-7.65]	[11.82]	[11.99]	[1.01]	[9.03]	[-0.45]

Table C.3 Average values for McLean regression coefficients (quarterly)
This table shows the average values of the coefficients from quarterly regressions of changes in cash on sources of cash, conducted similar to McLean [2011]. The regression model is:

$$\Delta Cash_i = \alpha + \beta_1 Equity_i + \beta_2 Debt_i + \beta_3 Cash\,flow_i + \beta_4 Other_i + \beta_5 Assets_i + \varepsilon_i.$$

$\Delta Cash$ is the change in the cash balance over the quarter. *Equity* represents the cash proceeds from the sale of new shares over the quarter, measured using two alternative measures: (1) Compustat item SSTKQ (Sale of common and preferred stock) and (2) proceeds measured using data from the daily CRSP files, based on product of the daily change in (split-adjusted) shares outstanding with the average (split-adjusted) share price over the day before and on the day of the issuance, dSM. Proceeds from the daily CRSP file are cumulated over each quarter. dSM excludes values identified as mergers from the Thomson One SDC Mergers and Acquisitions database, any remaining observations of the percentage change in shares outstanding greater than one or smaller than 0.2%. *Debt* is the cash proceeds from debt sales. $Cash\,flow$ is cash flow from operations. *Other* represents all other cash sources. All variables are scaled by lagged total assets. *Assets* is the log of total assets. Panel A reports the results for the specification that uses SSTK as the measure of proceeds from equity issuance. The specification in Panel B uses dSM as the measure of equity issuance proceeds and Panel C uses both. Test statistics are presented in parentheses.

	R^2	Intercept	Issue	dSM	Debt	Cash Flow	Other
Panel A							
Coefficient	0.43	-0.02	0.48		0.08	0.22	0.06
		[-17.95]	[18.66]		[13.93]	[18.31]	[7.74]
Panel B							
Coefficient	0.21	-0.02		0.21	0.08	0.14	0.06
		[-16.62]		[16.17]	[14.21]	[14.66]	[6.81]
Panel C							
Coefficient	0.42	0.00	0.71	0.30	0.12	0.26	0.066
		[-19.05]	[51.35]	[25.05]	[18.58]	[24.28]	[6.26]

C.2 Estimation

1 Model parameters

Table C.4 Summary of parameters used in the model.
This table provides a list of the parameters used in the model. Panel A lists the parameters that we calibrate and Panel B lists the parameters to be estimated. Parameters with the subscript H denote values in the high state and those with subscript L denote values in the low state. GMMSV groups are indexed by j, and groups based on three-digit SIC codes and size are indexed by f.

A. Parameters to calibrate		
	Aggregate	Group
Risk-free rate	r	
Rate of capital depreciation	δ	
Carry cost of cash	λ	
Price of risk for short-term shocks	η^A	
Price of risk for permanent shocks	η^P	
Price of risk for financing shocks	κ_H, κ_L	
Expected productivity growth		μ_j
Expected cash-flow shock		α_j
Volatility of productivity shock		σ_j^P
Volatility of cash-flow shock		σ_j^A
Correlation between $W_{j,t}^P$ and $W_{j,t}^A$		ρ_j
Correlation between $W_{j,t}^A$ and $W_t^{M_A}$		χ_j^A
Correlation between $W_{j,t}^P$ and $W_t^{M_P}$		χ_j^P

B. Parameters to estimate		
	Aggregate	Group
State transition intensity	ζ_H , ζ_L	
Investment adjustment cost parameter		θ
Liquidation value		l_f^H, l_f^L
Fixed cost of equity issuance		ϕ_f^H, ϕ_f^L
Marginal cost of equity issuance		γ_f^H, γ_f^L

2 Grouping firms with similar equity issuance activity

Table C.5 Industry and market capitalization groups
This table reports statistics on the number of firms and number of equity issues for groups based on three-digit SIC industry classification and market capitalization. The sample covers the 15,891 firms from Gryglewicz, Mancini, Morellec, Schroth and Valta (2020), over the period 1975 to 2016. Equity issuance is measured using the percentage change in the number of (split-adjusted) shares outstanding from the daily CRSP files, dS/S. dS/S excludes values identified as mergers from the Thomson One SDC Mergers and Acquisitions database, any remaining observations greater than one (to exclude other possible mergers) or smaller than 0.2% (to exclude proceeds related to exercises of employee stock options). The table reports the statistics for three-digit SIC industry groups split into market capitalization quintiles and deciles, each case also considering NYSE breakpoints.

	SIC3 grouping						
	Mean	SD	Min	25^{th}	50^{th}	75^{th}	Max
Industry bins							
No. of firms	67	131	1	14	31	65	1,152
No. of issues	785	1,368	0	166	383	832.5	11,368
Industry bins - quintiles							
No. of firms	15	27	1	4	7	14	224
No. of issues	176	281	4	49	97	184	2,182
Industry bins - quintiles - NYSE bpoints							
No. of firms	15	27	1	4	7	15	224
No. of issues	177	280	4	51	97	185	2,179
Industry bins - deciles							
No. of firms	7	14	1	2	4	7	112
No. of issues	87	140	2	23	48	90	1,090
Industry bins - deciles - NYSE bpoints							
No. of firms	8	14	1	2	4	7	112
No. of issues	89	140	2	26	48	93	1,090

3 Summary statistics on cash-flow shocks and correlations

Table C.6 Summary Statistics
This table presents summary statistics for short-term operating cash-flow shocks, dW^A, permanent shocks, dW^P, the 10-year rolling correlation between short-term shocks, dW_i^A, and the aggregate short-term cash-flow shocks, dW_{M_A}, denoted as χ_i^A and the 10-years rolling correlation between firm *i* permanent shocks, dW_i^P, and the (equity-market-value-weighted) average productivity shocks, dW_{M_P}, denoted as χ_i^P. The rolling correlations are computed using a minimum requirement for the number of data points available of 5. The data is based on estimates from 15,891 firms in GMMSV over the period 1975 to 2016. Each month I calculate the cross-sectional mean (*Mean*), standard deviation (*SD*), skewness (*Skew*), excess kurtosis (*Kurt*), minimum (*Min*), maximum (*Max*), median (*Med*). The table reports the time-series averages of these cross-sectional values. The column labeled *n* reports the average number of firms for which the variable is available each year. The data is trimmed for each individual gvkey at the 5th and 95th percentiles.

	Mean	Stdev	Skewness	Kurtosis	Min	Max	Median	n
dW_j^A	0.0027	0.65	0.62	-0.17	-1.17	1.75	-0.13	2,209
dW_j^P	-0.078	0.43	0.44	0.28	-1.00	1.22	-0.11	2,560
χ_j^A	0.05	0.40	-0.07	-0.70	-0.65	0.82	0.06	1,742
χ_j^P	0.15	0.34	-0.15	-0.70	-0.65	0.82	0.16	2,445

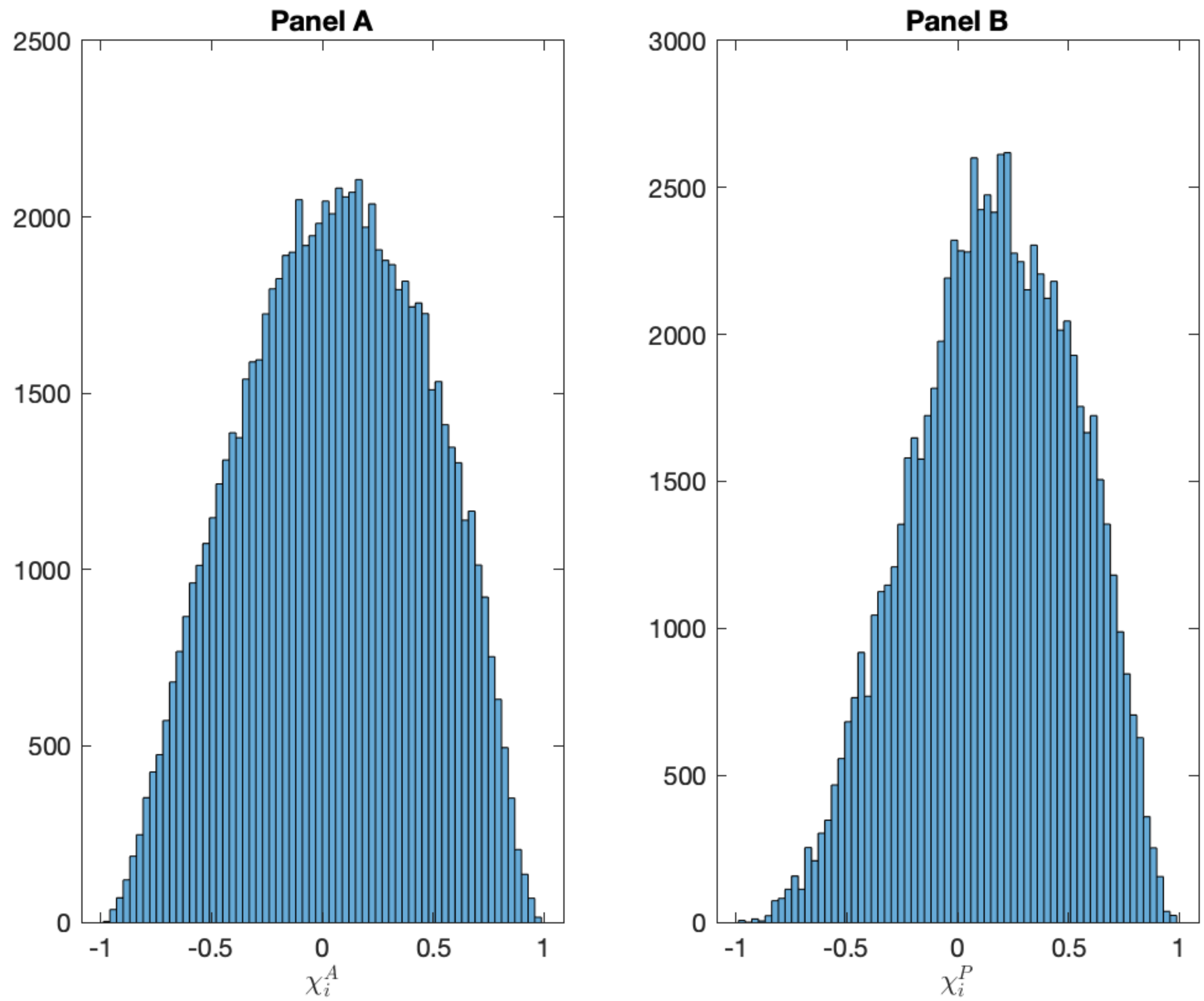


Fig. C.3 Distributions of 10-year rolling correlations between individual firm short-term and permanent operating cash-flow shocks with aggregate shocks of each type.
χ_i^A denotes the correlation between short-term shocks, dW_i^A, and the aggregate short-term cash-flow shocks, dW_{M_A}. χ_i^P denotes the correlation between firm i permanent shocks, dW_i^P, and the average productivity shocks, dW_{M_P}. The rolling correlations are computed using a minimum requirement for the number of data points available of 5. The average productivity shock each year is computed as the equity-market-value-weighted average of individual firm productivity shocks. The operating cash-flow shocks are identified in GMMSV, where the estimation uses data from 15,891 firms. The time period covers 1975 to 2016. Data is trimmed at the individual gvkey level at the 5th and 95th percentile.