The Cross-Section of January Effect*

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Abstract

We examine the cross-sectional January effect among portfolios that long sentiment-prone and difficult-to-arbitrage stocks and short sentiment-insensitive and easy-to-arbitrage stocks. These long-short portfolios on average earn over 20 times higher returns in January than in a non-January month. 85% of the cross-sectional January effect comes from its long legs, consistent with a sentiment-driven mispricing explanation. The cross-sectional January effect persists over time and remains significant after accounting for common risk factors and time-varying factor loadings.

Keywords: January effect, investor sentiment, limits to arbitrage, cross-section, stock returns.

JEL Classification: G12, G14

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* Errors and omissions remain the responsibility of the authors.

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"New beginnings are in order, and you are bound to feel some level of excitement as new chances come your way."

Auliq Ice

1 Introduction

The January effect is a well-documented anomaly that is at odds with the efficient market hypothesis. It refers to the tendency for stock prices to rise in January. Despite a large body of research, the exact cause of the January effect remains an open question. Furthermore, the January effect in aggregate returns of U.S. equity markets seems to have disappeared in recent years (Mehdian and Perry, 2001). This suggests that the January effect could be only a temporary phenomenon, and hence there may be little need to identify its cause. However, some recent studies suggest that the anomaly still exists in many emerging Asian markets (Wuthisatian, 2022; Aggarwal and Jha, 2023).

Understanding whether and why the January effect exists is important for investors who hope to generate excess returns by exploiting this anomaly. In this paper, we address both of these questions. First, we show that the January effect remains in the stock market – it persists over time in the cross-section of stock returns. Second, we provide an explanation based on investor sentiment and limits to arbitrage, which is consistent with not only the cross-sectional January effect that we document but also the disappearing January effect in market returns.

In the cross-section, we uncover remarkable patterns in the January effect. Investors holding portfolios that long speculative stocks and short non-speculative stocks earn most of their returns in the first month of a year—on average their January returns are 20 times higher than returns in a non-January month. In addition, 85% of the cross-sectional January returns come from their long legs and 15% come from their short legs.

There are some potential explanations for our results. One prominent explanation, motivated by the tax-loss selling hypothesis (Wachtel *et al.*, 1942; Ritter, 1988), is that speculative stocks earn low returns and investors want to gain a tax credit for realizing their losses at year-end by selling these stocks. Such an interpretation, however, is at odds with the fact that most speculative stocks have higher average returns than non-speculative stocks (Ding, Mazouz and Wang, 2019). Alternatively, motivated by window-dressing and risk-shifting behavior, institutional investors may sell speculative stocks in the last quarter and then buy them back in the first quarter (Ng and Wang, 2004). Their actual trading, however, provides little evidence that they drive the January effect (Lynch, Puckett and Yan, 2014). However, Wagner, Lee and Margaritis

(2022) attribute the January effect to a January seasonality in fund flows of retail and active mutual funds. Nevertheless, the seasonality in mutual fund flows originates from sentimental decisions made by retail investors. Since fund managers can exploit investor sentiment (Massa and Yadav, 2015), fund performance is an indirect channel through which sentiment affects the January seasonality in returns.

Our explanation is a mispricing hypothesis based on the cross-sectional effect of investor sentiment and limits to arbitrage. Stocks differ in both the exposure to shifts in market sentiment and the extent of arbitrage constraints. More speculative stocks such as small stocks are not only more prone to investor sentiment but also more difficult to arbitrage than non-speculative stocks such as large stocks (Baker and Wurgler, 2006, 2007). Lemmon and Portniaguina (2006) and Baker and Wurgler (2006) find that, when market sentiment is high, speculative stocks earn higher contemporaneous returns and lower subsequent returns than non-speculative stocks. Therefore, if January has higher market sentiment than other months, we expect portfolios with long speculative legs and short non-speculative legs to have higher returns in January than in other months.

Substantial evidence on the psychological effect of New Year's resolutions is in line with renewed optimism at the beginning of the year. Prior literature points out that about half of American adults consider the beginning of a year as an opportunity to make new resolutions (Norcross and Vangarelli, 1988; Norcross, Ratzin and Payne, 1989; Norcross, Mrykalo and Blagys, 2002; Polivy and Herman, 2002). Surveys by market research companies also confirm these findings (Ciccone, 2011). Most of these resolutions, however, fail subsequently and then are repeated every year. This cycle of wishful thinking is well documented in the literature as "the false hope syndrome" (Polivy and Herman, 2002).

Prior literature examines various survey-based investor sentiment measures to gauge investor sentiment, including the University of Michigan Consumer Sentiment Index, Conference Board Consumer Confidence Index, Investors' Intelligence Index, and the institutional (individual) Bull-Bear Ratio surveyed by the American Association of Individual Investor, among others. Both the Conference Board Consumer Confidence Index and the Consumer Confidence Index are widely employed as investor sentiment measures. These sentiment measures have been extensively employed to investigate the predictive ability of investor sentiment on stock returns (for example, Chen, 2011; Stambaugh, Yu and Yuan, 2012; Pan, 2020; Trichilli, Abdelhédi and Abbes, 2020).

It is crucial to consider that the sentiment indicator of each survey reflects the sentiment of different groups of respondents. For instance, the University of Michigan Consumer Sentiment Index primarily represents the sentiment of retail investors (Fisher and Statman, 2003). Conference Board Consumer Confidence Index (CCI) is a more widely employed survey-based sentiment indicator (Qiu and Welch, 2004). Notably, Lemmon and Portniaguina (2006) contend that consumer confidence measures serve as reliable proxies for sentiment due to their strong correlation with the Bull-Bear Ratio. Similarly, Qiu and Welch (2004) argue that the correlation between a new sentiment measure and direct survey indicators provides a more convincing validation, as the latter directly represents investors' opinions.

In our analysis, we utilize both the University of Michigan Consumer Sentiment Index and the Conference Board Consumer Confidence Index to demonstrate a consistent pattern of increasing investor sentiment in January. Furthermore, we conduct robustness tests using the Baker-Wurgler sentiment indicator and observe consistent findings, as illustrated by the histogram figures. These results are consistent with Ciccone (2011) and Chen and Daves (2018). Franses (2020) provides further evidence that forecasters are more optimistic in January than in other months.

Our finding of a cross-sectional pattern in the January effect supports the sentiment-driven mispricing hypothesis. We find further that, while the cross-sectional January effect is persistent over time, its magnitude, however, has declined. Such a decline is consistent with falling trading costs over time that has made arbitrage less costly (McLean and Pontiff, 2016). Some stocks, however, remain more difficult to arbitrage (McLean and Pontiff, 2016). Therefore, the January effect in these stocks is unlikely to disappear. In contrast, the January effect in aggregate market returns has disappeared since it can be inexpensively exploited by using mutual funds or stock index futures (Hensel and Ziemba, 2000; Rendon and Ziemba, 2007).

We then test the classical hypothesis that our results may arise from compensation for systematic risk, i.e., from the month-of-the-year seasonality in factor risk premiums or factor loadings. Such a test is important from investors' perspective as high cross-sectional returns should ideally come from abnormal returns rather than compensation for bearing systematic risk. The effect of time-varying beta loading of systematic risk in predicting returns begins with the conditional Capital Asset Pricing model proposed in studies including Campbell and Cochrane (2000), Lettau and Ludvigson (2001), and Menzly, Santos and Veronesi (2004). Baker and Wurgler (2006) condition the beta loading of systematic risk (i.e., market return premium factor in the CAPM model) on investor sentiment.

The fundamental explanation is that investor sentiment leads to higher contemporaneous stock returns as certain stocks contains higher certain risk (represented by the risk factors). If investor sentiment does not show a statistically significant influence on the beta loading of market return premium or if investor sentiment does not affect the beta loading in the expected way, then one could rule out the fundamental explanation that investor sentiment affects stock returns through changing the factor loading. The time-varying factor loading has also been investigated in recent studies such as Ang and Kristensen

(2012), Kelly, Moskowitz and Pruitt (2021), Novy-Marx and Velikov (2022). We follow the framework of Baker and Wurgler (2006) and extend the effect of sentiment on the time-varying beta loading of not only market return premium but also other widely-accepted risk factors.

We first control for common risk factors and find that the cross-sectional January anomaly is reduced, but remains economically and statistically significant. Then we use a conditional model that allows factor loadings to vary between January and other months. Such an approach enables us to distinguish the cross-sectional January effect that can be attributed to betas or to alphas. We find again a reduced but significant cross-sectional January effect. Taken together, the classical hypothesis helps but cannot fully explain our results.

Our paper contributes to the existing literature in several ways. First, our paper adds to a large literature on the January effect, which provides various explanations such as tax-loss selling (Ritter, 1988) or investors' trading behaviors (Doran, Jiang and Peterson, 2012; Ng and Wang, 2004). This literature rarely tests the cross-sectional January effect except for the stocks sorted by firm size (Keim, 1983; Roll, 1983; Dzhabarov and Ziemba, 2010; Aharon and Qadan, 2019), book-to-market ratio (Loughran, 1997; Cooper, McConnell and Ovtchinnikov, 2006) and analyst forecast dispersion (Ciccone, 2011). We focus on the sentiment-driven mispricing hypothesis and find supporting evidence of cross-sectional calendar patterns in stock returns. We show further that, while compensation for systematic risk helps explain the cross-sectional January effect, sentiment-driven mispricing plays an important role in this cross-sectional pattern. Our evidence is consistent with Chen and Daves (2018) who find that higher January sentiment predicts lower subsequent market and portfolio returns.

We also contribute to the literature on the cross-sectional seasonality in stock returns. Birru (2018) attributes the cross-sectional day-of-the-week effect to investor mood/sentiment, while Hirshleifer, Jiang and DiGiovanni (2020) posit that such cross-sectional seasonality arises from time variation in investor mood. We focus on the cross-sectional effect in January as compared to other months. Our findings suggest that market sentiment is indeed the highest in January, and the cross-sectional pattern of the January effect is consistent with the findings of Birru (2018) and Hirshleifer *et al.* (2020) that sentiment drives seasonality in the cross-section of stock returns. While Gould, Yang, Singh and Yeo (2023) find a stronger January effect in lottery-like stocks, which are also more prone to mispricing due to seasonality in investor mood, we differentiate our study from theirs by using portfolios constructed by Baker and Wurgler (2006) based on firm fundamentals, as opposed to using lottery-like features, e.g., idiosyncratic volatility, idiosyncratic skewness, maximum single-day return during a month, etc. While Gould *et al.* (2023) attribute the higher demand for lottery-like stocks to increased risk-seeking behavior during periods of economic downturn, we find that compensation for higher systematic risk can, at best, only partially explain the cross-sectional January effect.

2 Literature

The January effect, first documented by Wachtel *et al.* (1942), is one of the best-known calendar anomalies in financial markets. It refers to substantially higher asset returns in January than in other months, posing a challenge to the cornerstone of modern finance theory, the efficient market hypothesis. Early studies show that the January effect is sizable. For example, Rozeff and Kinney (1976) find that between 1904 and 1974, the average of aggregate market returns is 3.5% in January but is only 0.5% in other months. Such a seasonal pattern is prevalent in major industrialized countries (Gultekin and Gultekin, 1983).

The two most prominent explanations for the January effect are the tax-loss selling hypothesis and the window-dressing hypothesis. The tax-loss selling hypothesis is based on the motive that investors want to gain a tax credit for realizing their losses at year-end by selling the losing stocks (Wachtel *et al.*, 1942). The window-dressing hypothesis suggests that fund managers sell the losing stocks to improve the appearance of their portfolio before presenting it to their clients (Haugen and Lakonishok, 1988). In either case, the stocks are repurchased at the beginning of the new year, leading to abnormally high January returns.

Chen and Singal (2004) support tax-loss selling as the most probable explanation for the January effect. January effect in municipal bond closed-end funds, which are held by tax-sensitive individuals, also provides evidence to support the tax-loss hypothesis (Starks, Yong and Zheng, 2006). The absence of the January effect before the War Revenue Act of 1917 also supports the tax-based explanation (Schultz, 1985). However, some studies suggest this hypothesis is insufficient in explaining the January seasonality in countries where the tax year differs from the calendar year (Brown, Keim, Kleidon and Marsh, 1983; Fountas and Segredakis, 2002). Similarly, Haug and Hirschey (2006) support behavioral explanations related to the trading behavior of individual investors by finding that the January effect continued to exist even after the Tax Reform Act of 1986, which should theoretically encourage tax-motivated selling well before the end of the year.

There are other explanations for the January effect in the literature. According to Chang and Pinegar (1989, 1990), higher risk premiums for betas associated with industrial production growth, yield spread, and stock indices in January result in abnormally high returns. Similarly, Kramer (1994) finds that macroeconomic risk premiums and betas are higher for small firms in January. Kim (2006) provides another risk-based explanation by arguing that information uncertainty caused by earnings volatility explains a large fraction of the January effect. Kohers and Kohli (1992) associate the January effect with the business cycle. Some studies state that market microstructure effects in small and low-priced stocks, such as bid-ask spread and thin trading, also play a role in the January effect (Roll, 1981, 1983).[1] Ogden (1990) relates the abnormal returns in January to the reinvestment of year-end cash receipts. Ligon (1997) find that higher January returns are related to higher January trading volume and lower real interest rates.

Some studies link the January effect to the investors' trading behavior. For example, Fant and Peterson (1995) find a significant negative relation between the January returns and the prior three-year return and positive relation between the returns for February through December and the prior returns, which supports the existence of investors' overreaction. Doran *et al.* (2012) argue that individual investors' new year gambling preference leads to higher demand for lottery-type of assets. Importantly, lottery-type stocks in the US market (China) outperform their counterparts in January (Chinese new year month). Similarly, Chen, Schmidt and Wang (2021) find that retail investors pay more attention to depressed stocks at year-end as they seek higher risk due to renewed optimism; thus, strengthening the January effect for such stocks and translating into higher demand. On the other hand, Ng and Wang (2004) attribute the January effect to institutional trading behavior. Specifically, institutional investors sell small-sized losing stocks in the last quarter and then buy both winning and losing small-sized stocks in the first quarter. Moreover, such institutional trades are motivated by window-dressing and risk-shifting behavior instead of tax-loss selling.

There is empirical evidence of a decline in the magnitude and significance of the January effect since the 1980s. According to Riepe (1998), the January effect declined once it became public knowledge and future contracts on major US market indices became available to allow arbitrage against it. Evidence put forth by Gu (2003) and Mehdian and Perry (2002) also supports the disappearance of the January effect by the 1980s. However, Moller and Zilca (2008) contest that the evidence of decline is inconclusive because of the use of monthly returns in these studies. If returns are analyzed at daily frequency, there are abnormally high returns in the first half of January, followed by a decline (i.e., mean reversion) in the second half. Importantly, the magnitude of the January effect is unchanged despite this mean reversion.

Loughran (1997) shows that the predictability of the book-to-market ratio for the cross-section of stock returns is driven by its January seasonality, and low returns on small, young, growth stocks outside of January. The book-to-market ratio cannot explain the cross-section of returns of large firms outside of January. Tinic and West (1984) show that the risk-return relationship is positive in January and not significantly different from zero in other months. The superior performance of high-beta stocks in January

[1] See also Bhardwaj and Brooks (1992), Blume and Stambaugh (1983), Keim (1989), and Stoll and Whaley (1983).

implies a cross-sectional effect with respect to firm size because high-beta portfolios are mostly populated by small stocks. Cooper *et al.* (2006) find that market returns in January predict market returns for the rest of the year, termed as the 'Other January Effect'. Return predictability holds for both large and small-cap stocks, as well as for stocks with high or low book-to-market ratios. This effect has predictive power for the size premium (SMB) of Fama and French (1993) as well: the positive (negative) SMB return in January is followed by positive (negative) SMB average return for the remaining 11 months. All these studies show that the January effect has a cross-sectional pattern.

Our paper is also related to the vast literature on the effect of investor sentiment on asset prices. In particular, Lemmon and Portniaguina (2006) and Baker and Wurgler (2006) examine the role of investor sentiment in explaining cross-sectional stock returns. Stambaugh *et al.* (2012) argue that sentiment matters only in high sentiment periods when short-selling constraints are binding. In low sentiment periods, rational investors do not want to short stocks and therefore, the short-selling constraints do not bind. Taking into account the relationship between return seasonality and investor mood/sentiment (Hirshleifer *et al.*, 2020), we focus on the role of investor sentiment on cross-sectional stock returns in January versus other months.

3 Data

The firm-level accounting data are obtained from the Compustat database. Daily stock returns are collected from CRSP. We include all common stocks (share codes 10 and 11) listed on NYSE, NASDAQ and AMEX. We collect data for Fama-French five factors and momentum factors from Kenneth French's web page.[2] Accounting data for fiscal year-ends in calendar year $t - 1$ are used to sort stocks and merge with daily returns from July in year t through June in year $t + 1$. We follow Baker and Wurgler (2006) to construct various portfolios based on different firm characteristics. We build equally weighted[3] decile portfolios of the following firm characteristics: market capitalization (ME), firm age (Age), total risk (σ), earnings-to-book ratio for profitable firms (E/BE), dividend-to-book ratio for dividend payers (D/BE), fixed assets ratio (PPE/A), research and development ratio (RD/A), book-to-market ratio (BE/ME), external finance over assets ratio (EF/A), and sales growth ratio (GS). Following Baker and Wurgler (2006), we also build long-short portfolios from high, medium and low portfolios, where the High, Medium, and Low portfolios are defined as the top three, middle four and bottom three deciles, respectively.

[2] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french
[3] Our results are weaker but remain consistent when the portfolios are value-weighted.

The bottom (top) deciles of ME, Age, E/BE, D/BE, and PPE/A are considered as the most sentiment-prone; conversely, the top (bottom) deciles of σ and RD/A are considered as the most sentiment-prone. We construct "low minus high" and "high minus low" portfolios for these characteristics, respectively. We expect that BE/ME, EF/A, and GS are non-linearly related to sentiment due to their multi-dimensional nature (Baker and Wurgler, 2006; Ding, Mazouz and Wang, 2021). For example, Baker and Wurgler (2006) argue that high BE/ME portfolios are composed of extreme value stocks (which are likely to have high distress risk) while low BE/ME portfolios are composed of growth stocks. Both the top and bottom deciles of BE/ME are more prone to sentiment as compared to the middle deciles. Similar arguments hold for EF/A and GS portfolios. Thus, we also construct "low minus middle" and "high minus middle" portfolios for these characteristics. The sample period for all portfolios ranges from January 1, 1964, to December 31, 2019, except RD/A, which is available only between January 1, 1972, to December 31, 2019, since the coverage on R&D data by Compustat prior to 1972 is very poor (Baker and Wurgler, 2006).

To examine whether market sentiment is high in January compared to other months, we collect two survey-based monthly sentiment indicators, the Consumer Confidence Index by the University of Michigan (ICS) and the Conference Board Consumer Confidence Index (CCI) from Bloomberg. The ICS sample period runs from January 1978 to December 2019 and the CCI sample period runs from January 1965 to December 2019. These sentiment indicators reflect the sentiment of households.

4 Empirical Results

We start our analysis by testing the January effect on market sentiment. We then examine the January effect in aggregate market returns and the cross-section of stock returns. In the third part, we document the time variation of the cross-sectional January effect, testing whether it disappears in recent periods. In the fourth part, we test whether the cross-sectional January effect arises from the compensation for risk by controlling first for common risk factors, and then controlling for time-varying factor loadings. Finally, we examine whether high January returns in long-short portfolios mainly come from the speculative legs or non-speculative legs.

4.1 January effect in market sentiment

Is market sentiment higher in January than in other months? To examine this, we first calculate the change in the Michigan Consumer Confidence Index and the Conference Board Consumer Confidence Index.[4] For each sentiment indicator, we then average the change in sentiment for each month and plot these averages for the Michigan Consumer Confidence Index in Figure1 and the Conference Board Consumer Confidence Index in Figure 2.

Both Figures 1 and 2 show that, while there are differences in the two sentiment indicators, the increase in household sentiment in January is on average the highest among all months.[5] Such a strong January increment in sentiment over the prior month is consistent with the findings in Ciccone (2011). High household optimism at the beginning of a year is in line with the New Year's resolutions (Norcross and Vangarelli, 1988; Norcross *et al.*, 1989, 2002; Polivy and Herman, 2002) that about half of American adults repeatedly make, although, these resolutions typically fail subsequently (Polivy and Herman, 2002).

[Insert Figure 1 and 2 about here]

4.2 January effect in stock returns

If there are limits to arbitrage, increased investor sentiment in January can lead to higher stock returns in January. Indeed, the well-documented January effect shows that there is a tendency for higher stock returns in January than in other months (Wachtel *et al.*, 1942; Rozeff and Kinney, 1976; Ritter, 1988). To test the sentiment-driven mispricing hypothesis, we examine the calendar patterns in both aggregate and cross-sectional stock returns.

4 We consider the change in the sentiment index because we are interested in the stock returns in January. In the model of De Long, Shleifer, Summers and Waldmann (1990), the price of the risky asset is linear in the market sentiment, and therefore the return is linearly related to the change in investor sentiment.

5 We also examine whether the composite sentiment indicator of Baker and Wurgler (2006) has a January effect. This workhorse sentiment indicator is a market-based sentiment index that was extracted as a common component of five sentiment proxies, including closed-end fund discount, the number and the first-day returns of IPOs, the equity share in total new issues, and the dividend premium. We find that, among all months, the level (increment) of Baker-Wurgler sentiment is the highest (second highest) in January.

4.2.1 January effect in market returns

We calculate market returns in excess of Fama-French factors for each calendar month. Figure 3 reports the difference between returns in January and average returns of non-January months for each year, as well as the cumulative excess market returns of January, an average of non-January months and the difference between them. Over 56 years in the sample period, excess market returns in January exceeded the average of non-January months in 34 years, while being lower in the remaining 22 years. A time plot of the difference in cumulative returns shows that the January effect existed up to the 1980s approximately, evidenced by the upward-sloping line. However, the line became downward sloping in the last three to four decades, implying that the January effect vanished and sometimes even reversed in these later years. The disappearing January effect in aggregate market returns is consistent with the sentiment-driven mispricing hypothesis because the sentiment effect only persists in the presence of limits to arbitrage. Prior studies show that anomalies in aggregate market returns can be inexpensively exploited by using mutual funds or stock index futures (Hensel and Ziemba, 2000; Rendon and Ziemba, 2007). Therefore, it is unsurprising to see the decline of the January effect on market returns. This does not rule out the prevalence of the cross-sectional January effect because some stocks are still more difficult to arbitrage than other stocks (McLean and Pontiff, 2016).

[Insert Figure 3 about here]

4.2.2 Cross-sectional January returns

To test whether the January effect still exists in the cross-section, we build long-short portfolios based on different firm characteristics. Specifically, we long the more sentiment-prone portfolios and short the less sentiment-prone portfolios with respect to each firm characteristics. We then report the average January returns of these long-short portfolios. For ease of comparison, we also report the average non-January returns, as well as the difference (January returns minus the average of other months in the same year).

Table 1 shows the results for 16 long-short portfolios considered in Baker and Wurgler (2006). 13 out of 16 long-short portfolios have positive January returns, which are significant at the 1% level. The economic significance of average January returns on these portfolios is also large, with values (in percentage) ranging from 0.912 (high RD/A portfolios minus low RD/A portfolios) to 5.833 (negative E/BE portfolio minus positive E/BE portfolio). The "low minus middle" portfolio for BE/ME is also positive but insignificant. The only two exceptions are the "high minus low" portfolios for GS and EF/A, which are significantly negative. Since both the top and bottom deciles of GS and EF/A are considered to be more sentiment prone, the "high minus low" portfolios may have negative returns depending on which leg is comparatively more sentiment prone than the other. The positively significant averages of "high minus middle" and "low minus middle" portfolios for GS and EF/A are indeed consistent with the non-linear relationship between these characteristics and sensitivity to sentiment. The long positions on both low and high deciles accompanied by short positions on the less sentiment-prone middle deciles yield above-average returns in January. The averages of non-January returns are positively significant only for 4 long-short portfolios. They are either insignificant or negatively significant for all other portfolios. The magnitudes are smaller than January returns with the exception of the same "high minus low" portfolios for GS and EF/A described above.

Importantly, the differences between January and non-January averages are significantly positive for the same 13 long-short portfolios for which the January averages are significantly positive. Thus, returns for these 13 long-short portfolios with long speculative stocks and short non-speculative stocks are mostly earned in the first month of the year. The average January returns (2.513) are more than 20 times higher than those in a non-January month (0.113). These results suggest there is indeed substantial evidence of the cross-sectional January effect, and the striking cross-sectional patterns support the sentiment-driven mispricing hypothesis.

[Insert Table 1 about here]

4.3 Time trend in cross-sectional January returns

As indicated in Figure 3, the January effect in excess market returns is confined to pre-1980 periods and disappears afterwards. Does the cross-sectional January effect vary over time, and has it disappeared in recent years? We examine these questions by testing the cross-sectional January effects in different sub-sample periods.

Table 2 reports the mean January returns, non-January returns and their differences for three periods: 1964-1980, 1981-2000, and 2001-2019. In the 1964-1980 period, mean January returns are positively significant for 11 portfolios. The "high minus middle" portfolio for GS and "high minus low" portfolio for RD/A are positive but insignificant. However, the data for RD/A only starts from 1972, so there are only 8 years of data available in this sub-period. The 3 portfolios that have either insignificantly positive returns or significantly negative January returns in Table 1, continue to yield negatively significant returns in the first sub-period. In the 1981-2000 period, the "high minus middle" portfolio for GS and "high minus low" portfolio for RD/A are also positively significant, leading to a total of 13 portfolios having significantly positive mean January returns. These 13 portfolios are the same that have positively significant results in Table 1.

An important difference between the 1964-1980 and 1981-2000 periods is the lower magnitude of average January returns in the latter as compared to the former; even though there are some exceptions. Similarly, the differences between January and non-January average returns are generally lower in the 1981-2000 period as compared to the earlier period. In other words, the cross-sectional January effect has weakened over time. This trend continues in the 2001-2019 period; the January/Non-January differences are positively significant for 9 portfolios with smaller magnitudes and lesser statistical significance than in prior periods. Nevertheless, the January cross-sectional effect appears to be persistent over time, albeit becoming weaker in later years. These results are in sharp contrast with the previous findings that the January effect in aggregate market returns disappears or even reverses during the 1987-1999 period (Mehdian and Perry, 2001).

[Insert Table 2 about here]

One drawback of Table 2 is that time variation within each sub-sample period is not reported. To provide a complete picture of the cross-sectional January effect over time, we plot the cumulative January/Non-January/Difference returns over time for 16 portfolios described in Table 1. Figure 4 shows that the cross-sectional January effect persists over time for most (13 out of 16) long-short portfolios. These results are consistent with those in Table 2.

[Insert Figure 4 about here]

4.4 Risk compensation or sentiment-driven mispricing?

We have relied on sentiment-driven mispricing to explain the cross-sectional January effects. However, the January effect could potentially be explained as compensation for higher systematic risk in January: 1) Higher cross-sectional January returns are a rational manifestation of higher premiums for common risk factors in January; 2) Time-varying risk (or factor loadings) is higher in January as compared to other months.

The possibility of higher January risk premiums has been suggested by some studies (Chang and Pinegar, 1989, 1990; Kramer, 1994). Zaremba (2017) reports evidence that factor premiums also have their distinct seasonality. Therefore, we regress the January dummy on daily returns of the 16 long-short portfolios while controlling for Fama-French five factors and the momentum factor (Fama and French, 2018). The use of Fama-French factors also allows us to capture cross-sectional variation in exposure to a broad set of macroeconomic factors (Aretz, Bartram and Pope, 2010). We also add an October dummy variable to control for the October effect. The regression model is specified as:

$$\begin{aligned} R_{X,ls,t} \quad = \quad & \alpha + \gamma \text{January Dummy}_{\text{t}} + \beta_{R_m - R_f}(\text{R}_{\text{m}} - \text{R}_{\text{f}})_{\text{t}} + \beta_{SMB}\text{SMB}_{\text{t}} + \beta_{HML}\text{HML}_{\text{t}} \\ & + \beta_{RMW}\text{RMW}_{\text{t}} + \beta_{CMA}\text{CMA}_{\text{t}} + \beta_{MOM}\text{MOM}_{\text{t}} + \xi \text{October Dummy}_{\text{t}} + \epsilon_t \end{aligned} \tag{1}$$

where $R_{X,ls,t}$ denotes daily returns on day t from holding the long-short portfolio based on the firm characteristic X. The results reported in Table 3 reveal that the coefficients of January dummy are still positively significant for the same 13 portfolios which have positively significant results in Table 1. Therefore, the cross-sectional January effect is robust to the adjustment for common risk factors and October seasonality in returns. In other words, higher premiums for risk factors cannot fully explain the January effect.

[Insert Table 3 about here]

To examine the possibility that the January effect stems from a January seasonality in factor loadings (i.e., betas in January may be different from those in other months), we include interaction terms of January dummies with all the risk factors in Equation 1. If time-varying (seasonal) betas can fully account for the January effect, we expect significantly positive coefficients of the interaction terms, and the coefficients of January dummies to turn insignificant. The results in Table 4, however, indicate that the January dummy is still positively significant for 14 portfolios. Some interaction terms are indeed statistically significant but the pattern is neither uniform nor consistent with the expectation that factor loadings are higher in January because some coefficients are even negatively significant. MOM $\times$ Jan is negatively significant for 12 portfolios while positively significant for only 1 portfolio; CMA $\times$ Jan is positively significant for 10 portfolios but negatively significant for 2 portfolios; SMB $\times$ Jan is positively significant for 8 portfolios. Results for interaction terms for other factors are mostly insignificant. In summary, coefficients of January dummies remain qualitatively unchanged in the presence of interaction terms, and thus, higher risk premiums or factor loadings in January cannot fully account for the January effect in these portfolios.

Our findings are consistent with the study by Keloharju, Linnainmaa and Nyberg (2021), who attribute return seasonality to temporary mispricing rather than risk. Sentiment-prone stocks are indeed more susceptible to mispricing errors and hence, affected more by the January seasonality.

[Insert Table 4 about here]

4.5 Speculative and non-speculative legs

In our final analysis, we ask whether the cross-sectional January effect mainly comes from the speculative (long) legs or the non-speculative (short) legs of the long-short portfolios. Since speculative stocks are more affected by shifts in investor sentiment than non-speculative stocks, we expect the speculative legs to contribute more to the high January long-short portfolio returns than the short legs. To test our conjecture, we first regress the daily returns of the long legs from the long-short portfolios on a January dummy, Fama-French five factors, the momentum factor, and an October dummy. Since the long legs appear twice for BE/ME, EF/A and GS in the 16 long-short portfolios under study, we have a total of 13 unique long legs.

Table 5 shows that the coefficients on the January dummy are positive and statistically significant at the 1% level for all 13 long legs. These coefficients are larger than those in Table 3 when the long-short portfolio returns are the dependent variables, suggesting that the cross-sectional January effect mainly comes from the long legs.

[Insert Table 5 about here]

We run similar regressions for daily returns of the short legs using the same set of regressors. Since the short legs appear three times for BE/ME, EF/A and GS in the 16 long-short portfolios under study, we have a total of 10 unique short legs. The results in Table 6 indicate that in 8 out of 10 regressions January dummy has a positive and significant coefficient, suggesting that most of the short-leg portfolios earn positive returns in January. These returns, however, are substantially lower as compared to January returns of long legs. The average daily long-leg January returns across 13 portfolios are 0.182, while the average daily short-leg returns in January across 10 portfolios are 0.032. Thus, the speculative long legs account for 85% of the January effect in the long-short portfolios, while the non-speculative short legs account for the remaining 15%. These results are consistent with our conjecture that the speculative legs are the main contributor to the cross-sectional January effect and support the sentiment-driven mispricing hypothesis.

[Insert Table 6 about here]

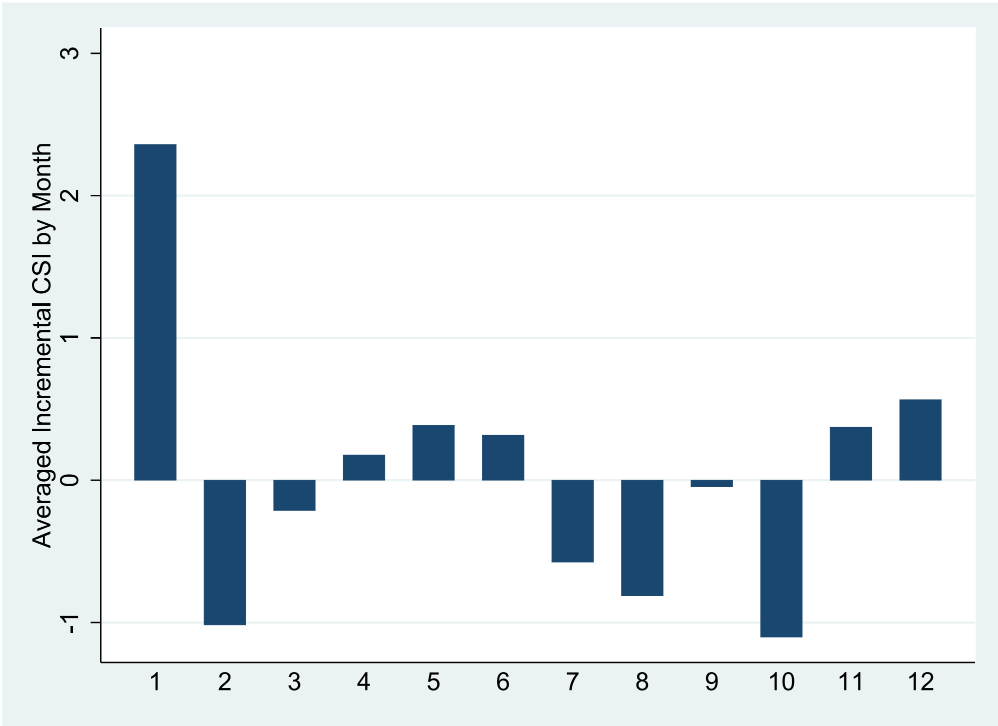
5 Conclusion

This paper uncovers remarkable cross-sectional patterns in the January effect for U.S. equity markets over the 1964-2019 period. Portfolios with speculative long legs and non-speculative short legs earn 20 times more returns in January than any other month. 85% of long-short portfolio returns in January come from the speculative legs, and 15% come from the non-speculative legs. We show that the increment in investor sentiment is the highest in January. Therefore, these cross-sectional patterns are consistent with a sentiment-driven mispricing hypothesis that investor sentiment has a differential cross-sectional effect on January seasonality. We also find that the cross-sectional January effect still exists in recent periods, despite it being time-varying and weakening over time. Furthermore, January returns are still higher for more sentiment-prone stocks after accounting for premiums of common risk factors and January seasonality in factor loadings. In summary, our results suggest that investor sentiment plays a central role in explaining the cross-section of the January effect, while the rational explanation based on a January seasonality in compensation of systematic risk cannot fully explain these cross-sectional patterns.

Irrational emotions can generate excess fluctuations in asset prices and destabilise the stock market. For regulators, it is essential to actively guide investors' irrational emotions based on different time points and market conditions to mitigate the negative impact of calendar effects on the market. For investors, they need to be conscious of the potential damaging effect of seasonal swings in mood. That said, calendar effects also present potential profit opportunities in the cross-section for investors to explore. They can develop reasonable trading strategies during the corresponding time periods, but they should also pay attention to the high risks associated with the profitability of such strategies.

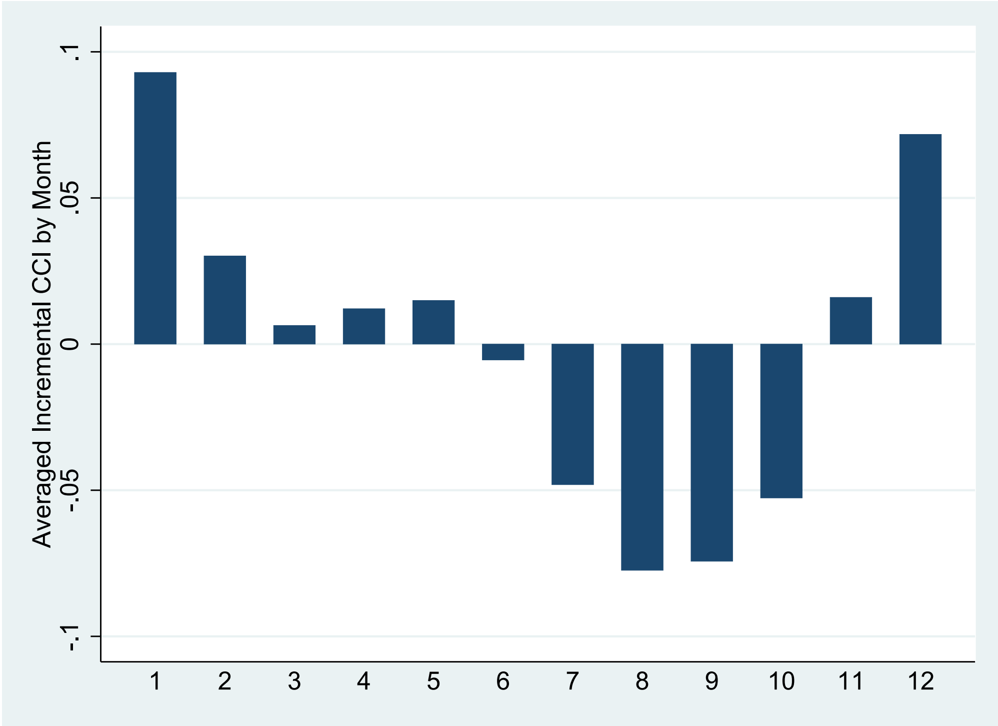
6 Tables and Figures

Figure 1: Michigan Consumer Confidence Index (ICS) in Different Months



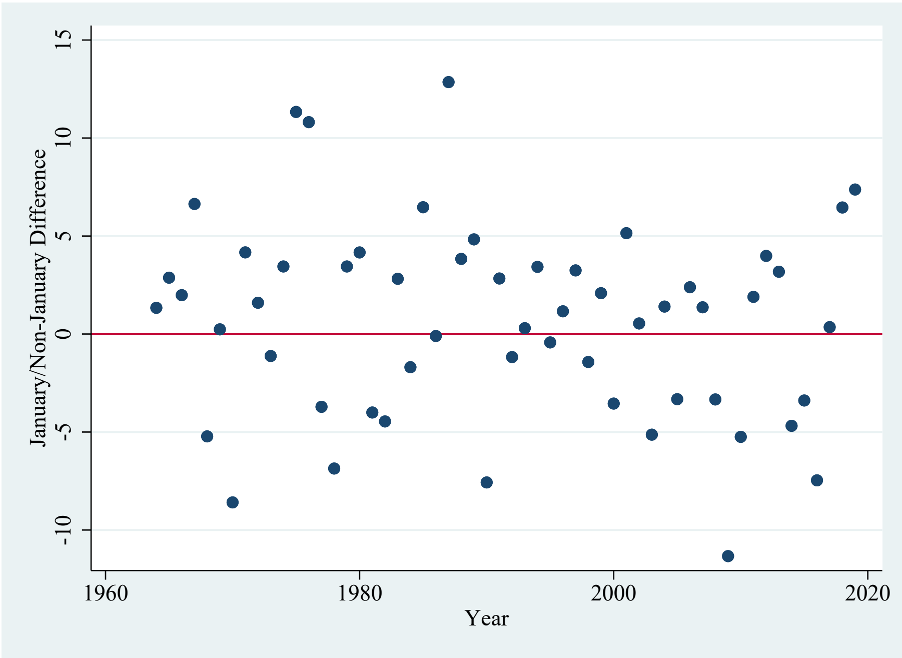
Note: The figures plot the average change in the Consumer Confidence Index by Michigan (CSI) in different months. The sample period is from February 1978 to December 2019.

Figure 2: Conference Board Consumer Confidence Index (CCI) in Different Months

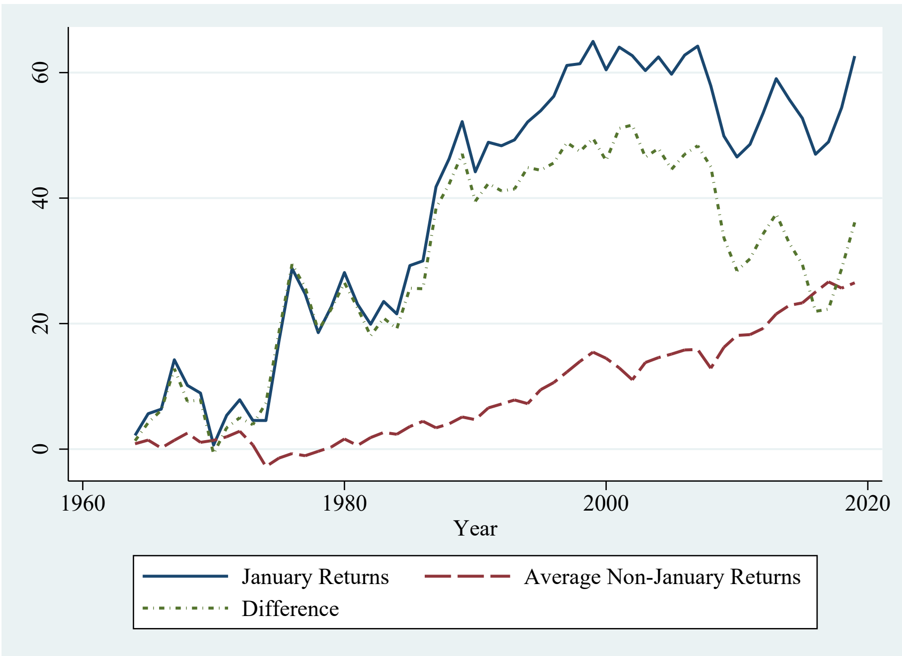


Note: The figures plot the average change in the Conference Board Consumer Confidence Index (CCI) in different months. The sample period is from February 1965 to December 2019.

Figure 3: Time-varying January Effect in Excess Market Returns



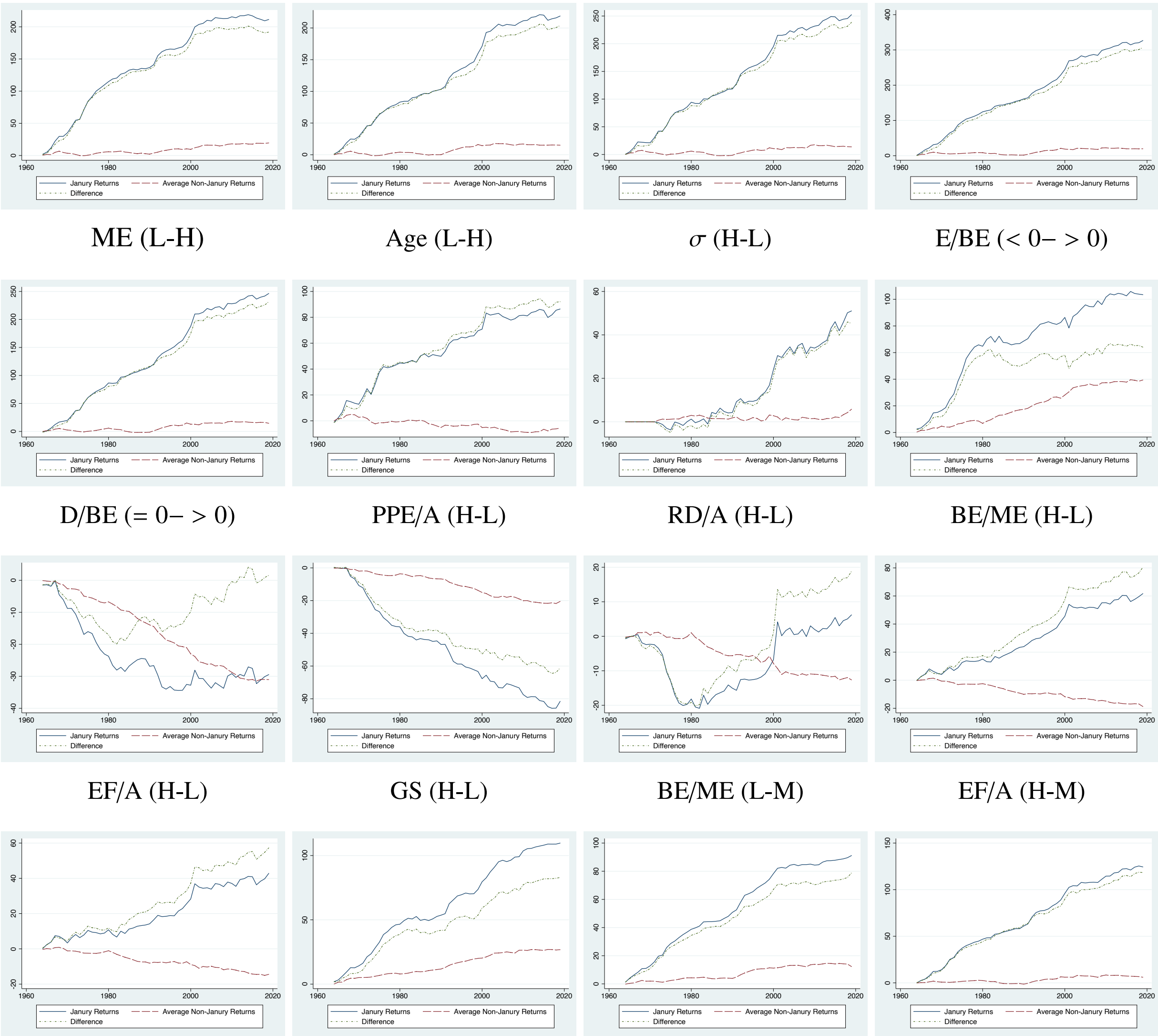
January/Non-January Difference in Excess Market Returns



Cumulative Excess Market Returns

Note: The figures plot the January/Non-January difference in excess market returns, and cumulative excess market returns over time. The excess market return is the value-weighted Fama-French excess market return. The sample period is January 1964 to December 2019.

Figure 4: Time Variation of January Returns



ME (L-H) | Age (L-H) | σ (H-L) | E/BE ($< 0- > 0$)

D/BE ($= 0- > 0$) | PPE/A (H-L) | RD/A (H-L) | BE/ME (H-L)

EF/A (H-L) | GS (H-L) | BE/ME (L-M) | EF/A (H-M)

GS (H-M) | BE/ME (H-M) | EF/A (L-M) | GS (L-M)

Note: The figure shows the cumulative January/Non-January/Difference returns over time for 16 portfolios described in Table 1. The blue solid line shows the cumulative January returns, the red long dash line shows the cumulative average returns in months other than January, and the green short dash line shows the cumulative difference between these two. Equally weighted decile portfolios are created for the following firm characteristics: market capitalization (ME), firm age (Age), total risk (σ), earnings-book ratio for profitable firms (E/BE), dividend-book ratio for dividend payers (D/BE), fixed assets ratio (PPE/A), research and development ratio (RD/A), book-to-market ratio (BE/ME), external finance over assets (EF/A), and sales growth ratio (GS). L-H (H-L) refers to long-short portfolios where the long leg is formed from the bottom (top) three deciles, and the short leg is formed from top (bottom) three deciles of the firm characteristic. L-M (H-M) refers to long-short portfolios where the long leg is formed from the bottom (top) three deciles, and the short leg is formed from the middle four deciles. $< 0- > 0$ ($= 0- > 0$) refers to long-short portfolios where the long leg is formed from stocks with negative (zero) values, and the short leg is formed from stocks with positive values of the firm characteristic. The sample period is January 1964 to December 2019.

Table 1: Mean January and Non-January Returns

This table reports the mean January returns, non-January returns and the difference between them. The sample period is January 1964 to December 2019. Equally weighted decile portfolios are created for the following firm characteristics: market capitalization (ME), firm age (Age), total risk (σ), earnings-book ratio for profitable firms (E/BE), dividend-book ratio for dividend payers (D/BE), fixed assets ratio (PPE/A), research and development ratio (RD/A), book-to-market ratio (BE/ME), external finance over assets (EF/A), and sales growth ratio (GS). L-H (H-L) refers to long-short portfolios where the long leg is formed from the bottom (top) three deciles, and the short leg is formed from top (bottom) three deciles of the firm characteristic. L-M (H-M) refers to long-short portfolios where the long leg is formed from the bottom (top) three deciles, and the short leg is formed from the middle four deciles. $< 0 - > 0$ ($= 0 - > 0$) refers to long-short portfolios where the long leg is formed from stocks with negative (zero) values, and the short leg is formed from stocks with positive values of the firm characteristic.The standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	ME	Age	σ	E/BE	D/BE	PPE/A	RD/A	BE/ME
	L-H	L-H	H-L	$< 0- > 0$	$= 0- > 0$	L-H	H-L	H-L
January	3.775***	3.909***	4.508***	5.833***	4.400***	1.544***	0.912***	1.848***
	(0.592)	(0.593)	(0.691)	(0.682)	(0.625)	(0.442)	(0.330)	(0.448)
Non-January	0.349**	0.269	0.247	0.353	0.261	-0.101	0.103	0.704***
	(0.155)	(0.165)	(0.216)	(0.218)	(0.189)	(0.138)	(0.092)	(0.124)
Difference	3.426***	3.640***	4.261***	5.481***	4.139***	1.645***	0.808**	1.144**
	(0.569)	(0.558)	(0.676)	(0.673)	(0.611)	(0.412)	(0.327)	(0.450)

	EF/A	GS	BE/ME	EF/A	GS	BE/ME	EF/A	GS
	H-L	H-L	L-M	H-M	H-M	H-M	L-M	L-M
January	-0.526**	-1.456***	0.111	1.102***	0.765***	1.959***	1.628***	2.221***
	(0.254)	(0.268)	(0.312)	(0.277)	(0.282)	(0.264)	(0.191)	(0.277)
Non-January	-0.554***	-0.366***	-0.226**	-0.335***	-0.258***	0.478***	0.219***	0.108
	(0.071)	(0.076)	(0.093)	(0.080)	(0.082)	(0.080)	(0.078)	(0.090)
Difference	0.028	-1.090***	0.337	1.437***	1.023***	1.481***	1.409***	2.113***
	(0.251)	(0.248)	(0.322)	(0.279)	(0.281)	(0.255)	(0.180)	(0.263)

Table 2: Mean January and Non-January Returns in Sub-periods

This table reports the mean January returns, non-January returns and their difference for 16 portfolios described in Table 1, over three sub-periods: 1964-1980, 1981-2000, and 2001-2019.The standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	ME	Age	σ	E/BE	D/BE	PPE/A	RD/A	BE/ME
Sample Periods	L-H	L-H	H-L	$<0-\>0$	$=0-\>0$	L-H	H-L	H-L
	Mean January Returns							
1964-1980	6.754***	4.885***	5.548***	7.325***	5.095***	2.630**	0.072	3.809***
	(0.983)	(0.715)	(1.193)	(0.902)	(0.866)	(0.984)	(0.294)	(0.747)
1981-2000	3.522***	4.411***	5.039***	6.002***	5.061***	1.306**	1.142*	1.082*
	(0.828)	(0.905)	(1.059)	(0.917)	(0.872)	(0.480)	(0.571)	(0.606)
2001-2019	1.377	2.508*	3.018**	4.321**	3.082**	0.823	1.421*	0.899
	(0.929)	(1.297)	(1.315)	(1.538)	(1.389)	(0.804)	(0.705)	(0.826)
	Mean Non-January Returns							
1964-1980	0.339	0.243	0.358	0.506	0.350	-0.037	0.174**	0.404*
	(0.355)	(0.320)	(0.387)	(0.356)	(0.293)	(0.316)	(0.076)	(0.206)
1981-2000	0.190	0.512	0.223	0.509	0.350	-0.226	-0.009	1.064***
	(0.229)	(0.320)	(0.380)	(0.417)	(0.401)	(0.225)	(0.179)	(0.173)
2001-2019	0.526**	0.037	0.172	0.052	0.086	-0.026	0.158	0.593**
	(0.233)	(0.210)	(0.375)	(0.354)	(0.271)	(0.184)	(0.188)	(0.244)
	Difference between January and Non-January Returns							
1964-1980	6.414***	4.642***	5.190***	6.820***	4.745***	2.667***	-0.102	3.405***
	(0.936)	(0.700)	(1.164)	(1.009)	(0.884)	(0.905)	(0.303)	(0.659)
1981-2000	3.332***	3.899***	4.816***	5.493***	4.712***	1.532***	1.150*	0.018
	(0.782)	(0.813)	(0.960)	(0.878)	(0.820)	(0.438)	(0.572)	(0.592)
2001-2019	0.850	2.471*	2.846*	4.270**	2.995**	0.849	1.262*	0.306
	(0.849)	(1.246)	(1.358)	(1.496)	(1.370)	(0.760)	(0.684)	(0.848)

Continued on next page

Table 2 – continued from previous page

	EF/A	GS	BE/ME	EF/A	GS	BE/ME	EF/A	GS
Sample Periods	H-L	H-L	L-M	H-M	H-M	H-M	L-M	L-M
	Mean January Returns							
1964-1980	-1.395***	-2.121***	-1.068**	0.886*	0.637	2.741***	2.281***	2.757***
	(0.386)	(0.463)	(0.421)	(0.455)	(0.430)	(0.389)	(0.285)	(0.460)
1981-2000	-0.453	-1.584***	0.568	1.525***	0.874**	1.650***	1.979***	2.458***
	(0.352)	(0.403)	(0.359)	(0.344)	(0.367)	(0.531)	(0.335)	(0.465)
2001-2019	0.175	-0.727	0.685	0.850	0.765	1.584***	0.675**	1.492***
	(0.510)	(0.494)	(0.701)	(0.614)	(0.648)	(0.386)	(0.248)	(0.484)
	Mean Non-January Returns							
1964-1980	-0.396***	-0.212*	0.060	-0.144	-0.062	0.464***	0.252**	0.150
	(0.124)	(0.112)	(0.140)	(0.140)	(0.133)	(0.143)	(0.110)	(0.091)
1981-2000	-0.812***	-0.571***	-0.445**	-0.465***	-0.392**	0.619***	0.347**	0.179
	(0.108)	(0.112)	(0.172)	(0.139)	(0.141)	(0.096)	(0.134)	(0.188)
2001-2019	-0.424***	-0.287*	-0.251	-0.368**	-0.293*	0.342*	0.055	-0.005
	(0.120)	(0.155)	(0.147)	(0.133)	(0.144)	(0.169)	(0.149)	(0.162)
	Difference between January and Non-January Returns							
1964-1980	-0.999***	-1.909***	-1.128***	1.030**	0.698*	2.277***	2.029***	2.607***
	(0.318)	(0.402)	(0.352)	(0.403)	(0.368)	(0.372)	(0.263)	(0.436)
1981-2000	0.359	-1.013**	1.013**	1.990***	1.266***	1.031*	1.631***	2.279***
	(0.337)	(0.371)	(0.388)	(0.363)	(0.378)	(0.497)	(0.284)	(0.430)
2001-2019	0.599	-0.440	0.936	1.218*	1.058	1.242***	0.619*	1.498***
	(0.532)	(0.464)	(0.717)	(0.631)	(0.661)	(0.391)	(0.300)	(0.479)

Table 3: January Effect after Accounting for Risk Factors

This table reports the regression of Fama-French five factors ($R_m - R_f$, SMB, HML, RMW, and CMA) plus the momentum factor (MOM), and dummy variables for January and October on the daily returns of the 16 long-short portfolios described in Table 1. The standard errors of the coefficients are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	ME	Age	σ	E/BE	D/BE	PPE/A	RD/A	BE/ME
	L-H	L-H	H-L	$< 0 - > 0$	$= 0 - > 0$	L-H	H-L	H-L
January Dummy	0.141***	0.128***	0.135***	0.218***	0.162***	0.068***	0.036***	0.062***
	(0.016)	(0.009)	(0.010)	(0.012)	(0.009)	(0.010)	(0.009)	(0.010)
$R_m - R_f$	-0.197***	-0.101***	0.326***	-0.019***	0.027***	0.002	0.075***	-0.216***
	(0.005)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
SMB		0.471***	0.524***	0.193***	0.289***	0.160***	0.020***	-0.041***
		(0.005)	(0.006)	(0.007)	(0.005)	(0.006)	(0.005)	(0.006)
HML	0.125***	-0.186***	-0.153***	-0.235***	-0.361***	-0.224***	-0.332***	
	(0.011)	(0.006)	(0.007)	(0.009)	(0.006)	(0.007)	(0.006)	
RMW	-0.398***	-0.325***	-0.295***	-0.539***	-0.391***	-0.168***	-0.281***	0.157***
	(0.013)	(0.008)	(0.008)	(0.011)	(0.008)	(0.009)	(0.007)	(0.008)
CMA	-0.030**	-0.257***	-0.132***	0.066***	-0.077***	-0.196***	-0.018**	0.459***
	(0.015)	(0.009)	(0.010)	(0.012)	(0.009)	(0.010)	(0.009)	(0.008)
MOM	0.051***	-0.032***	-0.060***	-0.024***	-0.013***	0.010**	0.023***	-0.029***
	(0.007)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
October Dummy	-0.073***	-0.005	-0.017*	-0.025**	-0.015	-0.004	-0.023***	-0.039***
	(0.015)	(0.009)	(0.010)	(0.012)	(0.009)	(0.010)	(0.009)	(0.010)
Constant	0.031***	0.027***	0.016***	0.031***	0.027***	0.003	0.014***	0.034***
	(0.005)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
Adj. R^2	0.187	0.577	0.698	0.298	0.514	0.265	0.459	0.511
N	13927	13927	13927	13927	13927	13927	12064	13927

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Table 3 – continued from previous page

	EF/A	GS	BE/ME	EF/A	GS	BE/ME	EF/A	GS
	H-L	H-L	L-M	H-M	H-M	H-M	L-M	L-M
January Dummy	-0.005	-0.049***	0.010	0.048***	0.029***	0.072***	0.054***	0.078***
	(0.006)	(0.007)	(0.007)	(0.006)	(0.006)	(0.007)	(0.006)	(0.007)
$R_m - R_f$	0.065***	0.095***	0.092***	0.057***	0.087***	-0.124***	-0.008***	-0.008***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
SMB	0.039***	0.066***	-0.004	0.116***	0.146***	-0.045***	0.077***	0.080***
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)
HML	-0.101***	-0.091***		-0.104***	-0.142***		-0.003	-0.051***
	(0.004)	(0.005)		(0.004)	(0.004)		(0.004)	(0.005)
RMW	-0.118***	0.048***	-0.204***	-0.153***	-0.165***	-0.047***	-0.035***	-0.212***
	(0.005)	(0.006)	(0.006)	(0.005)	(0.005)	(0.006)	(0.005)	(0.006)
CMA	-0.296***	-0.295***	-0.373***	-0.202***	-0.205***	0.087***	0.094***	0.090***
	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)
MOM	-0.030***	-0.015***	0.026***	-0.047***	-0.041***	-0.003	-0.017***	-0.026***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)
October Dummy	0.007	0.013*	0.011	-0.008	-0.001	-0.028***	-0.014**	-0.014**
	(0.006)	(0.007)	(0.007)	(0.006)	(0.006)	(0.007)	(0.006)	(0.007)
Constant	-0.021***	-0.018***	-0.006***	-0.007***	-0.006***	0.028***	0.014***	0.011***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Adj. R^2	0.462	0.439	0.419	0.436	0.528	0.247	0.101	0.187
N	13927	13927	13927	13927	13927	13927	13927	13927

Table 4: January Effect after Accounting for Time-varying Betas

This table reports the regression of Fama-French five factors ($R_m - R_f$, SMB, HML, RMW, and CMA) plus the momentum factor (MOM), dummy variables for January and October, and interaction terms between January dummy and the factors, on the daily returns of the 16 long-short portfolios described in Table 1. The standard errors of the coefficients are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	ME	Age	σ	E/BE	D/BE	PPE/A	RD/A	BE/ME
	L-H	L-H	H-L	$< 0 - > 0$	$= 0 - > 0$	L-H	H-L	H-L
January Dummy	0.073***	0.116***	0.125***	0.200***	0.147***	0.057***	0.035***	0.046***
	(0.015)	(0.009)	(0.010)	(0.013)	(0.009)	(0.010)	(0.009)	(0.010)
$(R_m - R_f) \times$ Jan	0.106***	0.027**	0.011	0.011	0.015	0.030**	0.014	0.051***
	(0.018)	(0.010)	(0.012)	(0.015)	(0.011)	(0.012)	(0.010)	(0.011)
SMB × Jan	0.929***	0.045**	0.006	0.084***	0.050***	0.076***	-0.002	0.006
	(0.030)	(0.019)	(0.021)	(0.026)	(0.019)	(0.021)	(0.018)	(0.020)
HML × Jan	-0.072**	-0.018	0.007	-0.038	0.005	0.014	-0.005	0.493***
	(0.036)	(0.021)	(0.024)	(0.030)	(0.022)	(0.025)	(0.020)	(0.022)
RMW × Jan	0.453***	0.014	-0.042	-0.065*	-0.043	0.008	-0.010	-0.036
	(0.044)	(0.026)	(0.029)	(0.036)	(0.027)	(0.030)	(0.025)	(0.028)
CMA × Jan	0.219***	0.100***	0.068**	0.134***	0.136***	0.048	0.045	-0.336***
	(0.050)	(0.030)	(0.033)	(0.041)	(0.031)	(0.034)	(0.029)	(0.032)
MOM × Jan	-0.118***	-0.109***	-0.102***	-0.140***	-0.089***	-0.048***	0.019	0.059***
	(0.021)	(0.012)	(0.014)	(0.017)	(0.013)	(0.014)	(0.012)	(0.013)
$R_m - R_f$	-0.200***	-0.104***	0.324***	-0.021***	0.025***	-0.000	0.074***	-0.219***
	(0.005)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
SMB		0.466***	0.522***	0.185***	0.284***	0.153***	0.021***	-0.045***
		(0.005)	(0.006)	(0.007)	(0.005)	(0.006)	(0.005)	(0.006)
HML	0.123***	-0.184***	-0.153***	-0.232***	-0.361***	-0.225***	-0.332***	
	(0.011)	(0.007)	(0.007)	(0.009)	(0.007)	(0.008)	(0.006)	
RMW	-0.400***	-0.325***	-0.290***	-0.531***	-0.386***	-0.168***	-0.280***	0.161***
	(0.013)	(0.008)	(0.009)	(0.011)	(0.008)	(0.009)	(0.008)	(0.009)
CMA	-0.049***	-0.266***	-0.139***	0.053***	-0.090***	-0.201***	-0.023**	0.453***
	(0.016)	(0.009)	(0.010)	(0.013)	(0.010)	(0.011)	(0.009)	(0.008)
MOM	0.063***	-0.019***	-0.048***	-0.009	-0.003	0.015***	0.021***	-0.025***
	(0.007)	(0.004)	(0.004)	(0.005)	(0.004)	(0.005)	(0.004)	(0.004)
October Dummy	-0.073***	-0.005	-0.017*	-0.025**	-0.015*	-0.005	-0.023***	-0.039***
	(0.015)	(0.009)	(0.010)	(0.012)	(0.009)	(0.010)	(0.009)	(0.009)
Constant	0.031***	0.027***	0.016***	0.031***	0.026***	0.003	0.014***	0.034***
	(0.005)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
Adj. R^2	0.242	0.580	0.699	0.303	0.518	0.267	0.459	0.528
N	13927	13927	13927	13927	13927	13927	12064	13927

Continued on next page

Table 4 – continued from previous page

	EF/A	GS	BE/ME	EF/A	GS	BE/ME	EF/A	GS
	H-L	H-L	L-M	H-M	H-M	H-M	L-M	L-M
January Dummy	-0.004	-0.045***	0.016**	0.045***	0.024***	0.063***	0.049***	0.070***
	(0.006)	(0.007)	(0.007)	(0.006)	(0.006)	(0.007)	(0.006)	(0.007)
$(R_m - R_f) \times$ Jan	0.006	0.001	-0.036***	0.005	0.001	0.015*	-0.001	0.001
	(0.007)	(0.008)	(0.009)	(0.007)	(0.007)	(0.009)	(0.007)	(0.008)
SMB × Jan	-0.012	-0.016	0.010	0.014	0.026**	0.016	0.027**	0.043***
	(0.013)	(0.014)	(0.015)	(0.013)	(0.013)	(0.015)	(0.012)	(0.014)
HML × Jan	-0.018	-0.013	-0.337***	-0.029**	0.008	0.156***	-0.011	0.021
	(0.015)	(0.016)	(0.017)	(0.015)	(0.015)	(0.017)	(0.014)	(0.016)
RMW × Jan	0.058***	0.061***	0.006	0.033*	0.032*	-0.031	-0.025	-0.029
	(0.018)	(0.020)	(0.021)	(0.018)	(0.018)	(0.021)	(0.017)	(0.019)
CMA × Jan	0.071***	0.035	0.229***	0.080***	0.074***	-0.107***	0.009	0.039*
	(0.021)	(0.022)	(0.024)	(0.020)	(0.020)	(0.024)	(0.019)	(0.022)
MOM × Jan	-0.012	0.006	-0.078***	-0.042***	-0.037***	-0.019*	-0.030***	-0.043***
	(0.009)	(0.009)	(0.010)	(0.008)	(0.008)	(0.010)	(0.008)	(0.009)
$R_m - R_f$	0.064***	0.095***	0.094***	0.056***	0.086***	-0.125***	-0.008***	-0.009***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
SMB	0.040***	0.067***	-0.003	0.114***	0.143***	-0.048***	0.074***	0.076***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)
HML	-0.100***	-0.090***		-0.102***	-0.143***		-0.002	-0.053***
	(0.005)	(0.005)		(0.004)	(0.004)		(0.004)	(0.005)
RMW	-0.124***	0.042***	-0.204***	-0.156***	-0.167***	-0.043***	-0.032***	-0.209***
	(0.006)	(0.006)	(0.007)	(0.005)	(0.005)	(0.007)	(0.005)	(0.006)
CMA	-0.303***	-0.298***	-0.368***	-0.210***	-0.213***	0.085***	0.093***	0.085***
	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)
MOM	-0.029***	-0.016***	0.027***	-0.043***	-0.038***	0.002	-0.014***	-0.022***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
October Dummy	0.007	0.013*	0.011	-0.008	-0.001	-0.028***	-0.015**	-0.014**
	(0.006)	(0.007)	(0.007)	(0.006)	(0.006)	(0.007)	(0.006)	(0.007)
Constant	-0.021***	-0.017***	-0.006***	-0.007***	-0.006***	0.028***	0.013***	0.011***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Adj. R^2	0.463	0.439	0.436	0.438	0.529	0.254	0.102	0.190
N	13927	13927	13927	13927	13927	13927	13927	13927

Table 5: January Returns on the Long Legs

This table reports the regression of the daily returns on the long legs of the 16 long-short portfolios (described in Table 1) on Fama-French five factors ($R_m - R_f$, SMB, HML, RMW, and CMA) plus the momentum factor (MOM), and dummy variables for January and October. The standard errors of the coefficients are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	ME	Age	σ	E/BE	D/BE	PPE/A	RD/A	BE/ME	BE/ME	EF/A	EF/A	GS	GS
	L	L	H	< 0	= 0	L	H	L	H	L	H	L	H
January Dummy	0.275***	0.167***	0.231***	0.275***	0.180***	0.107***	0.199***	0.099***	0.205***	0.157***	0.148***	0.197***	0.127***
	(0.017)	(0.011)	(0.014)	(0.014)	(0.010)	(0.010)	(0.015)	(0.011)	(0.014)	(0.010)	(0.012)	(0.012)	(0.011)
$R_m - R_f$	0.556***	0.790***	0.948***	0.840***	0.875***	0.827***	0.946***	0.962***	0.697***	0.819***	0.933***	0.807***	0.959***
	(0.005)	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)	(0.004)	(0.003)
SMB		0.809***	0.936***	0.858***	0.848***	0.745***	0.824***	0.730***	0.679***	0.778***	0.843***	0.784***	0.838***
		(0.006)	(0.008)	(0.008)	(0.005)	(0.006)	(0.008)	(0.006)	(0.008)	(0.006)	(0.007)	(0.007)	(0.006)
HML	0.106***	-0.005	-0.107***	-0.080***	-0.063***	0.145***	-0.462***			0.136***	-0.132***	0.021**	-0.094***
	(0.011)	(0.008)	(0.010)	(0.010)	(0.007)	(0.007)	(0.010)			(0.007)	(0.008)	(0.008)	(0.007)
RMW	-0.420***	-0.173***	-0.396***	-0.402***	-0.150***	-0.020**	-0.530***	-0.300***	-0.024**	0.002	-0.285***	-0.284***	-0.199***
	(0.013)	(0.009)	(0.012)	(0.012)	(0.008)	(0.009)	(0.012)	(0.009)	(0.011)	(0.009)	(0.010)	(0.010)	(0.009)
CMA	-0.072***	-0.069***	-0.073***	0.059***	-0.010	-0.092***	-0.024	-0.360***	0.316***	0.145***	-0.195***	0.162***	-0.225***
	(0.016)	(0.011)	(0.014)	(0.014)	(0.009)	(0.010)	(0.015)	(0.009)	(0.011)	(0.010)	(0.012)	(0.012)	(0.010)
MOM	-0.017**	-0.103***	-0.111***	-0.101***	-0.096***	-0.100***	-0.062***	-0.080***	-0.163***	-0.078***	-0.145***	-0.082***	-0.140***
	(0.007)	(0.005)	(0.006)	(0.006)	(0.004)	(0.004)	(0.006)	(0.004)	(0.005)	(0.004)	(0.005)	(0.005)	(0.004)
October Dummy	-0.083***	-0.010	-0.015	-0.026*	-0.016*	-0.005	-0.016	0.006	-0.050***	-0.016	-0.014	-0.023*	-0.001
	(0.016)	(0.011)	(0.014)	(0.014)	(0.009)	(0.010)	(0.015)	(0.010)	(0.013)	(0.010)	(0.011)	(0.012)	(0.010)
Constant	0.088***	0.050***	0.069***	0.071***	0.059***	0.047***	0.074***	0.039***	0.093***	0.069***	0.035***	0.068***	0.035***
	(0.005)	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)	(0.005)	(0.003)	(0.004)	(0.003)	(0.004)	(0.004)	(0.003)
Adj. R^2	0.576	0.868	0.858	0.830	0.910	0.881	0.872	0.911	0.748	0.870	0.894	0.843	0.912
N	13467	13467	13467	13467	13467	13467	11982	13467	13467	13467	13467	13467	13467

Table 6: January Returns on the Short Legs

This table reports the regression of the daily returns on the short legs of the 16 long-short portfolios (described in Table 1) on Fama-French five factors ($R_m - R_f$, SMB, HML, RMW, and CMA) plus the momentum factor (MOM), and dummy variables for January and October. The standard errors of the coefficients are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	ME	Age	σ	E/BE	D/BE	PPE/A	RD/A	BE/ME	EF/A	GS
	H	H	L	> 0	> 0	H	L	M	M	M
January Dummy	-0.017**	0.003	0.013*	0.054***	0.012**	0.029**	0.082***	0.051***	0.049***	0.047***
	(0.007)	(0.008)	(0.007)	(0.005)	(0.005)	(0.014)	(0.008)	(0.008)	(0.008)	(0.008)
$R_m - R_f$	1.053***	0.950***	0.480***	0.862***	0.849***	0.814***	0.820***	0.879***	0.847***	0.815***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.004)	(0.002)	(0.003)	(0.002)	(0.002)
SMB		0.148***	0.257***	0.669***	0.559***	0.574***	0.700***	0.724***	0.622***	0.607***
		(0.005)	(0.004)	(0.003)	(0.003)	(0.008)	(0.004)	(0.005)	(0.004)	(0.005)
HML	-0.014***	0.144***	0.145***	0.156***	0.298***	0.285***	0.205***		0.144***	0.181***
	(0.005)	(0.006)	(0.005)	(0.003)	(0.003)	(0.010)	(0.005)		(0.005)	(0.006)
RMW	0.143***	0.304***	0.109***	0.143***	0.245***	0.039***	0.174***	0.075***	0.076***	0.137***
	(0.005)	(0.007)	(0.006)	(0.004)	(0.004)	(0.012)	(0.006)	(0.007)	(0.006)	(0.007)
CMA	0.002	0.361***	0.116***	-0.004	0.067***	0.173***	0.078***	0.208***	0.120***	0.094***
	(0.006)	(0.008)	(0.007)	(0.005)	(0.005)	(0.014)	(0.008)	(0.007)	(0.007)	(0.008)
MOM	-0.116***	-0.046***	-0.021***	-0.079***	-0.083***	-0.077***	-0.094***	-0.119***	-0.055***	-0.066***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.006)	(0.003)	(0.003)	(0.003)	(0.003)
October Dummy	0.023***	-0.016*	0.007	0.000	0.000	-0.001	-0.015*	-0.004	0.001	-0.004
	(0.006)	(0.008)	(0.007)	(0.005)	(0.005)	(0.014)	(0.008)	(0.008)	(0.007)	(0.008)
Constant	0.021***	0.024***	0.041***	0.040***	0.032***	0.054***	0.045***	0.041***	0.046***	0.048***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.004)	(0.002)	(0.003)	(0.002)	(0.002)
Adj. R^2	0.963	0.917	0.802	0.968	0.964	0.767	0.929	0.919	0.925	0.910
N	13467	13467	13467	13467	13467	13467	11982	13467	13467	13467

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