Decomposing the Size Premium

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Abstract

We decompose firm size into four components: the lagged 5-year component that represents size five years ago, and the long-run, intermediate-run, and short-run components that capture changes in size in each horizon. Our analyses indicate that while the lagged 5-year component explains about 80% of the cross-sectional variation in size, it has little return predictability. In contrast, the long-run change in size component explains only 18% of size, but it completely captures the size premium. Our decomposition also sheds light on the January effect, the disappearance of the size premium since early 1980s, and the return behaviors of new entrants.

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1 Introduction

Size premium, the empirical finding that small stocks (measured by market capitalization) outperform big stocks on average, is one of the most well-known investment strategies in the stock market. In the asset pricing literature, besides the market factor, the small-minus-big (SMB) size factor is the only factor that is included in all leading multi-factor asset pricing models, including Fama and French (1993) three-factor model, Carhart (1997) four-factor model, and more recent Hou, Xue, and Zhang (2015) four-factor model based on q theory of investment and Fama and French (2015) five-factor model. In this paper, we examine the size premium from a different perspective from many existing studies in the literature. We decompose the firm size into four components and study how each component contributes to current firm size and to the size premium.

Our decomposition is motivated by the well-known cross-sectional stock return patterns at various horizons, namely, long-term contrarian (De Bondt and Thaler (1985)), intermediate-term momentum (Jegadeesh and Titman (1993)), and short-term reversal (Jegadeesh (1990)). The first component in our size decomposition is the (log) firm size five years ago, capturing the extremely persistent component of firm size. The second component, the long-run component, measures the cumulative change in (log) firm size during prior 13-60 months, following the timing of long-term contrarian strategy. The third component, the intermediate-run component, captures the cumulative change in (log) firm size during prior 2-12 months, corresponding to the timing of the price momentum strategy. The last component is the short-run component, defined as the prior 1-month change in (log) firm size, consistent with the timing of the short-term reversal.

Our empirical analyses suggest that despite being the most important determinant of current firm size, the lagged 5-year component has little predictive power for future stock returns. Compared with the 4.93% annual size premium, the premium based on the lagged 5-year component is only 1.53% per year with a t-statistic of 0.63. Controlling for the market factor further reduces the magnitude of the lagged 5-year size premium to -0.59% per year. Given that firm size is highly persistent, this result indicates that the size premium does not originate from the *level* of firm size; instead, it is the *changes* in firm size during past years that possess the predictive power for future stock returns. The second component is the long-run change in size, which explains an average of 18.4% of the cross-sectional variation in firm size. However, this component strongly predicts stock returns. In decile portfolios sorted by this long-run component, the difference in stock returns between firms with the most decrease in market value and firms with most increase in market value in the prior 13-60 months is 7.33% per year with an annual Sharpe ratio of 0.5. As a comparison, the Sharpe ratio for the size premium based on the same sample is only 0.3. The intermediate-run component is also a strong return predictor, with stocks with most increase in market value in the prior 2-12 months outperforming stocks with most decrease in market value by 8.64% per year, which has a similar magnitude to the momentum profit. All else being equal, small firms tend to have worse past stock performance than big firms, so the size strategy contains a short position in momentum which contributes negatively to the size premium. Despite its large premium, the intermediate-run component explains only about 2.6% of firm size, so its overall effect on the size premium is small. For the same reason, the short-run component only explains less than 1% of the cross-sectional variation in size.

The relative performances of the strategies based on size components suggest that the size premium is mainly driven by the long-run component, which we further confirm in several ways. First, in an independent double sort by firm size and its long-run component, we find that conditional on firm size, the average premium based on the long-run component is 5.42% with a t-statistic of 3.84, whereas the average size premium conditional on the long-run component is only 2.65% per year with a t-statistic of 1.31. Controlling for the market factor further amplifies the difference, generating a capital asset pricing model (CAPM) alpha of 6.11% and 1.41%, respectively. Second, we conduct linear factor model time series regressions tests. When size portfolio returns are regressed on the long-run size component factor (together with the market factor), none of these portfolios has a statistically significant abnormal return, including the long-short size portfolio. On the other hand, when returns of portfolios sorted by the long-run component are regressed on the size premium factor (together with the market factor), we find a significant abnormal return of more than 3 standard errors from zero for the long-short spread portfolio. Our last test is Fama-MacBeth regressions. Although firm size and its long-run component are both significant predictors for the future stock returns in univariate regressions, the coefficient on firm size becomes insignificant once controlling for its long-run component. Taken together, our results suggest that for size premium investors, a strategy that is based on its long-run component consistently dominates the traditional size strategy in terms of risk-return tradeoff.

Our decomposition is simple and straightforward. It also sheds lights on several other aspects of the size premium. For instance, the close link between changes in the firm size and stock returns provides a natural explanation for the negative (positive) correlation between momentum (long-term contrarian) profits and size premium. More interestingly, our decomposition uncovers a novel seasonality of the size premium in its exposure to the momentum factor due to the standard Fama and French (1992) timing. In Fama and French (1992), size portfolios are rebalanced at the end of every June, and firm size in June of year t is used to create size portfolios from July of year t to June of year $t+1$. This timing implies that the relative weight of the intermediate-run component decreases monotonically from July of current year to June of next year. If a large portion of the change in market equity is due to stock returns, we expect a similar seasonality in the momentum factor exposure of the Fama and French (1992) size premium. Indeed, in the time series regressions of the long-short Fama and French (1992) size portfolio returns on the market and momentum factors, we find the negative momentum factor loading peaks in the third quarter (-0.17 with a t-statistic of -2.72) and bottoms in the second quarter (0.05 but statistically insignificant). As a comparison, when we repeat the same analysis using the size portfolios sorted by the market value from the previous month, the seasonality in momentum betas disappears.

Our decomposition also provides insights into the January effect, the empirical finding that the size premium is concentrated in January (e.g., Keim (1983)). Two leading explanations for the January effect in the literature are the tax-loss selling hypothesis and institutional investor window dressing hypothesis, both of which posit that shortly before year-end, investors sell stocks that have had losses during the year. Since the stock performance within the past year is closely related to the intermediate-run and short-run components, our decomposition provides a quantitative evaluation of these two hypotheses. Our empirical analyses suggest that although all size components positively contribute to the strong performance of size strategies in January, the intermediate-run and short-run components combined only explain less than 20% of the January effect. In contrast, we find a surprisingly large January effect based on the lagged 5-year and the long-run components, which contribute about 60% and 30%, respectively, to the overall January effect. The results for the long-run component, and especially for the lagged 5-year component, pose a challenge to both leading hypotheses of the January effect, as neither interpretation traces firm performance for such a long horizon. Therefore, our analysis indicates that a large portion of January effect remains puzzling.

Size premium is found to have disappeared since its discovery in early 1980s. In a review paper on anomalies and market efficiency, Schwert (2003) writes that "it seems that the small-firm anomaly has disappeared since the initial publication of the papers that discovered it". Indeed, the average size premium between 1982 and 2002 is only 1.55% per year (t-statistic = 0.39) in our sample. However, we find that the long-run size component remains a significant return predictor during the same sample period. When firms are sorted into decile portfolios based on the long-run component, the long-short portfolio generates an average return of 8.22% per year (t-statistic = 2.16). Therefore, although the traditional size premium indeed disappears between early 1980s and early 2000s, the premium based on the component that is driving the size premium (i.e., the long-run component) was still alive and remains quite strong. Our analysis also suggests that the disappearance of the size premium is primarily due to the bad performance of the lagged 5-year component, which produces an average annual excess return of -2.19% in that sample period.

Lastly, we apply our decomposition to uncover a novel phenomenon among new entrants, which are excluded from our benchmark analyses. We find a positive relation between the size premium and firm age for firms that enter the CRSP dataset within the past 5 years. In the Fama-MacBeth univariate regressions of one-month ahead stock returns on the log firm size, the size coefficient decreases in magnitude from -0.22 for stocks of 4-5 years old to -0.03 (statistically insignificant) for stocks younger than one year old. Our decomposition provides a natural explanation for this interesting pattern. Since young firms do not have a long history, the long-run component, the component that drives the size premium, becomes less important in explaining the cross-sectional size variation, whereas the intermediate-run component that drags down the size premium becomes relatively more important. Our analysis indicates that although the premiums based on each size component remain quantitatively similar and stable across age groups, the change in the size composition with firm age implies a smaller size premium among younger firms.

The paper adds to the large literature on the firm size effect. Beginning with Banz (1981), size premium has been studied extensively in the past three decades. Fama and French (1995) find that size premium can be related to financial distress. Fama and French (1996) use the size premium factor to mimic the underlying risk factor that size premium represents. Studies most closely related to us are Berk (1995, 1996). Berk (1995) argues that size-related regularities should not be regarded as anomalies if size is measured by market value. All else being equal, a firm with higher discount rate has a smaller firm value and higher expected return, so even without specifying the underlying data generating process for stock returns, the negative relation between firm size and future stock returns should always be observed. Berk (1996) uses alternative non-market based measures of firm size, including book value of assets, book value of un-depreciated property, plant, and equipment, total value of annual sales, and total number of employees, but finds no return predictive power. The result of our analyses is consistent with Berk (1995, 1996). Instead of studying non-market based size measures, we find the lagged 5-year market value also doesn't predict stock returns, which suggests that it is not the level of market value, but its changes in recent years that predict stock returns. In addition, because past changes in market value have no direct relation with the current level of book asset, annual sale, or number of employees, the lack of return predictability of these variables that is documented in Berk (1996) should not be surprising.

Our decomposition and its implication for return predictability are motivated by the cross-sectional stock return regularities at various horizons, including long-term contrarian, intermediate-term momentum, short-term reversal, and equity issuance. The objective of this paper is not to explain these patterns.[1] Instead, we take these phenomena as given and study how the composition of these size components quantitatively affects the overall size premium. In terms of the methodology of variable decompositions, our paper is similar to Gerakos and Linnainmaa (2016) who decompose the book-to-market ratio to understand the value premium.

The paper proceeds as follows. Section 2 describes the data. In Section 3, we provide detailed discussions on how to decompose firm size into four components. Section 4 explores the return predictability of each size component. We document that the size premium is mainly driven by the component that captures the change in firm size in prior 13-60 months. In Section 5, we apply our size decomposition to other aspects of the size premium, including a novel seasonality in the momentum factor exposure, the January effect, the disappearance of size premium since early 1980s, and the behaviors of new entrants. Section 6 concludes.

[1]There is large literature on these phenomena in the cross section. For long-term contrarian and value premium, see, for instance, De Bondt and Thaler (1985), De Bondt and Thaler (1987), Lakonishok, Shleifer, and Vishny (1994), Zhang (2005), Lettau and Wachter (2007), Da (2009), Ai, Croce, and Li (2013), Ai and Kiku (2015), Kogan and Papanikolaou (2014). For intermediate-term momentum, see Jegadeesh and Titman (1993), Jegadeesh and Titman (2001), Johnson (2002), Liu and Zhang (2008), Liu and Zhang (2014). For short-term reversal, see Lehmann (1990), Jegadeesh (1990), Jegadeesh and Titman (1995), Nagel (2012), Da, Liu, and Schaumburg (2013). For equity issuance, see, Daniel and Titman (2006), Pontiff and Woodgate (2008), Lyandres, Sun, and Zhang (2008). A small line of research focuses on a joint explanation for these phenomena, especially for intermediate-term momentum, long-term contrarian, and value premium. See, for example, Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), Hong and Stein (1999), Sagi and Seasholes (2007), Li and Zhang (2017), and Li (2016). See Fama and French (2008) and Nagel (2013) for excellent literature reviews on the cross-sectional stock returns.

2 Data and Summary Statistics

Our data come from several sources. Stock data are from the monthly CRSP database. Accounting data are from Compustat Annually database. The Fama and French factors are from the Fama/French data library. Our sample include NYSE/AMEX/NASDAQ common stocks (with a share code of 10 or 11) with nonmissing market value at the end of June. Our sample period covers 630 months from July 1963 to December 2015. We use size and market value interchangeably unless specified otherwise. In addition, we follow Shumway (1997) to correct for the delisting bias.

Panel A of Table 1 presents the mean (R^e), standard deviation (Std), Sharpe ratio (SR), Skewness (Skew), and Kurtosis (Kurt) of the value-weighted excess returns, as well as the CAPM alpha (α^{CAPM}), of size decile portfolios and the spread portfolio that buys small firms and short-sells big firms (S-B). Panel B reports the firm characteristics of these portfolios. Following Fama and French (1992), at the end of each June, we form ten portfolios based on the market equity at June using NYSE breakpoints. The portfolios are then held for one year. Panel A of Table 1 confirms the finding in previous literature that small firms have higher average returns than big firms. The return difference between small and big firms is 3.28% per year, with an annualized Sharpe ratio of 0.2. The long-short portfolio return has large positive skewness and kurtosis, indicating that the size strategy has a small chance of gaining large positive returns. CAPM captures a portion of the size premium. After controlling for the market factor, the average abnormal return of the S-B portfolio becomes only 2.21% per year with a *t*-statistic of 0.89. The latter finding is consistent with Israel and Moskowitz (2013), who document that CAPM captures a sizable portion of the size premium.

[Insert Table 1 Here]

Panel B reports the characteristics of a typical firm in each size decile. These characteristics include the log market cap (ME), the book-to-market equity ratio (BM), prior 2-12 month stock returns (MOM), and the prior 13-60 month stock return (LTCON). This panel shows that there is a large cross-sectional dispersion in firm size. For instance, the average market value for a typical firm in the small size decile (Decile S) is only 20 million dollars, compared with 6.6 billion dollars in the big size decile (Decile B). Small (big) firms tend to be value (growth) firms, and the book-to-market ratio decreases monotonically from the small decile to the big decile. More importantly, big firms tend to have better past stock performance than small firms. Specifically, the average prior 2-12 month return (MOM) is 0.44% for small firms and 11.54% for big firms, and the average prior 13-60 month return (LTCON) is 6.66% for small firm and 69.72% for big firms.

The pattern above suggests that the size strategy contains a long position in long-term contrarian strategy that buys long-term losers and short-sells long-term winners, and a short position in the momentum strategy that buys momentum winners and short-sells momentum losers. The large profitability of the long-term contrarian and intermediate-term momentum strategies documented in the literature motivates us to decompose firm size into components over corresponding horizons.

3 Decomposing firm size

Based on the results from the previous section, we decompose the log firm size into four components. The first component, ΔME(SR), captures the change in firm size during the past 1-month, consistent with the timing of short-term reversal effect. As we will see later in this paper, although this short-run component may not be crucial for the Fama and French (1992) size strategy, it is an important component for the size strategy based the market value of the previous month, especially for its unique role in January effect. The second component, ΔME(IR), captures the change in firm size during prior 2-12 months, consistent with the timing of intermediate-term momentum effect. The third component, ΔME(LR), captures the changes in firm size during prior 13-60 months, consistent with the timing of the long-term contrarian effect. The last component, ME(lag5), measures the firm size five years ago and captures the extremely persistent component of firm size. For the benchmark analysis, we focus on the Fama and French (1992) timing in creating size portfolios using the market value at the end of June.[2] We also restrict our benchmark sample to only include firms that have non-missing market value in previous June and June 5 years ago. In Section 5.4, we apply our decomposition to understanding the behaviors of these new entrants.

With the Fama and French (1992) timing, the size portfolios are created at the end of June of year t, and the firm size at June and the resulting size decile is assigned to every month from July of year t to June of year $t+1$. In contrast, the short-run, intermediate-run, and long-run windows that correspond to the timing of short-term reversal, momentum, and long-term contrarian strategies are moving with the calendar month even within the twelve months following the rebalancing of size portfolios at the end of June. With this difference taken into consideration, each month, we decompose market equity as follows. For firms in July of year t, the (log) firm size contains all four components, because the size change from the beginning to the end of June of year t represents the short-run component. As a result, our decomposition is based on the following three cross-sectional regressions:

$$ME_{t,6} = a_{0t} + b_{0t} \times ME_{t,5} + \epsilon_{0t} \equiv \widehat{ME}_{0t} + \Delta\text{ME(SR)}_t \tag{1.1}$$

$$\widehat{ME}_{0t} = a_{1t} + b_{1t} \times ME_{t-1,6} + \epsilon_{1t} \equiv \widehat{ME}_{1t} + \Delta\text{ME(IR)}_t \tag{1.2}$$

$$\widehat{ME}_{1t} = a_{2t} + b_{2t} \times ME_{t-5,6} + \epsilon_{2t} \equiv \text{ME(lag5)} + \Delta\text{ME(LR)}_t, \tag{1.3}$$

where $ME_{t,6}$, $ME_{t,5}$, $ME_{t-1,6}$, $ME_{t-5,6}$, are the log market equity (in million dollars) at the end of June in year t, the end of May in year t, the end of June in year $t-1$, and the end of June in year $t-5$, respectively. In the cross-sectional regression equation (1.1), we regress the log size at the end of June of year t on the log size at the end of May of year t, and the residual component $\Delta\text{ME(SR)}_t$ is the short-run component for the size in July of year t. The predicted values $\widehat{ME}_{0t}$ from (1.1) are then used as the dependent variables in equation (1.2) to extract the intermediate-run component. Specifically, we regress $\widehat{ME}_{0t}$ on the log size at the end of June of year $t-1$, and

[2] In some analyses of this paper, we also consider an alternative size strategy that is based on the market value from the end of previous month.

the residual $\Delta\text{ME(IR)}_t$ is the intermediate-run component. Lastly, we regress the predicted values from equation (1.2), $\widehat{ME}_{1t}$, on the log size at the end of June of year $t-5$ in equation (1.3). The residual is the long-run component $\Delta\text{ME(LR)}_t$, whereas the predicted value is our lagged 5-year component ME(lag5).

For all other months from August of year t to June of year $t+1$, there are only three components, because the information about the change in size from the previous month is absent in the size at the end of June.[3] For each of these months, we first regress the log firm size onto the log size twelve months ago. The residual is the intermediate-run component $\Delta\text{ME(IR)}_t$, and the predicted values from the first step are then regressed onto the log size at the end of June of year $t-5$. For example, for size in August of year t, we perform the following decomposition:

$$ME_{t,6} = a_{1t} + b_{1t} \times ME_{t-1,7} + \epsilon_{1t} \equiv \widehat{ME}_{1t} + \Delta\text{ME(IR)}_t \tag{2.1}$$

$$\widehat{ME}_{1t} = a_{2t} + b_{2t} \times ME_{t-5,6} + \epsilon_{2t} \equiv \text{ME(lag5)} + \Delta\text{ME(LR)}_t, \tag{2.2}$$

The residuals from equations (2.1) and (2.2), $\Delta\text{ME(IR)}_t$ and $\Delta\text{ME(LR)}_t$, are the intermediate-run and long-run size components for firms in August year t, whereas the predicted value from equation (2.2), ME(lag5), represents the lagged 5-year component.

The decomposition implies that even though the firm size is a constant (fixed to be the market value at the end of previous June) within the twelve months following size portfolio rebalancing, its components do change from one month to the next. The change in the composition has novel implications on the factor loadings and the performance of new entrants, which we discuss in later sections. We also realize that there are other ways to decompose firm size in a similar spirit. We choose the current procedure because, by construction, it guarantees that: 1) the components add up to the (log) firm size in June; and 2) these components are orthogonal to each other.[4]

Figure 1 shows the time series variation of the relative importance of these size components in explaining the cross-sectional variance of firm size. Each month, we run cross-sectional univariate regressions of log size in June on each of these four components (or three components if not in July) and collect the adjusted R^2. The R^2 for year t is then calculated as the average R^2 from July year $t-1$ to June year t to remove the seasonality of the size components. The figure shows that among all four size components, the lagged 5-year component, ME(lag5), is the most important determinant that explains about 80.5% of the cross-sectional variance of firm size.[5] This result is expected because firm size is highly persistent over time – a big firm today is very likely to remain a big firm five years later. The next important component is the long-run component ΔME(LR), which explains an average of 18.4% of current size. Between late 1980s and early 2000s, we observe

[3] However, this short-run component is present every month for the size measure based on the market value at the end of the previous month.

[4] We repeat our analysis based on alternative decomposition procedures and find very similar results. For instance, when we construct size components by directly taking the difference in log size between the beginning and end of each horizon, instead of running regressions, the main finding is quantitatively similar. These results are available upon requests.

[5] These R^2s are reported in Panel A of Table 7 under Group 0.

an increase in the stock return idiosyncratic volatility, which could drive the increase in the R^2 of the long-run component relative to the lagged 5-year component. The last two components, the intermediate-run ΔME(IR) and short-run ΔME(SR), explain an average of 2.6% and 0.4%, respectively, of the cross-sectional size distribution. Given that the short-run component is only available in July, we ignore it in most discussions on the Fama and French (1992) size strategy.

[Insert Figure 1 Here]

Table 2 reports the firm characteristics of deciles sorted by the size components. Since our benchmark sample now imposes the restriction of non-missing size components, which differs from Table 1, we also report the characteristics of size deciles using this benchmark sample in Panel A. Besides properties of log size (ME), book-to-market (BM), prior 2-12 month returns (MOM), and prior 13-60 month returns (LTCON), we also report the results for size components– ME(lag5), ΔME(IR), and ΔME(LR). Panel A shows that the components display an increasing pattern from the small decile to the big decile size portfolios. For ΔME(IR), it is -0.06 for small firms and 0.05 for big firms. For ΔME(LR), it increases from -0.36 for small firms to 0.43 for big firms. Interestingly, the dispersion in lagged 5-year firm size is only slightly smaller than that in the current firm size, again indicating that firm size is highly persistent. This finding is also consistent with the large explanatory power of the lagged 5-year component for the cross-sectional variation in firm size plotted in Figure 1.

[Insert Table 2 Here]

Panels B, C, and D of Table 2 report the characteristics of the decile portfolios sorted by the size components. Since our decomposition procedure enforces an orthogonal condition among these components, sorting by one component does not create dispersions in other components, as shown in the last three rows of each panel. In Panel B, the intermediate-run component sorts create a large spread in the prior 2-12 month return. Firms with high ΔME(IR) have an average momentum (MOM) of 57.03%, in contrast with -27.19% for firms with low ΔME(IR). In Panel C, firms with high ΔME(LR) have a large long-term contrarian (LTCON) of 271.58%, compared with that among firms with low ΔME(LR) (-45.78%). Therefore, the strategies based on intermediate-run and long-run components are closely related to momentum and long-term contrarian strategies, respectively.[6] Similar to the patterns for the size portfolio in Panel A, Panel D also shows that firms with large lagged 5-year size have higher current size and lower book-to-market ratio than those with small lagged 5-year size.

[6]Changes in firm size can be due to both stock returns and net issuance. The existing studies document both variables predict future stock returns. We could have further decomposed the change in firm size at each horizon into the change in price and change in number of shares outstanding. We choose not to do this for the sake of parsimony.

4 Decomposing the Size Premium

Based on the size decomposition from the previous section, we study the return predictability of these components and quantitatively estimate their contributions to the overall size premium.

Table 3 reports the mean (R^{e}), standard deviation (Std), and Sharpe ratio (SR) of the value-weighted excess return, as well as CAPM alpha (α^{CAPM}), of decile portfolios sorted by size (Panel A), ΔME(IR) (Panel B), ΔME(LR) (Panel C), and ME(lag5) (Panel D). By restricting non-missing size components, the size premium becomes stronger: the average size premium is 4.93% per year (t-statistic = 2.02) with a Sharpe ratio of 0.3. However, controlling for the market factor reduces the size premium to 4.01% and the corresponding t-statistic becomes 1.68.

[Insert Table 3 Here]

Panel B reports the results for the intermediate-run component ΔME(IR). Stocks with the largest increase in firm size in the intermediate run (Decile Hi) have an average excess return of 10.32% per year (t-statistic = 3.36), compared with only 1.69% for the firms with the largest decrease in size (Decile 1) in the same horizon. The difference in average returns between the two extreme decile portfolios is 8.64%, which is more than 3.6 standard errors from zero. A long-short investment strategy that buys high ΔME(IR) firms and short-sells low ΔME(IR) generates a Sharpe ratio of 0.51. In addition, CAPM fails to explain the strategy returns; controlling for market exposures creates an abnormal return of 9.1% per year with a t-statistic of 3.85. This strategy performance is consistent with the momentum strategy that past intermediate-term winners have higher future returns than intermediate-term losers. Unfortunately, size premium investors do not benefit from its good performance at all, because the size strategy effectively takes a short position in it. In fact, this exposure consistently drags down the profitability of the size strategy over time.

Panel C reports the stock performance of the long-run component ΔME(LR). Opposite to the intermediate-run component, firms with the largest increase in size in the long run underperform firms with the largest decrease in firm size by 7.33% per year (t-statistic = 3.23). The long-short investment strategy based on ΔME(LR) generates a Sharpe ratio of 0.5, and this strong profitability is not captured by CAPM. The CAPM abnormal return is 7.76% with a t-statistic of 3.41. The result for the portfolios sorted by the lagged 5-year component is reported in Panel D. In contrast to the other two components from Panel B and Panel C, the return displays a hump shape from the low ME(lag5) decile to the high ME(lag5) decile. The long-short portfolio generates an insignificant average return of only 1.53% with a Sharpe ratio of 0.1. Controlling for the market factor further reduces this premium to a negative value (-0.59% per year).

The result in Table 3 indicates that among all components of firm size from our decomposition, only the long-run component, ΔME(LR), contributes positively to the overall size premium in an statistically and economically significant way. In other words, the size premium is likely to be mainly driven by this long-run component. To test this conjecture, we perform three different analyses. In the first analysis, we compare the performance of portfolios double sorted by size and its long-run component. In particular, we create 5-by-5 portfolios double-sorted independently by size and ΔME(LR). Panel A.1 of Table 4 reports the conditional size premium within each ΔME(LR) quintile and the average conditional size premium across ΔME(LR) quintiles. Among all ΔME(LR) quintiles, the conditional size premium is only significant in ΔME(LR) quintile 2. In the high ΔME(LR) quintile, the conditional size premium is negative at -1.24% per year, even though it is not statistically significant from zero. The average conditional size premium across ΔME(LR) quintiles is insignificant at 2.65%. The unconditional CAPM further reduces the abnormal conditional size premium to 1.41% per year. In sharp contrast, the conditional ΔME(LR) premium is significant in 4 out of 5 size quintiles. It ranges from 8.92% (t-statistic = 6.37) among small firms to 3.65% (t-statistic = 1.50) among big firms. The average conditional ΔME(LR) premium is 5.42% per year, which is more than 3.85 standard errors from zero. The CAPM alpha for the conditional ΔME(LR) premium is even higher at 6.11% per year, with a t-statistic of 4.33.

[Insert Table 4 Here]

The second test is a linear factor model test between size premium and ΔME(LR) premium. In Panel B.1 of Table 4, we test a two-factor model on size decile portfolios with the market factor and the ΔME(LR) premium factor as the factors. The ΔME(LR) premium factor is calculated as the return difference between the low ΔME(LR) decile and the high ΔME(LR) decile. Compared with the CAPM result from Panel A of Table 3, none of the ΔME(LR) deciles has a significant abnormal return in the two-factor model, and the long-short portfolio (L-H) has an abnormal return of -0.54% per year (t-statistic = -0.29). The reduction in abnormal returns is mainly due to the exposure to the ΔME(LR) factor, which decreases monotonically from 0.49 for small firms to -0.09 for big firms, and the difference is 12.6 standard errors from zero.

When we switch the order and regress the ΔME(LR) decile excess returns on a two-factor model with the market factor and size premium factor as the factors, the result looks quite different. In Panel B.2, we find that despite the strong decreasing pattern of the size factor exposures across ΔME(LR) portfolios, the abnormal return remains large in many portfolios. In addition, the long-short ΔME(LR) portfolio (L-H) has an abnormal return of 5.8% per year, which is more than 3.18 standard errors from zero. Adding the ΔME(IR) premium factor does not alter the result in a significant way (Panel C). If anything, the abnormal return of the long-short ΔME(LR) portfolio becomes even bigger (7.72% per year with a t-statistic = 4.38).

Our third test is Fama-MacBeth regressions. Compared to the value-weighted portfolio approach in the first two tests, Fama-MacBeth regressions put relatively more weights on small firms. Each month, we run a cross-sectional regression of one-month ahead stock returns on log size and its components ΔME(IR), ΔME(LR), and ME(lag5), and the time series average of these coefficients are reported in Table 5. Columns (1)-(4) report the univariate regression results. Consistent with the results from Table 3, we find that although size (ME) is a strong predictor for future stock returns, the coefficient on ME(lag5) is only -0.05 with a t-statistic of -1.43. In contrast, the other two components ΔME(IR) and ΔME(LR) have much stronger predictive power. The coefficient on ΔME(IR) is 0.73, which is more than 4 standard errors from zero. The coefficient on ΔME(LR) is

-0.41 with an even stronger t-statistic of -5.52. These results confirm the relative performance of the corresponding long-short portfolios reported in Table 3.

[Insert Table 5 Here]

Columns (5)-(7) present the horse race results from the Fama-MacBeth regressions using log size and one of its components as the return predictors. In Column (5), when both size and size 5 years ago are included into the same regression, the coefficient on size becomes more significant at -0.32 with a t-statistic of -4.4, compared with the univariate specification. On the other hand, the coefficient on ME(lag5) is now positive. This finding is intuitive from our decomposition: if the lagged 5-year component has no predictive power for stock return and is adding noise to the size premium, controlling this component would make the size premium stronger. We find a similar pattern when we control for the ΔME(IR) component (Column (7)). As we discussed earlier, the size premium strategy contains a short position in the ΔME(IR) premium, so controlling ΔME(IR) would enhance the performance of size strategies. In column (6), the horse race between size and its long-run component ΔME(LR), controlling for ΔME(LR), firm size has little predictive power for returns. Its coefficient decreases from -0.11 in the univariate regression in Column (1) to an insignificant value of -0.04 (t-statistic $= -1.12$). Interestingly, the coefficient on the ΔME(LR) becomes more statistically significant.

One advantage of the Fama-MacBeth regressions over the portfolio approach is that we can quantify the contribution of each size component to the overall size premium. If one component explains an average of X (or $100X$ percent) of the cross-sectional variation in size, and the Fama-MacBeth regression coefficient on this component is Y, its contribution to the coefficient on size in the Fama-MacBeth regression would be $X \times Y$. We use the coefficient estimates from Specifications (2)-(4) and the explanatory power of each component for the cross-sectional variation in firm size in Section 3 to estimate their contributions. For the lagged 5-year component, its percentage contribution is approximately 39.9% ($0.054 \times 80.5\%/0.109$), and this is compared with 69.4% ($0.411 \times 18.4\%/0.109$) for the long-run component and -17.5% ($-0.734 \times 2.6\%/0.109$) for the intermediate-run component.[7] This result indicates that although the 5-year component captures more than 80% of the firm size, it only contributes less than 40% of the size premium.[8] In contrast, the long-run component ΔME(LR) captures only 18% of firm size but contributes almost 70% of the size premium. In untabulated analyses, we find the ΔME(LR) premium is not driven by extremely small and illiquid firms, which is a criticism for the implementability of size strategies (Horowitz, Loughran, and Savin (2000)). For example, when we exclude from our sample firms with market value of less than 5 million dollars, or firms with end-of-June price lower than \$5 per

[7]The fact that the contributions from these components do not exactly add up to one can be due to: 1) we did not include the short-run component in this calculation; 2) there are seasonality in the size components within a year; and 3) the panel data is not balanced; we have more observations in later years than earlier years.

[8]The contribution from the lagged 5-year component is driven by its correlation with the premium based on the long-run component. In an untabulated analysis, we find that the ME(lag5) premium changes sign and becomes positive after controlling for the market factor and a ΔME(LR) premium factor.

share, the long-short ΔME(LR) portfolio still produces an average return of more than 7% per year with a t-statistic greater than 3.

Taken together, our analyses suggest that the size premium is driven by its long-run component ΔME(LR). Once controlling for this long-run component, firm size does not have significant predictive power for future stock returns. These findings are consistent with Berk (1995, 1996). Berk (1995) argues that size-related regularities should not be regarded as anomalies if size is measured by market value. All else being equal, a firm with a higher discount rate has a smaller firm value and higher expected return, so even without specifying the data generating process of stock returns of a firm, the negative relation between firm size and future stock returns should always be observed. Our findings can be consistent with this argument: firms that experience a large decrease in market value in the prior 13-60 months (i.e., in the long run) could have experienced positive shocks to discount rate (either rationally or irrationally). Their realized returns are negative but expected returns increase. However, we find the similar argument does not hold for the horizon of prior 2-12 months. Instead, this intermediate-run change in firm size, which is related to the momentum strategies, positively predicts future stock returns. Berk (1996) studies the size premium using alternative measures of firm size including book value of assets, book value of un-depreciated property, plant, and equipment, total value of annual sales, and total number of employees, but find no return predictive power. Our decomposition provides a natural interpretation for his findings. Particularly, it is not the level of market value, but its recent change, that predicts stock returns. Because the recent changes in market value have no direct relation with the level of these alternative size measures, it is not surprising these variables have no return predictive power. For size premium investors, our findings also suggest that investing in its long-run component is far better than investing in firm size itself from the perspective of risk-return tradeoff.

5 Further Implications

In this section, we explore additional implications of our size decomposition. In Section 5.1, we uncover an interesting seasonality in the momentum factor loading of size portfolios that is due to the Fama and French (1992) timing. In Section 5.2, we use our decomposition to evaluate leading explanations for the January effect in the existing literature. In Section 5.3, we discuss the disappearance of the size premium between early 1980s and early 2000s. We study how our decomposition can be applied to new entrants in Section 5.4.

5.1 Seasonality in momentum beta

Our size decomposition is performed at each month, so these components change from one month to the next. The rolling horizons of the intermediate-run and long-run components indicate that there is a seasonality of the intermediate-run and long-run components in the twelve months following the portfolio rebalancing at the end of each June. For instance, in July of year t, the intermediate-run component is based on the change in log market value from July of year $t-1$ to May of year t.

As time moves forward by one month, the horizon shrinks by one month, and the intermediate-run component in August of year t is based on the change in log market value from August of year $t-1$ to May of year t. In June of year $t+1$, although the firm size still corresponds to the market value at the end of June of year t, its intermediate-run component is only based on the change in size from May of year t to June of year t. Since the intermediate-run change in size is highly correlated with the price momentum, the size premium should also show a seasonality in its momentum factor exposure. Figure 2 presents this seasonality.

[Insert Figure 2 Here]

In Panel A of Figure 2, we plot the average quarterly momentum factor beta of the size premium following portfolio rebalancing at the end of June according to the Fama and French (1992) timing. For each quarter, we estimate the momentum beta by running time series regressions of the monthly long-short size portfolio excess return on the market excess return and the winner-minus-loser portfolio return from momentum deciles. We test this at the quarterly frequency to avoid even higher frequency seasonality such as the January effect. Panel A shows that for Quarter 3 (Q3) from July to September, i.e., the first quarter following portfolio rebalancing, the size premium has a large negative momentum factor loading of -0.174 (t-statistic = -2.72). This negative sign is consistent with the short position of the size premium in the momentum strategies. The momentum beta increases monotonically over time, and by Quarter 2 (Q2) from April to June, i.e., the last quarter of the 12-month holding period, it becomes positive at 0.05 but statistically insignificant (t-statistic = 0.56). As a comparison, we also estimate the momentum beta across quarters for the size premium based on the market value from the end of the previous month, and the result is plotted in Panel B of Figure 2. With this alternative timing, size deciles are rebalanced every month, and the horizon for the intermediate-run component is constant. Therefore, we do not expect a strong seasonality in momentum beta for this size strategy. Indeed, from Panel B of Figure 2, the size premium has a negative momentum exposure in all quarters: the momentum beta is -0.176 for Q3, -0.114 for Q4, -0.194 for Q1, and -0.13 for Q2. This confirms that the seasonality of momentum beta from Panel A is due to the Fama and French (1992) timing.

5.2 The January effect

The size premium itself is also highly seasonal. Banz (1981) and Reinganum (1983) document that the good stock market performance in January is mainly driven by small stocks. Keim (1983) finds that half of the size premium over the 1963 to 1979 period occurs during January, whereas Blume and Stambaugh (1983) show that all of the size effect occurs in January after adjusting for the "bid-ask spread" bias. Among alternative hypotheses explaining the puzzling January effect, two leading explanations are tax-loss selling hypothesis (see, e.g., Branch (1977), Dyl (1977), Givoly and Ovadia (1983), Starks, Yong, and Zheng (2006)) and the institutional investor window dressing hypothesis (see, for instance, Haugen and Lakonishok (1988), Musto (1997), and Ritter and Chopra (1989)). Both hypotheses argue that investors tend to sell stocks that have had bad performance, and this selling pressure depresses year-end stock prices which rebound in January. In the tax-loss selling hypothesis, investors sell losing stocks in order to lower taxes on net capital gains. In the institutional investor window dressing hypothesis, portfolio managers sell losing stocks to avoid revealing that they have held poorly performing stocks.

To evaluate these two hypotheses, we decompose the size premium in January in the same way as we decompose the overall size premium. Table 6 reports the result. We consider both the Fama and French (1992) size strategy, and the size strategy based on the previous-month-end market value to fully capture the stock performance during the previous year. Panel A presents the average explanatory power of each size component for the cross-sectional variation in firm size. For the Fama and French (1992) size strategy, there are three size components because the short-run component only exists in July. The lagged 5-year, long-run, and intermediate-run components explain 80.6%, 18.6%, and 2.3% of firm size, respectively. The composition looks very similar for the size premium based on the previous-month market value, except for the intermediate-run component, which doubles its explanatory power to 4.7%. Furthermore, the short-run component now shows up and explains about 0.6% of firm size.

[Insert Table 6 Here]

Panel B of Table 6 reports the results from Fama-MacBeth regressions. For the Fama and French (1992) timing, the coefficient on the log firm size in January is -1.62, which is 14.9 times greater than the estimate for all months (Column (1) of Table 5), confirming the January effect in our sample. In addition, these values suggest that the average size premium estimated from the Fama-MacBeth regression for non-January months is negative. The three size components all contribute positively to January effect. The estimated coefficient on ME(lag5) is -1.29, which is 23.9 times greater than that from Table 5, suggesting that even the lagged 5-year component displays a strong January effect. The coefficient on ΔME(LR) is -3.04, which is 7.4 times greater than that from Table 5. This result indicates that although the ΔME(LR) premium is significantly higher in January, it also exists in other months.[9] The coefficient on that ΔME(IR) is -3.27, which is 4.5 times greater than that for all months in magnitude but with an opposite sign. The latter pattern is consistent with the momentum literature that find the average momentum profit to be negative in January (e.g., Jegadeesh and Titman (1993)). The predictive power of the short-run and intermediate-run components for the January return is also consistent with Branch (1977)'s observation that stocks that had negative returns during the prior year also have high returns in January, a finding that motivates the tax-loss selling hypothesis.

In order to quantify the contribution of each size component to the January effect, we multiply the estimated R^2 from Panel A of Table 6 with the corresponding Fama-MacBeth regressions coefficients from Panel B. In the case of the Fama and French (1992) timing, the contributions from the lagged 5-year, long-run, and intermediate-run components are 64.0%, 34.8%, and 4.6%,

[9] Indeed, in an untabulated analysis, we find that the average value-weighted return of the long-short ΔME(LR) portfolio for non-January months is 4.5% with a t-statistic of 2.06.

respectively. In the case of the size strategy based on the market value from previous month, the intermediate-run component becomes more important and these three components contribute to 58.0%, 29.2%, and 11.5%, respectively. In addition, the short-run component appears in January and has a large negative predictability for the January return. The estimated coefficient of ΔME(SR) is -17.22 with a t-statistic of -7.23, indicating that stocks that perform poorly in previous December rebounds strongly in January. This pattern is consistent with the selling pressure on losing stocks in the tax-loss selling hypothesis and institutional investor window dressing hypothesis. Despite its significance, this component only explains about 5.8% of the overall January effect, due to its low explanatory power for firm size from Panel A.

Our quantitative results pose a challenge for both leading hypotheses for the January effect. Both hypotheses rely on investors' behaviors in reaction to the stock performance from the previous year. Our estimates suggest that the contribution from the stock performance in the previous year is well below 20%. The significant coefficient on the long-run component is consistent with De Bondt and Thaler (1985) and Chan (1986), and suggests that investors may wait for years before realizing losses. Still, there is about 60% the January size premium that comes from the lagged 5-year component. Therefore, a large portion of the January effect remains puzzling.[10]

5.3 The disappearance of size premium

It has been documented that the size premium has disappeared since its discovery. For example, Schwert (2003) reports an average CAPM alpha of 0.2% per month with a t-statistic of 0.67 between 1982 and 2002 for the Dimensional Fund Advisors (DFA) US 9-10 Small Company Portfolio, which closely mimics the size strategy described in Banz (1981). Several studies have proposed potential explanations for this disappearance. Hou and van Dijk (2014) argue that it is the large negative profitability shocks that drives the poor performance of small firms after early 1980s. Asness, Frazzini, Israel, Moskowitz, and Pedersen (2015) document that size premium is robust after controlling for quality. Shi and Xu (2015) emphasize the importance of the delisting bias. They document that there is a positive size premium for firms close to be delisted, and once excluding these observations, the size premium reappears. Ahn, Min, and Yoon (2016) find that the size effect is significantly positive at the bottom of the business cycles.

Our decomposition provides an alternative explanation for this phenomenon. Figure 3 plots the cumulative returns of the long-short portfolio based on firm size and its components. The figure shows that the strategy based on the long-run component outperforms the size strategy, whereas the intermediate-run and the lagged 5-year components perform poorly. For the full sample period from July 1963 to December 2015, the cumulative return is about 190.5% for the size premium, which is smaller than 327.3% for the ΔME(LR) premium. On the other hand, the cumulative return is only 14.4% for the lagged 5-year component, and -531.1% for the intermediate-run component.

[10] In untabulated analyses, we extend the horizon back further and find that the premium based on the lag 10-year or even 20-year market values still displays a strong January effect. This pattern is unlikely to be explained by the delayed realization of long-run losses by investors.

The large negative loss for the intermediate-run component is consistent with its strong return predictability documented in Section 4.

[Insert Figure 3 Here]

Narrowing the sample period down to 1982-2002 during which Schwert (2003) documents the disappearance of the size effect, we find that the average size premium is indeed only 1.55% per year, which is about 0.39 standard errors from zero. However, the premium based on the long-run component, ΔME(LR), is 8.22% per year with a t-statistic of 2.16. These results suggest that although the size premium has disappeared between early 1980s and early 2000s, the premium based on the component that drives the size premium (i.e., the long-run component) was still alive and remained quite strong. But what makes the overall size premium disappeared? Our analysis indicates that one main reason is the poor performance of the lagged 5-year component. When focusing on the pattern of the cumulative returns of the size premium and the lagged 5-year size premium between 1982 and early 2000s in Figure 3, we can see a strong comovement between these two time series. More importantly, the average premium of this lagged 5-year component is -2.19% per year during this sample period. This bad performance, together with its large explanatory power for the cross-sectional variation in size (Figure 1), drags down the average size premium.[11,12]

5.4 New entrants

Our analysis in previous sections focuses solely on firms that have non-missing size components from the decomposition. In particular, we exclude firms that entered the CRSP database within the previous 5 years. Fama and French (2004) document that firms that obtain public equity financing expands dramatically in the 1980s and 1990s. The cross section of the profitability of these firms are highly left skewed but their growth rates are highly right skewed. Therefore, the behavior of the size premium among these new entrants could potentially be different from those in our benchmark sample.

In this subsection, we apply our size decomposition to these new entrants. Different from a relatively mature firm in our benchmark sample, the composition of a newly entered young firm depends on the number of years since its entry. For example, a firm that enters the CRSP database 4 years ago has both the long-run and intermediate-run components. In contrast, for a firm that enters 11 months ago, the long-run component is absent. To control this cohort effect, we separate these new entrants into five groups. Group 1 includes stocks younger than 1 year, Group 2 includes

[11] One possible explanation for the negative ME(lag5) premium is the increased idiosyncratic volatility. In untabulated analyses, we notice that the level of common idiosyncratic volatility (CIV) (Herskovic, Kelly, Lustig, and Van Nieuwerburgh (2016)) doubled from early 1980s to early 2000s. Furthermore, we find a strong negative exposure of the ME(lag5) premium to the CIV shock, so unexpected increases in CIV lower the ME(lag5) premium in this sample period. A comprehensive exploration of these historically small firms can be interesting for future studies.

[12] Another explanation for the disappearance of size premium since early 1980s is the bad performance of the newly entered firms. See, for example, Fama and French (2004), Hou and van Dijk (2014). We discuss the implication of our decomposition on the performance of these firms in Section 5.4.

stocks older than 1 year but younger than 2 years, Group 3 includes stocks older than 2 years but younger than 3 years, Group 4 includes stocks older than 3 years but younger than 4 years, and Group 5 includes stocks older than 4 years but younger than 5 years. As a comparison, we also include stocks in our benchmark sample as Group 0. Since these new entrants do not have a long history up to 5 years, we define ME(lag) as the initial log market value when firms enter the CRSP database for firms in all groups other than Group 0.

Panel A of Table 7 reports the explanatory power (R^2) of each component for the cross-sectional variation in firm size. For all groups, the persistent component, ME(lag), has the most explanatory power, followed by ΔME(LR), ΔME(IR), and ΔME(SR). More importantly, there are clear patterns for these component R^2 across these age groups. The R^2 for ME(lag), ΔME(IR), and ΔME(SR) decreases monotonically from Group 2 to Group 5, whereas the R^2 for ΔME(LR) displays an opposite increasing pattern. Intuitively, compared to a relatively older firm, the probability for a young firm to have a big change in market value since its entry is small, so its entry size explains the majority of its current size. In addition, the short-run and intermediate-run components carry less weight as firms get older, because the long-run component gradually plays a more important role. For firms younger than 1 year old, the long-run component is absent, whereas the intermediate-run component may only cover a fraction of the 11-month horizon. Interestingly, the monotonic patterns do not extend to the benchmark sample (Group 0) that consists of more mature stocks. For example, the R^2 for ME(lag) is 80.5% in Group 0, which is higher than 55% in Group 5. Similarly, the R^2 for ΔME(LR) is only 18.4% for Group 0, even lower than 28.3% for Group 3. This break in monotonicity can be due to higher stock return volatility and more frequent equity issuance for these young firms, resulting a greater cumulative change in firm size within the past few years. This effect can be so strong that it dominates the effect from the horizon changes so that the mature firms in Group 0 is more predicted by their ME(lag).[13]

[Insert Table 7 Here]

In Panel B, we run univariate Fama-MacBeth regressions of one-month ahead stock returns on log firm size and its components. When the predictive variable is log firm size (ME), the estimated coefficient is negative for all age groups, but it is much smaller in magnitude for younger firms. For instance, the coefficient is -0.22 for firms that are 4 years old, compared with only -0.03 for firms younger than 1 year old. Therefore, we find a positive relation between size premium and firm age. To understand this pattern, the last four columns report the coefficients of the size components. Surprisingly, the estimated coefficients are very stable across age groups. For the ME(lag) component, it ranges from -0.049 to -0.092, but none of these estimates are statistically significant. This finding is consistent with what we documented in the benchmark sample that lagged 5-year size has no predictive power for future stock returns. Similar patterns are found for the other components. The estimated coefficient for firms in Groups 1-5 is between -0.56 and -0.69

[13] Indeed, we find the cross-sectional standard deviations of the monthly change in firm size in the intermediate-run and long-run horizons are 13.4% and 15.4% for firms in Group 5, significantly larger than the corresponding values of 10.4% and 11.6% for firms in Group 0.

for ΔME(LR), between 0.61 and 0.78 for ΔME(IR), and between -4.4 and -7.7 for ΔME(SR). Therefore, the relation between size premium and firm age for these new entrants must be mainly driven by the variation in the size components. In particular, for firms younger than 1 year old, the ME(lag) and ΔME(LR) components dominate, so the size premium is small and insignificant. As firms get older, the long-run component becomes more important and the corresponding R^2 is increased to 43.7% when firms are 4 years old (Group 5). As a result, the implied size premium among these firms is much stronger than firms in Group 1.

6 Conclusion

In this paper, we analyze the size effect by decomposing firm's market value into four components. Our result indicates that despite explaining about 80% of the cross-sectional variation in firm size, the lagged 5-year component, which measures firm size 5 years ago, has little predictive power for future stock returns. In contrast, the intermediate-run and long-run components, which measure the changes in firm size in the prior 2-12 and 13-60 month horizons, only capture 3% and 18% of firm size. However, they are strong return predictors: firms with the largest increase in size in the intermediate-run (long-run) outperform (underperform) firms with the largest decrease in size in intermediate-run (long-run) by 8.64% (7.33%). Therefore, the standard size strategy effectively takes a long position in the premium based on the long-run component and a short position in the intermediate-run component. These results also suggest that the size premium is mainly driven by this long-run component, which we confirm using double-sorted portfolios, linear factor time series regressions, and Fama-MacBeth cross-sectional regressions.

We apply this decomposition to several aspects of the size premium. First, we uncover an interesting seasonality in momentum factor beta of the size premium with Fama and French (1992) timing. Since a large fraction of change in firm size in the intermediate-run horizon is due to stock returns, the seasonality of the intermediate-run component from the decomposition procedure also implies a momentum exposure seasonality. Second, our size decomposition sheds light on the January effect quantitatively. Leading explanations such as the tax-loss selling hypothesis and the institutional investor window dressing hypothesis are based on the stock performance in the previous year. Our analysis suggests that the previous-year change can only explain less than 20% of the January effect. Instead, firm size 5 years ago captures more than 60% of the January effect, which poses a challenge to these explanations. Third, we relate our decomposition to the disappearance of size premium between early 1980s and early 2000s. Our result suggests that although the traditional size premium disappeared in this sample period, the premium from the long-run component that drives the size premium was still alive and quite strong. Lastly, we study the performance of new entrants, that is, firms that enter the CRSP database within the previous 5 years. We document a positive relation between size premium and firm age among these new entrants, and find that the change in the composition of size components with firm age is mainly responsible for this positive correlation.

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Table 1: Characteristics of size portfolios

This table reports the value-weighted average excess returns (Ret^e), standard deviation (Std), Sharpe Ratio (SR), Skewness (Skew), Kurtosis (Kurt), and intercepts from CAPM model (α^{CAPM}) of the decile Size portfolios in Panel A, and the time-series average of the cross-sectional median firm characteristics in Panel B. At the end of June each year, we sort NYSE/AMEX/NASDAQ common stocks by market equity into Size deciles. ME is log of market equity in million dollars. BM is the book value of equity divided by market value at the end of the last fiscal year. MOM is momentum, defined as prior 2-12 month returns, LTCON is long-term contrarian, defined as prior 13-60 month returns. The returns and alphas are annualized and reported in percentages. The t-statistics in parentheses are calculated based on the heteroskedasticity-consistent standard errors of Newey and West (1987). The sample period is from July 1963 to December 2015.

Panel A: Size portfolio excess returns

Port.	S	2	3	4	5	6	7	8	9	B	S-B
R^e	8.54	8.00	9.15	8.55	8.72	7.64	7.94	7.58	6.72	5.27	3.28
	(2.43)	(2.44)	(3.01)	(2.88)	(3.06)	(2.87)	(3.00)	(3.05)	(2.88)	(2.57)	(1.28)
Std	21.99	21.93	20.79	20.26	19.37	18.25	17.88	17.34	15.99	14.67	16.65
SR	0.39	0.36	0.44	0.42	0.45	0.42	0.44	0.44	0.42	0.36	0.20
Skew	-0.15	-0.25	-0.45	-0.45	-0.51	-0.56	-0.45	-0.48	-0.45	-0.36	0.73
Kurt	2.48	2.12	2.02	2.18	2.27	1.95	2.16	1.81	2.00	1.72	4.20
α^{CAPM}	1.91	0.76	2.02	1.53	1.81	0.99	1.32	1.08	0.65	-0.30	2.21
	(0.91)	(0.47)	(1.50)	(1.20)	(1.74)	(1.08)	(1.60)	(1.51)	(1.20)	(-0.63)	(0.89)

Panel B: Size portfolio characteristics

Port.	S	2	3	4	5	6	7	8	9	B
ME	3.00	4.48	5.03	5.47	5.88	6.29	6.72	7.21	7.83	8.80
BM	0.92	0.72	0.70	0.67	0.64	0.62	0.60	0.60	0.59	0.50
MOM	0.44	7.71	9.78	10.89	11.38	11.73	11.78	11.65	11.46	11.54
LTCON	6.66	41.07	52.69	56.19	61.98	64.68	64.43	61.88	64.41	69.72

Table 2: Characteristics of size and component portfolios

This table reports the time-series average of the cross-sectional median firm characteristics in the decile portfolios sorted by log size (ME, Panel A), intermediate-run change in log size (ΔME(IR), Panel B), long-run change in log size (ΔME(LR), Panel C), and lagged 5-year log size (ME(lag5), Panel D). At the beginning of each month, firms are sorted into deciles based on the sorting variables. ME is logarithms of market equity at June in million dollars following the timing in Fama and French (1992). BM is the book value of equity divided by market value at the end of the last fiscal year. MOM is momentum, defined as prior 2-12 month returns, LTCON is long-term contrarian, defined as prior 13-60 month returns. The size decomposition is described in Section XXX. The sample includes all NYSE/AMEX/NASDAQ common stocks with nonmissing size components from the size decomposition from July 1963 to December 2015.

Panel A: Size portfolios

Port.	Lo	2	3	4	5	6	7	8	9	Hi
ME	3.05	4.49	5.07	5.54	5.98	6.40	6.84	7.35	7.94	8.90
BM	1.06	0.82	0.77	0.73	0.70	0.66	0.62	0.62	0.59	0.48
MOM	2.34	8.48	10.31	10.88	11.41	11.67	11.76	11.41	11.47	11.54
LTCON	7.58	41.58	53.05	56.56	62.82	63.84	63.39	63.47	64.35	70.23
ΔME(IR)	-0.06	0.00	0.02	0.02	0.03	0.03	0.04	0.03	0.04	0.05
ΔME(LR)	-0.36	0.02	0.13	0.18	0.24	0.26	0.29	0.30	0.32	0.43
ME(lag5)	3.36	4.45	4.91	5.33	5.70	6.10	6.53	7.02	7.58	8.49

Panel B: Portfolios sorted by intermediate-run change in size (ΔME(IR))

Port.	Lo	2	3	4	5	6	7	8	9	Hi
ME	3.65	4.46	4.84	5.08	5.24	5.36	5.41	5.40	5.24	4.67
BM	0.80	0.81	0.80	0.79	0.78	0.78	0.77	0.75	0.75	0.73
MOM	-27.19	-9.79	-2.39	3.11	7.86	12.18	17.11	23.13	32.05	57.03
LTCON	25.68	37.08	41.09	43.13	44.82	46.00	46.18	47.13	45.71	29.41
ΔME(IR)	-0.38	-0.19	-0.11	-0.06	-0.01	0.04	0.08	0.14	0.21	0.40
ΔME(LR)	-0.07	0.00	0.04	0.05	0.07	0.08	0.08	0.09	0.07	-0.08
ME(lag5)	4.18	4.64	4.90	5.07	5.14	5.19	5.19	5.13	4.90	4.27

Panel C: Portfolios sorted by long-run change in size (ΔME(LR))

Port.	Lo	2	3	4	5	6	7	8	9	Hi
ME	3.09	4.00	4.53	4.96	5.24	5.46	5.59	5.67	5.74	5.71
BM	1.28	1.06	0.95	0.86	0.81	0.75	0.69	0.62	0.53	0.41
MOM	8.29	8.81	8.82	9.19	9.03	8.87	8.66	8.10	7.31	3.60
LTCON	-45.78	-7.44	13.91	31.06	46.95	63.78	82.43	107.21	147.88	271.58
ΔME(IR)	0.00	0.00	-0.01	0.00	0.00	0.00	0.01	0.01	0.01	0.00
ΔME(LR)	-1.10	-0.53	-0.27	-0.09	0.06	0.21	0.36	0.53	0.78	1.31
ME(lag5)	4.33	4.53	4.80	5.03	5.16	5.23	5.22	5.11	4.93	4.23

Panel D: Portfolios sorted by lagged 5-year size (ME(lag5))

Port.	Lo	2	3	4	5	6	7	8	9	Hi
ME	3.19	4.50	5.03	5.46	5.88	6.30	6.74	7.24	7.83	8.83
BM	0.92	0.82	0.80	0.78	0.74	0.72	0.69	0.67	0.66	0.57
MOM	5.80	8.21	8.98	9.70	9.44	9.88	9.72	10.45	9.51	9.39
LTCON	41.84	37.45	40.56	41.82	42.19	44.41	44.40	43.64	42.54	39.95
ΔME(IR)	-0.02	0.00	0.00	0.01	0.01	0.01	0.01	0.02	0.02	0.02
ΔME(LR)	-0.03	-0.03	0.02	0.04	0.05	0.08	0.12	0.12	0.13	0.16
ME(lag5)	3.31	4.53	5.00	5.41	5.81	6.20	6.62	7.10	7.67	8.57

Table 3: Returns and asset pricing tests of size and component portfolios

This table reports the value-weighted average excess returns (R^e), standard deviation (Std), Sharpe Ratio (SR), and intercepts from CAPM model (α^{CAPM}) of decile portfolios sorted by log size (ME, Panel A), intermediate-run change in log size (ΔME(IR), Panel B), long-run change in log size (ΔME(LR), Panel C), and lagged 5-year log size (ME(lag5), Panel D). The size decomposition is described in Section XXX. At the beginning of each month, firms are sorted into deciles based on the sorting variables. The returns and CAPM alphas are annualized and reported in percentages. The t-statistics in parentheses are calculated based on the heteroskedasticity-consistent standard errors of Newey and West (1987). The sample includes all NYSE/AMEX/NASDAQ common stocks with nonmissing size components from size decomposition from July 1963 to December 2015.

Panel A: Size portfolios

Port.	Lo	2	3	4	5	6	7	8	9	Hi	L-H
R^e	10.22	9.51	10.19	9.82	9.89	8.45	8.51	7.75	6.72	5.29	4.93
	(3.05)	(3.05)	(3.55)	(3.53)	(3.67)	(3.36)	(3.41)	(3.25)	(2.99)	(2.61)	(2.02)
Std	21.42	21.17	19.92	19.16	18.32	17.37	17.19	16.83	15.50	14.58	16.33
SR	0.48	0.45	0.51	0.51	0.54	0.49	0.49	0.46	0.43	0.36	0.30
α^{CAPM}	3.79	2.61	3.43	3.21	3.44	2.14	2.19	1.46	0.89	-0.22	4.01
	(1.88)	(1.60)	(2.51)	(2.55)	(3.06)	(2.23)	(2.37)	(1.93)	(1.34)	(-0.45)	(1.68)

Panel B: Portfolios sorted by intermediate-run change in size (ΔME(IR))

Port.	Lo	2	3	4	5	6	7	8	9	Hi	L-H
R^e	1.69	3.95	5.62	4.61	6.29	5.78	6.68	8.21	8.54	10.32	-8.64
	(0.49)	(1.5)	(2.48)	(2.17)	(3.13)	(2.89)	(3.29)	(3.96)	(3.54)	(3.36)	(-3.64)
Std	23.05	18.01	16.14	15.20	14.84	14.46	14.80	15.40	16.88	20.47	16.65
SR	0.07	0.22	0.35	0.30	0.42	0.40	0.45	0.53	0.51	0.50	-0.51
α^{CAPM}	-5.95	-2.08	0.04	-0.77	0.99	0.58	1.30	2.62	2.42	3.16	-9.10
	(-3.46)	(-1.41)	(0.04)	(-0.80)	(1.12)	(0.74)	(1.67)	(3.65)	(2.85)	(2.39)	(-3.85)

Panel C: Portfolios sorted by long-run change in size (ΔME(LR))

Port.	Lo	2	3	4	5	6	7	8	9	Hi	L-H
R^e	11.88	8.43	8.26	8.19	7.48	7.03	5.95	5.66	5.46	4.54	7.33
	(3.77)	(3.48)	(3.76)	(3.84)	(3.77)	(3.39)	(2.89)	(2.67)	(2.42)	(1.59)	(3.23)
Std	20.67	17.33	15.85	14.81	14.14	14.55	14.73	15.13	16.44	19.57	14.81
SR	0.57	0.49	0.52	0.55	0.53	0.48	0.40	0.37	0.33	0.23	0.50
α^{CAPM}	5.17	2.54	2.80	3.01	2.47	1.80	0.62	0.15	-0.58	-2.60	7.76
	(2.99)	(1.94)	(2.47)	(2.90)	(3.07)	(2.22)	(0.81)	(0.20)	(-0.69)	(-2.61)	(3.41)

Panel D: Portfolios sorted by lagged 5-year size (ME(lag5))

Port.	Lo	2	3	4	5	6	7	8	9	Hi	L-H
R^e	7.02	8.95	8.25	8.67	8.51	7.97	7.42	7.50	6.62	5.49	1.53
	(2.02)	(2.77)	(2.71)	(2.91)	(3.17)	(3.04)	(2.99)	(3.09)	(2.99)	(2.82)	(0.63)
Std	22.56	21.82	20.30	20.08	18.23	18.06	17.33	16.71	15.66	14.14	15.99
SR	0.31	0.41	0.41	0.43	0.47	0.44	0.43	0.45	0.42	0.39	0.10
α^{CAPM}	-0.41	1.46	1.10	1.53	1.91	1.35	1.00	1.18	0.71	0.18	-0.59
	(-0.23)	(1.03)	(0.91)	(1.37)	(1.88)	(1.51)	(1.31)	(1.99)	(1.40)	(0.35)	(-0.27)

Table 4: Relation between size and ΔME(LR) component

This table reports the relation between firm size and ΔME(LR) components. In Panel A, each month we construct 5-by-5 portfolios independently double-sorted by firm size and ΔME(LR) component. Panel A.1 reports the size premium (the annualized value-weighted excess returns and CAPM alphas difference between bottom and top size quintile portfolios) within and across ΔME(LR) quintiles. Panel A.2 reports the ΔME(LR) premium (the annualized value-weighted excess returns and CAPM alphas difference between bottom and top ΔME(LR) quintile portfolios) within and across size quintiles. Panel B reports the time series regression coefficients of size (Panel B.1) and ΔME(LR) (Panel B.2) decile portfolios in a two-factor model, with the market factor and the ΔME(LR) premium factor as the risk factors. Panel B.1 reports the intercept (α), the market beta (β_1), and the ΔME(LR) factor beta (β_2). Panel B.2 reports the intercept (α), the market beta (β_1) and the size factor (β_2). Panel C reports the time series regression coefficients of size (Panel C.1) and ΔME(LR) (Panel C.2) decile portfolios in a three-factor model with the addition of a ΔME(IR) premium factor. The returns and alphas are annualized and reported in percentages. The t-statistics in parentheses are calculated based on the heteroskedasticity-consistent standard errors of Newey and West (1987). The sample includes all NYSE/AMEX/NASDAQ common stocks with nonmissing size components from size decomposition from July 1963 to December 2015.

Panel A: Double sorts and conditional premium

Panel A.1: Conditional size premium across ΔME(LR) quintiles

ΔME(LR)	Lo	2	3	4	Hi	Average
R^e	4.02	4.06	3.35	3.06	-1.24	2.65
	(1.40)	(2.03)	(1.81)	(1.37)	(-0.5)	(1.31)
α^{CAPM}	2.46	2.91	2.11	1.82	-2.26	1.41
	(0.90)	(1.53)	(1.19)	(0.85)	(-0.91)	(0.74)

Panel A.2: Conditional ΔME(LR) premium across size quintiles

Size	Lo	2	3	4	Hi	Average
R^e	8.92	5.50	4.24	4.80	3.65	5.42
	(6.37)	(3.34)	(2.51)	(2.64)	(1.50)	(3.85)
α^{CAPM}	9.29	5.99	5.04	5.65	4.57	6.11
	(6.63)	(3.57)	(3.00)	(3.13)	(1.88)	(4.33)

Panel B: Size and ΔME(LR) portfolios in two-factor models

Panel B.1: Size portfolios

Port.	Lo	2	3	4	5	6	7	8	9	Hi	L-H
α	-0.04	-0.88	0.48	0.71	1.24	0.66	0.99	0.41	0.47	0.50	-0.54
	(-0.03)	(-0.71)	(0.45)	(0.67)	(1.32)	(0.76)	(1.17)	(0.64)	(0.75)	(1.08)	(-0.29)
β_1	1.11	1.18	1.16	1.13	1.10	1.07	1.07	1.06	0.98	0.91	0.20
	(31.41)	(43.10)	(47.04)	(43.64)	(45.01)	(51.78)	(55.62)	(75.20)	(63.40)	(90.75)	(4.67)
β_2	0.49	0.45	0.38	0.32	0.28	0.19	0.15	0.14	0.05	-0.09	0.59
	(12.56)	(14.30)	(14.33)	(12.28)	(10.94)	(8.77)	(7.18)	(7.40)	(3.34)	(-8.62)	(12.60)
R^2	0.71	0.80	0.84	0.85	0.87	0.90	0.91	0.94	0.94	0.95	0.30

Panel B.2: ΔME(LR) portfolios

Port.	Lo	2	3	4	5	6	7	8	9	Hi	L-H
α	3.39	1.83	2.51	2.95	2.42	1.82	0.96	0.63	-0.13	-2.41	5.80
	(2.68)	(1.55)	(2.25)	(2.88)	(2.97)	(2.26)	(1.28)	(0.88)	(-0.16)	(-2.44)	(3.18)
β_1	1.05	0.96	0.90	0.86	0.83	0.87	0.90	0.94	1.02	1.20	-0.15
	(33.38)	(31.30)	(30.77)	(32.69)	(36.29)	(41.22)	(36.32)	(41.53)	(38.94)	(51.86)	(-3.22)
β_2	0.44	0.18	0.07	0.01	0.01	0.00	-0.09	-0.12	-0.11	-0.05	0.49
	(10.22)	(4.88)	(1.49)	(0.47)	(0.38)	(-0.19)	(-3.16)	(-5.63)	(-5.51)	(-1.96)	(8.52)
R^2	0.82	0.79	0.79	0.81	0.83	0.85	0.88	0.89	0.90	0.88	0.29

Panel C: Size and ΔME(LR) portfolios in three-factor models

Panel C.1: Size portfolios

Port.	Lo	2	3	4	5	6	7	8	9	Hi	L-H
α	-0.04	-0.76	0.83	0.98	1.59	1.05	1.36	0.90	0.73	0.61	-0.65
	(-0.02)	(-0.58)	(0.76)	(0.91)	(1.62)	(1.15)	(1.54)	(1.37)	(1.07)	(1.26)	(-0.33)
β_1	1.11	1.18	1.15	1.12	1.09	1.06	1.06	1.05	0.97	0.91	0.20
	(30.92)	(42.53)	(46.74)	(43.71)	(44.80)	(50.88)	(53.93)	(75.42)	(61.36)	(90.76)	(4.64)
β_2	0.49	0.45	0.37	0.31	0.27	0.18	0.14	0.12	0.05	-0.10	0.59
	(11.51)	(12.38)	(12.87)	(11.33)	(10.53)	(8.48)	(6.85)	(6.82)	(3.05)	(-7.96)	(11.41)
β_3	0.00	0.01	0.03	0.02	0.03	0.03	0.03	0.04	0.02	0.01	-0.01
	(0.01)	(0.29)	(0.99)	(0.85)	(1.24)	(1.47)	(1.57)	(2.93)	(1.60)	(0.70)	(-0.16)
R^2	0.71	0.80	0.84	0.85	0.87	0.90	0.91	0.94	0.94	0.95	0.30

Panel C.2: ΔME(LR) portfolios

Port.	Lo	2	3	4	5	6	7	8	9	Hi	L-H
α	4.62	2.68	3.70	3.71	2.86	2.23	1.45	0.72	-0.32	-3.11	7.72
	(3.70)	(2.29)	(3.19)	(3.41)	(3.25)	(2.83)	(1.93)	(0.98)	(-0.37)	(-3.14)	(4.38)
β_1	1.05	0.95	0.89	0.86	0.83	0.87	0.90	0.94	1.03	1.20	-0.16
	(37.14)	(30.79)	(29.99)	(31.76)	(35.12)	(41.21)	(36.81)	(41.34)	(38.63)	(52.50)	(-3.77)
β_2	0.42	0.16	0.05	0.00	0.00	-0.01	-0.09	-0.12	-0.11	-0.04	0.46
	(10.70)	(4.80)	(1.15)	(0.08)	(0.13)	(-0.57)	(-3.49)	(-5.55)	(-5.36)	(-1.56)	(9.01)
β_3	0.13	0.09	0.12	0.08	0.05	0.04	0.05	0.01	-0.02	-0.07	0.20
	(4.58)	(3.81)	(3.92)	(2.89)	(1.78)	(2.02)	(2.12)	(0.54)	(-0.81)	(-3.31)	(4.99)
R^2	0.83	0.80	0.80	0.81	0.83	0.86	0.88	0.89	0.90	0.88	0.34

Table 5: Fama-MacBeth regressions

This table reports the results from Fama-MacBeth regressions of returns (in percentages) on firm characteristics, including the logarithm of the firm size and its components. The t-statistics in parentheses are calculated based on the heteroskedasticity-consistent standard errors of Newey and West (1987). The sample includes all NYSE/AMEX/NASDAQ common stocks with nonmissing size components from size decomposition from July 1963 to December 2015.

Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	1.724	1.460	1.234	1.229	1.442	1.406	1.788
	(4.49)	(3.91)	(5.07)	(5.05)	(3.89)	(3.77)	(4.67)
ME	-0.109				-0.323	-0.041	-0.123
	(-2.77)				(-4.4)	(-1.12)	(-3.11)
ME(lag5)		-0.054			0.273		
		(-1.43)			(4.24)		
ΔME(LR)			-0.411			-0.371	
			(-5.52)			(-6.15)	
ΔME(IR)				0.734			0.862
				(4.06)			(4.86)
R^2(%)	1.48	1.14	0.78	0.74	2.04	1.95	2.16

Table 6: January effect

This table analyzes January effect for two size strategies. The first strategy follows Fama and French (1992) timing and defines firm size as the market value at the end of previous June. The second strategy defines firm size as the market value at the end of previous month. Panel A reports the fraction of the cross-sectional variance of log firm size that is explained by its components. Panel B reports the coefficients from the univariate Fama-MacBeth regressions of returns (in percentages) on the logarithm of the firm size and its components. The t-statistics in parentheses are calculated based on the heteroskedasticity-consistent standard errors of Newey and West (1987). The sample includes all January from 1964 to 2015.

Panel A: Adj R^2 of size regressions

Size timing	ME(lag5)	ΔME(LR)	ΔME(IR)	ΔME(SR)
End of previous June	0.806	0.186	0.023	
End of previous month	0.790	0.171	0.047	0.006

Panel B: Fama-MacBeth regressions

Size timing	ME	ME(lag5)	ΔME(LR)	ΔME(IR)	ΔME(SR)
End of previous June	-1.62	-1.29	-3.04	-3.27	
	(-6.79)	(-6.13)	(-6.14)	(-4.50)	
End of previous month	-1.81	-1.32	-3.08	-4.39	-17.22
	(-6.91)	(-6.43)	(-6.00)	(-5.08)	(-7.23)

Table 7: New entrants

This table analyzes new entrants, defined as all NYSE/AMEX/NASDAQ common stocks that enter the CRSP database within the past five years but have non-missing market value at the end of previous June. At each month, Group 1 includes stocks younger than 1 year, Group 2 includes stocks older than 1 but younger than 2 years, Group 3 includes stocks older than 2 but younger than 3 years, Group 4 includes stocks older than 3 but younger than 4 years, and Group 5 includes stocks older than 4 years. As a comparison, we also report the result for the sample of firms used in Table 2 (Group 0). ME(lag) is the log market value 5 years ago for Group 0. For the other groups, ME(lag) is the log market value when firms enter the CRSP database. Panel A reports the fraction of the cross-sectional variance of log firm size that is explained by its components. Panel B reports the coefficients from the univariate Fama-MacBeth regressions of returns (in percentages) on the logarithm of the firm size and its components. The t-statistics in parentheses are calculated based on the heteroskedasticity-consistent standard errors of Newey and West (1987). The sample is monthly from July 1963 to December 2015.

Panel A: Adj R^2 of size regressions

Group	ME(lag)	ΔME(LR)	ΔME(IR)	ΔME(SR)
1	0.936		0.100	0.029
2	0.818	0.140	0.129	0.014
3	0.698	0.283	0.085	0.009
4	0.618	0.367	0.071	0.007
5	0.550	0.437	0.063	0.006
0	0.805	0.184	0.026	0.004

Panel B: Fama-MacBeth regressions

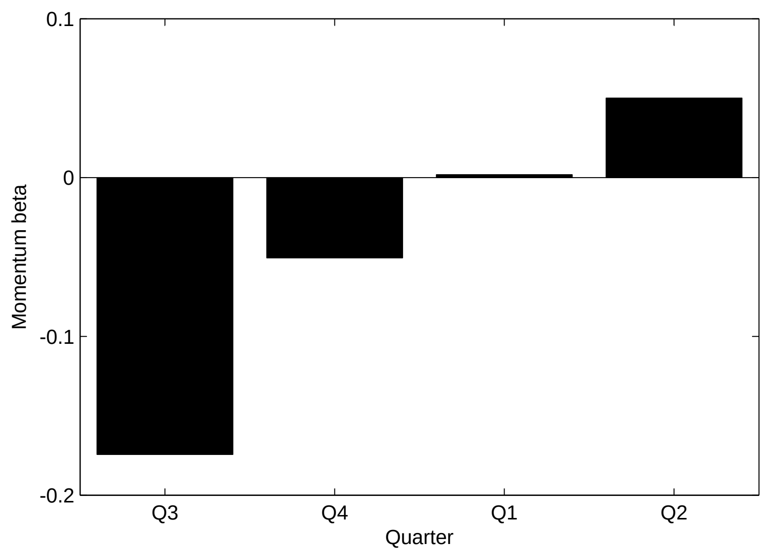
Group	ME	ME(lag)	ΔME(LR)	ΔME(IR)	ΔME(SR)
1	-0.030	-0.066		0.612	-4.390
	(-0.40)	(-0.86)		(1.28)	(-2.35)
2	-0.053	-0.074	-0.687	0.675	-6.105
	(-0.84)	(-1.06)	(-3.56)	(2.19)	(-2.92)
3	-0.219	-0.092	-0.639	0.779	-4.668
	(-3.27)	(-1.35)	(-4.10)	(2.87)	(-2.01)
4	-0.227	-0.049	-0.584	0.653	-7.701
	(-3.53)	(-0.72)	(-4.63)	(2.26)	(-3.45)
5	-0.223	-0.075	-0.558	0.658	-5.363
	(-3.75)	(-1.28)	(-5.48)	(2.62)	(-2.50)
0	-0.109	-0.054	-0.411	0.734	-6.010
	(-2.77)	(-1.43)	(-5.52)	(4.06)	(-4.24)

Figure 1: Fractions of cross-sectional variance of firm size explained by its components
This figure plots the fractions of cross-sectional variance of firm size explained by its components over time. At each month, we run a cross-sectional regression of log market equity from the previous June on each of its components (ME(lag5), ΔME(LR), ΔME(IR), and ΔME(SR)). For each component, the adjusted R^2 for year t is calculated as the average R^2 from July, year $t-1$ to June, year t. The sample includes all NYSE/AMEX/NASDAQ common stocks with nonmissing size components from size decomposition from July 1963 to December 2015.

Figure 2: Seasonality in momentum beta

This figure plots the seasonality in momentum beta of the Fama and French (1992) size premium (Panel A) and the size premium based on the market value of the previous month (Panel B). In each quarter, we estimate the momentum beta of the long-short size decile portfolios in a two-factor model with the market excess return and the winner-minus-loser portfolio return from momentum deciles as the risk factors. The sample includes all NYSE/AMEX/NASDAQ common stocks from July 1963 to December 2015.

Panel A: Size strategy based on Fama and French (1992) timing



Panel B: Size strategy based on the size of previous month

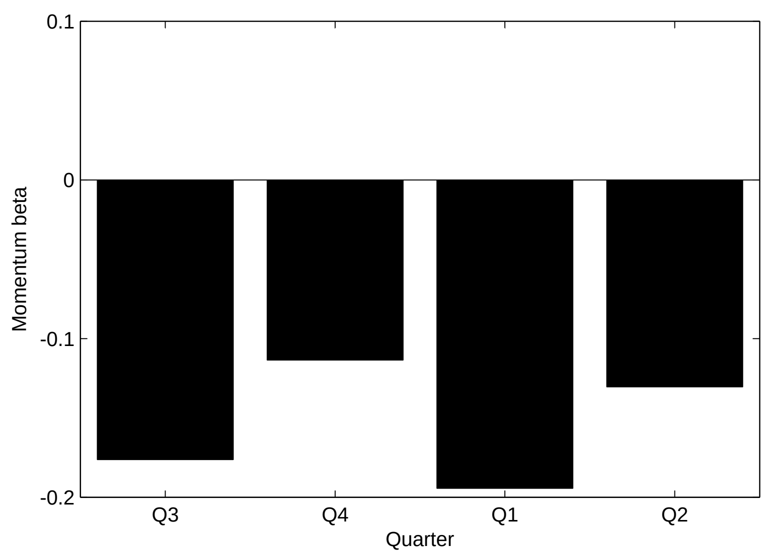


Figure 3: Cumulative returns of size and components strategies

This figure plots the cumulative returns of the long-short portfolio based on standard size and its components. To be consistent with the sign of the size premium, the long-short portfolio for each sorting variable is the difference between the bottom and top decile portfolios. The sample includes all NYSE/AMEX/NASDAQ common stocks with nonmissing size components from size decomposition from July 1963 to December 2015.