The Importance of Empirical Research Design in Asset Pricing

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Abstract

The selection of methodological alternatives in asset pricing analysis can serve to significantly alter the interpretation and possibly the statistical inference of empirical results. We examine the statistical and economic impact of subtle yet important changes to the methodological design of an important empirical study. We select the pricing of idiosyncratic volatility as our test model, and we find that equally valid test designs can generate significantly different results and conclusions. We estimate monthly alphas for portfolios sorted by idiosyncratic volatility and find a set of plausible monthly alphas that range from ‑1.478% to +0.044%. We expound upon the challenges posed to researchers by the effects of methodological test design alternatives on inference.

1. Introduction

Researchers must choose among numerous design decisions in order to construct an empirical test. These decisions can significantly impact both empirical results and conclusions. This is particularly true of empirical asset pricing tests. For the particular methodology of portfolio formation, the most obvious design decisions are selecting the control variables and sample. In addition, researchers are required to make more subtle decisions, such as choosing between equal-weighted or value-weighted portfolios, determining the number of quantiles, choosing between CRSP and NYSE breakpoints, determining the frequency of portfolio rebalancing, and many others. Typically, the alternative choices are not controversial and commonly recur in the literature. For example, Fama and French (2008) form quintile portfolios and report equal-weighted portfolio returns in addition to value-weighted returns. On the other hand, Pasquariello (2014) forms decile portfolios and reports only value-weighted returns. Ang et al. (2006) form quintile portfolios and report only value-weighted returns. Fama and French (1993) rebalance their portfolios annually, while Jegadeesh and Titman (1993) rebalance monthly. These valid design decisions, however, can materially affect the economic and statistical significance of parameter estimates, and in turn alter the interpretation of the results. The purpose of this study is to examine and quantify the impact different design decisions can have on inference.

A seminal study by Ang et al. (2006) relating idiosyncratic volatility to portfolio returns uncovered an empirical puzzle that has spurred a large body of literature. Ang et al. (2006) report a large, statistically significant, negative relation between idiosyncratic risk and returns. We use the empirical evidence produced by subsequent studies of idiosyncratic volatility as guidance for our methodological approach to examine the impact of empirical asset pricing test design decisions on inference.

Because Ang et al. (2006) laid the foundation for idiosyncratic volatility literature, we take the design decisions of that study as the “benchmark” against which we measure the impact of various other design decisions. We then seek to identify the effect of empirical asset pricing test design decisions on inference by quantifying the impact of various designs on the magnitude of estimated portfolio alphas.

Portfolio tests, as opposed to cross-sectional regressions, are commonly used in asset pricing studies because the point estimate of the portfolio alpha has economic significance in addition to statistical significance. A portfolio’s alpha is the average return from an investment strategy, controlling for other known strategies and risk. Ang et al. (2006) report the alpha for a zero-investment strategy that shorts stocks with low idiosyncratic volatility and uses the proceeds to purchase stocks with high idiosyncratic volatility. Their strategy has a monthly portfolio alpha of -1.31% (Ang et al., 2006, p.285, Table VI). The purpose of our study is to examine how the monthly portfolio alpha changes as we change the test to include uncontroversial, yet subtly different designs.

The test designs we have chosen to analyze represent design decisions that have been examined previously in the idiosyncratic volatility literature and found to be warranted and relevant to inference. Because of their inclusion in the literature and the evidence that they are plausibly better design decisions, we consider them to be uncontroversial.

Our study is most similar to Chen et al. (2012), but has several important differences. Primarily, we focus on the identical sample as Ang et al. (2006) while Chen et al. (2012) use an updated sample. Further, our focus is quite different. They focus on identifying the situations when idiosyncratic volatility is priced. We focus more on the discussion of the issues that are more generally applicable to all of empirical asset pricing and statistical inference of portfolio alphas.

We consider the impact of the following design decisions: value weighting versus equal weighting, inclusion of the turn-of-year effect, the effect of low-priced stocks, choosing NYSE versus CRSP breakpoints, augmenting the three-factor model with the momentum factor, augmenting the three-factor model with the reversal factor, and replacing the three-factor model with the Fama and French (2015) five-factor model. From this set of uncontroversial design alternatives, we estimate a set of alphas that differ substantially from each other and from Ang et al. (2006). Finally, we analyze the impact the different design decisions have on the economic significance of idiosyncratic volatility as an investment strategy.

2. The Benchmark Design of Idiosyncratic Volatility Pricing

Ang et al. (2006) revitalize interest in the pricing of idiosyncratic volatility by documenting a surprising negative relation to portfolio returns. They use the Fama and French (1993) three-factor model and daily returns in excess of the risk-free rate to construct a monthly measure of idiosyncratic volatility, for each month and for each stock, in their sample period from July 1963 to December 2000. Idiosyncratic volatility is defined as the standard deviation of the residuals from these regressions. This measure is then used to form five value-weighted portfolios based on the rank of each stock’s idiosyncratic volatility. All stocks in the sample are separated into portfolios based on idiosyncratic volatility breakpoints (the so-called “CRSP breakpoints”). The portfolios, sorted by their idiosyncratic volatility, are held for the following month and then rebalanced.

The price of idiosyncratic volatility is reached by estimating the alpha for a zero-investment portfolio that shorts the lowest idiosyncratic volatility portfolio and purchases the highest idiosyncratic volatility portfolio. The portfolio alpha is then estimated by again using the Fama and French (1993) three-factor model. We refer to this method of portfolio construction and estimation of alpha as our benchmark method. In order to insure that our benchmark method follows the original work of Ang et al. (2006), we try to replicate their results. The comparison is presented in Table 1.

Our replication of the Ang et al. (2006) study produces nearly identical results. Our alphas follow a pattern similar to that reported in Table VI in Ang et al. (2006). Our estimated alphas are only slightly different from those presented by Ang et al. with differences ranging between 3 and 6 basis points. There may be many potential reasons for this minor discrepancy, but the most likely candidate is that of data revisions. CRSP continually edits and revises the data, and our data are from a 15-year later vintage. Therefore, although we use the same data period as Ang et al., the data published by CRSP in 2001 and 2015 may not be identical. Our noted discrepancies are quite minor, however, and we are confident that our revised test designs are consistent with Ang et al. (2006).

The t-statistics we report are somewhat different from those reported by Ang et al., but we use a different methodology to estimate standard errors. We use OLS standard errors, while Ang et al. use Newey-West (1987) standard errors. The purpose of our study is to examine the variation in the point estimates of the alphas rather than t-statistics in total, and thus we do not replicate their standard error measurement.

3. Alternative Designs for Pricing Idiosyncratic Volatility

Many studies subsequent to Ang et al. (2006) examine the puzzling relation presented in Table 1. In this section, we review some of these studies and describe how we use their findings to create alternative empirical test designs.

**3.1 Portfolio Weighting**

In their thorough investigation of the robustness of the negative relation between idiosyncratic volatility and alpha, Bali and Cakici (2008) identify two key methodological issues that affect inference. The first issue is the weighting scheme of the portfolios. The standard in empirical asset pricing research is to report value-weighted portfolio results at the very least, and many researchers eschew reporting equal-weighted portfolio results. Ang et al. (2006) examine only value-weighted portfolios. Bali and Cakici (2008), however, find that the magnitude of the alpha is mitigated by the selection of equal-weighted portfolios.

 The choice of reporting alphas for equal-weighted portfolios in addition to value-weighted portfolios is an important one, and the effects of this choice on the interpretation of the results of asset-pricing tests need to be examined. The return on an equal-weighted portfolio better describes the return of a typical stock in the portfolio. Portfolio returns, however, may be overly influenced by small, illiquid stocks. Value weighting better captures the experience of a typical investor in the stocks of the portfolio, but value-weighted portfolios may not be well diversified (e.g., Malevergne et al., 2009). Fama and French (2008) advocate the use equal-weighted portfolios in addition to value-weighted portfolios. We report both value-weighted and equal-weighted portfolio results for all of our test designs.

**3.2 Portfolio Breakpoints**

In order to form a set of portfolios based on some variable, such as idiosyncratic volatility, researchers must choose some value, or breakpoint, to use to break up the sample of stocks in order to assign them to portfolios. Two common methods have developed to form portfolio quantiles. The first, called CRSP breakpoints, is to compute quantile breakpoints using all stocks available on CRSP. These so-called "CRSP breakpoints" have the advantage of maximizing dispersion of the variable used to form the portfolios. The second method, used by Fama and French (1992), is to set breakpoints for quantiles of stocks trading on the NYSE. These so-called "NYSE breakpoints" ensure that large, liquid stocks appear in all of the portfolios.

The second key issue identified by Bali and Cakici (2008) is that the conclusions of Ang, et al. (2006) depend on the choice of breakpoints. Ang, et al. (2006) only use CRSP breakpoints thorough their study. When replacing the CRSP breakpoints with NYSE breakpoints, Bali and Cakici (2008) find that the negative relation is no longer significant. This is important because both methods of setting breakpoints are commonly used and it is not clear which method is preferable.

**3.3 The Cahart Momentum Factor**

Arena et al. (2008) show that idiosyncratic volatility is linked to returns from the momentum strategy of buying short-term (up to one year) winners and selling short-term losers. They argue that idiosyncratic volatility limits arbitrageurs from correcting these prices and find that momentum profits are highest among high idiosyncratic volatility portfolios. To incorporate this finding in our analysis of idiosyncratic volatility, i.e., to see if the negative relation is a product of the known momentum anomaly, we augment the three-factor model with the Carhart (1997) momentum factor.

**3.4 The Huang et al. Reversal Factor**

Huang, Liu, Rhee, and Zhang (2010) further the analysis of the negative relation between idiosyncratic volatility and portfolio returns by incorporating the effect of serial correlation in returns. These authors argue that by ignoring serial correlation and using only value-weighted portfolios, Ang et al. (2006) may have induced downward bias in their estimation of the relation between returns and the previous month’s idiosyncratic volatility. Huang et al. (2010) control for the effect of short-term return reversal by adding a reversal factor to the three-factor model. We follow Huang et al.’s (2010) lead by including their reversal factorin our estimation of the portfolio alphas. The Huang et al. reversal factor represents a valid choice for addition to an asset-pricing test, and thus may influence economic inference.

**3.5 Fama and French’s Five-Factor Model**

Lehmann (1990) argues that the variance of the residuals from a mis-specified factor model should be related to average returns. Given that the Fama and French (1993) three-factor model has been unable to explain certain phenomena (e.g, momentum), it may be a mis-specified factor model. To address this possibility we estimate portfolio alphas using the Fama and French (2015) five-factor model. This is the three-factor model augmented with two new factors: an investment factor and an earnings factor.

The investment factor is represented by a portfolio that is short stocks with the lowest total asset growth over the previous year, and long stocks with the highest total asset growth. The earnings factor is represented by a portfolio that is short stocks with the lowest operating profits, and long stocks with the highest operating profits. These two factors are designed to capture two anomalies – asset growth and profitability – and may lead to a more correctly specified factor model.

**3.6 The Turn-of-Year Factor**

Peterson and Smedema (2011) find that there is a significant turn-of-year effect in the relation between expected returns and the Ang et al. (2006) measure of idiosyncratic volatility. By augmenting the Fama and French (1993) three-factor model with the Carhart (1997) momentum factor and a January indicator, the fragile results previously found by Bali and Cakici (2008) and Huang et al. (2010) become more significant and robust. Therefore, because the January indicator represents a valid methodological choice for risk-adjusting returns, we include the indicator in our estimation of the portfolio alphas.

**3.7 Low-Priced Stocks**

Bali and Cakici (2008) find that eliminating stocks with prices of less than $10 reduces the magnitude of the alpha of the idiosyncratic volatility designated zero-investment portfolios. To the contrary, Chen et al. (2012) find that the elimination of stocks with prices less than $5 actually increases the magnitude of the portfolio alpha. Proceeding with or without low-priced stocks are equally valid alternative methodologies. On the one hand, we should not unnecessarily eliminate data. On the other hand, the use of low-priced stocks may negatively impact inference because of potential liquidity issues. Further, determining what price is the cutoff for low priced stocks is quite subjective. Given the conflicting inferences from Bali and Cakici (2008) and Chen et al. (2012), and the difficulty in determining the correct price cutoff, we report the pricing of idiosyncratic volatility excluding both stocks with prices less than $5 and less than $10.

4. Data and Sample

The data come from CRSP and Kenneth French’s data library. From CRSP we obtain all data for returns, prices, shares outstanding, SIC codes, and exchange codes. From Kenneth French’s data library we obtain the risk-free rate, the market return factor, the size factor, the value factor, the momentum factor, and the short-term reversal factor. We apply standard filters and remove all stocks from the firms in the financial industry (SIC 6000 to 6999) and utilities (SIC 4900 to 4999). We also filter out all stocks that do not trade on the NYSE, American Stock Exchange, or NASDAQ. We filter out all observations that do not have data on returns, the end of month price, or sufficient daily returns to calculate idiosyncratic volatility from the previous month. Finally, we require stocks to have book value of equity available from COMPUSTAT. We use the Fama and French (1992) method for computing book value of equity. With these filters and data requirements, our full sample is 1,731,820 stock-month observations spanning from August 1962 to December 2000. We choose this end point to direct all comparisons to the original results in Ang et al. (2006) without fear of a change in market conditions (e.g., Han and Lesmond, 2011) as the cause of our different results.

5. The Effects of Alternative Empirical Designs

**5.1 The effect of alternative empirical designs on value-weighted portfolios**

In this section, we analyze the impact of our alternative empirical choices on estimated portfolio alphas for value-weighted portfolios, weighted by the stock’s market capitalization at the end of the previous month. In Table 2, we report again the Fama-French (1993) three-factor alphas in the row labeled “Benchmark”. We provide alphas for alternative empirical designs in the subsequent rows, labeled accordingly in the “Methodology” column. All portfolios are constructed with CRSP breakpoints, with the exception of the fifth row of alphas, which are constructed with NYSE breakpoints.

Table 2 shows that our different empirical design decisions lead to a large dispersion of results. While all of the estimated alphas from the *H-L* portfolio are negative and statistically significant for each research design, economic significance varies greatly. When we add the January indicator to the three-factor benchmark model, the alpha increases in magnitude by about 0.1% per month, which corresponds to a compound annual difference of ‑1.2%. The addition of the Momentum and Reversal Factors to our benchmark factor model has a negligible impact on the magnitude of the benchmark alpha. The other five changes to the methodology substantially increase the magnitude of the alphas. For example, using NYSE breakpoints increases the benchmark *H-L* alpha from ‑1.372% to ‑0.667%. On an annualized basis, this represents a substantial, economically significant shift from -15.28% (benchmark with CRSP breakpoints) to -7.72% (NYSE breakpoints) for the *H-L* portfolio. The smallest alpha occurs when we add all of the alternative design choices. From this model, the monthly alphas are ‑0.259% (or about ‑3% per year), which is over 1% per month different than the largest alpha from the January indicator model.

The annualized alphas range from ‑16.36% to ‑3.06% demonstrating an interesting aspect of Leamer (1983) and Leamer and Leonard’s (1983) concept of fragility. Their concept of fragility results from methodological changes generating a range of regression of estimates. “When the range of inferences is too wide…, then we must conclude that inferences…are too fragile to be useful” (Leamer and Leonard, 1983, p.306). The range of alphas in Table 2 is enormous, but there is no range in inferences as they are all significantly negative. As such, by the strict definition of robust (the opposite of fragile) from Leamer and Leonard (1983), these alphas are robust.

**5.2 The effect of alternative empirical designs on equal-weighted portfolios**

Table 3 presents the same regressions shown in Table 2, but for equal-weighted portfolios rather than value-weighted portfolios. Equal-weighted portfolios are more diversified than value-weighted portfolios, and they are immune to some biases that affect value-weighted portfolios (see Huang et al. 2010). Alphas from equal-weighted, zero-investment portfolios represent risk-adjusted returns of the average high volatility stock in excess of the risk-adjusted returns of the average low volatility stock. Whether to report equal-weighted portfolio alphas in addition to value-weighted portfolio alphas is an important decision that test designers should consider.

In Table 3, we report the benchmark results for equal-weighted portfolios in the first row. For the remaining rows, we present the alternative methodological choices using equal-weighted portfolios. Consistent with Bali and Cakici (2008), we find that equally weighting the portfolios causes estimated alphas to rise toward zero. The benchmark method using equal-weighted portfolios has an alpha of -0.358%. This alpha is economically significant, corresponding to a compound annual return of ‑4.21%, but much lower in magnitude than the -15.28% compound annual return from the value-weighted portfolio. Again, the dramatic increase in the magnitude of the alpha implies that the results may be fragile. However, since the alpha is still statistically significant at the 10% level, we should conclude, according to Leamer and Leonard (1983), that the results are robust.

For every empirical design, alphas for equal-weighted portfolios are higher than for their value-weighted counterparts. Again, the January indicator design produced the lowest *H-L* portfolio alpha, but it is about 0.6% greater than the analogous value-weighted portfolio alpha. Two of the designs – adding the momentum factor and using the Fama and French five-factor model – produces portfolio alphas not significantly different from zero. The five-factor model even produces a positive *H-L* portfolio alpha.

With the equal-weighted portfolios, the pricing of idiosyncratic volatility potentially fails to prove robustness. The range of the estimates of the alphas is 0.91% per month (11.5% annualized), which is, again, enormous. Further, with the equal-weighted portfolios, our methodological changes yield a range of inferences. The alpha estimates from a four-factor model with momentum and the five-factor model yield insignificant alphas. We now have a range of possible inferences (i.e., the strategy either earns a negative profit or no profit at all) in addition to a wide range of alpha estimates.

6. Discussion and Summary

We use the idiosyncratic volatility analysis of Ang et al. (2006) and the empirical results of subsequent studies as the framework of our analysis to determine how using different methodological test designs impact inference. Our results indicate that a strategy of shorting low idiosyncratic volatility stocks and purchasing high idiosyncratic volatility stocks produces a very economically significant dispersion, ranging from a risk-adjusted annual loss of -15.28% to a risk-adjusted annual profit of 0.53%. These are two very qualitatively and quantitatively different amounts. The wide range of portfolio alphas that result from making subtle choices between empirical test designs raises questions about the fragility of the interpretation of asset pricing test results. If the nature of the relation between idiosyncratic volatility and returns changes following simple changes in methods (e.g., using the equal-weighted rather than value-weighted portfolios), how can empirical asset pricing researchers appropriately draw inference about the true profitability from a particular investing strategy?

The cynical view of empirical research is that a researcher can estimate dozens of models and selectively report the results that tell the best story. Our results highlight the opportunity of this cynical view. In addition to the fear that a researcher will “cherry pick” the method that leads to the preferred conclusion, and given the rise of computing power and data availability, a researcher could find several models and methods that could give an additional appearance of robustness. Not only can researchers estimate dozens of models, they can also report the results of dozens, or even millions of models (Sala-I-Martin, 1997). While journals cannot feasibly publish in print all of the extra results, they could report them as an internet appendix. Alternatively, most researchers have their own personal pages on their university website on which they report their curriculum vitae, drafts of working papers, and computer code from research studies. Instead of reporting results selectively, we could strive to report results comprehensively.

Several researchers have contemplated how to combat any charge of “cherry picking” results in empirical research. Leamer (1983, 1985, and 2010) advocates a sensitivity analysis in which researchers estimate the extreme maximum and minimum values for regression coefficients. Sala-I-Martin (1997) argues that Leamer’s (1983) method is unnecessarily strict and prefers to estimate every possible combination of a set of control variables and the probability distributions of the set of regression coefficients. The concerns of those sympathetic with Leamer’s views stem from the rise of computing power and data availability.

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| **Table 1**Benchmark Alphas (%) for Idiosyncratic Volatility-Sorted Portfolios |
|  | L | ML | M | MH | H | H-L |
| Replication | 0.101\*\* | 0.116\* | 0.063 | -0.278\*\*\* | -1.271\*\*\* | -1.372\*\*\* |
|  | (2.524) | (1.840) | (0.790) | (-2.664) | (-8.546) | (-8.205) |
|  |  |  |  |  |  |  |
| Ang et al. | 0.04 | 0.09 | 0.08 | -0.32\*\* | -1.27\*\*\* | -1.31\*\*\* |
|  | (0.99) | (1.51) | (1.04) | (-3.15) | (-7.68) | (-7.00) |
| In this table, we report the portfolio alphas (×100) from our replication and the corresponding alphas from Ang et al. (2006) for idiosyncratic volatility-sorted portfolios. Idiosyncratic volatility is measured at monthly intervals from daily data. For each month in our sample period, we estimate the Fama and French (1993) three-factor model with daily excess returns (returns less the daily return on a portfolio of U.S. T-bills) and the daily factors from the previous calendar month. We measure monthly idiosyncratic volatility as the standard deviation of the residual from the daily three-factor regressions (*×√30*). We exclude all estimates that are made with fewer than 15 daily observations. When forming these portfolios, we follow Ang et al. (2006). We form quintile portfolios every month based on CRSP breakpoints. We form a long-short portfolio (H-L) by shorting the lowest quintile portfolio (L) and purchasing the highest quintile (H). We value-weight the portfolios based on each stock’s market capitalization (*price × shares outstanding*). We estimate the portfolio alphas by regressing the six time-series of portfolio returns on the Fama and French (1993) three factors. All return data is obtained from the CRSP daily and monthly files. The factors and the T-bill returns are obtained from Kenneth French’s data library. In the rows labeled ‘Replication,’ our sample period is identical to Ang et al. (2006), beginning July 1963 and ending December 2000. The values in the row labeled ‘Ang et al.’ originate from Table VI in Ang et al. (2006). We report the alphas in the first row and the OLS t-statistics in parentheses in the second row. \*, \*\*, \*\*\* denotes statistical significance at the 10%, 5%, and 1% levels, respectively. |

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| Table 2Alphas (%) for Value-Weighted, Idiosyncratic Volatility-Sorted Portfolios |
| Methodology | L | ML | M | MH | H | H-L |
| Benchmark | 0.101\*\* | 0.116\* | 0.063 | -0.278\*\*\* | -1.271\*\*\* | -1.372\*\*\* |
| (value-weighted) | (2.524) | (1.840) | (0.790) | (-2.664) | (-8.546) | (-8.205) |
|  |  |  |  |  |  |  |
| Turn-of-Year  | 0.089\*\* | 0.103 | 0.052 | -0.287\*\*\* | -1.389\*\*\* | -1.478\*\*\* |
| Factor | (2.181) | (1.582) | (0.628) | (-2.675) | (-9.187) | (-8.660) |
|  |  |  |  |  |  |  |
| Exclude  | 0.112\*\*\* | 0.101\* | 0.098 | -0.189\*\* | -0.673\*\*\* | -0.785\*\*\* |
| < $5 | (2.625) | (1.654) | (1.332) | (-2.064) | (-5.386) | (-5.477) |
|  |  |  |  |  |  |  |
| Exclude  | 0.111\*\* | 0.078 | 0.178\*\* | -0.007 | -0.450\*\*\* | -0.561\*\*\* |
| < $10 | (2.250) | (1.404) | (2.479) | (-0.085) | (-3.729) | (-3.914) |
|  |  |  |  |  |  |  |
| NYSE Break- | 0.136\*\*\* | 0.147\*\* | 0.109 | 0.085 | -0.530\*\*\* | -0.667\*\*\* |
| points | (2.694) | (2.483) | (1.508) | (1.026) | (-5.625) | (-5.515) |
|  |  |  |  |  |  |  |
| Momentum | 0.131\*\*\* | 0.187\*\*\* | 0.084 | -0.236\*\* | -1.208\*\*\* | -1.339\*\*\* |
| Factor | (3.149) | (2.871) | (1.003) | (-2.165) | (-7.768) | (-7.646) |
|  |  |  |  |  |  |  |
| Reversal  | 0.115\*\*\* | 0.086 | 0.061 | -0.287\*\*\* | -1.300\*\*\* | -1.416\*\*\* |
| Factor | (2.885) | (1.358) | (0.755) | (-2.723) | (-8.670) | (-8.413) |
|  |  |  |  |  |  |  |
| Fama-French | 0.027 | 0.078 | 0.154\* | -0.103 | -0.958\*\*\* | -0.985\*\*\* |
| Five Factor  | (0.706) | (1.228) | (1.917) | (-1.022) | (-6.825) | (-6.382) |
|  |  |  |  |  |  |  |
| All | 0.075 | 0.047 | 0.061 | 0.035 | -0.184\* | -0.259\*\* |
|  | (1.367) | (0.709) | (0.740) | (0.375) | (-1.793) | (-2.026) |
| In this table, we report the portfolio alphas (×100) from our benchmark methodology and several alternative choices for value-weighted idiosyncratic volatility-sorted portfolios. See Table 1 for discussion of our estimate of idiosyncratic volatility, our method for estimating alpha, and the methodological choices used to form our benchmark estimates. In the first column, we describe the methodological alternative choice for the corresponding set of alphas. In the ‘Benchmark’ row, we reproduce the alphas from Table 1. In the ‘January Indicator’ row, we report the alphas from Fama and French (1993) three-factor regressions augmented with a January indicator variable that takes the value of one if the observed return is from the month of January and zero otherwise. In the ‘Exclude < $5’ and ‘Exclude < $10’ rows, when forming our portfolios, we exclude all stocks with prices less than $5 and $10, respectively, at the end of the previous month. In the ‘NYSE Breakpoints’ row, instead of using all stocks in setting the portfolio breakpoints, we set the breakpoints between portfolios only using stocks that trade on the NYSE. In the ‘Momentum Factor’ row, we augment the Fama and French (1993) three-factor model with the Carhart (1997) momentum factor to estimate the portfolio alphas. In the ‘Reversal Factor’ row, we augment the Fama and French (1993) three-factor model with the short-term reversal factor to estimate portfolio alphas. In the ‘FF 5 Factor’ row, we use the Fama and French (2015) five-factor model. In the ‘All’ row, we use all of these alternative methodological choices in constructing our portfolios and estimating our portfolio alphas. The price data are from CRSP, and the momentum and reversal factors are from Kenneth French’s data library. We report the alphas in the first row and the OLS t-statistics in parentheses in the second row. \*, \*\*, \*\*\* denotes statistical significance at the 10%, 5% and 1% levels, respectively. |

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| Table 3Alphas (%) for Equal-Weighted, Idiosyncratic Volatility-Sorted Portfolios |
| Methodology | L | ML | M | MH | H | H-L |
| Benchmark | 0.047 | 0.214\*\*\* | 0.138\*\* | -0.109 | -0.311 | -0.358\* |
| (equal-weighted) | (0.689) | (3.362) | (2.018) | (-1.118) | (-1.645) | (-1.755) |
|  |  |  |  |  |  |  |
| Turn-of-Year  | 0.057 | 0.196\*\*\* | 0.056 | -0.303\*\*\* | -0.811\*\*\* | -0.868\*\*\* |
| Factor | (0.808) | (2.999) | (0.817) | (-3.299) | (-4.906) | (-4.764) |
|  |  |  |  |  |  |  |
| Exclude | 0.052 | 0.184\*\*\* | 0.224\*\*\* | 0.007 | -0.709\*\*\* | -0.761\*\*\* |
| < $5 | (0.784) | (2.752) | (3.682) | (0.120) | (-8.179) | (-5.950) |
|  |  |  |  |  |  |  |
| Exclude  | 0.018 | 0.124\* | 0.198\*\*\* | 0.100 | -0.243\*\* | -0.260\* |
| < $10 | (0.247) | (1.765) | (2.694) | (1.349) | (-1.969) | (-1.844) |
|  |  |  |  |  |  |  |
| NYSE Break- | 0.034 | 0.107 | 0.192\*\*\* | 0.095 | -0.249\*\* | -0.282\*\* |
| Points | (0.458) | (1.505) | (2.626) | (1.266) | (-1.981) | (-1.994) |
|  |  |  |  |  |  |  |
| Momentum | 0.166\*\* | 0.373\*\*\* | 0.285\*\*\* | 0.065 | -0.149 | -0.315 |
| Factor | (2.388) | (6.033) | (4.231) | (0.659) | (-0.757) | (-1.473) |
|  |  |  |  |  |  |  |
| Reversal | 0.023 | 0.170\*\*\* | 0.081 | -0.180\* | -0.356\* | -0.379\* |
| Factor | (0.330) | (2.719) | (1.228) | (-1.890) | (-1.873) | (-1.840) |
|  |  |  |  |  |  |  |
| Fama-French | -0.078 | 0.147\*\*\* | 0.177\*\*\* | 0.023 | -0.034 | 0.044 |
| Five Factors | (-1.307) | (2.592) | (2.662) | (0.244) | (-0.185) | (0.231) |
|  |  |  |  |  |  |  |
| All | -0.060 | 0.126\*\* | 0.156\*\* | 0.150\*\* | -0.339\*\*\* | -0.279\*\*\* |
|  | (-0.996) | (2.085) | (2.450) | (2.256) | (-4.796) | (-2.784) |
| In this table, we report the portfolio alphas (×100) from our benchmark methodology and several alternative choices for equal-weighted idiosyncratic volatility-sorted portfolios. See Table 1 for discussion of our estimate of idiosyncratic volatility, our method for estimating alpha, and the methodological choices used to form our benchmark estimates. In the first column of the table, we describe the methodological alternative choice for the corresponding set of alphas. In the ‘Benchmark’ row, we reproduce the alphas from Table 1 except we use equal-weighted rather than value-weighted portfolios. See Table 2 for discussion of our alternative methodological choices. We report the alphas in the first row and the OLS t-statistics in parentheses in the second row. \*, \*\*, \*\*\* denotes statistical significance at the 10%, 5% and 1% levels, respectively. |