DISCUSSION PAPER SERIES

DP16353

Dynamic Asset (Mis)Pricing: Build-up vs. Resolution Anomalies

Jules van Binsbergen, Martijn Boons, Christian Opp and Andrea Tamoni

FINANCIAL ECONOMICS

ISSN 0265-8003

Dynamic Asset (Mis)Pricing: Build-up vs. Resolution Anomalies

Jules van Binsbergen, Martijn Boons, Christian Opp and Andrea Tamoni

Discussion Paper DP16353
Published 10 July 2021
Submitted 01 July 2021

Centre for Economic Policy Research
33 Great Sutton Street, London EC1V 0DX, UK
Tel: +44 (0)20 7183 8801
www.cepr.org

Dynamic Asset (Mis)Pricing: Build-up vs. Resolution Anomalies

Abstract

We classify asset pricing anomalies into those that exacerbate mispricing (build-up anomalies) and those that resolve it (resolution anomalies). To this end, we estimate the dynamics of price wedges for a large number of well-known anomaly portfolios in the factor zoo and map them to firm-level mispricings. We find that several prominent anomalies like momentum and profitability further dislocate prices. While mispricing buildup is often quick, the subsequent resolution tends to be slow, suggesting the potential for material real economic consequences. Our results suggest that financial intermediaries chasing build-up anomalies in fact negatively affect price efficiency and associated real capital allocation

JEL Classification: N/A

Keywords: : Dynamic Price Wedges, Buildup, Resolution, Alphas, Persistence

Jules van Binsbergen - julesv@wharton.upenn.edu
University of Pennsylvania and CEPR

Martijn Boons - m.f.boons@tilburguniversity.edu
Tillburg University

Christian Opp - opp@rochester.edu
University of Rochester

Andrea Tamoni - atamoni@business.rutgers.edu
Rutgers Business School

Dynamic Asset (Mis)Pricing: Build-up versus Resolution Anomalies

J.H. van Binsbergen[*] M. Boons[†] C.C. Opp[‡] A. Tamoni[§]

June 24, 2021

Abstract

We classify asset pricing anomalies into those that exacerbate mispricing (build-up anomalies) and those that resolve it (resolution anomalies). To this end, we estimate the dynamics of price wedges for a large number of well-known anomaly portfolios in the factor zoo and map them to firm-level mispricings. We find that several prominent anomalies like momentum and profitability further dislocate prices. While mispricing buildup is often quick, the subsequent resolution tends to be slow, suggesting the potential for material real economic consequences. Our results suggest that financial intermediaries chasing build-up anomalies in fact negatively affect price efficiency and associated real capital allocation.

Keywords: Dynamic Price Wedges, Buildup, Resolution, Alphas, Persistence

[*]University of Pennsylvania and NBER. Email: julesv@wharton.upenn.edu.
[†]Tilburg University. Email: m.f.boons@tilburguniversity.edu.
[‡]University of Rochester and NBER. Email: opp@rochester.edu.
[§]Rutgers Business School. Email: atamoni@business.rutgers.edu.

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 *price changes* 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 prices' convergence to their informationally efficient levels. However, whether return anomalies exacerbate or eliminate existing mispricing remains an open empirical question.

In this paper, we classify anomalies into those that exacerbate price dislocations (what we term build-up anomalies) and those that resolve them (what we call resolution anomalies). We further provide a ranking of anomalies based on their likely effect on aggregate economic outcomes. Studying 57 of the most commonly used anomaly sorts, we document the following 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 find that a substantial fraction of proposed abnormal return patterns are build-up anomalies. That is, the expected abnormal 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, price wedges affect a substantial fraction of the aggregate market capitalization and are prevalent among high Q firms. Binsbergen and Opp (2019) argue that, under these circumstances, mispricing tends to lead to large real capital misallocation. While the size anomaly may have lost its appeal for fund managers due to its small alpha, our results indicate that it may in fact be associated with major aggregate price dislocations. This seemingly paradoxical result can emerge because size alphas are highly persistent and affect firms with high market capitalization (in the short leg). 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 buildup. 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.

A priori, it is unclear whether existing anomaly sorts predict a buildup or a resolution of mispricing. If mispricing buildup is the consequence of unpredictable sentiment shocks, anomaly sorts (by definition) cannot be used to predict further price dislocations. On the other hand, if a buildup in sentiment is predictable and for example caused by overextrapolation, anomaly sorts such as momentum can potentially be used as an early indicator of mispricing buildup. 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 buildup and the resolution phases of mispricing are in fact predictable, by two distinct subsets of our 57 anomaly sorting variables. Specifically, 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.

[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).

The fact that both the buildup and resolution of sentiment are predictable by particular sorting variables disciplines the potential explanations of observed asset pricing anomalies. Take for example momentum. One explanation for momentum is that investors initially underreact to 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 further, in which case the momentum return creates mispricing. Our approach helps disentangle these two behavioral explanations, favoring the latter over the former. Thus, 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 buildup.

As part of our method, we also provide a formal mapping between alphas and price wedges. As the latter are the accumulation of the former, taking into account the timing of cash flows, the resulting time series dynamics of these two objects can be substantially different. Consider for example momentum. We find that while the momentum alpha itself is short-lived, the associated price wedge remains large for an extended period of time.

Overall, we argue that studies of anomaly portfolio returns, which are typically done at a monthly frequency, are several steps removed from economically also relevant firm-level price wedges and their often slow-moving dynamic evolution. The price wedge processes are essential for 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, (3) the role of active management and financial intermediation in shaping real capital allocation and economic activity. This third application is particularly interesting to explore, as managers who chase build-up anomalies are in fact exacerbating firm-level mispricing and its associated real capital misallocations.

Our paper also contributes to a recent literature that tries to bring discipline to the large collection of recently discovered return factors (the factor zoo, see 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 et al., 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 et al., 2019; Kozak et al., 2020; Lettau and Pelger, 2020). While both these approaches are important steps forward in the literature, in this paper we categorize and rank anomalies by the extent to which they exacerbate mispricing (i.e., buildup) 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).[2]

In order to further gauge these effects on capital allocation and economic activity we need to explore two other 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 relevance for misallocation. Anomalies that (1) have persistent alphas, (2) affect a large 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. Conversely, we argue that there exist ample anomalies that have

[2]See Barro (1990), Morck, Shleifer, and Vishny (1990), Stein (1996), Baker, Stein, and Wurgler (2003), Gilchrist et al. (2005), Chen, Goldstein, and Jiang (2006), and Warusawitharana and Whited (2015), David, Hopenhayn, and Venkateswaran (2016) for previous work on the interaction between real investment and financial market (mis)pricing.

alphas that are highly statistically significant but are unlikely to be associated with material real misallocations. This is either because (1) the monthly alpha does not correspond to a large price wedge, (2) the affected market capitalization is small, or (3) the investment-to-price-wedge sensitivity of the affected firms is low.

We conclude this section by discussing other related literature. Keloharju et al. (2019) decompose 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 argue 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 buildup or the resolution of the mispricing. Baba-Yara et al. (2020) find many anomalies for which the persistence of the characteristic does not match the persistence of alphas. Whereas these authors focus on the monthly alphas between new and old sorts that result from this mismatch, we study the effect of persistence on the price-wedge.

Cohen et al. (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 is an essential object if one is interested in assessing the real distortions associated with anomalies.

2. Data and Motivating Evidence

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 Table C.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 et al. (2017) and Gu et al. (2019), we delay monthly variables by one month and annual variables by six months.[3] For each characteristic, we construct value-weighted decile portfolio splits at NYSE breakpoints to reduce the influence of microcap stocks on our results (see, also, Fama and French (2016) and Hou et al. (2018)). We track the buy-and-hold returns of these decile portfolios up to fifteen years after sorting, and split them into dividends and capital gains (see Section A for further details). For a characteristic X that predicts returns with a negative sign in the original papers documenting the anomaly (e.g., sorting firms by their market capitalization) we sort on $-X$. Throughout, we refer to the tenth (first) decile portfolio, which has positive (negative) one-month alphas according to the original papers, as the long (short) portfolio.

2.2 Cumulating Alphas

In Figure 1, we plot the average cumulative alpha for each of the 57 anomalies up to fifteen years after portfolio formation. For ease of exposition, we group the anomalies using the categorization of Freyberger et al. (2020). Given our sorting convention mentioned above, the cumulative alpha of each long-short portfolio should initially be upward sloping, reflecting positive alphas in the first month after portfolio formation. The graphs show that while this is true for the vast majority of anomalies, there are some notable exceptions.[4] The portfolio formation dates range from July 1964 to December 2002, such that we have the same number of time-series observations for the monthly alpha calculated at each horizon.[5]

[3] 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 $t-6$.

[4] As noted in Hou et al. (2018), not all anomaly sorts work out-of-sample.

[5] This approach is consistent with the price wedges we estimate below. Our conclusions are similar when using increasingly more observations (based on sorts after December 2002) for shorter horizons. In addition, we present in Figures D.1 and D.2 of the appendix the cumulative alphas for the long and short portfolio separately.

Note that a monthly alpha represents the amount of mispricing that is resolved or created in a single month. Thus, the cumulative alpha is a first (albeit rough) proxy for the total amount of mispricing that is associated with each characteristic. We formalize the link between alphas and price wedges in the next section, highlighting the importance of properly taking into account alphas' joint dynamics with cash flows. The graphs illustrate large heterogeneity across anomalies in terms of the magnitudes and the time it takes for cumulative alphas to level off. Perhaps more interestingly, the cumulative alphas switch signs for multiple anomalies, suggesting that these abnormal returns create price-wedge buildup rather than resolution.

Interesting examples of large cumulative alphas are: sales-to-price, book-to-market and dividend-to-price. These three characteristics in the value category generate cumulative alphas of 50% or more. The return reversal anomaly ($R_{36,13}$) in the past returns category generates a large cumulative alpha as well (about 40%), consistent with the idea that it is an alternative proxy for value (see, e.g., De Bondt and Thaler, 1985a; Fama and French, 1996; Gerakos and Linnainmaa, 2018). In contrast, various definitions of momentum ($R_{12,2}$, $R_{12,7}$, and $R_{6,2}$) generate negative cumulative abnormal returns in the long run, reflecting long-term reversal. In summary, the dynamics of cumulative alphas even within categories show vastly different patterns, which suggests that aggregation within anomaly categories could obfuscate essential aspects of the dynamics of alpha processes.

As argued above, while these cumulative alphas give us a preliminary idea of the total mispricing of a stock, they are not the same as a price wedge, as the latter properly accounts for the joint dynamics of alphas and cash flows. We formally derive this relationship in the next section.

3. Defining and Estimating Price Wedges

To measure the level of mispricing of a stock, we estimate the log deviation of the stock's market price from its informationally efficient value (also often called fundamental value), which for small deviations 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 under a benchmark SDF denoted by $\frac{m_t}{m_0}$. Our price wedge is then defined as:

$$PW_0 = \log\left(\frac{P_0}{\tilde{P}_0}\right) = -\log\left(E_0\left[\sum_{t=1}^{J}\frac{m_t}{m_0}\frac{D_t}{P_0} + \frac{m_J}{m_0}\frac{P_J}{P_0}\right]\right). \tag{1}$$

In addition to the observable market price P_0, estimating the price wedge requires data for dividends, capital gains, and a candidate SDF.[6] Moreover, we need to specify a horizon J after which the price wedge is assumed to have converged to zero. In our baseline specification, we set $J = 180$ (15 years), motivated by the empirical observation that cumulative alphas plateau before year 15 for the majority of characteristics (see Figure 1). We show in Figures D.3 and D.4 of the appendix that alternative choices for J, namely $J = 120$ (10 yeas) or 240 (20 years), yield similar price wedges.[7]

It may be tempting to assume that the cumulative alphas documented in Section 2.2 closely approximate the price wedges and their dynamics. However, this conclusion is premature. In Appendix B, we formally derive the relation between the two, showing that price wedges are a value weighted average of the cumulative abnormal returns (CARs) applying to an asset's dividend strips (see equation (B.2)). As such, the CAR at any given horizon can be larger or smaller than the price wedge. Further, the maximum CAR across all horizons

[6] In Appendix B, we show how our price wedge can be formally derived from the earlier work by Binsbergen and Opp (2019), and how it relates to the definition of mispricing in Cho and Polk (2021).

[7] The price wedges for $J = 120$ and $J = 240$ are correlated across characteristics at 0.98 and 0.97, respectively, with the price wedges for $J = 180$.

is always weakly greater than the price wedge.

This relation also implies that low duration cash flows discipline the amount of mispricing that a stock can be subject to. To see this point, consider two stocks with distinct constant growth rates and identical and constant undistorted discount rates (Gordon growth assumptions). The price of the stock with the high growth rate ("growth stock") is more sensitive to a given discount rate distortion, since its cash flow duration is higher. Another way of illustrating this point is to consider the ultimate "value" asset, which is a one-period dividend strip. The mispricing on this asset will by definition resolve after a single period. After all, at maturity, the price of the asset equals the realization of the cash flow that the holder is entitled to, even without trading. This also highlights an important distinction between the cumulative alphas plotted in Figure 1 and our price wedge measure: whereas, conditional on a given alpha process, cumulative alphas are not dependent on a stock's cash flow duration, the price wedge is.

Mispricing only exists relative to a particular benchmark asset pricing model. The importance of the econometrician's choice of a benchmark asset pricing model has been widely discussed in the context of the so-called joint-hypothesis problem (Fama, 1970, 1991). Rather than taking a definitive stance on the correct efficient benchmark, we illustrate our method based on a CAPM SDF in our main analysis. Other SDFs can easily be accommodated.

Specifically, the SDF we employ takes the following form:

$$\frac{m_{t+1}}{m_t} = \frac{1}{1+r_t^f} - b\left(R_{t+1}^m - E\left[R_{t+1}^m\right]\right), \tag{2}$$

where b is the price of risk of the market portfolio and is chosen such that the price wedge for the aggregate market portfolio is zero in-sample. This implementation is motivated by our focus on cross-sectional anomalies that do not take a stance on whether the market is correctly priced.

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 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).

4. Empirical Results

4.1 Price Wedges of Build-up and Resolution Anomalies

We now compute for each anomaly the price wedge defined in equation (1) based on the SDF defined in equation (2). 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 Figure 2, where anomalies are ordered according to the difference between the long and the short 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. Point estimates and t-statistics for the price wedges in the long and short portfolios, as well as their difference, are summarized in Columns 3 to 5 of Table I.

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 −34.6% indicating that these value stocks are substantially underpriced. Magnitudes are similar for size (−34.7%, SIZE) and long-term reversal (−27.3%, $R_{36,13}$), confirming the insight of Binsbergen and Opp (2019) that persistent low-alpha anomalies such as size can lead to large price wedges. This also raises the possibility that anomalies that have low correlation with each other in terms of contemporaneous monthly price-level changes can still lead to similarly-sized dynamic price wedges.

Second, while the average annualized *alphas* across many anomalies are in 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, idiosyncratic volatility (IDIOV) is associated with only relatively small price wedges, −0.1% for the least volatile and −6.6% for the most volatile decile portfolio. As argued before, two alphas that are of the same magnitude but have large differences in their persistence result in substantially different price wedges.

Third, the alpha and the price wedge are not always of opposite signs, highlighting the importance of distinguishing build-up and resolution anomalies.[8] A good illustration of a build-up anomaly is the loser portfolio, which contains the decile of stocks with the worst momentum ($R_{12,2}$). Given that the price wedge for this portfolio is negative (−20.4%), loser stocks are already underpriced and, through momentum returns, are first pushed down even further 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. Another example of a build-up anomaly is the low profitability portfolio, which contains the decile of stocks with lowest profitability (PROF). Unprofitable firms are already underpriced (−10.0%) and first move further away from the efficient price for several years 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 price wedge of −14.2%).

Fourth, a large share of the estimated price wedges is significant at the 5%-level (using Newey-West standard errors with 180 lags to correct for the overlapping nature of the mispricing measure): 12 positive and 25 negative (c.f., Table I). Of course, since we are

[8] In related work, Favero et al. (2020) propose a (co-)integrated methodology to factor modeling based on both prices and returns.

considering 57 characteristics, some price wedges may be significant by chance. To correct for potentially false discoveries, we follow the approach of Benjamini and Yekutieli (2001).[9] Interestingly, we still find 17 significant price wedges after this correction.

Next, we consider price wedges in deciles beyond the first and tenth. The first panel of Figure 3 shows that economically large price wedges are still present in the top and bottom three deciles. 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 effect is smaller than before when focusing only on the extreme deciles, we are now considering roughly three times as many stocks with significantly larger market capitalization. Thus, the total dollar value of mispricing is increasing substantially as we consider more deciles. We analyze the relation between mispricing and market capitalization in more detail below.

Finally, we conduct a subsample analysis. Figure 4 reveals that the ranking of price wedges across characteristics is quite robust across different time periods. Indeed, the across characteristic correlation between mispricing in the first and second half of the sample is 0.77 (split around the portfolio formation month of October 1983), with the largest price wedges lining up closely.

4.2 Determinants of Price Wedges

Next, we analyze the determinants of price wedges and their relative importance. The first determinant is the expected alpha over the first month after portfolio formation (see Section 2 above). Panel (a) of Figure 5 presents a scatter plot of the long-short price wedge versus the one-month alpha of the long-short portfolio. If all anomalies were resolution anomalies with equal alpha persistence and cash flow dynamics this correlation would be -1. In fact, we find this correlation to be small, with a value of -0.17. As we will show shortly, this

[9] This approach ensures (under arbitrary dependence assumptions) that when testing multiple hypotheses, the false discovery rate, or number of false positives, is kept at the 5% threshold.

low correlation is driven by substantial heterogeneity in the time-series properties of alphas (buildup vs. resolution and their relative speed) interacted with the differential timing of cash flows.

In particular, about one-third of the characteristics are build-up anomalies, implying that the sign of the price wedge and the one-month alpha are the same, while the other two thirds are resolution anomalies. Thus, while one may be inclined to interpret positive alphas as a signal of underpricing, our evidence shows that this interpretation is likely incorrect for one third of the anomalies we study. Another noteworthy feature is that price wedges vary more across characteristics than one-month alphas do. The coefficient of variation (the ratio of the standard deviation to the mean) for the long-short price wedge is about 3, whereas it is about 1 for one-month alphas.

We next investigate the relation between the level of the alpha and its persistence as well as the 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 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, such as real investment affecting book values. 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.

Holding the current level of alpha fixed, mispricing is larger for more persistent alphas. 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: $\alpha_{s+12} = \rho_\alpha \alpha_s + a_{s+12}$. We do not include an intercept in this regression, such that ρ_α measures how fast the alpha converges to zero.

Panel (a) of Figure 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 Figure 5 show that neither persistence measure is strongly correlated with the price wedge. Panels (b) and (c) of Figure 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 mispricing. In contrast, price wedges account for alpha, persistence, and their interaction.

4.3 Price Wedge Dynamics

As discussed in Binsbergen and Opp (2019), the real economic impact of an anomaly depends not only on the price wedge, but also the timing of its resolution. If mispricing is resolved later, there is more time for it to distort firms' investment decisions. We present for all characteristics the price wedge that remains five years after portfolio formation in Figure 7, using the assumption that all mispricing is resolved 15 years after portfolio formation.[10] 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

[10] 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 D.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). Economically, this evidence implies that most mispricing is indeed resolved before the fifteen year mark. This is also consistent with our robustness analysis in Figure D.3, which finds similar price wedge estimates when using $J = 120$ (10 years) instead of our baseline $J = 180$ (15 years).

formation D_{61} and ending with the continuation value P_{180}:

$$PW_{60} \equiv \log\left(\frac{P_{60}}{\tilde{P}_{60}}\right) = -\log\left(E_{60}\left[\sum_{t=61}^{J} \frac{m_t}{m_{60}} \frac{D_t}{P_{60}} + \frac{m_{180}}{m_{60}} \frac{P_{180}}{P_{60}}\right]\right). \tag{3}$$

In short, Figure 7 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 have an impact on real economic decisions. There is important variation in the speed of resolution across characteristics, however. For the resolution anomalies on the left, we find for the most mispriced characteristics (various characteristics from the value category and size) that about half of the initial long-short price wedge remains after five years.

To further explore the difference between build-up and resolution anomalies and the dynamics of their price wedges, we plot in Figure 8 five of the most prominent anomalies in the asset pricing literature at annual intervals up to fifteen years after portfolio formation. 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 over 40% 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.

Finally, we confirm that the persistence of mispricing is generally larger for portfolios that are overpriced, consistent with arbitrage asymmetry (i.e., the greater ability or willingness of investors to take a long position as opposed to a short position when perceiving mispricing). To see this, we regress the price wedge five years after portfolio formation (PW_{60} from equation (3)), on the price wedge at the time of portfolio formation (PW_0 from equation (1)), conditioning on the sign of the initial price wedge:

$$PW_{60,X(d)} = \underbrace{0.81}_{t=14.65} PW_{0,X(d)} \underbrace{-0.27}_{t=-3.99}(PW_{0,X(d)} \times \mathbf{I}_{PW_{0,X(d)}<0}) + \varepsilon_{X(d)}, \ R^2 = 0.77, \tag{4}$$

where we consider the top and bottom decile portfolios, $d = 1, 10$, for all 57 characteristics X.[11] On average, 81% of the initial price wedge remains after five years when a portfolio is overpriced, while this percentage is lower at 54% when the portfolio is underpriced. The case of book-to-market is representative: of the -35% underpricing in the high book-to-market portfolio at portfolio formation, only -16% remains after five years. For the overpriced low book-to-market portfolio, these numbers equal 17% and 12%, respectively.

4.4 Market-Capitalization-Adjusted Price Wedges

Price dislocations are more likely to matter if the total affected market capitalization is large, that is, when the price wedges affect a substantial fraction of the aggregate market. To estimate the dollar value mispricing of a portfolio as a fraction of CRSP market capitalization, we compute:

$$(1 - e^{-PW_0}) \cdot \frac{\text{Portfolio Market Cap}}{\text{CRSP Market Cap}} \tag{5}$$

The price wedges, PW_0 from equation (1), and the market value weights, $\frac{\text{Portfolio Market Cap}}{\text{CRSP Market Cap}}$, are reported separately in Table I. Figure 9 displays the market-capitalization-adjusted price wedges ranked from low to high according to the long-short differences of the price wedges.[12]

[11] The coefficient estimates are similar when we include all decile portfolios and when we focus on a smaller subset of portfolios with large price wedges.

[12] To compute equation (5), we use the unconditional average fraction of CRSP market capitalization allocated to a given portfolio over the full sample. We find similar results when we compute equation (5) in each sample month using the fraction of CRSP market capitalization allocated to the portfolio in that month. The former measure is less sensitive to outliers.

The largest long-short price wedges as a fraction of total market capitalization is generated by four value-related characteristics and size. These long-short price wedges each represent more than 4% of the total CRSP market capitalization. Interestingly, the long-short price wedge of the size anomaly is ranked sixth among our set of 57 anomalies, but when we apply the adjustment for market capitalizations, its rank increases to second place. The reason is that the short side of the size anomaly, while having lower alphas in absolute magnitude than the long side, involves big stocks that capture a large fraction of CRSP market capitalization. This result highlights that anomalies with small (perhaps even insignificant) alphas that are highly persistent and affect a large amount of market capitalization can end up causing the largest economy-wide distortions. A similar result obtains for the value-related characteristics. The price wedges as a fraction of CRSP market capitalization are about 3 to 4 times larger in absolute value for the short decile portfolios, even though the price wedges as a percentage of each portfolio value is about three times larger for the long decile portfolios.

To appreciate the economic magnitude of these effects, note that the US stock market is worth about 30 trillion dollars at the end of our sample (2017). Our evidence suggests that even the mispricing that is due to only the two most extreme decile portfolios of a single characteristic, like size or book-to-market, adds up to mispricing in the order of about 1.5 trillion dollars. That said, some anomalies, like idiosyncratic volatility and short term reversal, do not affect stocks with large market capitalization nor are they associated with large price wedges.

In Figure 10 we go beyond the extreme decile portfolios and instead consider the price wedges of the bottom and top three deciles. For a number of value-related characteristics that generate large price wedges, the total long-short price wedge as a fraction of CRSP market capitalization increases to about 8%, or about 2.5 trillion dollars, when we consider deciles 1 to 3 and deciles 8 to 10. An exception is size, for which the impact of considering additional deciles is slightly negative, because the second decile of biggest stocks is already a lot smaller and slightly underpriced.

4.5 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, as a function of a firm's current characteristics.

Our approach starts with a focus on the 57×2 extreme decile portfolios sorted on each of the 57 characteristics. We choose to extract PCs using only these extreme decile portfolios, since we find that the middle portfolios primarily add noise to the extraction process.[13] This approach is also consistent with a large fraction of the anomalies literature that focuses on long-short portfolios as factors and test assets. For each portfolio, we compute the unconditional average of all 57 characteristics. Next, to make the characteristics comparable, we rank-normalize each characteristic in the cross-section to range from 0 to 1.[14]

Table II shows that the first 6 PCs together explain about 89% of the total variation in price wedges. Moreover, the table shows the largest three (positive and negative) loadings for each of these PCs. The first PC loads strongly positively on various characteristics from the value category and strongly negatively on various characteristics from the profitability category. Furthermore, the fourth PC loads strongly positively on various characteristics from the investment category. For the remaining PCs, the top three loadings cannot be assigned

[13] The amount of variation in the price wedges that is explained by the largest PCs is considerably larger when we use only the high and low portfolios, suggesting that the middle portfolios are adding more noise than information. While the results using all portfolios are somewhat noisier, they do lead to similar estimates for both the PCs and the 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.

[14] Our results are robust to transformations of characteristics as proposed by Lochstoer and Tetlock (2020).

to one particular characteristics category, which again suggests that there is considerable heterogeneity within these broad categories. Table III shows the results from regressing the price wedges on (i) three or six PCs, (ii) the characteristics featured in the Fama-French model plus momentum, and (iii) each of these characteristics individually. Panels A and B show the results for the price wedges and the price wedges as a fraction of CRSP market capitalization, respectively.

Several results stand out. First, the amount of variation in the price wedge that is explained is similar using PC3, PC6 or five benchmark characteristics. The correlation between the predictions from these three methods is high, at over 0.90. Second, the R^2s for predicting the price wedges are similar to those for predicting the price wedges as a fraction of CRSP market capitalization. Interestingly, the correlation of the characteristic loadings between these two calculations is large at > 0.85, suggesting that the same "characteristic-features" that generate large price wedges also generate large price wedges as a fraction of CRSP market capitalization. Finally, when considering the most prominent characteristics in isolation, we obtain the following ranking by informativeness regarding price wedges (most to least): Value, Size, Investment, Momentum, and Profitability.

The ultimate goal of our approach is to analyze and interpret firm-level price wedge dynamics. The regressions of Table III represent a mapping from characteristics to their associated price wedges. Thus, given the characteristics of a firm, we can calculate its 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 Figure 11 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).[15] 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 buildup, 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 stock price against the price wedge-implied stock price in log terms. That is, we plot the market price of Apple as well as its fair value (=Market Price/e^{PW}). The fair value is below (above) the market value whenever the price wedge is negative (positive).

Importantly, Apple is not unique in that it switches between over- and underpricing over time. We report in Table IV 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 the price wedge. 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 falls to 41% and the probability of moving to the sixth decile or below increases to 8% (these probabilities equal 29% and 17%, respectively, for a five-year period).

[15] These results are not sensitive to the choice of sorting stocks in ten portfolios. We present results for twenty portfolios in Figures D.5 and D.6.

5. Price Wedges and Real Investment

In this section, we analyze the relation between price wedges, investment, and q. First, we investigate whether firm investment decisions correlate with price wedges. After all, ceteris paribus, a firm's overpricing (underpricing) can lead to real overinvestment (underinvestment). Second, the response of investment to mispricing is expected to be stronger among firms with high q due to the typical presence of asymmetric adjustment costs (see Binsbergen and Opp, 2019). We therefore also investigate whether the relation between mispricing and investment is stronger for firms with good investment opportunities, i.e., those with $q \geq 1$. While cleanly identifying causal relations between mispricing and investment is known to be very difficult, the evidence presented in this section at least reveals a positive correlation between mispricing and real investment as well as an increased sensitivity for high-q firms.

5.1 Is Investment Associated with Mispricing?

We consider the following two investment-related variables:[16] (i) investment at the time of portfolio formation, denoted INV_t, and (ii) the difference between the average investment in the five years *after* and the five year *before* portfolio formation, denoted $INV_{t+1y:t+5y} - INV_{t-4y:t}$. 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. We present the estimated investment measures (alongside the price wedges) in Table V for all characteristics.

In Figure 12, we explore the relation between price wedges and our two measures of investment among the 57 anomalies we study. To control for the level of the one-month alpha, we separately study this relation among the long and short (i.e., the two extreme

[16] We measure q and investment considering both physical and intangible assets, using the approach in Peters and Taylor (2017).

decile) portfolios, respectively.[17] 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, ranging from 0.53 to 0.66, consistent with the insight of Binsbergen and Opp (2019) that ultimately price level deviations (price wedges) are the key variable distorting real investment rather than merely the one-month alphas.

The bottom two panels 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 also large suggests that our results are not driven by persistent firm characteristics determining investment opportunities (fixed effects). Characteristic-sorted portfolios that are relatively more overpriced (underpriced) contain firms that increase their investment in the five years after relative to the five years before they enter the portfolio.

5.2 Investment Sensitivity for High-q Firms

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 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, for $q \geq 1$ and $q < 1$, for the long and short portfolios, and across five price wedge buckets. For each of these price wedges,

[17] The graphs once again confirm that the sign of the price wedge may be the same as the sign of the alpha. After all, the long (short) portfolios have positive (negative) alphas but also feature positive (negative) price wedges in about 1/3 of the cases, which we have termed build-up anomalies.

we calculate the corresponding investment measures. The scatter plots of price wedges against the two investment measures are shown in Figure 13 (INV_t in the left panel and $INV_{t+1y:t+5y} - INV_{t-4y:t}$ in the right panel). Moreover, point estimates and t-statistics for this analysis are summarized in Table VI.

The left panel of Figure 13 shows that, as predicted by q-theory, the average firm with high q invests at least 10% more than the average firm with low q. Going beyond this effect, after conditioning on high versus low q, characteristic-sorted portfolios that are relatively more overpriced further invest more at the time of portfolio formation (with a difference of 0.8% to 3.5% relative to the less overpriced portfolios). The relation between investment and price wedges is non-monotonic, however. As mentioned before, investment is subject to substantial heterogeneity across firms. For that reason, we look at changes in investment in the right panel. We find that these investment changes are on average larger for high-q firms than for low-q firms. Moreover, the relation between price wedges and changes in investment is substantially stronger among high-q firms. Indeed, among high-q firms, the most overpriced portfolios (in both the long and short portfolio) contain firms that increase their investment by about 1.5 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 their investment by about 1 percentage point. This difference of 2.5 percentage points is statistically significant and economically large (see Table VI). Moreover, this difference is large compared to the difference among low-q firms. For low-q firms, the most underpriced portfolios show investment changes of 1 percentage points lower than the least underpriced portfolios. The difference-in-difference between high and low-q firms of about 1.5 percentage points is also significant.

Overall, among high-q firms, the most overpriced portfolios contain firms that invest significantly more at the time of portfolio formation and the mean of investment is actually increasing after 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, which is consistent with the model of Binsbergen and Opp (2019).

5.3 Mispricing Among Large High-q Firms

The results in the previous sections suggest that high-q firms respond 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 large amount of market capitalization. To explore whether this is the case, we present in Figures 14 and 15 the ranking of characteristics based on two measures among firms with q greater than one: regular price wedges (as defined in equation (1)) and price wedges as a fraction of CRSP market capitalization (as defined in equation (5)). 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. As before, a number of characteristics we classified as build-up anomalies, such as profitability (PM, aPM, and IPM) and momentum ($R_{12,2}$, $R_{12,7}$ and $R_{6,2}$), still generate non-negligible price wedges. Given that we are conditioning on high-q firms (which tend to have low book-to-market ratios), these firms are more likely to be overpriced than underpriced already. That said, the winner momentum portfolio still experiences a further buildup of mispricing.

6. Conclusion

In this paper, we study the dynamic evolution of price wedges that measure the percentage deviation of market prices from their informationally efficient values. This analysis allows us to differentiate anomalies that resolve existing mispricing and those that exacerbate it. We find that out of 57 commonly-studied 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, though we document that the speed of this resolution varies greatly across anomalies.

Our results raise important questions regarding both the real economic consequences of informational inefficiencies as well as the value that financial intermediaries can add by trading against mispricing. 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.

We have also provided a method that allows researchers and practitioners to map portfolio-level price wedges into firm specific price dislocations. These results 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.

References

Abarbanell, J. S., Bushee, B. J., 1997. Fundamental analysis, future earnings, and stock prices. Journal of accounting research 35, 1–24.

Anderson, A.-M., Dyl, E. A., 2005. Market structure and trading volume. Journal of Financial Research 28, 115–131.

Ang, A., Hodrick, R. J., Xing, Y., Zhang, X., 2006. The cross-section of volatility and expected returns. Journal of Finance .

Asness, C. S., Porter, R. B., Stevens, R. L., 2000. Predicting stock returns using industry-relative firm characteristics. Available at SSRN 213872 .

Baba-Yara, F., Boons, M., Tamoni, A., 2020. New and old sorts: Implications for asset pricing. Working Paper.

Baker, M., Stein, J. C., Wurgler, J., 2003. When Does the Market Matter? Stock Prices and the Investment of Equity-Dependent Firms*. The Quarterly Journal of Economics 118, 969–1005.

Baker, M., Wurgler, J., 2006. Investor sentiment and the cross-section of stock returns. The journal of Finance 61, 1645–1680.

Balakrishnan, K., Bartov, E., Faurel, L., 2010. Post loss/profit announcement drift. Journal of Accounting and Economics 50, 20–41.

Bali, T. G., Cakici, N., Whitelaw, R. F., 2011. Maxing out: Stocks as lotteries and the cross-section of expected returns. Journal of Financial Economics 99, 427–446.

Ball, R., Gerakos, J., Linnainmaa, J. T., Nikolaev, V. V., 2015. Deflating profitability. Journal of Financial Economics 117, 225–248.

Bandyopadhyay, S. P., Huang, A. G., Wirjanto, T. S., 2010. The accrual volatility anomaly. Unpublished Manuscript, University of Waterloo .

Barro, R. J., 1990. The Stock Market and Investment. Review of Financial Studies 3, 115–131.

Basu, S., 1977. Investment performance of common stocks in relation to their price-earnings ratios: A test of the efficient market hypothesis. The journal of Finance 32, 663–682.

Basu, S., 1983. The relationship between earnings' yield, market value and return for nyse common stocks: Further evidence. Journal of financial economics 12, 129–156.

Benjamini, Y., Yekutieli, D., 2001. The control of the false discovery rate in multiple testing under dependency. Annals of statistics pp. 1165–1188.

Berk, J. B., 1995. A critique of size-related anomalies. The Review of Financial Studies 8, 275–286.

Bhandari, L. C., 1988. Debt/equity ratio and expected common stock returns: Empirical evidence. The journal of finance 43, 507–528.

Binsbergen, J. H. v., Opp, C. C., 2019. Real anomalies. The Journal of Finance 74, 1659–1706.

Brown, D. P., Rowe, B., 2007. The productivity premium in equity returns. Available at SSRN 993467 .

Chandrashekar, S., Rao, R. K., 2009. The productivity of corporate cash holdings and the cross-section of expected stock returns. McCombs Research Paper Series No. FIN-03-09 .

Chen, Q., Goldstein, I., Jiang, W., 2006. Price Informativeness and Investment Sensitivity to Stock Price. The Review of Financial Studies 20, 619–650.

Cho, T., Polk, C., 2021. Asset pricing with price levels. Available at SSRN 3499681 .

Chordia, T., Subrahmanyam, A., Anshuman, V. R., 2001. Trading activity and expected stock returns. Journal of Financial Economics 59, 3–32.

Chung, K. H., Zhang, H., 2014. A simple approximation of intraday spreads using daily data. Journal of Financial Markets 17, 94–120.

Cochrane, J. H., 2011. Presidential address: Discount rates. The Journal of finance 66, 1047–1108.

Cohen, R. B., Polk, C., Vuolteenaho, T., 2009. The price is (almost) right. The Journal of Finance 64, 2739–2782.

Connor, G., Korajczyk, R., 1986. Performance measurement with the arbitrage pricing theory: A new framework for analysis. Journal of Financial Economics 15, 373–394.

Connor, G., Korajczyk, R., 1988. Risk and return in an equilibrium apt: Application of a new test methodology. Journal of Financial Economics 21, 255–289.

Cooper, M. J., Gulen, H., Schill, M. J., 2008. Asset growth and the cross-section of stock returns. The Journal of Finance 63, 1609–1651.

Daniel, K., Hirshleifer, D., Subrahmanyam, A., 1998. Investor psychology and security market under- and overreactions. The Journal of Finance 53, 1839–1885.

Datar, V. T., Naik, N. Y., Radcliffe, R., 1998. Liquidity and stock returns: An alternative test. Journal of Financial Markets 1, 203–219.

David, J. M., Hopenhayn, H. A., Venkateswaran, V., 2016. Information, Misallocation, and Aggregate Productivity *. The Quarterly Journal of Economics 131, 943–1005.

Davis, J. L., Fama, E. F., French, K. R., 2000. Characteristics, covariances, and average returns: 1929 to 1997. The Journal of Finance 55, 389–406.

De Bondt, W. F., Thaler, R., 1985a. Does the stock market overreact? The Journal of finance 40, 793–805.

De Bondt, W. F., Thaler, R., 1985b. Does the stock market overreact? The Journal of finance 40, 793–805.

Fama, E. F., 1970. Efficient capital markets: A review of theory and empirical work. The journal of Finance 25, 383–417.

Fama, E. F., 1991. Efficient capital markets: Ii. The journal of finance 46, 1575–1617.

Fama, E. F., French, K. R., 1992. The cross-section of expected stock returns. the Journal of Finance 47, 427–465.

Fama, E. F., French, K. R., 1993. Common risk factors in the returns on stocks and bonds. Journal of financial economics 33, 3–56.

Fama, E. F., French, K. R., 1996. Multifactor explanations of asset pricing anomalies. The journal of finance 51, 55–84.

Fama, E. F., French, K. R., 2008. Dissecting anomalies. The Journal of Finance 63, 1653–1678.

Fama, E. F., French, K. R., 2016. Dissecting anomalies with a five-factor model. The Review of Financial Studies 29, 69–103.

Favero, C. A., Melone, A., Tamoni, A., 2020. Factor models with drifting prices. Working Paper.

Freyberger, J., Neuhierl, A., Weber, M., 2020. Dissecting Characteristics Nonparametrically. The Review of Financial Studies 33, 2326–2377.

Gandhi, P., Lustig, H., 2015. Size anomalies in us bank stock returns. The Journal of Finance 70, 733–768.

Garfinkel, J. A., 2009. Measuring investors' opinion divergence. Journal of Accounting Research 47, 1317–1348.

Gerakos, J., Linnainmaa, J. T., 2018. Decomposing value. The Review of Financial Studies 31, 1825–1854.

Gilchrist, S., Himmelberg, C. P., Huberman, G., 2005. Do stock price bubbles influence corporate investment? Journal of Monetary Economics 52, 805–827.

Gorodnichenko, Y., Weber, M., 2016. Are sticky prices costly? evidence from the stock market. American Economic Review 106, 165–99.

Green, J., Hand, J. R., Zhang, X. F., 2017. The characteristics that provide independent information about average us monthly stock returns. The Review of Financial Studies 30, 4389–4436.

Gu, S., Kelly, B. T., Xiu, D., 2019. Empirical asset pricing via machine learning, forthcoming. Review of Financial Studies .

Hahn, J., Lee, H., 2009. Financial constraints, debt capacity, and the cross-section of stock returns. The Journal of Finance 64, 891–921.

Harvey, C., Liu, Y., Zhu, H., 2016. and the cross-section of expected returns. Review of Financial Studies 29, 5–68.

Haugen, R. A., Baker, N. L., 1996. Commonality in the determinants of expected stock returns. Journal of financial economics 41, 401–439.

Hayek, F. A., 1945. The use of knowledge in society. The American economic review 35, 519–530.

Hirshleifer, D., 2020. Presidential address: Social transmission bias in economics and finance. The Journal of Finance 75, 1779–1831.

Hirshleifer, D., Hou, K., Teoh, S. H., Zhang, Y., 2004. Do investors overvalue firms with bloated balance sheets? Journal of Accounting and Economics 38, 297–331.

Hou, K., Xue, C., Zhang, L., 2018. Replicating anomalies. Review of Financial Studies .

Jegadeesh, N., 1990. Evidence of predictable behavior of security returns. The Journal of finance 45, 881–898.

Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. The Journal of finance 48, 65–91.

Kelly, B. T., Pruitt, S., Su, Y., 2019. Characteristics are covariances: A unified model of risk and return. Journal of Financial Economics 134, 501–524.

Keloharju, M., Linnainmaa, J. T., Nyberg, P., 2019. Long-term discount rates do not vary across firms. Tech. rep., National Bureau of Economic Research.

Kozak, S., Nagel, S., Santosh, S., 2020. Shrinking the cross-section. Journal of Financial Economics 135, 271–292.

Lakonishok, J., Shleifer, A., Vishny, R. W., 1994. Contrarian investment, extrapolation, and risk. The journal of finance 49, 1541–1578.

Lettau, M., Pelger, M., 2020. Factors that fit the time series and cross-section of stock returns. The Review of Financial Studies 33, 2274–2325.

Lewellen, J., 2015. The cross section of expected stock returns. Critical Finance Review .

Lewellen, J., Nagel, S., 2006. The conditional capm does not explain asset-pricing anomalies. Journal of financial economics 82, 289–314.

Litzenberger, R. H., Ramaswamy, K., 1979. The effect of personal taxes and dividends on capital asset prices: Theory and empirical evidence. Journal of financial economics 7, 163–195.

Lochstoer, L. A., Tetlock, P. C., 2020. What drives anomaly returns? Journal of Finance 75, 1417–1455.

Lyandres, E., Sun, L., Zhang, L., 2008. The new issues puzzle: Testing the investment-based explanation. The Review of Financial Studies 21, 2825–2855.

Morck, R., Shleifer, A., Vishny, R. W., 1990. The stock market and investment: Is the market a sideshow? Brookings Papers on Economic Activity 21, 157–216.

Novy-Marx, R., 2011. Operating leverage. Review of Finance 15, 103–134.

Novy-Marx, R., 2012. Is momentum really momentum? Journal of Financial Economics 103, 429–453.

Ou, J. A., Penman, S. H., 1989. Financial statement analysis and the prediction of stock returns. Journal of accounting and economics 11, 295–329.

Palazzo, B., 2012. Cash holdings, risk, and expected returns. Journal of Financial Economics 104, 162–185.

Peters, R. H., Taylor, L. A., 2017. Intangible capital and the investment-q relation. Journal of Financial Economics 123, 251–272.

Pontiff, J., Woodgate, A., 2008. Share issuance and cross-sectional returns. The Journal of Finance 63, 921–945.

Richardson, S. A., Sloan, R. G., Soliman, M. T., Tuna, I., 2005. Accrual reliability, earnings persistence and stock prices. Journal of accounting and economics 39, 437–485.

Sloan, R. G., 1996. Do stock prices fully reflect information in accruals and cash flows about future earnings? Accounting review pp. 289–315.

Soliman, M. T., 2008. The use of dupont analysis by market participants. The Accounting Review 83, 823–853.

Stein, J. C., 1996. Rational capital budgeting in an irrational world. Journal of Business 69, 429–455.

Stein, J. C., 2009. Presidential Address: Sophisticated Investors and Market Efficiency. Journal of Finance 64, 1517–1548.

Thomas, J. K., Zhang, H., 2002. Inventory changes and future returns. Review of Accounting Studies 7, 163–187.

Warusawitharana, M., Whited, T. M., 2015. Equity Market Misvaluation, Financing, and Investment. The Review of Financial Studies 29, 603–654.

TABLE I: **Price Wedges.** This table presents the price wedges ($PW \times 100$) for the long and short portfolios constructed by sorting individual stocks on each of 57 characteristics. In particular, we compare the price wedges in decile 1 (deciles 1 to 3) to the price wedge in decile 10 (deciles 8 to 10). The price wedge is calculated using the CAPM SDF that sets the price wedge for the aggregate market equal to zero, and we sort the characteristics on the difference in the price wedge between deciles 1 and 10. t-statistics are calculated using Newey-West standard errors with 180 lags and a * indicates significance at the 5% level using the multiple-testing adjustment of Benjamini and Yekutieli (2001). We also report the fraction of CRSP market capitalization allocated to the deciles.

		Decile 1 vs Decile 10				% of CRSP		Deciles 1-3 vs Deciles 8-10				% of CRSP	
		Long	Short	Diff	t-stat	Long	Short	Long	Short	Diff	t-stat	Long	Short
BEME	Book equity over market equity	-34.6	16.5	-51.1	-3.0*	2.8	25.6	-30.1	6.5	-36.6	-5.6*	13.7	52.0
S2P	Sales to price	-34.3	16.4	-50.7	-3.6*	2.2	24.1	-25.4	6.0	-31.4	-5.9*	11.0	54.1
Q	Tobins Q	-30.8	14.6	-45.4	-2.6*	3.0	26.2	-25.5	4.3	-29.8	-5.2*	14.5	51.0
aBEME	BEME - IndustryAdjusted	-35.3	9.8	-45.1	-2.2*	3.8	18.3	-24.1	4.1	-28.2	-3.3*	18.9	45.8
R3613	Long-term reversal	-27.3	15.5	-42.8	-3.1*	4.3	12.4	-21.8	7.7	-29.4	-4.8*	19.5	37.7
SIZE	Market cap	-34.7	7.0	-41.7	-1.7*	1.5	58.6	-33.1	-4.5	-28.5	-3.3*	4.5	80.8
dSOUT	Prc change in shares outstanding	-25.2	12.3	-37.5	-3.3*	8.5	8.8	-12.5	5.4	-17.8	-4.1*	31.6	28.8
ROC	Size + longterm debt - AT to cash	-22.4	13.2	-35.6	-2.2*	5.2	20.0	-17.0	5.6	-22.6	-2.9*	17.8	50.1
dSO	Log Change in shares outstanding	-23.7	9.1	-32.8	-3.6*	8.3	8.2	-13.1	4.9	-18.0	-6.1*	30.0	29.1
E2P	Income to market cap	-23.5	3.6	-27.1	-1.9	4.9	8.1	-24.4	8.3	-32.7	-4.4*	19.6	37.5
A2ME	Total assets over market cap	-12.1	14.6	-26.7	-2.2	6.2	25.9	-8.7	1.9	-10.5	-1.1	16.7	50.7
BETAd	Beta	-18.6	7.4	-26.0	-2.4	5.9	10.2	-15.6	5.3	-20.8	-3.2*	23.8	31.1
DP	Dividend to Price	-25.0	0.7	-25.7	-1.7	8.0	5.5	-18.3	8.1	-26.4	-3.9*	32.1	23.3
OA	Operating Accruals	-12.1	13.5	-25.6	-4.6*	5.3	9.6	-9.4	7.4	-16.8	-4.2*	22.1	30.9
D2P	Debt to Price	-6.4	14.7	-21.1	-1.5	4.8	17.1	-5.9	3.3	-9.2	-1.3	16.8	47.7
dPIA	Change in PPE and Inventory over AT	-16.8	4.2	-21.0	-2.7*	4.5	9.1	-9.9	5.3	-15.2	-5.9*	21.6	30.2
aSIZE	industry adjusted market cap	-13.4	6.9	-20.3	-2.0	2.6	58.4	-20.3	-5.4	-14.9	-3.1*	6.2	80.0
AOA	Absolute Operating Accruals	-7.8	11.6	-19.3	-2.4	7.0	9.2	-7.7	7.6	-15.3	-3.2*	25.4	29.2
I2A	Prc change in total assets	-14.2	4.5	-18.7	-1.8	4.0	9.7	-13.6	4.7	-18.3	-3.4*	19.4	31.8
AT	Total assets	-14.6	4.0	-18.6	-1.2	3.4	46.9	-19.5	-1.6	-18.0	-2.1	7.6	75.1
S2C	Sales to cash	-15.4	1.7	-17.1	-1.5	6.0	14.2	-8.8	1.9	-10.8	-1.7	20.8	41.4
OL	Cost of goods sold+expenses over AT	-13.9	3.2	-17.0	-1.9	5.3	10.4	-11.3	1.4	-12.7	-2.5	17.4	36.7
dCEQ	Prc change in equity book value	-7.4	9.5	-16.8	-2.0	4.8	9.4	-12.2	7.5	-19.7	-3.6*	21.2	33.2
SAT	Sales (sale) to total assets (at).	-12.3	4.2	-16.5	-1.9	5.5	10.5	-8.7	-1.5	-7.2	-1.3	19.7	32.3
SG	Percentage growth rate in sales	-14.6	1.8	-16.4	-1.7	4.7	9.6	-11.4	4.0	-15.3	-3.1*	21.3	30.4
CAT	Sales to Lagged Total Assets	-8.0	3.4	-11.4	-1.7	6.2	10.1	-5.6	-2.8	-2.8	-0.8	21.3	31.7
aSAT	Industry adjusted SAT	-10.7	-0.7	-10.0	-2.4*	6.8	10.0	-11.5	5.2	-16.7	-3.9*	23.8	33.5
TNOVR	Volume over shares outstanding	-6.0	3.1	-9.2	-1.4	13.4	8.1	-3.5	-0.2	-3.3	-0.9	35.8	23.4
IVC	Change in inventories over AT	-14.6	-6.4	-8.3	-1.6	4.2	6.2	-10.1	-2.0	-8.1	-2.2	26.7	23.2
NOA	Net operating assets over AT	2.3	9.9	-7.6	-1.1	13.0	7.5	0.0	2.7	-2.7	-0.6	38.2	23.9
RETVOL	Return volatility	-8.9	-2.3	-6.6	-0.8	15.0	4.2	-5.2	-4.1	-1.1	-0.2	44.4	15.5
R21	Short-term reversal	-7.5	-1.7	-5.8	-2.0	6.1	7.7	-5.6	-1.0	-4.5	-3.0*	24.7	29.6
ATO	Net sales over operating assets	-1.4	4.0	-5.4	-1.1	9.3	10.4	-3.1	0.1	-3.2	-1.0	28.7	30.7
SUV	Residual volume	-4.5	0.1	-4.6	-2.8*	8.9	12.5	-3.4	-0.6	-2.8	-6.7*	29.2	32.8
DTO	Detrended Turnover	-5.8	-1.3	-4.5	-1.5	6.5	6.3	-4.1	-3.8	-0.3	-0.2	31.3	19.9
MAXRET	Maximum daily return	-8.6	-5.0	-3.5	-0.4	13.4	4.3	-4.7	-4.2	-0.5	-0.1	41.2	16.9
EPS	Income to shares outstanding	-5.2	-7.8	2.6	0.4	27.2	3.7	-2.8	-1.4	-1.4	-0.6	54.6	14.1
PROF	Gross profitability over book equity	-5.4	-10.0	4.6	0.4	7.7	7.7	-4.3	-5.8	1.5	0.2	30.9	26.9
sdTURN	Stdev of turnover	2.0	-4.5	6.4	1.4	25.5	6.0	-0.1	-5.5	5.4	1.9	51.0	17.4
IDIOV	Idiosynctatic FF3M volatility	-0.1	-6.6	6.5	0.8	23.2	3.6	-0.4	-7.5	7.0	1.5	52.7	13.2
SPREAD	Bid ask spread	-3.5	-11.7	8.2	1.1	5.5	6.8	-3.0	-8.3	5.3	1.1	19.4	32.5
dGS	Gross margin - sales (Prc changes)	0.4	-9.1	9.4	2.8*	7.3	6.4	0.1	-3.5	3.6	2.9*	27.4	23.3
R62	Mom6-2	-0.3	-12.9	12.6	1.8	9.4	5.9	0.6	-9.9	10.5	2.8*	32.1	23.3
C2D	Cashflow to Debt	10.8	-3.4	14.1	1.8	18.4	4.7	-0.4	-0.2	-0.1	0.0	46.1	17.8
RNA	PM scaled by net operating assets.	9.2	-5.4	14.6	1.7	20.8	8.4	-0.7	-6.4	5.7	1.5	44.9	19.3
TAN	Tangibility	10.3	-6.8	17.1	1.8	12.0	8.7	4.4	-5.8	10.3	1.8	28.7	31.8
PCM	Sales minus cost of goods	3.7	-15.9	19.6	1.6	22.7	5.6	2.3	-7.0	9.3	1.6	45.9	19.4
ROE	Income to lagged BE	6.8	-13.0	19.9	1.5	15.6	3.5	6.2	-12.6	18.8	2.9*	45.2	16.7
C2A	Cash+Short-term Investments over AT	5.6	-14.5	20.2	2.1	14.9	8.8	1.8	-7.5	9.3	1.8	38.9	26.3
aPM	Industry adjusted PM	9.6	-11.1	20.6	1.7	20.7	6.0	1.4	-12.3	13.8	1.6	45.3	21.0
ROA	Income to AT	11.6	-10.0	21.5	1.9	20.3	4.2	-1.2	-4.7	3.5	0.7	45.5	18.1
R127	Mom12-7	3.2	-18.5	21.7	2.3*	9.9	5.6	2.3	-13.4	15.7	3.3*	33.1	22.7
R122	Mom12-2	2.7	-20.4	23.1	2.1	10.5	4.7	2.1	-15.5	17.6	3.4*	34.4	21.9
ROIC	Return on invested capital	7.9	-16.5	24.4	2.0	20.9	4.8	0.6	-7.7	8.2	1.1	42.2	20.1
PM	Operating Inc. after depr. to sales	9.9	-15.6	25.5	1.9	15.0	3.4	3.8	-12.7	16.5	2.8*	47.9	14.0
IPM	Pre-tax income over sales	12.7	-15.3	28.0	2.6*	19.6	3.4	3.1	-11.9	15.0	3.0*	50.5	12.9
sdDVOL	Stdev of volume	5.5	-25.3	30.8	2.8*	41.3	3.2	1.3	-19.9	21.2	5.3*	67.3	9.9

TABLE II: **Principal Component Analysis of Characteristics.** To determine 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 characteristics. To make the characteristics 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 III: **Explaining Price Wedges.** Panels A and B report estimates from a regression of portfolio-level price wedges (as defined in equation (1)) and market-capitalization-adjusted price wedges (as defined in equation (5)) on principal components extracted from portfolio-level characteristics (see Table II) and the five most commonly used characteristics.

Panel A: Price Wedge

	PC3	PC6	5 Characteristics	BEME	SIZE	I2A	PROF	R122
PC1	-0.15	-0.15						
PC2	0.03	0.03						
PC3	0.19	0.19						
PC4		0.02						
PC5		-0.10						
PC6		0.00						
BEME			-0.59	-0.69				
SIZE			0.14		0.51			
I2A			0.22			0.60		
PROF			-0.24				0.05	
R122			-0.04					0.60
R^2	0.77	0.79	0.76	0.66	0.30	0.37	-0.01	0.22

Panel B: Price Wedge as a Fraction of CRSP Market Capitalization

	PC3	PC6	5 Characteristics	BEME	SIZE	I2A	PROF	R122
PC1	-0.02	-0.02						
PC2	0.00	0.00						
PC3	0.02	0.02						
PC4		0.00						
PC5		-0.01						
PC6		-0.01						
BEME			-0.07	-0.07				
SIZE			0.03		0.06			
I2A			0.00			0.05		
PROF			-0.01				0.01	
R122			-0.03					0.05
R^2	0.65	0.67	0.67	0.58	0.35	0.23	0.00	0.16

TABLE IV: **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 their price wedges 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 4.5. 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	0.04	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	0.26	0.19	0.12	0.06	0.03	0.01	0.00
5	0.01	0.04	0.11	0.20	0.24	0.19	0.12	0.06	0.02	0.00
6	0.00	0.02	0.05	0.12	0.20	0.23	0.20	0.12	0.05	0.01
7	0.00	0.01	0.03	0.06	0.12	0.20	0.24	0.21	0.11	0.03
8	0.00	0.00	0.01	0.03	0.06	0.11	0.20	0.28	0.23	0.08
9	0.00	0.00	0.00	0.01	0.02	0.05	0.10	0.21	0.35	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	0.20	0.11	0.04	-0.01	-0.07	-0.12	-0.18	-0.24	-0.32	-0.48
Median	0.25	0.15	0.07	0.01	-0.04	-0.10	-0.15	-0.21	-0.28	-0.38
P95	0.37	0.19	0.10	0.04	-0.02	-0.07	-0.13	-0.18	-0.25	-0.33

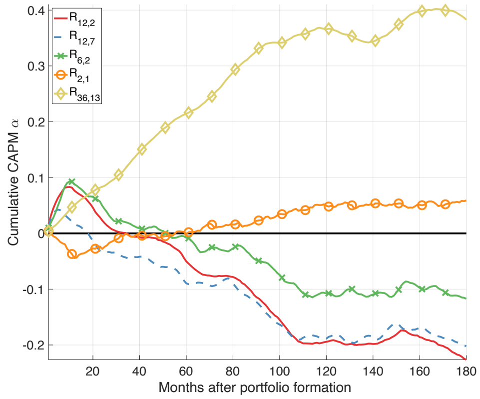
Table V: **Investment in Extreme Decile Portfolios.** This table presents the price wedges (defined in equation (1)) and measures of investment (×100) for the long and short portfolios (decile 1 and decile 10). These portfolios are constructed by sorting individual stocks on each of 57 characteristics. The price wedges are calculated using the CAPM SDF that sets the price wedge for the aggregate market equal to zero 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 difference between the average investment in the five years *after* and the five year *before* portfolio formation ($INV_{t+1y:t+5y} - INV_{t-4y:t}$). t-statistics are calculated using Newey-West standard errors with 180 lags.

		Long				Short			
		Price Wedge	Inv_t	$Inv_{t+1:t+5} - Inv_{t-4:t}$	t-stat	Price Wedge	Inv_t	$Inv_{t+1:t+5} - Inv_{t-4:t}$	t-stat
BEME	Book equity over market equity	-34.6	14.3	-2.5	(-3.3)	16.5	25.6	3.5	(6.2)
S2P	Sales to price	-34.3	17.0	-2.1	(-4.8)	16.4	26.3	3.0	(4.3)
Q	Tobins Q	-30.8	14.3	-2.0	(-2.6)	14.6	26.7	3.1	(5.4)
aBEME	BEME - IndustryAdjusted	-35.3	14.3	-2.3	(-3.3)	9.8	24.2	1.9	(4.3)
R3613	Long-term reversal	-27.3	16.9	-3.7	(-5.9)	15.5	23.0	2.7	(6.4)
SIZE	Market cap	-34.7	17.7	0.3	(0.7)	7.0	16.9	-0.8	(-1.4)
dSOUT	Prc change in shares outstanding	-25.2	15.9	-0.6	(-0.7)	12.3	22.4	2.4	(4.4)
ROC	Size + longterm debt - AT to cash	-22.4	15.1	-1.9	(-2.5)	13.2	22.5	1.3	(2.7)
dSO	Log Change in shares outstanding	-23.7	15.5	-0.5	(-0.6)	9.1	26.7	2.7	(3.2)
E2P	Income to market cap	-23.5	17.9	-0.9	(-2.8)	3.6	17.6	-1.0	(-1.4)
A2ME	Total assets over market cap	-12.1	14.5	-3.9	(-4.7)	14.6	26.6	3.0	(4.9)
BETAd	Beta	-18.6	15.7	-0.3	(-0.7)	7.4	25.9	1.0	(1.5)
DP	Dividend to Price	-25.0	12.9	-1.7	(-3.0)	0.7	18.2	0.8	(1.4)
OA	Operating Accruals	-12.1	16.8	-0.3	(-0.9)	13.5	27.9	1.9	(4.6)
D2P	Debt to Price	-6.4	15.1	-3.9	(-6.6)	14.7	23.7	2.6	(5.4)
dPIA	Change in PPE and Inventory over AT	-16.8	12.2	-0.8	(-1.8)	4.2	35.9	0.3	(0.7)
aSIZE	industry adjusted market cap	-13.4	17.1	0.2	(0.7)	6.9	16.8	-0.8	(-1.6)
AOA	Absolute Operating Accruals	-7.8	16.2	-0.4	(-1.0)	11.6	27.9	2.1	(5.2)
I2A	Prc change in total assets	-14.2	12.8	-1.4	(-2.7)	4.5	36.5	2.5	(3.9)
AT	Total assets	-14.6	19.6	1.9	(7.6)	4.0	13.5	-1.3	(-1.9)
S2C	Sales to cash	-15.4	18.3	-0.6	(-1.1)	1.7	23.4	3.1	(3.8)
OL	Cost of goods sold+expenses over AT	-13.9	21.3	0.3	(1.5)	3.2	19.9	0.0	(0.0)
dCEQ	Prc change in equity book value	-7.4	15.1	-1.5	(-3.9)	9.5	29.7	3.3	(4.8)
SAT	Sales (sale) to total assets (at).	-12.3	21.5	0.4	(1.8)	4.2	23.9	0.8	(0.6)
SG	Percentage growth rate in sales	-14.6	13.2	-1.7	(-3.3)	1.8	33.1	3.3	(5.3)
CAT	Sales to Lagged Total Assets	-8.0	25.3	1.0	(4.2)	3.4	17.2	0.4	(0.4)
aSAT	Industry adjusted SAT	-10.7	19.9	0.5	(1.6)	-0.7	19.9	0.0	(0.0)
TNOVR	Volume over shares outstanding	-6.0	15.8	-0.4	(-0.8)	3.1	24.4	1.3	(2.0)
IVC	Change in inventories over AT	-14.6	15.0	-1.1	(-2.3)	-6.4	27.0	1.8	(4.6)
NOA	Net operating assets over AT	2.3	19.9	1.8	(3.1)	9.9	30.9	-0.4	(-0.8)
RETVOL	Return volatility	-8.9	15.3	-0.4	(-0.6)	-2.3	20.2	0.2	(0.7)
R21	Short-term reversal	-7.5	20.3	-0.4	(-1.0)	-1.7	19.2	1.1	(3.1)
ATO	Net sales over operating assets	-1.4	26.5	1.7	(3.5)	4.0	18.4	0.7	(0.7)
SUV	Residual volume	-4.5	18.0	-0.1	(-0.3)	0.1	18.4	-0.1	(-0.2)
DTO	Detrended Turnover	-5.8	19.7	0.6	(1.7)	-1.3	22.7	0.9	(1.5)
MAXRET	Maximum daily return	-8.6	15.6	-0.5	(-0.8)	-5.0	19.6	0.4	(1.0)
EPS	Income to shares outstanding	-5.2	14.6	-0.1	(-0.2)	-7.8	17.0	-1.1	(-1.3)
PROF	Gross profitability over book equity	-5.4	21.6	-0.8	(-2.7)	-10.0	14.5	2.0	(2.5)
sdTURN	Stdev of turnover	2.0	15.5	-0.5	(-0.9)	-4.5	22.7	1.5	(3.2)
IDIOV	Idiosynctatic FF3M volatility	-0.1	15.3	-0.4	(-0.7)	-6.6	19.8	0.2	(0.6)
SPREAD	Bid ask spread	-3.5	20.8	0.1	(0.2)	-11.7	15.8	-0.2	(-0.4)
dGS	Gross margin - sales (Prc changes)	0.4	17.1	2.1	(7.5)	-9.1	18.5	-0.1	(-0.2)
R62	Mom6-2	-0.3	18.8	2.4	(7.8)	-12.9	21.6	-1.4	(-3.5)
C2D	Cashflow to Debt	10.8	21.5	1.7	(4.8)	-3.4	18.2	-1.3	(-2.9)
RNA	PM scaled by net operating assets.	9.2	29.3	2.3	(3.7)	-5.4	18.1	-1.0	(-3.2)
TAN	Tangibility	10.3	23.2	2.5	(6.8)	-6.8	14.9	-0.4	(-0.6)
PCM	Sales minus cost of goods	3.7	25.5	-0.5	(-1.2)	-15.9	14.9	0.9	(1.5)
ROE	Income to lagged BE	6.8	26.8	3.3	(4.7)	-13.0	16.1	-1.6	(-3.6)
C2A	Cash+Short-term Investments over AT	5.6	23.3	2.5	(4.6)	-14.5	16.7	-0.9	(-1.4)
aPM	Industry adjusted PM	9.6	20.7	-0.5	(-0.6)	-11.1	16.8	-0.8	(-3.4)
ROA	Income to AT	11.6	27.3	2.1	(4.1)	-10.0	16.3	-1.8	(-4.7)
R127	Mom12-7	3.2	19.1	2.8	(7.8)	-18.5	21.7	-1.9	(-4.9)
R122	Mom12-2	2.7	18.8	3.4	(9.9)	-20.4	22.4	-2.4	(-6.0)
ROIC	Return on invested capital	7.9	24.0	1.7	(3.5)	-16.5	16.8	-0.8	(-2.3)
PM	Operating Inc. after depr. to sales	9.9	21.5	1.0	(1.2)	-15.6	17.9	-1.0	(-2.3)
IPM	Pre-tax income over sales	12.7	21.9	2.1	(3.6)	-15.3	17.5	-1.8	(-3.1)
sdDVOL	Stdev of volume	5.5	16.8	-0.8	(-1.7)	-25.3	17.8	0.3	(0.7)

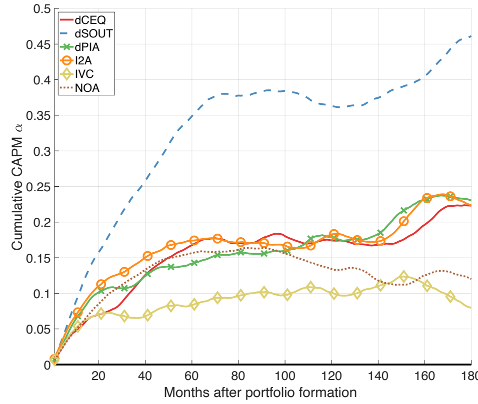
TABLE VI: **Investment and Price Wedges Conditional on $q \geq 1$ versus $q < 1$.** This table reports for both high- and low-q firms the relation between investment and the price wedge. For each of 57 characteristics, we calculate for the long and short quintile portfolio the average price wedge and the average of the two investment measures. We then sort the characteristics in five groups based on this price wedge. Our interest is in the "diff," which measures whether overpriced firms start investing more around the time of portfolio formation (than underpriced firms), and the "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						
Inv_t	26.33	24.30	25.92	26.09	28.63	2.30	15.87	14.89	17.07	17.46	16.66	0.79	1.51
	(16.62)	(23.12)	(19.23)	(17.55)	(11.95)	(2.33)	(71.57)	(51.81)	(44.73)	(55.46)	(62.17)	(2.93)	(1.21)
$Inv_{t+1:t+5} - Inv_{t-4:t}$	-1.34	-0.01	-0.10	1.20	1.20	2.54	-1.51	-1.09	-0.60	-0.69	-0.75	0.76	1.79
	(-1.79)	(-0.03)	(-0.25)	(3.12)	(2.28)	(2.95)	(-2.91)	(-2.14)	(-1.30)	(-1.47)	(-1.79)	(5.41)	(2.44)
Price Wedge	-11.09	3.16	7.49	11.79	17.97	29.06	-30.11	-22.20	-17.91	-15.01	-8.26	21.85	7.21
	(-0.65)	(0.22)	(0.53)	(0.89)	(1.27)	(3.83)	(-1.58)	(-1.21)	(-1.01)	(-0.88)	(-0.52)	(4.55)	(0.91)
	Short						Short						
Inv_t	28.36	32.06	29.59	30.10	31.88	3.52	15.55	15.01	17.42	18.21	19.02	3.47	0.05
	(17.14)	(12.65)	(12.76)	(15.51)	(14.31)	(5.99)	(55.08)	(46.06)	(47.23)	(46.47)	(58.84)	(12.79)	(0.07)
$Inv_{t+1:t+5} - Inv_{t-4:t}$	-0.72	-0.36	0.05	0.22	1.85	2.56	-1.66	-1.52	-0.88	-0.40	-0.22	1.43	1.13
	(-1.38)	(-0.65)	(0.08)	(0.55)	(3.79)	(4.81)	(-3.13)	(-2.97)	(-1.62)	(-0.79)	(-0.46)	(6.14)	(3.36)
Price Wedge	-0.32	8.53	11.71	13.96	18.77	19.09	-22.05	-15.25	-12.10	-8.15	-1.07	20.98	-1.88
	(-0.02)	(0.62)	(0.85)	(1.08)	(1.35)	(3.37)	(-1.15)	(-0.83)	(-0.69)	(-0.47)	(-0.07)	(6.80)	(-0.43)

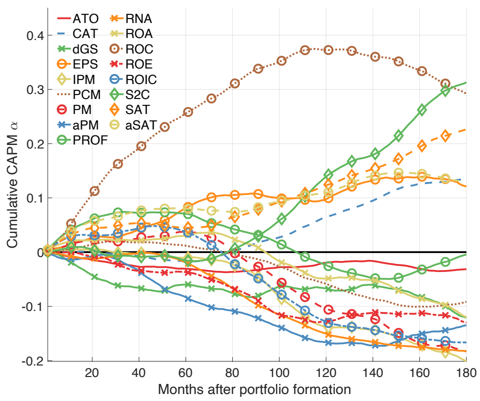
Figures



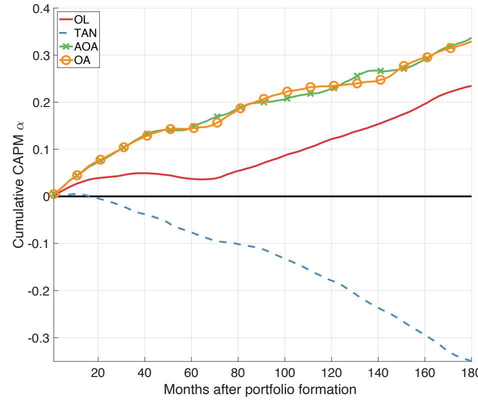
(a) Past Returns



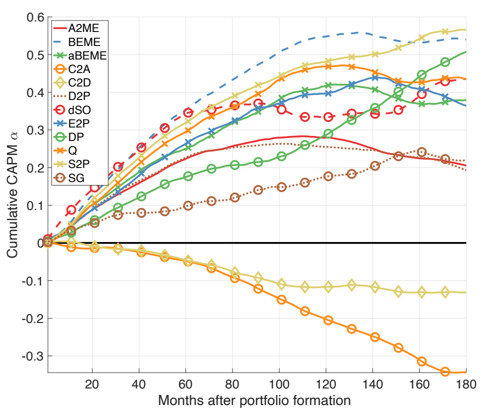
(b) Investment



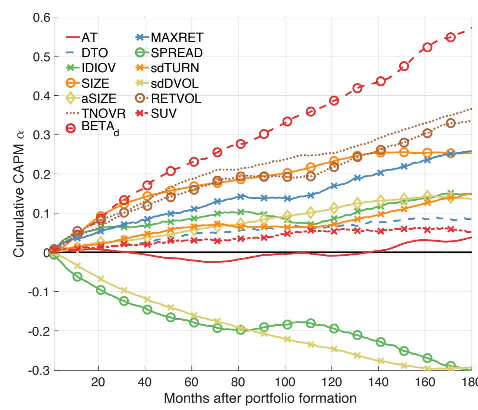
(c) Profitability



(d) Intangibles

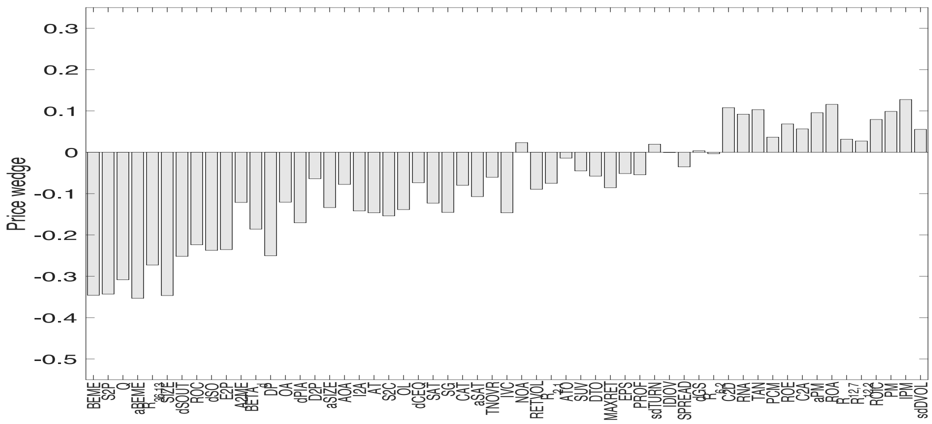


(e) Value

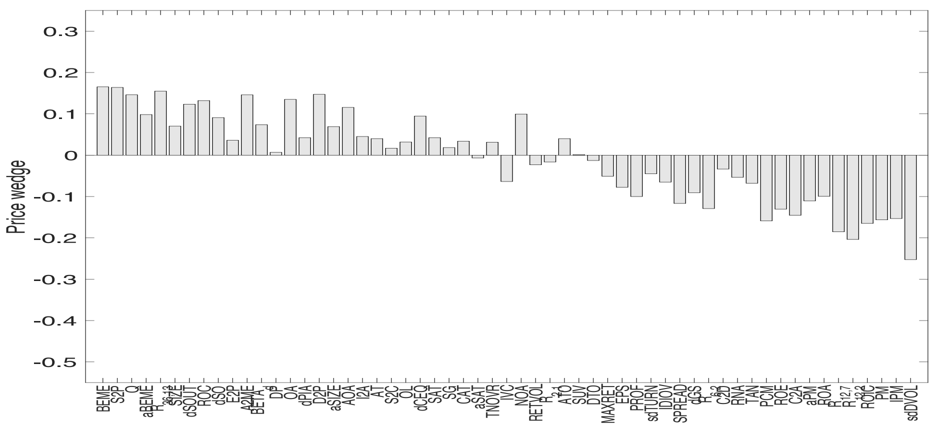


(f) Frictions

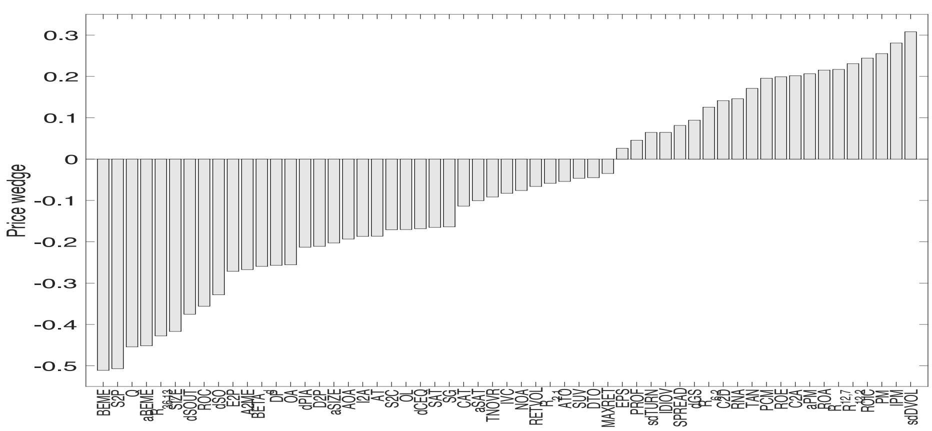
FIGURE 1: **Cumulative CAPM alphas (Long-Short).** This figure presents the log of the cumulative CAPM alpha of long-short decile portfolio from one month to fifteen years after portfolio formation ($\log(\prod_{s=1}^{180}(1+\alpha_s))$ for each of the 57 characteristics, where α_s is the one-month alpha of the long-short portfolio s months after portfolio formation). The six panels correspond to the characteristics categories used in Freyberger et al. (2020).



(a) Long

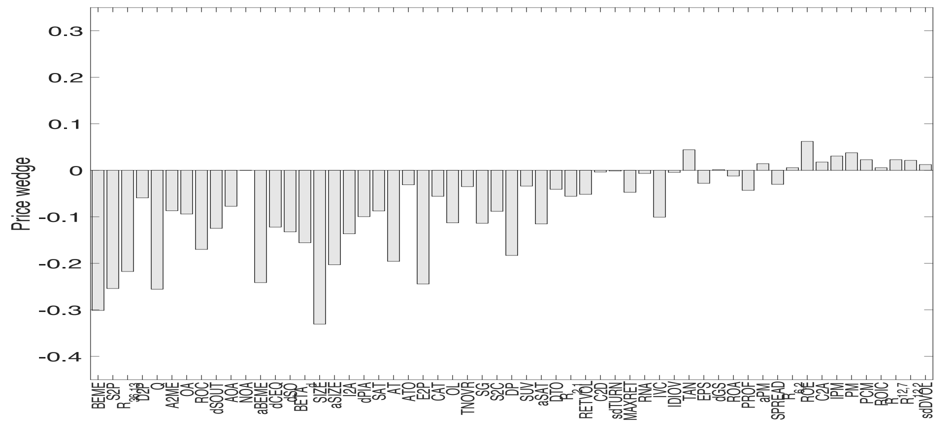


(b) Short

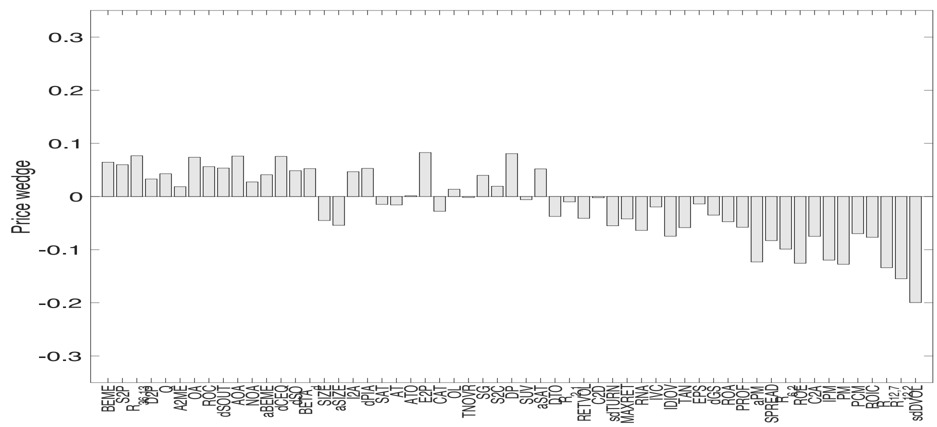


(c) Long-Short

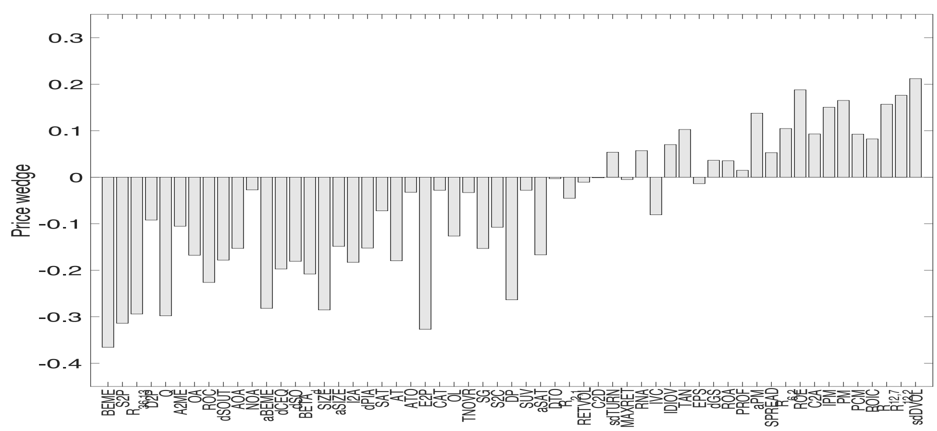
Figure 2: **Price Wedges.** This figure presents price wedges for the long and the short decile portfolios, as well as the long-short difference, from sorts on each of the 57 characteristics. The price wedge is calculated using the CAPM SDF that sets the price wedge equal to zero for the market portfolio. We sort the characteristics from low to high on the long-short difference of the price wedges (bottom panel).



(a) Deciles 1-3

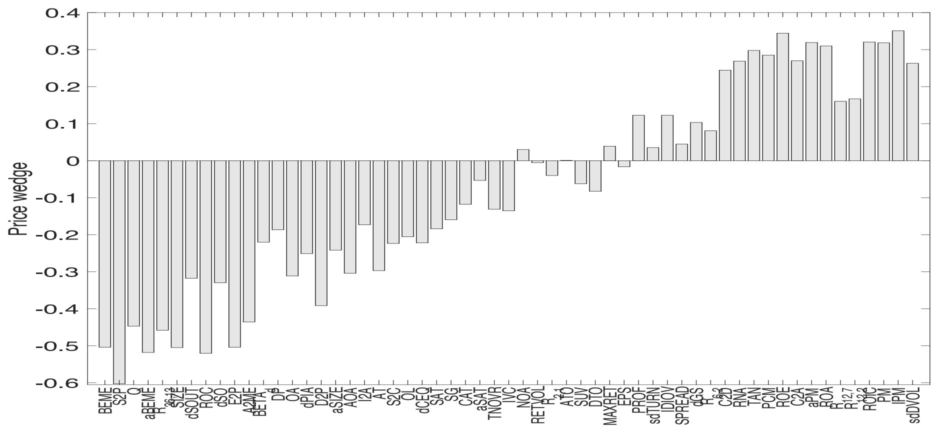


(b) Deciles 8-10

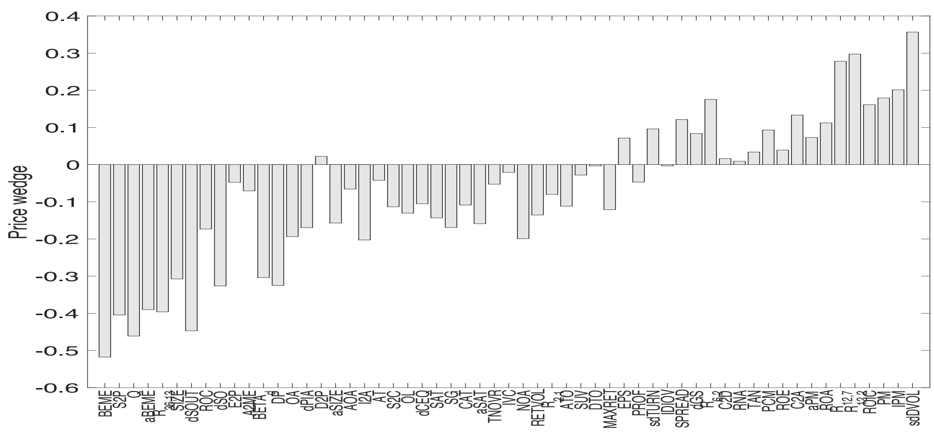


(c) Deciles 1-3 minus Deciles 8-10

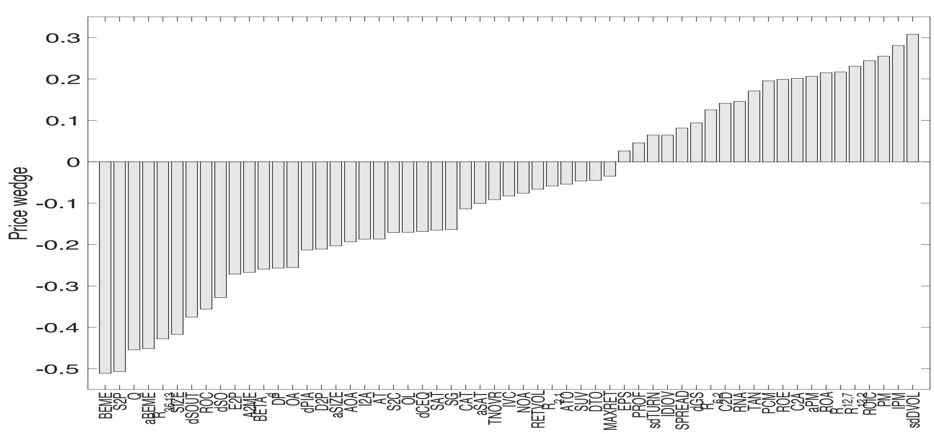
FIGURE 3: **Price Wedges of Deciles 1-3 and Deciles 8-10.** This figure presents the average price wedges of deciles 1 to 3 and deciles 8 to 10, as well as their difference, when sorting individual stocks on each of the 57 characteristics. In the figure, we order the characteristics by the long-short price wedge differences, which are presented in the bottom panel of Figure 2.



(a) First Half



(b) Second Half



(c) Full Sample

FIGURE 4: **Price Wedges in Subsamples.** This figure presents long-short price wedges for the first half and the second half of our sample (up to and including October 1983, and after October 1983). The bottom panel presents the results over the full sample.

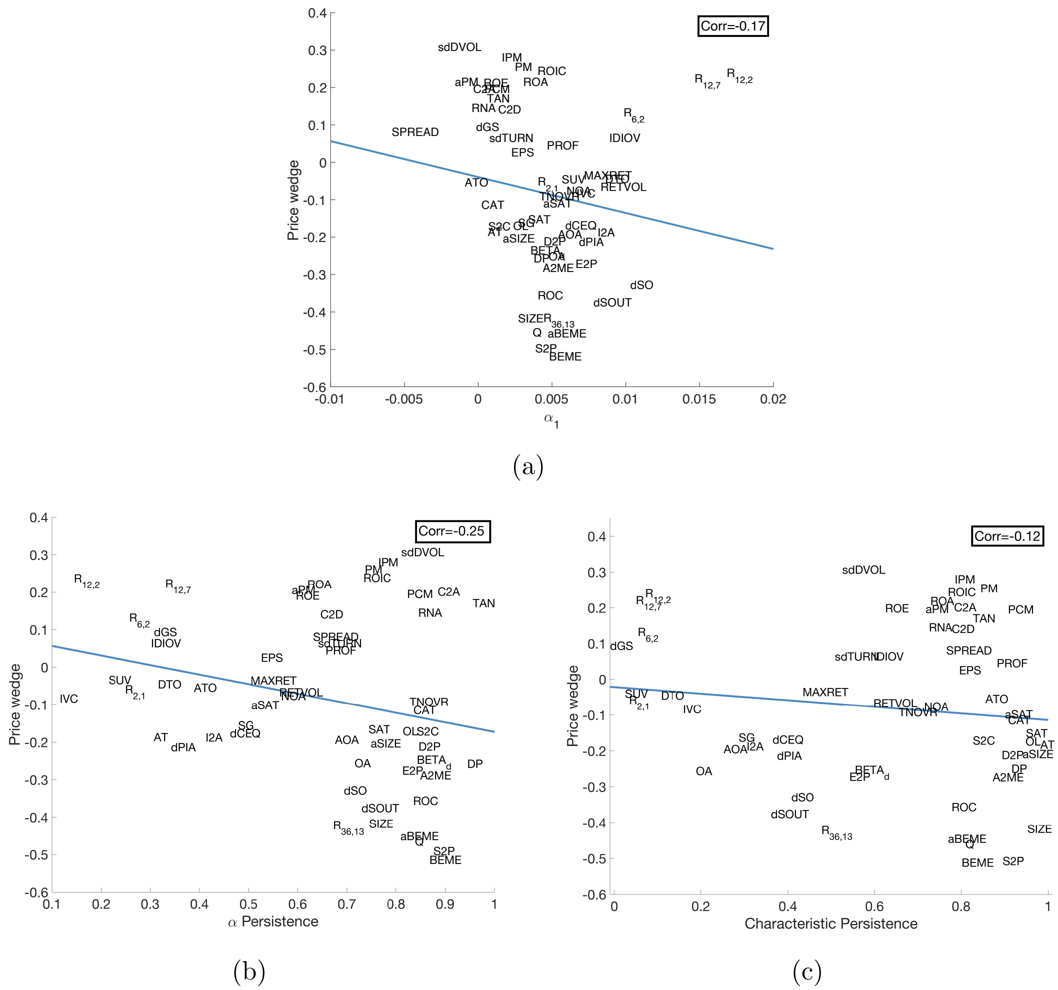
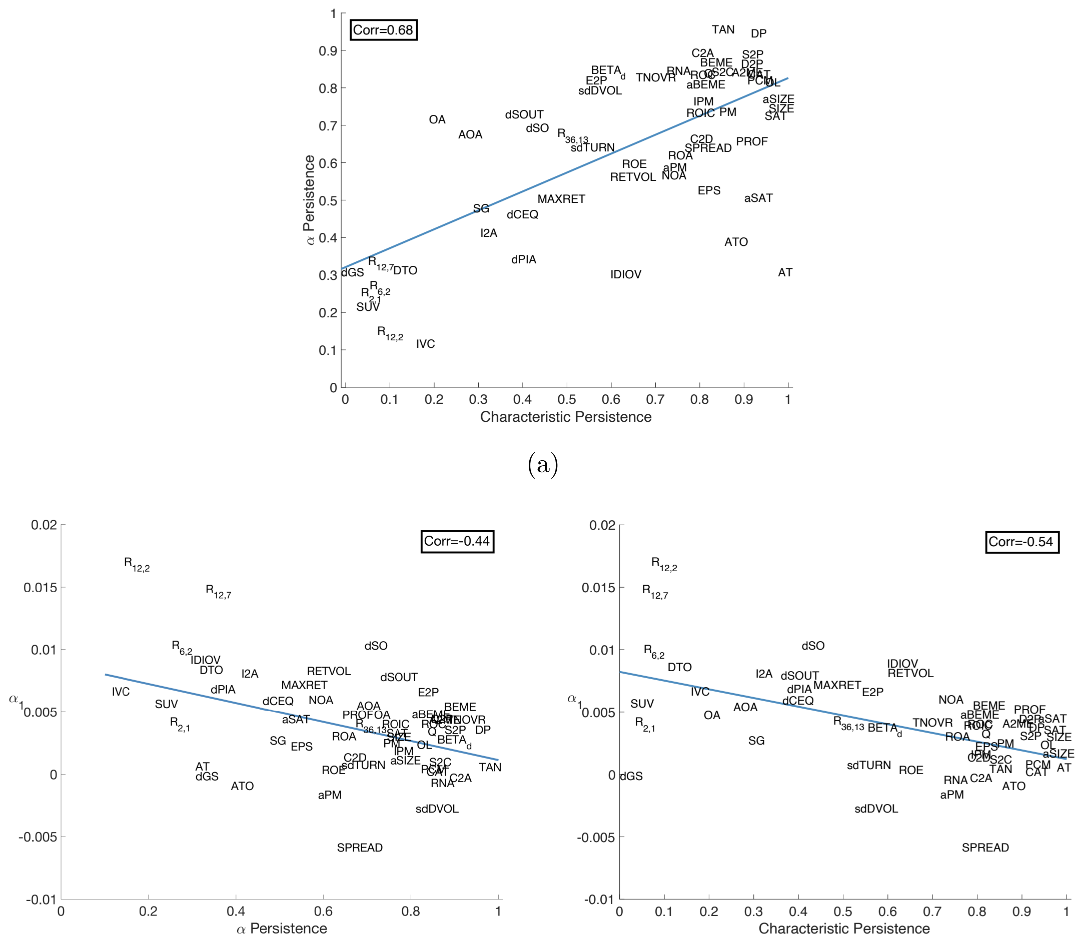


FIGURE 5: **Price Wedges, Alphas, and Persistence.** This figure presents scatter plots illustrating the relations between the long-short price wedge for all 57 characteristics and (i) the long-short alpha (α_1), (ii) alpha persistence, and (iii) characteristic persistence. The persistence of the long-short alpha ρ_α is computed for each anomaly with the following regression: $\alpha_{s+12} = \rho_\alpha \alpha_s + a_{s+12}$, 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 cross-sectional correlation $Corr(X_{i,t}, X_{i,t+12})$ across firms (indexed by i).



(a)

(b) (c)

Figure 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. The persistence of the long-short alpha ρ_α is computed for each anomaly with the following regression: $\alpha_{s+12} = \rho_\alpha \alpha_s + a_{s+12}$, 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 cross-sectional correlation $Corr(X_{i,t}, X_{i,t+12})$ across firms (indexed by i).

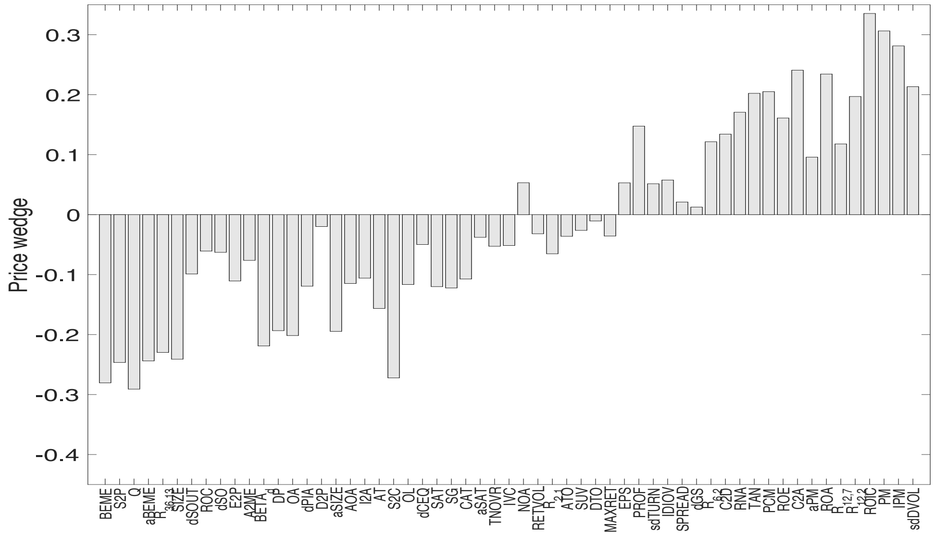


FIGURE 7: **Price Wedges 5 Years After Portfolio Formation.** This figure presents the price wedges of the long minus the short decile portfolios for all characteristics five years after portfolio formation. Given our assumption that the price wedge converges to zero 15 years after the original portfolio formation date, we use 10 years of cash flows to calculate these price wedges (from month 61 to 180 discounted to month 60).

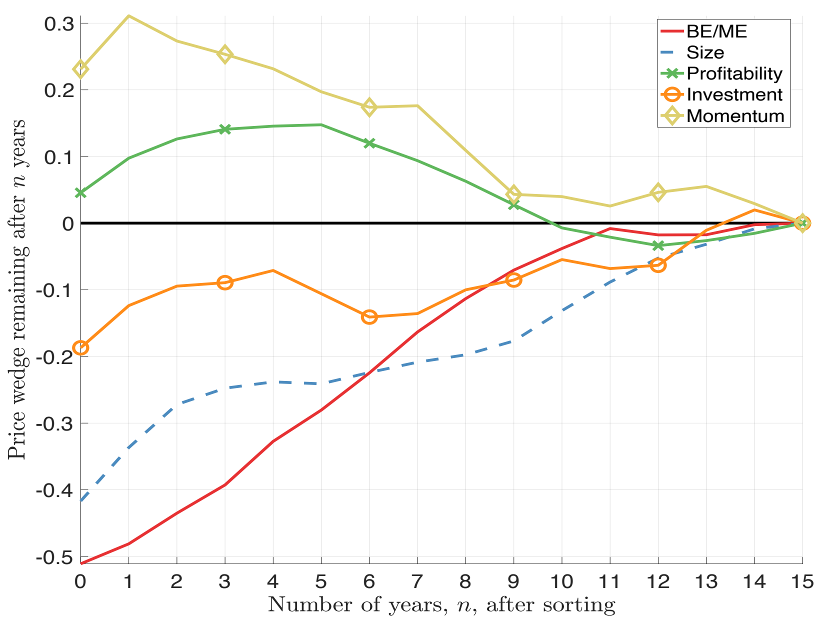
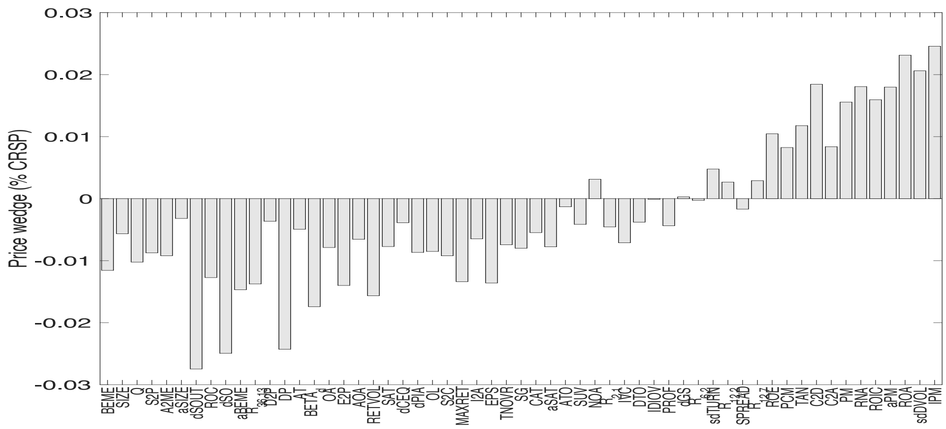
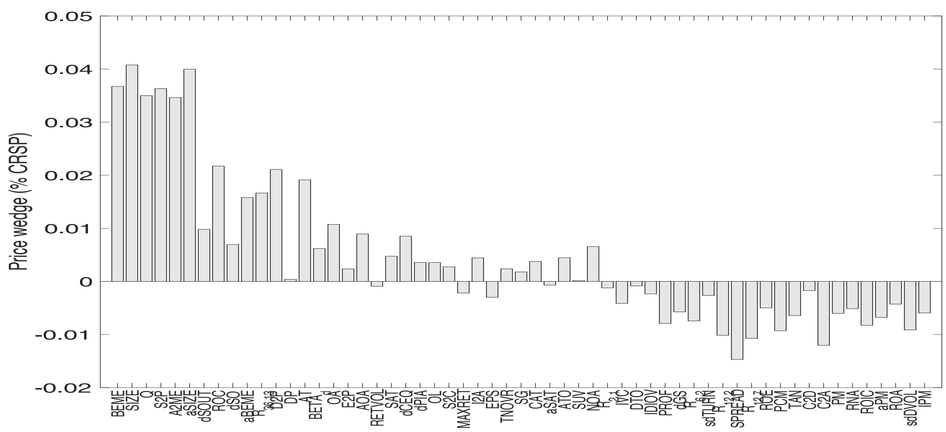


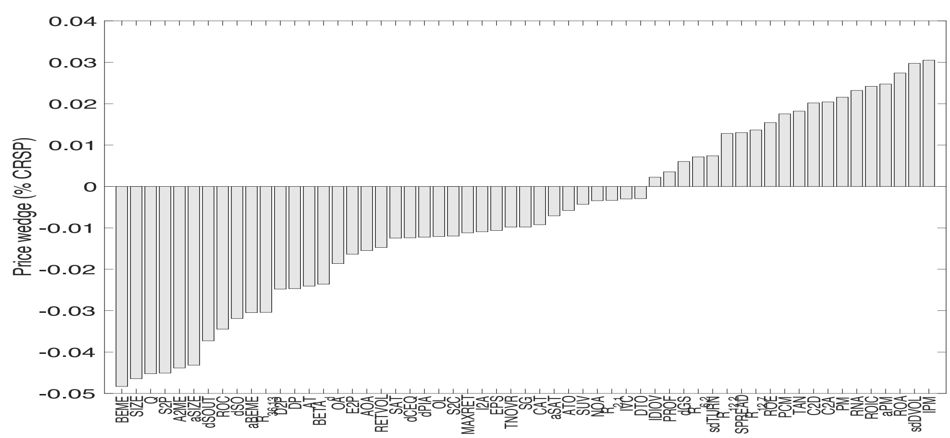
FIGURE 8: **Price Wedges n Years after Portfolio Formation for Select Characteristics.** This figure presents the long-short price wedges of select characteristics n years after portfolio formation (with $n = 0, ..., 15$), where $n = 0$ refers to the price wedge at the moment of portfolio formation (such that a total of 15 years of cash flows are used to calculate the price wedges). 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 discounted to month $n \times 12$).



(a) Long

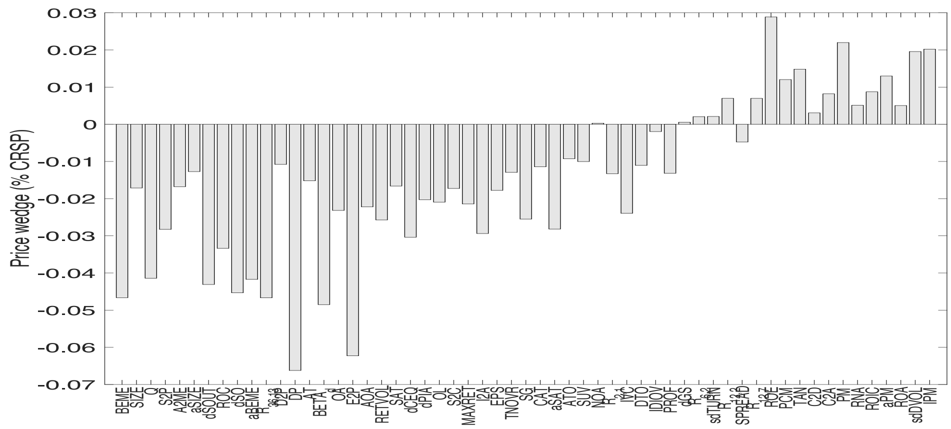


(b) Short

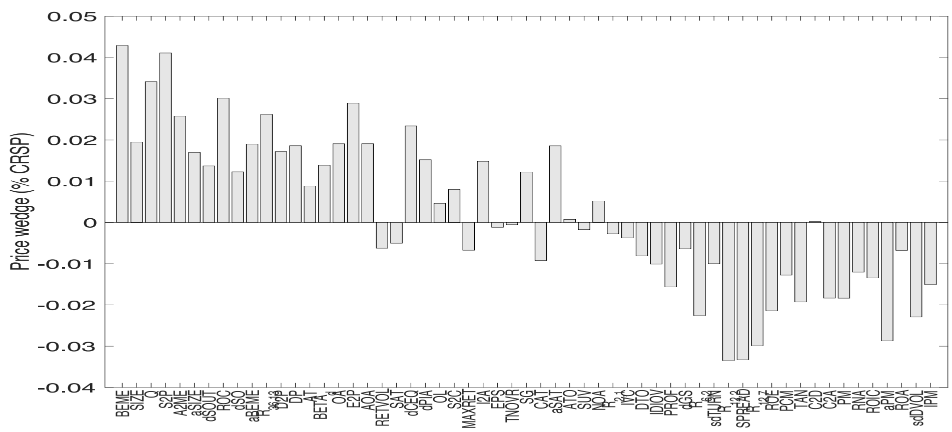


(c) Long-Short

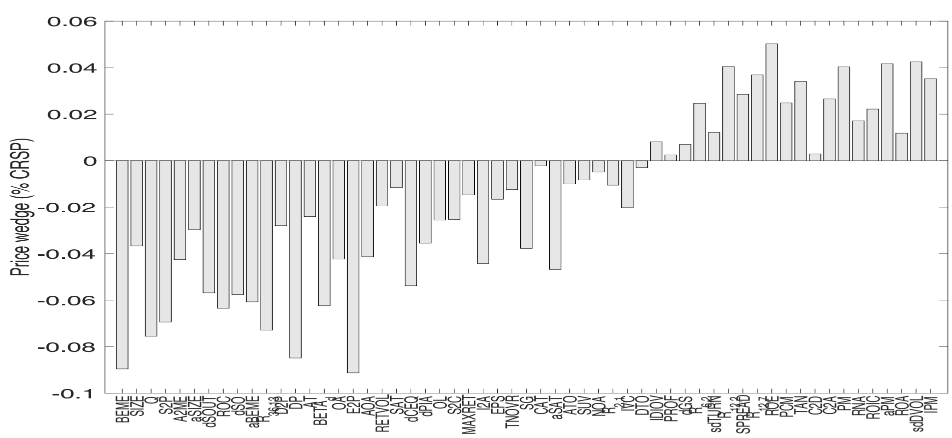
FIGURE 9: **Price Wedges as a Fraction of CRSP Market Capitalization.** The figure plots for each anomaly the total dollar value of mispricing in the long and the short decile portfolio, as well as their difference, as a fraction of total CRSP market capitalization. We calculate the price wedge for each portfolio and combine it with the average fraction of CRSP market capitalization allocated to that portfolio to obtain the dollar mispricing as a fraction of CRSP market capitalization (see equation (5)). In the figure, we order the characteristics based on the magnitudes of the market-capitalization adjusted long-short price wedges.



(a) Deciles 1-3



(b) Deciles 8-10



(c) Deciles 1-3 minus Deciles 8-10

FIGURE 10: **Market-Capitalization-Adjusted Price Wedges of Deciles 1-3 and Deciles 8-10.** The figure plots for each anomaly the total dollar value of mispricing in deciles 1 to 3 and deciles 8 to 10, as well as their difference, as a fraction of total CRSP market capitalization. We calculate the price wedge for each decile portfolio and combine it with the average fraction of CRSP market capitalization allocated to that portfolio to arrive at the dollar mispricing as a fraction of CRSP market capitalization (see equation (5)). We then sum over the three deciles. In the figure, we order the characteristics based on the magnitudes of the market-capitalization adjusted long-short price wedges presented in the bottom panel of Figure 9.

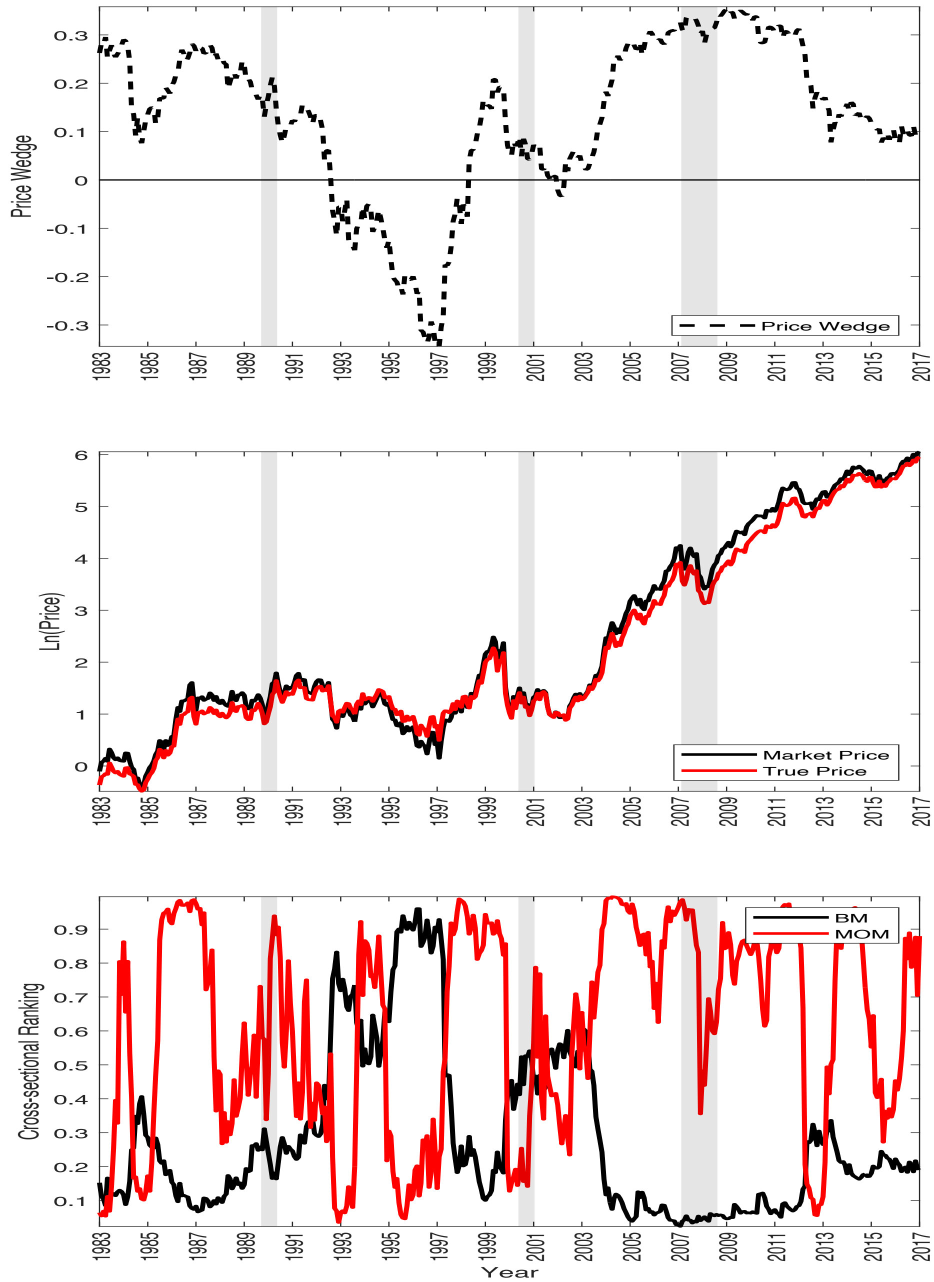
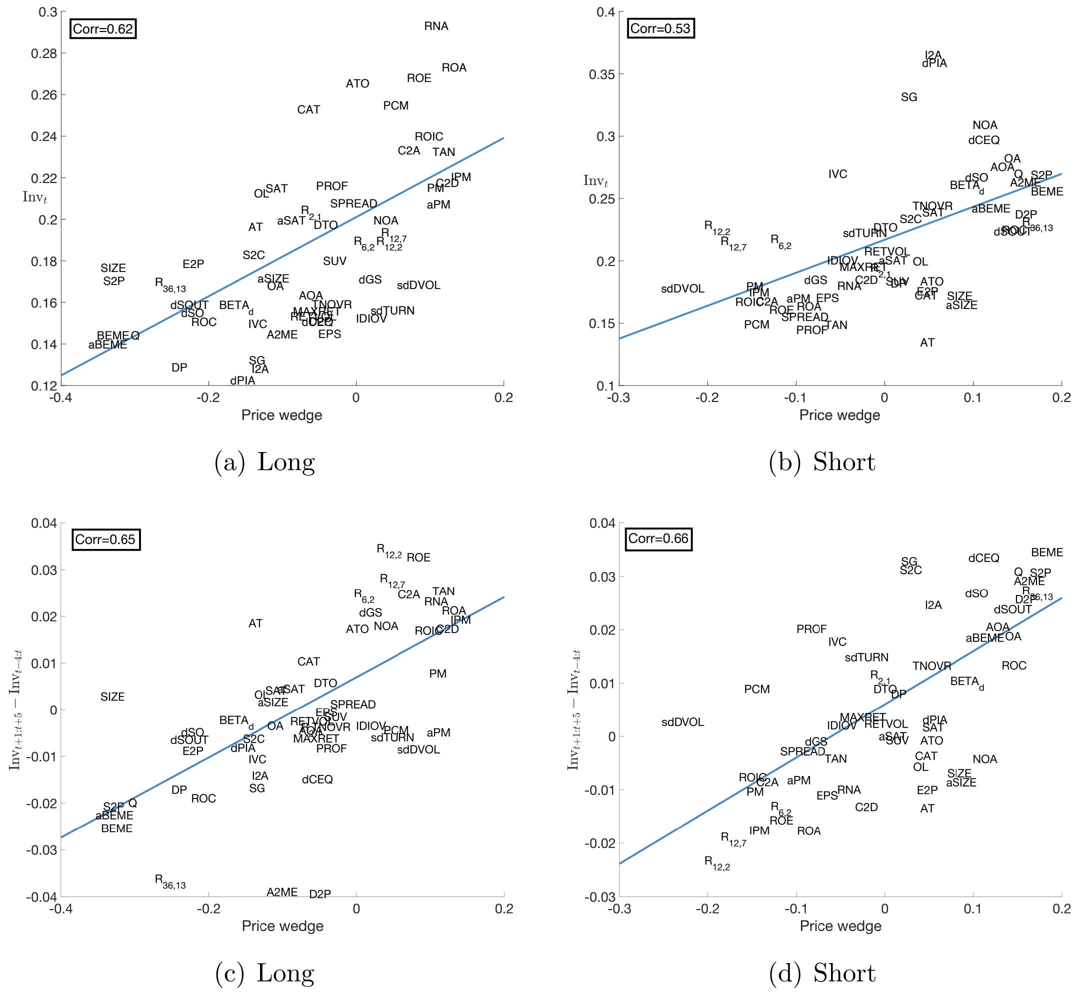


FIGURE 11: **Price Wedge Analysis for Apple.** Panel A of this figure plots our estimate for the price wedge of Apple stock since the firm's inception in 1983. Panel B plots (in logs) the market price versus our estimate of the informationally efficient (or fundamental) value labeled as "True Price" plotted in red. Panel C plots the book-to-market and momentum ranking of Apple in the cross-section of all firms, which ranking is normalized between zero and one.



(a) Long (b) Short

(c) Long (d) Short

FIGURE 12: **Price Wedges and Investment.** Panels (a) and (b) present scatter plots illustrating the relations between price wedges for both the long and short decile portfolios and investment at the time of portfolio formation, across the 57 characteristics. Panel (c) and (d) present scatter plots illustrating the relations 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.

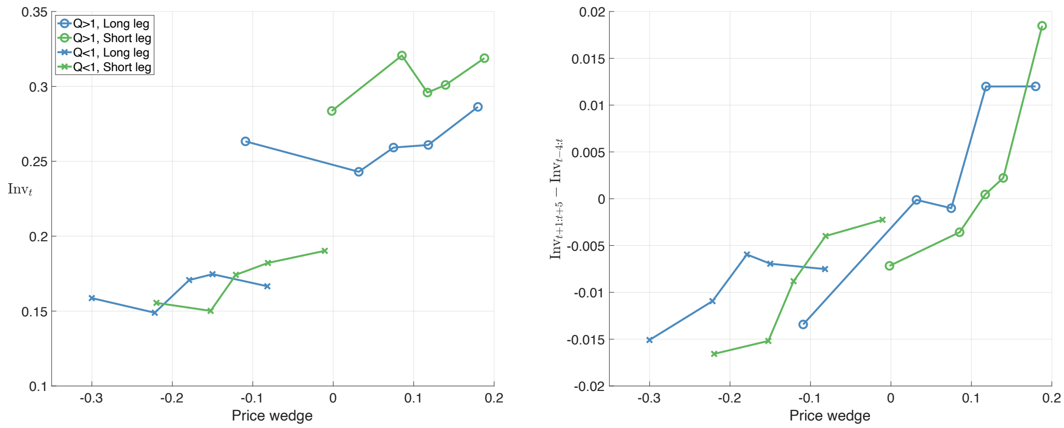
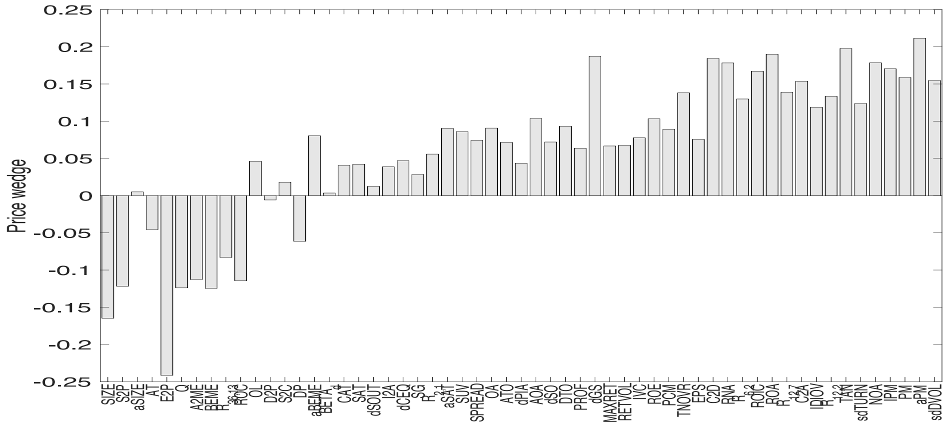
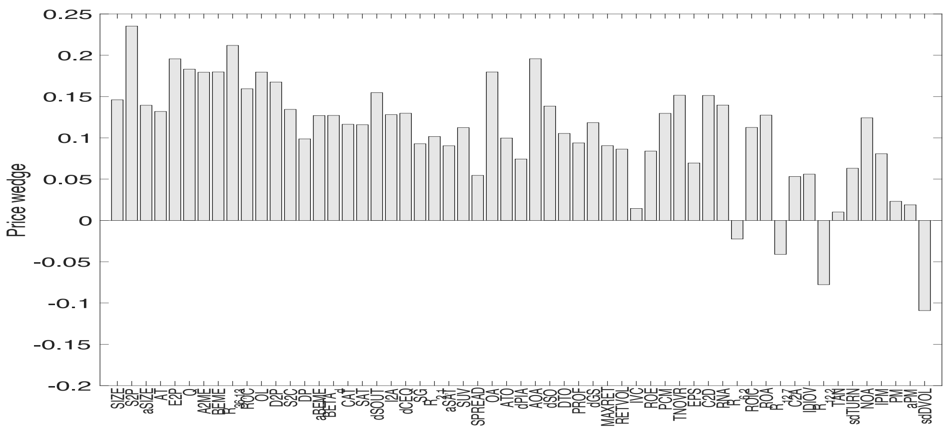


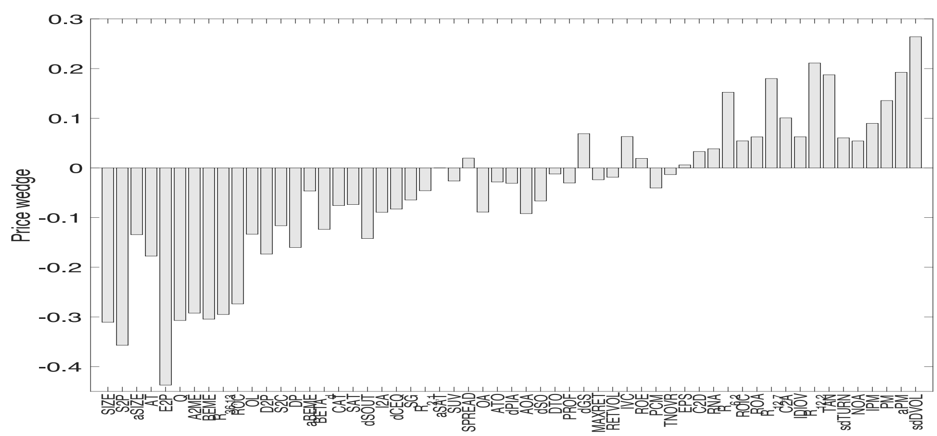
FIGURE 13: **Relation between Price Wedges and Investment for Firms with $q < 1$ and $q \geq 1$.** The top left figure plots on the y-axis investment at the time of portfolio formation (Inv_t) versus on the x-axis the price wedge for the long (blue line) or short (green line) decile portfolio. The top right figure plots the change in investment around the time of portfolio formation ($Inv_{t+1,t+5} - Inv_{t-4,t}$) on the y-axis. Each figure separately presents the relation for high q ($q \geq 1$, lines with circles) and low q ($q < 1$, lines with x-mark) firms. Each point on the line corresponds to one of five bins into which we sort the characteristics based on the price wedges in the long and short portfolios conditional on $q \geq 1$ ($q < 1$).



(a) Long

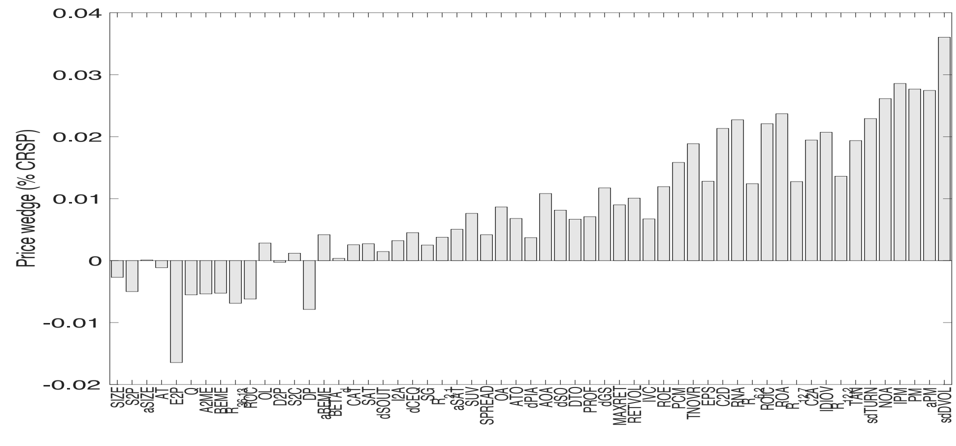


(b) Short

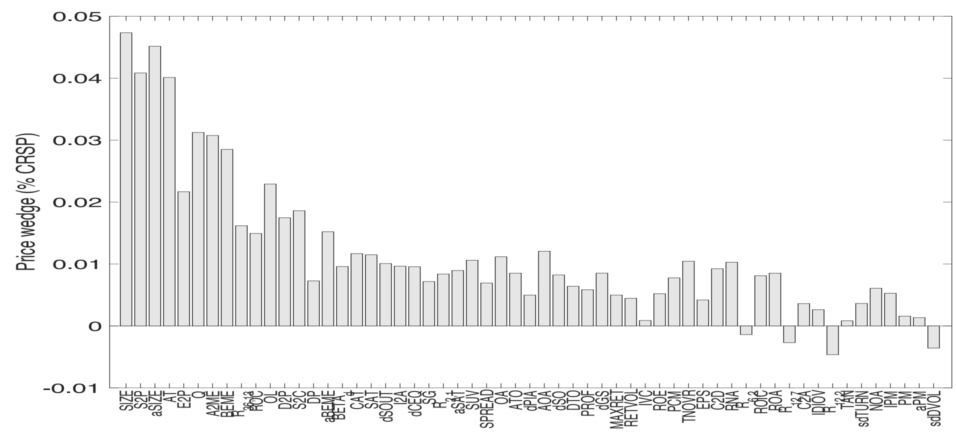


(c) Long-Short

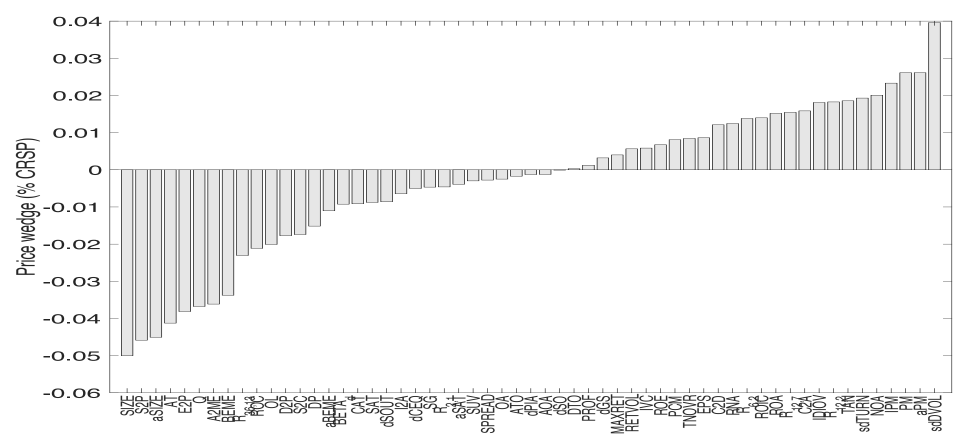
FIGURE 14: **Price Wedges for Firms with $q \geq 1$.** The figure presents for all 57 characteristics the price wedges of the long and short quintile portfolios, as well as the long-short difference, when considering only high q firms (firms with $q \geq 1$ at the time of portfolio formation). In the figure, we order the characteristics based on the market-capitalization-adjusted long-short price wedges, which are presented in the bottom panel of Figure 15.



(a) Long



(b) Short



(c) Long-Short

FIGURE 15: **Price Wedge as a Fraction of CRSP market cap for Firms with $q \geq 1$.** The figure plots the market-capitalization-adjusted price wedges of the long and short quintile portfolios, as well as their differences, when considering only high-q firms (that is, firms with $q > 1$ 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 market-capitalization-adjusted long-short price wedges, which are presented in the bottom panel.

A. Data Construction

For concreteness, let us consider an example of a portfolio that contains at time t all stocks $i = 1, ..., N$ with book-to-market above the NYSE 90th percentile of book-to-market with weights defined as:

$$w_{i,t} = MV_{i,t} / \sum_{i=1}^{N} MV_{i,t}. \tag{A.1}$$

We normalize the price of this portfolio $P_t = 1$. Using cum-dividend returns, $R_{i,t+1}$, and capital gains, $CG_{i,t+1}$, of the stocks over month $t+1$, we define the portfolio's cum dividend return

$$R_{t+1} = \sum_{i=1}^{N} w_{i,t} R_{i,t+1}, \tag{A.2}$$

and capital gain

$$CG_{t+1} = \sum_{i=1}^{N} w_{i,t} CG_{i,t+1}, \tag{A.3}$$

such that $P_{t+1} = P_t(1 + CG_{t+1})$. The portfolio's dividend is defined as:

$$D_{t+1} = P_t(R_{t+1} - CG_{t+1}). \tag{A.4}$$

To iterate this forward from $t+1$ to $t+2, t+3, ..., t+180$, we use that the weights in the portfolio of the buy-and-hold investor at the end of each month equal:

$$w_{i,t+1} = w_{i,t}(1 + CG_{i,t+1}) / \sum_{i=1}^{N} w_{i,t}(1 + CG_{i,t+1}), \tag{A.5}$$

which weights we can plug back into equations (A.2) to (A.5). Note that the buy-and-hold portfolio is market value-weighted at t and it will be market value-weighted at all $t+s, s > 0$, unless there are share issuances and/or repurchases. In case of share issuances and/or repurchases, the market value of firms in the portfolio will be affected, but our portfolio weights are unaffected, consistent with the experience of a buy-and-hold investor. When a stock delists, we reallocate the investment in this stock (net of the delisting return) to the non-missing stocks in the portfolio using value-weights.

To estimate price wedges, that is:

$$PW_t = \log\left(\frac{P_t}{\tilde{P}_t}\right) = -\log\left(E_t\left[\sum_{j=1}^{J} \frac{m_{t+j}}{m_t}\frac{D_{t+j}}{P_t} + \frac{m_{t+J}}{m_t}\frac{P_{t+J}}{P_t}\right]\right), \tag{A.6}$$

we need the dividends and the cumulative capital gain ($\frac{P_{t+J}}{P_t} = \prod_{j=1}^{180}(1+CG_{t+j})$) of the portfolio as well as the cumulative SDF defined in Section 3 up to the horizon J after which we assume the mispricing is resolved. We calculate these items monthly for portfolios constructed from June 1964 to December 2002, such that $\tilde{P}_t$ is estimated as an unconditional average over 463 time-series observations.

B. Alternative Mispricing Measures

Our definition of the price wedge is an empirical implementation of the definition in Binsbergen and Opp (2019, Eq. 35) for the price that is observed in financial markets:

$$P_0 = E_0\left[\sum_{t=1}^{\infty} \frac{m_t}{m_0} e^{-\sum_{j=0}^{t-1}\alpha_j} D_t\right], \tag{B.1}$$

where the $e^{-\sum_{j=0}^{t-1}\alpha_j}$ term represents cumulative abnormal discounting. We further define the undistorted price: $\tilde{P}_0 = E_0\left[\sum_{t=1}^{\infty} \frac{m_t}{m_0} D_t\right]$. Suppose that $\alpha_t = 0$ for $t > J$, that is, cumulative abnormal returns level out after J periods. The price has converged to the fair value at that point, $P_J = \tilde{P}_J$. Then

$$P_0 - \tilde{P}_0 = E_0\left[\sum_{t=1}^{J-1} (e^{-\sum_{j=0}^{t-1}\alpha_j} - 1) D_t \frac{m_t}{m_0} + (e^{-\sum_{j=0}^{J-1}\alpha_j} - 1)(D_J + P_J)\frac{m_J}{m_0}\right]. \tag{B.2}$$

As discussed in Section 3, since P_0 is observable, we don't need to estimate directly the cumulative abnormal discounts to estimate this absolute price dislocation:

$$P_0 - \tilde{P}_0 = P_0 - E_0\left[\sum_{t=1}^{J} \frac{m_t}{m_0} D_t + \frac{m_J}{m_0} P_J\right]. \tag{B.3}$$

To obtain a relative price dislocation measure, we define the (log) price wedge:

$$PW_0 = \log\left(\frac{P_0}{\tilde{P}_0}\right) = -\log\left(E_0\left[\sum_{t=1}^{J} \frac{m_t}{m_0}\frac{D_t}{P_0} + \frac{m_J}{m_0}\frac{P_J}{P_0}\right]\right). \tag{B.4}$$

Next, we derive the equivalence between our definition of the price wedge and the definition of mispricing proposed by Cho and Polk (2021). Starting from the absolute price wedge scaled by the market price, as in Cho and Polk (2021), we obtain:

$$
\begin{aligned}
\frac{P_0 - \tilde{P}_0}{P_0} &= 1 - \sum_{t=1}^{J} E_0\left[\frac{m_t}{m_0}\frac{D_t}{P_0} + \frac{m_J}{m_0}\frac{P_J}{P_0}\right]. \\
&= \sum_{t=1}^{J} E_0\left[\frac{m_{t-1}}{m_0}\frac{P_{t-1}}{P_0}\right] - \left[\sum_{t=1}^{J} E_0\left[\frac{m_t}{m_0}\frac{D_t}{P_0}\right] + \sum_{t=1}^{J} E_0\left[\frac{m_t}{m_0}\frac{P_t}{P_0}\right]\right] \\
&= \sum_{t=1}^{J} E_0\left[\frac{m_{t-1}}{m_0}\frac{P_{t-1}}{P_0}\underbrace{E_{t-1}\left[\frac{m_t}{m_{t-1}}R_{f,t}\right]}_{=1}\right] - \left[\sum_{t=1}^{J} E_0\left[\frac{m_t}{m_0}\frac{D_t}{P_0}\right] + \sum_{t=1}^{J} E_0\left[\frac{m_t}{m_0}\frac{P_t}{P_0}\right]\right] \\
&= \sum_{t=1}^{J} E_0\left[\frac{m_t}{m_0}\frac{P_{t-1}}{P_0}R_{f,t}\right] - \sum_{t=1}^{J} E_0\left[\frac{m_t}{m_0}\frac{D_t + P_t}{P_0}\right] \\
&= -\sum_{t=1}^{J} E_0\left[\frac{m_t}{m_0}\frac{P_{t-1}}{P_0}\left(\frac{P_t + D_t}{P_{t-1}} - R_{f,t}\right)\right] \\
&= -\sum_{t=1}^{J} E_0\left[\frac{m_t}{m_0}\frac{P_{t-1}}{P_0}R_j^e\right] \qquad \text{(B.5)}
\end{aligned}
$$

The last expression is the Cho and Polk (2021) identity linking current mispricing to subsequent returns. Hence, with the additional assumption that the SDF prices the risk-free asset conditionally ($E_{t-1}\left[\frac{m_t}{m_{t-1}}R_{f,t}\right] = 1$), the two mispricing-measures are equivalent. However, note that our definition of the price wedge does not rely on the risk-free rate assumption.

C. Definitions

TABLE C.1: **Characteristics.** This table lists the characteristics used in this paper. For each characteristic, we present the associated acronym, the original source and the definition of the characteristic.

Acronym	Author(s)	Definition
A2ME	Bhandari (1988)	Total assets (at) over market capitalization (prc x shrout)
AT	Gandhi and Lustig (2015)	Total assets (at)
ATO	Soliman (2008)	Net sales (sales) over lagged net operating assets. Net operating assets is the difference between operating assets and operating liabilities. Operating Assets is total assets (at) minus cash and short-term investments (che) minus investments and other advances (ivao). Operating Liabilities is total assets (at) minus debt in current liabilities (dlc) minus long-debt debt (dltt) minus minority interest (mib) minus preferred stock (pstk) minus common equity (ceq).
BEME (BM)	Davis et al. (2000)	Book equity to market equity. Book equity is shareholders' equity (seq), (if missing, common equity (ceq) plus preferred stock (pstk), if missing, total assets (at) minus total liabilities (lt)), plus deferred taxes and investment tax credit (txditc) minus preferred stock (pstrkrv), (if missing, liquidation value, (pstkl), if missing par value (pstk)). Market value of equity is shares outstanding (shrout) times price (prc).
aBEME	Asness et al. (2000)	$BEME$ minus average industry $BEME$. Industry level is defined as the Fama-French 48 industries.
C2A	Palazzo (2012)	Cash and short-term investments (che) to total assets (at).
C2D	Ou and Penman (1989)	Cashflow to debt. Cashflow is the sum of income and extraordinary items (ib) and depreciation and amortization (dp). And debt is to total liabilities (lt).
CAT	Haugen and Baker (1996)	Sales (sale) to lagged total assets (at).
D2P	Litzenberger and Ramaswamy (1979)	Debt to price. Debt is long-term debt (dltt) plus debt in current liabilities (dlc). Market capitalization is the product of shares outstanding (shrout) and price (prc).

Continued

Acronym	Author(s)	Definition
dCEQ	Richardson et al. (2005)	Annual % change in book value of equity (ceq).
dGS	Abarbanell and Bushee (1997)	% change in gross margin minus % change in sales (sale). Gross margin is the difference in sales (sale) and cost of goods sold (cogs).
dSO	Fama and French (2008)	Log change in the product of shares outstanding (csho) and the adjustment factor (ajex).
dSOUT	Pontiff and Woodgate (2008)	Annual % change in shares outstanding (shrout).
dPIA	Lyandres et al. (2008)	Change in property, plants and equipment (ppegt) and inventory (invt) over lagged total assets (at).
DTO	Garfinkel (2009)	Daily volume (vol) to shares outstanding (shrout) minus the daily market turnover and detrended by the 180 trading day median. To address the double counting of volume for NASDAQ securities, we follow Anderson and Dyl (2005) and scale down the volume of NASDAQ securities by 50% before and by 38% after 1997.
E2P	Basu (1983)	Income before extraordinary items (ib) to market capitalization (prc x shrout).
EPS	Basu (1977)	Income before extraordinary items (ib) to shares outstanding (shrout).
IDIOV	Ang et al. (2006)	Standard deviation of the residuals from a regression of excess returns on the Fama and French (1993) three-factor model.
I2A (INV)	Cooper et al. (2008)	Annual % change in total assets (at).
IPM		Pre-tax income (pi) over sales (sale).
IVC	Thomas and Zhang (2002)	Annual change in inventories (invt) in the last two fiscal years over the average total assets (at) over the last two fiscal years.
DP	Litzenberger and Ramaswamy (1979)	Sum of monthly dividend over the last 12 months to last month's price (prc).
SIZE	Fama and French (1992)	Price (prc) times shares outstanding (shrout) .
aSIZE	Asness et al. (2000)	$SIZE$ minus average industry $SIZE$. Industry level is defined as the Fama-French 48 industries.
TNOVR	Datar et al. (1998)	Volume (vol) over shares outstanding (shrout).
NOA	Hirshleifer et al. (2004)	Operating assets minus operating liabilities to lagged total assets (at). Operating assets is total assets (at) minus cash and short term investments (che) minus investment and other advances (ivao). Operating liabilities is total assets (at) minus debt in current liabilities (dlc) minus long-term debt (dltt) minus minority interest (mib) minus preferred stock (pstk) minus common equity (ceq).
OL	Novy-Marx (2011)	Sum of cost of goods sold (cogs) and selling, general and administrative expense (xsga) over total assets (at).
BETA_d	Lewellen and Nagel (2006)	The sum of the regression coefficients of daily excess returns on market excess returns and the lag of market excess returns.

Continued

Acronym	Author(s)	Definition
PCM	Gorodnichenko and Weber (2016)	Net sales (sale) minus cost of goods sold (cogs) all scaled by net sales (sale).
PM	Soliman (2008)	Operating Income after depreciation (oiadp) to sales (sale).
aPM	Soliman (2008)	PM minus average industry PM. Industry level is defined as the Fama-French 48 industries.
PROF	Ball et al. (2015)	Gross profitability (gp) over book equity as defined in $BEME$.
Q		Total assets (at) plus market value of equity (shrout x prc) minus book value of equity (ceq) minus deferred taxes (txdb) scaled by total assets (at).
MAXRET	Bali et al. (2011)	Maximum daily return in the previous month.
RNA	Soliman (2008)	Operating income after depreciation (oiadp) scaled by lagged net operating assets. Net operating assets is operating assets minus operating liabilities. Operating assets is total assets (at) minus cash and short term investments (che) minus investment and other advances (ivao). Operating liabilities is total assets (at) minus debt in current liabilities (dlc) minus long-term debt (dltt) minus minority interest (mib) minus preferred stock (pstk) minus common equity (ceq).
ROA	Balakrishnan et al. (2010)	Income before extraordinary items (ib) to lagged total assets (at).
ROC	Chandrashekar and Rao (2009)	Market value of equity (shrout x prc) plus long-term debt (dltt) minus total assets (at) all over cash and short-term investments (che).
ROE	Haugen and Baker (1996)	Income before extraordinary items (ib) to lagged book-value of equity.
ROIC	Brown and Rowe (2007)	Earnings before interest and taxes (ebit) less non-operating income (nopi) to the sum of common equity (ceq), total liabilities (lt), and cash and short-term investments (che).
R_12_2	Fama and French (1996)	Cumulative return from 12 months to 2 months ago.
R_12_7	Novy-Marx (2012)	Cumulative return from 12 months to 7 months ago.
R_6_2	Jegadeesh and Titman (1993)	Cumulative return from 6 months to 2 months ago.
R_2_1	Jegadeesh (1990)	Lagged one month return.
R_36_13	De Bondt and Thaler (1985b)	Cumulative return from 36 months to 13 months ago.
S2C	Ou and Penman (1989)	Net sales (sale) to cash and short-term investments (che).
S2P	Lewellen (2015)	Net sales (sale) to market capitalization (shrout x prc).
SG	Lakonishok et al. (1994)	% growth rate in sales (sale).
SAT	Soliman (2008)	Sales (sale) to total assets (at).
aSAT	Soliman (2008)	SAT minus average industry SAT. Industry level is defined as the Fama-French 48 industries.
SPREAD	Chung and Zhang (2014)	Average daily bid-ask spread in the previous month.

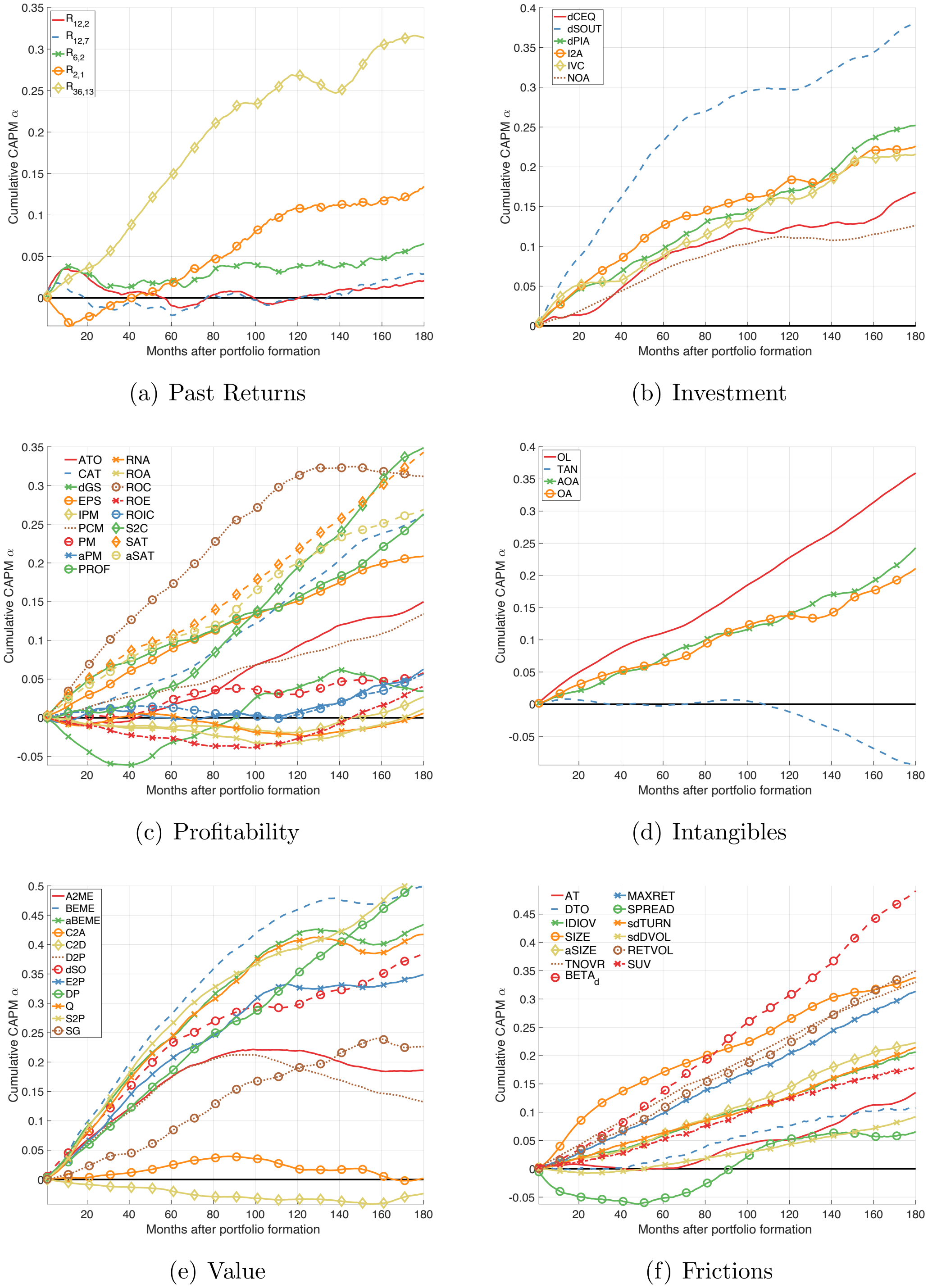
Continued

Acronym	Author(s)	Definition
sdTURN	Chordia et al. (2001)	Standard deviation of residuals from a regression of daily turnover on a constant. Turnover is volume (vol) times shares outstanding (shrout). Use one month of daily data requiring at-least 15 non-missing observations.
sdDVOL	Chordia et al. (2001)	Standard deviation of residuals from a regression of daily volume (vol) on a constant. Use one month of daily data requiring at-least 15 non-missing observations.
TAN	Hahn and Lee (2009)	Tangibility is defined as (0.715 x total receivables (rect) + 0.547 x inventories (invt) + 0.535 x property, plant and equipment (ppent) + cash and short-term investments (che)) / total assets (at).
RETVOL	Ang et al. (2006)	Standard deviation of residuals from a regression of excess returns on a constant using one month of daily data. We require there to be at least 15 non-missing observations.
SUV	Garfinkel (2009)	Difference between actual volume and predicted volume. Predicted volume is from a regression of previous month's daily volume on a constant and the absolute values of positive and negative previous month's returns. Unexplained volume is standardized by the standard deviation of the residuals from the regression.
OA	Sloan (1996)	Operating Accruals: Changes in non-cash working capital minus depreciation (dp), all scaled by lagged total assets (at). Changes in non-cash working capital is difference in current assets (act) minus difference in cash and short-term investments (che) minus difference in current liabilities (lct) minus difference in debt in current liabilities (dlc) minus difference in taxes payable (txp).
AOA	Bandyopadhyay et al. (2010)	Absolute value of OA

D. Additional Evidence

TABLE D.1: **Price Wedges up to 5 Years after Portfolio Formation: Alternative Resolution Assumption.** This table presents the long-short price wedge for select characteristics $n = 0, ..., 5$ years after portfolio formation, where $n = 0$ refers to the price wedge at the moment of portfolio formation. In the left panel, we use 15 years of cash flows to calculate the price wedge in year n (thus assuming that all mispricing is resolved $n + 15$ years after portfolio formation). In the right panel, we use $(15 - n)$ years of cash flows up to 15 years after portfolio formation as in Figure 8 of the paper. Results in the left panel are based on portfolios sorted from July 1964 to December 1997; results in the right panel are based on portfolios sorted from July 1964 to December 2002 (as in our baseline approach). In short, the ratio of the price wedge that remains five years after portfolio formation over the price wedge at the time of portfolio formation is similar for these two alternative resolution assumptions.

	Assumption: Mispricing resolved $n + 15$ years after portfolio formation						Assumption: Mispricing resolved 15 years after portfolio formation				
	BEME	Size	$R_{12,2}$	I2A	PROF		BEME	Size	$R_{12,2}$	I2A	PROF
0 to 15 yrs	-0.40	-0.32	0.17	-0.11	0.02	0 to 15 yrs	-0.51	-0.42	0.23	-0.19	0.05
1 to 16 yrs	-0.38	-0.29	0.27	-0.07	0.05	1 to 15 yrs	-0.48	-0.34	0.31	-0.12	0.10
2 to 17 yrs	-0.33	-0.25	0.24	-0.04	0.07	2 to 15 yrs	-0.44	-0.27	0.27	-0.09	0.13
3 to 18 yrs	-0.33	-0.21	0.24	-0.06	0.07	3 to 15 yrs	-0.39	-0.25	0.25	-0.09	0.14
4 to 19 yrs	-0.31	-0.20	0.23	-0.04	0.07	4 to 15 yrs	-0.33	-0.24	0.23	-0.07	0.15
5 to 20 yrs	-0.27	-0.19	0.20	-0.08	0.07	5 to 15 yrs	-0.28	-0.24	0.20	-0.11	0.15



(a) Past Returns

(b) Investment

(c) Profitability

(d) Intangibles

(e) Value

(f) Frictions

FIGURE D.1: **Cumulative CAPM Alphas (Long Portfolio).** This figure presents the log of the cumulative CAPM alpha for the long portfolio from one month to fifteen years after sorting for each of the 57 characteristics. We group the characteristics using the categorization of Freyberger et al. (2020).

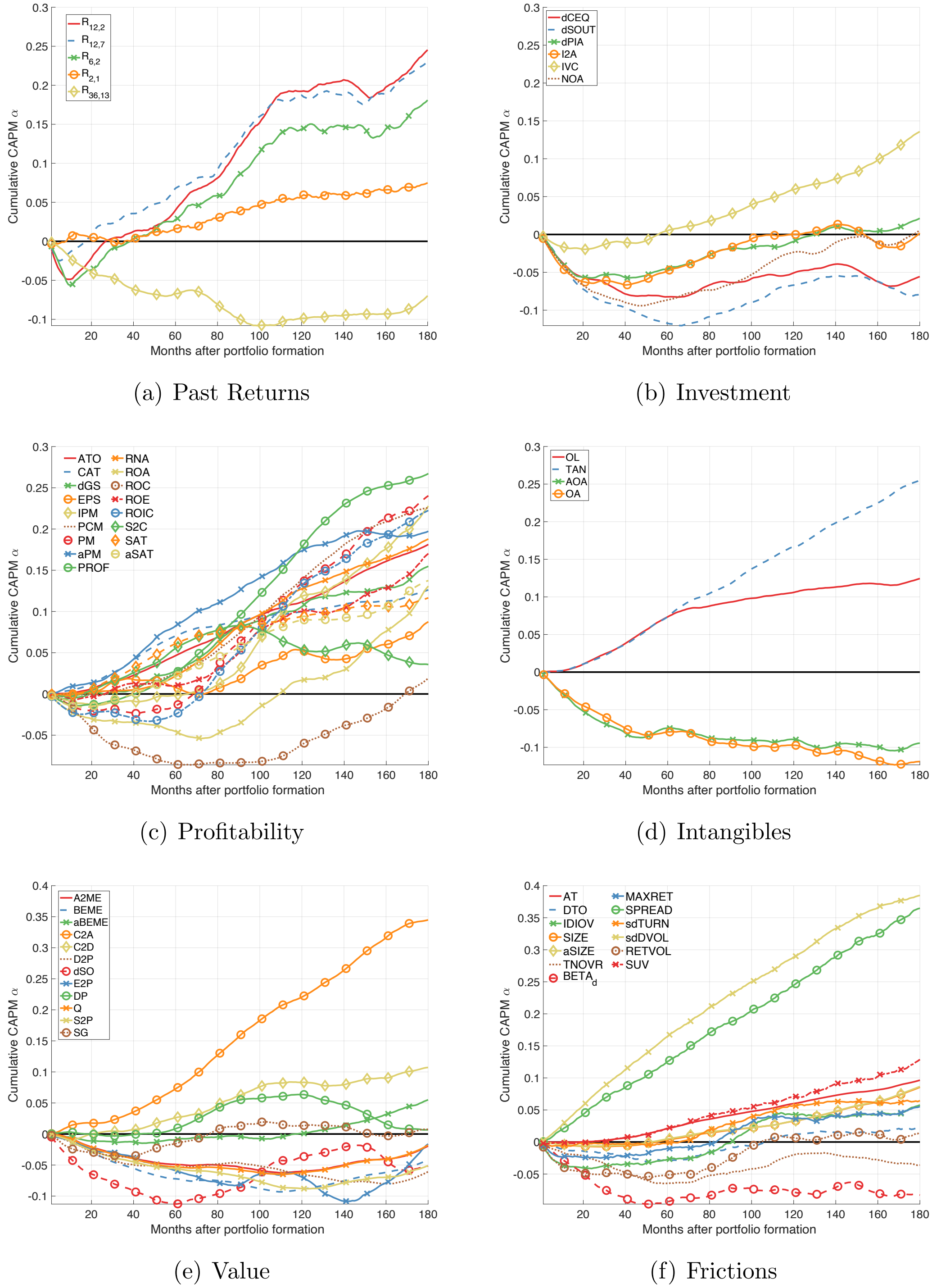
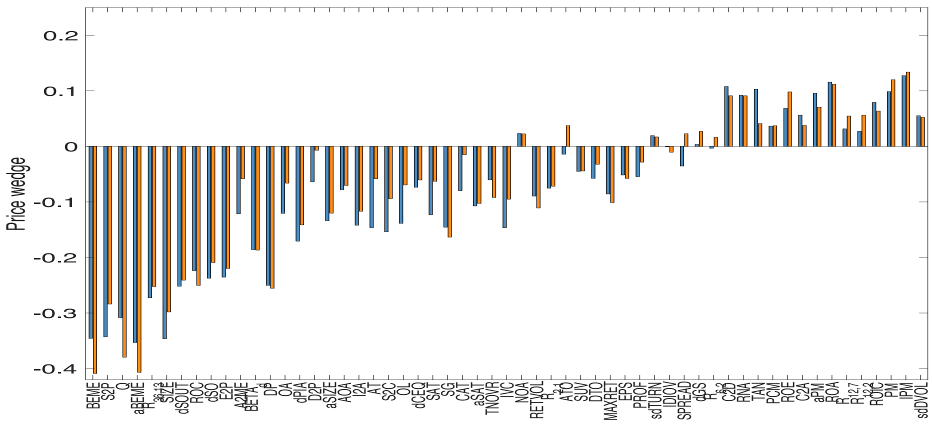
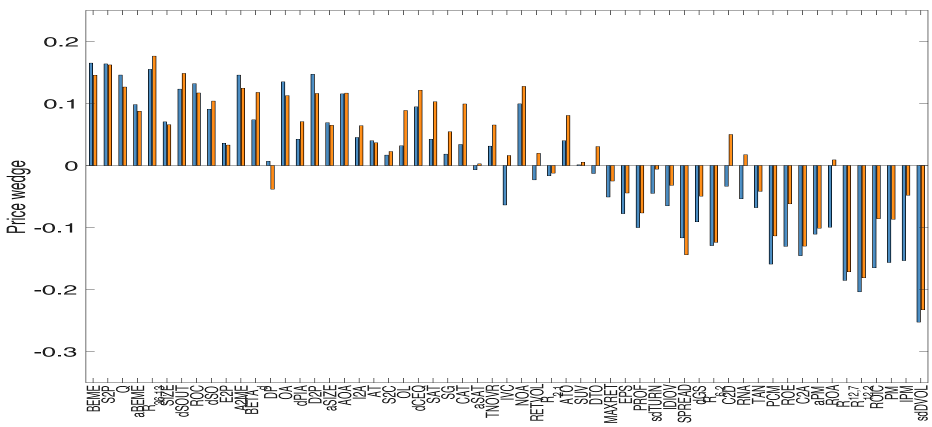


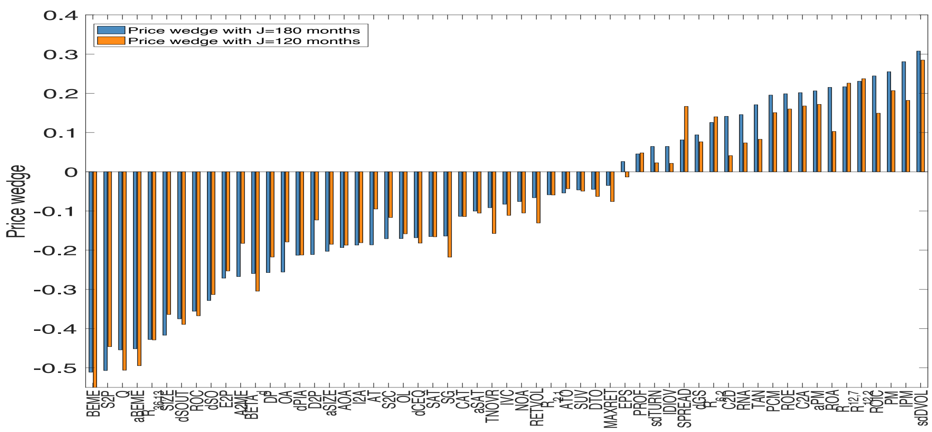
FIGURE D.2: **Cumulative CAPM Alphas (Short Portfolio).** The figure presents the log of the cumulative CAPM alpha of the short portfolio from one month to fifteen years for each of the 57 characteristics. We group the characteristics using the categorization of Freyberger et al. (2020).



(a) Long

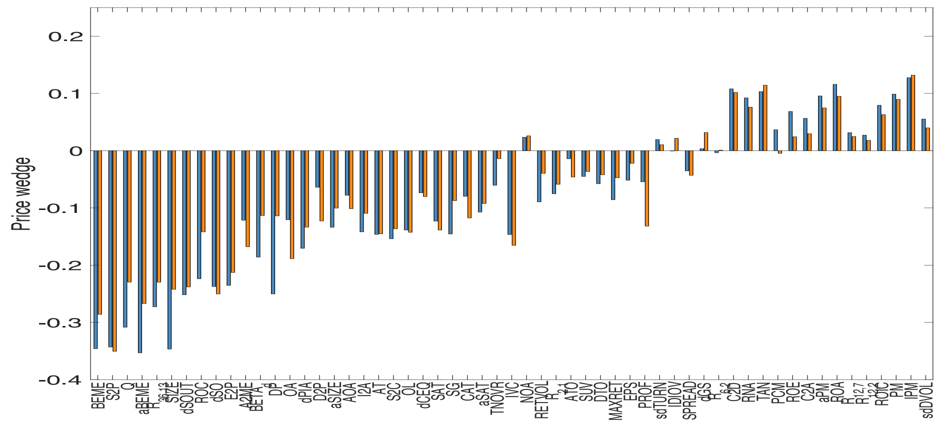


(b) Short

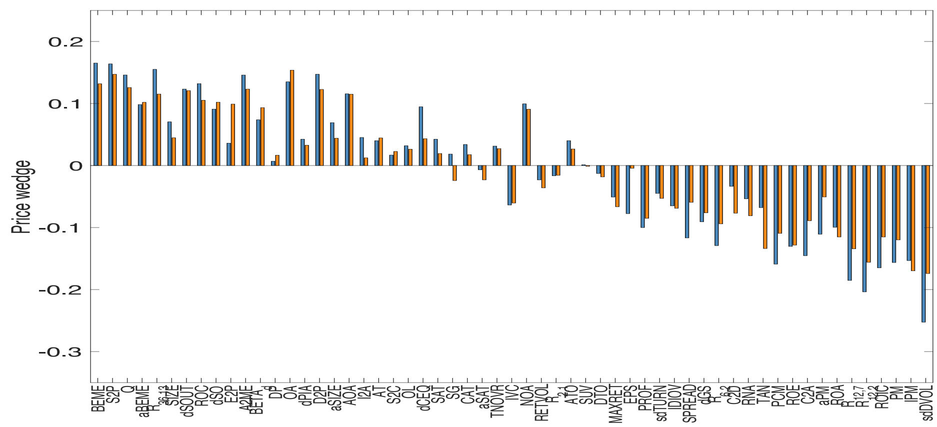


(c) Long-Short

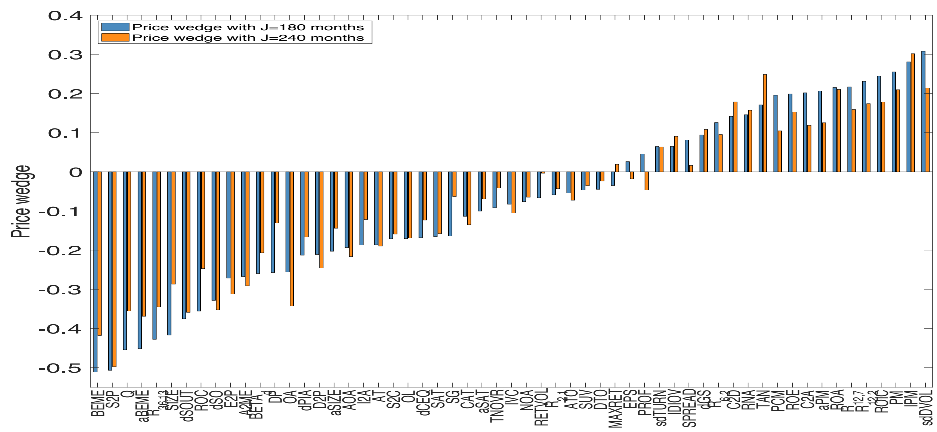
FIGURE D.3: **Price Wedges: Robustness for Convergence Horizon,** $J = 120$ **(10 years).** The figure presents price wedges for the long-short difference from sorts on each of the 57 characteristics. The price wedges are calculated using the CAPM SDF that sets the price wedge equal to zero for the market portfolio. In the panels, we order the characteristics from low to high according to the long-short differences of the price wedges obtained when considering $J = 180$ (15 years). Red bars refer to wedges when $J = 180$ (15 years). Blue bars refer to wedges when $J = 120$ (10 years).



(a) Long



(b) Short



(c) Long-Short

FIGURE D.4: **Price Wedges: Robustness for Convergence Horizon,** $J = 240$ **(20 years).** The figure presents price wedges for the long-short difference from sorts on each of the 57 characteristics. The price wedges are calculated using the CAPM SDF that sets the price wedge equal to zero for the market portfolio. In the panels, we order the characteristics from low to high according to the long-short differences of the price wedges obtained when considering $J = 180$ (15 years). Red bars refer to wedges when $J = 180$ (15 years). Blue bars refer to wedges when $J = 240$ (20 years).

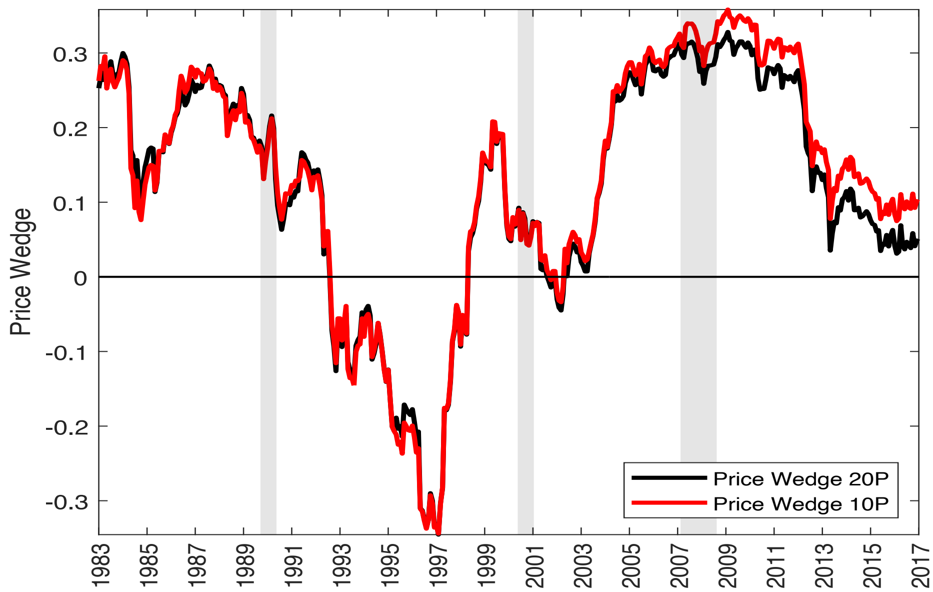


FIGURE D.5: **Price Wedge Analysis for Apple: 10 versus 20 Portfolios.** This figure plots our estimates for the price wedge of Apple's stock price when employing our method with either 10 or 20 portfolios for each of the 57 characteristics. We estimate the price wedge for each portfolio, map the portfolio-level price wedges to portfolio-level characteristics, and finally use this mapping to calculate firm-level price wedges based on firm-level characteristics.

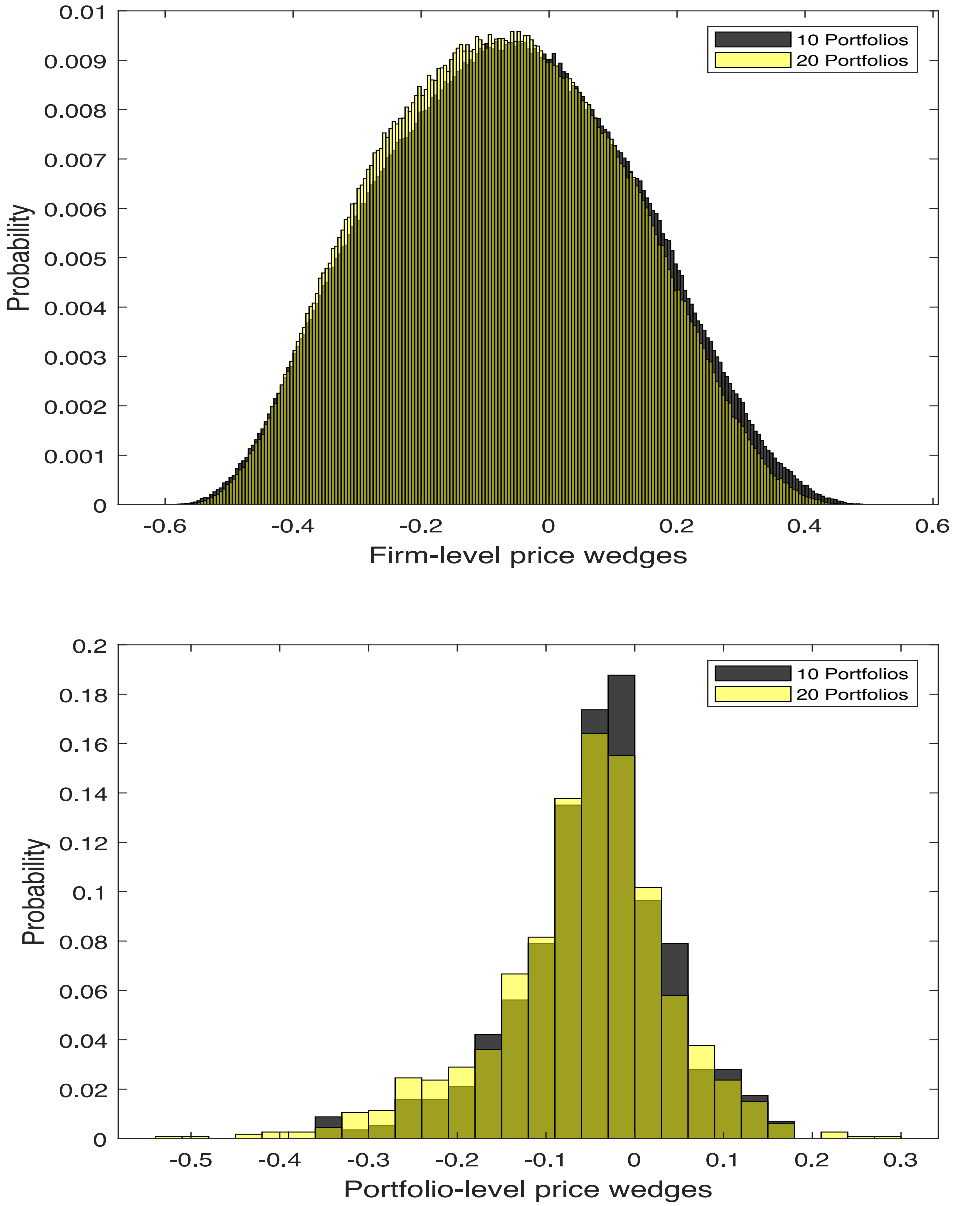


FIGURE D.6: **Histograms of Portfolio- and Firm-Level Price Wedges: 10 Versus 20 Portfolios.** The top panel plots the histogram of firm-level price wedges (the pool of price wedges covers all firm-months for which a price wedge can be estimated from 1964-07 to 2017-12). The distribution of firm-level price wedges does not change materially when we create a larger set of 20 portfolios (rather than 10 portfolios).