Internet Appendix for "Putting the Price in Asset Pricing"

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ABSTRACT

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IA.A. Supplementary Literature Review

IA.A.1. Additional Related Work

An important motivation for studying price levels is the link between stock price levels and corporate financing or investment decisions as explored by Stein (1996), Baker and Wurgler (2002), Baker et al. (2003), Shleifer and Vishny (2003), Cohen et al. (2009), Polk and Sapienza (2009), van Binsbergen and Opp (2019), and Whited and Zhao (forthcoming) among others. For example, Polk and Sapienza (2009) study how price distortion relates to corporate investment, using discretionary accruals to proxy for price distortion, and van Binsbergen and Opp (2019) study the link in a quantitative model of a production economy to study how abnormal returns on anomaly characteristics affect output. Dessaint et al. (2021) find evidence that the beta anomaly's CAPM abnormal price as perceived by firm managers affects the M&A decision. Gormsen and Huber (2023) and Gormsen and Huber (2022) explore how firms' perceived costs of capital relate to factor models and affect corporate investment.[2]

The asset pricing literature also explored the difference in the type of information that expected returns and price levels have about capital market efficiency. Shiller (1984) writes, "because real returns are nearly unforecastable, the real price of stocks is close to the intrinsic value . . . is one of the most remarkable errors in the history of economic thought" (pp. 458–459). Summers (1986) provides a numerical example that illustrates this argument and Campbell (2018) shows how an expected return that follows a persistent AR(1) process may leave little room for return predictability despite a large variance in the dividend-price ratio. Pastor and Veronesi (2003) show that high price levels may not be a signal of capital market inefficiency but of increased uncertainty

[2]Taking the link between price distortion and equity financing as given, Cho and Salarkia (2020) show that firms' equity issuance and repurchases in the face of apparent model-specific price distortion reveals the CAPM as the model most likely used by firms.

about future profitability. More recently, Liu et al. (2021) use a restriction on the price distortion process to revisit factor models of expected returns and Baba Yara et al. (2020) study the extent to which the permanent and transitory components of characteristics differently describe the cross-section of long-horizon average returns.[3]

Other strands of literature study price levels and long-horizon returns for different reasons. First, these quantities are important for the portfolio decision of long-term investors. For instance, Cochrane (2014) develops a mean-variance characterization of a stream of long-run payoffs that is useful even when risks and expected returns vary through time.[4] Second, Vuolteenaho (2002), Cohen et al. (2003), Cochrane (2011), De La O and Myers (2021), and Cho et al. (forthcoming) among many others study valuations, expected returns, and cash flows through the lens of an identity in the spirit of Campbell and Shiller (1988). Third, Lee et al. (1999), Bartram and Grinblatt (2018), Gerakos and Linnainmaa (2018), Asness et al. (2019), Golubov and Konstantinidi (2019), and Favero et al. (2020) take different approaches to come up with proxies for price distortion. Finally, Koijen et al. (2022) use a structural demand-based approach to study how different types of investors affect equity valuations.

Cumulative abnormal returns (CARs) or buy-and-hold abnormal returns (BHARs) are used extensively in the corporate finance literature. Barber and Lyon (1997), Kothari and Warner (1997), Fama (1998), Lyon et al. (1999), Brav (2000), and Bessembinder et al. (2018) have critically evaluated these approaches.

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[3]Other recent papers on the topic of market efficiency and price levels include Bai et al. (2016), Dávila and Parlatore (2020), Joel et al. (2022), and Jiang et al. (2020).

[4]See also Kandel and Stambaugh (1996), Campbell and Viceira (1999), Barberis (2000), and Viceira (2001) among several others.

IA.A.2. Detailed Response to van Binsbergen et al. (2023)

Internet Appendix C of van Binsbergen, Boons, Opp, and Tamoni (2023) (vBBOT) compares their dividend-based event-time approach to our calendar-time, (excess) return-based approach. This type of comparison is useful, as it allows us to reflect further on the advantages and (potential) disavantages of our proposed method. However, the first two (out of three) issues they point out apply to methodological aspects of an older version of our paper (Dec 2020) that are not present in our analysis. The third issue they point out is a weakness particular to their dividend-based approach and only helps highlight the strength of our excess-return-based approach. The last issue they point out is a matter of taste as to whether one prefers a simple or log measure of abnormal price and has little empirical consequence. We explain these points in further detail below.

1. Risk-free rate in the candidate SDF.

First, vBBOT argue that our candidate SDF does not discount returns more in times of high risk-free rates. They base this critique on an older version of our paper (Dec 2020) that used the excess return on the market as a factor in the candidate SDF:

$$\widetilde{M}_t = b_0 - b_1 R_t^{mkt,e}, \tag{IA.1}$$

where $R_t^{mkt,e}$ denotes market return in excess of the risk-free rate.

However, since that draft, we have switched to using the the gross return on the market in our loglinear SDF setup employed by Korteweg and Nagel (2016).

$$\widetilde{M}_t = \exp(b_0 - b_1 \log(1 + R_t^{mkt})), \tag{IA.2}$$

Since the gross market return includes the risk-free rate as a component, this candidate SDF does apply a large discount on returns in times of high risk-free rates, not just in times of high risk premium.[5]

The candidate SDF in vBBOT follows

$$\widetilde{M}_t = \exp(-\log(1 + R_{f,t}) + b_0 - b_1 \left(\log(1 + R_t^{mkt}) - \log(1 + R_{f,t]})\right)), \tag{IA.3}$$

where $R_{f,t}$ is the risk-free rate known at time $t-1$ and realized at time t. Whereas the risk-free rate component is embedded in the gross market return in equation (IA.2), equation (IA.3) disentangles the risk-free rate and the (log) market risk premium components of the SDF. However, we find that empirically using the candidate SDF in equation (IA.3) has little effect on either the estimates of δ or their associated p-values.

2. Computing excess returns with respect to the risk-free rate vs. market return

The second critique of vBBOT also does not apply to our paper's methodology. They argue that computing excess returns with respect to the Treasury bill rate as part of our identity,

$$\delta \equiv E\left[\frac{P_t - V_t}{P_t}\right] = -\sum_{j=1}^{\infty} E\left[\widetilde{M}_{t,t+j} \tfrac{P_{t+j-1}}{P_t} R^e_{t+j}\right], \tag{IA.4}$$

requires the candidate SDF to explain the T-bill rate conditionally. However, since the Dec 2020 draft, we have switched to using the market rather than the Treasury bill as the base asset with which to compute excess returns R^e_{t+j}. Since we estimate CAPM-based δ's, computing excess returns against the market is a natural methodological choice, given that the CAPM implies that the market is correctly priced, and follows other research (e.g., Campbell et al. (2018) and Korteweg and Nagel (2022)) that also prices returns in excess of the market.

[5]In earlier drafts, e.g., Apr 2021, we used a linearized SDF based on the gross market return: $\widetilde{M}_t = b_0 - b_1 R_t^{mkt}$, where R_t^{mkt} is the gross market return.

3. Inability of vBBOT to price Treasury bill strategies

vBBOT argue that both their dividend-based event-time framework and our framework are subject to a large bias that results from having to estimate SDF parameters in a finite sample. They rely on a back-of-the-envelope calculation to show that using their dividend-based method means that the strategy of rolling over T-bill investments for 15 years has an estimated δ of more than 50%, despite the fact that their candidate SDF is designed to price T-bill rates conditionally (Internet Appendix D.1 of vBBOT). We confirm that in our sample, applying an event-time *gross-return* approach to a strategy that rolls over T-bills results in an estimated δ of 0.497 (49.7%), similar to the number in vBBOT (which they then hope to correct through a bootstrapping adjustment).

We find that this source of bias has little effect on δ estimates based on our approach. When we apply our novel calendar-time, *excess-return* approach, the same roll-over strategy that is dramatically mispriced by vBBOT has an estimated δ of only 0.1% in our full sample (1948m6–2022m12) and 2.3% in the modern subsample (1972m6–2022m12). This finding is consistent with Figure 2A in our main paper, which confirms, based on Monte Carlo analysis, that our δ estimates are close to being unbiased.[6]

What is it about our approach ensures that strategies such as rolling over the T-bill do not have an artificially inflated δ estimate? Our method is not vulnerable to this defect in vBBOT's method primarily because our estimated δ aggregates future *excess* returns R^e_{t+j} (see equation (33) above) rather than gross returns.[7] To see why our approach is immune to this concern, suppose, for the sake of argument, that we bring equation (IA.4) to data by computing excess returns against the T-bill rate. Then, by definition, the

[6]Note that in our Monte Carlo, the interest rate is held fixed for the sake of tractability. We leave a generalization of our Monte Carlo model to allow for time-varying interest rates for future research.

[7]Note that the evidence in Figure A6 only confirms the equivalence between the event-time, dividend-based approach and an event-time, *gross-return* approach. Our main approach uses the calendar-time excess-return expression, which helps minimize the bias as well as serial correlations.

T-bill roll-over strategy earning the T-bill rate in each period has zero excess return in all periods and must have an estimated δ of zero.

In practice, of course, we compute excess returns against the market rather than the T-bill. Even so, the use of excess returns rather than gross returns in this way helps reduce the impact of measurement errors in a candidate $\widetilde{M}$ on our δ estimates. We explain this in detail in Section 3.2 of the main paper.

4. Log vs. simple mispricing

vBBOT choose to estimate the log abnormal price of Cohen et al. (2009) (equation (6)) rather than the simple abnormal price measure estimated in our paper. They implicitly acknowledge, however, that one definition is not inherently superior to another. We prefer working with simple abnormal price measure, as it allows us to develop a nonparametric estimator of abnormal price with several desirable properties, whereas log abnormal price does not.

IA.B. Empirical Appendix

IA.B.1. Basic data adjustments

We use domestic common stocks (CRSP share code 10 or 11) listed on the three major exchanges (CRSP exchange code 1, 2, or 3). We replace missing prices with the average bid-ask price when available and drop observations with missing share or price information in the previous month. We code missing returns as zero returns and add delisting returns to returns. If delisting returns are missing, but the CRSP delisting code is 500 or between 520 and 584, we use -35% (-55%) as the delisting returns for NYSE and AMEX stocks (for NASDAQ stocks) (Shumway (1997) and Shumway and Warther (1999)). To compute capital gains, we use the CRSP split-adjustment factor (CFACPR) to ensure that capital gains are not affected by split events. We use NYSE breakpoints when sorting stocks throughout the analysis and always study value-weight portfolios.

IA.B.2. Characteristics and portfolios

An important stock characteristic is the book-to-market-equity (B/M) ratio computed each year in June. B/M ratio is the stock's book value of equity in the previous fiscal year divided by its market value of equity in December of the previous calendar year. Book value of equity is defined as stockholders' equity SEQ (Compustat item 144) plus balance sheet deferred taxes and investment tax credit $TXDITC$ (item 35) minus book value of preferred stock ($BE = SEQ + TXDITC - BPSTK$). Book value of preferred stock $BPSTK$ equals the preferred stock redemption value $PSTKRV$ (item 56), preferred stock liquidating value $PSTKL$ (item 10), preferred stock $PSTK$ (item 130), or zero depending on data availability. If SEQ is unavailable, we set it equal to total assets AT (item 6) minus total liabilities LT (item 181). If $TXDITC$ is unavailable, it is assumed to be zero. In the pre-Compustat period, we use the book equity data from Davis et al. (2000). We treat zero or negative book values as missing.

Another stock characteristic used in our preliminary analysis is the quality measure of Asness et al. (2019) defined as a z-score based on four characteristics—profitability, growth, safety, and payout ratio—that determine the market-to-book ratio in a Gordon growth model and in the absence of mispricing: quality $= z\left(z_{\text{profitability}} + z_{\text{growth}} + z_{\text{safety}} + z_{\text{payout ratio}}\right)$. The four characteristic z scores are in turn obtained as an equal weighted average of z scores based different measures of each characteristic. When some of the underlying measures are missing, the z score is taken over all available measures. In the pre-Compustat period, we use the book equity numbers that Davis et al. (2000) collected from the Moody's Industrial, Public Utility, Transportation, and Bank and Finance Manuals to calculate measures that require book equity data. Quality is computed once a year at the end of June and requires the past six years of data in order to compute z_{growth}. See Asness et al. (2019) for further details.

As discussed in the main body of the paper, our core analysis uses a three-characteristic model of the value-to-price ratio named *adjusted value*. We simply add the z scores of B/M and profitability and subtract the z score of beta. For profitability, we use the z score of gross profitability when available, and the z score of return on equity otherwise.

We also examine portfolios sorted by seven additional characteristics: size, momentum, net issuance, beta, profitability, investment, and accruals. The first four characteristics can be computed in the pre-Compustat period, whereas the last three characteristics are available only in the post-Compustat period. Size is market equity calculated at the end of each month. Momentum is calculated is the cumulative gross return over the previous 12 months excluding the month before the portfolio formation and is also computed at the end of each month. Net issuance is calculated annually at the end of each June and is the split-adjusted growth in shares outstanding over the previous 12 months. Beta is the trailing 3-year market beta (minimum of 2 years) calculated each month based on overlapping 3-day returns.

Profitability is computed each year in June. Gross profitability ("profitability") in calendar year y equals sales $SALE$ (Compustat item 12) minus cost of goods sold $COGS$ (item 41) in fiscal year $y-1$ over total assets in fiscal year $y-1$ Asset growth ("investment") is also computed each year in June, and investment in calendar year y is total assets in fiscal year $y-1$ divided by total assets in fiscal year $y-2$. Accruals measures the degree to which earnings come from non-cash sources and is defined according to Sloan (1996).

IA.B.3. The GMM

To estimate the deltas of characteristic-sorted portfolios, write the sample moments and the GMM restriction as

$$\boldsymbol{g}_T(\boldsymbol{b}) = \frac{1}{T}\sum_{t=1}^{T}\boldsymbol{u}_t(\boldsymbol{b})$$

$$\boldsymbol{A}\boldsymbol{g}_T(\boldsymbol{b}) = \begin{pmatrix} 0 \\ 0 \end{pmatrix},$$

where the first two moments set the market portfolio's alpha and delta with respect to the candidate SDF to be zero:

$$\boldsymbol{u}_t(\boldsymbol{b}) = \begin{pmatrix} \widetilde{M}_t R_t^{mkt,e} & -\sum_{j=1}^{J}\widetilde{M}_{t-j,t-1}\frac{P^{mkt}_{(t-j),t-1}}{P^{mkt}_{(t-j),t-j}}\left(\widetilde{M}_t\left(1+R^{mkt}_{(t-j),t}\right)-1\right) & \tilde{\delta}_{1,t} & \dots & \tilde{\delta}_{N,t} \end{pmatrix}'$$

$$\boldsymbol{A} = \begin{pmatrix} J & 0 & 0 & \dots & 0 \\ 0 & 1 & 0 & \dots & 0 \end{pmatrix}.$$

Recall that we model one-period candidate SDF as $\widetilde{M}_t = \exp\left(b_0 - b_1 r_t^{mkt}\right)$ with r_t^{mkt} denoting log market return and cumulative candidate SDF as $\widetilde{M}_{(t-j),t} = \exp\left(b_0 j - b_1 r^{mkt}_{(t-j),t}\right)$ with $r^{mkt}_{(t-j),t}$ denoting log market return from $t-j$ to t. Hence, the asymptotic variance-covariance matrices of the parameters and the sample moments are

$$Var\left(\sqrt{T}\hat{\boldsymbol{b}}\right) = (AD)^{-1} ASA' (AD)^{-1,'}$$

$$Var\left(\sqrt{T}\boldsymbol{g}_T\left(\hat{\boldsymbol{b}}\right)\right) = \left[I_{N+2} - D(AD)^{-1} A\right] S \left[I_{N+2} - D(AD)^{-1} A\right]'$$

and the finite-sample variance estimates are

$$\hat{V}\left(\hat{\boldsymbol{b}}\right) = \frac{1}{T}\left(A\hat{D}\right)^{-1} A\hat{S}A'\left(A\hat{D}\right)^{-1,'}$$

$$\hat{V}\left(\boldsymbol{g}_T\left(\hat{\boldsymbol{b}}\right)\right) = \frac{1}{T}\left[I_{N+2} - \hat{D}\left(A\hat{D}\right)^{-1} A\right] \hat{S}\left[I_{N+2} - \hat{D}\left(A\hat{D}\right)^{-1} A\right]',$$

where S is the spectral density matrix and

$$D = E\left[\frac{\partial \boldsymbol{u}_t(\boldsymbol{b})}{\partial \boldsymbol{b}'}\right]$$

is estimated by $\hat{D}$, which equals

$$T^{-1}\sum_{t=1}^{T}\begin{bmatrix} \widetilde{M}_t(1+R_t^{mkt}) & -r_t^{mkt}\widetilde{M}_t(1+R_t^{mkt}) \\ -\sum_{j=1}^{J} j\widetilde{M}_{t-j,t}\frac{P^{mkt}_{(t-j),t-1}}{P^{mkt}_{(t-j),t-j}}R^{mkt,e}_{(t-j),t} & \sum_{j=1}^{J} r^{mkt}_{t-j,t}\widetilde{M}_{t-j,t}\frac{P^{mkt}_{(t-j),t-1}}{P^{mkt}_{(t-j),t-j}}R^{mkt,e}_{(t-j),t} \\ -\sum_{j=1}^{J} j\widetilde{M}_{t-j,t}\frac{P_{1,(t-j),t-1}}{P_{1,(t-j),t-j}}R^{e}_{1,(t-j),t} & \sum_{j=1}^{J} r^{mkt}_{t-j,t}\widetilde{M}_{t-j,t}\frac{P_{1,(t-j),t-1}}{P_{1,(t-j),t-j}}R^{e}_{1,(t-j),t} \\ \vdots & \vdots \\ -\sum_{j=1}^{J} j\widetilde{M}_{t-j,t}\frac{P_{N,(t-j),t-1}}{P_{N,(t-j),t-j}}R^{e}_{N,(t-j),t} & \sum_{j=1}^{J} r^{mkt}_{t-j,t}\widetilde{M}_{t-j,t}\frac{P_{N,(t-j),t-1}}{P_{N,(t-j),t-j}}R^{e}_{N,(t-j),t} \end{bmatrix}.$$

with $r^{mkt}_{0,0}$ defined to be 0. The spectral density matrix is estimated as follows:

$$\hat{S}_T\left(\hat{\boldsymbol{b}}\right) = \hat{\Gamma}_0 + \sum_{b=1}^{B}\frac{B-b}{B}\left(\hat{\Gamma}_b + \hat{\Gamma}_b'\right)$$

where B is the Newey-West bandwidth and

$$\hat{\Gamma}_0 = \frac{1}{T}\sum_{t=1}^{T}\left(\boldsymbol{u}_t\left(\hat{\boldsymbol{b}}\right) - \overline{\boldsymbol{u}}\left(\hat{\boldsymbol{b}}\right)\right)' \times \left(\boldsymbol{u}_t\left(\hat{\boldsymbol{b}}\right) - \overline{\boldsymbol{u}}\left(\hat{\boldsymbol{b}}\right)\right)$$

$$\hat{\Gamma}_b = \frac{1}{T}\sum_{t=b+1}^{T}\left(\boldsymbol{u}_t\left(\hat{\boldsymbol{b}}\right) - \overline{\boldsymbol{u}}_{t\geq b+1}\left(\hat{\boldsymbol{b}}\right)\right)' \times \left(\boldsymbol{u}_{t-b}\left(\hat{\boldsymbol{b}}\right) - \overline{\boldsymbol{u}}_{t\leq T-b}\left(\hat{\boldsymbol{b}}\right)\right).$$

IA.B.4. Adjusted value in a double sort

Recall that δ measures the percentage deviation of value from price, which can be written as a product of book equity over market price (B/M) and the present value of cash flows over book equity (V/B):

$$\delta_t = 1 - \frac{V_t}{P_t} = 1 - \frac{B_t}{M_t} \times \frac{V_t}{B_t}, \tag{IA.5}$$

where for convenience we equate market value M with per-share price P. Hence, sorting stocks on both B/M and V/B should generate a large variation in δ.

Although V/B is unobserved, the loglinear present-value model of Vuolteenaho (2002) shows that it can be written as a spread between future expected profitability and CAPM-implied discount rates. Hence, we simply model V/B as the spread between the z-score of profitability and the z-score of market beta today:

$$\frac{V}{B} \propto \text{ Profitability Spread} \equiv z(\text{Prof}) - z(\text{Beta}), \tag{IA.6}$$

Consistent with our prior, double sorting stocks based on B/M and profitability spread, our simple proxy for V/B, resurrects the ability of these characteristics to explain larger variation in δs (Table IA.VI). Furthermore, the variation in δ across the two dimensions of the table is consistent with our conjecture in Figure IA.5.

Abnormal price δ declines as we move from left to right, which amounts to holding B/M fixed while increasing profitability spread, and profitability spread appears to be an especially informative predictor of CAPM abnormal price among low-B/M (growth) stocks. Similarly, δ declines as we move from top to bottom, which amounts to holding profitability spread fixed while increasing B/M, and this variation leads to statistically significant differences in abnormal price among the middle tercile profitability spread stocks. Moving diagonally from the top left to the bottom right generates the largest variation in δs. We estimate low profitability spread, low-B/M stocks to be 57.6 percentage points more overpriced than high profitability spread, high-B/M stocks with a p-value of 0.0%.

IA.B.5. Adjusted value based on expected future profitability

Equation (29) shows that, strictly speaking, the value-to-price ratio depends on expected future profitability rather than current profitability. Hence, we estimate a VAR model in which

$$x_{t+1} = Ax_t$$

where x_t is a vector of z-scores of B/M, profitability, beta, and investment (which is the order we use to form the column vector). The resulting VAR coefficients is as follows:

$$A = \begin{pmatrix} .89 & -.07 & .02 & .02 \\ -.15 & .80 & .01 & -.10 \\ .00 & -.01 & .92 & .03 \\ -.22 & -.02 & .07 & .31 \end{pmatrix}$$

It is easy to show that the discounted sum of future profitability can be written as a linear combination of the four current characteristics:

$$FutureProf \equiv 1_{\text{prof}} A \left(I - \rho A\right)^{-1} x_t,$$

where 1_{prof} denotes a vector of zeros and the one in the row that corresponds to profitability. We use the z-score of the last expression as our profitability z-score that feeds into an alternative *adjusted value* measure in Table IA.V.

IA.B.6. Other proxies of misvaluation

Although we use a relatively simple three-characteristic signal of abnormal price dubbed *adjusted value*, one may wonder how well existing measures fare against *adjusted value* to predict abnormal price in the data. We examine two characteristics having been suggested as proxies for abnormal price: the analyst-forecast-based measure of Frankel and Lee (1998) and the market-multiples-based measure of Golubov and Konstantinidi (2019). Both signals have a relatively short sample period, and the signal based on analyst forecasts is limited by the availability of analyst forecast data. The market-multiples-based approach requires within-industry cross-sectional regressions, which can have a very small cross-section of data in the 1970s and earlier. Hence, our analysis is restricted to (roughly) the same sample periods used in the original papers, starting in the mid 1970s, giving us post-formation return data from 1991m6 to 2022m12.[8]

Table IA.IX shows that the V/P signal based on analyst forecasts does not predict CAPM mispricing in the direction we expect, consistent with the observation of Chen and Zimmermann (2021). The same table shows that although the signal based on market multiples generates a larger variation in CAPM δs, it is also not significant in such a short sample period. It is possible that this signal proxies for mispricing in a longer sample, although even in Golubov and Konstantinidi (2019), their market-multiples-based V/P signal is not a stronger signal of abnormal return than B/M itself (e.g., see the second panel of Figure 1 of their paper, which shows the value-weight returns on their V/P signal—called firm-specific error—are lower than those of B/M). Of course, part of their relatively weak performance could be a feature of the sample.

[8]A related measure by Bartram and Grinblatt (2018) was defined from year 1987, which would lead to an even shorter sample period, so we do not consider the measure.

IA.B.7. Incremental information about prices when controlling for adjusted value: book-to-market, profitability, and beta

Table VI studies the incremental information about prices contained in characteristics other than ones used to construct adjusted value. Here, we also examine characteristics we *do* use to construct adjusted value. Table IA.X shows that controlling for adjusted value reduces the ability of the other characteristic to predict CAPM mispricing. In particular, the δ variation associated with beta drops dramatically. Controlling for adjusted value, however, increases the magnitude of mispricing associated with profitability. On the other hand, controlling for one of the underlying characteristics does not affect the economic magnitude or the statistical significance of δ associated with adjusted value. However, the substantial correlation between the two signals means that controlling for beta no longer makes adjusted value a statistically significant predictor of CAPM mispricing.

IA.C. Theory Appendix

IA.C.1. Mispricing identity: an illustrative example

An example shows how our identity correctly recovers the initial price deviation with respect to a candidate SDF, even when there is *no subsequent correction* in mispricing.

An asset pays a perpetual dividend of $D_{t+j} = \lambda$ and has a constant price of $P_{t+j} = 1$ in all periods. We posit a candidate SDF that explains the constant risk-free rate $R_f > \lambda$, even if it may not explain the returns and prices of the asset in consideration:

$$\widetilde{M}_{t+j} = \frac{1}{1+R_f}$$

Then, the asset's present value of dividends with respect to $\widetilde{M}$ is $V_t = \lambda / R_f$, so the asset has a positive abnormal price with respect to the candidate SDF:

$$\delta_t = \frac{P_t - V_t}{P_t} = \frac{R_f - \lambda}{R_f} > 0.$$

That is, the asset is overpriced with respect to $\widetilde{M}$.

Does our excess-return-based identity correctly recover the same level of overpricing? Applying our identity and using the risk-free asset as the base asset,

$$\delta_t = -\sum_{j=1}^{\infty} \widetilde{M}_{t,t+j} \frac{P_{t+j-1}}{P_t} R^e_{t+j} = -\sum_{j=1}^{\infty} \frac{1}{(1+R_f)^j} (\lambda - R_f) = \frac{R_f - \lambda}{R_f},$$

so the answer is yes!

Intuitively, how does our formula correctly recover initial overpricing even if overpricing does not get corrected in the long run? The reason is that if price stays high, the dividend yield component of future return is (abnormally) low, and our formula detects that as signal of initial overpricing.

To be more specific, overpricing with respect to $\widetilde{M}$ lowers the dividend yield from R_f

to λ, which leads to lower return and lower excess return. The artificially low dividend yield is detected by perpetually negative excess returns, which our identity discounts back to the present to arrive at overpricing of one.

- Dividend yield with respect to the "correct" value of $V_{t+j} = \lambda / R_f$:

$$\frac{D_{t+j}}{V_{t+j-1}} = R_f$$

- Dividend yield with respect to market price $P_{t+j} = 1$:

$$\frac{D_{t+j}}{P_{t+j-1}} = \lambda$$

- Return: $R_{t+j} = \underbrace{\frac{P_{t+j} - P_{t+j-1}}{P_{t+j-1}}}_{\text{capital gain}} + \underbrace{\frac{D_{t+j}}{P_{t+j-1}}}_{\text{dividend yield}} = \frac{1-1}{1} + \lambda = \lambda$

- Excess return: $R^e_{t+j} = \lambda - R_f$

- Return-identity-based $\delta_t = -\sum_{j=1}^{\infty} \widetilde{M}_{t,t+j} \frac{P_{t+j-1}}{P_t} R^e_{t+j} = \dfrac{R_f - \lambda}{R_f}$

In the absence of overpricing, the dividend yield would be R_f such that excess returns and return-based delta would be zero.

In contrast, if the asset's price does come down to be consistent with $\widetilde{M}$, the capital gain component of return is abnormally low, and our formula detects the corresponding low excess return as a sign of initial overpricing.

As a sidenote, our formula also does not rely on the candidate SDF being the true SDF. However, We need the base-asset return to satisfy the fundamental asset pricing equation with respect to the candidate SDF.

IA.C.1.1. Mispricing identity: the special case of zero dividend

Our excess-return-based identity continues to be valid in the special case when an asset pays zero dividend and there is permanent mispricing with respect to a candidate SDF. This amounts to setting $\delta = 0$ in the previous example.

Suppose we are still interested in computing abnormal price with respect to the candidate SDF, $\widetilde{M}_{t+j} = \frac{1}{1+R_f}$. An "asset" with permanently zero dividend has a positive price $P_{t+j} > 0$ in all $j \geq 0$, leading to a permanent overpricing of

$$\delta_{t+j} = 1 - \frac{V_{t+j}}{P_{t+j}} = 1$$

in all periods, including the initial period at t.

Does our excess-return-based identity correctly recover the same level of overpricing? Applying our identity,

$$\delta_t = -\sum_{j=1}^{\infty} \frac{1}{(1+R_f)^j} (-R_f) = \frac{R_f}{R_f} = 1,$$

so the answer is again a resounding yes. Intuitively, initial overpricing is reflected in subsequent negative excess returns of $-R_f$, which our identity correctly discounts to the present to find $\delta_t = 1$.

IA.C.2. The estimator in Cohen, Polk, and Vuolteenaho (2009)

CPV proposes estimating average log abnormal price. Based on the Campbell and Shiller (1988) decomposition,

$$\delta_t^{log} \approx -\sum_{j=1}^{\infty} \rho^{j-1} E_t[r_{t+j}] - E_t[r_{V,t+j}], \tag{IA.7}$$

where $r_t \equiv \log(P_t + D_t) - \log(P_{t-1})$ and $r_{V,t} \equiv \log(V_t + D_t) - \log(V_{t-1})$ denote log returns on price and value, respectively, and $\rho < 1$ is a parameter. Since $E_{t+j-1}[e^{r_{V,t+j}+\widetilde{m}_{t+j}}] = 1$

and $E_{t+j-1}[e^{r_{b,t+j}+\widetilde{m}_{t+j}}]=1$, the conditional joint normality of the log quantities implies

$$E_{t+j-1}[r_{V,t+j}]=E_{t+j-1}[r_{b,t+j}]+\frac{1}{2}Var_{t+j-1}(r_{b,t+j})-\frac{1}{2}Var_{t+j-1}(r_{V,t+j})+Cov_{t+j-1}(r^{e}_{V,t+j},-\widetilde{m}_{t+j}), \tag{IA.8}$$

where r^e_V denotes log return on value in excess of the base asset return. Plugging this into equation (IA.7), using the approximation $E_{t+j-1}[R_{t+j}]\approx E_{t+j-1}[r_{t+j}]+\frac{1}{2}Var_{t+j-1}(r_{t+j})$, applying unconditional expectation, and rearranging,

$$\begin{aligned} E\left[\sum_{j=1}^{\infty}\rho^{j-1}R_{t+j}\right] \approx\; & E\left[\sum_{j=1}^{\infty}\rho^{j-1}R_{b,t+j}\right]+E\left[\sum_{j=1}^{\infty}\rho^{j-1}Cov_{t+j-1}(r^{e}_{V,t+j},-\widetilde{m}_{t+j})\right] \\ & +\frac{1}{2}E\left[Var_{t+j-1}(r_{t+j})-Var_{t+j-1}(r_{V,t+j})\right]-\delta^{log}. \end{aligned} \tag{IA.9}$$

This decomposition motivates CPV to estimate δ^{log} using a closely related equation (their Equation 9) in the cross-section of portfolios, where k indexes a portfolio and the horizon is capped at J:

$$E\left[\sum_{j=1}^{J}\rho^{j-1}R_{k,t+j}\right]=\lambda_0+\lambda_1\,\beta^{CF}_k+u_k, \tag{IA.10}$$

where β^{CF}_k is measured by regressing the portfolio's long-horizon cash flows on that of the market.

Besides the potentially large measurement errors in estimated β^{CF}_k, two additional difficulties arise. First, under the null where $r_v=r$, justifying equation (IA.10) requires strong intertemporal restrictions that guarantee

$$E\left[\sum_{j=1}^{\infty}\rho^{j-1}Cov_{t+j-1}(r^{e}_{t+j},r^{mkt}_{t+j})\right]=Cov\left(\sum_{j=1}^{\infty}\rho^{j-1}r^{e}_{t+j},\sum_{j=1}^{\infty}\rho^{j-1}r^{mkt}_{t+j}\right), \tag{IA.11}$$

in which case $\lambda_1=b_1Var\left(\rho^{j-1}r^{mkt}_{t+j}\right)$ if the candidate SDF is given by $\widetilde{m}_t=b_0-b_1r^{mkt}_t$ for log market return r^{mkt}. The simplest way to guarantee equation (IA.11) is to assume that returns are independently and identically distributed (i.i.d.). However, in a world with i.i.d. returns, it makes little sense to explore the distinctions between abnormal price and short-horizon abnormal returns.

To quantify the extent of the problem, rewrite the conditional variance on the left-hand side of equation (IA.11) as $r^e_{t+j} = \beta_{t+j-1} r^{mkt}_{t+j} + u_{t+j}$, which implies that the value of the left-hand side can be estimated as

$$E\left[\sum_{j=1}^{\infty} \rho^{j-1} \beta_{t+j-1} \sigma^2_{mkt,t+j-1}\right] \tag{IA.12}$$

with β_{t+j-1} and $\sigma^2_{mkt,t+j-1}$ denoting the portfolio's time $t+j$ conditional return beta and the market portfolio's time $t+j$ conditional variance, respectively. We estimate the conditional return beta using past 36 months' return data and realized market variance using daily market returns over the month. The right-hand side of the equation can be estimated from the observed values of portfolio and market returns.

We find that there is indeed a large empirical difference between the two sides of equation (IA.11), 0.192 (left-hand side) vs. 0.132 (right-hand side) for the high abnormal profitability quintile portfolio. Since we estimate the log candidate SDF's loading on the log market return to be larger than 3, in the context of CPV's equation (IA.7), this translates into an estimation error in log abnormal price of more than 18 percentage points. Two forces contribute to the left-hand side of equation (IA.11) being larger than the right-hand side in the high abnormal profitability portfolio. First, the portfolio's unconditional beta is less than one but tends to rise in times of high market volatility. This fact makes the left-hand side larger (more positive) than it would be under i.i.d. Second, the right-hand side of equation (IA.11) involves cross-autocovariances between portfolio excess log returns and market log returns that are likely to be negative due to the long-term reversal effect. This fact pushes the right-hand side to be smaller.

Second, under the alternative where $r_v \neq r$, interpreting the error term u in equation

(IA.10) as δ^{log} in equation (IA.9) requires that the long-horizon sum of volatility of log returns is the same for price and value:

$$E\left[\sum_{j=1}^{\infty}\rho^{j-1}Var_{t+j-1}(r_{t+j})\right] = E\left[\sum_{j=1}^{\infty}\rho^{j-1}Var_{t+j-1}(r_{V,t+j})\right]. \tag{IA.13}$$

This fact can add to the bias in estimated δ^{log} under the alternative in which mispricing shocks with respect to $\widetilde{M}$ makes r substantially more volatile than r_V.[9]

IA.C.3. Comparison to the abnormal return identity in van Binsbergen and Opp (2019)

van Binsbergen and Opp (2019) use a different identity to link price to subsequent abnormal returns:

$$P_t = E_t\left[\int_t^{\infty}\widetilde{M}_{t,t+\tau}e^{-\int_t^{\tau}\alpha_u^{*}du}d\Pi_t\right],$$

or in discrete time,

$$P_t = \sum_{j=1}^{\infty}E_t\left[\frac{\widetilde{M}_{t,t+j}}{\Pi_{k=1}^{j}\left(1+\alpha_{t+k}^{*}\right)}D_{t+j}\right], \tag{IA.14}$$

where $1+\alpha_{t+k}^{*} \equiv E_t\left[\widetilde{M}_{t+1}\left(1+R_{t+1}\right)\right]$. van Binsbergen and Opp use the term "mispricing wedge" to refer to the stochastic cumulation of abnormal returns, $1/\left[\Pi_{k=1}^{j}\left(1+\alpha_{t+k}^{*}\right)\right]$, which is different from the definition of ex-ante abnormal price $\delta_t = E_t\left[1-V_t/P_t\right]$ we introduce in our paper.

To derive their discrete-time identity in equation (IA.14), begin with

$$1+\alpha_{t+1}^{*} \equiv E_t\left[\widetilde{M}_{t+1}\left(1+R_{t+1}\right)\right] = E_t\left[\widetilde{M}_{t+1}\frac{P_{t+1}+D_{t+1}}{P_t}\right].$$

[9] Having the correct estimate of abnormal price under the alternative is important, just as the error term in an asset pricing regression for returns can be interpreted as abnormal returns under the alternative.

Rearranging terms and iterating forward,

$$
\begin{aligned}
P_t &= E_t\left[\frac{\widetilde{M}_{t+1}}{1+\alpha^*_{t+1}}D_{t+1} + \frac{\widetilde{M}_{t+1}}{1+\alpha^*_{t+1}}P_{t+1}\right] \\
&= E_t\left[\frac{\widetilde{M}_{t+1}}{1+\alpha^*_{t+1}}D_{t+1} + \frac{\widetilde{M}_{t+1}\widetilde{M}_{t+2}}{\left(1+\alpha^*_{t+1}\right)\left(1+\alpha^*_{t+2}\right)}D_{t+2} + \ldots\right] \\
&= \textstyle\sum_{j=1}^{\infty} E_t\left[\frac{\widetilde{M}_{t,t+j}}{\Pi_{k=1}^{j}(1+\alpha_{t+k})}D_{t+j}\right].
\end{aligned}
$$

To see what equation (IA.14) implies about unconditional ex-ante abnormal price we define, write

$$
\delta = E\left[1 - V_t/P_t\right] = \sum_{j=1}^{\infty} E\left[\widetilde{M}_{t,t+j}\left(\frac{1}{\Pi_{k=1}^{j}\left(1+\alpha^*_{t+k}\right)} - 1\right)\frac{D_{t+j}}{P_t}\right]. \qquad \text{(IA.15)}
$$

Compared to the analysis based on the Campbell-Shiller approximation in equation (**??**), equation (IA.15) helpfully clarifies that the "mispricing wedge," $1/\left[\Pi_{k=1}^{j}\left(1+\alpha^*_{t+k}\right)\right]$, has to be stochastically discounted using with the cumulative SDF to arrive at ex-ante mispricing.

However, it is not obvious how to take equation (IA.15) to data to estimate δ using returns. For instance, one could rewrite equation (IA.15) in terms of returns,

$$
\delta = \sum_{j=1}^{\infty} E\left[\widetilde{M}_{t,t+j}\left(\frac{1}{\Pi_{k=1}^{j}E_{t+k-1}\left[\widetilde{M}_{t+k}\left(1+R_{t+k}\right)\right]} - 1\right)\frac{D_{t+j}}{P_t}\right], \qquad \text{(IA.16)}
$$

but the conditional expectation in the denominator, $E_{t+k-1}[\ ]$, prevents one from taking equation (IA.16) to data without making additional assumptions about which state variables help forecast the time series of conditional abnormal returns. Our identity circumvents this issue by making the intentional decision to use a definition of mispricing that has price P_t in the denominator, which results in subsequent abnormal returns appearing in the numerator and leads to our expression for unconditional mispricing in equation (19) as well as our return-based calendar-time estimator in equation (2).

IA.C.4. Portfolio δ

In practice, one would typically estimate the δ of a portfolio of stocks, which requires expressing the portfolio δ as a function of post-formation capital gains and returns on the portfolio. These capital gains and returns should be those based on a buy-and-hold strategy that does not rebalance the portfolio (or equivalently, use the original weight times the stock's cumulative capital gain to rebalance the portfolio every month). If $w_{i,t}$ is the portfolio weight on security i at the time of portfolio formation t,

$$\begin{aligned}
\delta_t &= \sum_{i=1}^{N} w_{i,t}\delta_{i,t} \\
&= \sum_{i=1}^{N} w_{i,t}\left(-\sum_{j=1}^{\infty} E_t\left[\widetilde{M}_{t,t+j}\frac{P_{i,t+j-1}}{P_{i,t}}R^e_{i,t+j}\right]\right) \\
&= -\sum_{j=1}^{\infty} E_t\left[\widetilde{M}_{t,t+j}\sum_{i=1}^{N}\left(w_{i,t}\frac{P_{i,t+j-1}}{P_{i,t}}R^e_{i,t+j}\right)\right] \\
&= -\sum_{j=1}^{\infty} E_t\left[\widetilde{M}_{t,t+j}\sum_{i\in N_{t+j}}\left(w_{i,t}\frac{P_{i,t+j-1}}{P_{i,t}}R^e_{i,t+j}\right)\right],
\end{aligned} \tag{IA.17}$$

where N_{t+j} denotes the set of firms surviving (not delisted) at the end of $t+j-1$ and therefore have return data for $t+j$. Hence,

$$\begin{aligned}
\delta_t &= -\sum_{j=1}^{\infty} E_t\left[\widetilde{M}_{t,t+j}\left(\sum_{i\in N_{t+j}} w_{i,t}\frac{P_{i,t+j-1}}{P_{i,t}}\right)\left(\sum_{i\in N_{t+j}}\frac{w_{i,t}\frac{P_{i,t+j-1}}{P_{i,t}}R^e_{i,t+j}}{\sum_{i\in N_{t+j}} w_{i,t}\frac{P_{i,t+j-1}}{P_{i,t}}}\right)\right] \\
&= -\sum_{j=1}^{\infty} E_t\left[\widetilde{M}_{t,t+j}\frac{P_{t+j-1}}{P_t}R^e_{t+j}\right],
\end{aligned} \tag{IA.18}$$

where

1. we normalize the time t portfolio price P_t to be 1.

2. the buy-and-hold time $t+j-1$ portfolio price is $P_{t+j-1} = \sum_{i\in N_{t+j}} w_{i,t}\frac{P_{i,t+j-1}}{P_{i,t}}$.

3. the buy-and-hold portfolio weight on asset i between $t+j-1$ and $t+j$ is

$$w_{i,t+j} = \frac{w_{i,t}\frac{P_{i,t+j-1}}{P_{i,t}}}{\sum_{i\in N_{t+j}} w_{i,t}\frac{P_{i,t+j-1}}{P_{i,t}}}$$

4. the buy-and-hold portfolio excess return is then given by $R^e_{t+j} =$

$\sum_{i \in N_{t+j}} w_{i,t+j} R^e_{i,t+j}$.

IA.C.5. Monte Carlo analysis

We analyze our estimator's statistical properties and compare them to those of alternative approaches by simulating the asset market. We do this by adopting the model used in the Monte Carlo analysis of Korteweg and Nagel (2016) (KN) to our purposes.[10]

As in KN, the log one-period (candidate) SDF and log market returns follow, respectively,

$$\widetilde{m}_t = b_0 - b_1 r_t^{mkt} \quad \text{(IA.19)}$$

$$r_t^{mkt} = r_f + b_1\sigma^2 - \frac{1}{2}\sigma^2 + \sigma\epsilon_t, \quad \text{(IA.20)}$$

where b_0 and b_1 are parameters, r_f is the constant log risk-free rate, σ is the volatility of log market return, and $\epsilon_t \sim N(0,1)$ are i.i.d. so that r_t^{mkt} also is. Given this setup, the candidate SDF explains market returns and the risk-free rate if $b_0 = -r_f + b_1(r_f + b_1\sigma^2 - \frac{1}{2}\sigma^2) - \frac{1}{2}b_1^2\sigma^2$, which we assume.[11] To keep the model lean, we assume that there is single market portfolio and do not model how market portfolios formed in different periods could be different due to IPOs, delistings, and net issuance.[12]

[10]We present the model in a similar manner to KN for an easy comparison and specify the cash flow and mispricing processes.

[11]Furthermore, equation (IA.20) implies that b_1 is pinned down by choosing r_f, σ^2, and the average log market return $E[r_t^{mkt}]$: $b_1 = (E[r_t^{mkt}] - r_f)/\sigma^2 + 1/2$

[12]One can think of that as the market portfolio being a single Lucas tree. Practically, this assumption means that investors in our model receive the same return and cash flows at each t regardless of when the investor began buying and holding the market portfolio. Of course, this implication is not true in reality, but we find that it is a reasonable approximation, since the correlation between market returns and post-formation market returns tends to be extremely high. The sample correlation between returns on the market portfolio formed a month ago versus 15 years ago (the largest gap) is 97.8% over 1948m6–2022m12.

Since market returns are i.i.d., the market has a constant log price-dividend ratio y^{mkt}, which we define as the log of one plus the ratio of price to dividend. Then, the log dividend growth, $\Delta d_t^{mkt} = \log(D_t^{mkt}/D_{t-1}^{mkt})$, follows[13]

$$\Delta d_t^{mkt} = r_t^{mkt} - y^{mkt} + \log\left(\exp\left(y^{mkt}\right) - 1\right), \tag{IA.21}$$

which allows us to back out y^{mkt} from $E[\Delta d_t^{mkt}]$. The constant price-dividend ratio also implies that the log capital gain follows the same process as the log dividend growth.

Next, we specify the returns on a characteristic-based portfolio's present value. The portfolio formed at $(t-j)$ for $j \geq 1$ has a time-t log return on value of

$$r_{v,(t-j),t} = r_f + \beta_v(r_t^{mkt} - r_f) + \frac{1}{2}\beta_v\sigma^2 - \frac{1}{2}(\beta_v^2\sigma^2 + \sigma_\eta^2) + \eta_{(t-j),t}, \tag{IA.22}$$

where $\boldsymbol{\eta}_t = \begin{pmatrix} \eta_{(t-1),t} & \cdots & \eta_{(t-J),t} \end{pmatrix}' \sim MVN\left(0, \sigma_\eta^2\Gamma_\eta\right)$ and Γ_η is a J-by-J cross-sectional correlation matrix with $\rho_\eta^{|i_1-i_2|+|j_1-j_2|}$ as the correlation between entries (i_1, j_1) and (i_2, j_2) in the matrix. $\boldsymbol{\eta}_t$ has zero time-series *auto*correlations. This correlation structure ensures that cross-sectional correlations among the portfolio's post-formation returns fall as the difference in the portfolio formation periods increases. It is easy to check that the expected return on $r_{v,(t-j),t}$ is consistent with the candidate SDF and market return processes. We also assume that the portfolio's dividend growth has a β_v exposure to the market dividend growth and an expected value of $\beta_v E[\Delta d_t^{mkt}]$.

Since portfolio returns on value are i.i.d. over time (though not in the cross-section), the portfolio should have a constant log value-dividend ratio of y. This means that the portfolio's log dividend growth follows

$$\Delta d_{(t-j),t} = r_{v,(t-j),t} - y + \log\left(\exp\left(y\right) - 1\right). \tag{IA.23}$$

[13]To see this, $r_t^{mkt} = \log\left(P_t^{mkt} + D_t^{mkt}\right) - \log P_{t-1}^{mkt} = \log\left(1 + P_t^{mkt}/D_t^{mkt}\right) + \log\left(D_t^{mkt}/D_{t-1}^{mkt}\right) - \log\left(P_{t-1}^{mkt}/D_{t-1}^{mkt}\right) = y^{mkt} + \Delta d_t^{mkt} - \log\left(\exp\left(y^{mkt}\right) - 1\right)$.

This equation and the fact that we assume $E[\Delta d_{(t-j),t}] = \beta_v E[\Delta d_t^{mkt}]$ pins down the value of y and of $\Delta d_{(t-j),t}$. Under the null of a correct SDF, there is no mispricing such that the log return is the return on value and price is the intrinsic value: $r = r_v$ and $P = V$. In this case, a constant price-dividend ratio also means that capital gain again equals the dividend growth. This is the process used to examine size.

To examine power, we need to allow for mispricing in the characteristic-based portfolio. We do this by specifying log abnormal price, $\delta_t^{log} = -\log(1-\delta_t) = \log(P_t/V_t)$. We allow the formation-period abnormal price to be autocorrelated across time:

$$\delta_{(t),t}^{log} = (1-\phi_{init})\overline{\delta}^{log} + \phi_{init}\delta_{(t-1),t-1}^{log} + e_t, \tag{IA.24}$$

where $e_t \sim N(0, \sigma_e^2)$ such that portfolio-formation period log abnormal price tends to mean revert to $\overline{\delta}^{log}$. In each simulation, we draw the first portfolio-formation period abnormal price $\delta_{(0),0}^{log}$ from a normal distribution with mean $\overline{\delta}^{log}$ and variance $(1-\phi_{init}^2)^{-1}\sigma_e^2$. On the other hand, post-formation log abnormal price tends to converge to zero:

$$\delta_{(t-j),t}^{log} = \phi_{post}\delta_{(t-j),t-1}^{log} + u_{(t-j),t} \text{ for } j \geq 1, \tag{IA.25}$$

where $\boldsymbol{u}_t = \begin{pmatrix} u_{(t-1),t} & \cdots & u_{(t-J),t} \end{pmatrix}' \sim MVN\left(0, \sigma_u^2\Gamma_u\right)$ is cross-sectionally correlated across portfolios formed in different time periods (different j's) and Γ_u is a J-by-J matrix with elements $\rho_u^{|i_1-i_2|+|j_1-j_2|}$ as the correlation between entries (i_1, j_1) and (i_2, j_2) in the matrix. We allow ϕ_{init} and ϕ_{post} to be different. Both e_t and $\boldsymbol{u}_t$ have zero time-series autocorrelations. Simple algebra implies that the return on price in the presence of mispricing is

$$r_{(t-j),t} = \Delta d_{(t-j),t} + \log\left(\exp\left(\delta_{(t-j),t}^{log}\right)(\exp(y)-1)+1\right) - \delta_{(t-j),t-1}^{log} - \log(\exp(y)-1) \tag{IA.26}$$

and that the log capital gain is

$$\log\left(\frac{P_t}{P_{t-1}}\right) = \Delta d_t + \delta_t^{log} - \delta_{t-1}^{log}. \qquad \text{(IA.27)}$$

We choose the parameters of the model to match the key moments of the market portfolio and the high abnormal profitability portfolio, which serves as our benchmark for the characteristic-based portfolio under the alternative. Table IA.II compares a number of key moments from simulations and data.

IA.C.6. Estimation in the presence of mispricing in firm-level returns

Cohen et al. (2009) explain that tests of the CAPM may be distorted when there is market-wide mispricing. Their use of a ROE CAPM, as motivated by the Vuolteenaho (2002) decomposition, nicely avoids this. Of course, we can also use a ROE-based SDF in our return-based identity approach. Mispricing in *firm-level* returns, on the other hand, does not hinder us when using the distorted covariance between returns and the candidate SDF to estimate δ based on our identity.

The easiest way to see that mispricing in firm-level returns does not hinder us from using the covariance between distorted returns and the candidate SDF when estimating δ is to recognize that the direct discount of cash flows is equivalent to an event-time, gross-return version of our return-based-identity (i.e., a version of our identity that does not exploit the calendar-time reformulation and the excess return restriction used in the paper). Therefore, the direct discount of cash flows is not superior to our method in the presence of firm-level mispricing.

The event-time return-identity-based formula for $\delta(J)$ can be written as

$$\delta(J) = -\sum_{j=1}^{J} E\left[\widetilde{M}_{t,t+j-1}\frac{P_{(t),t+j-1}}{P_{(t),t}}(\widetilde{M}_{t+j}\left[(1+R_{(t),t+j})-(1+R_{b,(t),t+j})\right])\right], \qquad \text{(IA.28)}$$

where R_b denotes the return on the base asset (for which we use the market portfolio).

This equation is the basis for an event-time return-identity-based estimator of abnormal price that we could use were it not for the serial correlation or the time discount issue:

$$-\frac{1}{T}\sum_{t=1}^{T}\sum_{j=1}^{J}\left[\widetilde{M}_{t,t+j}\frac{P_{(t),t+j-1}}{P_{(t),t}}R^{e}_{(t),t+j}\right]. \tag{IA.29}$$

Since $1 = E_{t+j-1}\left[\widetilde{M}_{t+j}(1+R_{b,(t),t+j})\right]$ by definition, we can also write

$$\delta(J) \;=\; -\sum_{j=1}^{J} E\left[\widetilde{M}_{t,t+j-1}\frac{P_{(t),t+j-1}}{P_{(t),t}}(\widetilde{M}_{t+j}(1+R_{(t),t+j})-1)\right] \tag{IA.30}$$

The sample analogue of equation (IA.30) is

$$\begin{aligned}
& -\frac{1}{T}\sum_{t=1}^{T}\sum_{j=1}^{J}\left[\widetilde{M}_{t,t+j-1}\frac{P_{(t),t+j-1}}{P_{(t),t}}(\widetilde{M}_{t+j}(1+R_{(t),t+j})-1)\right] \\
= & -\frac{1}{T}\sum_{t=1}^{T}\sum_{j=1}^{J}\left[\widetilde{M}_{t,t+j}\frac{P_{(t),t+j}+D_{(t),t+j}}{P_{(t),t}} - \widetilde{M}_{t,t+j-1}\frac{P_{(t),t+j-1}}{P_{(t),t}}\right] \\
= & \frac{1}{T}\sum_{t=1}^{T}\left[1-\sum_{j=1}^{J}\widetilde{M}_{t,t+j}\frac{D_{(t),t+j}}{P_{(t),t}} - \widetilde{M}_{t,t+j}\frac{P_{(t),t+J}}{P_{(t),t}}\right],
\end{aligned} \tag{IA.31}$$

which is the sample delta expression for the cash-flow method. Figure IA.6 verify empirically that the two methods generate identical point estimates.

Since equation (IA.29) can be stated using returns or using cash flows, taking (IA.31) to the data cannot provide any additional advantage in terms of improving the point estimate. In contrast, using the calendar-time expression for equation (IA.29) has the advantage of having low serial correlation in its time-series observations.

To show exactly how this equivalence works, we next analyze a simple example. Consider a three-period setting ($t = 0, 1, 2$) with two states at time 1 with equal probability ($s_1 = L, H$) and two cumulative states at time 2 due to the two time-1 states. The candidate SDF follows the following dynamics:

$$\widetilde{M}_t = \begin{array}{ccc} \underline{t=1} & & \underline{t=2} \\ 1+\mu \text{ if } s_1 = H & & 1 \text{ if } s_1 = H \\ & \longrightarrow & \\ 1-\mu \text{ if } s_1 = L & & 1 \text{ if } s_1 = L \end{array}$$

where $\mu > 0$. The market return is the inverse of the candidate SDF: $R_t^{mkt} = \widetilde{M}_t^{-1} - 1$.

There is a stock portfolio paying no cash flow other than a deterministic liquidating dividend of V at time 2. Since $\widetilde{M}_t$ has a conditional mean of one in all periods, the stock's correct price with respect to the candidate SDF is $V_t = V$ in all periods.

Besides analyzing the case with no mispricing with respect to $\widetilde{M}$, we also consider two cases of mispricing. Case 1 is when there is an overvaluation by a factor of $(1-\mu)^{-1}(1+2\epsilon)$ in the low-M state at time 1, but the price is correct in all other periods and states. Hence, there is no ex-ante mispricing at time 0. Case 2 is when there is the same overvaluation in the low-$\widetilde{M}$ state at time 1, AND the time-0 price also takes the resulting distorted market beta into account: $P_0 = E_0\left[\widetilde{M}_1 P_1\right] = 0.5V + 0.5(1-\mu)\left(V(1-\mu)^{-1}(1+2\epsilon)\right) = V(1+\epsilon)$. Hence, in Case 2, there is an initial overpricing of $(P_0 - V_0)/P_0 = \epsilon/(1+\epsilon)$ at time 0.

		$t=0$	$t=1$	$t=2$
D_t			0	V
P_t	No mispricing	V	V	0
	Mispricing: Case 1	V	V if $s_1 = H$ $V(1-\mu)^{-1}(1+2\epsilon)$ if $s_1 = L$	0
	Mispricing: Case 2	$V(1+\epsilon)$	V if $s_1 = H$ $V(1-\mu)^{-1}(1+2\epsilon)$ if $s_1 = L$	0

Now consider computing the initial abnormal price measured using either the conventional cash-flow expression or our return-based identity:

$$\delta_{CF,t} = 1 - E_t\left[\widetilde{M}_{t+1}\frac{D_{t+1}}{P_t}\right] - E_t\left[\widetilde{M}_{t,t+2}\frac{D_{t+2}+P_{t+2}}{P_t}\right]. \tag{IA.32}$$

$$\delta_t = -E_t\left[\widetilde{M}_{t+1}R^e_{t+1}\right] - E_t\left[\widetilde{M}_{t,t+2}\frac{P_{t+1}}{P_t}R^e_{t+2}\right], \tag{IA.33}$$

where the excess return is with respect to the market return. We want to check that one can rely on either formula to correctly find the initial abnormal price, whether or not there is a distorted covariance with the candidate SDF.

No mispricing

In this case,

$$\delta_{CF,0} = 1 - E_t\left[\widetilde{M}_{t,t+2}\frac{D_{t+2}}{P_t}\right] = 1 - \frac{V}{V} = 0.$$

Also,

$$\delta_0 = -E_0\left[\widetilde{M}_1\left(0 - R_1^{mkt}\right)\right] = -\frac{1}{2}\left[(1+\mu)\left((1+\mu)^{-1}-1\right) + (1-\mu)\left((1-\mu)^{-1}-1\right)\right] = 0$$

so that we recover the initial abnormal price of zero in both cases.

Mispricing Case 1 (no initial mispricing)

In this case,

$$\delta_{CF,0} = 1 - E_t\left[\widetilde{M}_{t,t+2}\frac{D_{t+2}}{P_t}\right] = 1 - \frac{V}{V} = 0.$$

Also,

$$\begin{aligned}\delta_0 &= \begin{array}{c} -\frac{1}{2}\left[\widetilde{M}_{1,s_1=H}\left(R_{1,s_1=H}-R^{mkt}_{1,s_1=H}\right)+\widetilde{M}_{1,s_1=L}\left(R_{1,s_1=L}-R^{mkt}_{1,s_1=L}\right)\right] \\ -\frac{1}{2}\widetilde{M}_{1,s_1=L}\frac{P_{1,s_1=L}}{P_0}\left(R_{1,s_1=L}-R^{mkt}_{2,s_1=L}\right)\end{array} \\ &= \begin{array}{c} -\frac{1}{2}\left[(1+\mu)\left(0-\left((1+\mu)^{-1}-1\right)\right)-(1-\mu)\left(\left((1-\mu)^{-1}(1+2\epsilon)-1\right)-\left((1-\mu)^{-1}-1\right)\right)\right] \\ -\frac{1}{2}(1-\mu)(1-\mu)^{-1}(1+2\epsilon)\left(\left(\frac{1}{(1-\mu)^{-1}(1+2\epsilon)}-1\right)-0\right)\end{array} \\ &= 0\end{aligned}$$

Hence, we recover an initial mispricing of zero in both cases in spite of the distorted covariance with $\widetilde{M}$ due to mispricing. Our identity neutralizes this distortion through the cumulative capital gain term multiplying the cumulative candidate SDF and excess returns. Of course, this result generalizes to the case with additional periods.

Mispricing Case 2 (initial overpricing)

In this case,

$$\delta_{CF,0}=1-E_t\left[M_{t,t+2}\frac{D_{t+2}}{P_t}\right]=1-\frac{V}{V\left(1+\epsilon\right)}=1-\frac{1}{1+\epsilon}=\frac{\epsilon}{1+\epsilon}.$$

When applying the Cho-Polk identity, the difference from Case 1 arises in R_1 and $\frac{P_1}{P_0}$.

$$\begin{aligned}\delta_0 &= \begin{array}{c} -\frac{1}{2}\left[(1+\mu)\left(\left((1+\epsilon)^{-1}-1\right)-\left((1+\mu)^{-1}-1\right)\right)-(1-\mu)\left(\left((1+\epsilon)^{-1}(1-\mu)^{-1}(1+2\epsilon)-1\right)-\left((1-\mu)^{-1}-1\right)\right)\right] \\ -\frac{1}{2}(1-\mu)(1+\epsilon)^{-1}(1-\mu)^{-1}(1+2\epsilon)\left(\left(\frac{1}{(1-\mu)^{-1}(1+2\epsilon)}-1\right)-0\right)\end{array} \\ &= \begin{array}{c} -\frac{1}{2}(1+\mu)\left((1+\epsilon)^{-1}-1\right)-\frac{1}{2}(1-\mu)\left((1+\epsilon)^{-1}-1\right)(1-\mu)^{-1}(1+2\epsilon) \\ -\frac{1}{2}(1-\mu)\left((1+\epsilon)^{-1}-1\right)(1-\mu)^{-1}(1+2\epsilon)\left(\frac{1}{(1-\mu)^{-1}(1+2\epsilon)}-1\right)\end{array} \\ &= \epsilon/\left(1+\epsilon\right)\end{aligned}$$

Hence, we recover an initial abnormal price of $\epsilon/\left(1+\epsilon\right)$ in both cases in spite of the distorted covariance with $\widetilde{M}$ due to mispricing.

IA.D. Additional Figure and Tables

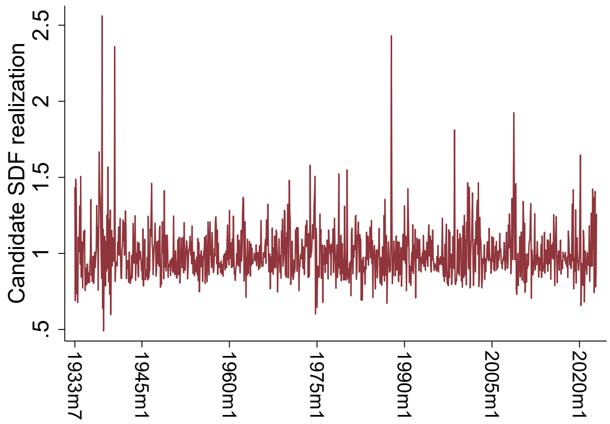

Figure IA.1. Estimated CAPM-implied Candidate SDF. The figure plots the time-series realizations of the CAPM-implied candidate SDF: $\widetilde{M}_t = \exp(b_0 - b_1 r_t^{mkt})$ with r_t^{mkt} denoting log market returns.

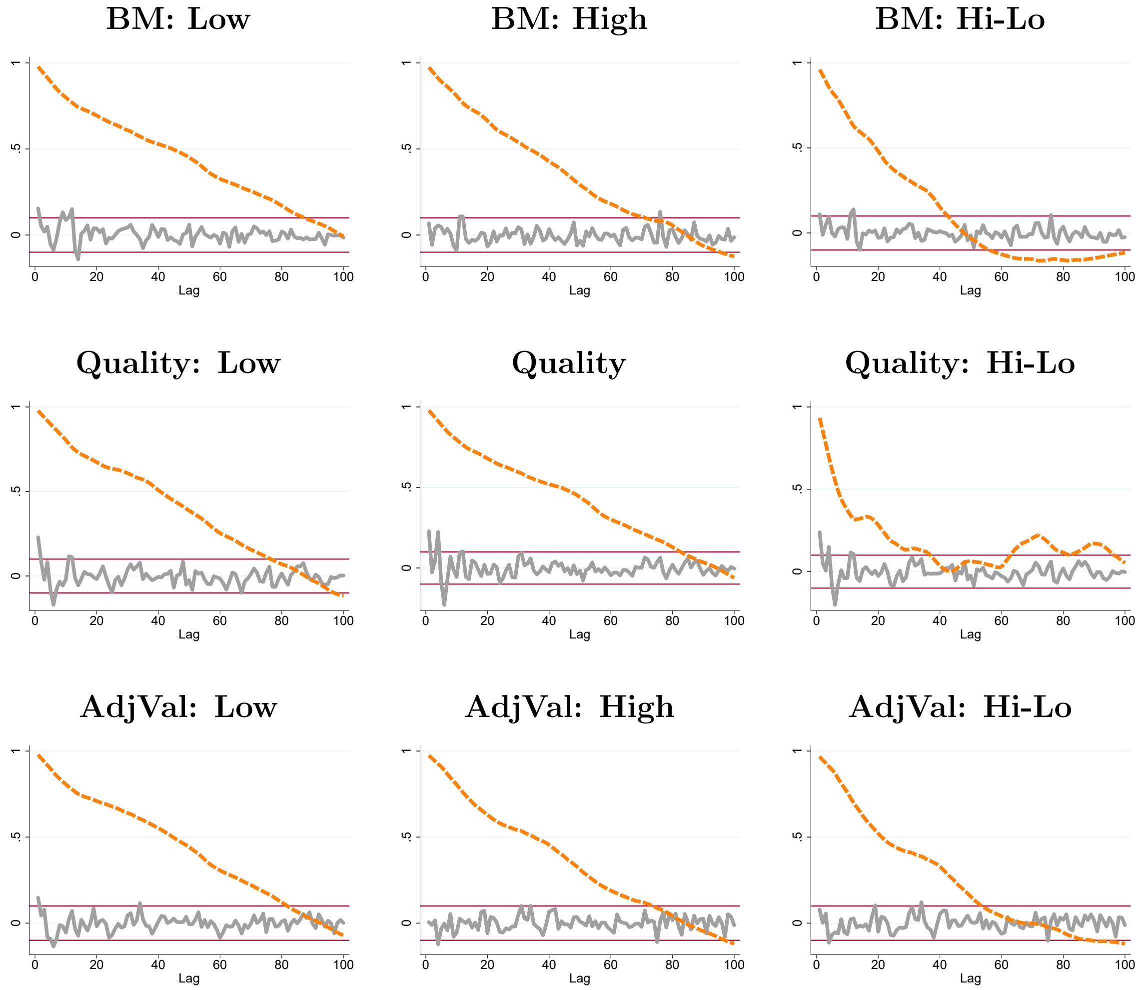

Figure IA.2. Autocorrelation by Estimation Approach: B/M, Quality, and Adjusted value. The figure reports the 1- to 100-month autocorrelations in time-series δs estimated based on the return-identity-based approach (solid grey) and the dividend-based approach using event-time (dash orange). We provide the comparison for the low-, high-, and high-minus-low quintile portfolios (in different columns) sorted on the book-to-market, quality, and adjusted value (in different rows).

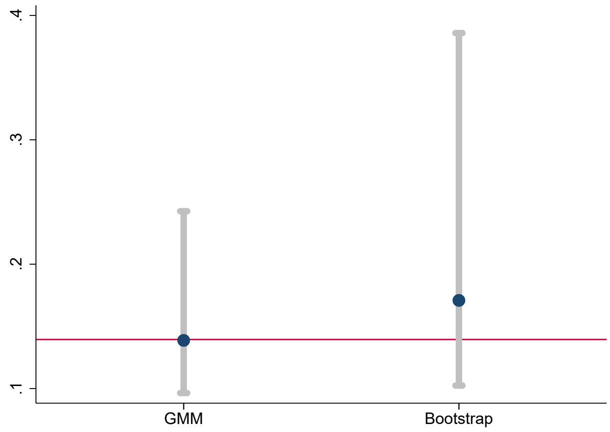

Figure IA.3. GMM vs. Bootstrap Standard Errors: Monte Carlo. The figure shows the true standard deviation of the delta estimator (red solid line), median GMM standard error (blue solid circle), median bootstrap standard error, and the 10% and 90% values for the two standard errors based on Monte Carlo. The comparison shows that GMM standard errors have a median that almost exactly matches the true standard deviation of $\widehat{\delta}$ and a much narrower confidence interval than the bootstrap standard error. Both GMM and bootstrap standard errors use a bandwidth / blocklength of 2 years.

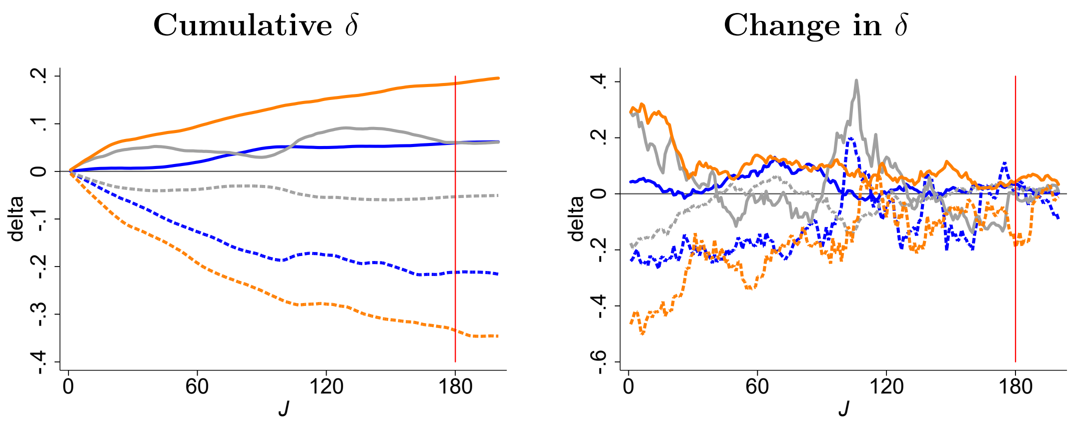

Figure IA.4. Estimated δ by the Choice of J. The left plot shows the way estimated δ changes as we vary the total number of post-formation months J used in the estimate. The right plot shows the corresponding change in δ by J. The plotted lines are for the high (dotted lines) and low (solid lines) quintile portfolios sorted on the market-to-book (blue), quality (grey), and quality-to-price (orange). The two plots suggest that estimated δs tend to plateau after $J = 15$ years (180 months).

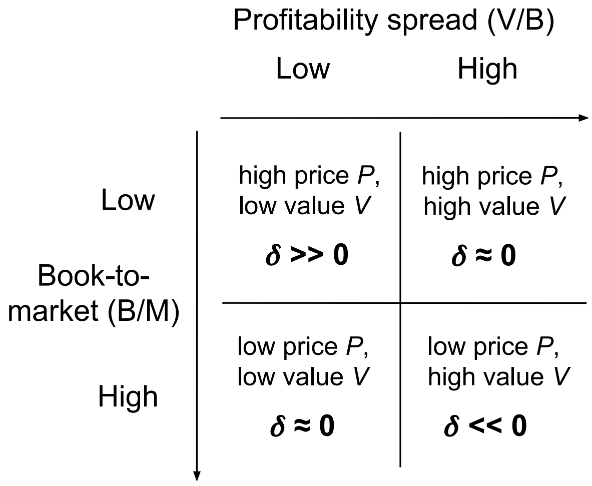

Figure IA.5. A Double Sort on B/M and Profitability Spread (V/B): Illustration. This diagram illustrates how a double sort on the book-to-market equity ratio and a proxy for the value-to-book ratio should generate large cross-sectional variation in mispricing δ. We proxy the value-to-book ratio with a two-characteristic signal dubbed *profitability spread.*

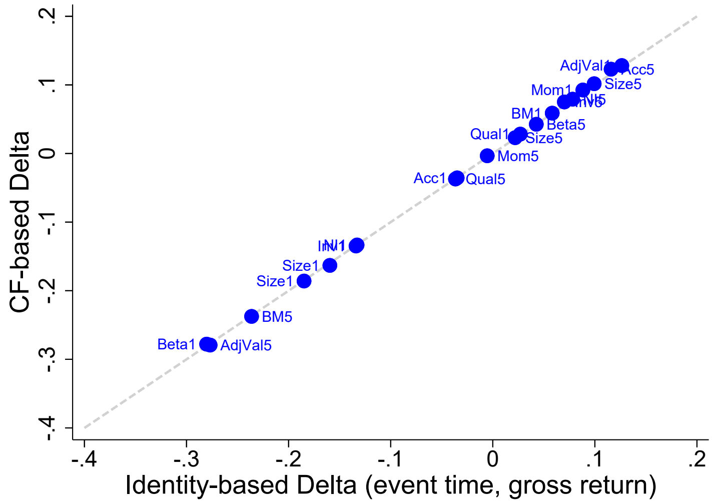

Figure IA.6. Delta Based on the Gross-Return Identity vs. Cash Flows. The figure plots the delta estimate using two theoretically equivalent approaches: the direct discount of future cash flows and a terminal value (price in 15 years; vertical axis) and the event-time, gross-return version of the return-identity-based approach (horizontal axis). The two approaches yield very similar results, with only differences of a few basis points due to measurement errors and estimation noise. The identity-based point estimates reported in our main analysis differ from those reported here due to the use of the calendar time rearrangement as well as the excess return restriction. Table I shows, however, that the gross-return-identity approach is subject to a potentially large bias (and naturally, the cash-flow-based approach as well).

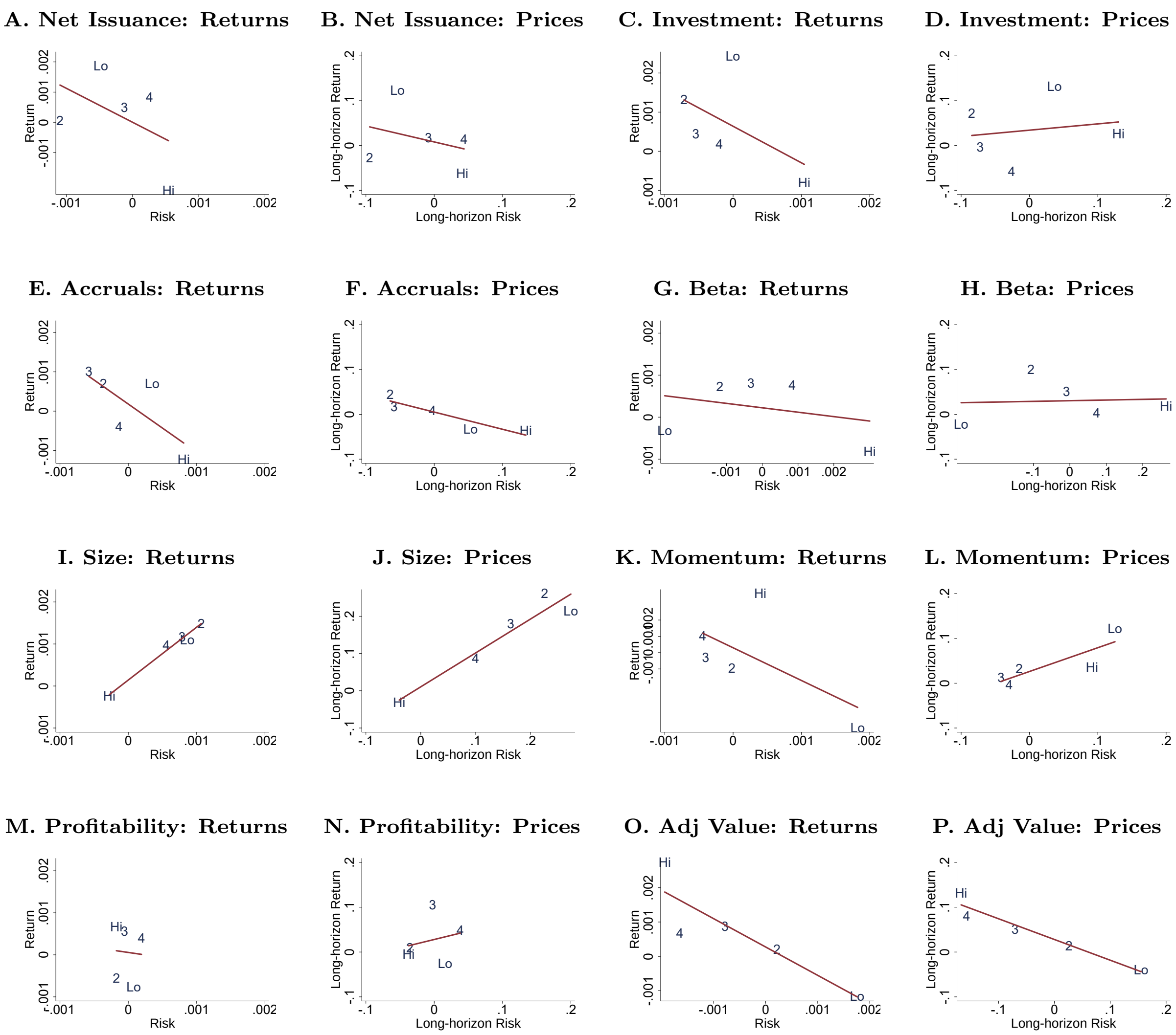

Figure IA.7. The Risk-Return Relations in Returns and Price Levels (Other Return Anomalies). The plots, for portfolios sorted on various return anomaly characteristics, the relation between long-horizon risk and long-horizon return versus that between short-horizon risk and return. Risks are measured with respect to the market portfolio. See the description in Figure 3 for more details. The sample period is 1948m6–2022m12.

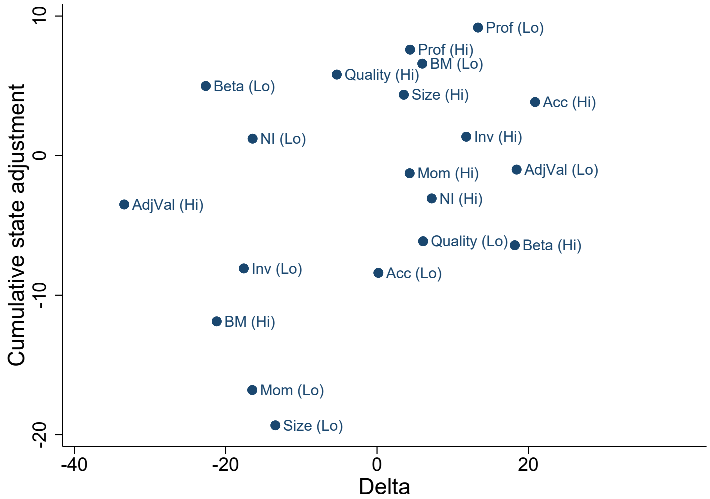

Figure IA.8. Delta vs. Cumulative State Adjustment. The figure plots the abnormal price estimate (horizontal axis) against the cumulative state adjustment (vertical axis) for the twenty extreme quintile portfolios. The cumulative state adjustment component arises from the three-way decomposition of long-horizon return presented in Corollary 4:

$$\underbrace{\sum_{j=1}^{J} E_T\left[\phi_{(t-j),t-1}\right] E_T\left[\widetilde{M}_t\right] E_T\left[R^e_{(t-j),t}\right]}_{\text{"long-horizon return"}} = -\,\hat{\delta} \;+\; \underbrace{\sum_{j=1}^{J} E_T\left[\phi_{(t-j),t-1}\right] Cov_T\left(R^e_{(t-j),t}, -\widetilde{M}_t\right)}_{\text{"long-horizon risk"}}$$

$$\underbrace{-\sum_{j=1}^{J} E_T\left[\phi_{(t-j),t-1}\right] Cov_T\left(\frac{\phi_{(t-j),t-1}}{E_T\left[\phi_{(t-j),t-1}\right]}, \widetilde{M}_t R^e_{(t-j),t}\right)}_{\text{"cumulative state adjustment"}}$$

The plot shows that the cumulative state adjustment typically has an absolute magnitude below 10% and does not have a clear univariate cross-sectional relation with abnormal price δ.

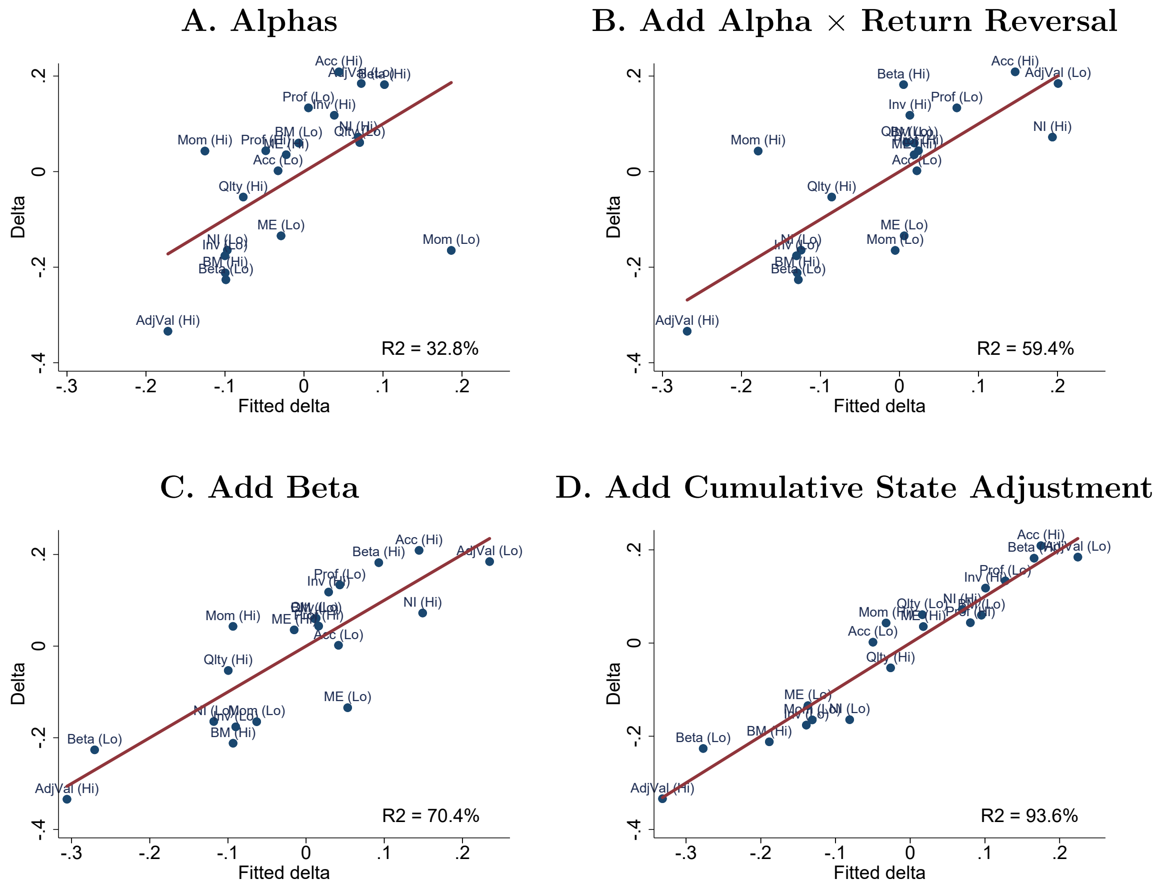

Figure IA.9. Predicting Abnormal Price (δ) with Short-horizon Alpha and Other Factors. The figures plot the cross-sectional relation between estimated delta and a fitted value based on the portfolio's short-horizon abnormal return (alpha), its interaction with a dummy variable for return reversal, short-horizon beta, and cumulative state adjustment. Panel A uses only short-horizon alpha to predict abnormal price, whereas Panel B adds the interaction of alpha and the return reversal dummy. Panel C adds short-horizon beta and Panel D also adds the cumulative state adjustment. Short-horizon alpha is the one-month abnormal return on the portfolio immediately following portfolio formation. Return reversal is a dummy variable that takes the value of one if the average excess return in years three-to-15 following portfolio formation is opposite in sign to the average excess return in the first post-formation month. Short-horizon beta is the portfolio's one-month market beta immediately following portfolio formation. Cumulative state adjustment is as defined in Section III.C. The sample period is 1948m6–2022m12.

Table IA.I. Size and power of the return-identity-based estimator of abnormal price. This table reports the size and power of our abnormal price estimator for different choices of the standard error. Panel A shows that under the null of $\delta = 0$, a Newey-West (NW) bandwidth of 2 years ("SE_{2y}") yields a conservative rejection rate of 2.4% as opposed to the 5% significance level. Under the alternative of $\delta = 36.6$, the null is rejected 75% of the time. For comparison, Panel B reports the size and power of a short-horizon abnormal return (α) test, showing that an annualized alpha of around 3.2% (12×0.26bp) paired with GMM standard errors with no lag ("SE_{0m}") has a similar statistical power as a price-level test on a delta of -36.6% and GMM standard errors with a NW lag of 2 years. We choose the parameters in our Monte Carlo simulation to match the key moments of the high-*adjusted-value* portfolio. For all tests, we use 1,000 simulations of the same number periods as in the actual data ($1,074$ months spanning 89.5 years).

A. Abnormal Price (δ)

	True SD	SE_{1y}	SE_{2y}	SE_{3y}	SE_{4y}	SE_{5y}	SE_{10y}	SE_{15y}
Size	0.047	0.016	0.024	0.027	0.035	0.042	0.072	0.098
Power	0.750	0.686	0.750	0.796	0.818	0.835	0.873	0.891

B. Abnormal Return (α)

	True SD	SE_{0m}	SE_{3m}	SE_{3m}	SE_{1y}	SE_{2y}	SE_{3y}	SE_{5y}
Size	0.051	0.056	0.053	0.050	0.054	0.058	0.064	0.069
Power	0.606	0.720	0.717	0.715	0.714	0.697	0.690	0.690

Table IA.II. Monte Carlo Moments. The table reports the key moments from simulations and data. The portfolio parameters are from the high adjusted value decile portfolio.

	Simulation					
Portfolio parameter	$\delta = 0$	$\delta \neq 0$	Data	Market-level parameter	Simulation	Data
δ	0	−0.366	n/a			
$E\left[\hat{\delta}\right],\ \hat{\delta}$	0.003	−0.360	−0.335			
σ_r	0.039	0.046	0.041	σ^{mkt}	0.043	0.043
$\overline{r}$	0.008	0.010	0.010	$\overline{r^{mkt}}$	0.0087	0.0087
β	0.830	0.830	0.827	r_f	0.0032	0.0032
$\rho(r_{(t-1),t}, r_{(t-2),t})$	0.999	0.997	0.996			
$\rho(r_{(t-1),t}, r_{(t-180),t})$	0.875	0.778	0.817			

Table IA.III. Estimated Candidate SDF Parameters. The table reports the estimated parameters of the model SDF, $\widetilde{M}_t = \exp(b_0 - b_1 r_t^{mkt})$ with r_t^{mkt} denoting log market returns, along with the 95% confidence intervals in brackets.

J	b_0	b_1
1mo	0.015	3.294
	[0.000,0.030]	[1.518,5.070]
1yr	0.014	3.007
	[-0.000,0.027]	[1.251,4.764]
3yrs	0.014	3.127
	[-0.002,0.030]	[1.362,4.892]
5yrs	0.015	3.306
	[-0.002,0.032]	[1.548,5.064]
10yrs	0.014	3.184
	[-0.002,0.031]	[1.435,4.933]
15yrs	0.015	3.399
	[-0.006,0.037]	[1.634,5.165]

Table IA.IV. Autocorrelation by Estimation Approach: All Characteristics. The table reports the 1-month, 12-month, 60-month, and 180-month autocorrelations in time-series δs estimated based on the return-identity-based approach ("Return identity") and the dividend-based approach using event time ("Cash flow"). We provide the comparison for the low-, high-, and high-minus-low quintile portfolios sorted on all ten characteristics studied in the paper.

		Low				High				Hi - Lo			
		Autocorrelation lag											
Sort	Approach	1	12	60	180	1	12	60	180	1	12	60	180
Book-to-market	Cash flow	0.98	0.78	0.34	-0.86	0.98	0.77	0.18	-0.95	0.96	0.63	-0.14	-0.34
	Return identity	0.15	0.15	-0.05	0.01	0.07	0.11	-0.01	0.00	0.11	0.14	-0.03	0.00
Quality	Cash flow	0.98	0.77	0.26	-0.94	0.98	0.77	0.31	-0.80	0.93	0.32	0.03	-0.18
	Return identity	0.23	0.11	-0.02	0.02	0.23	0.10	-0.05	-0.00	0.24	0.11	-0.03	0.01
Adjusted value	Cash flow	0.98	0.80	0.32	-0.82	0.98	0.77	0.19	-0.95	0.97	0.70	0.04	-0.13
	Return identity	0.15	0.07	-0.09	-0.05	0.01	0.01	-0.04	-0.05	0.08	0.03	-0.06	-0.06
Net issuance	Cash flow	0.98	0.76	0.30	-0.76	0.98	0.79	0.35	-0.80	0.95	0.48	0.03	-0.32
	Return identity	0.20	0.11	-0.04	-0.00	0.23	0.09	-0.10	0.04	0.20	0.11	-0.08	0.01
Investment	Cash flow	0.98	0.82	0.24	-1.18	0.98	0.74	0.37	-0.71	0.97	0.66	-0.06	-0.24
	Return identity	0.01	-0.00	0.02	0.04	0.02	0.12	-0.07	-0.05	-0.05	0.11	-0.02	-0.00
Beta	Cash flow	0.97	0.75	0.24	-1.02	0.98	0.82	0.33	-0.80	0.96	0.65	0.01	0.07
	Return identity	0.16	0.06	-0.05	-0.05	0.11	0.12	-0.09	-0.03	0.16	0.09	-0.08	-0.05
Accruals	Cash flow	0.98	0.83	0.40	-0.70	0.98	0.77	0.30	-0.78	0.94	0.32	0.09	-0.29
	Return identity	0.08	-0.02	-0.01	-0.02	0.21	0.06	-0.09	-0.03	0.12	-0.04	-0.02	0.01
Size	Cash flow	0.98	0.80	0.23	-0.85	0.98	0.79	0.32	-0.84	0.96	0.60	-0.06	-0.51
	Return identity	0.03	0.15	-0.04	0.03	0.02	0.12	-0.06	0.01	0.03	0.15	-0.05	0.03
Momentum	Cash flow	0.97	0.76	0.17	-1.06	0.97	0.71	0.37	-0.77	0.94	0.45	-0.14	-0.44
	Return identity	0.21	0.11	-0.05	0.01	0.20	0.05	-0.09	-0.01	0.09	0.16	-0.00	0.01
Profitability	Cash flow	0.98	0.80	0.32	-0.55	0.98	0.77	0.35	-0.84	0.98	0.76	0.35	-0.08
	Return identity	0.24	-0.00	-0.02	0.03	0.12	0.15	-0.02	0.01	0.22	0.08	-0.02	0.02
Average	Cash flow	0.98	0.79	0.28	-0.87	0.98	0.77	0.31	-0.83	0.96	0.56	0.01	-0.25
	Return identity	0.15	0.08	-0.03	0.00	0.12	0.09	-0.06	-0.01	0.12	0.09	-0.04	-0.00

Table IA.V. Alternative Constructions of *Adjusted Value*. The table presents the deltas and p-values associated with alternative constructions of our adjusted value characteristic. p-values are based on GMM standard errors with the Newey-West kernel and a 24-month bandwidth.

	AdjVal	$z_{BM} + z_{z(Prof)-z(Beta)}$	AdjVal (Future Prof)	$z_{BM} + z_{z(FutureProf)-z(Beta)}$	$z_{Prof} - z_{Beta}$	$z_{BM} - z_{Beta}$	$z_{BM} + z_{Prof}$
delta difference	-0.519	-0.508	-0.547	-0.552	-0.394	-0.352	-0.467
(p-value)	0.002	0.005	0.001	0.003	0.164	0.134	0.130

Table IA.VI. Pricing B/M-and-Profitability-Spread-sorted Portfolios: A Double Sort. The table shows that abnormal price relative to the CAPM is large for portfolios double-sorted on the book-to-market equity ratio (B/M) and profitability spread, our proxy for the value-to-book ratio: Profitability Spread $= z_{\text{prof}} - z_{\text{beta}}$, where z is a z-score. We form nine value-weight portfolios by independently sorting stocks into three B/M bins and three profitability spread bins based on the associated 30% and 70% NYSE breakpoints. We form portfolios and track post-formation returns for 15 years. The reported δs are estimated values of abnormal price defined as $\delta = E\left[\frac{P_t - V_t}{P_t}\right] \approx \delta(180) = -E\left[\sum_{j=1}^{180} \widetilde{M}_{t-j,t} \frac{P_{(t-j),t-1}}{P_{(t-j),t-j}} R^e_{(t-j),t}\right]$, where $(t-j)$ denotes the portfolio formation month and t denotes the month in which returns are realized. We use the candidate SDF implied by the CAPM, $\widetilde{M}_{t-j,t} = \exp\left(b_0 j - b_1 \sum_{s=0}^{j-1} r^{mkt}_{t-s}\right)$, where r^{mkt}_t is log market returns and b_0 and b_1 are chosen to make the market portfolio's prices (δ) and returns ($\delta(1)$) correct in sample. We report t-statistics (in parentheses) and p-values (in brackets) based on GMM standard errors that account for time-series and cross-sectional covariances in the data and uncertainty in estimating the parameters of the candidate SDF. The sample period is 1948m6–2022m12.

	$\delta \times 100$ (t-statistic) [p-value]			
	Profitability spread			
Book-to-market	Lo	2	Hi	Hi - Lo
Lo	26.7	4.1	-11.7	-26.4
	(3.04)	(2.91)	(1.61)	(-1.95), [0.052]
2	18.6	-12.7	-33.1	-38.4
	(1.50)	(2.21)	(1.96)	(-1.54), [0.124]
Hi	0.3	-34.4	-31.0	-19.3
	(1.49)	(1.43)	(1.92)	(-0.74), [0.462]
Hi - Lo	-38.4	-51.8	-31.2	
	(-1.63), [0.104]	(-2.11), [0.035]	(-1.93), [0.053]	

	δ difference	t-statistic	p-value	δ^{RN} diff (t-stat)
$100 \times (\delta_{HH} - \delta_{LL})$	-57.6	-3.61	0.000	-18.5 (-0.95)

Table IA.VII. Abnormal Price vs. Cumulative Abnormal Return (CAR). The table compares the magnitudes and the p-values of abnormal price vs. CAR estimates. CAR is the conventional calendar-time cumulative abnormal return with respect to the CAPM :

$$\widehat{CAR} = \sum_{j=1}^{J} \hat{\alpha}_j.$$

When reporting CAR, we flip the sign for a better comparison with delta. To be consistent with the delta estimates, CAR uses portfolio excess returns with respect to post-formation market returns. p-values are based on GMM standard errors with the Newey-West kernel and a 24-month bandwidth.

	Delta						Cumulative abnormal return					
	δ			p-value			CAR $\times -1$			p-value		
Sort	Lo	Hi	Hi-Lo	Lo	Hi	Hi-Lo	Lo	Hi	Hi-Lo	Lo	Hi	Hi-Lo
Book-to-market	0.060	-0.212	-0.272	0.625	0.206	0.337	-0.012	-0.100	-0.088	0.868	0.390	0.567
Quality	0.061	-0.053	-0.114	0.629	0.603	0.609	0.138	-0.129	-0.266	0.088	0.019	0.054
Adjusted value	0.184	-0.334	-0.519	0.001	0.007	0.002	0.243	-0.316	-0.559	0.000	0.000	0.000
Net issuance	-0.164	0.072	0.237	0.008	0.278	0.006	-0.199	0.122	0.321	0.000	0.036	0.000
Investment	-0.176	0.118	0.294	0.020	0.154	0.035	-0.114	0.102	0.216	0.089	0.176	0.089
Accruals	0.002	0.209	0.207	0.983	0.047	0.222	0.097	0.183	0.086	0.316	0.017	0.580
Beta	-0.226	0.182	0.408	0.060	0.041	0.029	-0.311	0.302	0.613	0.001	0.000	0.000
Size	-0.134	0.035	0.170	0.595	0.300	0.549	0.026	-0.009	-0.035	0.884	0.741	0.836
Momentum	-0.165	0.043	0.208	0.248	0.460	0.136	-0.010	0.066	0.076	0.889	0.094	0.145
Profitability	0.133	0.044	-0.090	0.527	0.812	0.805	0.054	-0.025	-0.080	0.695	0.807	0.661

Table IA.VIII. Explaining Delta Using Short-horizon Alpha. The table explains the cross-section of CAPM abnormal price (δ) based on short-horizon abnormal return (α), its interaction with a dummy variable for return reversal, short-horizon beta (β), and cumulative state adjustment (Cumul. state adj.). Return reversal is a dummy variable that takes the value of one if the average excess return in years three-to-15 following portfolio formation is opposite in sign to the average excess return in the first post-formation month. All regressors are cross-sectionally standardized for the ease of interpreting the point estimates. We use the extreme quintile portfolios for each characteristic, resulting in a cross-section of twenty observations. We report t-statistics (in parentheses) based on heteroskedasticity-robust standard errors.

	(1)	(2)	(3)	(4)
α	-0.09	-0.17	-0.11	-0.05
	(-1.79)	(-5.00)	(-2.34)	(-1.95)
$\alpha \times$ Reversal		0.12	0.12	0.07
		(2.74)	(4.03)	(4.78)
β			0.09	0.14
			(2.27)	(6.22)
Cumul. state adj				0.09
				(9.93)
r2	0.33	0.59	0.70	0.94

Table IA.IX. Pricing Portfolios Sorted on Other Proxies for V/P (1991m6-). The table reports estimated abnormal price with respect to the CAPM for portfolios sorted on characteristics proposed in the literature to proxy for the value-to-price ratio. This table studies the analyst-forecast-based measure of Frankel and Lee (1998) and the market-multiples-based measure of Golubov and Konstantinidi (2019) using the sample period from 1991m6 (these signals are first available in 1976m7 and therefore the entire 15 years of post-formation return data are first available in 1991m6. We report t-statistics (in parentheses) and p-values based on GMM standard errors that account for time-series and cross-sectional covariances in the data and uncertainty in estimating the parameters of the candidate SDF.

	$\delta \times 100$						
Sort	Lo	2	3	4	Hi	Hi - Lo	p(Hi - Lo)
Analyst V/P	-6.85	-0.12	13.66	-2.44	1.67	8.52	0.762
	(-0.33)	(-0.04)	(0.84)	(-0.27)	(0.19)	(0.30)	
Multiples V/P	0.04	-16.76	-32.23	-12.78	-22.41	-22.45	0.368
	(0.00)	(-1.52)	(-1.47)	(-0.93)	(-0.94)	(-0.90)	

Table IA.X. Incremental Information About Prices: Adjusted Value vs. Others. The table studies the CAPM abnormal price of portfolios that bet on a characteristic while controlling for the adjusted value characteristic and vice versa. This table studies the three characteristics comprising adjusted value using nine value-weight portfolios based on independent 30% and 70% NYSE breakpoints for both adjusted value and the second sorting characteristic specified in column one. Adjusted value combines the information in book-to-market, profitability, and beta using their z scores: $z_{B/M} + z_{Prof} - z_{Beta}$. The left-hand side of the table reports the estimated δ and associated t-statistic for each portfolio. The right-hand-side of the table reports the δs associated with the combination of the portfolios that results in either a characteristic-neutral portfolio that bets on adjusted value or a adjusted-value-neutral portfolio that bets on the second characteristic. We report t-statistics (in parentheses) and p-values (in brackets) based on GMM standard errors that account for time-series and cross-sectional covariances in the data and uncertainty in estimating the parameters of the candidate SDF. The sample period is 1948m6–2022m12 except for profitability, which has a sample period of 1967m6–2022m12.

	Adjusted value sort									*AdjVal* sort (Second sort neutral)	Second sort (*AdjVal* neutral)
	Low			2			High			$\frac{1}{3} * ((H1 + H2 + H3)$	$\frac{1}{3} * ((L3 + 23 + H3)$
Second sort →	1	2	3	1	2	3	1	2	3	$-(L1 + L2 + L3))$	$-(L1 + 21 + H1))$
Book-to-market	12.49	19.43	8.50	-9.00	-14.92	-11.87	-36.50	-35.37	-32.59	-48.29	-0.98
	(1.93)	(1.06)	(0.30)	(-0.60)	(-1.26)	(-0.72)	(-2.04)	(-2.58)	(-2.15)	(-2.31), [0.021]	(-0.04), [0.970]
Beta	14.22	7.48	18.42	-17.04	-10.14	-12.82	-32.17	-41.34	-69.01	-60.88	-9.48
	(0.75)	(1.12)	(2.60)	(-1.74)	(-1.65)	(-0.73)	(-2.64)	(-1.83)	(-0.78)	(-1.39), [0.164]	(-0.23), [0.817]
Profitability	23.55	-3.71	20.96	-11.38	-19.73	-3.31	-26.59	-54.01	-44.94	-55.45	-4.29
	(1.08)	(-0.36)	(0.97)	(-0.65)	(-1.51)	(-0.18)	(-1.62)	(-1.89)	(-2.14)	(-2.74), [0.006]	(-0.14), [0.887]

IA.E. Modern Subsample

Table IA.XI. Pricing B/M- or quality-sorted Portfolios: Returns vs. Prices (Modern Subsample). The table shows that B/M and V/B are weak signals of abnormal price relative to the CAPM (the last row), although they tend to predict abnormal one-month returns better (the first row). It repeats Table III in the paper using the modern subsample: 1972m6–2022m12. We report t-statistics (in parentheses) and p-values based on GMM standard errors that account for time-series and cross-sectional covariances in the data and uncertainty in estimating the parameters of the candidate SDF.

Panel A. CAPM δ

	B/M						*Quality*					
	$\delta \times 100$						$\delta \times 100$					
J	Lo	2	3	4	Hi	Hi - Lo	Lo	2	3	4	Hi	Hi - Lo
1mo	0.06	-0.05	-0.12	-0.18	-0.27	-0.33	0.26	-0.06	0.03	-0.04	-0.16	-0.42
("return")	(1.12)	(-0.98)	(-1.78)	(-1.98)	(-2.52)	(-2.23)	(2.76)	(-0.77)	(0.62)	(-0.96)	(-3.17)	(-3.23)
1yr	0.82	-0.89	-1.12	-2.75	-3.69	-4.51	2.27	-0.34	0.17	-0.95	-1.53	-3.81
	(1.02)	(-1.30)	(-1.02)	(-2.04)	(-2.52)	(-2.10)	(1.99)	(-0.32)	(0.23)	(-1.84)	(-2.15)	(-2.22)
3yrs	1.73	-2.12	-2.15	-7.54	-10.28	-12.01	4.59	0.02	0.08	-1.81	-2.84	-7.43
	(0.63)	(-1.24)	(-0.67)	(-1.97)	(-2.54)	(-1.84)	(1.48)	(0.01)	(0.05)	(-1.17)	(-1.27)	(-1.49)
5yrs	4.16	-3.03	-4.64	-11.18	-16.26	-20.42	3.64	0.12	-0.69	-1.97	-2.38	-6.02
	(0.82)	(-1.15)	(-0.89)	(-1.72)	(-2.22)	(-1.69)	(0.73)	(0.02)	(-0.21)	(-0.87)	(-0.58)	(-0.70)
10yrs	8.69	-2.20	-4.08	-18.14	-23.81	-32.50	5.25	2.91	-0.22	-2.22	-2.74	-7.99
	(0.90)	(-0.46)	(-0.38)	(-1.55)	(-1.65)	(-1.37)	(0.50)	(0.30)	(-0.03)	(-0.76)	(-0.33)	(-0.44)
15yrs	10.96	-2.09	-5.97	-19.76	-28.78	-39.74	2.65	6.04	0.72	-4.61	-2.12	-4.77
("price")	(0.79)	(-0.29)	(-0.41)	(-1.23)	(-1.48)	(-1.22)	(0.18)	(0.45)	(0.06)	(-1.19)	(-0.18)	(-0.18)

Panel B. Risk-neutral δ

	B/M						*Quality*					
	$\delta \times 100$						$\delta \times 100$					
J	Lo	2	3	4	Hi	Hi - Lo	Lo	2	3	4	Hi	Hi - Lo
1mo	0.04	-0.04	-0.08	-0.14	-0.25	-0.29	0.14	-0.06	0.04	-0.04	-0.10	-0.24
("return")	(0.75)	(-0.72)	(-1.30)	(-1.59)	(-2.35)	(-1.96)	(1.49)	(-0.81)	(0.85)	(-0.92)	(-1.95)	(-1.85)
15yrs	10.41	-5.18	-9.60	-15.92	-29.27	-39.68	-14.92	-1.14	-0.86	-5.04	9.50	24.42
("price")	(0.92)	(-0.95)	(-0.92)	(-1.16)	(-1.90)	(-1.52)	(-1.37)	(-0.11)	(-0.10)	(-1.11)	(1.22)	(1.37)

Table IA.XII. Pricing Portfolios Sorted on Adjusted Value: Returns vs. Prices (Modern Subsample). The table shows that the adjusted value signal that combines B/M, profitability, and beta into single characteristic is a strong signal of CAPM abnormal price (the last row) and abnormal returns (the first row). It repeats Table IV in the paper using the modern subsample: 1972m6–2022m12. We report t-statistics (in parentheses) and p-values based on GMM standard errors that account for time-series and cross-sectional covariances in the data and uncertainty in estimating the parameters of the candidate SDF.

	$\delta \times 100$							
J	Lo	2	3	4	Hi	Hi - Lo	p(Hi - Lo)	$[\text{Hi - Lo}]^{RN}$
1mo	0.22	0.01	-0.14	-0.23	-0.49	-0.71	0.000	-0.38
("return")	(3.19)	(0.17)	(-2.12)	(-2.98)	(-4.87)	(-4.87)		(-2.72)
1yr	2.63	0.21	-1.65	-3.15	-5.35	-7.99	0.000	-4.06
	(2.90)	(0.26)	(-2.00)	(-2.91)	(-4.33)	(-4.35)		(-2.32)
3yrs	6.28	1.07	-4.10	-8.42	-13.12	-19.40	0.000	-7.75
	(2.61)	(0.52)	(-1.55)	(-2.90)	(-3.83)	(-3.84)		(-1.56)
5yrs	9.41	3.07	-6.66	-13.01	-20.49	-29.90	0.000	-11.45
	(2.99)	(1.13)	(-1.65)	(-3.31)	(-3.29)	(-3.70)		(-0.87)
10yrs	15.01	1.82	-9.59	-23.86	-30.64	-45.65	0.001	-15.21
	(3.17)	(0.51)	(-1.89)	(-3.61)	(-2.94)	(-3.40)		(-0.45)
15yrs	18.92	4.26	-13.41	-33.96	-38.21	-57.12	0.002	-13.96
("price")	(2.97)	(0.78)	(-2.53)	(-2.70)	(-2.69)	(-3.10)		(-0.60)

Table IA.XIII. Pricing B/M-and-Profitability-Spread-sorted Portfolios (Modern Subsample). The table shows that abnormal price relative to the CAPM is large for portfolios double-sorted on the book-to-market equity ratio and our proxy for the value-to-book ratio. It repeats Table IA.VI using the modern subsample: 1972m6–2022m12. We report t-statistics (in parentheses) and p-values based on GMM standard errors that account for time-series and cross-sectional covariances in the data and uncertainty in estimating the parameters of the candidate SDF.

	$\delta \times 100$ (t-statistic) [p-value]			
	Profitability spread			
Book-to-market	Lo	2	Hi	Hi - Lo
Lo	24.9	5.4	-6.0	-30.0
	(2.42)	(2.37)	(1.31)	(-1.91), [0.056]
2	15.3	-18.0	-39.4	-46.1
	(1.24)	(1.80)	(1.70)	(-1.59), [0.111]
Hi	-5.2	-40.6	-37.2	-31.1
	(1.25)	(1.15)	(1.52)	(-1.02), [0.308]
Hi - Lo	-30.9	-54.7	-32.0	
	(-1.14), [0.253]	(-2.07), [0.038]	(-1.77), [0.078]	
	δ difference	t-statistic	p-value	δ^{RN} diff (t-stat)
$100 \times (\delta_{HH} - \delta_{LL})$	-62.0	-3.32	0.001	-22.0 (-0.87)

Table IA.XIV. Pricing Anomaly-sorted Portfolios (Modern Subsample). The table reports estimated abnormal price with respect to the CAPM for portfolios sorted on characteristics conceptually linked to abnormal price or on prominent return anomaly characteristics. This table repeats Table V with the modern subsample, 1972m6–2022m12, and therefore the results for investment, accruals, and profitability are the same as in Table V. We report t-statistics (in parentheses) and p-values based on GMM standard errors that account for time-series and cross-sectional covariances in the data and uncertainty in estimating the parameters of the candidate SDF.

	$\delta \times 100$							
Sort	Lo	2	3	4	Hi	Hi - Lo	p(Hi - Lo)	$[\text{Hi - Lo}]^{RN}$
Net issuance	-16.45	-4.24	2.02	-0.18	7.22	23.67	0.006	8.62
	(-2.67)	(-0.40)	(0.52)	(-0.03)	(1.08)	(2.72)		(0.93)
Investment	-17.61	-17.82	-2.96	8.99	11.80	29.41	0.035	16.68
	(-2.33)	(-2.50)	(-0.68)	(1.67)	(1.43)	(2.11)		(1.08)
Accruals	0.18	-11.66	0.18	4.88	20.89	20.71	0.222	9.40
	(0.02)	(-1.97)	(0.03)	(0.93)	(1.98)	(1.22)		(0.59)
Beta	-22.63	-15.89	-4.95	5.28	18.21	40.85	0.029	-26.86
	(-1.88)	(-2.19)	(-1.11)	(1.00)	(2.05)	(2.18)		(-1.21)
Size	-13.44	-16.91	-20.64	-13.50	3.54	16.98	0.549	54.62
	(-0.53)	(-0.92)	(-1.19)	(-1.14)	(1.04)	(0.60)		(1.91)
Momentum	-16.49	-7.67	-3.68	2.56	4.31	20.80	0.136	22.48
	(-1.15)	(-1.89)	(-1.10)	(0.53)	(0.74)	(1.49)		(1.85)
Profitability	13.35	-9.30	-14.43	-4.96	4.37	-8.98	0.805	2.25
	(0.63)	(-0.66)	(-1.27)	(-0.41)	(0.24)	(-0.25)		(0.08)

Table IA.XV. Incremental Information About Prices: Adjusted Value vs. Others (Modern Subsample). The table studies the CAPM abnormal price of portfolios that bet on a particular characteristic while controlling for the adjusted value characteristic and vice versa. The table studies the characteristics that do not comprise adjusted value based on the nine portfolios from a 3 × 3 independent sort. This table repeats Table VI with the modern subsample, 1972m6–2022m12, and therefore the results for investment and accruals are the same as in Table VI. We report t-statistics (in parentheses) and p-values based on GMM standard errors that account for time-series and cross-sectional covariances in the data and uncertainty in estimating the parameters of the candidate SDF.

	Adjusted value sort									*Adj val* sort (Second sort neutral)	Second sort (*Adj val* neutral)
	Low			2			High			$\frac{1}{3} * ((H1 + H2 + H3)$	$\frac{1}{3} * ((L3 + 23 + H3)$
Second sort →	1	2	3	1	2	3	1	2	3	$-(L1 + L2 + L3))$	$-(L1 + 21 + H1))$
Net issuance	13.37	18.60	10.28	-18.90	-7.71	-8.86	-40.57	-39.55	-31.23	-51.21	5.43
	(1.39)	(3.23)	(0.96)	(-2.34)	(-1.01)	(-1.26)	(-3.12)	(-2.89)	(-1.78)	(-2.84), [0.005]	(0.53), [0.595]
Investment	0.55	16.97	19.88	-25.06	-10.01	-3.90	-44.06	-41.42	-35.40	-52.76	16.39
	(0.05)	(2.17)	(2.29)	(-2.95)	(-1.42)	(-0.44)	(-2.80)	(-2.67)	(-2.16)	(-2.95), [0.003]	(1.62), [0.106]
Accruals	8.33	12.13	26.95	-14.54	-11.05	-1.05	-43.42	-33.93	-46.72	-57.16	9.60
	(0.79)	(1.90)	(2.46)	(-1.86)	(-1.23)	(-0.10)	(-1.94)	(-2.58)	(-2.16)	(-2.80), [0.005]	(0.81), [0.416]
Size	-3.37	-7.59	17.98	-16.99	-30.10	-8.55	-52.88	-41.92	-37.50	-46.44	15.06
	(-0.11)	(-0.40)	(3.32)	(-0.64)	(-1.53)	(-1.06)	(-1.56)	(-1.89)	(-2.48)	(-2.67), [0.007]	(0.52), [0.602]
Momentum	0.84	15.76	17.21	-29.39	-13.32	-3.57	-55.13	-39.13	-33.22	-53.76	21.37
	(0.09)	(2.11)	(2.29)	(-2.43)	(-1.96)	(-0.46)	(-2.12)	(-2.96)	(-2.32)	(-2.85), [0.004]	(1.75), [0.080]

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