Dynamic asset (mis)pricing: Build-up versus resolution anomalies ☆

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Abstract

We classify asset pricing anomalies into those exacerbating mispricing (build-up anomalies) and those resolving it (resolution anomalies). We estimate the dynamics of price wedges for well-known anomaly portfolios and map them to firm-level mispricings. We find that several prominent anomalies like momentum and profitability further dislocate prices. Multi-factor models designed to eliminate one-month alphas still produce large price wedges. Our estimates yield a novel decomposition of Tobin's q, revealing that q's mispricing component has substantial explanatory power for firm investment. Overall, our results suggest that financial intermediaries chasing build-up anomalies negatively affect price efficiency and associated real capital allocation.

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1. Introduction

Over the past few decades, the finance literature has produced a vast body of work arguing that classic asset pricing models are unable to explain patterns in the cross-section of average stock returns. By sorting firms into portfolios based on particular firm characteristics, researchers have uncovered dozens (if not hundreds) of different sorting criteria that could potentially be indicative of deviations of expected returns from model-implied predictions, which is what the literature has termed alphas. While these patterns in monthly abnormal *returns* may be interesting in their own right, they are distinct from dislocations of the price *level*, which we term asset price wedges. In particular, a common conjecture of the asset pricing literature is that positive (negative) alphas are associated with underpricing (overpricing). This supposition implicitly assumes that return anomalies contribute to the convergence of prices to their informationally efficient levels. However, whether return anomalies exacerbate or eliminate existing mispricing remains an open empirical question.

In this paper, we classify return anomalies into those that exacerbate price dislocations (what we call build-up anomalies) and those that resolve them (what we call resolution anomalies). Studying 57 of the most commonly used anomaly sorts, we document the following four stylized facts. First, we find large cross-sectional variation in the price wedges of anomaly portfolios, with double-digit percentage magnitudes. Second, contrary to the view that anomaly returns resolve existing mispricing, we document that a substantial fraction of proposed abnormal return patterns are build-up anomalies. In these cases, the abnormal expected returns exacerbate price dislocations. Our most prominent examples of such build-up anomalies are momentum and profitability, whereas the value, size, and investment anomalies are resolution anomalies. Third, persistent price wedges affect a substantial fraction of the aggregate market capitalization and are prevalent among high q firms. Binsbergen and Opp (2019) show that, under these circumstances, mispricing tends to lead to material real capital misallocation. For instance, while the size anomaly may have lost some of its appeal for fund managers due to its small alpha, our results indicate that it may in fact be associated with material aggregate price dislocations and real misallocations. This seemingly paradoxical result can emerge because size alphas are highly persistent and affect firms with high market capitalization (in the anomaly's short leg). Fourth, our estimates yield a novel decomposition of Tobin's q, revealing that the mispricing component of the empirically observed q has substantial explanatory power for firm investment. This new result confirms that informational inefficiencies in financial markets can indeed lead to material real misallocations.

In addition to documenting these stylized facts, we provide a method of mapping portfolio-level price wedges to firm-level mispricings, uncovering rich dynamic interplays between price wedge resolution and build-up. This approach facilitates estimating the dynamic deviations of a stock price from its fundamental value, which can be useful in a variety of applications considered by academics, practitioners, and firm managers.

For instance, price wedge processes are essential for at least three types of applications: (1) studies of the informational role of prices in real capital allocation, (2) dynamic, horizon-specific portfolio choice where optimal turnover accounts for price impact and trading costs, and (3) the role of active management and financial intermediation in shaping real capital allocation and economic activity.

A priori, it is unclear whether existing anomaly sorts predict a build-up or a resolution of mispricing. If mispricing build-up is the consequence of unpredictable sentiment shocks, anomaly sorts cannot be used to predict further price dislocations (by definition). On the other hand, if a build-up in sentiment is predictable and for example caused by overextrapolation, certain anomaly sorts can potentially be used as an early indicator of mispricing build-up. The resolution of mispricing, on the other hand, is a priori more likely to be predictable. After all, valuation ratios that incorporate the current market price are mechanically related to expected returns and thus are likely helpful in identifying existing mispricing.[1] Our paper provides evidence that both the build-up and the resolution phases of mispricing are in fact predictable, by two distinct subsets of anomaly sorting variables.[2]

The fact that both the build-up and resolution of mispricing are predictable by particular sorting variables disciplines the potential explanations of observed asset pricing anomalies. Take for example momentum. One explanation for the loser portfolio's returns is that investors initially underreact to bad news, implying that the momentum return is itself the resolution of existing mispricing. An alternative explanation is that upon receiving bad news, investors overreact and push down the price too much, in which case the negative momentum return creates mispricing. Our approach helps disentangle these two behavioral explanations, favoring the latter over the former. We find that momentum is a build-up anomaly, consistent with Daniel, Hirshleifer, and Subrahmanyam (1998) and Hirshleifer (2020) who argue that momentum results from continuing overreaction and sluggish correction, rather than from pure underreaction.[3] More generally, our results not only contribute to the literature that estimates the current level of sentiment (see, e.g., Baker and Wurgler, 2006) but also helps identify signals that predict its build-up.

Distinguishing between build-up and resolution anomalies is also critical for gauging whether quantitative equity funds facilitate price corrections or contribute to further price dislocations. For example, if funds chase momentum strategies, they may contribute to a faster and potentially more severe mispricing buildup in that prices are pushed further away from their informationally efficient values and potentially for a longer period of time. While increased capital allocation to momentum strategies may reduce momentum alphas, this in no way implies that prices converge to their correct values faster. Quite the opposite, they diverge faster.

[1] This logic is related to Stein's (2009) argument that so-called anchored trading strategies, like value, have a stabilizing effect on prices, whereas unanchored positive-feedback strategies, like momentum, are potentially destabilizing (see also Berk, 1995).

[2] Note that a number of anomaly portfolios have significant alphas but small price wedges. If the current market price equals the fundamental value, any alpha necessarily implies the build up of mispricing.

[3] See also De Long, Shleifer, Summers, and Waldmann (1990), Barberis, Shleifer, and Vishny (1998), Hong and Stein (1999), Grinblatt and Han (2005), and Jegadeesh and Titman (2001).

In contrast, trading strategies that bet on value-type characteristics tend to facilitate an earlier resolution of mispricing. As such, our findings provide crucial context to the literature that explores the importance of intermediary positions for the performance of factor strategies.

For instance, Lettau, Ludvigson, and Manoel (2018) find that mutual funds and ETFs do not systematically tilt their portfolios towards profitable factors (such as value, momentum, profitability, and investment), which usually would be interpreted as limiting these funds' potential contribution to price efficiency. Yet our results suggest that as far as momentum and profitability are concerned, this behavior is desirable in the sense that it does not contribute toward further price dislocations. Edelen, Ince, and Kadlec (2016) find that in their sample institutional investors have a tendency to buy stocks that we classify as overpriced (e.g., low book-to-market), which suggests that these institutions may contribute to the build-up of mispricing.[4] Finally, Hanson and Sunderam (2014) argue that value and momentum returns are dependent on the available arbitrage capital managed by intermediaries. In light of our findings, these results suggest that abundance of arbitrage capital may be a double-edged sword: while it may contribute toward price resolution when used for strategies such as value, it may induce further price dislocations when employed for trades targeting anomalies such as momentum.

As part of our method, we provide a formal mapping between alphas, cumulative alphas, and price wedges, and show that these objects generally have substantially different statistical properties. Consider once again the momentum effect as an example. At the time of portfolio formation, the momentum portfolios are already mispriced and the subsequent momentum returns exacerbate these existing price dislocations. While the momentum alpha itself is short-lived, the associated price wedge remains large for an extended period of time. Further, cumulative alphas to momentum and reversal strategies do not identify the initial (at the time of portfolio formation) magnitude of over- or underpricing. The latter can only be determined by also accounting for firms' cash flow dynamics. Overall, our findings highlight that studies of anomaly portfolio returns, which are typically done at a monthly frequency, are several steps removed from price wedges and their often slow-moving dynamic evolution.

Our paper also contributes to a recent literature that tries to bring discipline to the large collection of recently discovered return factors (coined the factor zoo in Cochrane, 2011). This literature has the potential to focus the field's attention on a smaller set of anomalies that warrant further investigation. There are several criteria that could be used to separate the weed from the chaff. For example, one could use the statistical robustness of the return patterns by adjusting the inference for multiple testing (Harvey, Liu, and Zhu, 2016). Alternatively, one could look for common patterns across different anomalies through data reduction techniques, such as principal component type analyses (Connor and Korajczyk, 1986, 1988; Kelly, Pruitt, and Su, 2019; Kozak, Nagel, and Santosh, 2020; Lettau and Pelger, 2020). While both these approaches are

[4] See also Avramov, Cheng, and Hameed (2020).

important steps forward in the literature, in this paper we categorize and rank anomalies by the extent to which they exacerbate mispricing (i.e., build-up) or resolve it. This focus is motivated by a long-standing literature examining the role of financial market prices in guiding real capital allocation (Hayek, 1945). As quantified in Binsbergen and Opp (2019), persistent mispricing is associated with substantial efficiency losses from capital misallocations. If price levels are persistently too high (low), firms overinvest (underinvest).[5]

In order to evaluate the effects of mispricing on real economic activity we explore two other important characteristics of anomalies. The first is the market capitalization of the affected firms. The second is the sensitivity of real firm investment to the aforementioned price wedges. Firms with low Tobin's q are unlikely to change their investment policies in response to mispricing, contrary to high Tobin's q firms (see Binsbergen and Opp, 2019).

Combining these two additional characteristics with the measured price wedges allows us to provide a ranking of anomalies in terms of their likely relevance for misallocation. Anomalies that (1) correspond to a large price wedge, (2) affect a significant fraction of the stock market, and (3) affect firms with a high investment-to-price-wedge sensitivity are more likely to lead to large real investment distortions. A substantial fraction of anomalies has alphas that are highly statistically significant but do not meet these criteria and thus, are unlikely to be associated with material real misallocations. Yet when considering all anomalies, our findings indicate that mispricing is materially related to firm investment. Using our firm-level price wedge estimates, we find that the distortions of Tobin's q that are due to mispricing have substantial explanatory power for firm investment.

We conclude this section by discussing other related literature. Keloharju, Linnainmaa, and Nyberg (2021) decompose return anomalies into permanent and transitory components. They find that for the average characteristic, it is the transitory component that predicts returns, whereas there is no information in the permanent component. We show in this paper that even if anomaly returns are transitory, they can still be associated with persistent price wedges. Only after determining the dynamics of price wedges can one assess whether a return pattern leads to the build-up or the resolution of the mispricing. Baba-Yara, Boons, and Tamoni (2020) find that for many anomalies the persistence of the characteristic does not match the persistence of alphas, and they study the monthly alphas between new and old sorts that result from this mismatch.

Cohen, Polk, and Vuolteenaho (2009) empirically study relative price levels of growth and value stocks. They find that these relative prices in the 1940-2000 period appear to be quite well explained by some CAPM specifications using cash flow betas. In contrast, we compute price wedges, their direction, and their dynamic evolution, which are essential if one is interested in assessing the real distortions associated with anomalies.

[5]See also Barro (1990), Morck, Shleifer, and Vishny (1990), Stein (1996), Baker, Stein, and Wurgler (2003), Gilchrist, Himmelberg, and Huberman (2005), Chen, Goldstein, and Jiang (2006), Warusawitharana and Whited (2015), and David, Hopenhayn, and Venkateswaran (2016) for studies on the interaction between real investment and financial markets.

Finally and importantly, Cho and Polk (2021) are also interested in measuring price level dislocations but study neither the dynamics of price wedges (and thus the difference between build-up and resolution anomalies) nor the effects of mispricing on real firm investment. Further, there are several important methodological differences between the two papers that have non-trivial implications for the empirical measurement of price wedges, as further discussed in Section 3 and Appendices C, D, and F.

2. Data and motivating evidence

In this section, we discuss our data sources and present as motivating evidence a replication of the literature's findings on alphas and cumulative alphas.

2.1. Data

We analyze a large set of 57 firm characteristics that the previous literature has identified as cross-sectional predictors of abnormal stock returns. We provide a description of these characteristics in Appendix Table A.1. For all US common stocks traded on the NYSE, AMEX or NASDAQ from July 1964 to December 2017, we collect monthly and daily stock market data from the Center for Research in Security Prices (CRSP) and annual balance-sheet data from COMPUSTAT. Following Green, Hand, and Zhang (2017) and Gu, Kelly, and Xiu (2020), we delay monthly variables by one month and annual variables by six months.[6] For each characteristic, we construct value-weighted decile portfolios split at NYSE breakpoints to reduce the influence of microcap stocks on our results (see also Fama and French, 2016; Hou, Xue, and Zhang, 2020). We track the buy-and-hold dividends and capital gains of these decile portfolios up to (at least) fifteen years after sorting. We sign each characteristic X so that its long-short return generates a positive one-month CAPM alpha after portfolio formation. For example, when sorting firms by their book-to-market ratio (market capitalization), we sort on X $(-X)$.

2.2. Alphas

A monthly alpha represents the amount of mispricing that is resolved or created in a single month. Yet, the alpha by itself does not indicate whether it contributes to mispricing build up or resolution. We formalize the link between alphas and price wedges in the next section, where we highlight (i) the importance of properly taking into account alphas' joint dynamics with cash flows and (ii) that cumulative alphas cannot be used as a valid measure for the total mispricing of a stock.

That said, for the interested reader we start by investigating average cumulative long-short CAPM alphas for each of the 57 anomalies up to fifteen years after portfolio formation in Appendix Fig. G.1. Further, we present in Figs. G.2 and G.3 the cumulative alphas for the long and short portfolio separately. For ease

[6] Thus, to predict returns for month $(t+1)$, the characteristics use monthly variables as they were reported at the end of month t and annual variables as they were reported at the end of month $(t-6)$.

of exposition, we group the anomalies using the categorization of Freyberger, Neuhierl, and Weber (2020). Given our sorting convention mentioned above, the cumulative alpha of each long-short portfolio is initially upward sloping, reflecting positive alphas in the first month after portfolio formation. The portfolio formation dates range from July 1964 to December 2002, such that for each accumulation horizon, we have the same number of observations for the calculation of monthly alphas.

The figures show large heterogeneity across anomalies (also within anomaly categories) in terms of the magnitudes and the time it takes for cumulative alphas to level off. Interestingly, the cumulative alphas switch signs for multiple anomalies. Given the theoretical relation between cumulative alphas and price wedges we discuss in the next section, such switches are initial indicators of potential mispricing build-up. However, as explained in detail below, while cumulative alphas are related to price wedges, there are important differences between these two objects, both theoretically and empirically. Identifying build-up and resolution anomalies crucially requires the formal estimation of price wedges, which we turn to next.

3. Defining, estimating, and interpreting price wedges

In this section, we formally define our price wedge measure and our estimation approach. Further, we conceptually contrast price wedges with cumulative alphas.

3.1. Defining price wedges

To measure a stock's mispricing, we estimate the log deviation of the stock's market price from its informationally efficient value (also often called fundamental value), which for small differences can be interpreted as a percentage deviation. We refer to this log deviation as the *price wedge*. Let P_t denote the market price of a stock at time t, and $\tilde{P}_t$ the fundamental value defined as the present value of future dividends $\{D_s\}_t^\infty$ under a benchmark SDF denoted by $\frac{m_{t+s}}{m_t}$. Our price wedge is then defined as:

$$PW_t = -\log\left(\frac{\tilde{P}_t}{P_t}\right) \tag{1}$$

where the ratio of the fundamental price to the market price can be expressed as:

$$\frac{\tilde{P}_t}{P_t} = E_t\left[\sum_{s=1}^{J}\frac{m_{t+s}}{m_t}\frac{D_{t+s}}{P_t} + \frac{m_{t+J}}{m_t}\frac{P_{t+J}}{P_t}\right], \tag{2}$$

and where E_t denotes the expectation operator under the objective probability measure that efficiently incorporates all information available in the economy as of date t. We denote by J the horizon after which the price wedge is assumed to have converged to zero.[7]

[7] In Appendix C, we discuss how our price wedge concept builds on the earlier work of Binsbergen and Opp (2019) and how it relates to the measure of mispricing considered in Cho and Polk (2021).

3.2. Estimating Price Wedges

In this paper, we start by estimating the price wedges of common characteristics-sorted decile portfolios and then map these estimates to firm-level price wedges in Section 4.4. Suppose that the price wedge of each *monthly-rebalanced* characteristic-sorted portfolio is an unknown constant. Then we can estimate the ratio in Eq. (2) by computing the following unconditional average across the $N-J+1$ portfolio cohorts:

$$\hat{E}\left[\sum_{s=1}^{J}\frac{m_{t+s}}{m_t}\frac{D_{t+s}}{P_t}+\frac{m_{t+J}}{m_t}\frac{P_{t+J}}{P_t}\right]=\frac{1}{(N-J+1)}\sum_{t=0}^{N-J}\left[\sum_{s=1}^{J}\left(\frac{m_{t+s}}{m_t}\frac{D_{t+s}}{P_t}\right)+\frac{m_{t+J}}{m_t}\frac{P_{t+J}}{P_t}\right]. \tag{3}$$

In addition to the observable market price P_t, computing the right-hand side of Eq. (3) requires data on dividends, capital gains, and a candidate SDF.[8] In our baseline specification we set $J = 180$ months (15 years), but our results are robust with respect to alternative choices.[9] Two economic forces contribute to this robustness. First, there is significant mean-reversion in portfolio characteristics over longer horizons. Second, in the calculation of price wedges, substantial cumulative discounting is applied to price dislocations that might still remain after 15 years.

Note that just as an alpha is estimated as the average of abnormal realized returns (the product of the SDF and each realized excess return), this equation estimates the ratio of the fundamental value to the market value with the average of scaled abnormal cash flow realizations (the product of the SDF and each scaled cash flow). This method therefore does *not* impose perfect foresight by agents but rather is consistent with the premise that fundamental stock valuations $\tilde{P}$ are based on rational expectations (which are equal to the average realized outcome).

To arrive at the final estimate of our price wedge we take the natural logarithm of the right-hand side of Eq. (3). Since the right-hand side of (3) is a noisy estimator of the rational expectation E, taking a non-linear transformation of this object introduces bias. We correct for this bias as further explained below (and in more detail in Appendix D.2).[10]

Mispricing only exists relative to a particular benchmark asset pricing model. The importance of the econometrician's choice regarding this benchmark model has been widely discussed in the context of the so-called joint-hypothesis problem (Fama, 1970, 1991). We interpret our results below conditional on the premise that price wedges measure informational inefficiencies. This is not to say that our results cannot be

[8] In Appendix B, we further examine how cash flows associated with issuances and repurchases affect our estimates.

[9] We show in Appendix Fig. G.4 that alternative choices for J, namely $J = 120$ (10 years) or 240 (20 years), yield similar price wedges. For instance, the correlation across characteristics between price wedges for $J = 120$ ($J = 240$) and $J = 180$ equals 0.94 (0.96).

[10] We study the distributional properties of our estimator in Appendix F and show it is well behaved in the sense that it does not feature large outliers that could have an outsized influence on the inference. Our method shares similarities with Korteweg and Nagel's (2016) approach in the context of venture capital, though an important difference is that we study bias-adjusted log-price wedges. These price wedges are corrected for the Jensen effect that drives the skewed distribution of realized SDF-adjusted returns, as highlighted by Martin (2012). We only consider deviations from the market portfolio, study portfolio-level cash flows, and a CAPM-based SDF, all of which reduce volatility and outliers relative to other settings considered in the literature (see, e.g., Gupta and van Nieuwerburgh, 2021).

applied under the alternative view that market prices are always informationally efficient. Conditional on that premise, our estimates quantify the relevance of various characteristics in shaping price *level* dynamics, which are key for real economic activity (see Section 6 in Binsbergen and Opp, 2019, for a detailed discussion).

While our method can be implemented using any SDF, we will focus our attention on SDFs m_t from the class of exponentially affine multifactor models:[11]

$$\frac{m_{t+J}}{m_t} = e^{-\sum_{s=1}^{J} r_{f,t+s} - \frac{\Gamma'\Sigma\Gamma}{2}J - \Gamma' \cdot \left(\sum_{s=1}^{J}(\mathbf{r}_{t+s} - r_{f,t+s}) - J\mu\right)}, \tag{4}$$

where $r_{f,t}$ is the continuously compounded monthly risk-free short rate, $\mathbf{r}_t$ is a vector of continuously compounded monthly factor returns, Γ is the vector of risk prices, Σ is the covariance matrix and μ is the vector of mean excess factor returns.[12] The parameters in Γ, Σ, and μ are estimated. As a baseline specification, we illustrate our general method based on the single-factor CAPM, where the factor return is the market return. As a robustness check, we present evidence for commonly-used multi-factor specifications in Section 4.5. We choose the risk price Γ (a scalar in the one-factor specification) such that the price wedge of the market is equal to zero.[13] This approach is the price-wedge equivalent of the usual assumption in the cross-sectional asset pricing literature that the market return has a zero alpha.

There are two important biases that we address in our estimation procedure. First, the econometrician only observes a noisy estimate of the mean excess factor returns μ. This noisy estimate induces biases in the estimated price wedges, as the multi-period SDF is a non-linear function of μ and the SDF's Jensen-term adjustment becomes increasingly inaccurate when there is substantial overlap between the data used to estimate μ and the horizon over which price wedges are calculated (180 months). To address this issue, we introduce a bias correction as laid out in Appendix D.1. Second, as noted above, taking the natural logarithm of the noisy estimator in Eq. (3) leads to a second bias. We correct for this bias using a novel bootstrap approach described in Appendix D.2.

Throughout, we denote with PW the price wedge estimates that are adjusted for both these biases. However, in some of our robustness analyses, we present price wedges that are only corrected for the first bias. We denote these price wedges with $PW^\star$.

3.3. Contrasting price wedges with cumulative alphas

It may be tempting to assume that the cumulative alphas of individual anomaly portfolios (see Figs. G.2 and G.3) closely approximate the price wedges of these portfolios and their dynamics. However, this conclusion is premature. As shown in Appendix C, the deviation of the market price from the fundamental

[11] We thank the referee for suggesting the use of this class of SDFs as opposed to linear projection SDFs. Chernov, Lochstoer, and Lundeby (2022) test asset pricing models using multi-horizon excess returns and document that prominent linear factor models do a poor job of pricing such returns.

[12] To be precise, for the value factor for example, we include both the extreme value and growth portfolios separately and impose that their risk prices are of opposite sign but the same in absolute value, such that the risk-free rate cancels.

[13] Appendix E describes how we proceed with the estimation in the multi-factor case.

value is the sum of cumulative abnormal discounts applied to an asset's dividend strip values (see Eq. (C.2)). As such, the cumulative abnormal discounting at any given horizon can be larger or smaller than the price wedge. Finally and perhaps most importantly, neither the sign of a one-period alpha nor its persistence identifies whether an anomaly is a build-up anomaly or a resolution anomaly. This is because price wedges are a function of the joint time series dynamics of both alphas and cash flows.

As an illustration of how cash flow duration is critical in determining the relation between price wedges, alphas, and cumulative alphas, consider two stylized stocks under Gordon growth assumptions. Under these assumptions, the dividend yields are given by $D/P = r + \alpha - g$, where r denotes the fair risk-adjusted expected return, α is a permanent expected anomaly return, g is the dividend growth rate, and all three rates are constant.

Suppose that the first stock (a low duration stock) would have a dividend yield of 5% if it were fairly priced. However, it also has a resolution alpha of -1% implying that the current price is inflated, bringing the dividend yield down to 4%. In this case, the sum of all future alphas (cumulative alpha) is minus infinity, but the price wedge is only $\log(5\%/4\%) = 22.3\%$. Now consider a second stock (a high duration stock) that features the same resolution anomaly return of $\alpha = -1\%$, but that would have a dividend yield of 1.2% at informationally efficient prices. Correspondingly, this stock has an actual dividend yield of just 0.2%, due to mispricing. Now the cumulative alpha is again minus infinity, but the price wedge is much larger for the high-duration stock than it is for the low-duration stock: $\log(1.2\%/0.2\%) = 179.2\%$. These two examples highlight that (1) cumulative alphas and price wedges can have completely different magnitudes and (2) holding alpha dynamics fixed, the magnitudes of price wedges are materially affected by the duration of cash flows.

While these examples illustrated cases of resolution anomalies, it is also important to note that the Cumulative Abnormal Returns (CARs) of build-up and resolution phases cannot be simply compared to gauge the magnitude of an anomaly portfolio's price wedge. Alphas that are realized in the near-term are more important in shaping the magnitudes and signs of a current price wedge than later alphas, and these asymmetries are more pronounced the lower a stock's cash flow duration is. For example, if the CAR of an anomaly portfolio first increases as a function of time and then reverts back to zero, the portfolio was likely underpriced at formation. Yet, the magnitude of underpricing can only be determined by actually estimating price wedges as we propose in this paper. As a result, CARs also do not identify whether short-term anomaly returns lead to the build-up or resolution of mispricing. In sum, researchers should be careful not to interpret evidence from existing studies on CARs and the persistence of alphas when making statements about the magnitudes, directions, and dynamics of mispricing.

4. Empirical results

In this section, we present our main empirical results on the magnitudes and dynamics of price wedges. We start by computing price wedges at the portfolio level and then provide a mapping to firm-level price dislocations. We also discuss several robustness analyses.

4.1. Price wedges and their dynamics

In this subsection, we estimate for each anomaly portfolio the price wedge defined in Eq. (1) based on the single-factor version of the SDF defined in Eq. (4). We first separately study the long and the short side of each anomaly, by focusing on the first and tenth decile portfolios.

The results are presented in Fig. 1, which illustrates the relation between alphas one month after portfolio formation and price wedges. The figure provides a scatter plot of the estimated price wedges against the estimated one-month alphas of all 114 decile portfolios ('L' indicates long and 'S' indicates short). Resolution anomalies are located in quadrants II and IV, where the alpha and the price wedge have the opposite sign. In contrast, build-up anomalies reside in quadrants I and III, where the alpha and the price wedge have the same sign. A good example of a build-up anomaly is the short momentum portfolio, because it has a monthly alpha of -1.0% (with a t-statistic of -4.9) while being underpriced at an estimated -21.6% price wedge (with a p-value of 0.011; see details in Appendix F). Fig. 2 plots the magnitudes of price wedges for the 114 decile portfolios, ordering the anomalies according to the difference between the long and the short portfolios' price wedges. The two top panels of the figure plot the results for the long and the short side separately, while the bottom panel plots the difference. We summarize all point estimates of price wedges in Table 1.

The estimates reveal four important insights. First, the price wedges for several prominent anomalies are large, reaching magnitudes exceeding 30% in absolute value. Take for example the price wedge of the value portfolio, which contains the decile of stocks with the highest book-to-market ratios (BEME). The price wedge equals -36.5% (with a p-value of 0.011; see details in Appendix F) indicating that these value stocks are substantially underpriced. We find similar amounts of underpricing (below -30%) for the long portfolios of several other value-related characteristics and size. The latter result regarding the size characteristic confirms the insight of Binsbergen and Opp (2019) that persistent low-alpha anomalies can lead to large price wedges. In particular, whereas the monthly alpha of the long size portfolio is statistically insignificant at 26 bps (t-stat = 1.27) the price wedge exceeds -40% with a p-value of 0.049. The correlation between alphas and price wedges is a mere -0.31, highlighting that one-month alphas alone contain limited information about the magnitudes of price dislocations.[14]

[14] These facts also raise the possibility that anomalies that have low correlation with each other in terms of contemporaneous monthly price-level *changes* (abnormal returns) can still lead to similarly-sized price wedge dynamics.

Second, for about one-third of the portfolios, the alpha and the price wedge are of the same sign (quadrants I and III in Fig. 1), providing evidence that a subset of known return anomalies lead to mispricing buildup. A good illustration of a build-up anomaly is momentum ($R_{12,2}$). The first decile portfolio (or loser portfolio) has an estimated price wedge of -21.6% (p-value=0.011), indicating that loser stocks are already underpriced at portfolio formation. Through negative momentum returns, their prices are first pushed even further away from the informationally efficient level before entering the resolution phase. This pattern suggests that the momentum effect is associated with a rapid *buildup* of mispricing, rather than the resolution of an existing price wedge. Our estimates also provide evidence that the low-profitability portfolio exhibits mispricing buildup. Unprofitable firms are already underpriced at portfolio formation (-12.9%, p-val=0.070) and their prices first move further away from the efficient level before converging back up. In contrast, anomalies related to investment all appear to be resolution anomalies (e.g., with the portfolio of firms with lowest investment-to-assets, I2A, having a positive alpha and a price wedge of -14.2%).

To place these results in context, consider the following theoretical asymptotic counterfactuals that appear to be implicitly assumed when researchers casually relate findings about alphas to mispricing. First, if all anomalies were resolution anomalies, only quadrants II and IV would be populated in Fig. 1. Second, if in addition the alphas and cash flows featured the same time-series dynamics (and thus persistence), there would be a monotonic negative relationship between alphas and price wedges.

A third and perhaps surprising insight from the estimated price wedges is that the most extreme mispricings (i.e., largest absolute price wedges) are found among the long-leg anomaly portfolios. The set of the most underpriced portfolios have price dislocations that are about twice as large as those of the most overpriced portfolios. This once again illustrates that studying price wedges and alphas can lead to very different inferences about relevant asset pricing theories. Several recent papers have highlighted the importance of short sale constraints for cross-sectional asset pricing phenomena, both theoretically and empirically (see Scheinkman and Xiong, 2003; Stambaugh, Yu, and Yuan, 2012). Our results suggest that while short sale constraints are undoubtedly important, they may prove insufficient to explain extreme cross-sectional dislocations in price levels.

Fourth, while the average annualized *alphas* across many anomalies are of the same order of magnitude, the dispersion in *price wedges* across different anomalies is large. For instance, in contrast to size and book-to-market, anomalies like short-term reversal (R21) and idiosyncratic volatility (IDIOV) are associated with only relatively small price wedges of -7.9% and -1.9% for stocks in the respective long portfolios. As argued before, two alphas that are of the same magnitude but have large differences in their persistence, can result in substantially different price wedges.

In the remainder of this subsection, we shed light on the dynamics of price wedges following the first month after portfolio formation. As discussed in Binsbergen and Opp (2019), the real economic impact of an anomaly depends not only on the price wedge, but also on the timing of its resolution. If mispricing is resolved later, there is more time for it to distort firms' investment decisions. In Fig. 3, we present for all characteristics the price wedges that remain five years after portfolio formation, maintaining the assumption that all mispricing is resolved 15 years after portfolio formation.[15] Hence, we calculate at the end of the fifth year after portfolio formation the price wedge using ten years of cash flows starting with the dividend paid in the 61st month after portfolio formation D_{61} and ending with the continuation value P_{180}.

Fig. 3 shows that even after five years, a considerable fraction of the initial price wedge has not been resolved for a substantial number of characteristics. This finding implies that mispricing is sufficiently persistent for the associated price dislocations to potentially have an impact on real allocations. There is important variation in the speed of resolution across characteristics, however. For various resolution anomalies from the value category and size, about half of the initial long-short price wedge remains after five years. In contrast, for some of the build-up anomalies the price wedges remaining after five years are close to (e.g., momentum) or larger than (e.g., profitability) the price wedge at the time of portfolio formation.

To further explore the difference between build-up and resolution anomalies and the dynamics of their price wedges, we plot in Fig. 4 price wedges at annual intervals up to fifteen years after portfolio formation for five of the most prominent anomalies in the asset pricing literature. Mispricing of the high-minus-low book-to-market portfolio resolves gradually, remaining the most mispriced portfolio up to 6 years after portfolio formation, with about 50% of the original price wedge remaining at that point in time. Mispricing resolves quite gradually as well for size and investment. In contrast, the price wedge of momentum increases over the first year, as the large (small) return of the winners (losers) makes these stocks relatively more overpriced (underpriced), after which it is resolved gradually. For profitability, mispricing builds up over the first five years after portfolio formation, after which it enters the resolution phase.

4.2. Dissecting price wedges

Next, we consider the determinants of price wedges and their relative empirical importance. A first component is the alpha (expected abnormal return) over the first month after portfolio formation (see Section 2 above). Panel (a) of Fig. 5 presents a scatter plot of the long-short price wedge versus the one-month alpha of the long-short portfolio, revealing a correlation of 0.06. This is even lower than the one we found when studying the long and short portfolios separately (see Fig. 1). As we will show shortly, this low correlation is driven by substantial heterogeneity in the time-series properties of alphas (build-up vs. resolution and their relative speed) interacted with the differential timing of cash flows. Another noteworthy feature is that price wedges vary more across characteristics than one-month alphas do. The coefficient of variation (the ratio

[15] Although this assumption implies that fewer and fewer cash flows can be mispriced as time passes after portfolio formation, we find that the resolution of mispricing is not affected much by this assumption. Table G.1 of the appendix shows that price wedges converge to zero at a similar pace when we calculate the price wedge that remains up to five years after portfolio formation using fifteen years of cash flows (from 1 to 16 years, 2 to 17 years, and so on). Furthermore, we have already shown in Fig. G.4 that price wedge estimates are similar when using $J = 120$ (10 years) instead of our baseline $J = 180$ (15 years).

of the standard deviation to the mean) for the long-short price wedge is about 2, whereas it is about 1 for one-month alphas.

Next, we investigate the relation between alphas, their persistence, and characteristic persistence. We define characteristic persistence as the unconditional average cross-sectional Spearman rank correlation between a firm-level characteristic $X_{i,t}$ and its 12-month lag $X_{i,t-12}$. There are reasons why one could expect the persistence of characteristics to be related to the persistence of alphas. Suppose a stock is in the high characteristic portfolio at time t and provides an alpha. If this characteristic is persistent, this same stock is likely to still be in the portfolio at $t + 12$. What is not clear is whether such a stock is still contributing to the portfolio's alpha. The reason is that the sorting characteristic is driven not only by alpha dynamics but also by other non-return related state variables. For example, the book-to-market ratio's dynamics are not only driven by alpha dynamics but also by real investment opportunities. This additional state variable variation can break the perfect correlation between a firm's alpha and its sorting variable. Put differently, the persistence of the sorting variable is driven by both the persistence of the alpha as well as the persistence of other state variables.[16]

While the time-series dynamics of alphas can be quite complex, we next examine the first-order autocorrelation of each anomaly's alphas. That is, we measure the persistence of alphas as the coefficient in a regression of the realized alpha $s + 12$ months after portfolio formation on the alpha s months after portfolio formation: $\alpha_{s+12} = \rho_\alpha \alpha_s + \epsilon_{s+12}$. We do not include an intercept in this regression, implying that ρ_α measures how fast the alpha converges to zero.

Panel (a) of Fig. 6 shows that there is a positive association between characteristic persistence and alpha persistence, with a correlation equal to 0.68. Yet Panels (b) and (c) of Fig. 5 show that neither persistence measure is strongly correlated with the price wedge. Panels (b) and (c) of Fig. 6 reveal why this is the case: the one-month alpha is negatively correlated with both measures of persistence (with a correlation of about -0.5), that is, large (small) one-month alphas tend to be transitory (persistent). This finding indicates that the previous literature — by focusing on short-term alphas — has inadvertently focused on characteristics that lead to less persistent return anomalies.

Finally, we revisit the discussion in Section 3.3 on the theoretical differences between cumulative alphas and price wedges, but now from an empirical perspective. Examining the linear relation between price wedges and the corresponding cumulative 15-year alphas of the 114 extreme decile portfolios, we find a correlation equal to a mere -0.69, implying that over 50% of the variance in price wedges is unexplained by cumulative alphas.[17] We find a slope substantially above -1, refuting the prior that the price wedge of an asset can

[16]See Binsbergen and Opp (2019) for a detailed discussion and Baba-Yara, Boons, and Tamoni (2020) for empirical work on the persistence of alphas versus sorting variables.

[17]To ensure comparability, we employ the same exponential SDF when calculating price wedges and cumulative alphas. This approach leads to slightly different alpha estimates when compared to those resulting from standard CAPM regressions, as reported in Section 2.2.

simply be approximated by multiplying the cumulative alphas by -1. This once again confirms that price wedges cannot be accurately inferred from (cumulative) alphas as price wedges depend on the timing of cash flows, alpha dynamics, and their interaction.

4.3. Dollar mispricing

Price dislocations are more likely to matter if the total affected market capitalization is large. To illustrate the importance of each anomaly portfolio, we report in the last two columns of Table 1 the CRSP value weights. For example, the top 10% largest firms (SIZE) account on average for 58.6% of total CRSP market capitalization.

To further gauge the relevance of market capitalization when assessing the total dollar amount of mispricing, we can compute for each decile portfolio the product:

$$(1 - e^{-PW^\star}) \cdot \text{Portfolio Market Capitalization.} \tag{5}$$

Here, we employ our estimator PW^* rather than PW since we compute an absolute dollar value deviation rather than a log deviation. While this computation can in principle be applied to a portfolio at any point in time, we present in Table 2 results considering market capitalization numbers at the end of our sample (December 2017). We also calculate the total mispricing generated by each anomaly sort, by summing the absolute values of dollar mispricing across the ten decile portfolios.[18] Before discussing the results, note that while price wedges generally have a monotonic pattern across decile portfolios, the same cannot be expected for dollar mispricing. This is because dollar mispricing accounts for the market capitalization of a portfolio, which may or may not be correlated with the sorting criterion.

The results for dollar mispricing can be summarized as follows. First, the largest dollar mispricing is generated by several value characteristics (E2P, BEME, S2P, and DP), amounting to around $4 trillion per anomaly. This is substantial compared to the total CRSP market capitalization in December 2017 of $27.3 trillion. Second, anomalies that have small (perhaps even statistically insignificant) one-month alphas, but that are highly persistent and affect a large amount of market capitalization, can end up causing the largest economy-wide dislocations. For instance, consider once again the size anomaly. We have already established that monthly size alphas are relatively small, yet the price wedge (which is a log-percentage deviation) is large. Moreover, small stocks have a five times larger price wedge than large stocks (-41.8% vs. $+7.1\%$). Now that we evaluate the importance of market capitalization, we see that the absolute dollar mispricing is in fact much bigger for large stocks. The reason is that large stocks have about 40 times more market capitalization than small stocks.

[18] Note that whereas the dollar mispricing numbers reported for each portfolio are unbiased estimates, taking the sum across the absolute values leads to an inflated estimate in the presence of estimation error. Yet, under the assumption that the measurement error equally affects this measure across anomalies, the ranking by these summed absolute values still serves its purpose.

4.4. From portfolio- to firm-level price wedges

To evaluate the dynamics of price wedges at the individual firm level, we now estimate a mapping from portfolio-level characteristics to portfolio-level price wedges using principal components (PCs), and then use this mapping to compute firm-level price wedges. Although the portfolio-level mapping will be based on unconditional moments, our estimates of firm-level price wedges will be time-varying, since they are a function of firm characteristics.

As a first step, we extract the PCs of the rank-normalized unconditional average characteristic values of the 57×2 extreme decile portfolios. Rank normalization ensures that the characteristics values are comparable. Moreover, using the extreme decile portfolios is consistent with a large fraction of the anomalies literature that focuses on long-short portfolios as factors and test assets.[19] Table 3 shows that the first six PCs together explain about 89% of the total variation in characteristics. The table also lists the largest three (positive and negative) loadings for each of these PCs. The first PC has a strong positive loading on various characteristics from the value category and a strong negative loading on various characteristics from the profitability category. Furthermore, the fourth PC has a strong positive loading on various characteristics from the investment category. For the remaining PCs, the top three loadings cannot be assigned to one particular category of characteristics, which again suggests that there is considerable heterogeneity within these broad categories.

In a second step, we regress the portfolio-level price wedges on (i) three or six PCs, (ii) the characteristics featured in the Fama-French 5-factor model plus momentum, (iii) the same model as in (ii) but without the investment factor, and (iv) each of these Fama-French characteristics individually. We will use model (iii) in a robustness test in Section 5.4. Table 4 reveals several relevant facts. First, the amount of variation in portfolio-level price wedges that is explained is similar using three PCs, six PCs, or the five benchmark characteristics. The correlation between the fitted values from these three methods is high, at over 0.90. When restricting our focus on the benchmark characteristics, we obtain the following ranking by informativeness regarding portfolio-level price wedges (from most to least): Value, Investment, and Size, which are all resolution anomalies. Momentum and Profitability on the other hand are less useful in explaining current levels of mispricing. By virtue of being build-up anomalies, they help identify securities that have not yet reached their peak level of mispricing (see Section 4.1).

The ultimate goal of our approach is to analyze and interpret firm-level price wedge dynamics. The regressions of Table 4 represent a mapping from rank-normalized characteristics to their associated price wedges. Thus, given the rank-normalized characteristics of a firm (in the cross-section of all firms), researchers

[19] The results using all the 57×10 portfolios lead to similar estimates for both the PCs and the firm-level price wedges. Moreover, using partial least squares, i.e., extracting factors from the characteristics using directly their relation to price wedges, delivers similar results as classical PC analysis. Finally, our results are similar when forming ventile (instead of decile) portfolios to estimate the mapping between price wedges and rank-normalized characteristics (see for instance, Figs. G.5 and G.6).

can easily calculate a firm's price wedge using this mapping. For our estimates below, we use the specification with three PCs, although our results are similar using the other specifications mentioned above.

As an example, we present in Panel A of Fig. 7 the price wedge for Apple. This price wedge exhibits large and persistent deviations from the baseline of zero. Starting in 1992 the stock ended up in a negative momentum spiral (see Panel C for the value and momentum rankings), resulting in a negative price wedge that bottoms out at around -35% in 1997. At that time, Apple had become a value firm (highest book-to-market decile, see Panel C). The mean reversion implied by this value effect combined with the appointment of Steve Jobs as CEO turned the company into a top quintile momentum firm, leading to several years of momentum build-up, resulting in a positive price wedge of about $+20\%$ in 1999. The price then converged back to fair value over the next 3 years before entering a prolonged positive momentum spiral. This momentum turned Apple into the ultimate growth stock for the next 7 years, after which the price largely converged back to fair value by 2017. Panel B plots the observed log market price and the log of the efficient value, the latter of which is computed as log[Market Price] $- PW$.

Importantly, Apple is not unique in that its price wedge repeatedly switches signs over time. We report in Table 5 the annual Markov transition matrix of firm-level price wedges sorted into deciles. The diagonal elements of this matrix are informative about the persistence of price wedges. We find that firms have a substantial probability of staying in a given decile one year later. The average diagonal element across all deciles is roughly one-third, whereas the diagonal element for the two extreme deciles is two-thirds. More specifically, for a firm that is currently in the high price wedge decile (the firm is strongly overpriced), the probability of remaining in that decile is 68%, whilst the probability of transitioning over the course of a single year to the sixth decile or below is about 1%. Over a three year period, the probability of remaining in the highest decile is 41% and the probability of moving to the sixth decile or below is 8% (these probabilities equal 29% and 18%, respectively, for a five-year period).

Finally, note that our approach of mapping portfolio-level price wedges to firm-level price wedges is well suited to calculate price wedges out of sample. To illustrate this, we calculate price wedges for our characteristic-sorted portfolios using the first half of the sample (portfolio formation dates up to September 1983). These price wedges are based on post-formation returns until September 1998. The correlation between full-sample price wedge estimates and price wedges estimated in this subsample is 0.92 for the 57×2 top and bottom decile portfolios.[20] We then proceed by projecting these price wedges on the first three principal components of portfolio-level characteristics, which are again calculated using only data up to September 1998. Finally, we map firm-level characteristics from October 1998 onwards to firm-level price wedges, using the portfolio-level mapping estimated using only data from before October 1998. Over the

[20]Appendix Fig. G.7 shows that the correlation between price wedges estimated using the first and second half of portfolio formation dates is also high at 0.77, with the largest price wedges lining up closely.

period from October 1998 to December 2017, these out-of-sample firm-level price wedges have a correlation of 0.98 with the full sample price wedge estimates. These results confirm once more the robustness of our approach.

4.5. Robustness analyses

In this section, we present several robustness analyses.

4.5.1. Multi-factor SDFs

First, we consider alternative specifications of the SDF. In particular, we present in Table E.1 of the Appendix price wedge estimates using the factors in either the Fama and French (1993) three-factor model (FF3) or the Fama and French (2015) five-factor model including the momentum factor (FF5+MOM). Following Eq. (4), the SDF is defined for a general K-factor model, including the market and $(K-1)$ long-short portfolios, as:

$$\frac{m_{t+1}}{m_t} = e^{-r_{f,t} - \frac{\Gamma'\Sigma\Gamma}{2} - \Gamma' \cdot ((\mathbf{r}_{t+1} - r_{f,t}) - \mu)}, \tag{6}$$

where the vector $\mathbf{r}$ denotes the $(2(K-1)+1) \times 1$-vector of log returns of the factor portfolios (market, small, big, value, and growth, in the FF3) and μ its mean. Furthermore, Γ is a $(2(K-1)+1) \times 1$ vector of risk-prices, which we restrict as follows to obtain long-short factors:

$$\Gamma = [\gamma_0, \gamma_1, ..., \gamma_{K-1}, -\gamma_1, ..., -\gamma_{K-1}]. \tag{7}$$

Consistent with our baseline analysis, we determine the market price of risk, γ_0, such that the price wedge of the market portfolio is zero, while additionally setting the risk-prices $\gamma_1, ..., \gamma_{K-1}$ such that the alphas of the factor portfolio returns are equal to zero (see Eq. (E.8) in Appendix E).[21] Table E.1 shows that the long-short price wedge differences obtained from employing the FF3 and FF5+MOM factors are similar to those from our benchmark CAPM specification (at correlations of 0.7 and 0.5, respectively).

The results of this analysis have important implications for the asset pricing literature, revealing that theories and models fitting existing return patterns may have significant shortcomings in explaining price levels. While popular multi-factor specifications typically reduce alphas, this is not the case for price wedges. Although the mean-squared price wedge roughly halves when using the factors of the FF3 model instead of the CAPM, it triples in the FF5+MOM specification.

Moreover, adding a long-short factor related to a given anomaly characteristic does not necessarily eliminate the price wedges of the portfolios sorted on that characteristic. Take the book-to-market factor of the FF3 model as an example. It is well known since Fama and French (1993) that this factor captures the one-month CAPM alpha of portfolios sorted on book-to-market. Nevertheless, the price wedges of the value and

[21] As in our baseline analysis, we correct price wedge estimates for the bias induced by estimating the vector μ with error.

growth decile portfolios remain economically large after including the book-to-market factor (the long-short difference is -37.5%). This finding again illustrates that price wedges and alphas are distinct objects both statistically and economically (see related discussions in Sections 3.3 and 4.2), highlighting that asset pricing and asset returning are two fundamentally different endeavors. Price wedges and their dynamics yield a rich set of additional moments that the asset pricing literature can employ.

4.5.2. Cash flows associated with stock issuances and repurchases

When market prices are equal to informationally efficient fundamental values, the stock price of a company can be computed using the following two present value identities. The first one takes the perspective of a buy-and-hold investor who never participates in either stock issuances or repurchases. The second takes the perspective of a representative investor who (by definition) participates in all issuances and repurchases. When issuances and repurchases are executed at fundamental value, these two present value relationships yield identical results. However, under the premise that there might exist mispricing, these two approaches no longer yield the same valuations. In particular, a buy-and-hold investor can either lose (dilution) or benefit (the opposite of dilution) from issuances and repurchases if they are done at prices that deviate from fundamental values.

To explore the importance of this issue, we repeat our analysis taking the second approach, that is, to determine the fundamental value for a representative equity investor who participates in all issuances and repurchases at going market prices. The results of this analysis are presented in Table B.1 and Fig. B.1. Overall, we find that the differences in price wedge estimates relative to our baseline specification are small in magnitude, though these differences provide some interesting insight into market timing. First, firms with the smallest market capitalization are 11% less underpriced when incorporating issuances and repurchases (-27.6% vs -38.6%). This result is consistent with buy-and-hold investors benefiting from firms' timing ability regarding issuances and repurchases. When a firm is underpriced and repurchases shares, the shareholders participating in those repurchases receive a lower payment than the fundamental value, resulting in a value transfer from them to the buy-and-hold investors of the firm. As such, the fundamental value for a buy-and-hold investor is higher, implying a larger wedge relative to the current market price (which is the same for both types of investors). More broadly, we find that the average price wedge is larger for buy-and-hold investors (by 0.5% for long portfolios and by 2.5% for short portfolios), which is again consistent with firms timing the market to generate additional value for their buy-and-hold investors.

4.5.3. Going from decile to tercile portfolios

The first panel of Fig. G.8 hows that economically large price wedges are still present if we expand our analysis to the top and bottom three decile portfolios. For instance, various anomalies in the value category (BEME, S2P and Q) are associated with price wedges in deciles 1 to 3 of -25% or below. While this number is smaller in percentage terms than for the extreme deciles (i.e., first and tenth), we are now considering roughly three times as many stocks with significantly larger market capitalization (see also Section 4.3).

5. Price wedges and real investment

In this section, we analyze the relation between investment, price wedges, and Tobin's q. In order to do so, we present a novel decomposition of q into its informationally efficient component and a mispricing component. The key result of this section, which is presented in Section 5.4, is that the mispricing component contributes materially to explaining firm investment. This implies that financial market mispricing has potentially large implications for real economic activity.

Before presenting this main result, we document three results at the anomaly portfolio level that are motivated by the insights and predictions of Binsbergen and Opp (2019) regarding the conditions under which mispricing matters for real allocations. First, we document a significant correlation between firm investment and unconditional price wedges across anomaly portfolios (Section 5.1). Second, we show that the response of investment to mispricing is stronger among firms with high q ($q \geq 1$), which is consistent with the presence of asymmetric adjustment costs (Section 5.2). Third, we document that among these high-q firms a large fraction of aggregate market capitalization is affected by mispricing (Section 5.3).

5.1. Investment and mispricing at the portfolio level

We consider the following two investment-related variables: (i) the investment rate at the time of portfolio formation, denoted INV_t, and (ii) the difference between the average investment rates in the five years *after* and the five year *before* portfolio formation, denoted $INV_{t+1y:t+5y} - INV_{t-4y:t}$.[22] To counter the effect of outliers at the firm level, we first take the median of each investment measure across firms within a portfolio and then calculate the time-series average of these medians. This yields one average investment number for each portfolio. We then investigate the relation between these investment measures and unconditional prices wedges across anomaly portfolios as documented in Table 6 for all characteristics.

Fig. 8 presents the relations between price wedges and each of our two investment measures. We separately study this relation among the long and short (i.e., the two extreme decile) portfolios, respectively. The top two panels use the first investment measure and the bottom two panels the second. In all cases we find a strong positive correlation between investment and price wedges of up to 0.65. These numbers are particularly high when compared to a correlation of -0.25 between investment and one-month alphas.[23] This finding is

[22] We measure q and investment considering the sum of physical and intangible assets, following the approach of Peters and Taylor (2017).

[23] Morck, Schleifer, and Vishny (1990) find that prices have little incremental explanatory power for firms' investment spending. As noted in Binsbergen and Opp (2019), for mispricing to have real effects, it is not a necessary condition that prices have *incremental* explanatory power for investment, after controlling for a wide range of observables. In particular, there may be no effect when other endogenous observable variables included in the analysis already reflect disinformation associated with mispricing. Yet our results indicate that our properly measured mispricing estimates alone explain a substantial fraction of the variation in investment rates.

consistent with Binsbergen and Opp (2019), who argue that price level deviations (price wedges) are the key variable distorting real investment, not one-month alphas.

The bottom two panels, which consider changes in investment rates, help alleviate concerns related to unobserved heterogeneity in investment opportunities and adjustment costs across firms. The fact that the correlation between price wedges and *changes* in investment is particularly high suggests that our results are not driven by persistent firm characteristics determining investment opportunities (fixed effects). Rather, our results imply that when a firm enters a characteristic-sorted portfolio that is relatively more overpriced (underpriced), this firm tends to increase (decrease) its investment over the next five years relative to the five years before it entered the portfolio. While these results hold across portfolios, it is not obvious how this translates to standard firm-level investment-q regressions. As noted above, we will investigate these relations in Section 5.4.

5.2. Sensitivity of investment to mispricing for high-q portfolios

Having investigated the association between investment and price wedges, we next analyze whether this relation is stronger for firms with good real investment opportunities than for those with poor ones (i.e., $q \geq 1$ versus $q < 1$). In order to do so, we first split our sample into two corresponding subsamples at each sorting date. We then sort the firms in each subsample into five quintile portfolios by each characteristic, resulting in $2 \times 5 \times 57$ portfolios overall. Next, we calculate the price wedge, PW, for the first and fifth quintile portfolios, which we refer to below as the long and short portfolio, respectively, resulting in $2 \times 2 \times 57$ portfolios. Finally, we sort the 57 long and short portfolios into five buckets according to their price wedges. The result is a total of $2 \times 2 \times 5 = 20$ price wedges, corresponding to (1) $q \geq 1$ and $q < 1$, (2) long and short portfolios, and (3) five price wedge buckets. For each of these portfolios, we calculate the change in investment from five years before to five years after portfolio formation ($INV_{t+1y:t+5y} - INV_{t-4y:t}$), which we report in Table 7.

Comparing the portfolios in the left and right panels of Table 7 shows that firms with high q invest more on average than firms with low q, as predicted by q-theory. For the average firm with high q, the change in investment is about 1% larger than for the average firm with low q.[24] Going beyond this effect, after conditioning on high versus low q, firms entering characteristic-sorted portfolios that are relatively more overpriced exhibit larger changes in investment around the time they enter the portfolio (with a difference ranging from 0.78% to 2.67% relative to the less overpriced portfolios). Furthermore, the relation between price wedges and changes in investment is substantially stronger among high-q firms. Among high-q firms, the most overpriced portfolios (on both the long and short side) contain firms that increase their investment by about 1.5 to 2 percentage points (in the five years after portfolio formation relative to the five years before portfolio formation), whereas those firms in the most underpriced characteristic-sorted portfolios decrease

[24] The difference in the level of investment, INV_t, is an order of magnitude larger, at around 10%.

their investment by about 1 percentage point. The difference of over 2.5 percentage points is statistically significant and economically large. For low-q firms, the most underpriced portfolios show investment changes of about 1 percentage point lower than the least underpriced portfolios. The difference-in-difference between high and low-q firms of about 1.5 percentage points is significant, both statistically and economically.

Overall, among high-q firms, firms entering portfolios that are the most overpriced on average start investing significantly more around the time of portfolio formation. For low-q firms, we find effects that are consistent in sign, but considerably smaller in magnitude. This result obtains even though the difference in the price wedge between the two extreme groups of characteristics is similar among high-q and low-q firms. We conclude that the relation between mispricing and investment is stronger among high-q firms, consistent with the model of Binsbergen and Opp (2019).

5.3. Mispricing among large high-q firms

The results in the previous sections are consistent with high-q firms responding more to mispricing. However, for this relation to have significant economic consequences another condition needs to be met: mispriced high-q firms also need to represent a significant amount of market capitalization. To explore whether this is the case, we present in Figs. 9 and 10 the ranking of characteristics based on two measures among firms with q greater than one: regular price wedges (as defined in Eq. (1)) and dollar mispricing (see Eq. (5)) as a fraction of CRSP market capitalization. Several of the characteristics that are ranking highly based on the price wedge among all firms, also rank highly based on the price wedge among firms with q greater than one. The largest price wedges when adjusted for market capitalization are observed for size and a number of value-related characteristics. Furthermore, a number of characteristics we classified as build-up anomalies, such as profitability (PROF, PM, ROA, and IPM) and momentum ($R_{12,2}$, $R_{12,7}$ and $R_{6,2}$), still generate material price wedges resulting in potentially significant real misallocations.

5.4. q Theory and price wedges

In the previous three subsections, we have conducted analyses of the relation between portfolio-level price wedges and investment, including several that focused on firms with high q and large market capitalization. While suggestive, there are two potential downsides of these analyses. First, they do not separately identify actual investment opportunities and mispricing at the firm level. Second, these analyses do not conform to the standard firm-level investment-q regressions grounded in q theory. We address both issues in this section, building on a novel decomposition of the observed q into an informationally efficient component and a mispricing component. Specifically, for an all-equity firm, we obtain the following simple relation that expresses the log of a firm's informationally efficient q as the sum of the observed $\log(q)$ and the firm's price wedge:

$$\log(\text{Efficient } q) = \log(q) + PW. \tag{8}$$

For levered firms, we additionally have to take a stance on the informational efficiency of debt values, as our mispricing estimates pertain to the equity component of a firm's balance sheet. Following Binsbergen and Opp (2019), we assume that a firm's debt is not mispriced. Then we obtain the following representation for the log of efficient q for levered firms:

$$\log(\text{Efficient } q) = \log(q) + \underbrace{\log\left(\frac{\text{Equity}}{\text{Equity + Debt}} \times e^{-PW} + \frac{\text{Debt}}{\text{Equity + Debt}}\right)}_{\text{Price wedge applying to the total firm value}}, \tag{9}$$

where we proxy debt values with book values, as is standard in the corporate finance literature. The second term on the right-hand side of Eq. (9) is the price wedge applying to the total assets of the firm (i.e., firm value), which represents the weighted average of mispricing on the equity and debt components of a firm's balance sheet.

Table 8 presents results from OLS regressions of log investment in year $t+1$ on $\log(q)$, $\log(\text{Efficient } q)$, and the price wedge applying to total firm value in year t (see the highlighted term in Eq. 9). Firms' price wedges are calculated considering three different mappings between characteristics percentiles and price wedges. The first model ("All Characteristics") uses the mapping between price wedges and the first three principal components of portfolio-level characteristics (see Section 4.4). The second model ("Five Characteristics") employs the five characteristics from the Fama-French five factor model plus momentum (size, book-to-market, profitability, investment, and momentum). The third model ("Excl. Investment") uses the latter model, but excludes the investment characteristic.[25] See Table 4 for these estimated mappings.

The investment-q regressions include firm and year fixed effects, and we focus on the within R^2, as the coefficient estimates are generally subject to measurement error bias (see Erickson and Whited, 2000; Peters and Taylor, 2017). In Panel A, we use the full sample to estimate both the three characteristics-to-price-wedge mappings and the investment-q regressions. In Panel B, we provide an out-of-sample analysis, where the three characteristics-to-price-wedge mappings are estimated using only pre-1999 data and the investment-q regressions employ post-1999 data.

The first column in Panel A shows that q explains a substantial share of the variation in investment in our sample, with an R^2 of 0.119. Interestingly, the price wedge by itself explains an even larger share of the variation, with an R^2 of 0.160. Both these regressions do not identify to what extent actual investment opportunities or mispricing fundamentally drive investment, as the two can be correlated. To address this issue, we use the theoretical relation (9) between efficient q, observed q, and price wedges and evaluate the relative importance of each measure in multivariate regressions.

The results are presented in the third and fourth column of Table 8. When adding the price wedge as

[25] The model that uses the first three principal components ("All Characteristics") is estimated with about 20% fewer firm-year observations than the "Five Characteristics" and "No Investment" models, because data for all 57 firm characteristics have to be available for a given firm to compute the mapping using principal components.

an explanatory variable to a regression that includes efficient q, the R^2 increases from 0.101 to 0.181. The results are similar when we consider the 5-characteristics model and still strong when we exclude investment in the characteristics-to-price-wedge mapping. In the latter model, the R^2 still increases from 0.126 to 0.159. Throughout, the coefficients on efficient q and the price wedge are positive and highly statistically significant. While omitting investment percentiles in the characteristics-to-price-wedge mapping can alleviate concerns that investment is mechanically related to a firm's previous-year investment percentiles (due to autocorrelation at the firm-level), we should in principle still include investment percentiles in the mapping if it provides more accurate price wedge estimates.

Estimating the relation between characteristics and price wedges using data from our full sample may raise concerns about look-ahead biases. To alleviate this issue, we also consider firm-level price wedges that are based on out-of-sample mappings that are estimated using only data up to 1998 (see Section 4.4). Panel B of Table 8 documents that in the shorter sample from 1999 to 2017 the variation captured by these out-of-sample price wedges is similar to our baseline results ($R^2 = 0.156$). Moreover, adding the price wedge to efficient q generates a similar improvement in R^2 (from 0.115 to 0.188), confirming the robustness of our baseline estimates. Finally, even when we exclude investment in the characteristics-to-price-wedge mappings, price wedges help increase the R^2 from 0.142 to 0.171. That is, mispricing explains about 3% of firm investment even under the most conservative specification. Overall, these results suggest that misvaluations have an impact on firms' investment decisions, confirming that distortions in real capital allocation as a consequence of mispricing are a valid concern.

6. Conclusion

In this paper, we study the dynamic evolution of price wedges that measure the log deviations of market prices from their informationally efficient values. We find that the one-month abnormal returns (alphas) commonly studied in the asset pricing literature identify neither the direction nor magnitudes of mispricing and its dynamics. Our analysis differentiates anomalies that resolve existing mispricing and those that exacerbate it. We find that out of 57 commonly-studied return anomalies about one third appear to drive prices further away from their fundamental value, which we coin *build-up* anomalies. Other anomaly returns are associated with price wedge *resolution*. Moreover, our estimates yield a novel decomposition of Tobin's q. This decomposition reveals that q's mispricing component has substantial explanatory power for firm investment.

Perhaps surprisingly, commonly-used multi-factor models designed to eliminate one-month alphas still produce large price wedges. This is particularly puzzling for those factor portfolios that are included in the stochastic discount factor. As such, the price wedges provided in this paper yield important new moments that asset pricing models should aim to explain. After all, the purpose of asset pricing is to price assets, not just to fit one-month alphas.

Finally, our results raise important questions regarding both the real economic consequences of informational inefficiencies and the value that financial intermediaries can add by trading to exploit anomaly returns. After all, those intermediaries that choose to trade in the same direction as a build-up anomaly may in fact be adversely affecting real economic allocations by further distorting price signals. Overall, our approach may prove useful for future studies examining the interplay between firm-level investment distortions and price efficiency, which remains an important area for future research.

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Table 1
Price wedges.
This table presents estimates for the price wedges ($PW \times 100$) of the long (decile 1) and short (decile 10) portfolios constructed by sorting individual stocks on each of 57 characteristics. The price wedge is calculated using the exponentially affine CAPM SDF that sets the price wedge for the aggregate market equal to zero, using the two bias adjustments discussed in Appendix D. We sort the characteristics on the difference in the price wedge between deciles 1 and 10. The p-values are derived from our bootstrap method with block length equal to 180 months (see the description in Appendix F). We also report the price wedge estimates that are not log-bias adjusted (denoted by $PW^{\star}$). Finally, we report the fraction of CRSP market capitalization allocated to the decile portfolios.

Characteristic		Long PW	p-val	Short PW	p-val	L-S PW	Long $PW^{\star}$	Short $PW^{\star}$	L-S $PW^{\star}$	Long % CRSP	Short % CRSP
BEME	Book equity over market equity	-36.5	(0.011)	18.8	(0.039)	-58.3	-34.1	19.5	-53.6	2.8	25.6
aBEME	BEME - IndustryAdjusted	-40.5	(0.003)	15.1	(0.031)	-57.4	-38.0	15.8	-53.8	3.8	18.3
S2P	Sales to price	-33.9	(0.031)	18.2	(0.033)	-54.7	-32.8	18.9	-51.7	2.2	24.1
Q	Tobin's Q	-34.4	(0.014)	16.6	(0.046)	-54.1	-31.8	17.3	-49.1	3.0	26.2
SIZE	Market cap	-41.8	(0.049)	7.1	(0.120)	-50.4	-38.6	7.3	-45.8	1.5	58.6
R3613	Long-term reversal	-28.1	(0.019)	17.8	(0.004)	-49.2	-26.8	18.9	-45.7	4.3	12.4
ROC	Size + longterm debt - AT to cash	-29.7	(0.000)	14.8	(0.071)	-46.6	-28.1	15.4	-43.6	5.2	20.0
DP	Dividend to Price	-32.7	(0.004)	0.2	(0.475)	-43.5	-29.4	3.3	-32.7	8.0	5.5
dSOUT	Prc change in shares outstanding	-28.5	(0.003)	10.2	(0.219)	-40.2	-27.9	10.7	-38.6	8.5	8.8
BETAd	Beta	-22.8	(0.013)	7.9	(0.329)	-39.3	-21.3	10.6	-31.9	5.9	10.2
dSO	Log Change in shares outstanding	-26.6	(0.009)	7.7	(0.239)	-35.1	-26.3	8.0	-34.3	8.3	8.2
E2P	Income to market cap	-25.0	(0.009)	3.6	(0.255)	-32.9	-24.2	6.1	-30.3	4.9	8.1
A2ME	Total assets over market cap	-13.7	(0.170)	16.4	(0.047)	-32.3	-11.3	17.1	-28.5	6.2	25.9
sdDVOL	Stdev of volume	-25.2	(0.057)	4.9	(0.253)	-30.9	-23.5	5.0	-28.5	3.2	41.3
C2A	Cash+Short-term Investments over AT	-18.4	(0.010)	8.6	(0.159)	-30.0	-17.4	9.5	-26.9	8.8	14.9
aPM	Industry adjusted PM	-15.4	(0.031)	10.2	(0.056)	-27.0	-14.8	10.6	-25.4	6.0	20.7
D2P	Debt to Price	-8.5	(0.339)	16.2	(0.035)	-26.5	-4.9	17.0	-21.9	4.8	17.1
OA	Operating Accruals	-12.4	(0.094)	13.2	(0.099)	-26.3	-11.7	13.9	-25.6	5.3	9.6
dPIA	Change in PPE and Inventory over AT	-19.7	(0.032)	4.9	(0.194)	-25.5	-19.1	5.3	-24.4	4.4	9.1
S2C	Sales to cash	-17.9	(0.013)	3.9	(0.588)	-24.5	-17.5	4.8	-22.2	6.0	14.2
aSIZE	industry adjusted market cap	-16.6	(0.151)	7.0	(0.123)	-24.5	-15.3	7.2	-22.4	2.6	58.4
AT	Total assets	-20.7	(0.093)	2.8	(0.510)	-24.2	-18.6	2.9	-21.5	3.4	46.9
dCEQ	Prc change in equity book value	-9.3	(0.177)	11.6	(0.068)	-22.9	-8.8	12.6	-21.3	4.8	9.4
I2A	Prc change in total assets	-14.2	(0.159)	5.6	(0.385)	-22.5	-13.4	6.6	-20.0	4.0	9.7
OL	Cost of goods sold+expenses over AT	-12.4	(0.201)	5.3	(0.377)	-22.3	-11.8	7.7	-19.5	5.3	10.4
SG	Percentage growth rate in sales	-15.5	(0.101)	3.3	(0.512)	-22.2	-14.5	4.4	-18.9	4.7	9.6
AOA	Absolute Operating Accruals	-8.8	(0.153)	11.8	(0.119)	-22.0	-8.3	12.8	-21.2	7.0	9.2
SAT	Sales (sale) to total assets (at).	-10.8	(0.229)	6.4	(0.354)	-21.3	-10.2	8.7	-18.9	5.5	10.5
SPREAD	Bid ask spread	-14.9	(0.055)	-2.8	(0.458)	-20.3	-13.4	-0.3	-13.2	6.8	5.5
RNA	PM scaled by net operating assets.	-4.6	(0.297)	11.6	(0.071)	-17.1	-3.7	12.1	-15.8	8.4	20.8
CAT	Sales to Lagged Total Assets	-5.4	(0.354)	5.3	(0.374)	-14.9	-4.7	7.7	-12.3	6.2	10.1
TNOVR	Volume over shares outstanding	-4.7	(0.726)	4.4	(0.264)	-14.8	-3.4	6.1	-9.5	13.4	8.1
RETVOL	Return volatility	-12.1	(0.041)	-4.9	(0.315)	-14.2	-11.0	-2.6	-8.3	15.0	4.2
aSAT	Industry adjusted SAT	-10.9	(0.078)	0.1	(0.428)	-12.0	-10.6	0.5	-11.1	6.8	10.0
IVC	Change in inventories over AT	-16.6	(0.044)	-6.5	(0.214)	-10.8	-16.2	-6.1	-10.1	4.2	6.2
dGS	Gross margin - sales (Prc changes)	-10.7	(0.055)	-0.9	(0.533)	-10.2	-10.4	-0.4	-10.0	6.4	7.3
MAXRET	Maximum daily return	-11.2	(0.030)	-7.2	(0.254)	-8.8	-10.4	-5.6	-4.8	13.4	4.3
R21	Short-term reversal	-7.9	(0.095)	-1.4	(0.369)	-6.9	-7.7	-1.1	-6.6	6.1	7.7
DTO	Detrended Turnover	-5.8	(0.169)	-0.5	(0.491)	-6.8	-5.6	0.7	-6.3	6.5	6.3
SUV	Residual volume	-4.9	(0.061)	0.3	(0.241)	-5.2	-4.8	0.3	-5.1	8.9	12.5
NOA	Net operating assets over AT	7.5	(0.045)	8.5	(0.073)	-1.7	8.0	8.8	-0.8	13.0	7.5
EPS	Income to shares outstanding	-6.3	(0.037)	-10.2	(0.261)	-0.7	-6.0	-8.1	2.1	27.2	3.7
sdTURN	Stdev of turnover	1.1	(0.480)	-3.8	(0.441)	1.6	1.3	-2.5	3.8	25.5	6.0
IDIOV	Idiosynctatic FF3M volatility	-1.9	(0.383)	-9.5	(0.226)	2.5	-1.5	-7.7	6.1	23.2	3.6
ATO	Net sales over operating assets	7.8	(0.126)	3.7	(0.089)	2.6	9.0	4.5	4.6	10.4	9.3
C2D	Cashflow to Debt	10.8	(0.127)	-2.2	(0.437)	9.9	11.5	-0.5	11.9	18.4	4.7
PROF	Gross profitability over book equity	0.5	(0.400)	-12.9	(0.070)	11.9	1.4	-12.5	13.9	7.6	7.7
R62	Mom6-2	0.3	(0.482)	-14.3	(0.036)	12.6	1.0	-13.6	14.6	9.4	5.9
TAN	Tangibility	13.0	(0.121)	-5.5	(0.341)	17.2	13.9	-4.8	18.7	12.0	8.7
R127	Mom12-7	3.8	(0.339)	-19.8	(0.007)	21.1	4.9	-19.0	23.8	9.9	5.6
R122	Mom12-2	3.5	(0.388)	-21.6	(0.011)	21.9	4.8	-20.5	25.4	10.5	4.7
PCM	Sales minus cost of goods	5.8	(0.257)	-19.6	(0.045)	23.0	6.2	-18.8	25.0	22.7	5.6
ROE	Income to lagged BE	9.6	(0.073)	-17.3	(0.131)	23.4	10.0	-15.5	25.5	15.6	3.5
PM	Operating Inc. after depr. to sales	10.9	(0.158)	-17.1	(0.182)	23.9	11.7	-15.6	27.3	15.0	3.4
ROA	Income to AT	14.1	(0.040)	-12.6	(0.098)	24.9	14.8	-11.6	26.4	20.3	4.2
ROIC	Return on invested capital	10.2	(0.076)	-19.5	(0.123)	26.6	10.6	-18.0	28.6	20.9	4.8
IPM	Pre-tax income over sales	13.5	(0.032)	-17.6	(0.160)	27.5	13.7	-15.8	29.6	19.6	3.4

Table 2

Dollar mispricing in 2017.

This table presents dollar mispricing estimates for each decile portfolio of each of the 57 anomaly sorts, using market capitalization numbers from the end of our sample (December 2017). Following equation (5), we define these dollar price dislocations using the market capitalization allocated to each portfolio (in $ Trillions). In the last column, we present total mispricing (ranked from high to low), which is calculated as the sum of the absolute value of the dollar mispricing estimates across the ten deciles.

Characteristic	Long (Decile 1)	2	3	4	5	6	7	8	9	Short (Decile 10)	Total (Absolute)
E2P	-0.49	-0.88	-1.42	-0.79	-0.48	-0.24	0.00	0.21	0.26	0.03	4.79
BEME	-0.19	-0.72	-0.63	-0.62	-0.38	-0.22	-0.15	0.00	0.37	0.98	4.27
S2P	-0.19	-0.30	-0.20	-0.31	-0.39	-0.38	-0.38	-0.12	0.34	1.23	3.83
DP	-1.07	-0.87	-0.70	-0.23	-0.12	-0.08	0.18	0.37	0.11	0.07	3.81
ROC	-0.45	-0.40	-0.33	-0.32	-0.37	-0.44	-0.40	-0.18	0.40	0.35	3.63
BETAd	-1.00	-0.90	-0.52	-0.59	-0.26	-0.11	0.02	0.05	0.07	0.05	3.56
Q	-0.14	-0.87	-0.41	-0.31	-0.18	-0.16	-0.23	-0.03	0.14	1.10	3.56
A2ME	-0.31	-0.09	-0.16	-0.19	-0.39	-0.33	-0.26	-0.30	0.13	1.07	3.23
aBEME	-0.52	-0.38	-0.36	-0.16	-0.31	-0.07	0.15	0.18	0.05	0.66	2.83
SIZE	-0.08	-0.10	-0.16	-0.18	-0.14	-0.16	-0.18	-0.27	-0.22	1.28	2.77
dCEQ	-0.16	-0.55	-0.51	-0.28	-0.40	0.03	0.05	0.25	0.16	0.37	2.76
R3613	-0.16	-0.29	-0.29	-0.55	-0.48	-0.20	-0.11	0.01	0.26	0.41	2.76
aSIZE	-0.06	-0.07	-0.16	-0.18	-0.14	-0.16	-0.18	-0.30	-0.23	1.26	2.73
ROE	0.51	0.49	0.24	0.04	-0.21	-0.44	-0.25	-0.19	-0.11	-0.16	2.64
D2P	-0.08	-0.09	-0.16	-0.12	-0.25	-0.33	-0.49	-0.33	0.32	0.38	2.55
ROA	0.98	-0.13	-0.33	-0.30	-0.27	-0.21	0.05	0.04	-0.01	-0.11	2.44
OA	-0.33	-0.40	-0.28	-0.17	-0.33	-0.20	-0.11	-0.04	0.26	0.21	2.33
PM	0.70	0.54	-0.14	-0.04	-0.10	-0.08	-0.06	-0.18	-0.23	-0.22	2.30
AOA	-0.30	-0.54	-0.15	-0.14	-0.30	-0.23	-0.09	-0.06	0.25	0.16	2.22
SPREAD	-1.18	-0.70	-0.20	-0.01	0.00	0.01	0.01	0.00	-0.02	0.00	2.14
IPM	1.14	-0.06	-0.03	-0.15	-0.14	-0.13	-0.11	-0.03	-0.16	-0.18	2.13
TAN	0.52	0.15	-0.02	-0.15	-0.19	-0.16	-0.34	-0.36	-0.11	-0.14	2.13
C2A	-0.21	-0.22	-0.03	-0.20	-0.16	-0.11	-0.29	-0.13	0.23	0.53	2.10
dSOUT	-1.01	-0.51	0.01	-0.15	0.01	0.04	-0.04	0.03	0.15	0.15	2.09
sdDVOL	-0.16	-0.23	-0.23	-0.29	-0.37	-0.20	-0.11	-0.08	0.07	0.32	2.06
ROIC	0.75	-0.13	0.05	-0.07	-0.06	-0.24	-0.13	-0.31	-0.03	-0.24	2.01
aPM	-0.26	-0.42	-0.51	-0.23	0.02	-0.01	-0.06	-0.03	0.01	0.47	2.01
C2D	0.43	0.00	-0.64	-0.35	-0.29	-0.07	-0.12	0.01	0.10	0.00	2.01
dSO	-0.70	-0.90	-0.02	0.00	0.02	0.05	-0.05	0.10	0.04	0.11	1.98
I2A	-0.14	-0.18	-0.45	-0.26	-0.20	-0.01	0.12	0.15	0.21	0.25	1.97
PROF	0.04	-0.10	0.00	0.19	0.40	0.18	-0.33	-0.33	0.03	-0.25	1.84
NOA	0.31	0.19	-0.25	-0.33	-0.24	-0.17	-0.11	-0.08	0.04	0.10	1.82
RNA	-0.11	-0.26	-0.03	-0.14	-0.07	-0.05	-0.09	-0.23	-0.09	0.72	1.80
aSAT	-0.22	-0.30	-0.22	-0.06	0.05	0.08	0.13	0.52	0.20	0.01	1.79
S2C	-0.16	-0.16	-0.09	-0.26	-0.23	-0.07	-0.16	-0.03	0.22	0.32	1.70
R122	0.18	0.14	0.03	-0.02	-0.17	-0.21	-0.24	-0.30	-0.20	-0.13	1.63
SAT	-0.18	-0.22	0.00	-0.05	-0.02	0.27	0.10	-0.35	-0.06	0.29	1.55
dPIA	-0.19	-0.17	-0.13	-0.13	-0.22	-0.12	0.15	0.15	0.17	0.11	1.54
SG	-0.21	-0.29	-0.25	-0.15	-0.05	0.00	0.02	0.11	0.27	0.12	1.48
PCM	0.37	0.20	0.03	-0.14	-0.20	-0.10	-0.05	-0.05	-0.06	-0.27	1.48
ATO	0.34	-0.05	-0.10	-0.29	0.16	0.10	0.00	-0.14	-0.06	0.15	1.39
R127	0.18	0.22	0.02	0.00	-0.16	-0.14	-0.17	-0.17	-0.14	-0.09	1.28
IVC	-0.15	-0.33	-0.37	-0.03	-0.02	0.05	0.14	0.03	0.04	-0.09	1.25
R62	0.02	0.01	0.08	-0.02	-0.17	-0.15	-0.19	-0.16	-0.30	-0.15	1.25
AT	-0.10	-0.12	-0.14	-0.10	-0.12	-0.07	-0.04	-0.11	0.02	0.43	1.24
RETVOL	-0.71	-0.28	-0.08	-0.01	0.00	-0.02	-0.01	-0.05	-0.05	-0.01	1.22
CAT	-0.11	-0.13	0.02	0.00	0.06	0.16	0.02	-0.35	-0.11	0.25	1.21
TNOVR	-0.13	-0.19	-0.19	-0.10	-0.15	-0.11	-0.10	-0.10	0.00	0.07	1.14
MAXRET	-0.66	-0.22	-0.02	-0.01	-0.02	0.00	0.00	-0.03	-0.03	-0.06	1.05
EPS	-0.47	-0.13	-0.09	0.05	0.06	0.06	0.01	0.02	0.08	-0.09	1.05
OL	-0.21	-0.20	-0.10	0.01	-0.02	-0.03	0.02	-0.06	-0.03	0.28	0.95
DTO	-0.11	-0.11	-0.13	-0.14	-0.07	-0.11	-0.12	-0.05	-0.05	0.01	0.91
sdTURN	0.09	-0.05	-0.13	-0.05	-0.15	-0.12	-0.09	-0.08	-0.07	-0.03	0.85
R21	-0.10	-0.11	-0.15	-0.20	-0.12	-0.06	-0.03	-0.01	0.00	-0.01	0.80
SUV	-0.35	-0.22	-0.07	-0.07	-0.03	0.00	-0.02	-0.01	-0.01	0.00	0.78
dGS	-0.11	-0.07	0.07	-0.19	-0.06	0.02	0.01	0.04	-0.06	0.00	0.65
IDIOV	-0.12	-0.02	-0.05	-0.02	-0.03	-0.07	-0.07	-0.09	-0.07	-0.03	0.58

Table 3
Principal component analysis of characteristics.
To extract principal components, we start with the extreme decile portfolios sorted on each of the 57 characteristics, for a total of 114 portfolios. For each portfolio, we compute the unconditional average of all 57 characteristics, and we extract principal components (PCs) from the resulting 114 × 57 matrix of characteristic values. To make the characteristics values comparable, we rank-normalize each characteristic in the cross-section to range from 0 to 1. The table displays the variance explained by each PC as well as the characteristics on which each PC loads most strongly, which we define as the characteristics that receive the largest three positive and the largest three negative loadings.

	Explained Variance (%)	Largest Positive Loadings			Largest Negative Loadings		
		1	2	3	1	2	3
1	37.7	BEME	A2ME	aBEME	ROA	ROE	ROIC
2	24.1	RETVOL	IDIOV	CAT	AT	DP	PM
3	14.2	Q	C2A	ROC	S2P	S2C	SAT
4	6.7	I2A	dPIA	NOA	R122	OL	SAT
5	4.1	C2A	TAN	sdDVOL	S2C	SIZE	AT
6	2.4	sdDVOL	NOA	dPIA	TNOVR	BETAd	sdTURN
Cumulative	89.2						

Table 4
Explaining price wedges.
The table reports estimates from a regression of portfolio-level price wedges (as defined in equation (1)) on principal components extracted from portfolio-level rank-normalized characteristics (see Table 3) as well as the characteristics used in the Fama and French five-factor plus momentum model. The column labeled "No Investment" refers to the same model as the 5 characteristics model except that the investment factor is excluded.

	PC3	PC6	5 Characteristics	No Investment	BEME	SIZE	PROF	I2A	R122
PC1	-0.17	-0.17							
PC2	0.04	0.04							
PC3	0.21	0.21							
PC4		0.01							
PC5		-0.08							
PC6		-0.02							
BEME			-0.68	-0.80	-0.79				
SIZE			0.15	0.21		0.56			
PROF			-0.21	-0.18			0.13		
I2A			0.23					0.68	
R122			-0.05	-0.16					0.68
Intercept	-0.05	-0.05	0.22	0.41	0.34	-0.31	-0.11	-0.39	-0.38
R^2	0.76	0.77	0.74	0.72	0.67	0.29	0.00	0.37	0.22

Table 5
Markov matrix for price wedges.
Panel A reports the Markov matrix for the dynamics of price wedges. We sort all firms into ten deciles based on the price wedge in year t and estimate the annual transition probabilities across deciles (from year t to year $t+1$). The price wedge of a firm is estimated using its characteristics in year t and the mapping from portfolio-level characteristics to firm-level price wedges as explained in Section 4.4. Portfolio-level price wedges are estimated using the CAPM SDF and the mapping is based on three principal components of characteristics. In Panel B, we report percentiles 5, 50, and 95 of the distribution of price wedges (averaged over time) within each decile portfolio.

Panel A: Markov Transition Matrix										
Deciles	t+1									
t	H	2	3	4	5	6	7	8	9	L
H	0.68	0.21	0.06	0.03	0.01	0.01	0.00	0.00	0.00	0.00
2	0.22	0.38	0.21	0.10	0.05	0.02	0.01	0.01	0.00	0.00
3	0.06	0.23	0.30	0.20	0.11	0.06	0.03	0.01	0.00	0.00
4	0.02	0.10	0.21	0.25	0.19	0.12	0.06	0.03	0.01	0.00
5	0.01	0.04	0.11	0.20	0.23	0.19	0.12	0.06	0.02	0.00
6	0.00	0.02	0.06	0.12	0.19	0.23	0.20	0.12	0.05	0.01
7	0.00	0.01	0.03	0.06	0.12	0.19	0.24	0.21	0.11	0.03
8	0.00	0.00	0.01	0.03	0.06	0.11	0.20	0.27	0.23	0.08
9	0.00	0.00	0.01	0.01	0.02	0.05	0.11	0.21	0.34	0.24
L	0.00	0.00	0.00	0.00	0.01	0.02	0.04	0.08	0.22	0.63
Panel B: Distribution of Price Wedges Within Decile										
P5	0.22	0.13	0.05	-0.01	-0.07	-0.13	-0.20	-0.27	-0.35	-0.54
Median	0.28	0.17	0.09	0.02	-0.05	-0.11	-0.17	-0.24	-0.31	-0.42
P95	0.42	0.21	0.12	0.05	-0.02	-0.08	-0.14	-0.20	-0.28	-0.36

Table 6

Investment in extreme decile portfolios.

This table presents the price wedges (defined in equation (1)) and measures of investment ($\times100$) for the long and short portfolios (decile 1 and decile 10). These portfolios are constructed by sorting individual stocks on each of the 57 characteristics. The price wedges are calculated using the CAPM SDF and we sort the characteristics on the difference in the price wedges between deciles 1 and 10. The investment measures are investment at the time of portfolio formation (INV_t) and the change in average investment from the five years *before* to the five years *after* portfolio formation ($INV_{t+1y:t+5y} - INV_{t-4y:t}$). t-statistics on the change in investment are calculated using Newey-West standard errors with 180 lags.

	Long (Decile 1)				Short (Decile 10)			
Characteristic	PW	Inv_t	$Inv_{t+1:t+5} - Inv_{t-4:t}$	t-stat	PW	Inv_t	$Inv_{t+1:t+5} - Inv_{t-4:t}$	t-stat
BEME	-36.5	14.3	-2.5	(-3.3)	18.8	25.5	3.5	(6.2)
aBEME	-40.5	14.3	-2.3	(-3.3)	15.1	24.2	1.9	(4.3)
S2P	-33.9	17.0	-2.1	(-4.8)	18.2	26.3	3.0	(4.3)
Q	-34.4	14.3	-2.0	(-2.6)	16.6	26.7	3.1	(5.4)
SIZE	-41.8	17.7	0.3	(0.7)	7.1	16.9	-0.8	(-1.4)
R3613	-28.1	16.9	-3.7	(-6.0)	17.8	23.0	2.7	(6.4)
ROC	-29.7	15.1	-1.9	(-2.5)	14.8	22.5	1.3	(2.7)
DP	-32.7	12.9	-1.7	(-3.0)	0.2	18.2	0.8	(1.4)
dSOUT	-28.5	15.9	-0.6	(-0.7)	10.2	22.4	2.4	(4.4)
BETAd	-22.8	15.7	-0.3	(-0.7)	7.9	25.9	1.0	(1.5)
dSO	-26.6	15.5	-0.5	(-0.6)	7.7	26.7	2.7	(3.2)
E2P	-25.0	17.8	-0.9	(-2.8)	3.6	17.6	-1.0	(-1.4)
A2ME	-13.7	14.5	-3.9	(-4.7)	16.4	26.6	3.0	(4.9)
sdDVOL	-25.2	17.8	0.3	(0.7)	4.9	16.8	-0.8	(-1.7)
C2A	-18.4	16.7	-0.9	(-1.4)	8.6	23.3	2.5	(4.6)
aPM	-15.4	16.8	-0.8	(-3.4)	10.2	20.7	-0.5	(-0.6)
D2P	-8.5	15.1	-3.9	(-6.6)	16.2	23.7	2.6	(5.4)
OA	-12.4	16.8	-0.3	(-0.9)	13.2	27.9	1.9	(4.7)
dPIA	-19.7	12.2	-0.8	(-1.9)	4.9	35.9	0.3	(0.7)
S2C	-17.9	18.3	-0.6	(-1.1)	3.9	23.4	3.1	(3.8)
aSIZE	-16.6	17.1	0.2	(0.7)	7.0	16.8	-0.8	(-1.6)
AT	-20.7	19.6	1.9	(7.6)	2.8	13.5	-1.3	(-1.9)
dCEQ	-9.3	15.1	-1.5	(-3.9)	11.6	29.7	3.4	(4.8)
I2A	-14.2	12.8	-1.4	(-2.6)	5.6	36.5	2.5	(3.9)
OL	-12.4	21.3	0.3	(1.5)	5.3	19.9	0.0	(0.0)
SG	-15.5	13.2	-1.7	(-3.3)	3.3	33.2	3.3	(5.4)
AOA	-8.8	16.2	-0.4	(-1.0)	11.8	27.9	2.0	(5.1)
SAT	-10.8	21.5	0.4	(1.8)	6.4	23.9	0.8	(0.6)
SPREAD	-14.9	15.8	-0.2	(-0.4)	-2.8	20.8	0.1	(0.2)
RNA	-4.6	18.1	-1.0	(-3.1)	11.6	29.3	2.3	(3.7)
CAT	-5.4	25.3	1.0	(4.2)	5.3	17.2	0.4	(0.4)
TNOVR	-4.7	15.8	-0.4	(-0.8)	4.4	24.4	1.3	(2.0)
RETVOL	-12.1	15.3	-0.4	(-0.6)	-4.9	20.2	0.2	(0.7)
aSAT	-10.9	19.9	0.5	(1.6)	0.1	19.9	0.0	(0.0)
IVC	-16.6	15.0	-1.1	(-2.3)	-6.5	27.0	1.8	(4.6)
dGS	-10.7	18.5	-0.1	(-0.2)	-0.9	17.1	2.1	(7.5)
MAXRET	-11.2	15.6	-0.5	(-0.8)	-7.2	19.6	0.4	(1.0)
R21	-7.9	20.3	-0.4	(-1.0)	-1.4	19.2	1.1	(3.1)
DTO	-5.8	19.7	0.6	(1.7)	-0.5	22.7	0.9	(1.5)
SUV	-4.9	18.0	-0.1	(-0.3)	0.3	18.4	-0.1	(-0.2)
NOA	7.5	19.9	1.8	(3.1)	8.5	30.9	-0.4	(-0.8)
EPS	-6.3	14.6	-0.1	(-0.2)	-10.2	17.0	-1.1	(-1.3)
sdTURN	1.1	15.5	-0.5	(-0.9)	-3.8	22.7	1.5	(3.2)
IDIOV	-1.9	15.3	-0.4	(-0.7)	-9.5	19.8	0.2	(0.6)
ATO	7.8	18.4	0.7	(0.7)	3.7	26.5	1.7	(3.5)
C2D	10.8	21.5	1.7	(4.8)	-2.2	18.2	-1.3	(-2.9)
PROF	0.5	21.6	-0.8	(-2.7)	-12.9	14.5	2.0	(2.5)
R62	0.3	18.8	2.4	(7.8)	-14.3	21.6	-1.4	(-3.5)
TAN	13.0	23.2	2.5	(6.8)	-5.5	14.9	-0.4	(-0.6)
R127	3.8	19.1	2.8	(7.8)	-19.8	21.7	-1.9	(-4.9)
R122	3.5	18.8	3.4	(9.8)	-21.6	22.4	-2.4	(-6.0)
PCM	5.8	25.5	-0.5	(-1.2)	-19.6	14.9	0.9	(1.5)
ROE	9.6	26.8	3.3	(4.7)	-17.3	16.1	-1.6	(-3.6)
PM	10.9	21.5	1.0	(1.2)	-17.1	17.9	-1.0	(-2.3)
ROA	14.1	27.3	2.1	(4.1)	-12.6	16.3	-1.8	(-4.7)
ROIC	10.2	24.0	1.7	(3.5)	-19.5	16.8	-0.8	(-2.3)
IPM	13.5	21.9	2.1	(3.6)	-17.6	17.5	-1.8	(-3.1)

Table 7

Investment and price wedges conditional on $q \geq 1$ versus $q < 1$.

This table reports for both high- and low-q firms the relation between changes in investment and the price wedge. For each of the 57 characteristics, we calculate for the long and short quintile portfolio the average price wedge and the average of the 5-year change in investment ($INV_{t+1y:t+5y} - INV_{t-4y:t}$). We then sort the characteristics in five groups based on the price wedge. Our interest is in the difference (Diff) which measures whether overpriced firms start investing more around the time of portfolio formation than underpriced firms, and the difference-in-difference (Diff-in-Diff), which measures whether this relative increase is larger among high-q firms than among low-q firms. t-statistics are calculated using Newey-West standard errors with 180 lags.

	High-q Firms ($q \geq 1$)						Low-q Firms ($q < 1$)						
	Underpriced	2	3	4	Overpriced	Diff	Underpriced	2	3	4	Overpriced	Diff	Diff-in-Diff
	Long						Long						
PW	-12.52	2.95	8.49	12.66	18.49	31.01	-35.60	-26.92	-22.72	-18.60	-9.41	26.19	4.82
$Inv_{t+1:t+5} - Inv_{t-4:t}$	-0.94	-0.48	-0.16	0.15	1.65	2.59	-1.56	-1.14	-0.80	-0.85	-0.78	0.78	1.82
	(-1.4)	(-0.9)	(-0.4)	(0.5)	(3.0)	(3.5)	(-2.8)	(-2.3)	(-1.5)	(-1.9)	(-1.9)	(4.0)	(3.2)
	Short						Short						
PW	4.04	12.41	15.71	18.84	22.44	18.40	-22.90	-16.37	-13.50	-9.51	-1.11	21.79	-3.39
$Inv_{t+1:t+5} - Inv_{t-4:t}$	-0.69	0.01	0.03	0.51	1.98	2.67	-1.71	-1.22	-0.43	-0.60	-0.22	1.49	1.18
	(-1.3)	(0.0)	(0.1)	(1.2)	(3.5)	(4.2)	(-3.2)	(-2.4)	(-0.9)	(-1.2)	(-0.5)	(5.2)	(2.8)

Table 8

Investment-q regressions and price wedges.

This table presents results from firm-level OLS regressions of investment in year $t+1$ on log(q), log(Efficient q), and the total firm value price wedge in year t. Throughout, the debt mispricing is assumed to be zero. In Panel A, we use the sample from 1975 to 2017, in which case the firm-level PW is calculated using a firm's characteristics and the mapping between full-sample-portfolio-level price wedges and (i) the first three principal components of portfolio-level characteristics (estimated in the first column of Table 4), (ii) five portfolio-level characteristics (size, book-to-market, profitability, investment and momentum; estimated in the third column of Table 4), and (iii) four characteristics (excluding investment from the set of five; estimated in the fourth column of Table 4). In Panel B, we use only data from 1999 to 2017 and "out-of-sample" (OOS) firm-level price wedges that are based on the mapping between portfolio-level price wedges and portfolio-level characteristics estimated using only data pre-1999 (see Section 4.4). The regressions include firm and year fixed effects and the t-statistics (reported in brackets) are based on standard errors calculated using firm and year clustering.

	All Characteristics				Five Characteristics				Excl. Investment			
						Panel A: Full Sample						
log(q)	0.0285				0.0352				0.0352			
	(22.24)				(19.22)				(19.22)			
PW		0.286		0.230		0.280		0.212		0.240		0.152
		(30.87)		(27.23)		(23.17)		(20.00)		(20.86)		(16.28)
log(Efficient q)			0.0279	0.0146			0.0349	0.0206			0.0358	0.0264
			(20.86)	(14.05)			(18.21)	(12.72)			(18.60)	(14.83)
R^2 (within)	0.119	0.160	0.101	0.181	0.139	0.156	0.118	0.188	0.139	0.104	0.126	0.159
						Panel B: Out of Sample						
log(q)	0.0293				0.0357				0.0357			
	(13.14)				(10.76)				(10.76)			
PW		0.275		0.211		0.212		0.136		0.187		0.115
		(14.96)		(15.80)		(10.42)		(12.32)		(10.10)		(11.73)
log(Efficient q)			0.0288	0.0170			0.0361	0.0277			0.0362	0.0297
			(12.36)	(10.96)			(10.20)	(9.59)			(10.22)	(9.73)
R^2 (within)	0.134	0.156	0.115	0.188	0.157	0.109	0.140	0.177	0.157	0.0882	0.142	0.171

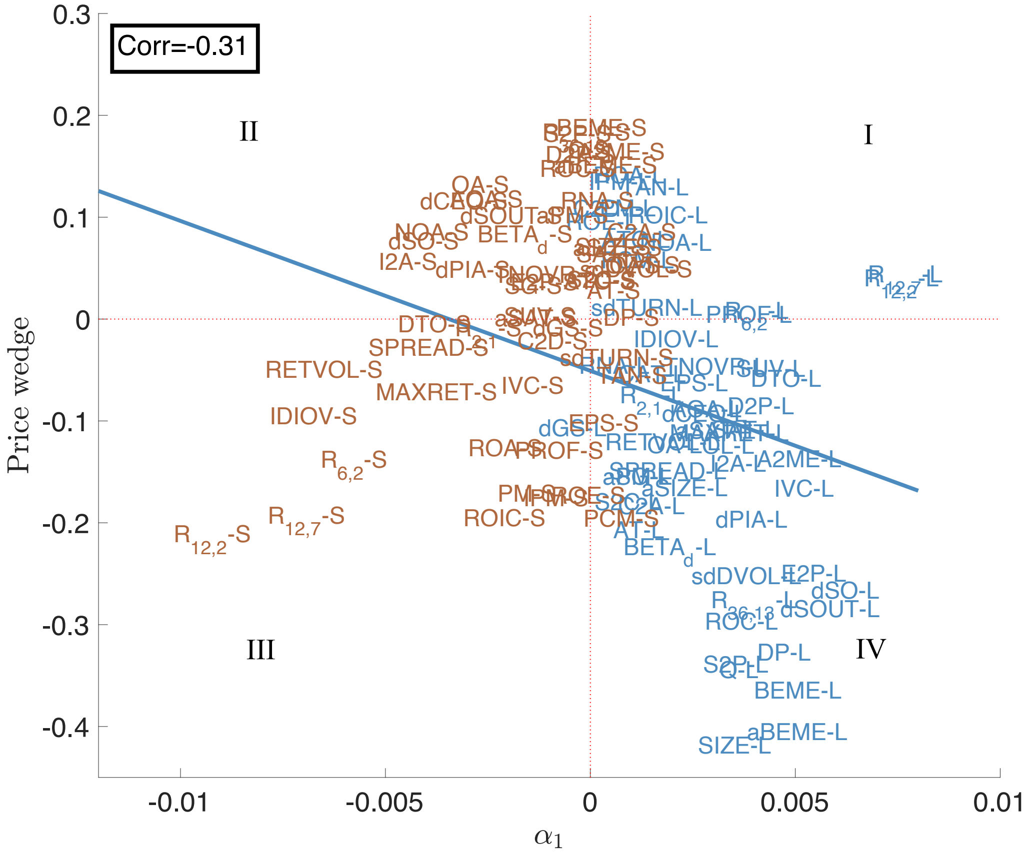
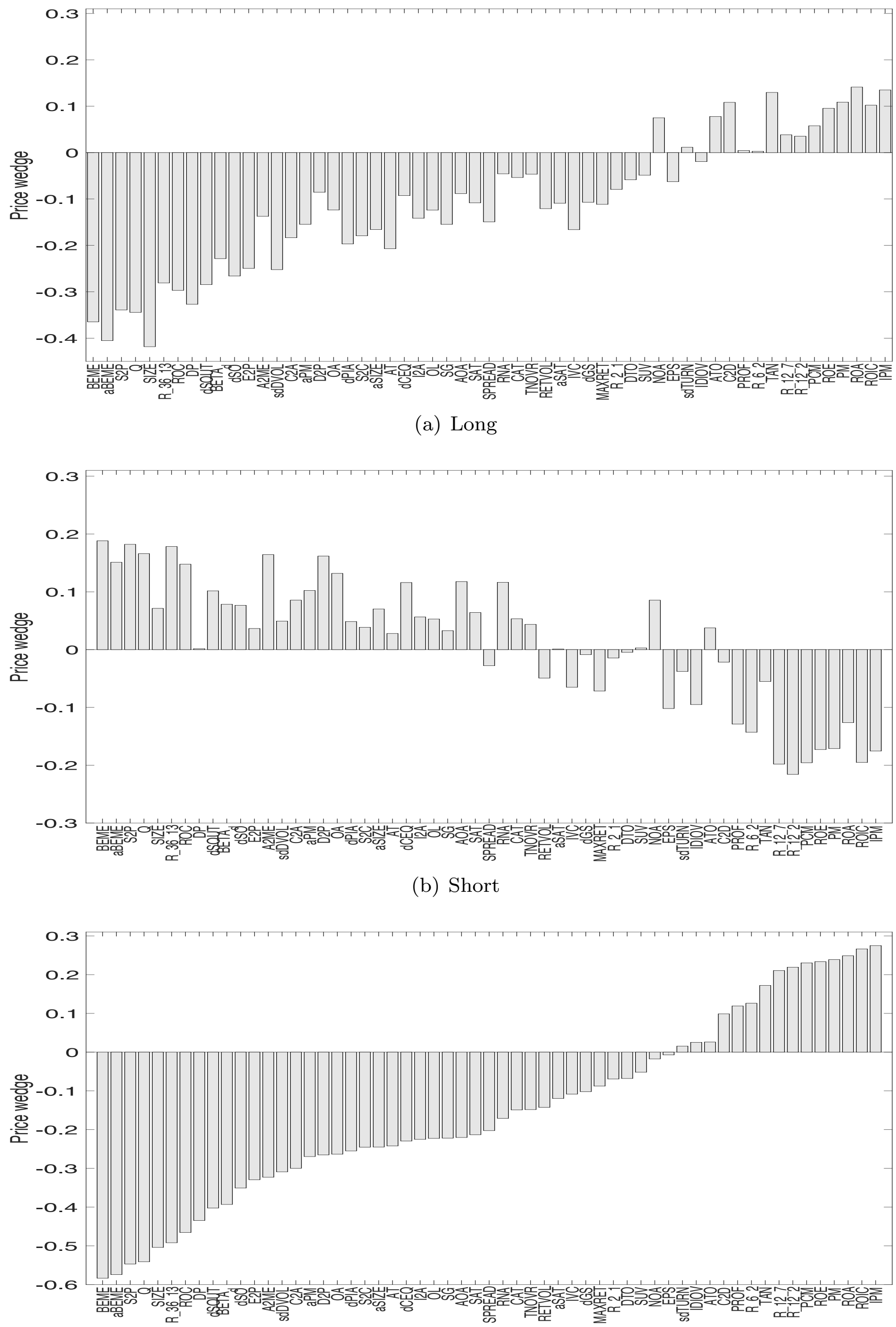


Fig. 1. Price wedges and alphas. This figure illustrates the relation between alphas one month after portfolio formation and price wedges. The graph presents a scatter plot of the estimated price wedges against the estimated one-month alphas of all 114 long (L) and short (S) decile portfolios. Resolution anomalies are located in quadrants II and IV, where the alpha and the price wedge have the opposite sign. Build-up anomalies reside in quadrants I and III, where the alpha and the price wedge have the same sign.



(a) Long

(b) Short

(c) Long-Short

Fig. 2. Price wedges. This figure presents price wedges for the long and the short decile portfolios, as well as the long-short difference, from sorts on each of the 57 characteristics. The price wedge is calculated using the CAPM SDF. We sort the characteristics from low to high according to the long-short difference of the price wedges (bottom panel).

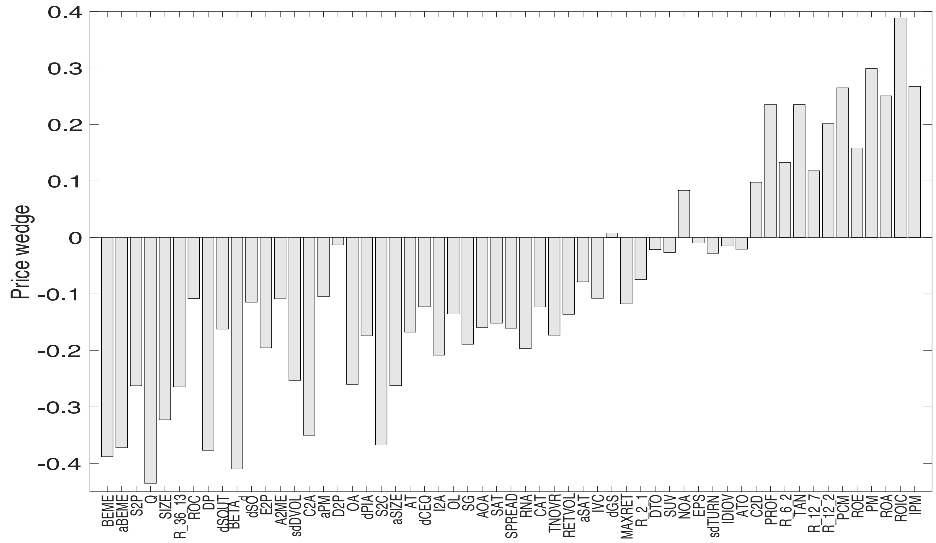


Fig. 3. Price wedges 5 years after portfolio formation. This figure presents the price wedges of the long minus the short decile portfolios for all characteristics five years after portfolio formation. Given our assumption that the price wedge converges to zero 15 years after the original portfolio formation date, we use 10 years of cash flows (from month 61 to 180) that are discounted back to month 60.

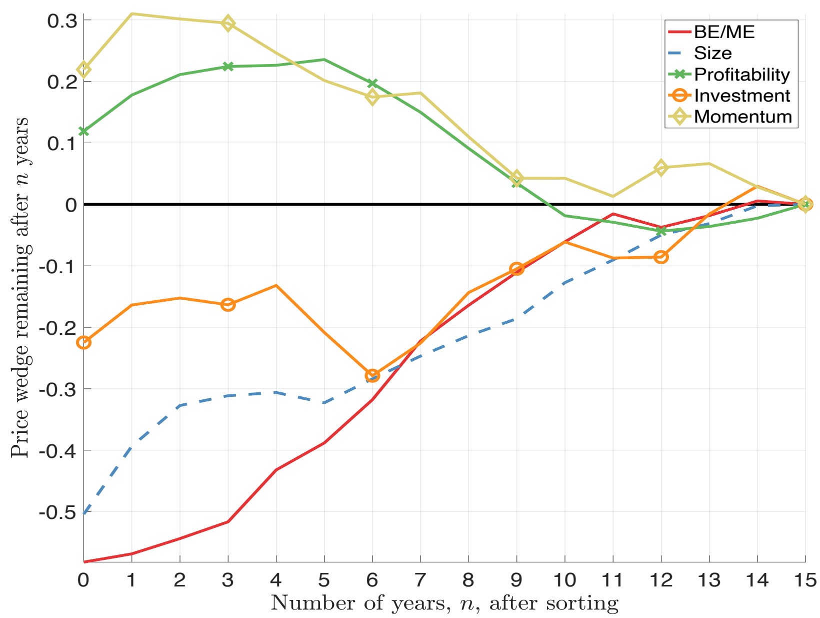
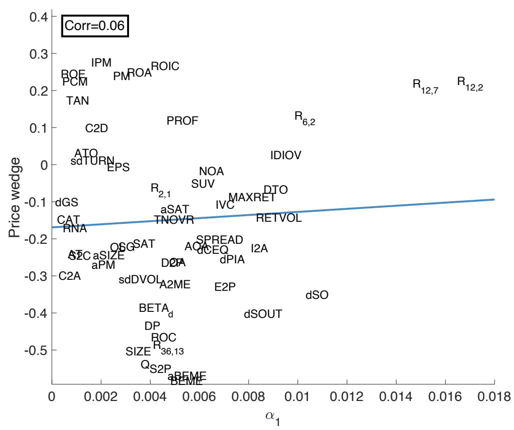
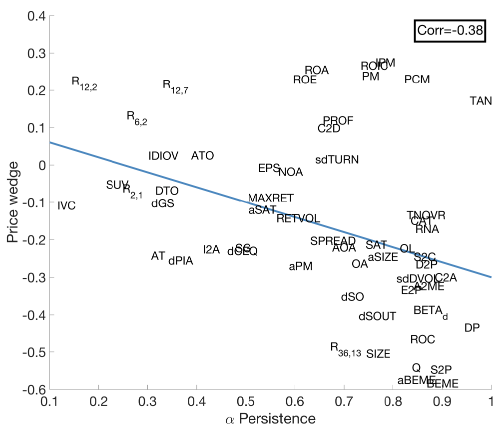


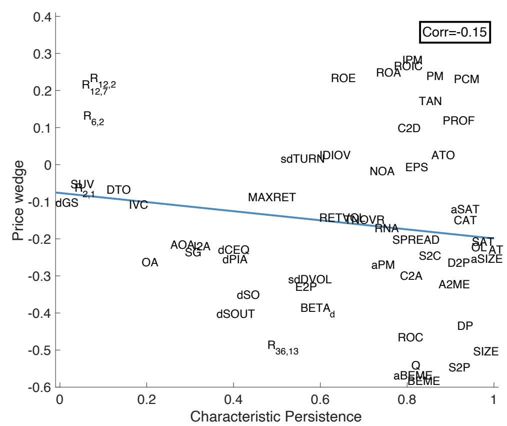
Fig. 4. Price wedges n years after portfolio formation for select characteristics. This figure presents the long-short price wedges of select characteristics n years after portfolio formation (with $n = 0, ..., 15$). $n = 0$ refers to the price wedge at the moment of portfolio formation, such that a total of 15 years of cash flows is used to calculate the price wedge. For $n > 0$, we report the price wedges n years after portfolio formation, such that $15 - n$ years of cash flows are used to calculate the price wedges (i.e., cash flows from month $n \times 12 + 1$ to 180 are discounted back to month $n \times 12$).



(a)

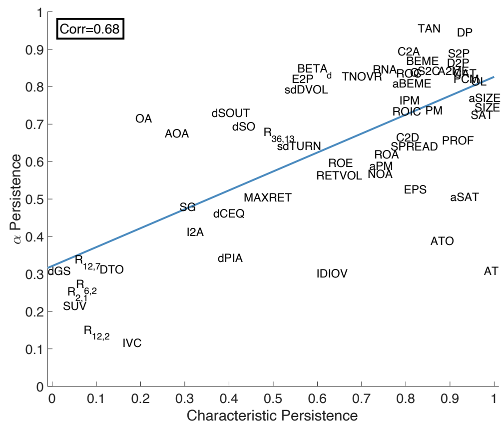


(b)

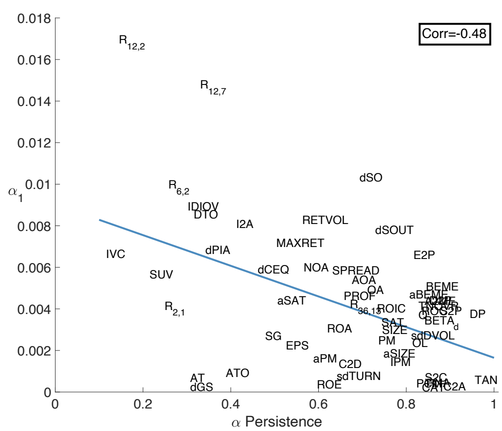


(c)

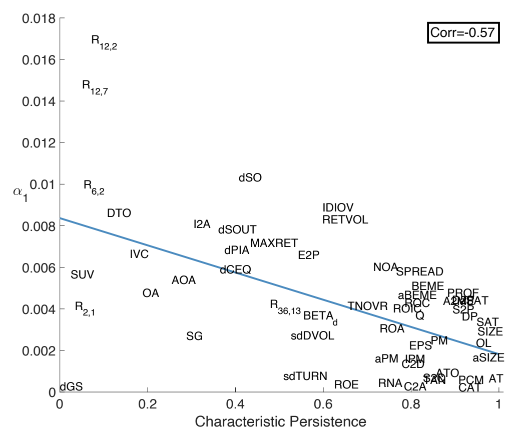
Fig. 5. Price wedges, alphas, and persistence. This figure presents scatter plots illustrating the relations between the long-short price wedges across all 57 characteristics and (i) the long-short alpha (α_1), (ii) alpha persistence, and (iii) characteristic persistence. The persistence of the long-short alpha ρ_α is computed for each anomaly with the following regression: $\alpha_{s+12} = \rho_\alpha \alpha_s + \epsilon_{s+12}$, where α_s is the realized alpha from a time-series regression and $s = 1, 2, ..., 168$. The persistence of a characteristic is measured as the time-series average of the Spearman rank correlation $Corr(X_{i,t}, X_{i,t+12})$ across firms indexed by i.



(a)

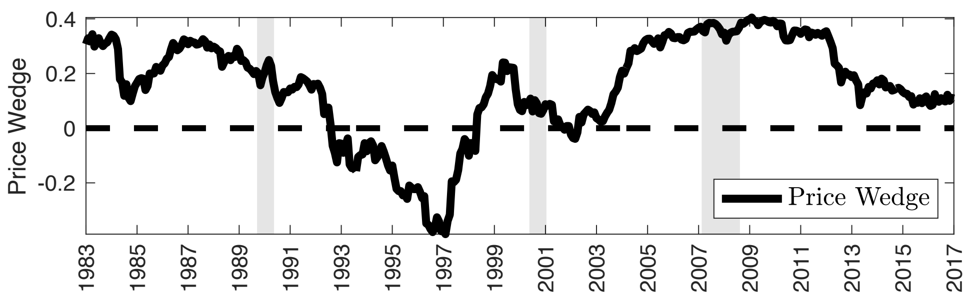


(b)

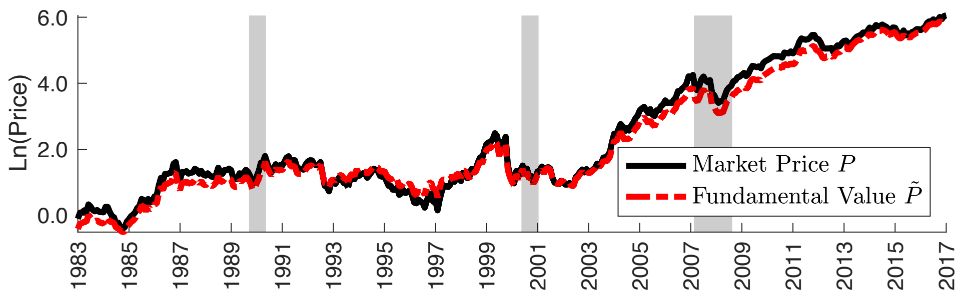


(c)

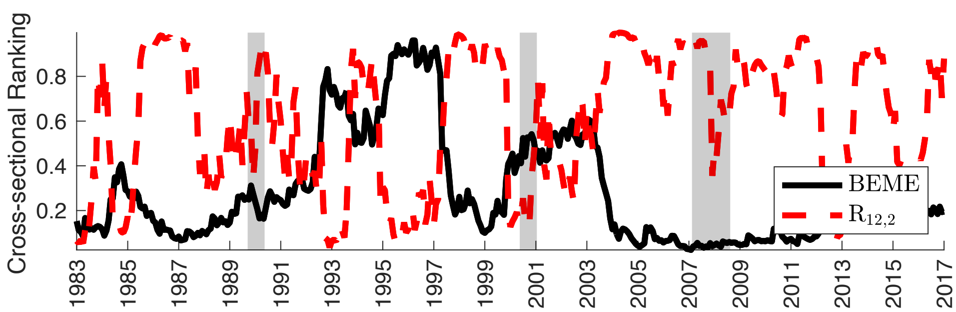
Fig. 6. Alphas and persistence. The figure presents scatter plots illustrating the relations between (i) the long-short alpha one month after portfolio formation (α_1) and alpha persistence, (ii) the long-short alpha and characteristic-persistence, and (iii) alpha persistence and characteristic-persistence, respectively.



(a) Price wedge

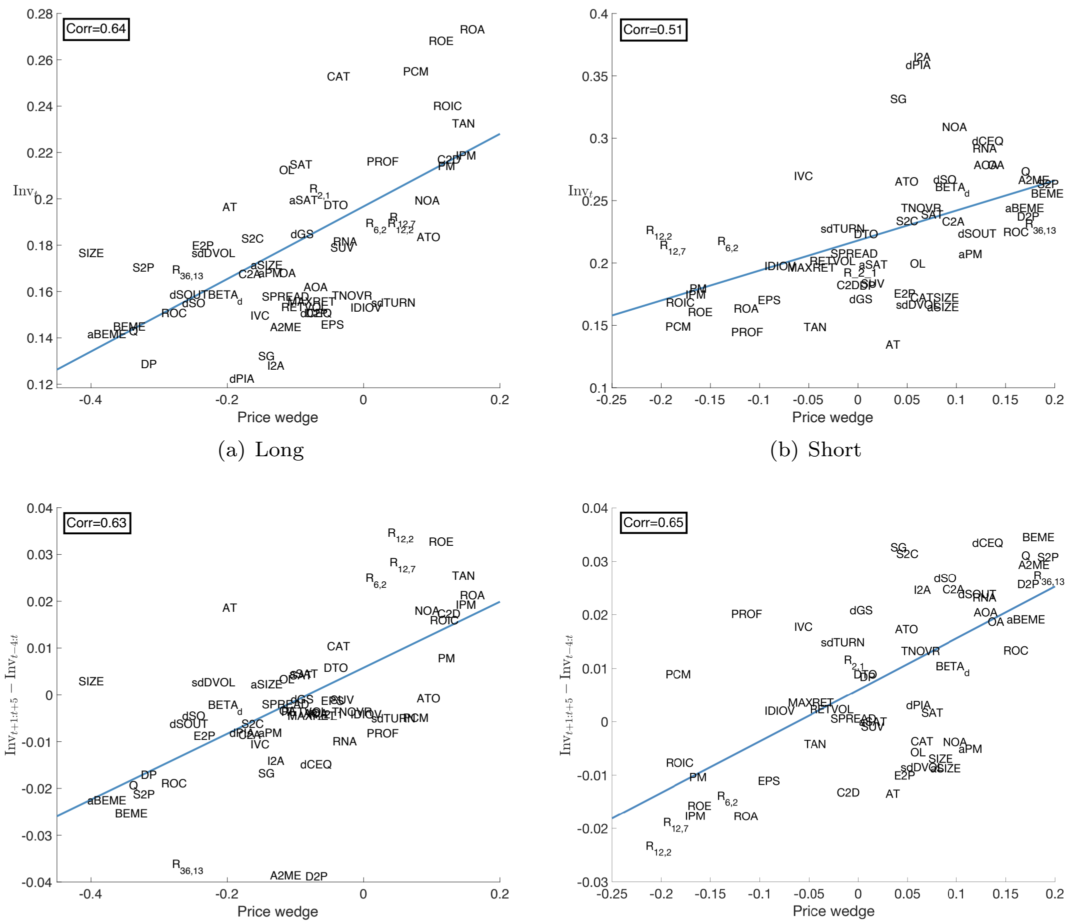


(b) Log prices



(c) Cross-sectional ranking

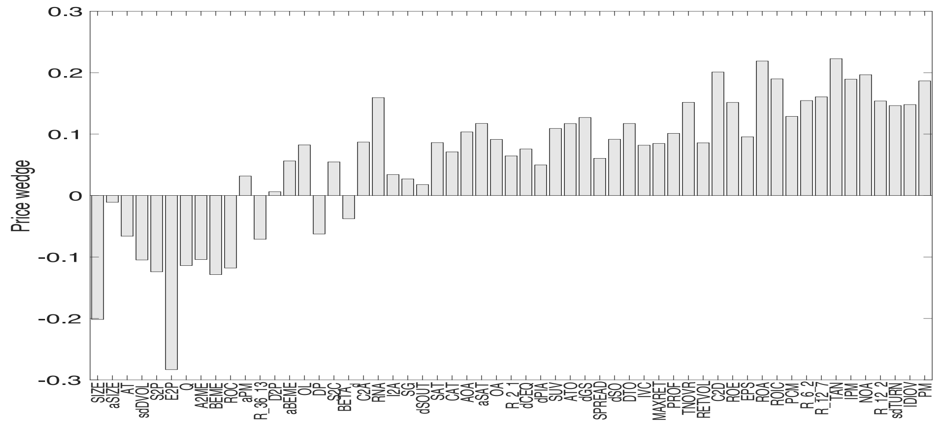
Fig. 7. Price wedge analysis for Apple. Panel A of this figure plots our estimate for the price wedge of Apple shares since the firm's inception in 1983. Panel B plots (in logs) the market price versus our estimate of the informationally efficient (or fundamental) value labeled as "Fundamental Price" plotted in red. Panel C plots the book-to-market and momentum ranking of Apple in the cross-section of all firms, which is normalized between zero and one.



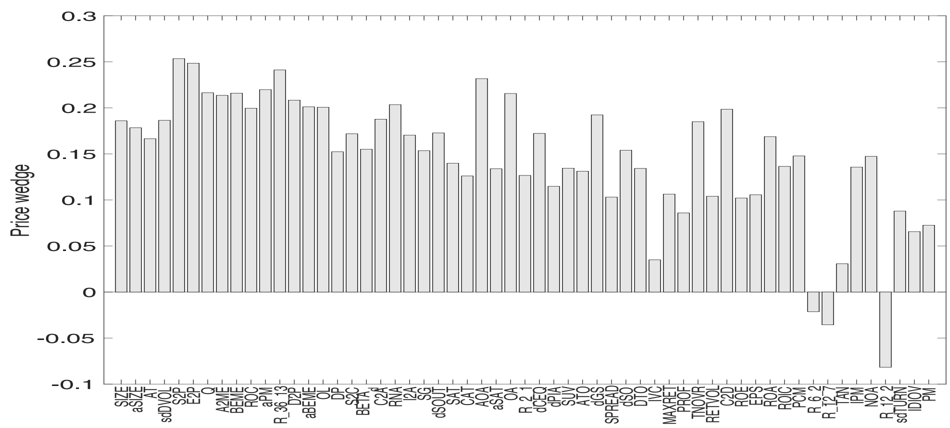
(a) Long (b) Short

(c) Long (d) Short

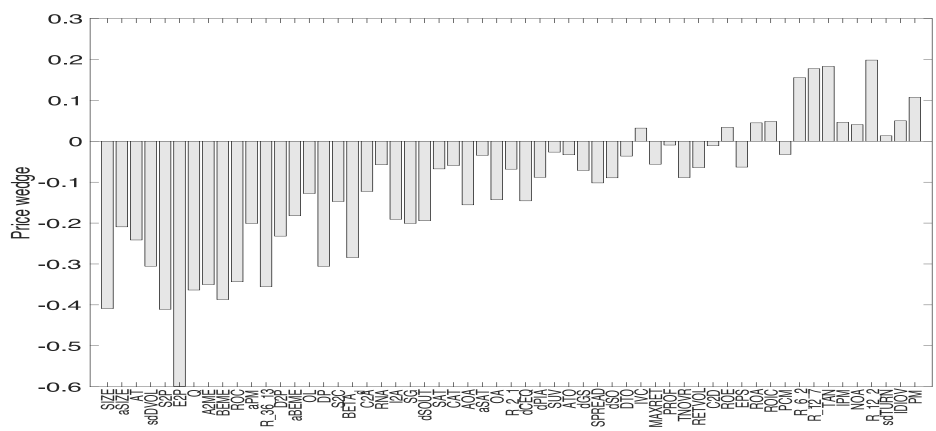
Fig. 8. Price wedges and investment rates. Panels (a) and (b) present scatter plots between price wedges for both the long and short decile portfolios and investment at the time of portfolio formation, across the 57 characteristics. Panels (c) and (d) present scatter plots between price wedges and changes in investment around the time of portfolio formation (i.e., the average investment in the five years after minus the average investment in the five year before portfolio formation, $Inv_{t+1,t+5} - Inv_{t-4,t}$). We aggregate the investment measures by taking the median within a portfolio and averaging these medians over time.



(a) Long

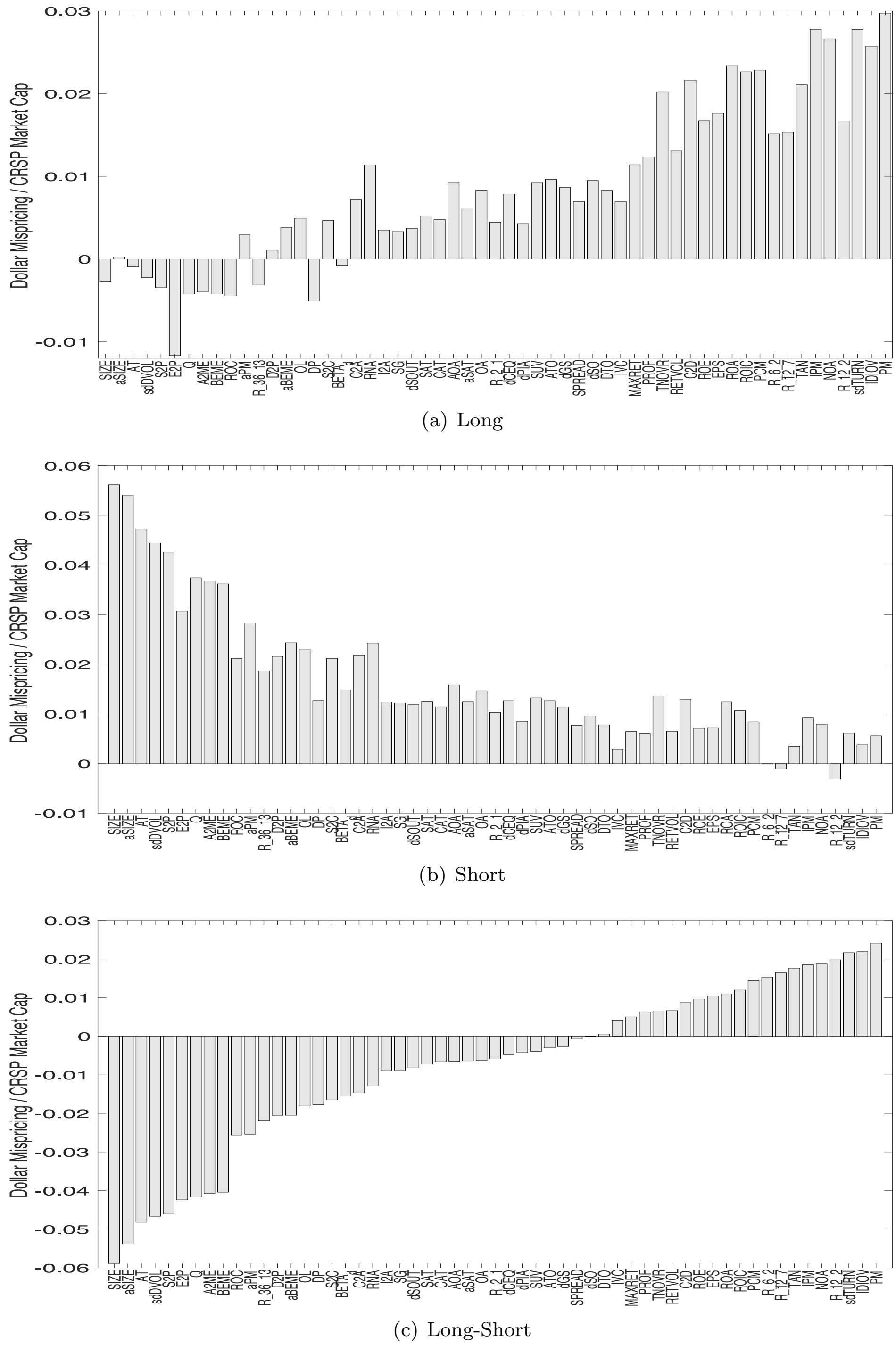


(b) Short



(c) Long-Short

Fig. 9. Price wedges for firms with $q \geq 1$. The figure presents for all 57 characteristics the price wedges of the long and short quintile portfolios as well as the long-short difference, when considering only high q firms (firms with $q \geq 1$ at the time of portfolio formation). In the figure, we order the characteristics based on the long-short dollar price wedges, which are presented in the bottom panel of Figure 10.



(a) Long

(b) Short

(c) Long-Short

Fig. 10. Dollar mispricing as a fraction of CRSP market capitalization for Firms with $q \geq 1$. The figure plots the dollar mispricing as a fraction of CRSP market capitalizaiton of the long and short quintile portfolios as well as their differences, when considering only high-q firms (that is, firms with $q \geq 1$ at the time of portfolio formation). We calculate the price wedge for each portfolio and then combine it with the average fraction of CRSP market capitalization allocated to that portfolio. In each panel, we order the characteristics based on the long-short dollar price wedges, which are presented in the bottom panel.