New and Old Sorts: Implications for Asset Pricing☆

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Abstract

We study the returns to characteristic-sorted portfolios up to five years after portfolio formation. Among a set of 56 characteristics, we find large pricing errors between the contemporaneous returns of new and old sorts, where new sorts use the most recent observations of firm characteristics. These relative pricing errors are not captured by existing asset pricing models and have been overlooked by standard tests using only returns to new sorts. Thus, pricing errors across horizons provide new and powerful information to test asset pricing models. Further, we show that these pricing errors are strongly related to a characteristic's market beta and connected to the difference in return between new and old stocks in the characteristic-sorted portfolios.

Keywords: Characteristic-Based Return Predictability, Horizon, Pricing Errors, Tests of Asset Pricing Models, Factors

JEL Classification: G11, G12

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In this paper, we study characteristic-based return predictability over horizons up to five years. Although existing literature on cross-sectional predictability almost exclusively focuses on the short-term returns to characteristic-based investing, studying longer horizon returns is interesting for various reasons. First, the horizon of most investors is considerably longer than a single month. Similarly, capital budgeting decisions of firms usually rely on discounting long-term cash flows. Furthermore, characteristics that predict returns more persistently are relatively important for the real economy (Van Binsbergen and Opp, 2019). Finally, and the main focus in this paper, longer horizon returns provide a new set of useful moments to evaluate asset pricing models.

We present a novel, but simple, approach to derive these moments from the relative performance of new and old characteristic-sorted portfolios. In particular, we show how standard asset pricing tests based on the intercepts from time-series regressions can be used to analyze pricing errors across horizons. We follow Freyberger et al. (2020) and start from a large set of 56 characteristics that previous literature finds to predict stock returns in the cross-section. For each characteristic X, we construct value-weighted decile portfolios and track the buy-and-hold return of the high-minus-low strategy from one month up to five years after portfolio formation. This approach provides us with a three-dimensional panel of returns denoted $R_{X,(t-s),t+1}$, where $(t-s)$ refers to the sorting date and $s = 0, ..., 60$. A pricing error across horizons is then defined as the intercept or alpha in a regression of the return to an older sort, $R_{X,(t-s),t+1}$ for $s > 0$, on the contemporaneous return of the newest sort, $R_{X,(t),t+1}$. A significant alpha indicates that the maximum Sharpe ratio increases when an investment in the newest sort is combined with an investment in the older sort.

Our null hypothesis is that these alphas are equal to zero. We show that this null holds when expected returns decay after sorting at the same speed as the characteristic spread between the high and low portfolio. Equivalently, this null holds when the compensation for a portfolio's loading on a characteristic at a given point in time is independent of how long ago the portfolio was formed, an assumption which is implicit in previous literature.[1]

This null is strongly rejected in the data. Old sorts provide a significant alpha relative to the newest sort for more than half of the characteristics we study over the sample from 1974 to 2017. For instance, three years after portfolio formation, a high-minus-low book-to-market strategy provides an alpha of 43 basis points per month (t-stat=2.95) relative to the newest book-to-market strategy. We show that such pricing errors across horizons are not due to the fact that the persistence of return predictability varies across characteristics.[2] Rather, these pricing errors are due to the fact that the persistence of characteristic-based return predictability does not match the persistence of the characteristic. For over one-third of the 56 characteristics we study, the older sorts provide a significantly negative alpha, indicating that average returns decay too fast after portfolio formation relative to the decay in the characteristic spread. For over one-sixth of the characteristics, the older sorts provide a significantly positive alpha, indicating that average returns decay too slow. We perform a simulation study under the null to show that these results are unlikely due to chance. A variety of robustness checks confirm that our conclusions extend in subsamples and when estimating conditional alphas.

Existing asset pricing models fail to capture the alphas between old and new sorts; said differently, existing models do not capture the horizon-dynamics of characteristic-sorted portfolio returns. To understand this failure, note that correlations between new and old characteristic-sorted portfolios are generally high and decrease slowly as time passes after portfolio formation. For the median characteristic, the correlation between the return of the newest sort and the return of older sorts that were performed one and five years ago, respectively, equals 0.85 and 0.64. While there is variation in this correlation across characteristics – consistent with variation in persistence in the ranking of firms – we find that this variation is unrelated to the alphas between old and new sorts. When

[1]A unit book-to-market spread may capture a different compensation today than it did three years ago, because characteristic premia vary over time. Our null only states that if a portfolio formed three years ago presents a 0.5 book-to-market spread today, this spread should capture half the expected return compensation of a unit book-to-market spread on a portfolio formed today.

[2]For instance, while book-to-market and size predict returns up to five years out, the predictability from profitability and momentum is relatively short-lived.

old and new sorts are highly correlated, but there is a large alpha separating these two returns, models that do a good job explaining returns of older sorts will have a hard time explaining returns of newer sorts and vice versa.

There is an important trade-off in the number of factors, however. Small models, like the CAPM, do relatively well pricing the older sorts (consistent with Kothari et al. (1995) and Cohen et al. (2009), among others), but are firmly rejected using the returns of newer sorts. In contrast, big models, like the five-factor model of Fama and French (2015), do relatively well pricing the newer sorts, but are firmly rejected using the returns of older sorts. A large literature adds factors to the CAPM to improve the model's explanatory power for cross-sections of returns at short horizons after portfolio formation (i.e., new sorts). We show that these additional factors do not help to eliminate pricing errors across horizons. As argued in Harvey and Liu (2019), some of the improved fit for short-term returns is likely due to overfitting, which harms the performance of these models in tests that use our new moments.

The tension between new and old sorts is perhaps clearest when we apply principal component analysis (PCA) to the returns at each horizon. We treat the principal components extracted from the returns of the newest sorts, $R_{X,(t),t+1}$, as statistical factors in an asset pricing model (as in Lettau and Pelger (2020), Haddad et al. (2020), and Kozak et al. (2019)). In GRS tests, we find that these statistical factors do not price the principal component factors extracted from older sorts. Interestingly, the rejection in the GRS test is driven almost completely by a pricing error across horizons in the first principal component of returns. Consistent with this finding, our evidence suggests that adding a single factor extracted from old sorts to three statistical factors extracted from the newest sorts goes a long way to capture the pricing errors across horizons. This model also does a relatively good job capturing variation in average returns in cross-sections of new and old sorts. In fact, it is the only model for which the cross-sectional R^2 is positive when factor risk premia are forced to match their sample average return.

Our analysis further uncovers a new dimension to the low beta anomaly, as the pricing errors across horizons are related to market beta. The low beta anomaly refers to the result – first documented in Black et al. (1972) – that a sort of stocks on market beta yields a large spread in beta, but not in average returns. Consequently, a high-minus-low market beta portfolio obtains a large negative CAPM alpha. Similarly, we sort characteristic-sorted portfolios on their market beta. We find that it is among low market beta characteristics that the pricing errors are relatively large and negative, meaning that average returns decay too fast relative to the characteristic. Existing asset pricing models do not capture the difference in pricing errors between low and high market beta characteristics either.

The fact that returns immediately after portfolio formation are different from returns longer after portfolio formation, suggests that "new" stocks recently entering the extreme decile portfolio have a different contribution to returns than "old" stocks that entered the portfolio a long time ago. To see whether this is the case, we decompose $R_{X,(t),t+1}$ into the part coming from new and old stocks. These stocks together make up the extreme high or low characteristic-sorted portfolio today, but it is only the old stocks that were relatively close to that same characteristic-sorted portfolio in the past.

We find that the old-minus-new return differential lines up well with the pricing errors across horizons among the 56 characteristics we study. For instance, a book-to-market strategy that uses only new stocks (that have recently seen a relatively large change in book-to-market), obtains a return that is 57 bps (t-stat = 2.18) lower than a strategy that uses only old stocks. This result obtains even though these two sets of stocks generate the same spread in book-to-market today. In addition, it is among low (high) market beta characteristics that an old-minus-new stock strategy provides a significant negative (positive) return that is not captured by existing asset pricing models. This result implies that characteristic-based investment strategies should take into account the dynamics of characteristics at the firm level. This practical insight is important, because most stock-picking applications ignore these dynamics and explicitly reduce the information set to the most recent values of firm characteristics.[3]

In all, we provide evidence for statistically and economically large pricing errors across horizons. These pricing errors are not explained by existing factor models, which is perhaps unsurprising given that previous asset pricing tests in the literature have ignored the moments we derive from old characteristic-sorted portfolios.[4] However, since our new set of moments shed light on the dynamics of return predictability and the performance of factors at different horizons, our results are relevant not only for academics interested in evaluating asset pricing models, but also for characteristic-based investment strategies and for estimating discount rates used in firm's capital budgeting decisions.

Literature

The literature on characteristics-based return predictability is vast, but almost exclusively studies the relation between characteristics and short-term future returns in the cross-section of stocks. In recent machine learning literature, the goal is to find the (potentially higher-order) functional form of a large set of characteristics that best predicts these returns (see, e.g., Freyberger et al. (2020), Gu et al. (2019), and Kozak et al. (2019)). Similarly, empirical tests of asset pricing models typically use both factors and test assets derived from sorting stocks on recent observations of characteristics (see, e.g., Fama and French (2015, 2018), Hou, Xue, and Zhang (2015, 2018a)). We instead investigate whether and how characteristics predict returns over horizons up to five years. We derive pricing errors across horizons from these returns, which we use as new moments to test asset pricing models.

[3]See, among many others, Brandt et al. (2009), Lewellen (2014), Light et al. (2017), and Gu et al. (2019) as well as the factor models of BARRA (`https://www.msci.com/www/research-paper/the-barra-us-equity-model-use4/014291992`) and Bloomberg (Baturin et al., 2010) that are popular in the industry.

[4]Our results also present a challenge for the leading theoretical explanations of characteristics-based return predictability, because the main focus in existing models is to match the relation between one-period ahead returns and current firm characteristics. To see this by example, we find that there is little difference between the returns of new and old sorts, as well as between new and old stocks, when we simulate from the models of Gomes et al. (2003) and Zhang (2005).

Keloharju et al. (2020) and Cho and Polk (2019) analyze returns to characteristic-based investing over even longer horizons of ten and fifteen years, respectively. Keloharju et al. (2020) show that return predictability vanishes quickly as time passes after portfolio formation for the average characteristic. Cho and Polk (2019) study how long-term abnormal returns impact current price levels. In contrast to both papers, we study the relative performance of new and old sorts at the monthly frequency, which allows us to highlight new implications for characteristic-based investing and return predictability. Moreover, we are the first to show that existing asset pricing models are unable to explain the relative performance of new and old sorts. Chernov et al. (2018) show that the restrictions implied by a stochastic discount factor (SDF) that prices single period returns of popular factors, like those of Fama and French, do not hold for long-term returns of the same factors. Our paper is different in important dimensions: (i) our test uses returns at longer horizons after characteristic-based portfolios are formed, whereas their test uses multi-period compounded returns of factors that are rebalanced annually; (ii) our empirical approach is relatively flexible, such that we can apply standard time-series regression techniques to test asset pricing models; (iii) we study a much larger set of 56 characteristics; and (iv) we document the relative contribution of new versus old stocks to the returns from characteristic-based investing.

Our new-versus-old decomposition of characteristic-sorted portfolio returns is new to the literature. In a recent paper, Keloharju et al. (2020) decompose characteristics in permanent and transitory components. The authors then sort the full cross-section of stocks on these components and find that it is the transitory component that drives return predictability for the average characteristic. Instead, our decomposition separates the stocks within the extreme high and low decile portfolios in a new and old group. The fact that the old-minus-new return differential varies in sign across characteristics remains hidden when focusing on the average characteristic. Our results imply that past values of characteristics (or changes in characteristics) contain information for the cross-section of stock returns that is not already contained in the most recent value of these characteristics. We thus extend Cochrane (2011) and Gerakos and Linnainmaa (2018), who draw a similar conclusion for book-to-market and size.

Daniel et al. (2020b) (see, also, Daniel and Titman (1997) and Herskovic et al. (2019)) argue that factors can be traded more profitably by combining a factor, like the high-minus-low book-to-market portfolio (HML), with an offsetting position in a hedge portfolio that has a zero loading on the characteristic (book-to-market), but a maximum loading on the factor. We argue that combinations of newer and older sorts are attractive investments and show that these combinations provide returns that are not captured by popular factors, among which are the optimally hedged factors of Daniel et al. (2020b). In fact, our evidence is inconsistent with their assumption that firms' loadings on the SDF are a function of recent values of size, book-to-market, profitability and investment. The reason is that our old-minus-new stock strategy is approximately neutral with respect to recent values of these characteristics, but has a non-zero average excess return. More generally, our evidence rejects the assumption that the expected return of a portfolio, in a given period and holding its loadings on characteristics fixed, is independent of the time this portfolio was formed. Finally, we uncover a new – across-characteristic – dimension to the low beta anomaly, which contributes to recent literature that documents low beta anomalies in a range of asset classes (see, e.g., Asness et al. (2012) and Frazzini and Pedersen (2014)).

1. Null hypothesis

We are the first to test whether the returns to older sorts are spanned by the newest sort. This null hypothesis holds under two assumptions. Let $X_{H-L,(t)}$ denote the characteristic spread – the difference between the average characteristic in the long and short portfolio – for the sort performed at t; let $R_{X,(t),t+1}$ denote the returns to the newest sort; and, let $R_{X,(t-s),t+1}$ denote the returns to older sorts. First, we assume that the long-short portfolio for a characteristic X is neutral with respect to other characteristics, at all horizons after sorting. Second, consistent with Daniel et al. (2020b, see Eq. (18)) and many others in the literature, we assume that each characteristic X represents a linear combination of exposures, denoted $\beta_{X,(t)}$, to priced fundamental factors with returns F_{t+1}. This combination may vary across X.

Under these two assumptions, we can write for the newest sorts:

$$E(R_{X,(t),t+1}) = \beta'_{X,(t)}\mu_F = X_{H-L,(t)}\gamma_X, \tag{1}$$

where μ_F is the vector of risk premia for the fundamental factors and γ_X translates the characteristic spread to a particular factor mix. For the older sorts, we have that

$$E(R_{X,(t-s),t+1}) = X_{H-L,(t-s)}\gamma_X = \frac{X_{H-L,(t-s)}}{X_{H-L,(t)}}E(R_{X,(t),t+1}), \tag{2}$$

where $X_{H-L,(t-s)}$ denotes the high-minus-low characteristic spread at time t for the old sort performed at $t-s$. This equation states our main result, which is that expected returns decay after sorting at the same speed as the characteristic spread. This result holds equally if the risk premia μ_F are time-varying. The result does require that risk premia are independent of when the portfolio was sorted (i.e., $E(R_{X,(t),t+1})/X_{H-L,(t)} = E(R_{X,(t-s),t+1})/X_{H-L,(t-s)} = \gamma_X)$, which assumption is implicit in previous literature.

Realized returns on both the new and old sorts contain factor risk as well as uncorrelated residual risk: $R_{X,(t),t+1} = \beta'_{X,(t)}F_{t+1} + e_{(t),t+1}$. In the regression

$$R_{X,(t-s),t+1} = \alpha_s + \beta_s R_{X,(t),t+1} + \varepsilon_{X,(t-s),t+1}, \tag{3}$$

we will then have that $\alpha_s = 0$ (and $\beta_s = (X_{H-L,(t-s)}/X_{H-L,(t)})$). Thus, under our two assumptions, pricing errors between old and new sorts (or, more generally, across horizons) are zero.

We acknowledge that the first assumption – the portfolios remain characteristic-neutral at all horizons after sorting – may be a strong one. However, even if the first assumption is violated, any relative pricing error between old and new sorts is eliminated by controlling for the fundamental factors in Eq. (3) as long as the second assumption holds. Given that the true set of fundamental factors is unknown, we control for the factors in a large set of benchmark models in our empirical analysis. While in theory the null can also be rejected due to non-linearities in the relation between characteristics, factor exposures, and thus expected returns, we show in Section 5 that non-linearities are unlikely to explain our results.

Our empirical investigation of pricing errors across horizons answers at least three important questions. First, do existing (multi-factor) asset pricing models price $R_{X,(t-s),t+1}$ and suitable combinations of $R_{X,(t-s),t+1}$ and $R_{X,(t),t+1}$? Almost all existing literature has focused on finding factors that explain return variation shortly after portfolio formation (i.e., $R_{X,(t),t+1}$), which has raised concerns of data mining (see, e.g., Harvey and Liu, 2019). Our method provides a new set of moments to test asset pricing models. Second, if existing models do price $R_{X,(t-s),t+1}$, which factors are more important at different horizons? For instance, Keloharju et al. (2020) show that for the average characteristic, the CAPM does a great job in pricing characteristic-sorted portfolio returns at longer horizons after portfolio formation. Whereas their focus is on the average characteristic, we highlight in this paper the variation across characteristics. Third, how should investors optimally construct characteristic-based portfolios? The large literature on cross-sectional return predictability typically only studies the return one month (or a few months) after sorting. However, a significant pricing error implies that the maximum Sharpe ratio from investing in a combination of the older and the newest sorts is larger than the Sharpe ratio from an investment in the newest sort alone.

2. Data and Methodology

We test this null hypothesis for a large set of firm characteristics that previous literature finds to predict stock returns in the cross-section. Our choice of 56 characteristics follows

Freyberger et al. (2020) and we provide a detailed description in Table IA.I.[5] 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.[6]

We construct for each characteristic value-weighted decile portfolios split at NYSE breakpoints to reduce the influence of microcap stocks on our results (see, also, Fama and French (2016) and Hou et al. (2018b)). We track the buy-and-hold returns to these decile portfolios up to five years after sorting. When a stock goes missing, we reallocate the investment in this stock to the non-missing stocks in the portfolio using value-weights. The return to a characteristic-sorted portfolio is defined as the return of the zero-cost, long-short portfolio formed from buying the High portfolio and selling the Low portfolio:[7]

$$R_{X,(t-s),t+1} = R^{High}_{X,(t-s),t+1} - R^{Low}_{X,(t-s),t+1}.$$

In this definition, the first subscript refers to the characteristic, $X = 1, \ldots, 56$, the second subscript refers to the date of portfolio formation or sorting date, $(t-s)$ where $s = 0, ..., 60$, and the third subscript refers to the return realization date, $t+1$. For brevity and because some characteristics are updated only once per year, we focus on $s = 0, 12, 24, ..., 60$.[8]

[5] Freyberger et al. (2020) use 62 characteristics. We exclude characteristics that have missing observations in the beginning of the sample, because our tests require a common sample start. We also exclude two characteristics that measure conditional market beta, because we study in detail the link between market beta and our results in Section 4.3.

[6] Thus, to predict returns for month $t+1$, the characteristics use monthly variables as they were reported at the end of month t and annual variables as they were reported at the end of month $t-6$. Using the most up-to-date characteristic values helps to differentiate new and old sorts.

[7] For a characteristic X that predicts returns with a negative sign, like size, we sort on $-1 \times X$. Signing the characteristic-sorted portfolio returns in this way makes our results more comparable to previous work (e.g., Freyberger et al. (2020) and Haddad et al. (2020)), but leaves our conclusions unchanged. If some return R_X expands the mean-variance frontier, $-R_X$ will do so as well; and, if an asset pricing model does not price R_X, it will not price $-R_X$ either.

[8] We focus on returns up to five years after portfolio formation, because it is only for a handful of characteristics that returns beyond the five-year horizon provide an alpha relative to both the newest sort ($s = 0$) and the older sorts with $s \leq 60$. For instance, ten years after portfolio formation, $R_{X,(t-120),t+1}$ provides a significant alpha for 12 (out of 56) characteristics relative to $R_{X,(t),t+1}$ and for 2 characteristics

Throughout, we refer to $R_{X,(t),t+1}$ as the return to the newest sort, and to $R_{X,(t-s),t+1}$ for $s > 0$ as the return to older sorts. Following Jegadeesh and Titman (1993), we combine six sorts for each horizon $s > 0$ to reduce noise.[9]

The novelty of our method is in varying the sorting date, so that one observes contemporaneous returns to portfolios sorted on the same characteristic at different lags. In this way, we can run standard asset pricing tests using monthly returns, like Jensen's (1968) alpha and the Gibbons et al. (1989, GRS) test, while studying effectively the return to a multi-period investment in a characteristic-sorted portfolio.

For an unconditional test of the null hypothesis, we estimate the alpha of older sorts to the newest sort with the full-sample regression:

$$R_{X,(t-s),t+1} = \alpha_s^u + \beta_s^u R_{X,(t),t+1} + \varepsilon_{X,(t-s),t+1}. \tag{4}$$

Intuitively, α_s^u is the average return to a strategy that invests in $R_{X,(t-s),t+1}$ and hedges unconditionally the exposure to $R_{X,(t),t+1}$. We denote the return of this strategy $R^{u-hedge}_{X,(t-s),t+1} = R_{X,(t-s),t+1} - \beta_s^u R_{X,(t),t+1}$. We also consider a conditional test. To this end, we construct the returns to a strategy that hedges in each month $t+1$ using only information available up to t:

$$R^{c-hedge}_{X,(t-s),t+1} = R_{X,(t-s),t+1} - \beta^c_{s,t} R_{X,(t),t+1}, \text{ with } \beta^c_{s,t} \text{ from:} \tag{5}$$

$$R_{X,(\tau-s),\tau+1} = \alpha_s + \beta^c_{s,t} R_{X,(\tau),\tau+1} + \varepsilon_{X,(t-s),\tau+1}, \ \tau = t-59:t. \tag{6}$$

We denote by α_s^c the average return to $R^{c-hedge}_{X,(t-s),t+1}$, which is the return to an investment in $R_{X,(t-s),t+1}$ that is hedged with a position in $R_{X,(t),t+1}$ equal to the beta estimated over a 60-month historical rolling window.[10] These conditional alphas represent an out-of-sample test of the relative performance of old and new sorts. Because we need to (i)

relative to $R_{X,(t-60),t+1}$. There is no characteristic for which both these alphas are significant.

[9] For instance, the monthly return five years after portfolio formation is defined as: $\sum_{\tau=-2}^{3} R_{X,(t-60+\tau),t+1}/6$.

[10] The pre-estimation of $\beta^c_{s,t}$ leads to errors-in-variables. Since these hedged returns are mostly used as dependent variables in our paper, the consistency of most of our estimates will be unaffected.

observe contemporaneous returns $R_{X,(t),t+1}$ and $R_{X,(t-60),t+1}$ and (ii) estimate conditionally hedged returns using only historical data, we lose a total of ten years at the start of our sample. Hence, we analyze returns to characteristic-sorted portfolios from July 1974 to December 2017 in the following.

3. Pricing errors across horizons: Do new sorts span old sorts?

In this section, we test whether the newest sort spans older sorts, as predicted by our null hypothesis. We first zoom in on a subset of four characteristics that are popular in the literature and then present the evidence for the full set of 56 characteristics.

3.1 Pricing errors for four popular characteristics

We analyze the four characteristics that feature in the Fama and French (2015) five-factor model: book-to-market, size, investment, and profitability. In Panel A of Table I, we present summary statistics for the characteristic-sorted portfolios up to five years after portfolio formation. We report the average number of firms in the High plus Low portfolio as a reality check for the method. Five years after portfolio formation, these portfolios still contain about 55% of the original number of stocks, which suggests that the portfolios remain sufficiently diversified. Next, we confirm previous literature in that each of the four characteristic-sorted portfolios obtains a positive average return one month after portfolio formation, ranging from 31 bps for size to 53 bps for book-to-market.

[Insert Table I about here]

At longer horizons after portfolio formation, the differences across characteristics become larger, however. The book-to-market and size effects are large and (marginally) significant at all horizons up to five years after portfolio formation. In fact, both effects are largest one year after portfolio formation (at 61 bps and 50 bps, respectively), after which they slowly decrease (to 38 and 36 bps, respectively, after five years). In contrast, the profitability and investment effects are small and insignificant from two years after portfolio formation onward. Thus, the persistence of return predictability varies considerably across these popular characteristics.

Characteristic-persistence, that is persistence in the cross-sectional ranking of stocks, also varies considerably across these characteristics, however. For instance, the time-series average of the cross-sectional (rank-order) correlation between book-to-market at t and $t-12$ equals 0.76, whereas this correlation is only 0.25 for investment. The higher the persistence of a characteristic, the more likely it is that a stock in the high portfolio at $t-12$ is also in the high portfolio at t, which mechanically generates correlation between the returns of old and new sorts. For this reason exactly, our main interest is not in a comparison of average returns between old and new sorts. Rather, we are interested in pricing errors between old and new sorts – the unconditional and conditional alphas of Eqs. (4) and (5) – that control for this correlation.

We report these alphas in Panel B of Table I. We find that a large number of alphas are economically large and significant. In fact, these alphas share many of the patterns we saw in average returns, suggesting that the variation across characteristics is not merely driven by variation in exposure of the older sorts to the newest sort. Let us focus on the conditional α_s^c from Eq. (5). This alpha is positive and (marginally) significant at all horizons up to five years out for book-to-market (at about 40 bps) as well as size (at about 20 bps). In contrast, we see mostly negative alphas for profitability, which are significant at about -24 bps from three to five years after portfolio formation, as well as for investment, which are (marginally) significant at about -26 bps four and five years after portfolio formation. In conclusion, we reject the null hypothesis presented in Section 1 even for the most popular characteristics: there are significant pricing errors across horizons, which indicates that returns from the newest sort do not unequivocally span the returns of older sorts.

To appreciate the practical relevance of this conclusion, we present in Panel C the improvement in Sharpe ratio when optimally combining the old sort with the newest sort in a single portfolio.[11] For book-to-market, the Sharpe ratio from investing in the newest sort, $R_{BM,(t),t+1}$, equals 0.28. The Sharpe ratio doubles to 0.56 (= 0.28 + 0.28) when an investment in the older sort, $R_{BM,(t-12),t+1}$, is added. Similarly, for size, the optimal combination of $R_{Size,(t-12),t+1}$ and $R_{Size,(t),t+1}$ obtains a Sharpe ratio that is more than double the Sharpe ratio of an investment in $R_{Size,(t),t+1}$: 0.53 versus 0.23. For both book-to-market and size, the increase in Sharpe ratio falls gradually as time passes after portfolio formation, although it remains economically large at over 0.11 for all s. For profitability and investment, the largest increases in Sharpe ratio are observed when the return five-years after portfolio formation is combined with the return one-month after portfolio formation, at 0.14 and 0.10, respectively. In Panel D of Table I, we ask whether a five-factor model, including the market return as well as the return on the four newest characteristic-sorted portfolios, captures the alphas we document in Panel B. We find that the alphas at most horizons remain economically large and (marginally) significant for book-to-market, size, and profitability. Consequently, the GRS tests presented in the last column reject the null that the four alphas are equal to zero at all horizons. This rejection implies that the maximum Sharpe ratio obtained by investing in a portfolio that combines the older sorts with the newest sorts and the market is significantly larger than the maximum Sharpe ratio obtained when restricting the position in the older sorts to zero.

These findings are interesting in light of recent work by Daniel et al. (2020b) (see also Daniel and Titman (1997) and Herskovic et al. (2019)), who argue that factors can be traded more profitably by combining a factor, like the newest high-minus-low book-to-market portfolio (HML), with an offsetting position in a hedge portfolio. We instead

[11]The unconditional mean-variance optimal portfolio of the old and new sorts invests $\alpha_s^u/\sigma^2_{\epsilon_{(t-s)}}$ in $R_{X,(t-s),t+1}$ and $E(R_{X,(t),t+1})/\sigma^2_{(t)} - (\alpha_s^u/\sigma^2_{\varepsilon_{(t-s)}})\beta_s^u$ in $R_{X,(t),t+1}$. For instance, for book-to-market, the optimal portfolio invests 0.83 in $R_{X,(t-36),t+1}$ and 0.17 in $R_{X,(t),t+1}$. Although these optimal weights are extreme for some horizons for some of the 56 characteristics studied below, we find in those cases that the improvement in Sharpe ratio (relative to investing only in $R_{X,(t),t+1}$) is only slightly smaller when we restrict the weights to be in the interval $[-2, +2]$.

argue that combining the newest portfolio with an older portfolio improves investment opportunities.

3.2 Pricing errors for all 56 characteristics

We present in Figure 1 the unconditional α_s^u from Eq. (4) as well as the conditional α_s^c from Eq. (5) for all 56 characteristics. To facilitate interpretation, we sort the characteristics from low to high on the conditional alphas. For the sake of brevity, we focus on the alpha of a strategy that averages over the returns from one to five years after portfolio formation, denoted $R_{X,(t-60:t-12),t+1}$.

[Insert Figure 1 about here]

In contrast to the null hypothesis of zero alphas, we find that the older sorts provide an alpha relative to the newest sort for over half of the characteristics (both in the unconditional and conditional specification).[12] For over one-third of the characteristics (22 in total), the conditional alpha is negative with a t-statistic below -1.65. These (marginally) significant negative alphas range from -59 to -10 bps. A negative alpha implies that the decay in average returns is too fast relative to the decay in the characteristic spread. Among these negative alphas, we find a relatively large number of characteristics related to profitability (such as $PROF$, ROA, and profit margin, PM). For over one-sixth of the characteristics (11 in total), the alpha is positive with a t-statistic above 1.65. These (marginally) significant positive alphas range from 11 to 37 bps. A positive alpha implies that the decay in average returns is too slow relative to the decay of the characteristic spread. Among these positive alphas, we find a relatively large number of characteristics related to value (such as BM, Q, and sales-to-price, $S2P$). Given the fatter left tail of

[12] Figure IA.1 plots the average returns of the newest and the older characteristic-sorted portfolios. We see that there is large variation across characteristics in the difference between these average returns (Panel C). On average the difference is negative, which is consistent with the idea that return predictability fades as time passes after portfolio formation (e.g., Keloharju et al., 2020). We further see that the returns of the older sorts line up quite well with the alphas of Figure 1, which is not the case for the newest sorts.

the distribution of alphas, we conclude that average returns decay too fast for the average characteristic.

A variety of robustness checks confirms that pricing errors across horizons are a pervasive phenomenon among the characteristics we study. We present in Appendix A a simulation study that shows these results are unlikely to be generated under the null of zero alphas, even when the simulations respect the correlation structure (and other moments) of the data. Figure IA.2 shows that the alphas between old and new sorts are similar when we split our sample in two halves. Figure IA.3 and IA.4, respectively, show that the alphas are not driven by a small set of extreme returns in NBER recessions nor exclusively by periods of high sentiment. Figure IA.5 shows that alphas between old and new sorts are virtually identical when we correct for survivorship bias. While the return of the old sort, $R_{X,(t-s),t+1}$, conditions on firm survival from $t-s$ to t, the return of the newest sort, $R_{X,(t),t+1}$, does not. For these survivorship bias-corrected alphas, we calculate the return of the newest sort using only those stocks that were already in the CRSP file at $t-s$. We plot in Figure IA.6 the increase in Sharpe ratio from optimally combining the older sort ($R_{X,(t-60:t-12),t+1}$) with the newest sort ($R_{X,(t),t+1}$). Consistent with the large amount of significant (negative and positive) alphas, we see that large increases in Sharpe ratio of over 0.10 are common to 31 out of 56 characteristics.[13]

Our null predicts not only that the alpha of old sorts ($\alpha_s = 0$) is zero, but also that $\beta_s = X_{H-L,(t-s)}/X_{H-L,(t)}$. This prediction means that the exposure of old sorts to the newest sort, β_s, is equal to the high-minus-low characteristic spread that remains s months after portfolio formation, $X_{H-L,(t-s)}$, as a fraction of the same spread at portfolio formation, $X_{H-L,(t)}$. We calculate these spreads using the median value of the characteristic in the high and low portfolio to reduce the impact of outliers. Figure 2 plots these exposures and characteristic spreads at three horizons $s = 12, 36, 60$ in the same order as the conditional alphas in Figure 1. We see that variation across characteristics

[13]We find even larger increases in Sharpe ratio when we optimally choose one of the five older sorts to be included in a portfolio with the newest sort. The horizon s of the older sort for which this maximum Sharpe ratio is obtained varies across characteristics, which is why we focus on the average of the five older sorts.

in the exposure of old to new sorts lines up well with the characteristic spread at all horizons. At the three-year horizon, for instance, their correlation equals 0.86. This finding suggests that more persistent characteristics, such as size, generate larger correlation between old and new sorts. Less persistent characteristics, such as momentum and short-term reversal, generate substantially smaller correlation. Variation in persistence across characteristics cannot explain the pricing errors we document, however. Our estimates of these pricing errors explicitly control for the correlation between old and new sorts and Figure 3 shows that the pricing errors are virtually unchanged when we impose in their calculation the null-condition on β_s.

[**Insert Figures 2 and 3 about here**]

What drives the rejection of the null hypothesis then? Average returns after portfolio formation do not decay at the same speed as characteristic spreads. To see this by example, consider book-to-market. Average returns to this strategy are roughly constant until five years after portfolio formation (see Table I), even though only 80%, 53%, and 41% of the high-minus-low book-to-market spread remains one, three, and five years after portfolio formation, respectively. If the expected return compensation for a portfolio's loading on book-to-market was independent of the time the portfolio was formed, we would see an average return, e.g., three years after portfolio formation of 28bps (53% × 53bps), which is well below the average return of 49bps in the data. This mismatch between the persistence of the book-to-market characteristic and its returns generates the positive alpha of the old versus new book-to-market sorts.

Our rejection of the null hypothesis would not be surprising if old and new sorts are exposed differently to fundamental factors. In the next section, we show that exposure to the factors in benchmark asset pricing models cannot explain the alphas we document. To see the intuition for this result, we present the exposures of older sorts ($R_{X,(t-s),t+1}$, for $s = 12, ..., 60$) to the newest sort $R_{X,(t),t+1}$ in Figure 4. We see that these betas are quite large and persistent for most characteristics. The median beta (across characteristics) equals 0.77 one year after portfolio formation (i.e., for $R_{X,(t-12),t+1}$) and falls only slowly to 0.55 five years after portfolio formation (i.e., for $R_{X,(t-60),t+1}$).[14] Hence, models that do a good job explaining the returns to a characteristic-sorted portfolio at one horizon (e.g., the newest sort) will have a hard time explaining returns at another horizon (e.g., the older sorts), when (i) there is a large alpha separating these two returns and (ii) these returns are highly correlated. This tension is at the root of the asset pricing implications we derive from old and new sorts.

[**Insert Figure 4 about here**]

4. Implications for asset pricing models

To analyze the asset pricing implications of our results, we reduce the dimensionality of the data and extract, at each horizon, principal components from the characteristic-sorted portfolios. In the spirit of existing literature on the cross-section, we treat the principal components extracted from the newest sorts – with returns one month after portfolio formation – as statistical factors in an asset pricing model. We ask if these statistical factors as well as benchmark factor models from the literature capture the pricing errors across horizons. The benchmark models are the single-factor CAPM (Sharpe (1964), Lintner (1965), Mossin (1966)); the three-factor model of Fama and French (1993, FF3M); the five-factor model of Fama and French (2015, FF5M); and finally, a six-factor model including the factors in the FF5M and momentum (FF5M+MOM). We focus on these models to show the important trade off between small and big models. Results for the models of Hou et al. (2015, HXZ), Frazzini and Pedersen (2014, BAB), Daniel et al. (2020b, DMRS), Stambaugh and Yuan (2016, SY), and Daniel et al. (2020a, DHS) are consistent and summarized in Table IA.II of the Internet Appendix. To provide additional economic intuition, we relate the pricing errors across horizons to market beta.

[14] Correlations between old and new sorts are slightly larger, because $R_{X,(t),t+1}$ is typically more volatile than $R_{X,(t-s),t+1}$ (the median correlation equals 0.85 for $R_{X,(t-12),t+1}$ and 0.64 for $R_{X,(t-60),t+1}$).

4.1 Principal component analysis (PCA) of new and old sorts

PCA is a popular technique to extract latent factors from a large cross-section of returns. The motivation is that the SDF can be suitably approximated using only a few dominant principal component factors, when characteristic-sorted portfolios do not each represent an independent source of priced risk (Kozak et al., 2019; Haddad et al., 2020). We differ from existing literature, because we apply PCA not only to the returns of new sorts but also to the returns of old sorts. To be precise, we extract three principal components from $R_{X,(t-s),t+1}$ at horizons $s = 0, 12, ..., 60$. At each horizon, the three principal components explain about 60% of the total variation in returns.[15]

We perform GRS tests to determine whether (i) the principal components extracted from $R_{X,(t),t+1}$ (denoted $3PC_{(t),t+1}$), or (ii) benchmark asset pricing models, price the principal components extracted from $R_{X,(t-s),t+1}$, $s = 12, 24, ..., 60$. This question is interesting, because the test assets in most existing literature are returns to relatively "new" portfolios that are sorted on recent observations of characteristics. The factors in the FF5M, for instance, have been added sequentially to the CAPM, because they perform well for such test assets (Fama and French (1993, 1996, 2015)). We know relatively little about the performance of these factors for returns over longer horizons after portfolio formation.

Table II presents the results. In Panel A, we see that the GRS test rejects with a p-value of 0.0014 that the statistical factor model $3PC_{(t),t+1}$ prices the three principal components extracted from $R_{X,(t-12),t+1}$. At longer horizons, the rejection is even stronger at p-values < 0.0001. The fact that three statistical factors that explain most of the variation in $R_{X,(t),t+1}$ do not price the dominant components of $R_{X,(t-s),t+1}$, confirms that the relative pricing errors we document in Section 3 are statistically large. For the benchmark models, several results stand out. First, small models do relatively poorly at pricing the statistical factors extracted from $R_{X,(t),t+1}$: the GRS test rejects at a p-

[15] Our conclusions are unchanged when we extract the principal component factors using the approach of Lettau and Pelger (2020). Also, for reasons that will be clear below, the choice of the number of principal component factors has little impact on our conclusions.

value < 0.0001 for the CAPM and FF3M. In contrast, relatively large models do better at pricing these returns, as the GRS test does not reject at a p-value of 0.23 for the FF5M and 0.41 for the FF5M+MOM. Second, both small and large benchmark models fail to price the principal components extracted from returns at most horizons $s > 0$ after portfolio formation. However, if anything, the smaller models perform relatively well. For instance, the GRS test does not reject at the 10%-level for the CAPM and FF3M at the five-year horizon ($s = 60$), in contrast to the FF5M(+MOM).

[Insert Table II about here]

In all, these GRS tests confirm that there are large pricing errors across horizons and that existing asset pricing models fail to jointly price both the newest and older sorts. To understand which component is driving this result, we present in Table III the alpha for individual principal components at each horizon after portfolio formation. We estimate these alphas by running the following regressions:

$$\lambda'_{(t),z} R_{X,(t-s),t+1} = \alpha_s + \beta_s F_{t+1} + \epsilon_{(t-s),t+1}, \tag{7}$$

where F_{t+1} is one of the five candidate factor models: $3PC_{(t),t+1}$, CAPM, FF3M, FF5M, FF5M+MOM. Note that we apply the same loadings to returns at all horizons s after sorting, that is, the loadings $\lambda_{(t),z}$ of the z-th principal component extracted from the newest sorts with returns $R_{X,(t),t+1}$. In this way, we abstract from variation in the loadings of the z-th principal component across horizons, such that our results derive only from the relative pricing of $R_{X,(t-s),t+1}$ versus $R_{X,(t),t+1}$. Having said that, this choice does not affect our main conclusions, because the characteristic-sorted portfolio returns at different horizons are highly correlated (see Figure 4 and the related discussion in Section 3.2).

[Insert Table III about here]

In Panel A, we see that the first principal component of returns provides a large and significant alpha with respect to the statistical factor model $3PC_{(t),t+1}$ at longer horizons after portfolio formation. The estimated alpha is 68 bps (t-stat = 3.69) for $s = 12$ and is larger than 100 bps for $s > 12$ (t-stat > 5). For the second and third principal components, returns at longer horizons after portfolio formation are explained well by the $3PC_{(t),t+1}$ model. For the benchmark models in Panels B to E, several results stand out. Similar to the model with three statistical factors, the larger benchmark models do not price the return to the first principal component at longer horizons after portfolio formation. The alpha in the FF5M as well as FF5M+MOM are over 100 bps at horizons $s > 12$ (t-stat > 3). These larger models do price the return of the first principal component at horizons $s = 0, 12$. In contrast, the smaller benchmark models price the returns to the first principal component at longer horizons after portfolio formation ($s > 12$). These models fail completely at shorter horizons, however. For instance, the alpha at $s = 0$ is around -2.2% per month in the CAPM and FF3M. Finally, in contrast to the statistical factor model $3PC_{(t),t+1}$, the benchmark models also perform poorly pricing the second principal component of returns. The performance of small and big models again differs importantly. While the alpha of the second principal component is negative in the CAPM (around -1% and marginally significant at all horizons $s > 0$), it is positive in the larger factor models (around 70 bps and significant at most horizons s).

In all, the pricing errors across horizons are for the largest part driven by the first principal component of characteristic-sorted portfolios. This is easily verified in Figure 5, which plots the loadings of the first principal component on each characteristic.[16] We see that the loadings are almost monotonically increasing from left to right, in line with a correlation of 0.78 between these loadings and the alphas of old versus new sorts (as reported in Figure 1). The strength of this relation is surprising, because the principal component loadings are determined only by the variances and covariances of returns of the newest sorts. In light of this strong relation, it is unsurprising that a strategy that uses the principal component loadings as portfolio weights, obtains a return, say,

[16]These loadings are robust. When we split our sample in two halves around March 1996, the loadings of the first principal component in the first half of the sample are correlated at 0.81 with the loadings of the first principal component in the second half of the sample.

three years after portfolio formation that is hard to explain from the point of view of returns immediately after portfolio formation. The intuition behind this result is clear from the summary statistics presented in Panel B of Table II. The correlation between $\lambda'_{(t),1} R_{X,(t),t+1}$ and $\lambda'_{(t),1} R_{X,(t-36),t+1}$ is high at 0.91, whereas the average returns of these strategies is remarkably different at −60 bps versus 94 bps, respectively.

[Insert Figure 5 about here]

Given the high correlation between these two returns, differential exposure to the benchmark factors is unlikely to explain the difference in average returns. This suggestion is confirmed in Panel F of Table III. Here, we ask whether the benchmark models price a strategy that is long the first principal component of older sorts and short the first principal component of the newest sorts: $\lambda'_{(t),1}(R_{X,(t-36),t+1} - R_{X,(t),t+1})$. For all models and at all horizons s, this strategy provides a large and significant alpha. The larger models perform relatively well in this exercise, because the alphas decrease, for instance for $s = 36$, from 2.04% (t-stat=5.91) in the CAPM to 1.16% (t-stat = 3.47) in the FF5M+MOM.

In Panel B of Table IA.II of the Internet Appendix, we find a similarly large alpha for this strategy relative to three of the five alternative models: HXZ (1.21%, $t = 3.49$), BAB (1.38%, $t = 3.51$), and DMRS (1.64%, $t = 5.14$). For the remaining models, SY and DHS, the alpha of this strategy is only marginally significant at about 70 bps. Although these two models do relatively well at pricing this combination of the older and the newest sorts, both these models fail to price the first principal component of older sorts in isolation (see Panel A of Table IA.II). In conclusion, none of the benchmark models we study is able to price the returns to both new and old sorts. Consequently, a combination of the newest sort, which is the focus of most existing literature, with an older sort, provides a risk-return trade-off that is hard-to-explain from the point of view of existing asset pricing models.

4.2 What do factor models need to capture pricing errors across horizons?

Asset pricing models should jointly price newer and older sorts. We have seen that models with factors that are based on new sorts alone fail this challenge. What about models with factors based on new and old sorts? To answer this question, we consider a four-factor model that adds to the three principal components extracted from the newest sorts, a single factor capturing the return differential between older and newer sorts. In line with the above setup, we define this factor $\lambda'_{(t),1} R_{X,(t-36),t+1}$ and denote this model $4PC_{(t,t-36),t+1}$.

In Panel A of Table IV we present alphas for the principal components at each horizon with respect to this four-factor model. We see that the pricing errors across horizons for the first principal component are quite small, especially compared to alphas of > 1% in the three-factor model $3PC_{(t),t+1}$ (see Panel A of Table III). Having said that, the alpha is significant in the four-factor model at about 36 bps at the longest horizons ($s = 48, 60$). Similarly, the GRS test (which considers jointly the alphas of the first three principal components) does not reject at the 5%-level at shorter horizons, but rejects marginally at the longest horizons. This result marks a big improvement over the three-factor model $3PC_{(t),t+1}$, for which model the GRS test firmly rejects at all horizons with p-values well below 0.0001 (see Table II).

[**Insert Table IV about here**]

The improved fit of the four-factor model is not specific to the first three principal components. In Panel A we also show that the four-factor model is not rejected at the 5%-level at any horizon when we use as test assets the first five principal components of characteristic-sorted portfolio returns. Moreover, we ask in Panel B whether the models capture the pricing errors across horizons in the large set of 56 characteristic-sorted portfolios. To this end, we regress the returns of the unconditionally and conditionally hedged strategies (see Eqs. (4) and (5)) on the four-factor model as well as the benchmark factor models. We report the mean absolute alpha (MAA) and the number of alphas that are significant (at the 5%-level) at each horizon s.[17] We see that our proposed model, $4PC_{(t,t-36),t+1}$, performs relatively well. For instance, at the three-year horizon ($s = 36$), we find only 7 (8) unconditional (conditional) alphas that are significant. For comparison, these counts equal 15 (14) for the CAPM and 14 (14) for the FF5M+MOM. Also, the mean absolute alpha is smallest for the four factor model at 9 bps versus 15 bps for the CAPM and FF5M+MOM.

The outperformance of $4PC_{(t,t-36),t+1}$ is even starker in cross-sectional regressions. Figure 6 presents cross-sectional R^2s when the test assets are 112 characteristic-sorted portfolios (56 portfolios from (t) and $(t-s)$) and factor risk premia are forced to match their sample average returns. At all horizons s, this R^2 is negative in all four benchmark models, marginally above zero for the three-factor model $3PC_{(t),t+1}$, but large and positive (about 0.40) for the $4PC_{(t,t-36),t+1}$. Thus, benchmark factors based on the returns of new sorts provide a poor fit to explain the joint cross-section of old and new sorts. In contrast, adding a single factor based on old sorts (to a model based on new sorts) goes a long way to capture relative pricing errors across horizons. This finding is consistent with the fact that these pricing errors are driven by the first principal component of returns. Let us now turn to the identity of this first principal component.

[Insert Figure 6 about here]

4.3 Market beta and pricing errors across horizons

When test assets are long-only stock or portfolio returns, the first principal component typically loads quite similarly on each asset, such that it is close to the market portfolio. Our first principal component of long-short characteristic-sorted portfolio returns has loadings that are negative for about half of the characteristics. Nonetheless, it is also

[17]Note that these alphas are the result of a two-stage test, where in the first stage we regress $R_{X,(t-s),t+1}$ on $R_{X,(t),t+1}$ and in the second stage we regress $R_{X,(t-s),t+1} - \beta_s R_{X,(t),t+1}$ on the benchmark factors. Although this has little impact on our conclusions, the results for the unconditional test use GMM standard errors that correct for this errors-in-variables.

strongly exposed to the market. To see this, consider the large CAPM alpha of -2.32% per month for the first principal component of the newest sorts in Panel B of Table III. This alpha is only for a small part due to a low average return (-60 bps, Panel B of Table II). For a much larger part, this alpha is due to a large market beta of 2.63.[18] Indeed, there is a strong relation ($corr$ = 0.96) across characteristics between the market exposure of $R_{X,(t),t+1}$ and the loading of the first principal component on $R_{X,(t),t+1}$. Since the first principal component drives pricing errors across horizons, market beta holds promise to contain timely information about these pricing errors.[19]

Each month t, we sort the 56 long-short characteristic portfolios in three groups split at the terciles of ranked market betas.[20] These market betas are estimated for the newest sort over a 60 month historical rolling window (i.e., using $R_{X,(t-60),t-59}$ to $R_{X,(t-1),t}$). Then, within each market beta group, we take an equal-weighted average over the characteristic-sorted portfolio returns at each horizon. For instance, we denote the returns in the high market beta group by $R_{H\beta,(t-s),t+1}$. We will also analyze the alphas of old versus new sorts across market beta groups. To this end, we take in each group an equal-weighted average of the unconditionally and conditionally hedged returns (defined in Eqs. (4) and (5)). We denote these returns, $R^{u-hedge}_{H\beta,(t-s),t+1}$ and $R^{c-hedge}_{H\beta,(t-s),t+1}$, for instance. To conserve space, we focus on the horizons $s = 0$ and $s = 36$, because these horizons are representative of the general patterns in the data.

In Panel A of Table V, we first see that average returns among high beta characteristics decrease relatively slowly after portfolio formation, from an average return of 30 bps for $s = 0$ to 25 bps for $s = 36$. In contrast, among low beta characteristics, average returns decrease considerably faster and fall from a positive 24 bps for $s = 0$ to a negative -12 bps for $s = 36$. These two facts together imply that the difference in average return between

[18]As is standard in PCA, the loadings, which we use as portfolio weights, have Euclidean norm = 1, which scales up the return and beta of this portfolio. This scaling has no effect on the statistical significance of our results, which is why we stick with it.

[19]Similar to us, Haddad et al. (2020) extract the first principal component of long-short characteristic-sorted portfolios. In contrast to us, these authors use market-neutral portfolios in the PCA. We do not clean the portfolios from market exposure to show that the market beta of a characteristic-sorted portfolio is informative about pricing errors across horizons.

[20]Our conclusions are not sensitive to the chosen number of groups.

high and low beta characteristics is increasing from 7 bps ($s = 0$) to 38 bps ($s = 36$) as time passes after portfolio formation. Thus, a first take-away from the sort on market beta is that the persistence of return predictability is larger for high market beta characteristics. As mentioned before, average returns are not the most interesting statistic in the context of old and new sorts that are differentially correlated across characteristics.

[Insert Table V about here]

We therefore turn to the returns of the hedged strategies, which measure the alpha of older sorts relative to the newest sort. We find that both unconditional and conditional alphas are increasing from low to high market beta. For instance, among low beta characteristics, the return of a portfolio sorted three years ago provides a significantly negative conditional alpha relative to the newest sort of −23 bps (t-stat=−4.35). In contrast, among high beta characteristics, the same portfolio provides a positive conditional alpha of 10 bps (t-stat=2.86). These effects add up to a large alpha for the high-minus-low market beta portfolio of 33 bps (t-stat=4.42). Thus, we conclude that pricing errors across horizons are also strongly related to market beta. The fact that relatively large, negative pricing errors are observed for low market beta characteristics implies that average returns decay too fast after portfolio formation for such characteristics.

In Panel B, we ask if popular asset pricing models capture these patterns. First, we see that the smaller models, CAPM and FF3M, fail to capture the difference in returns between high and low market beta characteristics one month after portfolio formation. The CAPM and FF3M alpha for the high-minus-low market beta portfolio are significant at -40 and -43 bps, respectively.[21] This alpha is mostly driven by a large positive alpha of over 50 bps in the low market beta group. Thus, among low beta characteristics, the average return one month after sorting is not only anomalously high relative to returns longer after portfolio formation, but also relative to the market. These small models

[21] We already saw in the previous subsection that an unconditional CAPM cannot explain our results. Because we have now sorted the characteristics on their conditional market betas, the current evidence suggests that a conditional CAPM cannot explain our results either.

perform much better pricing returns longer after portfolio formation. For $s = 36$, returns fall in line with the CAPM in the low market beta group, such that the alpha of the high-minus-low market beta portfolio is small and insignificant. The performance of bigger models is quite the opposite. Both the FF5M and FF5M+MOM capture the difference in returns between high and low market beta characteristics immediately after portfolio formation. However, three years after portfolio formation, the high-minus-low market beta portfolio obtains a large and significant alpha of about 42 bps (t-stat ≈ 3.5).

We thus see the same trade-off between big and small models as in Table III. The fact that none of the benchmark models prices returns of both older and newer sorts is driven by two things: returns of the new and old sorts are highly correlated, but the average return is different.[22] Consistent with the evidence in Panel F of Table III, we next confirm that all models fail to capture the return of the strategies that hedge an investment in the old sort with a position in the new sort. The alpha of these strategies is significantly smaller among low market beta characteristics by about 30 bps (t-stat > 3) in all four benchmark models. In fact, this result holds true equally for the five alternative models considered in Panel C of Table IA.II of the Internet Appendix. Thus, existing asset pricing models do not capture the relatively large pricing errors across horizons among low beta characteristics.

In Panel C, we see that the four-factor model proposed in the previous subsection, $4PC_{(t,t-36),t+1}$, does capture the relatively large pricing errors across horizons among low beta characteristics. As a result, this model eliminates almost completely the difference between high and low beta characteristics in (conditionally and unconditionally) hedged returns. Although the performance of $4PC_{(t,t-36),t+1}$ generally compares favorably to the other models studied in Table V, the fit of the model is not perfect. For instance, high market beta characteristics provide an alpha relative to this four-factor model both one month and three years after portfolio formation. Pricing both new and old sorts, and thus combinations between them, is hard and we leave a more thorough investigation of

[22]The correlation between $R_{H-L,(t),t+1}$ and $R_{H-L,(t-36),t+1}$ is high at 0.80, but their average returns are 7 bps and 38 bps, respectively (see Panel A of Table V).

this issue for future work.

To conclude, we uncover a new dimension of the low beta anomaly by grouping characteristic-sorted portfolios on their market beta. We find that pricing errors across horizons are strongly related to market beta: average returns of the newest sorts are too high relative to older sorts among low market beta characteristics. This pricing error across horizons is not captured by market beta and therefore translates to a large alpha relative to the CAPM, and also relative to larger factor models.

5. The contribution of new and old stocks

Our evidence so far suggests that there is a range of characteristics – that is, those with low market betas – for which the return immediately after portfolio formation is too high (given its characteristic spread) relative to the return (and characteristic spread) longer after portfolio formation. Similarly, there are characteristics for which this return is too low. To understand which stocks drive these results, we split the stocks that are used to calculate the return of the newest *sort*, $R_{X,(t),t+1}$, into relatively new and old *stocks*. To this end, we perform a dependent double sort into ten X_t deciles and within the high and low decile into two portfolios split at the (within-portfolio) median of X_{t-36}. This decomposition is natural and ensures that the new and old portfolios (roughly) contain the same number of stocks for all characteristics. In particular, $R^{Old}_{X,(t),t+1}$ is the return of a strategy that is long (short) a value-weighted portfolio of the stocks for which, among all stocks in the highest (lowest) decile portfolio at time t, the characteristic X is above (below) the median value of that characteristic 36 months ago. The return for new stocks, $R^{New}_{X,(t),t+1}$, uses all remaining stocks in the high and low portfolio at time t.[23] Intuitively, the new stocks are those that have seen a relatively large change in the characteristic

[23] We also allocate stocks that are recently introduced in CRSP to the new portfolio. We have considered an alternative new-versus-old decomposition that defines as old stocks only those stocks that are in the high (or low) portfolio today as well as 36 months ago. This decomposition generates large differences in the number of stocks in the old versus the new portfolio depending on the persistence of the characteristic considered.

over the last three years.

This decomposition is new to the literature and different from the transitory-permanent decomposition of Keloharju et al. (2020). These authors decompose a characteristic at the firm level in its historical average (the permanent component) and a residual (the transitory component). Whereas we focus on the intermediate three-year horizon, Keloharju et al. (2020) define the permanent component using a ten-year average. Moreover, we sort the stocks within the high and low decile portfolio in a new and old group, whereas Keloharju et al. (2020) sort the whole cross-section of stocks using their two components. Thus, our decomposition of stocks within the high and low decile portfolio can uncover new information about how changes in characteristics predict returns. To see this, consider book-to-market. This characteristic generates a positive old-minus-new return difference of 57 bps (t-stat = 2.18). This finding implies that past changes in book-to-market predict returns with a negative sign among stocks that are in the extreme book-to-market portfolios today.[24]

We first perform a reality-check of our decomposition. The results above suggest that the returns of older sorts are highly correlated to the returns of the newest sort for most characteristics. One would expect this correlation to be driven by old stocks. Figure 7 plots the relative contribution to the R^2 in a joint regression of $R_{X,(t-36),t+1}$ on $R^{Old}_{X,(t),t+1}$ and $R^{New}_{X,(t),t+1}$ and confirms this intuition. For the vast majority of characteristics, the R^2 is driven by the old stocks that have extreme characteristic values in the past as well as today. Across characteristics, the median contribution to R^2 is about three times larger for the old stocks than for the new stocks. We also see that these relative contributions to R^2 do not line up in any particular way with the pricing errors we document in Figure 1, which suggests again that persistence of the characteristic is not the main driver of our results.

[Insert Figure 7 about here]

[24]In contrast, Gerakos and Linnainmaa (2018) find that changes in book-to-market predict returns with a positive sign in the full cross-section of stocks, which result we replicate in our data.

Next, we analyze the difference in average returns and alphas between the characteristic-sorted portfolios that use either old or new stocks. To increase power, we test these differences across the three market beta groups of Section 4.3. Our decomposition in new versus old stocks is coarse, and averaging over different characteristics within each group will smooth out this noise.[25] Table VI presents descriptive statistics for these three groups and confirms that the new and old stock portfolios are similar in important dimensions.

First, the new and old stock portfolio represent a similar high-minus-low characteristic spread, which suggests that an old-minus-new strategy is roughly characteristic-neutral. For instance, on average among low market beta characteristics, the old-minus-new portfolio provides a characteristic spread that is only 3% (1.02-0.99) of the characteristic spread in the not-decomposed long-minus-short decile portfolio. Second, the difference in total market cap allocated to the new and old portfolio is small, which suggests that the new portfolio is not overpopulated by small (and therefore illiquid) stocks. For instance, among low market beta characteristics, on average 9% of total CRSP market cap is allocated to the new stocks in the high plus low portfolio, which is relative to 11% for old stocks. Third, the old and new stock portfolios are balanced in the spread between the high and low portfolio in size, book-to-market, investment and profitability. For each of these characteristics, the difference between the old and new portfolio is small. To see this, we present the characteristic spread that is obtained in a single sort of stocks on these characteristics, which spreads are larger than the old-minus-new characteristic spreads by a factor eight or more. Thus, any model that defines expected excess returns as a linear function of these four characteristics (e.g., Daniel et al., 2020b) predicts that return differences between old and new stock portfolios are small.

[**Insert Tables VI and VII about here**]

We present average returns and alphas with respect to existing factor models in Table

[25] Figure IA.7 presents the return-differences between old and new stocks for all 56 characteristics. We see that these return differences are roughly increasing from the characteristics on the left (like idiosyncratic volatility) to the characteristics on the right (like book-to-market), consistent with the idea that the difference in returns between old and new *stocks* in the extreme portfolios contributes to the alpha between old and new *sorts*.

VII. We present results for the newest characteristic-sorted portfolios ($R_{X,(t),t+1}$) as a benchmark, but our main interest is in the (difference between) the contribution of new and old stocks ($R^{New}_{X,(t),t+1}$ and $R^{Old}_{X,(t),t+1}$). To start, we see that old stocks underperform new stocks among low market beta characteristics by a significant -18 bps. This finding confirms that the negative alphas of old with respect to new sorts among low market beta characteristics (see Section 4.3) are driven by returns that are relatively too high immediately after portfolio formation. Indeed, recall that the portfolios of old and new stocks present roughly the same characteristic spread. Among high beta characteristics, the old stocks outperform the new stocks by a significant 19 bps, consistent with a positive alpha between old and new sorts among this set of characteristics. The diff-in-diff between old and new stock among high versus low beta characteristics is large and significant at 37 bps ($t = 3.18$).

Neither small (e.g., the CAPM) nor big (e.g., the FF5M+MOM) models fully capture the relative performance differential between new and old stocks. Indeed, in all models, we find a large and (marginally) significant spread in the alpha of the old-minus-new strategy between high and low market beta characteristics. This alpha equals 27 bps in the CAPM and 43 bps in the FF5M+MOM.[26] Consistent with previous evidence, we see the trade-off between small and big models. Small models, like the CAPM, capture the high-minus-low market beta spread among old stocks, but do not capture the high-minus-low market beta spread among new stocks. In contrast, big models, like the FF5M+MOM, capture the high-minus-low market beta spread among new stocks, but do not capture the high-minus-low market beta spread among old stocks. Thus, existing asset pricing models do not jointly price new and old *stocks*.

This result provides an interesting link with our previous conclusion that existing models do not jointly price new and old *sorts*. Intuitively, old stocks capture the long-term returns to characteristic-based investing, whereas the new stocks capture the short-

[26] In the five alternative models considered in Panel D of Table IA.II of the Internet Appendix, this alpha is similarly large and ranges from 35 bps ($t = 3.39$) in the DMRS model to 45 bps ($t = 3.70$) in the DHS model.

term returns. This evidence marks an important contribution to Keloharju et al. (2020). These authors find that returns are mostly driven by the transitory (not the permanent) component of the average characteristic. We instead show that the relative performance differential between new stocks, which return is likely closer to their transitory component, and old stocks, which return is likely closer to their permanent component, varies in sign across characteristics.

More generally, our evidence indicates that return spreads from stocks that have been in the extreme portfolios for a while are not the same as return spreads from stocks that are new to the extreme portfolios, even when these old and new stocks have the same current level of the characteristic. In other words, there are subsets of stocks for which the same characteristic spread is compensated with a different risk premium. In the context of our null hypothesis (see Section 1), this finding indicates that the pricing errors we document are not likely due to a non-linear relation between characteristics and expected returns. Indeed, non-linearity cannot explain why two sets of stocks with the same characteristic spread have a different average return. Moreover, this finding contributes to Daniel and Titman (1997), who show that returns can vary with a characteristic even holding risk exposure fixed. We show that returns can vary even holding the characteristic fixed. One may be inclined to conclude that this variation is due to differences in the loading of new and old stocks on *other* characteristics. With that prior it is surprising that the difference between new and old stocks is not captured by any of the factor models we consider, because the factors in these models are derived from sorts of stocks on these *other* characteristics. Consider, for instance, the five-factor models FF5M and DMRS. As seen in Table VI, there is not much difference between old and new stocks in the characteristics that define the factors in these models. Consequently, these models fail to capture the old-minus-new return differences. These findings also imply a rejection of the assumption in Daniel et al. (2020b) that stock's loadings on the SDF are a function of recent values of size, book-to-market, profitability and investment.

What existing models miss is information in past values of, or changes over time in, characteristics. The fact that past values contain additional independent information about expected returns in the cross-section of stocks is interesting in and of itself. The return differentials we document imply that investors wanting to trade characteristics should carefully consider the distinction between new and old stocks for their portfolio. Our new and old stock portfolios are tradable and require a position in much fewer stocks than the original strategies. Old stock portfolios will require relatively little rebalancing, thus lowering transaction costs even further.[27]

6. Theoretical explanations of characteristic-based return predictability

Many production-based asset pricing theories seek to explain cross-sectional return patterns associated with characteristics. In the model of Gomes et al. (2003), current size and book-to-market predict returns in the cross-section, because these characteristics are correlated to the firm's true conditional market beta. We already saw that the CAPM is unlikely to fully explain our results. In addition, their model shares an important feature with alternative theories of characteristic-based return predictability (such as Berk et al. (1999) and Zhang (2005)): the focus is on relating one-period ahead expected returns to current characteristics. Since the previous section shows that past values of characteristics contain additional information about the cross-section of returns, our results likely provide a difficult challenge for these models. To see this, we analyze where our empirical estimates lie in the simulated distribution generated under the null of the models of Gomes et al. (2003) and Zhang (2005).[28]

In Panel A of Table VIII, we report the average return of older and newer portfolios

[27]Relatedly, combinations of new and old sorts (such as those proposed in Section 3) are likely less expensive to trade than an investment in $R_{X,(t),t+1}$ alone. The reason is that positions in selected stocks for $R_{X,(t),t+1}$ and $R_{X,(t-s),t+1}$ are likely to cancel out (see DeMiguel et al., 2019).

[28]A potential concern is that these models are at a disadvantage because their economies are stationary, precluding entry and exit of firms. Recall, however, that the alphas between old and new sorts are similar when we define both returns using only those firms that are in the sample at t and $t-36$ (see Figure IA.5).

sorted on simulated book-to-market ratios. Both models generate a high-minus-low book-to-market spread one month after portfolio formation. This spread is relatively small in the model of Gomes et al. (2003), consistent with the original study. More important in the context of our paper, we see that return predictability in both models fades relatively fast as time passes after portfolio formation. In Panel B, we also see that neither model generates the relatively large alphas between the older sorts and the newest sort (as defined in Eq. (4)). The simulated alphas have a median of zero and are generally small at all horizons. Our estimates of these alphas (about 35 bps per month) are above the 99th percentile of the simulated distributions. Similarly, in Panel C we see that neither model generates as large a difference between old and new book-to-market stocks (defined in Section 5) as we observe in the data. Having said that, the median old-minus-new return difference when simulating from the model of Zhang (2005) is about 20 bps, which is non-negligible economically.

In all, we reject the models, because neither model generates a large difference in returns between old and new sorts as well as between old and new stocks.

[Insert Table VIII about here]

7. Conclusion

In contrast to most existing literature that focuses on characteristic-based return predictability over short horizons, we study horizons up to five years. We uncover large pricing errors across horizons, measured as the alpha in a regression of returns to old sorts on the returns to new sorts. These alphas imply that returns do not in general decay at the same speed as characteristics and exist even though the returns of the new and old sorts tend to be highly correlated. Combining these two facts, it is easy to see why existing factor models fail to eliminate the relative pricing errors between old and new sorts. However, there is an important trade-off between small (e.g., the CAPM) and big (e.g., the FF5M) models. Neither prices both old and new sorts, because big models only price relatively new sorts, whereas small models only price relatively old sorts. We thus argue that longer horizon returns to characteristic-based investing provide a useful new set of moments to distinguish between asset pricing models.

We further find that the relative pricing errors are mostly driven by the first principal component of returns, which explains why adding a single factor based on old sorts (to a model with factors based on new sorts) goes a long way to capture the pricing errors across horizons. Having said that, we leave for future work the challenge of finding the most parsimonious factor representation that jointly prices new and old sorts. Furthermore, pricing errors across horizons are (i) strongly related to a characteristic's market beta, which contributes a new dimension to the low beta anomaly, and (ii) connected to the difference in returns between "new" and "old" stocks, which are stocks in the extreme decile portfolios that have recently experienced, respectively, large and small changes in the characteristic.

Our empirical evidence has important implications for practitioners trading characteristics as well as empiricists testing asset pricing models. Future empirical research can use the decompositions developed in this paper (in new versus old sorts, and in new versus old stocks) to shed light on the dynamics of return predictability for a newly discovered characteristic or anomaly; this will, in turn, help evaluating the breadth of its asset pricing implications. An interesting avenue for future theoretical work is to understand the economic drivers of the pricing errors across horizons and, more specifically, why the expected return compensation for a unit loading of a portfolio on a characteristic seems to depend on the time this portfolio was formed.

Appendix A. Simulation

We run a number of Monte Carlo simulations to assess the size of our tests. The main concern is that returns across the 56 characteristic-sorted portfolios are correlated, which may affect the inference from our tests. In the simulations, we impose the null of zero alpha between the old and new sort, but respect the correlation structure (as well as other moments) in the data. We analyze the regression of Eq. (4) focusing on $s = 36$:

$$R_{X,(t-36),t+1} = \alpha + \beta R_{X,(t),t+1} + \epsilon_{X,(t-36),t+1}. \tag{8}$$

In each of 10000 simulations, we first create for each characteristic $X = 1, ..., 56$ an artificial time-series of returns to the new sorts collected in the $T \times 56$ matrix: $R^{sim}_{(t),t+1} = [R^{sim}_{1,(t),t+1}, ..., R^{sim}_{56,(t),t+1}]$. These returns are drawn from a multivariate normal distribution, $R^{sim}_{(t),t+1} \sim N(\mu_{(t)}, \Sigma_{(t)})$, where $\mu_{(t)}$ and $\Sigma_{(t)}$ are the vector of means and the variance-covariance matrix of $R_{(t),t+1}$ in the data. Next, we create artificial returns to the old sorts, imposing zero alpha: $R^{sim}_{X,(t-36),t+1} = \beta^{sim}_X R^{sim}_{X,(t),t+1} + u^{sim}_{t+1}$. The exposure of the old sort to the new sort, β^{sim}_X is drawn from a normal distribution with mean (standard deviation) equal to the average (standard deviation) of β in the data taken over the 56 characteristics. The residuals are drawn from a multivariate normal distribution $u^{sim}_{t+1} \sim N(0_{56}, \Sigma_u)$, where Σ_u is the variance-covariance matrix of the residuals from Eq. (8) in the data. As a benchmark, we also present results for a simulation that assumes the variance-covariance matrices, $\Sigma_{(t)}$ and Σ_u, are diagonal (rather than full), which thus ignores the correlation between characteristics. Finally, we consider 10000 bootstrap simulations that account for the fact that return(-innovations) are not normal in the data. Each bootstrap resamples (with replacement) from the original time index $t = 1, ..., T$ both the returns of the newest sort and residuals from Eq. (8) in the data. We combine these bootstrapped time-series with the simulated β^{sim}_X's to create returns to the older sort.

For each set of artificial data, we estimate Eq. (8) and present below the 50, 90, 95 and 99 percentiles of the simulated distribution of the number of significant (at the 10%

level) α's out of 56. In the data, we find that 23 out of 56 characteristics have an alpha (between the old sort at $s = 36$ and the newest sort at $s = 0$) that is significant at the 10% level. This number is unlikely to be generated under the null, because in 99% of the simulations that respect the correlation structure in the data (using either normal returns or bootstrapped returns) the number of significant α's is below 16.

TABLE A.I: **Simulated distribution of number of significant alphas**
We simulate returns to the older sort at $s = 36$ under the null of zero alpha with respect to the newest sort at $s = 0$. We report the 50, 90, 95, and 99 percentiles of the distribution (in 10000 simulations) of the number of alphas of the older sort with respect to the newest sort that are significant (out of a total of 56 and estimated as in Eq.(8)).

Percentiles	50	90	95	99	Data
# Significant					23
Diagonal	5	9	9	11	
Full	5	10	12	16	
Bootstrap	5	10	12	16	

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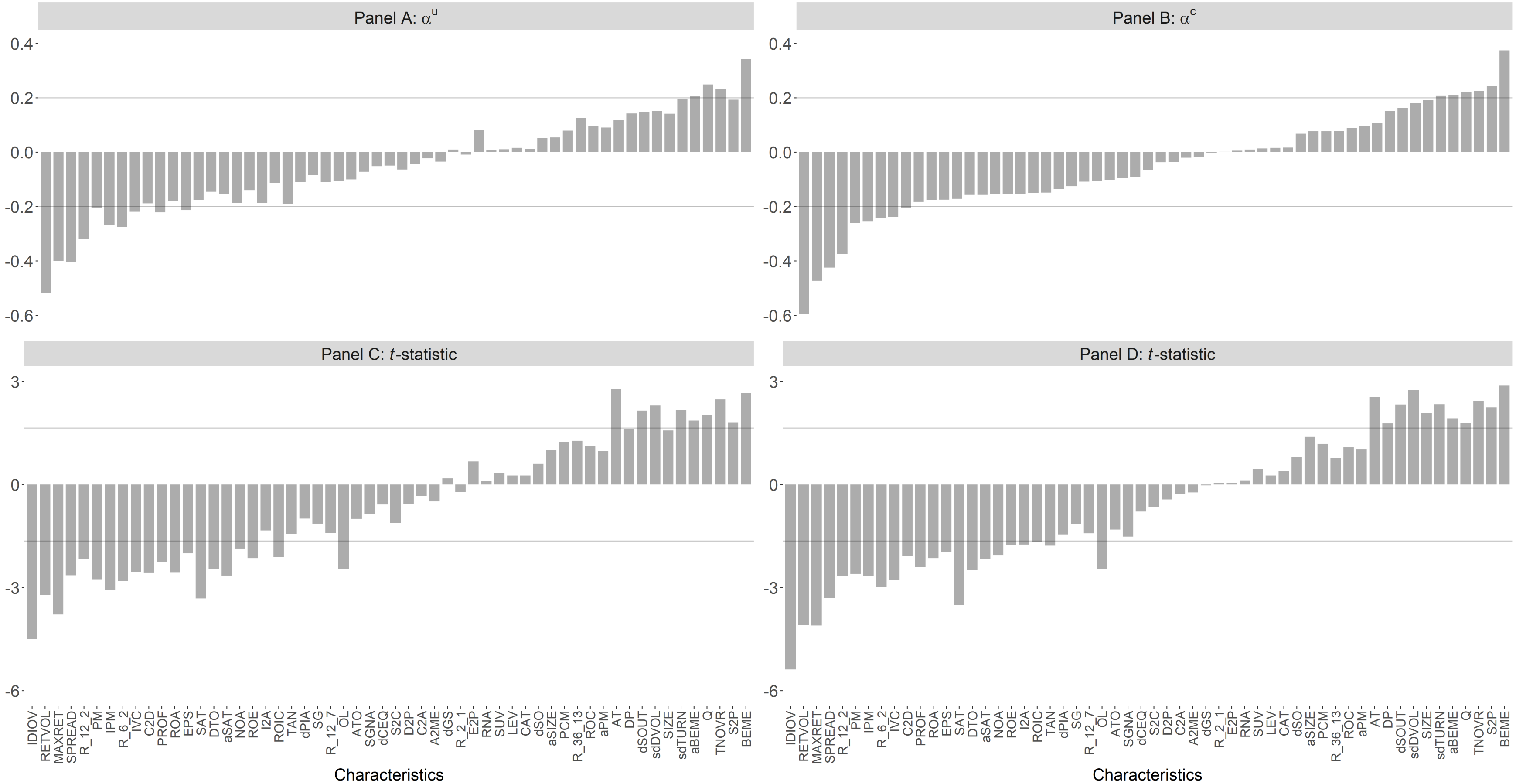

FIGURE 1: **Relative pricing errors between old and new sorts**

This figure presents the unconditional (α^u, Panel A) and conditional (α^c, Panel B) alpha (with associated White et al. (1980) heteroskedasticity-consistent t-statistics in Panels C and D) of the old sorts with respect to the newest sort for 56 characteristics (as defined in Table IA.I). We report this alpha for a single combination of five old sorts: $R_{X,(t-60:t-12),t+1} = 1/5(R_{X,(t-12),t+1} + R_{X,(t-24),t+1} + \ldots + R_{X,(t-60),t+1})$, such that it represents the abnormal return from one to five years after portfolio formation. The unconditional alpha is estimated using a single time-series regression of $R_{X,(t-60:t-12),t+1}$ on $R_{X,(t),t+1}$ (see Eq. (4)). The conditional alpha represents the average return to a strategy that invests in $R_{X,(t-60:t-12),t+1}$ but hedges in each month t the conditional exposure to $R_{X,(t),t+1}$ (see Eq. (5)). To facilitate interpretation, we sort the characteristics from low to high α^c. The sample period runs from July 1974 to December 2017.

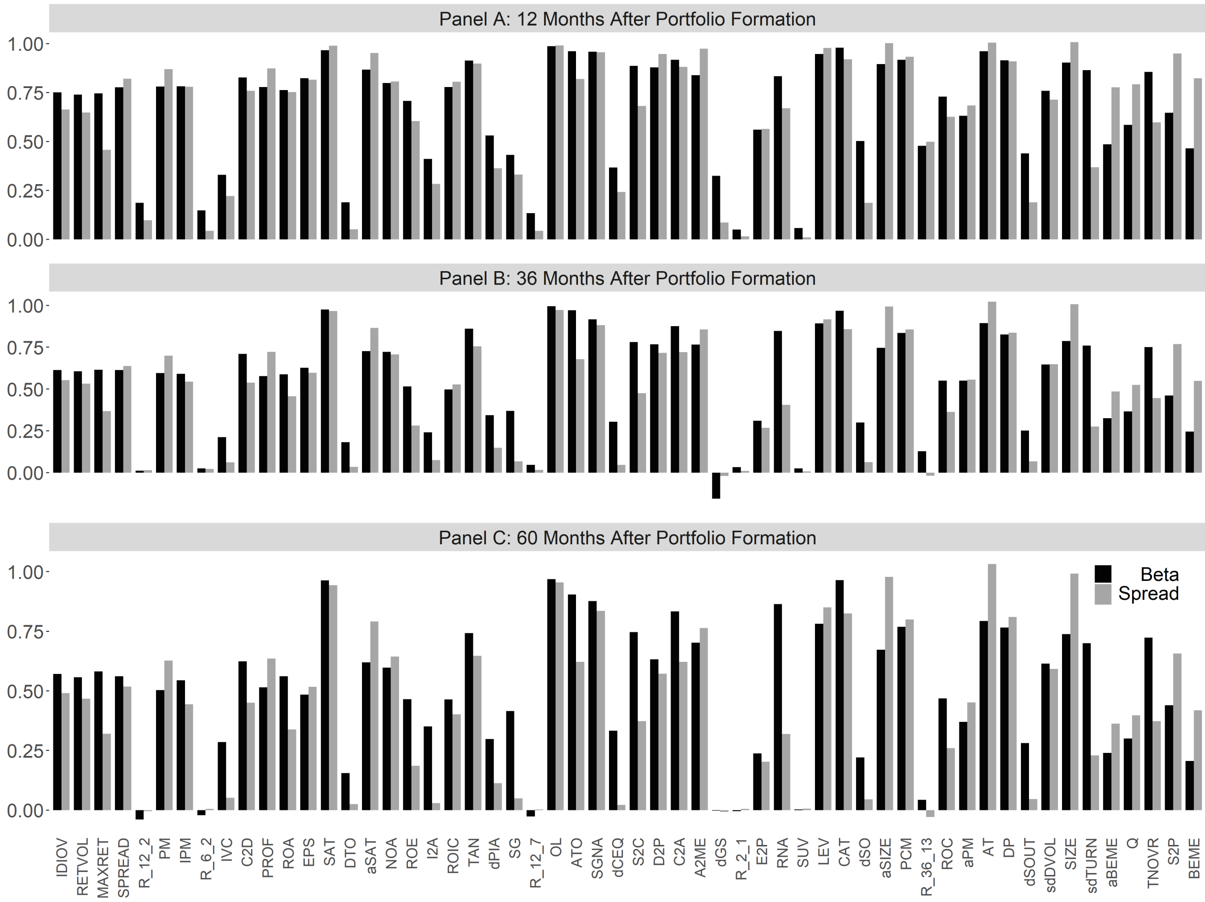

FIGURE 2: **Persistence and the beta of old to new sorts**
This figure presents the persistence of the 56 characteristics we study (in the same order as the conditional alphas from Figure 1) as well as the beta in a regression of old to new sorts, β_s for $s = 12, 36, 60$. Persistence is measured as the high-minus-low characteristic spread that remains s months after portfolio formation as a fraction of the same spread at portfolio formation. Persistence equals beta under the null of Section 1: $\left(X_{H-L,(t-s)}/X_{H-L,(t)}\right) = \beta_s$. The sample period runs from July 1974 to December 2017.

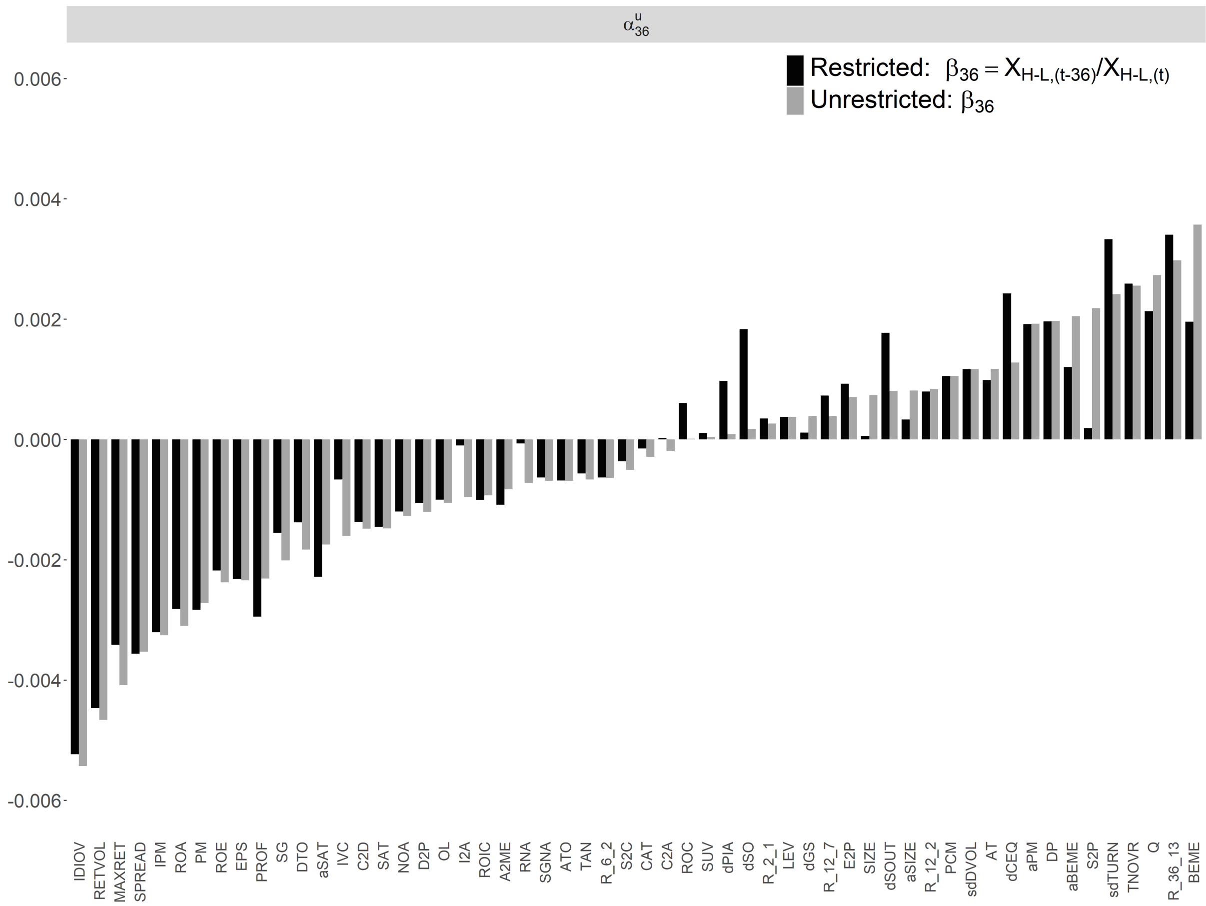

FIGURE 3: **Restricted versus unrestricted pricing errors**

This figure presents two alternative alphas from a regression of the old sort ($s = 36$) on the newest sort for 56 characteristics. The first alpha is the regression intercept when the slope coefficient β_s is estimated freely; the second alpha is the intercept when we fix $\beta_s = X_{H-L,(t-s)}/X_{H-L,(t)}$, as under the null. The sample period runs from July 1974 to December 2017.

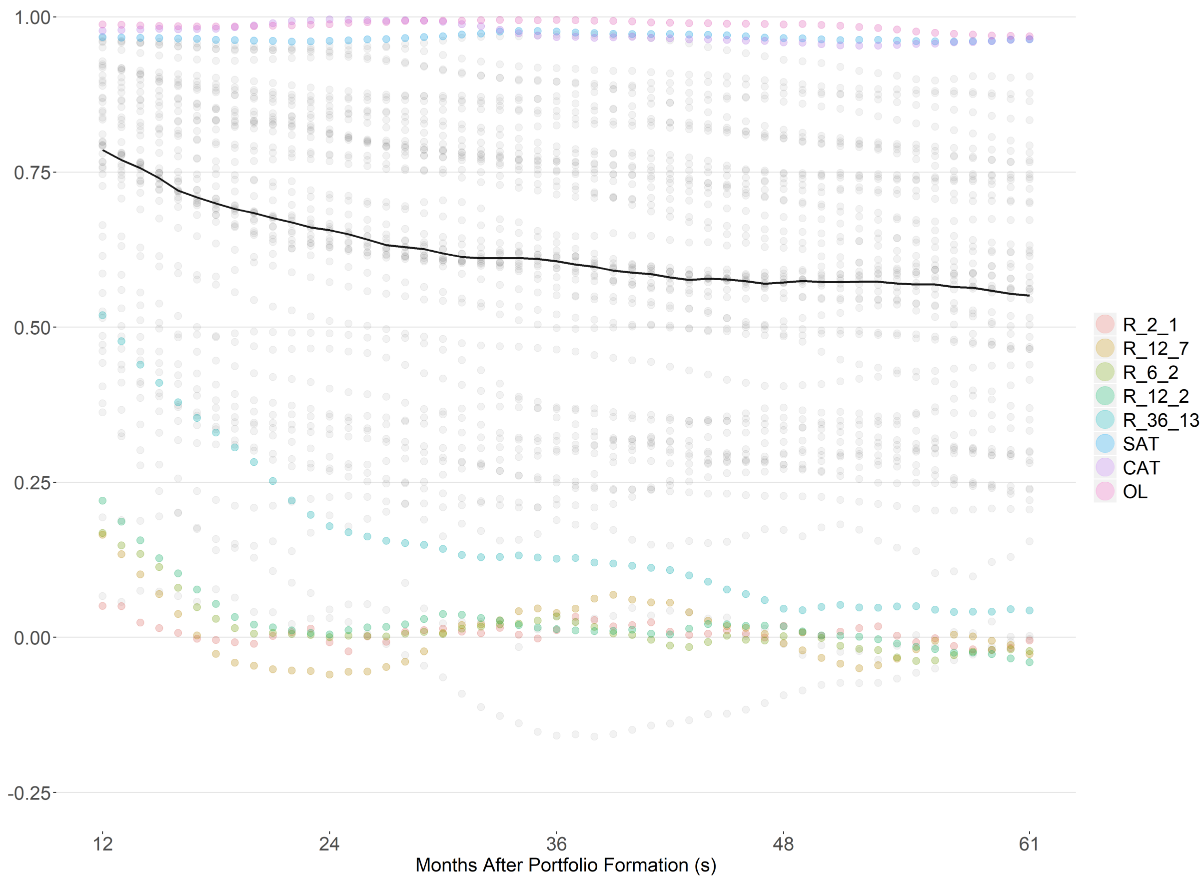

FIGURE 4: **Betas of old with respect to new sorts**
This figure presents the distribution across 56 characteristics of the beta in a regression of older sorts, with returns $R_{X,(t-s),t+1}$ for $s = 12, ..., 60$, on the newest sort, with return $R_{X,(t),t+1}$. The solid line highlights the median. We also highlight the relatively low betas for the past-return-based characteristics (as defined in Table IA.I) and the relatively high betas for three characteristics related to sales. The sample period runs from July 1974 to December 2017.

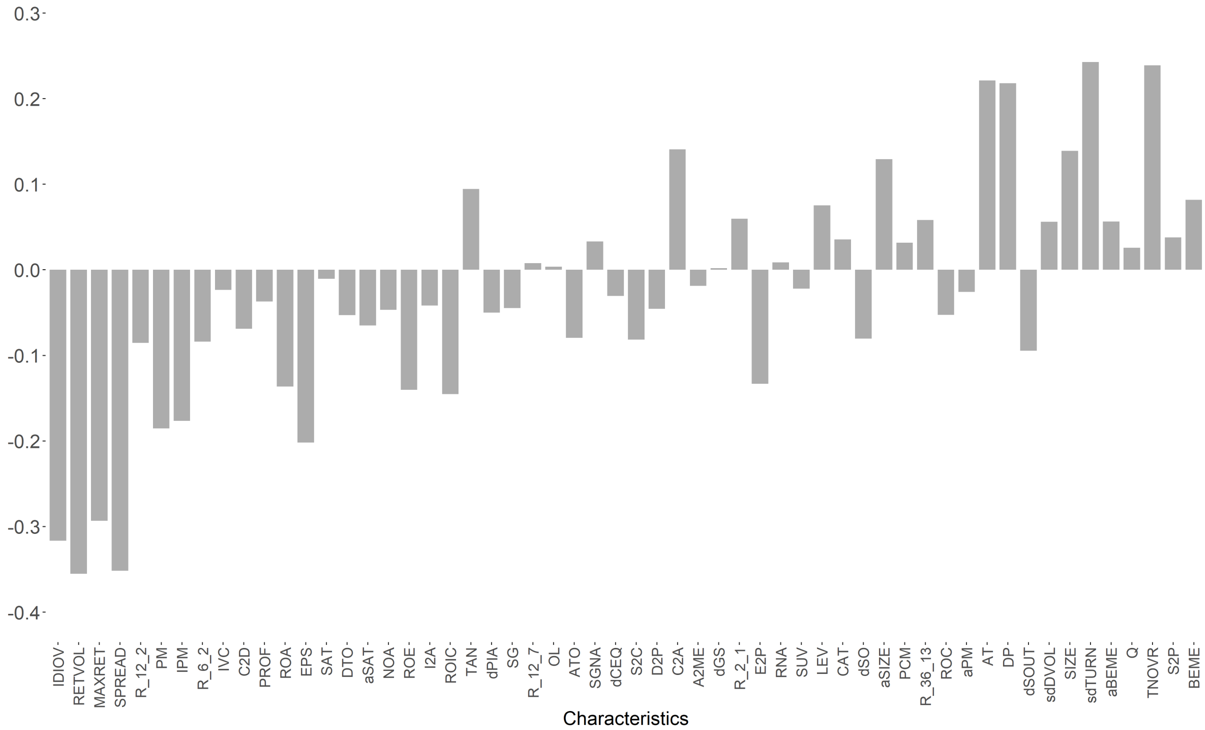

FIGURE 5: **Principal component loadings**
This figure plots the loadings of the first principal component extracted from returns of the newest sorts, $R_{X,(t),t+1}$ from July 1974 to December 2017 and in the same order as the conditional alphas from Figure 1.

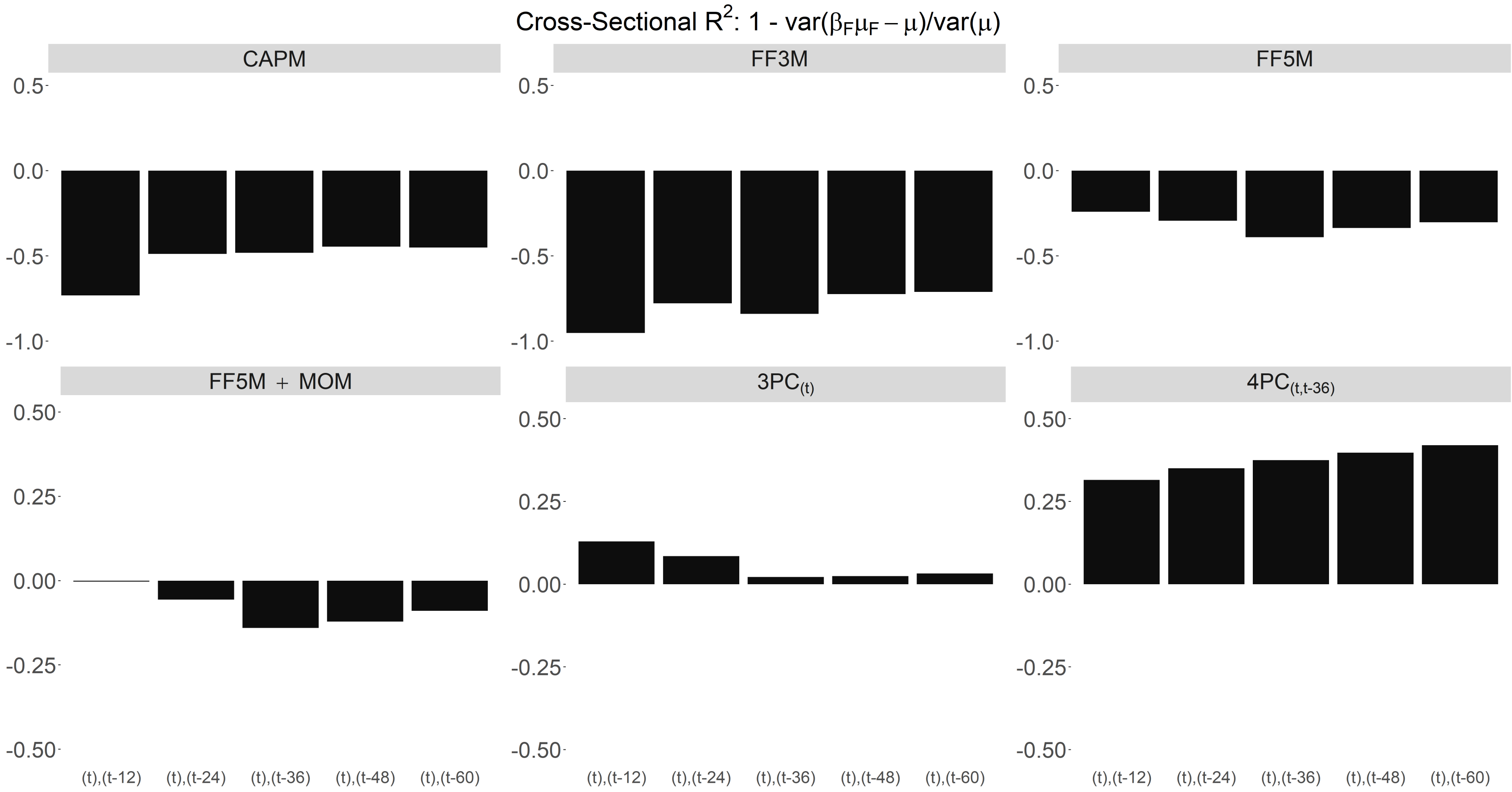

FIGURE 6: **Cross-sectional R^2s**

This figure presents for each factor model (defined as in Table IV) the cross-sectional R^2 when the test assets are 112 characteristic-sorted portfolios (56 returns to new sorts, $R_{X,(t),t+1}$, and 56 returns to old sorts, $R_{X,(t),t+1}$, with sample average return denoted μ) and the factor risk premia are set equal to the sample average factor returns (denoted μ_F). Thus, $R^2 = 1 - var(\mu - \beta'_F\mu_F)/var(\mu)$. The sample period runs from July 1974 to December 2017.

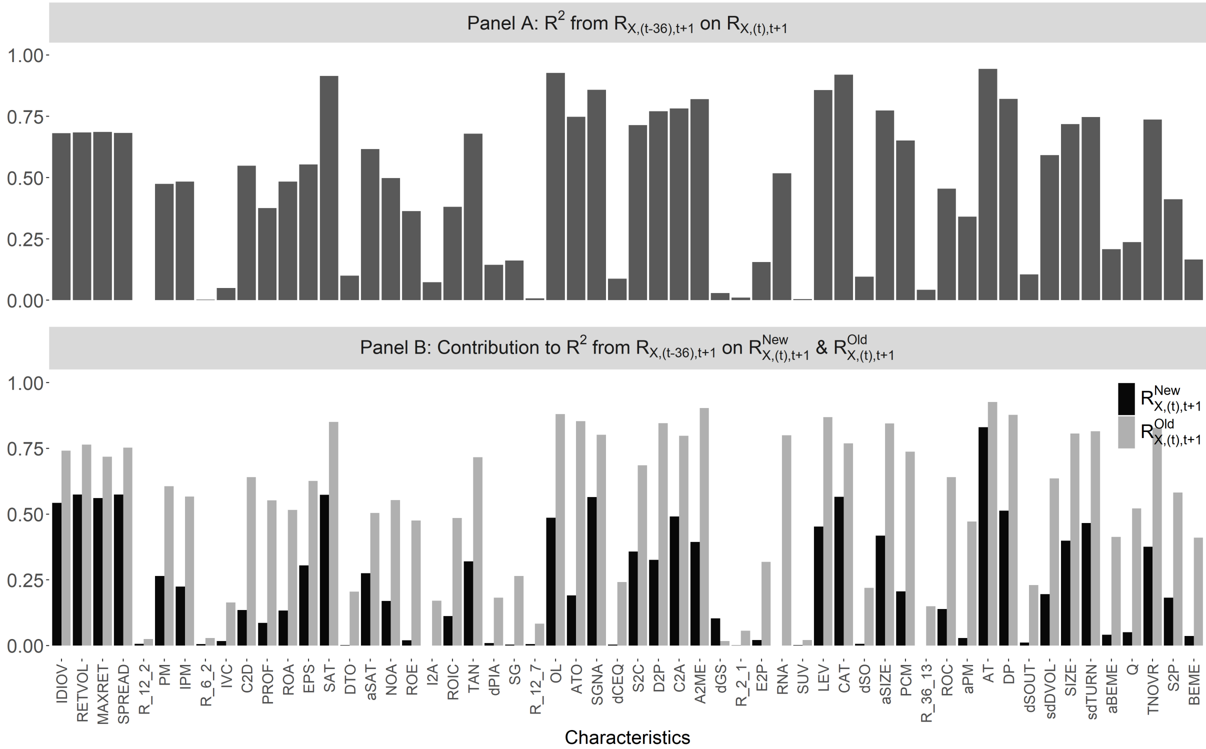

FIGURE 7: **Contribution to R^2 from old and new stocks**
In Panel A of this figure we report the R^2 from a regression of an old sort ($R_{X,(t-36),t+1}$) on the newest sort ($R_{X,(t),t+1}$). Panel B plots the relative contribution to the R^2 in a regression of the old sort ($R_{X,(t-36),t+1}$) on the new stock component ($R^{New}_{X,(t),t+1}$) and the old stock component ($R^{Old}_{X,(t),t+1}$) that together make up the return of the newest sort. The old stock component is the return to a strategy that goes long the subset of stocks for which, among all stocks in the High portfolio at time t, the characteristic X is above the median value of that characteristic 36 months ago. Conversely, this strategy goes short the subset of stocks for which, among all stocks in the Low portfolio at time t, the characteristic X is below the median value of that characteristic 36 months ago. The new stock component uses all remaining stocks in the High and Low portfolio at time t. To smooth out temporary variation in characteristics, we do not directly use the values of firm characteristics at $t-36$, but instead use the average ranking of the firm from 24 to 48 months. The sample period runs from July 1974 to December 2017.

Table I: **The relative performance of old and new sorts for four popular characteristics**

This table reports the relative performance of old and new sorts on book-to-market, size, profitability, and investment. To this end, we track the returns of long-short decile portfolios (value-weighted and split at NYSE breakpoints) for each characteristic from one month to five years after portfolio formation. Panel A reports the average number of firms in the high plus low portfolios (Firms) as well as the average high-minus-low return. Panel B reports the intercept, α^u, and slope coefficients, β^u, from a regression of the return of an old sort on the contemporaneous return of the newest sort: $R_{X,(t-s),t+1} = \alpha^u_s + \beta^u_s R_{X,(t),t+1} + \epsilon_{X,(t-s),t+1}$. This unconditional alpha represents the average return to a strategy that invests in $R_{X,(t-s),t+1}$ but hedges unconditionally the exposure to $R_{X,(t),t+1}$ (see Eq. (4)). We also report the conditional alpha, α^c, which represents the average return to a strategy that invests in $R_{X,(t-s),t+1}$ but hedges in each month t the conditional exposure to $R_{X,(t),t+1}$. Following Eq. (5), we estimate this exposure over a 60 month historical rolling window. Panel C reports the Sharpe ratio of returns immediately after portfolio formation, Sharpe($R_{X,(t),t+1}$), and the maximum increase in Sharpe ratio achievable from combining the newest sort with the (unconditionally or conditionally hedged returns of the) older sort. Panel D reports the intercepts, α^u and α^c, from a regression of the unconditionally hedged, $R^{u-hedge}_{X,(t-s),t+1}$, or conditionally hedged, $R^{c-hedge}_{X,(t-s),t+1}$, returns on a five factor model that includes as pricing factors the returns to the four newest characteristic-sorted portfolios and the market. White et al. (1980) heteroskedasticity consistent t-statistics are reported in parentheses in Panels A, B and D. The reported p-values for the GRS tests in Panel D are robust to conditional heteroskedasticity. The sample period runs from July 1974 to December 2017.

Panel A: Summary statistics

	Book-to-market			Size			Profitability			Investment		
	Firms	Ret.	t-stat	Firms	Ret.	t-stat	Firms	Ret.	t-stat	Firms	Ret.	t-stat
$R_{X,(t),t+1}$	1155	0.53	1.86	2121	0.31	1.55	1085	0.43	3.28	1343	0.51	3.48
$R_{X,(t-12),t+1}$	1029	0.61	3.12	1882	0.50	2.49	960	0.26	2.13	1193	0.22	1.80
$R_{X,(t-24),t+1}$	917	0.50	2.85	1661	0.41	2.05	848	0.14	1.14	1054	0.09	0.75
$R_{X,(t-36),t+1}$	821	0.49	2.84	1476	0.32	1.71	756	0.02	0.15	937	0.03	0.22
$R_{X,(t-48),t+1}$	738	0.51	3.02	1316	0.37	2.06	677	0.02	0.13	837	0.00	0.03
$R_{X,(t-60),t+1}$	664	0.38	2.25	1176	0.36	1.93	610	-0.01	-0.04	750	-0.06	-0.44

Panel B: Relative pricing errors across horizons

	Book-to-market			Size			Profitability			Investment		
	α^u	β^u	α^c	α^u	β^u	α^c	α^u	β^u	α^c	α^u	β^u	α^c
$R_{X,(t-12),t+1}$	0.36	0.47	0.43	0.22	0.90	0.26	-0.08	0.78	-0.08	0.01	0.41	-0.01
	(2.68)	(7.93)	(3.35)	(2.69)	(18.46)	(3.40)	(-1.29)	(15.80)	(-1.43)	(0.05)	(11.86)	(-0.14)
$R_{X,(t-24),t+1}$	0.33	0.32	0.42	0.15	0.84	0.21	-0.13	0.63	-0.12	-0.05	0.28	-0.06
	(2.28)	(6.49)	(3.03)	(1.46)	(16.93)	(2.16)	(-1.55)	(9.84)	(-1.51)	(-0.40)	(6.38)	(-0.51)
$R_{X,(t-36),t+1}$	0.36	0.24	0.43	0.07	0.79	0.13	-0.23	0.58	-0.23	-0.10	0.24	-0.14
	(2.35)	(4.78)	(2.95)	(0.77)	(18.37)	(1.44)	(-2.35)	(9.60)	(-2.59)	(-0.74)	(6.30)	(-1.10)
$R_{X,(t-48),t+1}$	0.39	0.23	0.43	0.14	0.75	0.20	-0.22	0.55	-0.24	-0.18	0.37	-0.23
	(2.56)	(4.79)	(2.97)	(1.43)	(17.78)	(2.13)	(-2.25)	(10.03)	(-2.66)	(-1.42)	(6.97)	(-1.76)
$R_{X,(t-60),t+1}$	0.27	0.21	0.28	0.13	0.74	0.18	-0.23	0.52	-0.25	-0.24	0.35	-0.29
	(1.75)	(4.62)	(1.93)	(1.20)	(14.21)	(1.75)	(-2.19)	(7.26)	(-2.60)	(-1.79)	(5.68)	(-2.22)

Continued

	Book-to-market		Size		Profitability		Investment			
	Panel C: Improvement in Sharpe ratio									
	u	c	u	c	u	c	u	c		
	Sharpe($R_{X,(t),t+1}$)									
$R_{X,(t),t+1}$	0.28		0.23		0.50		0.53			
	Max. Sharpe($R_{X,(t-s),t+1}$, $R_{X,(t),t+1}$) - Sharpe($R_{X,(t),t+1}$)									
$R_{X,(t-12),t+1}$	0.19	0.28	0.21	0.30	0.04	0.05	0.00	0.00		
$R_{X,(t-24),t+1}$	0.16	0.25	0.08	0.16	0.05	0.05	0.00	0.01		
$R_{X,(t-36),t+1}$	0.16	0.24	0.03	0.08	0.12	0.14	0.01	0.03		
$R_{X,(t-48),t+1}$	0.19	0.24	0.08	0.16	0.11	0.15	0.04	0.06		
$R_{X,(t-60),t+1}$	0.10	0.12	0.06	0.11	0.10	0.14	0.07	0.10		
	Panel D: Alphas in five-factor model									
	α^u	α^c	α^u	α^c	α^u	α^c	α^u	α^c	GRS F-stat [p-val]	
$R_{X,(t-12),t+1}$	0.20	0.24	0.29	0.30	-0.03	-0.03	0.08	0.05	3.33	3.74
	(1.63)	(1.98)	(3.50)	(3.74)	(-0.51)	(-0.53)	(0.73)	(0.43)	[0.0104]	[0.0052]
$R_{X,(t-24),t+1}$	0.23	0.31	0.31	0.33	-0.07	-0.04	0.03	0.01	3.16	3.66
	(1.64)	(2.25)	(3.35)	(3.55)	(-0.81)	(-0.47)	(0.27)	(0.08)	[0.0139]	[0.0060]
$R_{X,(t-36),t+1}$	0.33	0.39	0.24	0.26	-0.19	-0.16	-0.06	-0.10	3.23	3.86
	(2.10)	(2.58)	(2.85)	(3.05)	(-1.87)	(-1.81)	(-0.44)	(-0.79)	[0.0123]	[0.0042]
$R_{X,(t-48),t+1}$	0.36	0.40	0.26	0.29	-0.19	-0.19	-0.15	-0.19	3.90	4.70
	(2.26)	(2.62)	(2.98)	(3.31)	(-1.92)	(-2.09)	(-1.11)	(-1.40)	[0.0039]	[0.0010]
$R_{X,(t-60),t+1}$	0.16	0.19	0.28	0.29	-0.19	-0.19	-0.15	-0.19	3.15	3.63
	(1.03)	(1.24)	(2.71)	(2.83)	(-1.74)	(-1.96)	(-1.08)	(-1.46)	[0.0142]	[0.0063]

TABLE II: **Do factor models price principal components at longer horizons after portfolio formation?**

In Panel A of this table, we present F-statistics and p-values from GRS tests, where the test assets are the first three principal components extracted from characteristic-sorted portfolio returns at different horizons after portfolio formation ($\lambda'_{(t-s),z=1,2,3} R_{X,(t-s),t+1}$). We ask whether these returns are priced by one of five models. The first is a statistical factor model that uses the first three principal components extracted from $R_{X,(t),t+1}$ as factors, denoted $3PC_{(t),t+1}$. Next, we also consider the single-factor CAPM (Sharpe (1964), Lintner (1965), Mossin (1966)); the three-factor model of Fama and French (1993, FF3M); the five-factor model of Fama and French (2015, FF5M); and a six-factor model that augments FF5M with momentum (FF5M+MOM). These returns are taken directly from Kenneth French's website. Panel B presents the summary statistics for the first principal component extracted from $R_{X,(t-s),t+1}$. The sample runs from July 1974 to December 2017.

Panel A: GRS tests

$\lambda'_{(t-s),z=1,2,3} R_{X,(t-s),t+1}$	$3PC_{(t),t+1}$		CAPM		FF3M		FF5M		FF5M+MOM	
s	F-stat	p-val	F-stat	p-val	F-stat	p-val	F-stat	p-val	F-stat	p-val
0			8.06	0.0000	8.43	0.0000	1.45	0.2284	0.96	0.4128
12	5.27	0.0014	5.52	0.0010	5.40	0.0012	3.48	0.0159	2.98	0.0310
24	9.85	0.0000	2.48	0.0607	2.98	0.0310	5.16	0.0016	5.39	0.0012
36	9.77	0.0000	2.30	0.0768	3.10	0.0264	5.89	0.0006	5.67	0.0008
48	10.71	0.0000	2.27	0.0794	2.90	0.0346	6.81	0.0002	6.85	0.0002
60	9.54	0.0000	1.59	0.1901	2.42	0.0656	6.18	0.0004	6.30	0.0003

Panel B: Summary statistics for the first principal component

$\lambda'_{(t-s),1} R_{X,(t-s),t+1}$	Avg. Ret.	Correlations					
s		0	12	24	36	48	60
0	-0.60	1.00	0.96	0.93	0.91	0.90	0.90
12	0.36	0.96	1.00	0.98	0.96	0.95	0.94
24	0.86	0.93	0.98	1.00	0.98	0.97	0.95
36	0.94	0.91	0.96	0.98	1.00	0.98	0.96
48	1.03	0.90	0.95	0.97	0.98	1.00	0.98
60	1.02	0.90	0.94	0.95	0.96	0.98	1.00

Table III: **Alphas of individual principal components at longer horizons after portfolio formation**

This table presents the intercept (α) and associated t-statistic (based on White et al. (1980) heteroskedasticity consistent standard errors) from regressing the returns at longer horizons after portfolio formation for each of three principal component strategies on five candidate factor models (Panels A to E). These returns are defined as the linear combination of (i) the loadings $\lambda_{(t),z}$ of the z-th principal component extracted from $R_{X,(t),t+1}$ and (ii) characteristic-sorted portfolio returns at horizons $s = 12, 24, ..., 60$ after portfolio formation (see Section 4.1 for more detail). The five models are: the statistical factor model $3PC_{(t),t+1}$, CAPM, FF3M, FF5M and FF5M+MOM, respectively, as in Table II. Panel F presents the alpha from a regression of returns to an old-minus-new strategy (i.e., a simple long-short combination of $R_{X,(t-s),t+1}$ and $R_{X,(t),t+1}$, weighted by $\lambda_{(t),1}$) on the same factor models. The sample period runs from July 1974 to December 2017.

$\lambda'_{(t),z}R_{X,(t-s),t+1}$	PC1 ($z = 1$)		PC2 ($z = 2$)		PC3 ($z = 3$)	
s	α	t-stat	α	t-stat	α	t-stat
			Panel A: $3PC_{(t),t+1}$			
12	0.68	3.69	0.07	0.39	-0.38	-1.34
24	1.13	5.06	0.20	0.80	-0.28	-0.95
36	1.27	4.99	0.25	0.79	0.00	-0.01
48	1.39	5.39	0.09	0.28	-0.21	-0.81
60	1.38	5.13	0.11	0.33	-0.39	-1.46
			Panel B: CAPM			
0	-2.32	-3.26	-0.36	-0.51	1.45	3.39
12	-1.09	-1.69	-1.25	-2.04	-0.02	-0.06
24	-0.45	-0.73	-1.07	-1.86	-0.03	-0.09
36	-0.28	-0.47	-0.87	-1.58	0.37	1.19
48	-0.16	-0.29	-1.03	-1.92	0.20	0.60
60	-0.15	-0.27	-0.96	-1.77	-0.01	-0.04
			Panel C: FF3M			
0	-2.18	-4.46	1.67	3.37	0.85	2.36
12	-0.86	-2.04	0.69	2.40	-0.31	-1.01
24	-0.13	-0.31	0.61	1.81	-0.46	-1.64
36	0.09	0.23	0.65	1.79	-0.13	-0.44
48	0.21	0.57	0.41	1.11	-0.34	-1.16
60	0.17	0.46	0.41	1.04	-0.55	-1.93
			Panel D: FF5M			
0	-0.33	-0.86	1.19	2.04	0.51	1.33
12	0.60	1.81	0.81	2.90	-0.32	-1.01
24	1.12	3.27	0.81	2.34	-0.52	-1.68
36	1.30	3.85	0.80	2.02	-0.19	-0.59
48	1.36	4.31	0.57	1.41	-0.51	-1.68
60	1.28	4.01	0.66	1.58	-0.76	-2.38
			Panel E: FF5M+MOM			
0	0.10	0.25	0.01	0.04	-0.36	-1.69
12	0.64	1.87	0.69	2.41	-0.58	-1.80
24	1.09	3.13	0.88	2.55	-0.56	-1.78
36	1.26	3.63	0.86	2.22	-0.24	-0.73
48	1.36	4.20	0.64	1.59	-0.61	-1.96
60	1.30	3.92	0.77	1.84	-0.74	-2.18

Continued

Panel F: Old-minus-new sorts								
$\lambda'_{(t),1}(R_{X,(t-s),t+1} - R_{X,(t),t+1})$	CAPM		FF3M		FF5M		FF5M+MOM	
	α	t-stat	α	t-stat	α	t-stat	α	t-stat
12	1.23	5.00	1.32	5.67	0.93	3.63	0.54	2.26
24	1.87	6.22	2.05	7.19	1.45	4.63	0.99	3.48
36	2.04	5.91	2.27	6.82	1.63	4.66	1.16	3.47
48	2.16	6.04	2.39	7.08	1.69	4.82	1.26	3.61
60	2.17	5.92	2.35	6.81	1.61	4.65	1.20	3.40

Table IV: **Does a four-factor model capture the alpha between old and new sorts?**
This table presents results from asset pricing tests for the principal components extracted from new and old characteristic-sorted portfolios. Panel A reports the intercept (α, with accompanying t-statistic) from simple regressions of each of the first five principal components on a four factor model, $4PC_{(t,t-36),t+1}$, that augments the first three principal components extracted from $R_{X,(t),t+1}$ with the first principal component extracted from $R_{X,(t-36),t+1}$. Consistent with Table III, this factor is defined as $\lambda'_{(t),1} R_{X,(t-36),t+1}$, where $\lambda_{(t),1}$ is the vector of loadings of the first principal component extracted from $R_{X,(t),t+1}$. We also report the GRS test statistic and associated p-values from pricing the first three or first five principal components extracted from the returns at each horizon. Panel B reports the mean absolute alpha (MAA) and number of test statistics significant at the 5%-level (#) from simple regressions of new and old characteristic-sorted portfolio returns for each of the 56 characteristics on the five candidate factor models. We report results for both unconditionally hedged returns, $R^{u-hedge}_{X,(t-s),t+1}$ and conditionally hedged returns, $R^{c-hedge}_{X,(t-s),t+1}$. The sample period runs from July 1974 to December 2017.

Panel A: Alphas of principal components in $4PC_{(t,t-36),t+1}$ model

$\lambda'_{(t),z} R_{X,(t-s),t+1}$	PC1 ($z=1$)		PC2 ($z=2$)		PC3 ($z=3$)		PC4 ($z=4$)		PC5 ($z=5$)		GRS_3		GRS_5	
s	α	t-stat	α	t-stat	α	t-stat	α	t-stat	α	t-stat	F-stat	p-val	F-stat	p-val
0	0.00	0.19	0.00	-0.95	0.00	11.98	0.21	0.60	0.47	1.52				
12	0.06	0.46	0.03	0.21	-0.60	-2.02	0.31	0.94	0.22	0.88	1.36	0.25	1.38	0.23
24	0.22	1.64	0.22	0.84	-0.54	-1.83	0.10	0.32	0.17	0.72	1.99	0.11	1.36	0.24
36	0.00	0.14	0.48	1.46	-0.26	-0.97	0.08	0.26	0.41	1.77				
48	0.30	2.30	0.31	0.91	-0.44	-1.56	0.17	0.55	0.24	0.97	2.72	0.04	1.94	0.09
60	0.45	2.40	0.27	0.75	-0.40	-1.48	0.02	0.08	0.00	-0.02	3.48	0.02	2.09	0.06

Panel B: Alphas of 56 characteristic-sorted portfolios

	Benchmark models															
	CAPM				FF3M				FF5M				FF5M+MOM			
	Uncond.		Cond.		Uncond.		Cond.		Uncond.		Cond.		Uncond.		Cond.	
s	MAA	#	MAA	#	MAA	#	MAA	#	MAA	#	MAA	#	MAA	#	MAA	#
12	0.13	12	0.14	14	0.11	9	0.12	10	0.11	9	0.11	8	0.11	12	0.11	9
24	0.15	15	0.16	15	0.15	13	0.15	14	0.14	12	0.13	13	0.15	14	0.14	14
36	0.15	15	0.15	14	0.15	15	0.15	15	0.15	14	0.14	14	0.15	14	0.15	14
48	0.17	20	0.18	18	0.17	14	0.18	20	0.17	14	0.17	15	0.16	14	0.17	14
60	0.16	18	0.16	19	0.15	16	0.15	17	0.17	13	0.17	14	0.18	15	0.17	15

Continued

	Statistical models							
	$3PC_{(t),t+1}$				$4PC_{(t,t-36),t+1}$			
	Uncond.		Cond.		Uncond.		Cond.	
s	MAA	#	MAA	#	MAA	#	MAA	#
12	0.10	8	0.11	11	0.08	4	0.10	7
24	0.13	16	0.14	14	0.09	8	0.09	8
36	0.14	15	0.14	16	0.09	7	0.09	8
48	0.16	17	0.17	19	0.09	11	0.10	12
60	0.16	19	0.16	20	0.09	10	0.10	11

Table V: **Relative pricing errors across market beta groups**

This table presents pricing errors across horizons for three market beta groups. To this end, we sort the 56 characteristics using the market beta of the newest characteristic-sorted portfolio estimated over a 60 month rolling window. Characteristic-sorted portfolio returns are equal-weighted within each market beta group. We report results for unhedged returns ($R_{X,(t-s),t+1}$), unconditionally hedged returns ($R^{u-hedge}_{X,(t-36),t+1}$), and conditionally hedged returns ($R^{c-hedge}_{X,(t-36),t+1}$). Panel A reports average returns for the newest portfolio ($s = 0$) and an older portfolio ($s = 36$). Panel B reports the intercept from regressing the market beta-sorted portfolios on benchmark factor models. Panel C reports the intercept from regressing the market beta-sorted portfolios on the statistical factor models of Tables II and IV. t-statistics use White et al. (1980) heteroskedasticity consistent standard errors. The sample period runs from July 1974 to December 2017.

	Low	Mid	High	H-L	Low	Mid	High	H-L
	Panel A: Average returns of old versus new sorts							
	Avg. Ret.				t-stat			
$R_{X,(t),t+1}$	0.24	0.37	0.30	0.07	1.65	5.82	2.91	0.28
$R_{X,(t-36),t+1}$	-0.12	0.13	0.25	0.38	-1.10	3.05	2.72	1.89
$R^{u-hedge}_{X,(t-36),t+1}$	-0.22	-0.01	0.11	0.32	-3.85	-0.33	3.00	4.06
$R^{c-hedge}_{X,(t-36),t+1}$	-0.23	-0.01	0.10	0.33	-4.35	-0.31	2.86	4.42
	Panel B: Benchmark factor models							
	α				t-stat			
	CAPM							
$R_{X,(t),t+1}$	0.53	0.43	0.13	-0.40	4.70	7.01	1.45	-2.09
$R_{X,(t-36),t+1}$	0.09	0.15	0.10	0.01	0.91	3.60	1.23	0.08
$R^{u-hedge}_{X,(t-36),t+1}$	-0.17	-0.01	0.08	0.26	-3.14	-0.31	2.37	3.29
$R^{c-hedge}_{X,(t-36),t+1}$	-0.20	-0.01	0.07	0.27	-3.77	-0.30	2.18	3.71
	FF3M							
$R_{X,(t),t+1}$	0.51	0.32	0.08	-0.43	5.52	5.71	1.14	-2.79
$R_{X,(t-36),t+1}$	0.03	0.10	0.09	0.06	0.45	2.40	1.52	0.47
$R^{u-hedge}_{X,(t-36),t+1}$	-0.23	-0.02	0.08	0.31	-4.74	-0.43	2.38	4.49
$R^{c-hedge}_{X,(t-36),t+1}$	-0.24	-0.01	0.07	0.30	-4.76	-0.33	2.00	4.38
	FF5M							
$R_{X,(t),t+1}$	0.21	0.19	0.23	0.02	2.48	3.52	3.21	0.15
$R_{X,(t-36),t+1}$	-0.19	0.04	0.24	0.43	-2.71	0.81	3.99	3.59
$R^{u-hedge}_{X,(t-36),t+1}$	-0.27	-0.02	0.10	0.37	-4.85	-0.59	2.65	4.78
$R^{c-hedge}_{X,(t-36),t+1}$	-0.25	-0.02	0.07	0.32	-4.29	-0.52	2.08	4.18

Continued

	Low	Mid	High	High-Low	Low	Mid	High	High-Low
			α				t-stat	
				FF5M+MOM				
$R_{X,(t),t+1}$	0.14	0.21	0.23	0.10	1.38	3.44	2.89	0.57
$R_{X,(t-36),t+1}$	-0.18	0.03	0.24	0.42	-2.60	0.70	3.81	3.44
$R^{u-hedge}_{X,(t-36),t+1}$	-0.24	-0.04	0.08	0.32	-4.14	-1.09	1.96	3.84
$R^{c-hedge}_{X,(t-36),t+1}$	-0.22	-0.05	0.06	0.28	-3.62	-1.15	1.49	3.33
				Panel C: Statistical models				
				$3PC_{(t),t+1}$				
$R_{X,(t),t+1}$	0.11	0.30	0.32	0.21	1.84	5.98	5.34	1.92
$R_{X,(t-36),t+1}$	-0.19	0.09	0.29	0.48	-3.38	2.44	5.25	4.78
$R^{u-hedge}_{X,(t-36),t+1}$	-0.23	-0.02	0.10	0.34	-4.69	-0.68	2.79	4.49
$R^{c-hedge}_{X,(t-36),t+1}$	-0.24	-0.02	0.09	0.33	-4.61	-0.70	2.59	4.41
				$4PC_{(t,t-36),t+1}$				
$R_{X,(t),t+1}$	0.07	0.24	0.27	0.20	1.14	4.80	4.18	1.75
$R_{X,(t-36),t+1}$	-0.02	0.10	0.15	0.18	-0.48	2.65	3.11	2.10
$R^{u-hedge}_{X,(t-36),t+1}$	-0.05	0.01	0.02	0.07	-1.55	0.27	0.68	1.47
$R^{c-hedge}_{X,(t-36),t+1}$	-0.06	0.01	0.02	0.08	-1.62	0.44	0.65	1.52

Table VI: **Descriptives for new and old stock portfolios across market beta groups** This table presents descriptive statistics for the new and old stock portfolios, which together make up the newest characteristic-sorted portfolio. Each statistic is presented for three groups of characteristics sorted on market beta and we equal-weight within each group. We present for both the old and new stock portfolio: (i) the high-minus-low characteristic spread as a fraction of the characteristic spread in the not-decomposed portfolio; (ii) the total market cap (as a fraction of total CRSP market cap) in the high and low portfolio; (iii) the high-minus-low difference in market cap (as a fraction of total CRSP market cap); and (iv-vi) the difference in median book-to-market, profitability, and investment between the high and low portfolio. To put these differences in perspective, the table also reports the characteristic spread that is obtained in a single sort of stocks on these characteristics.

	Market beta Low	Mid	High	
	Characteristic Spread			
New	0.99	1.04	0.90	
Old	1.02	0.98	1.04	
Not Decomposed				1
	% CRSP Market Cap (High + Low)			
New	0.09	0.09	0.10	
Old	0.11	0.11	0.15	
Not Decomposed				0.61
	% CRSP Market Cap (High - Low)			
New	0.00	0.00	0.01	
Old	0.01	0.02	0.05	
Not Decomposed				0.58
	Book-to-Market (BM)			
New	1.44	1.36	1.44	
Old	1.49	1.41	1.52	
Not Decomposed				1.98
	Profitability ($PROF$)			
New	1.20	1.24	1.21	
Old	1.24	1.31	1.30	
Not Decomposed				2.13
	Investment ($I2A$)			
New	23.66	28.53	22.58	
Old	14.20	17.79	14.65	
Not Decomposed				85.89

Table VII: **The relative performance of new versus old stocks in characteristic-sorted portfolios**

This table presents results for the returns of new versus old stocks across three market beta groups. The returns of new ($R^{New}_{X,t,t+1}$) and old ($R^{Old}_{X,t,t+1}$) stocks together make up the return to the newest sort ($R_{X,t,t+1}$). The old stock component is the return to a strategy that goes long the subset of stocks for which, among all stocks in the High portfolio at time t, the characteristic X is above the median value of that characteristic 36 months ago. Conversely, this strategy goes short the subset of stocks for which, among all stocks in the Low portfolio at time t, the characteristic X is below the median value of that characteristic 36 months ago. The new stock component uses all remaining stocks in the High and Low portfolio at time t. All returns are equal-weighted within market beta groups. We report the intercept from regressing the market beta-sorted portfolios on benchmark asset pricing models as defined in Table II. t-statistics use White et al. (1980) heteroskedasticity consistent standard errors. The sample period runs from July 1974 to December 2017.

	Market beta				Market beta			
	Low	Mid	High	H-L	Low	Mid	High	H-L
	Avg. Ret.				t-stat			
$R_{(t)t+1}$	0.24	0.37	0.30	0.07	1.65	5.82	2.91	0.28
$R^{New}_{X,t,t+1}$	0.31	0.34	0.19	-0.12	2.45	4.99	1.84	-0.53
$R^{Old}_{X,t,t+1}$	0.14	0.40	0.38	0.25	0.79	5.29	3.67	0.94
$R^{Old}_{X,t,t+1}$ - $R^{New}_{X,t,t+1}$	-0.18	0.06	0.19	0.37	-2.13	0.90	3.13	3.18
	α				t-stat			
	CAPM							
$R_{(t)t+1}$	0.53	0.43	0.13	-0.40	4.70	7.01	1.45	-2.09
$R^{New}_{X,t,t+1}$	0.56	0.39	0.03	-0.53	5.44	5.89	0.36	-2.91
$R^{Old}_{X,t,t+1}$	0.47	0.48	0.22	-0.26	3.33	6.58	2.34	-1.17
$R^{Old}_{X,t,t+1}$ - $R^{New}_{X,t,t+1}$	-0.09	0.09	0.18	0.27	-1.09	1.39	3.09	2.39
	FF3M							
$R_{(t)t+1}$	0.51	0.32	0.08	-0.43	5.52	5.71	1.14	-2.79
$R^{New}_{X,t,t+1}$	0.56	0.27	-0.03	-0.58	6.19	4.33	-0.36	-3.80
$R^{Old}_{X,t,t+1}$	0.41	0.35	0.18	-0.22	3.67	5.52	2.44	-1.32
$R^{Old}_{X,t,t+1}$ - $R^{New}_{X,t,t+1}$	-0.15	0.07	0.21	0.36	-1.94	1.19	3.60	3.37
	FF5M							
$R_{(t)t+1}$	0.21	0.19	0.23	0.02	2.48	3.52	3.21	0.15
$R^{New}_{X,t,t+1}$	0.29	0.18	0.11	-0.19	3.41	2.57	1.34	-1.23
$R^{Old}_{X,t,t+1}$	0.04	0.20	0.32	0.28	0.41	3.36	4.30	1.85
$R^{Old}_{X,t,t+1}$ - $R^{New}_{X,t,t+1}$	-0.25	0.02	0.22	0.47	-3.42	0.29	3.43	4.30
	FF5M+MOM							
$R_{(t)t+1}$	0.14	0.21	0.23	0.10	1.38	3.44	2.89	0.57
$R^{New}_{X,t,t+1}$	0.23	0.22	0.13	-0.10	2.21	3.01	1.39	-0.53
$R^{Old}_{X,t,t+1}$	-0.03	0.19	0.30	0.34	-0.32	2.92	3.83	1.98
$R^{Old}_{X,t,t+1}$ - $R^{New}_{X,t,t+1}$	-0.26	-0.04	0.17	0.43	-3.39	-0.56	2.58	3.71

TABLE VIII: **Simulating from Gomes, Kogan and Zhang (2003) and Zhang (2005)** This table reports results from 1500 simulations of the models in Gomes et al. (2003) and Zhang (2005). We thank the authors for sharing the code on their websites. These models endogenously generate a positive spread in returns between high and low book-to-market stocks. We ask whether these models can match the relative performance of old versus new *sorts* and *stocks* that we observe for book-to-market in the data, while matching other moments of interest. Indeed, we run these simulations using the same parameters as those used in the original studies. Panel A reports the average returns of the newest, $R_{BM,(t),t+1}$, and older, $R_{BM,(t-s),t+1}$, high-minus-low book-to-market portfolios. Panel B reports the intercept from a regression of the older sorts on the newest sort. Panel C reports the difference in average returns between old, $R^{Old}_{BM,(t),t+1}$, and new, $R^{New}_{BM,(t),t+1}$, stocks that together make up the newest sort (following the definition in Table VII). In each panel, we report the percentiles of the simulated distribution as well as our estimate in the data.

	Percentiles	1	5	10	50	90	95	99	Data
	Panel A: Average returns of new and old sorts								
Z05	$R_{BM,(t),t+1}$	0.17	0.40	0.47	0.62	0.74	0.78	0.85	0.53
	$R_{BM,(t-12),t+1}$	0.19	0.24	0.27	0.36	0.43	0.45	0.49	0.61
	$R_{BM,(t-24),t+1}$	0.09	0.12	0.15	0.22	0.28	0.29	0.33	0.50
	$R_{BM,(t-36),t+1}$	0.04	0.07	0.09	0.14	0.19	0.20	0.23	0.49
	$R_{BM,(t-48),t+1}$	0.00	0.03	0.04	0.09	0.13	0.15	0.17	0.51
	$R_{BM,(t-60),t+1}$	-0.01	0.01	0.02	0.06	0.10	0.11	0.13	0.38
GKZ03	$R_{BM,(t),t+1}$	0.00	0.04	0.06	0.11	0.16	0.17	0.18	0.53
	$R_{BM,(t-12),t+1}$	-0.03	-0.01	0.00	0.05	0.09	0.10	0.14	0.61
	$R_{BM,(t-24),t+1}$	-0.05	-0.04	-0.02	0.03	0.07	0.07	0.09	0.50
	$R_{BM,(t-36),t+1}$	-0.07	-0.04	-0.04	0.01	0.05	0.06	0.06	0.49
	$R_{BM,(t-48),t+1}$	-0.08	-0.05	-0.04	0.00	0.05	0.05	0.07	0.51
	$R_{BM,(t-60),t+1}$	-0.07	-0.05	-0.04	0.00	0.04	0.05	0.06	0.38
	Panel B: Alphas of old versus new sorts								
Z05	$R_{BM,(t-12),t+1}$	-0.08	-0.05	-0.04	0.01	0.08	0.11	0.17	0.36
	$R_{BM,(t-24),t+1}$	-0.08	-0.06	-0.04	0.00	0.05	0.07	0.13	0.33
	$R_{BM,(t-36),t+1}$	-0.08	-0.05	-0.05	-0.01	0.04	0.06	0.09	0.36
	$R_{BM,(t-48),t+1}$	-0.08	-0.05	-0.04	-0.01	0.04	0.05	0.08	0.39
	$R_{BM,(t-60),t+1}$	-0.07	-0.05	-0.04	0.00	0.04	0.05	0.07	0.27
GKZ03	$R_{BM,(t-12),t+1}$	-0.08	-0.05	-0.04	0.00	0.04	0.05	0.07	0.36
	$R_{BM,(t-24),t+1}$	-0.08	-0.05	-0.04	0.00	0.04	0.05	0.06	0.33
	$R_{BM,(t-36),t+1}$	-0.08	-0.06	-0.05	-0.01	0.03	0.04	0.05	0.36
	$R_{BM,(t-48),t+1}$	-0.09	-0.06	-0.05	-0.01	0.04	0.04	0.06	0.39
	$R_{BM,(t-60),t+1}$	-0.08	-0.06	-0.05	-0.01	0.03	0.04	0.05	0.27
	Panel C: Average returns of old versus new stocks								
Z05	$R^{Old}_{BM,(t),t+1}$ - $R^{New}_{BM,(t),t+1}$	-0.39	-0.03	0.06	0.20	0.29	0.31	0.35	0.56
GKZ03	$R^{Old}_{BM,(t),t+1}$ - $R^{New}_{BM,(t),t+1}$	-0.22	-0.17	-0.14	-0.03	0.08	0.11	0.15	0.56

Internet Appendix for "New and Old Sorts: Implications for Asset Pricing"

A. Additional empirical evidence

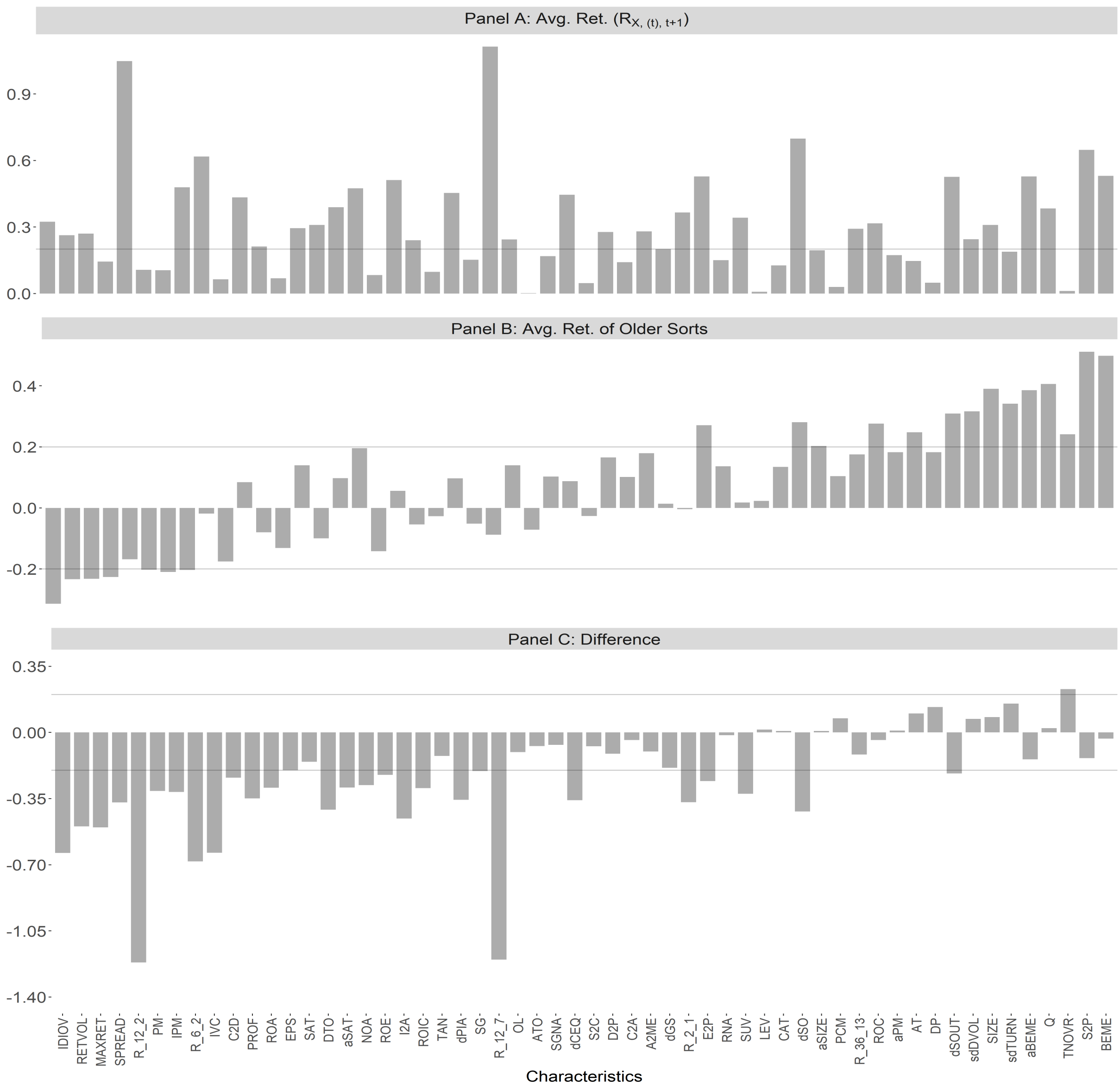

FIGURE IA.1: **Average returns of new and old characteristic-sorted portfolios**
This figure presents the average return of the newest sort ($R_{X,(t),t+1}$) and a single combination of five old sorts: $R_{X,(t-60:t-12),t+1} = 1/5(R_{X,(t-12),t+1} + R_{X,(t-24),t+1} + ... + R_{X,(t-60),t+1})$. Thus, $R_{X,(t-60:t-12),t+1}$ represents the average return from one to five years after portfolio formation. To facilitate interpretation, the characteristics are sorted in the same order as the conditional alphas, α^c, from Figure 1.

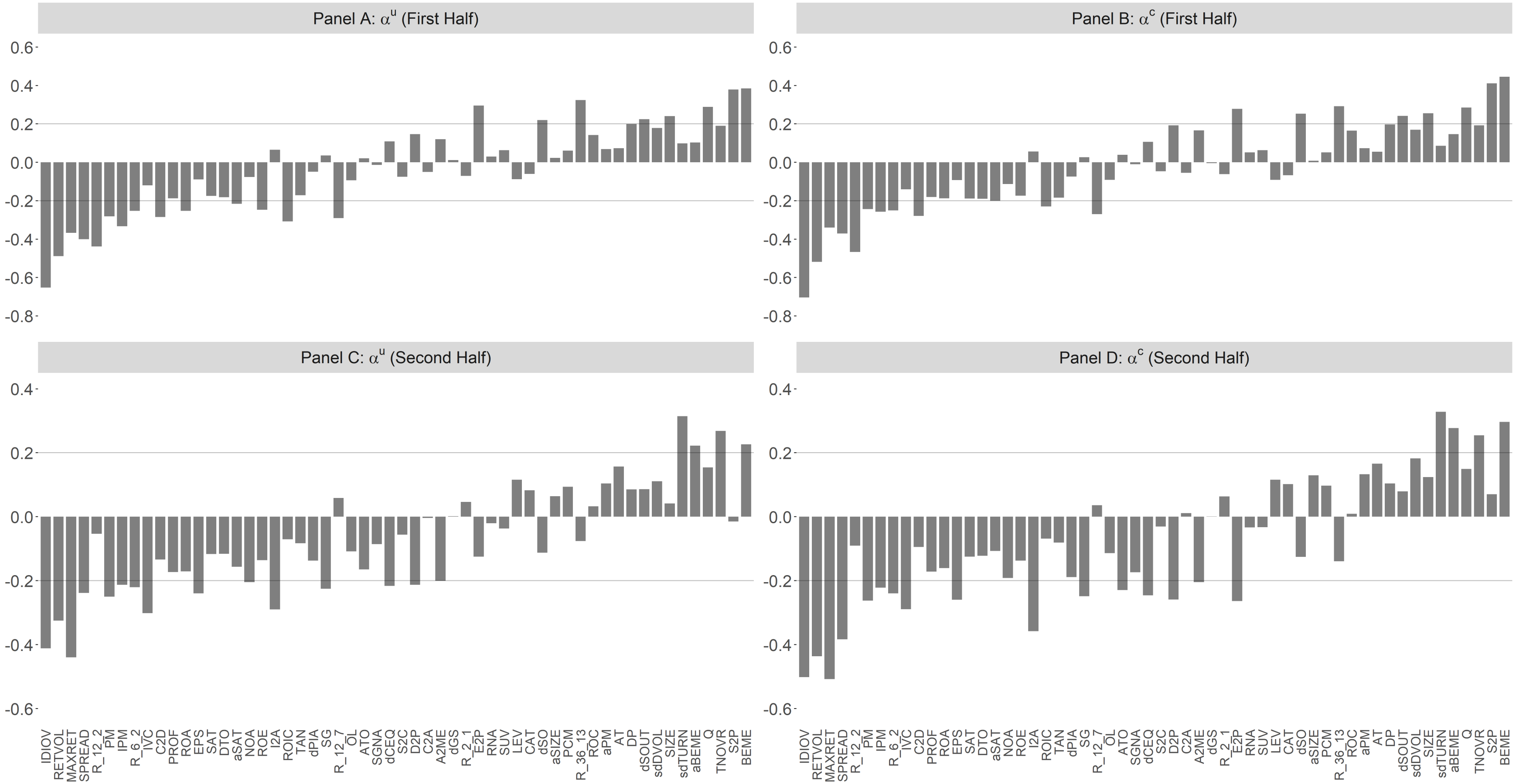

FIGURE IA.2: **Relative pricing errors between old and new sorts in subsamples**
This figure presents the unconditional and conditional alpha of the older sorts (with return $R_{X,(t-60:t-12),t+1}$) relative to the newest sort (with return $R_{X,(t),t+1}$) over two subsamples split around March 1996. In each subsample, the unconditional alpha is the average of $R^{u-hedge}_{X,(t-s),t+1}$ defined in Eq. (4), whereas the conditional alpha is the average of $R^{c-hedge}_{X,(t-s),t+1}$ defined in Eq. (5). To facilitate interpretation, the characteristics are sorted in the same order as the conditional alphas, α^c, from Figure 1.

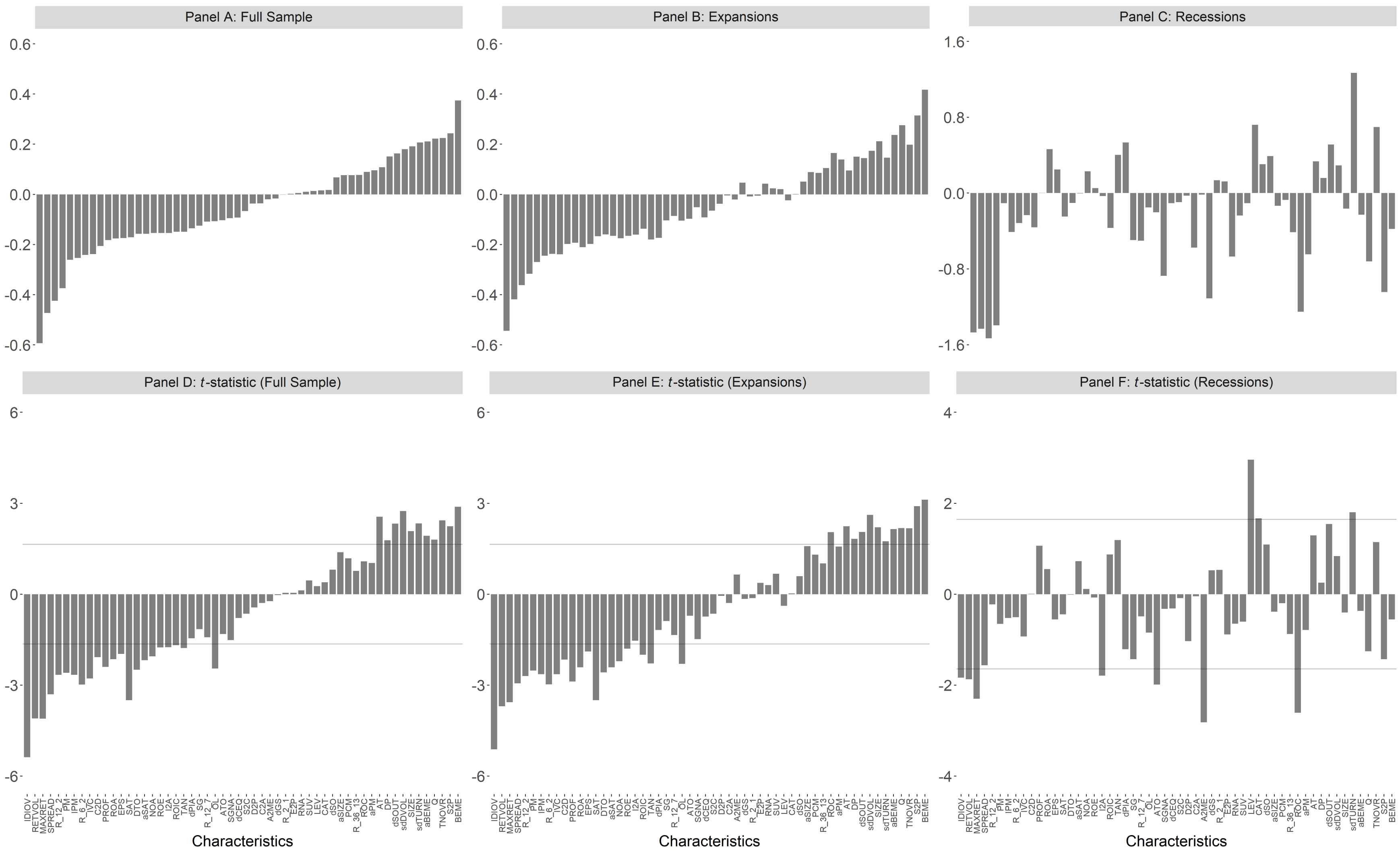

FIGURE IA.3: **Relative pricing errors old and new sorts in expansions versus recessions**
This figure presents the conditional alpha of the older sorts (with return $R_{X,(t-60:t-12),t+1}$) relative to the newest sort (with return $R_{X,(t),t+1}$) in NBER expansions and recessions. In each subsample, the conditional alpha is the average of $R^{c-hedge}_{X,(t-s),t+1}$ defined in Eq. (5). To facilitate interpretation, the characteristics are sorted in the same order as the conditional alphas, α^c, from Figure 1.

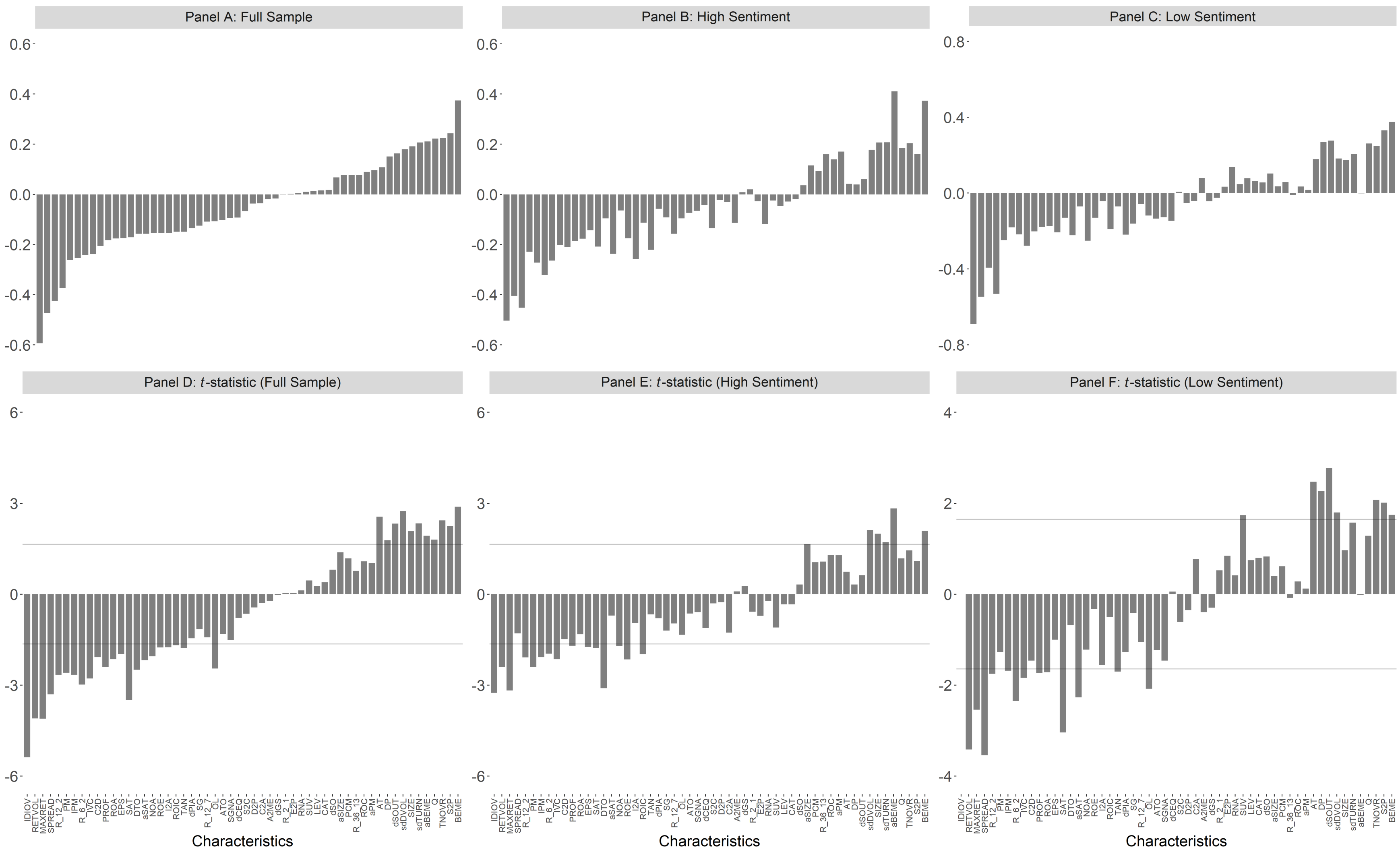

FIGURE IA.4: **Relative pricing errors old and new sorts in high versus low sentiment regimes**
This figure presents the conditional alpha of the older sorts (with return $R_{X,(t-60:t-12),t+1}$) relative to the newest sort (with return $R_{X,(t),t+1}$) in high and low sentiment regimes using the sentiment index of Baker and Wurgler (2006). We follow Stambaugh et al. (2012) and define a high-sentiment month as one in which the sentiment index is above its historical mean. To facilitate interpretation, the characteristics are sorted in the same order as the conditional alphas, α^c, from Figure 1.

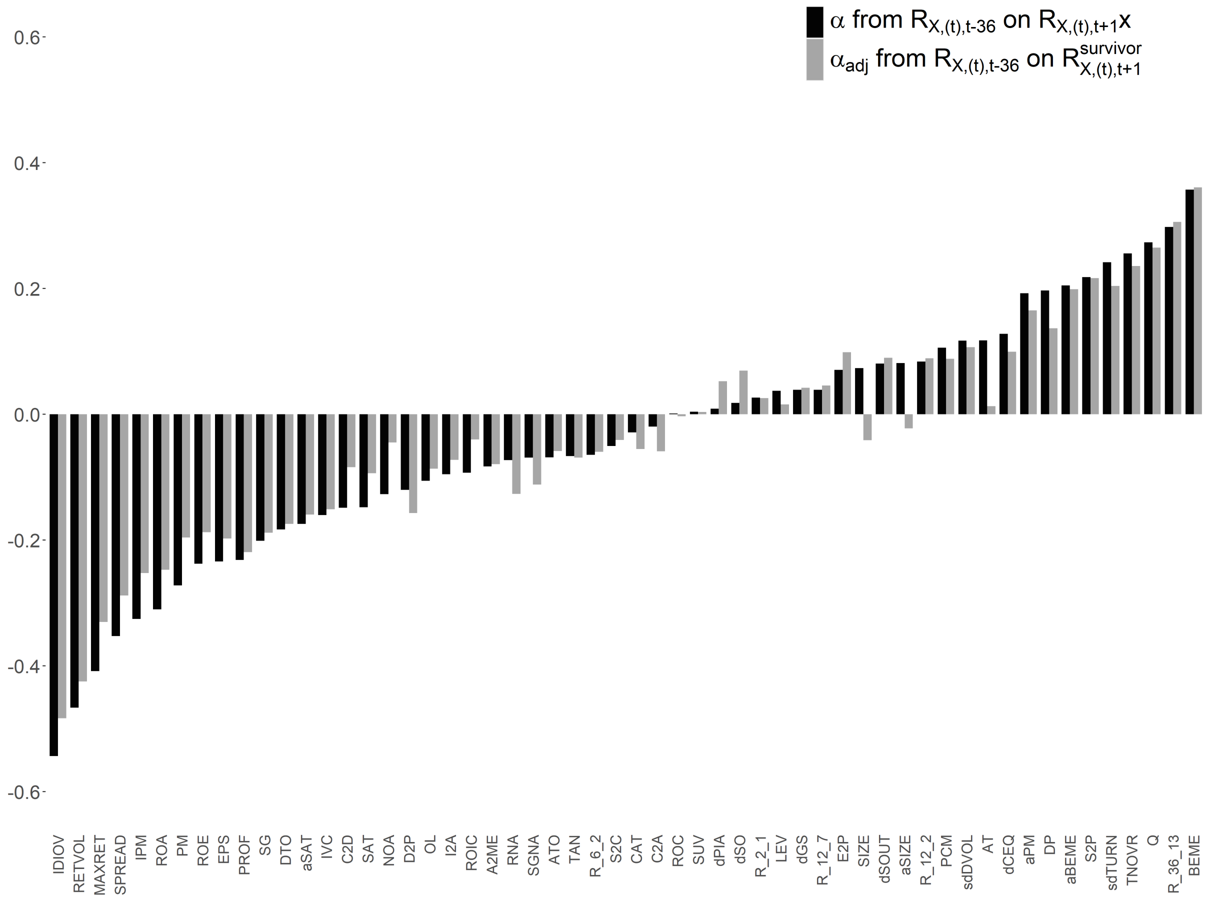

FIGURE IA.5: **Survivorship bias-adjusted alphas**
This figure presents the unconditional alpha of the old sort with return $R_{X,(t-36),t+1}$ relative to the newest sort with return $R_{X,(t),t+1}$ (estimated using the regression in Eq. (4)). It also reports a survivorship bias-adjusted version of the newest sort, for which we exclude from the high and low portfolio at time t all stocks that were not in the CRSP file at $t-36$. In this way, we condition on firm survival on both sides of the regression, such that we estimate a survivorship bias-adjusted α.

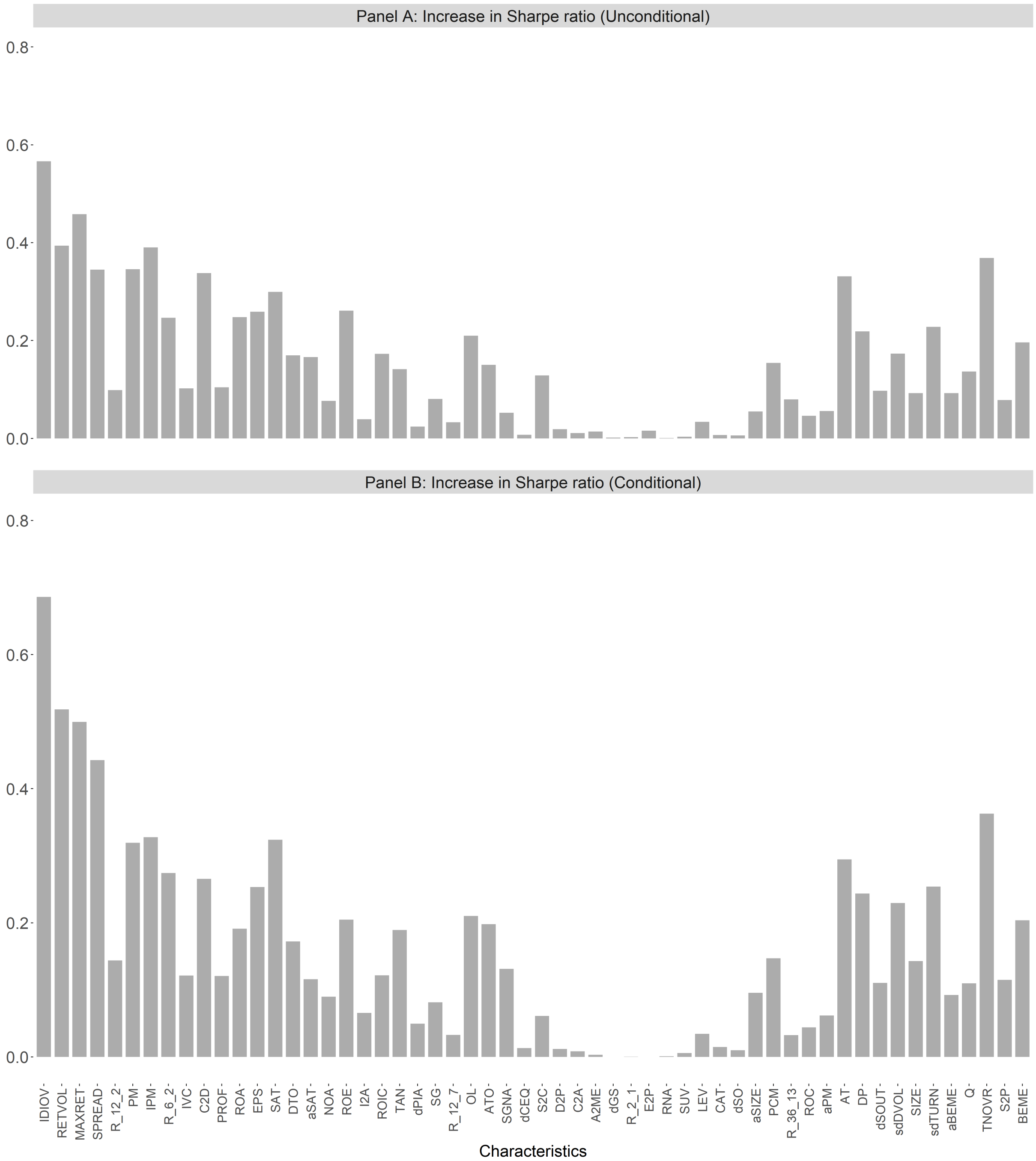

FIGURE IA.6: **Increases in Sharpe Ratio**

This figure presents the maximum improvement in Sharpe ratio from combining the newest sort ($R_{X,t,t+1}$) with a single combination of five old sorts ($R_{X,(t-60:t-12),t+1}$). The improvement is formally defined as: Max. Sharpe($R_{X,(t-60:t-12),t+1}$, $R_{X,(t),t+1}$) - Sharpe($R_{X,(t),t+1}$).

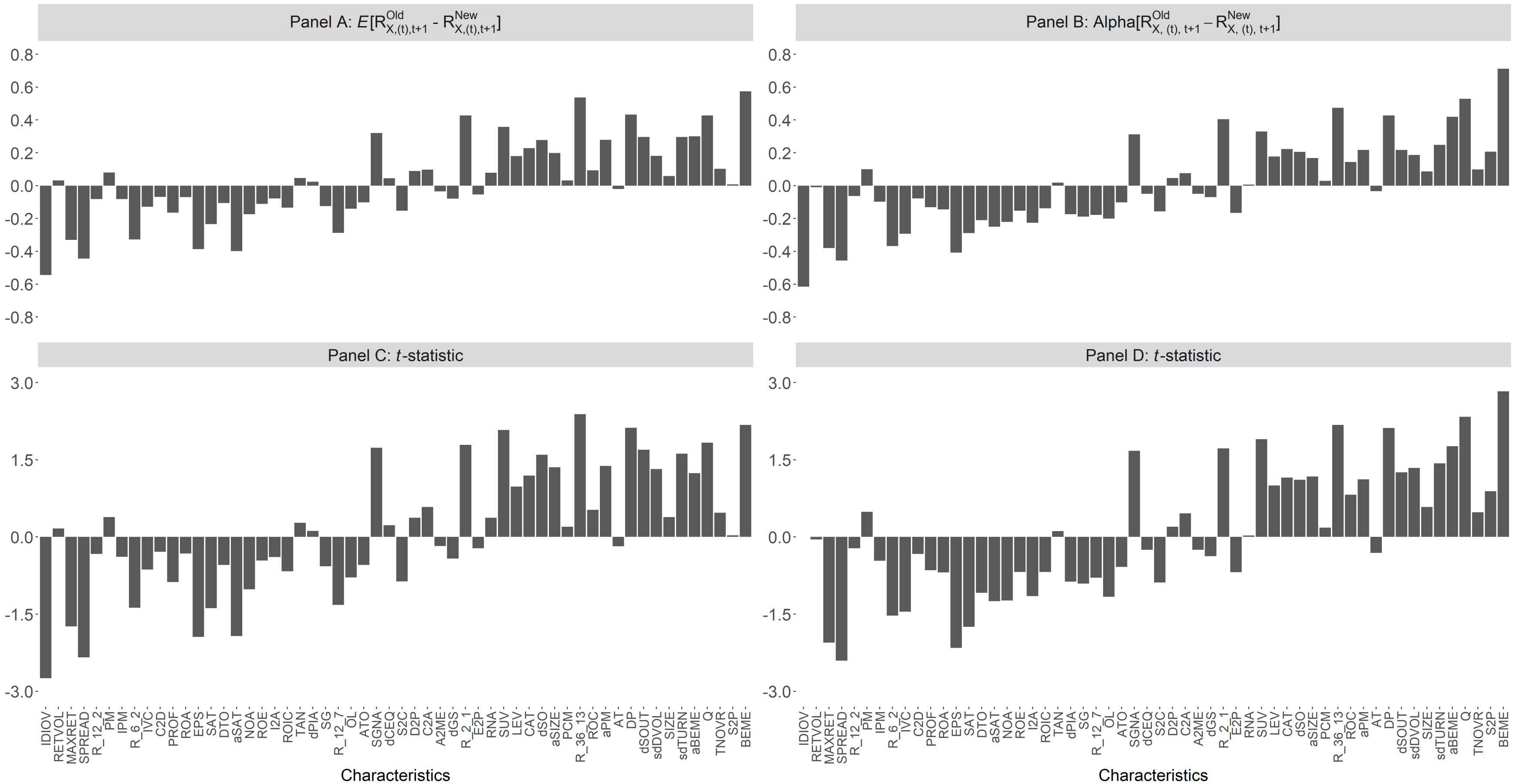

FIGURE IA.7: **The average return of old versus new stocks in characteristic-sorted portfolios**

In Panel A of this figure, we present the difference in average return between old ($R^{Old}_{X,(t),t+1}$) and new ($R^{New}_{X,(t),t+1}$) stocks, which together make up the newest long-short characteristic-sorted portfolio ($R_{X,(t),t+1}$). Panel B presents the intercept from a regression of old-minus-new returns on the newest sort. Panels B and D present White et al. (1980) t-statistics. The sample period runs from July 1974 to December 2017.

Table IA.I: **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).
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).
dPIA	Lyandres et al. (2008)	Change in property, plants and equipment (ppegt) and inventory (invt) over lagged total assets (at).
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).
DP	Litzenberger and Ramaswamy (1979)	Sum of monthly dividend over the last 12 months to last month's price (prc).

Continued

Acronym	Author(s)	Definition
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).
I2A (INV)	Cooper et al. (2008)	Annual % change in total assets (at).
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.
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.
LEV	Lewellen (2015)	long-term debt (dltt) plus current liabilities (dlc) over the sum of long term debt (dltt), debt in current liabilities (dlc) and stockholders equity (seq).
MAXRET	Bali et al. (2011)	Maximum daily return in the previous month.
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).
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 common equity (ceq) minus deferred taxes (txdb) all scaled by total assets (at).
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_2_1	Jegadeesh (1990)	Lagged one month return.
R_36_13	De Bondt and Thaler (1985)	Cumulative return from 36 months to 13 months ago.
R_6_2	Jegadeesh and Titman (1993)	Cumulative return from 6 months to 2 months ago.
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.

Continued

Acronym	Author(s)	Definition
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).
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).
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.
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.
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.
SG	Lakonishok et al. (1994)	% growth rate in sales (sale).
SGNA		Selling, general and administrative expenses (XSGA) to net sales (sale).
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.
SPREAD	Chung and Zhang (2014)	Average daily bid-ask spread in the previous month.
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.
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).
TNOVR	Datar et al. (1998)	Volume (vol) over shares outstanding (shrout).

TABLE IA.II: **Overview of results for alternative asset pricing models**

This table presents an overview of alphas from old versus new sorts and stocks relative to the models of Hou et al. (2015, HXZ), Frazzini and Pedersen (2014, BAB), Daniel et al. (2020b, DMRS), Stambaugh and Yuan (2016, SY), and Daniel et al. (2020a, DHS). In Panel A, we report the alpha of the first principal component of returns at all horizons $s = 0, 12, ..., 60$ after sorting (defined as $\lambda'_{(t),1} R_{X,(t-s),t+1}$ as in Table III). In Panel B, we report the alpha of a strategy that is long the first principal component of older sorts and short the first principal component of the newest sort (analogous to Panel F of Table III). In Panel C, we report the alpha of a strategy that is long (short) an equal-weighted portfolio of the conditionally hedged returns (defined as in Eq. (5)) of high (low) market beta characteristics (analogous to Table V). In Panel D, we report the alpha of a strategy that is long (short) an equal-weighted portfolio of high (low) market beta characteristics (analogous to Table VII). The return of each characteristic portfolio is split into the return coming from new and old stocks, and we also report the old-minus-new difference. t-statistic are based on White et al. (1980) heteroskedasticity consistent standard errors. The sample period runs from July 1974 to the end of the sample over which the factors are report on the author's web sites. We thank the authors for sharing the factor data.

	HXZ		BAB		DMRS		SY		DHS	
	α	t	α	t	α	t	α	t	α	t
Panel A: Alpha of first principal component of old and new sorts										
$\lambda'_{(t),1} R_{X,(t-s),t+1}$										
0	0.21	0.45	-0.33	-0.43	-1.14	-2.89	0.34	0.71	1.31	2.16
12	0.81	1.73	0.58	0.78	-0.14	-0.46	0.51	1.13	1.74	3.25
24	1.21	2.56	0.99	1.35	0.39	1.26	0.83	1.89	1.97	3.89
36	1.42	3.22	1.05	1.52	0.49	1.59	1.05	2.47	1.98	3.91
48	1.55	3.76	1.18	1.76	0.59	2.00	1.10	2.77	1.93	4.01
60	1.39	3.41	1.14	1.81	0.58	1.92	1.06	2.65	1.77	3.62
Panel B: Alpha of old-minus-new sorts										
$\lambda'_{(t),1}(R_{X,(t-s),t+1} - R_{X,(t),t+1})$										
12	0.60	2.35	0.91	3.15	1.00	4.26	0.17	0.70	0.43	1.47
24	1.00	3.33	1.32	3.85	1.53	5.46	0.49	1.70	0.66	1.84
36	1.21	3.49	1.38	3.51	1.64	5.14	0.71	1.98	0.68	1.63
48	1.34	3.77	1.51	3.84	1.74	5.31	0.75	2.03	0.62	1.49
60	1.18	3.34	1.47	3.79	1.73	5.08	0.71	1.82	0.47	1.13
Panel C: Alpha of conditionally hedged strategies (in High-minus-Low market beta portfolio)										
$R^{c-hedge}_{X,(t-12),t+1}$	0.04	0.57	0.08	1.12	0.05	0.90	0.09	1.12	0.13	1.80
$R^{c-hedge}_{X,(t-24),t+1}$	0.21	2.63	0.24	3.11	0.24	3.65	0.15	1.82	0.25	3.25
$R^{c-hedge}_{X,(t-36),t+1}$	0.28	3.36	0.31	3.48	0.31	4.52	0.24	2.70	0.30	3.47
$R^{c-hedge}_{X,(t-48),t+1}$	0.35	4.22	0.34	3.63	0.34	4.95	0.28	3.12	0.34	3.86
$R^{c-hedge}_{X,(t-60),t+1}$	0.35	3.83	0.35	3.72	0.32	4.26	0.28	2.85	0.32	3.44
Panel D: Alpha of Old versus New stocks (in High-minus-Low market beta portfolio)										
$R^{New}_{X,t,t+1}$	-0.11	-0.60	-0.06	-0.30	-0.24	-1.65	0.03	0.15	0.25	1.15
$R^{Old}_{X,t,t+1}$	0.33	1.81	0.31	1.37	0.11	0.70	0.42	2.24	0.70	3.36
$R^{Old}_{X,t,t+1} - R^{New}_{X,t,t+1}$	0.45	3.70	0.37	2.93	0.35	3.39	0.39	3.07	0.45	3.70