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RESEARCH ARTICLE

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Do Arbitragers Exploit the January Effect?

Abstract The January effect has been well documented since the 1970s. This study examines whether the January effect still exists and if it does, whether arbitrageurs exploit it. We find that the January effect is still persistently significant. Furthermore, we find that arbitrageurs appear to exploit the January effect, especially in good market years when the number of losing firms is limited and are therefore more easily identifiable. We also find that the January effect tends to be higher for losing stocks with high arbitrage costs relative to those with low arbitrage costs.

Keywords January effect, tax-loss selling, arbitrage costs, market efficiency

1 Introduction

The "January" or the "turn-of-the-year" effect is a well-documented anomaly in which primarily small capitalization stocks have been found to earn abnormally high returns around the turn-of-the-year (e.g., Rozeff and Kinney, 1976; Reinganum, 1983).[1] The literature provides several hypotheses to explain the January effect,[2] among which the tax-loss selling hypothesis (e.g., Branch, 1977;

[1] Other studies examining the January effect include Banz (1981), Keim (1983), Blume and Stambaugh (1983), and Roll (1983).

[2] The tax-loss selling hypothesis (e.g., Branch, 1977; Dyl, 1977; Reinganum, 1983; Starks, Yong, and Zheng, 2006), the window dressing hypothesis (e.g., Haugen and Lakonishok, 1988; Musto, 1997; Maxwell, 1998; Meier and Schaumburg, 2004), the insider trading (information release) hypothesis (e.g., Seyhun, 1988), and the seasonality of the risk-return relationship hypothesis (e.g., Tinic and West, 1984; Ritter and Chopra, 1989).

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Roll, 1983) has the most supporting evidence.[3] Although the January effect has been widely recognized, it has not disappeared (Schwert, 2003). Its long-term existence has been a challenge to the efficient market hypothesis, which suggests that as an anomaly appears, arbitrageurs will trade on and eliminate any such price discrepancies. Roll (1983) suggests that there is an information barrier for arbitrageurs to execute such trades. He argues that it might be difficult for the arbitrageurs to target the stocks that are going to have the most tax-loss sellers. If this is true, one could posit that arbitrage may be easier when the number of losers is small. In this study, we examine whether the January effect still exists and if so under what conditions it is exploited by arbitrageurs.

The tax-loss selling hypothesis depends on tax-motivated trading. Branch (1977) documents high January returns for stocks that have declined in value in the previous year. Roll (1983) argues that investors sell stocks that have declined in value (losers) prior to the year-end to realize capital losses. Consequently, immediately following the year-end, prices tend to rebound to the equilibrium level resulting in relatively abnormally higher returns of those stocks.

According to the tax-loss selling hypothesis, the selling pressure in December and the price rebounding pressure in January will be concentrated primarily on the previous year's losers. Because there are fewer losers in good market years relative to bad market years, the tax-loss sellers have fewer choices to realize capital losses in good years. Therefore, in good years, the information barrier is less prevalent for arbitrageurs who can more easily identify those few losing stocks. One would expect arbitrageurs to trade on the opposite side of the tax-loss-sellers in order to profit from the January effect. This should in turn reduce the abnormal return in January. Alternatively, in bad market years, arbitrageurs may not be able to easily identify which stocks will be affected. Hence, the aggregate January effect should be more prevalent in those years.

We find that the arbitrageurs appear to exploit the January effect, especially in good market years. That is, losing stocks tend to earn lower returns in the January immediately after good years relative to bad years.

Arbitrage will also occur only if arbitrageurs are able to earn high enough risk-adjusted returns after taking arbitrage costs, including transaction costs and

[3] The existing empirical evidence does not support the insider trading or risk-return seasonality hypotheses (Brauer and Chang, 1990; Ritter and Chopra, 1989; Rozeff and Kinney, 1976; Seyhun, 1988; Tinic and West, 1984).

holding costs, into account.[4] Pontiff (2006) suggests that transaction and holding costs prevent rational investors from exploiting anomalies and eliminating mispricing effectively. He identifies idiosyncratic volatility as a major holding cost faced by arbitrageurs. Because arbitrageurs are unable to hedge idiosyncratic risk, they tend to take limited positions in mispriced stocks with high idiosyncratic volatilities, ceteris paribus. Shleifer and Vishny (1997) argue that arbitrage is costly and arbitrageurs are usually under-diversified. Therefore arbitrage risks may deter their trading ability to eliminate anomalies. Similarly, Roll (1983) suggests that the January effect is not exploitable because of the transaction costs.

Our results show that the January returns of losing stocks with high arbitrage costs are significantly higher than that of losing stocks with low arbitrage costs. This suggests that high arbitrage costs on losing stocks deter arbitrageurs from eliminating the January effect. In other words, arbitrageurs' activities tend to be limited on high arbitrage cost stocks relative to low arbitrage cost stocks.

Our analysis provides two contributions to the January effect literature. Firstly, we show that the January effect still exists. Secondly, we lend evidence as to why the January effect has not been arbitraged away after being well documented by researchers and recognized by practitioners. Our results suggest that arbitrageurs concentrate their trades on losing stocks with low arbitrage costs primarily in good years. This in turn drives losing stock prices toward fair levels producing a smaller January effect in the subsequent year.

The rest of the paper is organized as follows. In Section 2, we review related literature and develop testable hypotheses. Section 3 explains the data and methodology used in this study. In Section 4, we present empirical evidence and our interpretation of the results. Section 5 provides some concluding remarks.

2 Literature Review and Hypothesis Development

There have been several possible explanations for the January effect since it was

[4] The relation between arbitrage costs and mispricing has been demonstrated in many studies, for example, Pontiff (1996) on closed-end fund discounts, Ali, Hwang, and Trombley (2003) on book-to-market anomaly, Pontiff and Schill (2001) on long-run seasoned equity offering (SEO) abnormal returns, Mendenhall (2004) on post-earnings-announcement-drifts, Mashruwala, Rajgopal, and Shevlin (2006) on accrual anomaly, Lipson, Mortal and Schill (2012) on asset growth effect, and Stambough, Yu and Yuan (2014) on various market anomalies.

first documented by Rozeff and Kinney (1976) and Reinganum (1983). The two dominant proposed theories relate to either end of the year tax-loss selling or window dressing.

The tax-loss selling hypothesis posits that in December investors sell losing stocks to realize capital losses so as to lower capital gains taxes. While this tax-motivated selling pressure on losing stocks depresses the stock prices at the end of the year, it disappears in early January. Prices then rebound so that those losing stocks have higher January returns.

Empirical evidence has been supportive of this hypothesis. Dyl (1977) examines the relation between capital gains taxation and year-end trading volume and finds abnormally high volumes in December for stocks that have declined in value during the year. Givoly and Ovadia (1983) relate high returns in January to the existence of selling pressure for tax purposes at the end of the year and find abnormally high January returns for stocks that have had 12-month lows in December. Reiganum (1983) builds portfolios based on market capitalization and a measure of potential tax-loss selling (PTS). He finds that returns in early January are related to both variables, i.e., small losing stocks have abnormally high daily returns in early January. However, he also shows that even small stocks without price declines have very high January returns. Tinic, Baroni-Adesi, and West (1987) study the Canadian stock market and find the turn-of-the-year effect existed prior to the introduction of capital gains taxation. A recent study by Starks, Yong, and Zheng (2006) examines the return and volume patterns of municipal bond closed-end funds around the turn of the year and provides evidence supporting the tax-loss selling hypothesis. Chen and Singal (2004) investigate several possible reasons for the January effect and conclude that tax-loss selling is the dominant explanation.

An alternative explanation, the window-dressing hypothesis of Haugen and Lakonishok (1988) suggests that the January effect is the result of rebalancing activities mainly from institutions rather than individual investors. The claim is that institutions rebalance at year-end either because portfolio managers are evaluated relative to their peers at the period end or because they need to disclose the portfolio performance to the claimholders with returns information for each stock held in the portfolio rather than for the portfolio return as a whole. Therefore, they have the incentive to buy winners and sell losers before the end of the year.

Empirical evidence of the window-dressing hypothesis is also mixed. On the one hand, Musto (1997) examines window-dressing among money market instruments and finds a January effect among those instruments that do not generate capital losses. He concludes that the January effect can at least be partially explained by the window-dressing activities of institutional investors. Ritter and Chopra (1989) and Meier and Schaumburg (2004) provide similar supporting evidence for the window-dressing hypothesis.

Sias and Starks (1997) evaluate the tax-loss selling and window-dressing hypotheses by studying transaction data for stocks dominated by institutional investors versus those dominated by individual investors. Although they find that institutions tend to buy recent winners, which is consistent with the window-dressing hypothesis, they do not find any evidence of institutions selling losers. Their data do not show whether or not the winner-buying institutions have year-end disclosures. Chen and Singal (2004) find no evidence for the window-dressing hypothesis by examining stock returns and volume patterns around the semi-annual period end (June-July) when tax-loss selling is not expected.

This study looks at the relation between market performance and the January effect in order to examine whether arbitrageurs have noticed these trading patterns and if so, why they have failed to exploit and eliminate this anomaly. A popular view on Wall Street, among traders in hedge funds, is that trading strategies based on the January effect tend to be profitable but risky[5]. If arbitrageurs trade on the January effect, i.e., they buy losers in December and gain abnormally high returns in January when the pressure from tax-loss selling is relieved, we would expect a smaller January effect because of those arbitrage activities.

However, when the market performs well in a year, there are only a few losers for the tax-loss sellers to realize capital losses. Therefore tax-loss selling is concentrated on those few losers. Arbitrageurs who trade on the opposite side of those tax-loss sellers are then able to identify and concentrate their trades on the few losers in good years. In other words, arbitrageurs tend to buy past losers in December and close their positions in January in order to exploit the January effect. Consequently, the January effect could be mitigated to a greater extent

[5] See Pontiff (2006) and Shleifer and Vishny (1997) for the arguments about arbitrage costs.

immediately after good years relative to bad years. We posit the following hypothesis:

Hypothesis 1. Stocks that have declined in value during a year earn relatively lower January returns immediately after good years relative to bad years.

If arbitrageurs tend to exploit the January effect, especially in good years, one would also expect the magnitude of the January effect to be related to arbitrage costs. Shleifer and Vishny (1997) argue that arbitrage is costly and recognize the importance of arbitrage risk in the existence of mispricing. Pontiff (2006) emphasizes and clarifies that idiosyncratic risk is an important arbitrage cost, which deters an arbitrageur's trading against mispricing, regardless of the arbitrageur's level of diversification. Idiosyncratic risk is part of holding costs that are incurred when a position remains open. Idiosyncratic volatility therefore deters arbitrage activities.

Other types of arbitrage costs include short-sale constraints and transaction costs. Because costs of short selling do not constrain arbitrageurs from buying losers at the year end, arbitrageurs' trading to exploit the January effect is not affected by short-sale constraints. Therefore, we exclude short selling costs from our analysis.[6] Transaction costs, on the other hand, affect arbitrageurs' ability to trade and remove any price discrepancies, the January effect included. In sum, arbitrage costs limit the extent to which arbitrageurs are able to eliminate anomalies, including the January effect. Therefore, losing stocks with high arbitrage costs are expected to have a higher January effect relative to losing stocks with low arbitrage costs, ceteris paribus.

If Hypothesis 1 is true, and if arbitrage costs deter trading activity, losing stocks with low arbitrage costs should be expected to have a smaller January effect compared to losing stocks with high arbitrage costs. Therefore, we posit the following hypothesis:

Hypothesis 2. Losing stocks with high arbitrage costs have higher January

[6] Although those investors only take long positions in order to exploit the January effect, they are still profit-minded and rational investors. Following Pontiff (2006), we call them arbitrageurs. However, they are subject to market risks since they only take long positions. In our empirical analysis, we control for market risks for that reason.

returns than losing stocks with low arbitrage costs, ceteris paribus.

3 Data and Methodology

The principal data for this study come from the Center for Research in Security Prices (CRSP) daily and monthly stock files. Our sample period is from 1926 to 2013. We obtain daily prices, shares outstanding and daily/monthly returns (including and excluding dividends) for all the common stocks traded on NYSE, AMEX and Nasdaq.

3.1 Measurement of Good/Bad Years

We obtain the monthly returns of the value-weighted and equally-weighted CRSP indices (excluding dividends[7]) as the market returns and calculate the average monthly returns for the value-weighted and equally-weighted CRSP indices for each year during 1926–2013. We then rank the average monthly returns to get year deciles, where 0 is the lowest returns decile, i.e., bad years, and 9 is the highest returns decile, i.e., good years.

We also calculate the compounded monthly returns using the value-weighted and equally-weighted indices (excluding dividends) for each year in our sample period as alternative measures of the good/bad years. Similarly, we stratify the compounded returns into 10 groups, where decile 0 is the lowest compounded returns group, i.e., bad years, and decile 9 is the highest compounded returns group, i.e., good years.

Although the rankings of the years from the four measures (average value-weighted monthly return, average equally-weighted monthly return, compounded value-weighted return, and compounded equally-weighted return) are slightly different from each other, the empirical results are similar using each measure.[8]

[7] We use the index returns excluding dividends because dividends should not affect the tax-loss sellers' decision to realize losses in order to reduce capital gains taxes (Dyl, 1977). In this study, we posit that the January effect is mostly related to investors' tax motivated trading. Therefore, we proxy good/bad years and loser/winners by only measuring price depreciation or appreciation.

[8] We report results based on good/bad year measures of average equally-weighted monthly returns. Results on other good/bad year measures are robust and available upon request.

3.2 Measurement of Winner/Losers

For each year, we calculate the compounded monthly returns from February to November for each stock to measure the percentage appreciation (or depreciation) during those ten months. This measure provides us the magnitude of the unrealized gains or losses an investor could incur if he/she holds the stock from February to November. The compounded return of security i from February to November of year n, R_{in}, is computed as follows:

$$R_{in} = \prod_{i=2}^{11}(1 + R_{it}) - 1, \tag{1}$$

where R_{it} is the monthly return of security i in month t excluding dividends. We rank the stocks by the compounded monthly returns and group them into deciles, with decile 0 as the lowest compounded monthly return group, i.e., losers,[9] and decile 9 as the highest compounded monthly return group, i.e., winners.

This ten-month buy-and-hold return gives us a measure of the price depreciation or appreciation if the investor buys at the beginning of February and holds until November. The measure can only be a proxy since we know only a small fraction of the investors with holdings in November actually purchases the stocks in February. Following Rozeff (1986), we also calculate the compounded monthly returns from July to November to measure losers and winners accordingly and get similar empirical results as the February to November specification.

To check for robustness, we also proxy the loser/winner stocks using average monthly returns from February to November and from July to November. Therefore, we have four measures of loser/winner stocks. Based on each measure, we stratify the stocks into 10 loser/winner portfolios.[10]

3.3 Measurement of Arbitrage Costs

We measure arbitrage costs for each stock in every December, because only December and January's arbitrage costs will play a role in the arbitrageurs'

[9] As a robustness test, we remove all the positive return stocks from the losers' portfolio (decile 0) and confirm our main results.

[10] We report results based on a winner/loser measure of compounded monthly returns from February to November. Results on other winner/loser measures are robust and available upon request.

trading to profit from and eliminate the January effect. Without losing generality, we assume that arbitrage costs do not change dramatically from December to January. Therefore, we proxy each stock's arbitrage costs in every December from 1926 to 2013, data permitting.

We measure idiosyncratic volatility (IDIO) by the standard deviation of residuals from regressing an individual stock's monthly return against the Fama-French three-factor and four-factor including momentum models over the previous 60 months.[11] Monthly data of the factors are obtained from Kenneth R. French's data library[12]. Because the regression requires at least 60 months of data, our proxy of the idiosyncratic volatility is from 1931 to 2013. The portfolio's IDIO is the average IDIO of the stocks in the portfolio. Then we calculate the median IDIO of the 10 loser/winner portfolios each December and define a dummy variable *H_IDIO* as 1 if the portfolio's IDIO is higher than the median level, and 0 otherwise. The measure, *H_IDIO*, is therefore the proxy for idiosyncratic volatility for each loser/winner portfolio.

For transaction costs, we follow Lesmond, Ogden, and Trzcinka (1999) and Ali, Hwang, and Trombley (2003) and use a comprehensive measure of transaction costs, the frequency of zero return days within the past 12 months (Zerofreq). The argument is that when the transaction cost is high, investors hesitate to trade unless they have information and can make a profit after taking the transaction costs into account. Therefore, a high frequency of zero return days proxies a high transaction cost on the stock. We measure Zerofreq at the end of December for the past year. So our Zerofreq measure is from December 1926 to December 2013. Then we calculate the median Zerofreq for the 10 loser/winner portfolios and define a portfolio level dummy variable *H_Zerofreq* as 1 if the Zerofreq of the portfolio is higher than the median, and 0 otherwise. We also include another measure of the transaction cost,

[11] Brown and Kapidia (2007) suggest that young firms tend to have larger idiosyncratic volatility. Kerr and Nanda (2009) find that young firms are more likely to get delisted. When we use monthly returns over the previous 60 months in the regression, we might neglect some stocks with high idiosyncratic risks. Therefore, to check for robustness, we also measure idiosyncratic volatility by the standard deviation of residuals from regressing an individual stock's daily return against the daily market return over previous 6 months. The results are robust.

[12] The data library is available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

illiquidity (ILLI), following Amihud (2002). For each December, we divide the absolute value of daily returns by daily dollar volume (in millions) and calculate the average over the month. Then in a similar fashion, we calculate the median ILLI for the 10 loser/winner portfolios and define a portfolio level dummy variable *H_ILLI* as 1 if the ILLI of the portfolio is higher than the median, and 0 otherwise.

4 Results

For every test in this study, we use four measures of the year deciles and four measures of the loser/winner deciles, respectively. Therefore, we generate sixteen (four by four) different combinations as robustness checks for each test. For brevity, we only report the results with one combination, i.e., average monthly equally-weighted CRSP index return as the proxy for good/bad year and compounded monthly returns from February to November as the measure of loser/winner at the turn-of-the-year.[13]

Table 1 presents the descriptive statistics of our full sample, 1926–2013, shown in Panel A, as well as that of eight sub-periods displayed in Panel B. The average firm in our sample has $985 million market value of equity (*Size*) and the median firm Size is $55 million. Because the Size variable is highly skewed and has a wide distribution, we use the natural logarithm of *Size* in the subsequent analysis. The average illiquidity (*ILLI*) across all firms in our sample is 29 and the median is 3. The average idiosyncratic volatility (*IDIO*) for the full sample is .12 and the median is .10. The average zero frequency days in a year (*Zerofreq*) is 62 and the median is 49.

Table 1 Sample Description

Panel A Full Sample, 1926–2013							
	Mean	Std Dev	P10	P25	P50	P75	P90
Size	984.96	7,596.48	4.81	13.86	54.50	264.60	1155.30
ILLI	28.84	266.60	.06	.42	3.06	16.26	51.84
IDIO	.12	.08	.05	.07	.10	.15	.22
Zerofreq	62	53	7	24	49	81	139

(*To be continued*)

[13] All other results are robust and available upon request.

(*Continued*)

Panel B Subperiod 1, 1926–1939							
	Mean	Std Dev	P10	P25	P50	P75	P90
Size	54.53	173.78	.99	3.02	10.15	36.18	124.91
ILLI	243.01	1078.40	3.64	12.63	47.37	147.74	410.47
IDIO	.13	.07	.06	.08	.12	.17	.23
Zerofreq	50	34	17	27	41	65	97
Subperiod 2, 1940–1949							
	Mean	Std Dev	P10	P25	P50	P75	P90
Size	53.88	182.45	2.04	5.25	12.83	36.29	111.00
ILLI	114.91	703.72	5.91	15.49	40.35	82.48	156.74
IDIO	.08	.04	.04	.05	.07	.09	.13
Zerofreq	55	27	28	37	49	67	93
Subperiod 3, 1950–1959							
	Mean	Std Dev	P10	P25	P50	P75	P90
Size	139.88	565.38	5.50	11.82	31.59	94.21	267.84
ILLI	34.28	160.59	2.53	5.71	14.27	33.53	62.64
IDIO	.06	.02	.03	.04	.05	.07	.09
Zerofreq	53	24	26	36	49	66	86
Subperiod 4, 1960–1969							
	Mean	Std Dev	P10	P25	P50	P75	P90
Size	256.59	1,213.20	5.61	13.85	44.47	156.85	518.66
ILLI	22.07	76.72	1.52	3.46	9.09	25.10	54.59
IDIO	.08	.04	.04	.05	.07	.09	.13
Zerofreq	46	27	18	27	41	60	84
Subperiod 5, 1970–1979							
	Mean	Std Dev	P10	P25	P50	P75	P90
Size	198.83	1,104.02	2.72	6.76	22.43	93.33	380.80
ILLI	21.28	35.88	.82	2.45	8.08	24.41	56.09
IDIO	.11	.05	.05	.07	.10	.13	.17
Zerofreq	93	63	28	43	72	139	199
Subperiod 6, 1980–1989							
	Mean	Std Dev	P10	P25	P50	P75	P90
Size	330.46	1,645.18	4.01	10.33	35.09	145.44	615.46
ILLI	14.20	83.46	.17	.75	2.87	10.59	31.25
IDIO	.12	.08	.06	.07	.11	.15	.22
Zerofreq	93	59	30	48	77	126	192

(*To be continued*)

(*Continued*)

Subperiod 7, 1990–1999							
	Mean	Std Dev	P10	P25	P50	P75	P90
Size	929.58	5,424.05	7.06	19.93	72.74	318.20	1,385.44
ILLI	17.92	69.32	.08	.35	1.88	11.73	44.17
IDIO	.14	.09	.05	.08	.12	.17	.23
Zerofreq	64	43	20	36	57	79	113
Subperiod 8, 2000–2013							
	Mean	Std Dev	P10	P25	P50	P75	P90
Size	2,793.67	1,4647.55	19.23	56.98	235.04	1,024.00	3,997.66
ILLI	11.69	124.90	.01	.05	.27	2.25	16.33
IDIO	.15	.09	.06	.08	.12	.19	.26
Zerofreq	17	20	2	4	9	23	44

Notes. This table reports the descriptive statistics of our sample and the variables used in the tests. *Size* is the market value of equity (in millions), which equals stock price at the end of December times the shares outstanding in December. Following Amihud (2002), we use *ILLI* as a measure of illiquidity, which is the average ratio of the absolute value of daily returns by daily dollar volume (in millions) over December. *IDIO* is a proxy for idiosyncratic volatility, which is the standard deviation of residuals from regressing an individual stock's monthly return against the Fama-French three factors and the momentum factor over the previous 60 months. It is also measured in each December. *Zerofreq* is a comprehensive measure of transaction costs, following Lesmond, Ogden, and Trzcinka (1999) and Ali, Hwang, and Trombley (2003), which is the frequency of zero return days within the past 12 months.

Table 2 shows the estimates of the January effect from Model (2) for eight sub-periods 1927–1939,[14] 1940–1949, 1950–1959, 1960–1969, 1970–1979, 1980–1989, 1990–1999, and 2000–2013.

$$PortRet = \alpha_0 + \alpha_1 Jan + \varepsilon. \quad (2)$$

The dependent variable, *PortRet*, is the daily equally-weighted[15] average return of the portfolio formed for each winner/loser decile. The independent variable, *Jan*, equals one when the daily return occurs during the first fifteen

[14] We exclude the January effect in 1926 in the following analysis due to lack of data over 1925.

[15] Following the advice of an anonymous referee, we also use the daily value-weighted average return of the winner/loser portfolio to perform the analysis. The results are consistent with those using daily equally-weighted average returns.

calendar days of January,[16] and zero otherwise. Thus, the coefficients on the *Jan* dummy measure the difference between the average daily return during the first fifteen days of January and the rest of the year, i.e., the January effect. The last column of Table 2 reports the January effect of the hedge portfolio, i.e., the estimates of α_1 when the dependent variable is the difference in the daily return of the loser portfolio (decile 0) and that of the winner portfolio (decile 9), *L*-*W*. If the difference in returns between losing and winning stocks is higher for the first half of January than the rest of the year, α_1 should be significantly positive for the hedge portfolio (*L*-*W*). In that case, the January effect of the hedge portfolio is significant.

The results in Table 2 consistently show that the January effect has not disappeared. The estimates of the turn-of-the-year coefficient α_1 on the hedge portfolio (*L*-*W*) range from .46 percent to 1.01 percent per day over the sub-periods.[17] The positive returns on the hedge portfolio (*L*-*W*) are primarily generated from the losers' portfolio, whose average daily returns in the first half of January are significantly positive. Alternatively, average daily returns from the winning stocks are not significantly different from zero. This evidence is in support of the tax-loss selling explanation of the January effect, which suggests that the abnormally high January returns mainly come from past losers, but not from past winners. In sum, the January effect is persistent and significantly positive and the magnitude of the effect is in line with Keim (1983) and Reinganum (1983).

The time series pattern of the difference in average daily returns for all securities in our sample between the first fifteen days of January and the rest of the year during 1927–2013 is illustrated in Figure 1. The horizontal axis is Year and the vertical axis, *Jan Ret* (%), is the difference in the average daily return between the first fifteen days of January and the rest of the year (i.e., the estimates of α_1 in Model (2)). Figure 1 shows that the January effect has not disappeared throughout the years. The difference in the average daily return

[16] Reiganum (1983) finds that the January effect is most prominent in the first few trading days of January. We have followed the advice of an anonymous referee using all trading days in January to run the tests and find that the results are not sensitive to the choice of the number of trading days in January.

[17] We also perform the tests in Tables 2, 4–6 spanning the period 1927 to 2013 using characteristic-adjusted returns (Daniel, Grinblatt, Titman, and Wermers, 1997; Wermers, 2003). The results remain robust.

Table 2 The January Effect for Loser/Winner Deciles in Different Sub-periods

	Losers	1	2	3	4	5	6	7	8	Winners	L-W
1926–2013	.94***	.60***	.44***	.37***	.30***	.26***	.22***	.19***	.17***	.19***	.76***
	(18.47)	(12.99)	(10.75)	(9.24)	(7.62)	(6.70)	(5.72)	(4.69)	(4.18)	(3.91)	(20.77)
1926–1939	1.27***	.97***	.72***	.67***	.50***	.50***	.57***	.42**	.37**	.29	.99***
	(5.60)	(4.50)	(3.85)	(3.55)	(2.68)	(2.74)	(3.10)	(2.31)	(2.13)	(1.51)	(6.00)
1940–1949	.80***	.42***	.38***	.34***	.29***	.24**	.18*	.15	.21*	.2	.60***
	(5.38)	(3.30)	(3.22)	(2.98)	(2.61)	(2.36)	(1.72)	(1.41)	(1.76)	(1.42)	(6.08)
1950–1959	.52***	.37***	.29***	.22***	.27***	.15**	.08	.11*	.04	.06	.46***
	(6.40)	(5.27)	(4.51)	(3.63)	(4.65)	(2.57)	(1.40)	(1.65)	(.56)	(.75)	(8.16)
1960–1969	.81***	.54***	.41***	.38***	.30***	.30***	.20***	.18***	.16**	.15	.67***
	(9.52)	(7.41)	(6.18)	(5.85)	(4.80)	(4.86)	(3.00)	(2.62)	(1.98)	(1.39)	(10.12)
1970–1979	1.06***	.89***	.75***	.62***	.53***	.46***	.41***	.31***	.26***	.28***	.77***
	(9.94)	(9.29)	(8.33)	(7.42)	(6.72)	(6.29)	(5.44)	(4.00)	(3.12)	(2.91)	(12.60)
1980–1989	.88***	.63***	.46***	.39***	.31***	.28***	.24***	.21***	.23***	.25**	.63***
	(10.15)	(7.98)	(6.28)	(5.48)	(4.58)	(4.09)	(3.42)	(2.81)	(2.69)	(2.45)	(10.12)

(*To be continued*)

(*Continued*)

	Losers	1	2	3	4	5	6	7	8	Winners	L-W
1990–1999	1.10***	.38***	.22***	.13**	.07	.03	–.01	–.02	–.03	.08	1.01***
	(10.98)	(4.84)	(3.31)	(2.09)	(1.21)	(.57)	(–.24)	(–.37)	(–.35)	(.86)	(12.26)
2000–2013	1.01***	.51***	.27**	.19	.1	.05	.04	.08	.08	.15	.86***
	(6.29)	(3.62)	(2.08)	(1.59)	(0.84)	(.44)	(.35)	(.62)	(.62)	(.97)	(7.46)

Notes. This table reports the January effect for loser/winner deciles in the full sample period of 1927–2013 and eight different sub-periods. The January effect (α_1, %) is estimated from the following model, $PortRet = \alpha_0 + \alpha_1 Jan + \varepsilon$, where *PortRet* is the daily equally-weighted average return of the portfolio formed for each winner/loser decile. The independent variable, *Jan*, equals one when the daily return occurs during the first fifteen calendar days of January, and zero otherwise. Losers/winners are measured as compounded monthly returns from February to November. Then we rank the stocks according to the measure and put them into 10 groups, where 0 is the lowest return group, i.e., losers, and 9 is the highest return group, i.e., winners. The *t*-statistics is reported in parentheses. *, **, and *** denote two-tailed significance at the 10, 5, and 1 percent levels, respectively.

between January and other months ranges from –.52 percent to 1.24 percent, with more positives than negatives.

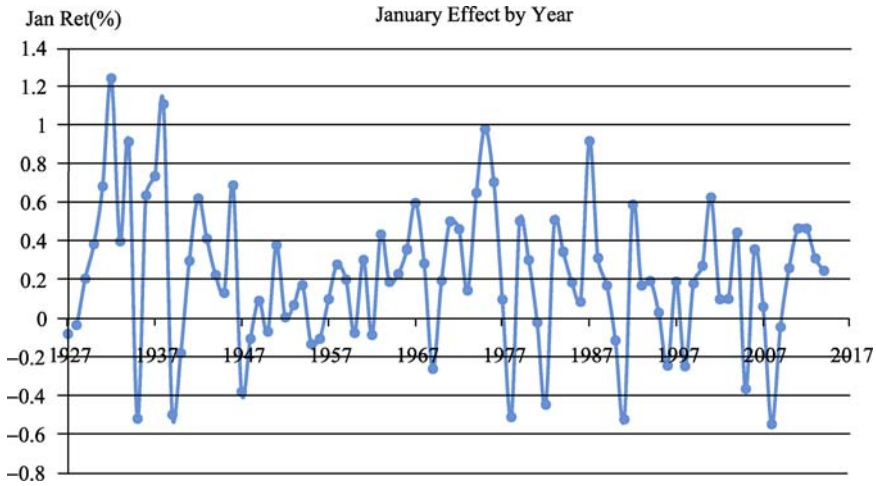

Figure 1 January Effect by Year

Notes. This figure illustrates the difference in average daily returns between the first fifteen calendar days of January and the rest of the year from 1927–2013. The horizontal axis is Year and the vertical axis, Jan Ret (%), is the difference in the average daily return between the first fifteen days of January and the rest of the year.

We plot the estimates of the January effect on the hedge portfolio (*L*-*W*) in Figure 2. The CRSP equally-weighted market index is also plotted in Figure 2 as the benchmark. The loser/winner deciles are measured as the compounded monthly return from February to November in year t[18]. The green dots in Figure 2 indicate the difference in the average daily return during the first half of January in year t+1 between losers and winners (α_1 in Model (2), labeled as "Jan Ret"). The purple squares illustrate the average monthly returns on the CRSP equally-weighted index in year t (labeled as "Mkt Ret"). Figure 2 shows that the January effect is persistently positive and tends to be negatively related with the market performance of the previous year. The January effect in general tends to be smaller for the loser-minus-winner portfolios immediately after good years relative to bad years, which is in support of Hypothesis 1. Taken together, Table 2

[18] The other measures of the winner/loser deciles generate similar time-series patterns as Figure 2.

and Figure 2 clearly show that the January effect has not disappeared, although it has been documented and thoroughly studied since the 1970s.

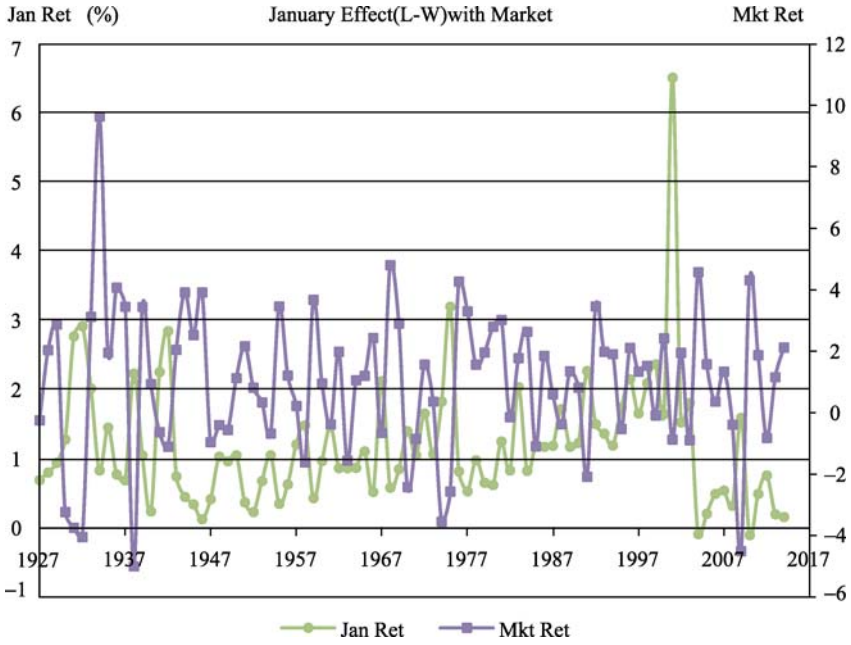

Figure 2 January Effect on the Hedge Portfolio (L-W) with Market Returns

Notes. This figure presents the estimates of the January effect on the hedge portfolio (L-W). The CRSP equally-weighted market index is also plotted as the benchmark. The loser/winner deciles are decided based on the compounded monthly return over February to November in year *t*. The green dots in Figure 2 indicate the difference in the average daily return during the first half of January in year *t*+1 between losers and winners. The purple squares illustrate the average monthly returns on the CRSP equally-weighted index in year *t*.

Table 3 reports the percentage of losing stocks in each year from 1926–2013 in Panel A and the average percentage of losers in each good/bad year decile. Losers are stocks that have negative compounded monthly returns from February to November. Good/bad years are measured as average monthly equally-weighted CRSP index returns and then ranked and grouped into deciles. The results in Panel A show that the percentage of losers ranges from 1.08 percent in 1945 to 99.21 percent in 1937. Panel B shows that the average percentage of losers almost monotonically increases from 18.79 percent in good years (decile 9) to 91.92 percent in bad years (decile 0). Although there are still

18.79 percent losers on average in good years, they are much easier for arbitrageurs to identify and concentrate on to trade than in bad years when there are 91.92 percent losers on average. The evidence in Table 3 is in support of our argument that it is more difficult to identify the losing stocks that have high January abnormal returns.

Table 3 Sample Description on Percentage of Losing Stocks

Panel A			
Year	Percentage of losers	Year	Percentage of losers
1926	61.78	1970	72.94
1927	29.91	1971	66.79
1928	25.00	1972	57.81
1929	88.96	1973	90.38
1930	94.35	1974	90.17
1931	95.34	1975	35.59
1932	74.61	1976	42.96
1933	12.75	1977	41.11
1934	71.35	1978	35.24
1935	15.68	1979	41.71
1936	29.57	1980	35.66
1937	99.21	1981	53.75
1938	25.32	1982	35.69
1939	52.28	1983	32.35
1940	69.36	1984	66.89
1941	62.59	1985	46.02
1942	44.82	1986	47.66
1943	24.47	1987	81.55
1944	11.43	1988	46.64
1945	1.08	1989	48.71
1946	88.77	1990	76.36
1947	72.54	1991	36.07
1948	69.55	1992	50.87
1949	40.18	1993	42.34
1950	31.52	1994	69.61
1951	51.52	1995	31.80
1952	50.48	1996	42.01
1953	70.99	1997	37.32

(*To be continued*)

(*Continued*)

Panel A			
Year	Percentage of losers	Year	Percentage of losers
1954	8.87	1998	66.50
1955	30.35	1999	57.88
1956	50.43	2000	63.14
1957	79.66	2001	58.96
1958	6.23	2002	65.28
1959	49.76	2003	11.94
1960	60.00	2004	45.48
1961	28.29	2005	47.56
1962	84.97	2006	39.98
1963	46.85	2007	61.76
1964	32.24	2008	90.96
1965	35.49	2009	26.79
1966	82.82	2010	37.11
1967	26.26	2011	67.01
1968	17.70	2012	49.62
1969	83.13	2013	26.02

Panel B		
	Year deciles	Average percentage of losers
Good years	9	18.79
	8	40.67
	7	44.27
	6	51.24
	5	51.48
	4	52.61
	3	63.50
	2	70.67
	1	73.56
Bad years	0	91.92

Notes. This table reports the percentage of losers in each year in Panel A and average percentage of losers in each year decile in Panel B. Losers are stocks that have negative compounded monthly returns from February to November. Good/bad years are measured as average monthly equally-weighted CRSP index returns and then ranked and grouped into deciles. Numbers are in percentages.

Table 4 reports the regression result of the following model:

$$PortRet_t = \alpha_0 + \alpha_1 Jan_t + \alpha_2 Bad_{t-1} + \alpha_3 Good_{t-1} + \alpha_4 Jan_t * Bad_{t-1} + \alpha_5 Jan_t * Good_{t-1} + \varepsilon, \quad (3)$$

where $PortRet_t$ and Jan_t are measured in year t and are the same as in Model (2). Bad_{t-1} is equal to one if the good/bad year measure in year t–1 is in the bottom two deciles (decile 0 or 1), and zero otherwise. Similarly, $Good_{t-1}$ is one if the good/bad year measure in year t–1 is in the top two deciles (decile 8 or 9), and zero otherwise. Jan_t*Bad_{t-1} and Jan_t*Good_{t-1} are the interactions of the variables. We report the estimates of all the coefficients in Model (3) in the upper half of Table 4.

In order to interpret the coefficients, we analyze four cases as follows. The first case estimates average daily returns in the first half of January immediately after extreme bad market years, i.e., Jan_t=1 and Bad_{t-1}=1. The Model (3) thus becomes $RortRet_t^1 = \alpha_0 + \alpha_1 + \alpha_2 + \alpha_4$. The second case estimates average daily returns in the first half of January immediately after extreme good market years, i.e., Jan_t=1 and $Good_{t-1}$=1. The Model therefore becomes $RortRet_t^2 = \alpha_0 + \alpha_1 + \alpha_3 + \alpha_5$. The third case estimates average daily returns in days other than the first half of January immediately after extreme bad years, i.e., Jan_t=0 and Bad_{t-1}= 1. The Model (3) in this case is $RortRet_t^3 = \alpha_0 + \alpha_2$. Finally, the fourth case estimates average daily returns in days other than the first half of January immediately after extreme good years, i.e., Jan_t=0 and $Good_{t-1}$=1. Then the model turns into $RortRet_t^4 = \alpha_0 + \alpha_3$. The difference between $RortRet_t^1$ and $RortRet_t^3$, stands for the difference in average daily returns between the first half of January and the rest of the year in extreme bad market years (this difference is labeled as "Jan effect: bad years" in Table 4). The difference between $RortRet_t^2$ and $RortRet_t^4$, presents the difference in average daily returns between the first half of January and the rest of the year in extreme good market years (this difference is labeled as "Jan effect: good years" in Table 4). The amount calculated as ($RortRet_t^2$ – $RortRet_t^4$)–($RortRet_t^1$ – $RortRet_t^3$), illustrates the difference in average daily returns between the first half of January and the rest of the year in extreme good compared to bad market years (this difference is labeled as "Jan effect: good VS bad years" in Table 4). We report the test results of our analysis in the bottom half of Table 4.

If the January effect still exists, one would expect the first two tests for the hedge portfolio (L-W) to be positive and significant. Our results in Table 4 show

Table 4 Average Daily Returns of Loser/Winner Decile Portfolios to January Dummy, Good/Bad Year Dummies and Interaction between January and Year Dummies

	Losers	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**Winners**	**L-W**
Intercept	.18***	.07**	.04	–.01	.02	–.01	–.01	.02	.06**	.05	–.35***
	(4.24)	(2.02)	(1.49)	(–.46)	(.66)	(–.57)	(–.39)	(.79)	(2.30)	(1.59)	(–7.82)
Jan_t	.43***	.14***	.06**	.01	–.04	–.07***	–.12***	–.14***	–.13***	–.13***	.55***
	(9.67)	(4.91)	(2.49)	(.31)	(–1.62)	(–3.93)	(–6.58)	(–6.74)	(–5.80)	(–4.57)	(8.94)
Bad_{t-1}	–.05	.02	.04*	.02	.01	.01	–.02	.02	–.02	–.02	–.04
	(–1.18)	(.86)	(1.87)	(1.02)	(.54)	(.65)	(–1.44)	(1.14)	(–.71)	(–0.85)	(–.73)
$Good_{t-1}$	–.10**	–.05	–.01	–.02	.03	0	–.01	–.02	0	–.02	.02
	(–2.18)	(–1.58)	(–.43)	(–.96)	(1.41)	(–.14)	(–.61)	(–0.76)	(–.09)	(–0.84)	(.38)
Jan_t*Bad_{t-1}	.26***	.07	–.05	–.01	–.02	.02	.05	–.06	–.03	–.07	.33
	(2.81)	(1.28)	(–1.04)	(–0.19)	(–.33)	(.64)	(1.39)	(–1.37)	(–.70)	(–1.22)	(1.20)
Jan_t*Good_{t-1}	.01	.11**	.10**	.06	–.03	–.02	.06*	0	.14***	.22***	–.21**
	(1.01)	(1.96)	(2.02)	(1.42)	(–.60)	(–.63)	(1.69)	(–0.10)	(3.16)	(3.87)	(2.0)

(*To be continued*)

(*Continued*)

	Losers	1	2	3	4	5	6	7	8	Winners	L-W
Tests:											
Jan effect: Bad years	.69***	.22***	.01	0	–.05	–.05	–.07**	–.19***	–.16***	–.20***	.89***
	(6.88)	(4.33)	(.25)	(–.04)	(–1.33)	(–1.55)	(–2.23)	(–5.51)	(–4.19)	(–4.07)	(6.59)
Jan effect: Good years	.44***	.26***	.16***	.06*	–.06	–.09***	–.06*	–.14***	.01	.09**	.35***
	(4.69)	(5.11)	(3.76)	(1.81)	(–1.63)	(–3.00)	(–1.86)	(–4.02)	(1.00)	(2.11)	(8.46)
Jan effect: Good vs Bad years	–.25**	.04	.05	.06	–.01	–.04	.01	.05	.17**	.29**	–.54**
	(–2.02)	(.97)	(1.05)	(1.08)	(–.17)	(–1.0)	(.36)	(1.03)	(2.01)	(2.07)	(–2.14)

Notes. This table reports the regression result of the following model, $PortRet_t = \alpha_0+\alpha_1 Jan_t+\alpha_2 Bad_{t-1}+\alpha_3 Good_{t-1}+\alpha_4 Jan_t*Bad_{t-1}+ \alpha_5 Jan_t*Good_{t-1}+\varepsilon$. The dependent variable, $PortRet_t$, is the daily equally-weighted average return in year t on the portfolio formed for each winner/loser decile. Jan_t equals one when the daily return occurs during the first fifteen days of January in year *t*, and zero otherwise. Good/bad years are measured as average monthly equally-weighted CRSP index returns. Bad_{t-1} is equal to one if the good/bad year measure in year *t*–1 is in the bottom two deciles (decile 0 or 1), and zero otherwise. Similarly, $Good_{t-1}$ is one if the good/bad year measure in year *t*–1 is in the top two deciles (decile 8 or 9), and zero otherwise. Jan_t*Bad_{t-1} and Jan_t*Good_{t-1} are the interactions of the variables. Losers/winners are measured as compounded monthly returns from February to November of year *t*–1. Then we rank the stocks according to the measure and put them into 10 groups, where 0 is the lowest return group, i.e., losers, and 9 is the highest return group, i.e., winners. In the last column of every sub-table, L-W, is the regression result for the hedge portfolio, which is longing the losers portfolio (decile 0) and shorting the winners portfolio (decile 9). Three test results are reported in the bottom half of Table 4. "Jan Effect: Bad years" presents the difference in average daily returns between the first half of January and the rest of the year in extreme bad market years. "Jan Effect: Good years" shows the difference in average daily returns between the first half of January and the rest of the year in extreme good market years. "Jan Effect: Good vs Bad years" illustrates the difference in average daily returns in the first half of January between extreme good and bad market years. The *t*-statistics is reported in parentheses. *, **, and *** denote two-tailed significance at the 10, 5, and 1 percent levels, respectively.

that the January effect has not disappeared.[19] Specifically, the hedge portfolio return for "Jan effect: bad years" (*L*-*W*) is .69 percent, while in good years the difference is only .44 percent.

The third test, shown in the last row of Table 4, examines the January effect after extreme good years compared to that after bad years. Hypothesis 1 suggests that arbitrageurs exploit the January effect, especially in good years when they can identify and concentrate their trades on the few losers; therefore, one would expect the "Jan effect: good VS bad years" to be negative and significant. The results in Table 4 support Hypothesis 1. Specifically, the average daily returns of the hedge portfolio (*L*-*W*) in the first half of January compared to the rest of the year are .54 percent smaller in good years than in bad years.[20]

In the following analysis, we include the measures of arbitrage costs and examine the relationship between arbitrage costs and the January effect in good/bad years. Hypothesis 1 suggests that arbitrageurs buy losers and sell winners in December and unwind their positions in January, especially when they can identify and concentrate on a few losers easily, i.e., in good years. If this is true, arbitrage costs definitely play an important role in the process. Therefore, as specified in Hypothesis 2, one would expect a higher January effect for the losing stocks with high arbitrage costs relative to those with low arbitrage costs.

Table 5 reports the regression results of the following models:

$$\begin{aligned} PortRet_t = {} & \alpha_0 + \alpha_1 MKT_t + \alpha_2 Log(Size_{t-1}) + \alpha_3 Jan_t + \alpha_4 Bad_{t-1} \\ & + \alpha_5 Good_{t-1} + \alpha_6 H_IDIO_{t-1} + \alpha_7 Jan_t * Bad_{t-1} \\ & + \alpha_8 Jan_t * Good_{t-1} + \alpha_9 Jan_t * H_{IDIO_{t-1}} + \varepsilon, \end{aligned} \tag{4A}$$

$$\begin{aligned} PortRet_t = {} & \alpha_0 + \alpha_1 MKT_t + \alpha_2 Log(Size_{t-1}) + \alpha_3 Jan_t + \alpha_4 Bad_{t-1} \\ & + \alpha_5 Good_{t-1} + \alpha_6 H_ILLI_{t-1} + \alpha_7 Jan_t * Bad_{t-1} \end{aligned}$$

[19] We also examine Model (3) using eight sub-periods 1927–1939, 1940–1949, 1950–1959, 1960–1969, 1970–1979, 1980–1989, 1990–1999, 2000–2013. The results for those sub-periods are robust and available upon request.

[20] We examine December returns in a similar test as in Table 4. The results show that losers have significantly worse returns in December in bad years relative to good years. This evidence supports our argument in Hypothesis 1. It is much more difficult for arbitrageurs to identify losers in bad years than in good years. Therefore, arbitrageurs who tend to exploit the January effect cannot focus their trades on the many losers in bad years, which leads to a worse return for losers in December in bad years than in good years. The results are available upon request.

$$+\alpha_8 Jan_t * Good_{t-1} + \alpha_9 Jan_t * H_{ILLI\,t-1} + \varepsilon, \quad (4B)$$

$$PortRet_t = \alpha_0 + \alpha_1 MKT_t + \alpha_2 Log(Size_{t-1}) + \alpha_3 Jan_t + \alpha_4 Bad_{t-1} + \alpha_5 Good_{t-1} + \alpha_6 H_Zerofreq_{t-1} + \alpha_7 Jan_t * Bad_{t-1} + \alpha_8 Jan_t * Good_{t-1} + \alpha_9 Jan_t * H_{Zerofreq\,t-1} + \varepsilon, \quad (4C)$$

where $PortRet_t$, Jan_t, Bad_{t-1} and $Good_{t-1}$ are the same as in Model (3). MKT_t is the daily returns of the value-weighted CRSP index in year *t*. $Log(Size_{t-1})$ is the natural logarithm of the market value of equity of the portfolio as of December of year *t*–1. H_IDIO_{t-1}, H_ILLI_{t-1}, and $H_Zerofreq_{t-1}$ represent three dummy variables of the portfolios' arbitrage costs as of December of year *t*–1, measuring two aspects of the arbitrage costs, i.e., idiosyncratic volatility (*IDIO*) and transaction costs including illiquidity (*ILLI*) and the frequency of zero return days within the past 12 months (*Zerofreq*). These measures are defined in the methodology section. We examine the effect of each aspect of the arbitrage costs on the January effect respectively in the above Models (4A)–(4C).We also include interactions of Jan_t with Bad_{t-1}, $Good_{t-1}$, and the dummy variables of the loser/winner portfolios' arbitrage costs. Tables 5A–5C report the regression results on Models (4A)–(4C).

In order to interpret the coefficients, we examine the following two cases. The first case estimates average daily returns in the first fifteen days of January for high arbitrage cost portfolios in extreme good years, i.e., Jan_t=1, $Good_{t-1}$= 1, and H_IDIO_{t-1}=1 in Model (4A) (H_ILLI_{t-1}=1 in Model (4B), or $H_Zerofreq_{t-1}$=1 in Model (4C)). The specific model then becomes $PortRet_t^1 = \alpha_0 + \alpha_1 MKT_t + \alpha_2 Log(Size_{t-1}) + \alpha_3 + \alpha_5 + \alpha_6 + \alpha_8 + \alpha_9$. The second case estimates average daily returns in the first half of January for low arbitrage cost portfolios in extreme good years, i.e., Jan_t=1, $Good_{t-1}$= 1, and H_IDIO_{t-1}= 0 in Model (4A) (H_ILLI_{t-1}=0 in Model (4B), or $H_Zerofreq_{t-1}$=0 in Model (4C)). Thus, the model is $PortRet_t^2 = \alpha_0 + \alpha_1 MKT_t + \alpha_2 Log(Size_{t-1}) + \alpha_3 + \alpha_5 + \alpha_8$. In order to test Hypothesis 2, we take the difference between $PortRet_t^1$ and $PortRet_t^2$, which equals $\alpha_6 + \alpha_9$, labeled as "Jan for stocks with high vs low *IDIO*/*ILLI*/*Zerofreq*"). It illustrates the difference in average daily returns in the first half of January between high and low arbitrage cost

stocks.[21] Hypothesis 2 suggests this difference to be positive and significant. In other words, if arbitrageurs exploit the January effect, i.e., buying losers in December and rewinding their positions the following January, the losing stocks with high arbitrage costs will have higher January returns relative to low arbitrage cost stocks.

Table 5A shows that the differences in average daily returns between high and low idiosyncratic volatility (*IDIO*) stocks in the loser portfolio as well as in the hedge portfolio (*L*-*W*) in the first fifteen days of January are positive and significant. Furthermore, evidence on the relationship between transaction costs and the January effect also appears to support Hypothesis 2. Specifically, by using illiquidity (*ILLI*) as the measure of transaction costs in Table 5B, the difference in average daily returns on the hedge portfolio (*L*-*W*) in the first fifteen days of January between high and low illiquidity stocks is not significant. However, by using the frequency of zero return days in the past 12 months (*Zerofreq*) as the measure of transaction costs in Table 5C, hedge portfolios (*L*-*W*) with high transaction costs have significantly higher January returns than those with low transaction costs.

In sum, the results in Tables 5A–5C tend to support Hypothesis 2. The January effect is stronger for stocks with high arbitrage costs relative to low arbitrage cost stocks.

Lastly, we run a cross-sectional Fama and MacBeth style (1973) regression of daily returns during the first fifteen days of January on firm characteristics and arbitrage costs, with a dummy variable indicating loser stocks. According to Pontiff (2006), arbitrage costs impede arbitrageurs from taking proper positions on mispriced securities in order to eliminate mispricing. Therefore, mispricing

[21] The test specified here works for both good years and bad years. For bad years, the first case becomes Jan_t=1, Bad_{t-1}= 1, and H_IDIO_{t-1}= 1 in Model (4A) (H_ILLI_{t-1}=1 in Model (4B), or $H_Zerofreq_{t-1}$=1 in Model (4C)). The specific model then becomes $PortRet_t^1 = \alpha_0 + \alpha_1 MKT_t + \alpha_2 Log(Size_{t-1}) + \alpha_3 + \alpha_4 + \alpha_6 + \alpha_7 + \alpha_9$. The second case is Jan_t = 1, Bad_{t-1} = 1, and H_IDIO$_{t-1}$= 0 in Model (4A) (H_ILLI_{t-1}=0 in Model (4B), or $H_Zerofreq_{t-1}$=0 in Model (4C)). Thus, the model is $PortRet_t^2 = \alpha_0 + \alpha_1 MKT_t + \alpha_2 Log(Size_{t-1}) + \alpha_3 + \alpha_4 + \alpha_7$. The difference between $PortRet_t^1$ and $PortRet_t^2$ is also α_6+ α_9, which is the same as the tests for the good years. Therefore, we label the difference as "Jan for stocks with high vs low *IDIO/ILLI/Zerofreq*" without specifying good or bad years.

Table 5 Average Daily returns of Loser/Winner Decile Portfolios to Market factor, Size, January Dummy, Year Dummies, Arbitrage Costs, and Interactions

Table 5A

	Losers	1	2	3	4	5	6	7	8	Winners	L-W
Intercept	.09	.08*	.19***	.10***	.17***	.11***	.09***	.09***	.07**	.05	–.12***
	(.88)	(1.70)	(5.01)	(3.12)	(4.78)	(3.73)	(3.07)	(2.62)	(2.02)	(.76)	(–2.64)
MKT_t	1.29***	1.16***	1.02***	.98***	.93***	.90***	.87***	.90***	.90***	1.02***	.28***
	(78.96)	(107.3)	(109.59)	(124.67)	(106.71)	(124.51)	(122.66)	(112.61)	(105.02)	(96.85)	(13.48)
$Log(Size_{t-1})$	.02	.03***	.03***	.05***	.03***	.04***	.05***	.04***	.04***	.04***	–.18***
	(1.17)	(2.85)	(3.58)	(7.48)	(4.14)	(6.56)	(7.41)	(6.55)	(6.20)	(5.03)	(–7.43)
Jan_t	–.13	.03	–.03	–.01	–.05*	–.08***	–.13***	–.17***	–.24***	–.61***	.56***
	(–.68)	(.39)	(–.77)	(–.45)	(–1.88)	(–3.51)	(–5.99)	(–6.56)	(–7.43)	(–5.43)	(9.16)
Bad_{t-1}	–.04	.03	.05*	.03	.01	.03	0	.04	–.01	–.02	–.06
	(–.93)	(.96)	(1.67)	(1.35)	(.58)	(1.40)	(.14)	(1.64)	(–.39)	(–.54)	(–.95)
$Good_{t-1}$	–.14***	–.09***	–.05**	–.05**	.01	–.04*	–.04**	–.05**	–.02	–.05	–.05
	(–3.05)	(–2.84)	(–1.98)	(–2.01)	(.21)	(–1.74)	(–2.16)	(–2.02)	(–.71)	(–1.56)	(–.82)
Jan_t*Bad_{t-1}	.16*	.12*	0	–.01	.01	.04	.03	–.05	0	–.03	.19
	(1.66)	(1.92)	(–.03)	(–.31)	(.22)	(.92)	(.63)	(–1.11)	(–.02)	(–.48)	(1.49)
Jan_t*$Good_{t-1}$	.21**	.16**	.15***	.08*	0	.01	.09**	.03	–.08	–.13**	.38***
	(2.25)	(2.50)	(2.88)	(1.68)	(–.09)	(.22)	(2.19)	(.67)	(–1.56)	(–2.18)	(3.16)

(*To be continued*)

(*Continued*)

	Losers	1	2	3	4	5	6	7	8	Winners	L-W
H_IDIO_{t-1}	.32***	.21***	.02	–.01	–.13***	–.08**	–.03	.05**	.08***	.12**	.20***
	(3.43)	(6.12)	(1.05)	(–.48)	(–4.48)	(–2.25)	(–1.02)	(2.47)	(4.16)	(2.31)	(2.81)
Jan_t*H_IDIO_{t-1}	.58***	.13*	.13***	.06*	.14**	.04	.12**	.10***	.21***	.49***	.09**
	(3.01)	(1.86)	(2.85)	(1.66)	(2.42)	(.50)	(2.28)	(2.59)	(5.33)	(4.43)	(2.26)
Test:											
Jan for stocks with high VS low *IDIO*	.91*** (5.28)	.34*** (5.53)	.15*** (3.84)	.05 (1.63)	.01 (.16)	–.05 (–.7)	.09** (2.02)	.15*** (4.32)	.29*** (8.37)	.62*** (6.34)	.29*** (5.81)

Table 5B

	Losers	1	2	3	4	5	6	7	8	Winners	L-W
Intercept	.43***	.19***	.17***	.09***	.12***	.08***	.06**	.17***	.18***	.24***	–.10**
	(7.14)	(4.68)	(4.81)	(2.88)	(3.55)	(2.69)	(2.28)	(5.61)	(5.65)	(5.81)	(–2.25)
MKT_t	1.29***	1.16***	1.03***	.99***	.94***	.89***	.87***	.90***	.90***	1.01***	.28***
	(80.48)	(105.92)	(110.42)	(124.39)	(107.20)	(124.83)	(123.52)	(115.98)	(107.54)	(97.85)	(13.81)
$Log(Size_{t-1})$	.01	.03***	.03***	.05***	.04***	.04***	.05***	.04***	.03***	.03***	–.17***
	(.47)	(3.20)	(3.85)	(7.73)	(5.37)	(6.59)	(7.71)	(5.78)	(4.05)	(3.15)	(–7.23)
Jan_t	.57***	.13***	.07*	.05	–.04	–.05**	–.10***	–.15***	–.13***	–.13***	.52***
	(7.02)	(2.68)	(1.91)	(1.53)	(–1.34)	(–2.21)	(–3.88)	(–5.67)	(–4.52)	(–3.78)	(7.96)

(*To be continued*)

(*Continued*)

	Losers	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**Winners**	**L-W**
Bad_{t-1}	–.05	.05	.05*	.03	.02	.01	–.02	.05**	–.02	–.03	–.06
	(–1.16)	(1.43)	(1.78)	(1.35)	(.78)	(.64)	(–1.10)	(2.06)	(–.70)	(–1.02)	(–.99)
$Good_{t-1}$	–.15***	–.10***	–.04	–.04*	.01	–.03	–.04*	–.06***	–.04	–.07**	–.05
	(–3.31)	(–2.96)	(–1.57)	(–1.86)	(.20)	(–1.28)	(–1.81)	(–2.58)	(–1.52)	(–2.16)	(–.82)
Jan_t*Bad_{t-1}	.09	.1	–.04	.01	0	.04	.07	–.05	–.01	–.05	.17
	(.97)	(1.51)	(–.64)	(.18)	(.04)	(1.03)	(1.60)	(–.99)	(–.29)	(–.81)	(1.41)
Jan_t*$Good_{t-1}$	.20**	.14**	.13**	.10**	0	.01	.09**	.03	–.11**	–.19***	.40***
	(2.12)	(2.20)	(2.31)	(2.14)	(.06)	(.13)	(2.10)	(.70)	(–2.21)	(–3.03)	(3.29)
H_ILLI_{t-1}	0	.10***	.04**	–.01	–.01	.06***	.03**	–.14***	0	–.05*	–.11
	(–.03)	(3.79)	(2.13)	(–.37)	(–.27)	(3.35)	(2.02)	(–7.48)	(–.07)	(–1.90)	(–1.60)
Jan_t*H_ILLI_{t-1}	–.17*	.03	–.01	–.07*	.02	–.04	–.03	.03	0	.01	.22
	(–1.94)	(.54)	(–.30)	(–1.85)	(.51)	(–1.03)	(–.82)	(0.85)	(.05)	(.22)	(1.53)
Test:											
Jan for stocks with	–.17**	.12***	.03	–.08**	.01	.02	.01	–.10***	0	–.04	.11
high VS low *ILLI*	(–2.18)	(2.68)	(.82)	(–2.31)	(.42)	(.67)	(.18)	(–3.1)	(.01)	(–.82)	(0.86)

Table 5C

	Losers	1	2	3	4	5	6	7	8	Winners	L-W
Intercept	.56***	.17***	.15***	.06*	.10***	.07**	.08***	.12***	.19***	.25***	–.12***
	(5.87)	(3.58)	(3.95)	(1.85)	(2.90)	(2.48)	(2.65)	(3.95)	(5.98)	(5.93)	(–2.71)
MKT_t	1.28***	1.16***	1.03***	.99***	.94***	.89***	.87***	.90***	.90***	1.01***	.28***
	(80.96)	(105.59)	(110.40)	(125.15)	(107.62)	(124.65)	(123.41)	(114.99)	(107.52)	(97.38)	(13.79)
$Log(Size_{t-1})$	–.01	.03***	.03***	.05***	.04***	.05***	.05***	.04***	.03***	.03***	–.17***
	(–.35)	(2.85)	(3.99)	(6.58)	(5.33)	(7.42)	(7.85)	(5.72)	(3.69)	(3.11)	(–7.24)
Jan_t	1.46***	.32***	.07	–.02	–.07**	–.07***	–.11***	–.12***	–.13***	–.15***	.55***
	(8.38)	(4.67)	(1.36)	(–.60)	(–1.97)	(–3.16)	(–5.11)	(–5.10)	(–4.78)	(–4.19)	(8.98)
Bad_{t-1}	–.07	.02	.05*	.03	.02	.02	–.02	.02	–.02	–.03	–.06
	(–1.42)	(.56)	(1.94)	(1.37)	(.88)	(.97)	(–1.06)	(1.01)	(–.68)	(–1.01)	(–.94)
$Good_{t-1}$	–.17***	–.08**	–.04	–.03	0	–.03	–.04**	–.05**	–.03	–.06**	–.04
	(–3.55)	(–2.53)	(–1.37)	(–1.22)	(.12)	(–1.30)	(–1.99)	(–2.03)	(–1.33)	(–2.02)	(–.65)
Jan_t*Bad_{t-1}	.06	.11*	–.03	.01	.01	.04	.07	–.04	–.01	–.05	.16
	(.61)	(1.72)	(–.59)	(.22)	(.18)	(.86)	(1.58)	(–.80)	(–.29)	(–.83)	(1.35)
Jan_t*Good_{t-1}	.1	.13**	.13**	.11**	0	.01	.09**	.04	–.10**	–.19***	.38***
	(1.08)	(2.01)	(2.30)	(2.29)	(–.07)	(.18)	(2.20)	(.77)	(–2.04)	(–3.14)	(3.14)
$H_Zerofreq_{t-1}$	–.1	.11***	.05**	.09***	.04*	.02	0	.01	–.03	–.06**	–.04***
	(–1.32)	(3.25)	(2.11)	(4.97)	(1.95)	(.92)	(.19)	(.34)	(–1.15)	(–2.43)	(–3.02)
$Jan_t*H_Zerofreq_{t-1}$	1.04***	–.21***	–.01	.05	.06	.02	0	–.06	–.01	–.06	1.10***
	(6.09)	(–2.89)	(–.12)	(1.22)	(1.46)	(.62)	(.03)	(–1.38)	(–.26)	(–1.33)	(5.92)

(To be continued)

(*Continued*)

	Losers	1	2	3	4	5	6	7	8	Winners	L-W
Test:											
Jan for stocks with	.94***	–.1	.04	.14***	.10***	.04	.01	–.06	–.04	–.12	1.06***
high VS low *Zerofreq* (5.37)	(–1.54)	(0.98)	(4.10)	(2.73)	(1.21)	(.14)	(–1.38)	(–.92)	(–.19)	(6.10)	

Notes. Table 5A reports the regression result of the following model, $PortRet_t = \alpha_0 + \alpha_1 MKT_t + \alpha_2 Log(Size_{t-1}) + \alpha_3 Jan_t + \alpha_4 Bad_{t-1} + \alpha_5 Good_{t-1} + \alpha_6 H_IDIO_{t-1} + \alpha_7 Jan_t * Bad_{t-1} + \alpha_8 Jan_t * Good_{t-1} + \alpha_9 Jan_t * J_IDIO_{t-1} + \varepsilon$. Table 5B presents the regression result of the following model, $PortRet_t = \alpha_0 + \alpha_1 MKT_t + \alpha_2 Log(Size_{t-1}) + \alpha_3 Jan_t + \alpha_4 Bad_{t-1} + \alpha_5 Good_{t-1} + \alpha_6 H_ILLI_{t-1} + \alpha_7 Jan_t * Bad_{t-1} + \alpha_8 Jan_t * Good_{t-1} + \alpha_9 Jan_t * J_ILLI_{t-1} + \varepsilon$. Table 5C shows the regression result of the following model, $PortRet_t = \alpha_0 + \alpha_1 MKT_t + \alpha_2 Log(Size_{t-1}) + \alpha_3 Jan_t + \alpha_4 Bad_{t-1} + \alpha_5 Good_{t-1} + \alpha_6 H_Zerofreq_{t-1} + \alpha_7 Jan_t * Bad_{t-1} + \alpha_8 Jan_t * Good_{t-1} + \alpha_9 Jan_t * H_Zerofreq_{t-1} + \varepsilon$. The dependent variable in every model above, $PortRet_t$, is the daily equally-weighted average return in year t on the portfolio formed for each winner/loser decile. MKT_t is the daily returns of the value-weighted CRSP index in year *t*. $Log(Size_{t-1})$ is the natural logarithm of the market value of equity of the portfolio as of December of year *t*–1. Jan_t equals one when the daily return occurs during the first fifteen days of January of year t, and zero otherwise. Good/bad years are measured as average monthly equally-weighted CRSP index returns. Bad_{t-1} is equal to one if the good/bad year measure in year *t*–1 is in the bottom two deciles (decile 0 or 1), and zero otherwise. Similarly, $Good_{t-1}$ is one if the good/bad year measure in year *t*–1 is in the top two deciles (decile 8 or 9), and zero otherwise. H_IDIO_{t-1}, H_ILLI_{t-1}, and $H_Zerofreq_{t-1}$ represent three dummy variables of arbitrage cost as of December of year *t*–1. H_IDIO_{t-1} equals 1 if a portfolio's *IDIO* is higher than the median across all portfolios and 0 otherwise. *IDIO* is a proxy of idiosyncratic volatility, which is the standard deviation of residuals from regressing an individual stock's monthly return against the Fama-French three factors and the momentum factor over the previous 60 months. It is measured in each December. A portfolio's *IDIO* is the average *IDIO* over all the stocks in the portfolio. H_ILLI_{t-1} equals 1 if a portfolio's *ILLI* is higher than the median and 0 otherwise. Following Amihud (2002), we use *ILLI* as a measure of illiquidity, which is the average ratio of absolute value of daily returns by daily dollar volume over December. $H_Zerofreq_{t-1}$ equals 1 if a portfolio's *Zerofreq* is higher than the median and 0 otherwise. *Zerofreq* is a comprehensive measure of transaction costs, following Lesmond, Ogden, and Trzcinka (1999) and Ali, Hwang, and Trombley (2003), which is the frequency of zero return days within the past 12 months. Interactions of the variables are also included. Losers/winners are measured as compounded monthly returns from February to November of year *t*–1. Then we rank the stocks according to the measure and put them into 10 groups, where decile 0 is the lowest return group, i.e., losers, and decile 9 is the highest return group, i.e., winners. In the last column of every sub-table, *L-W*, is the regression result for the hedge portfolio, which is longing the losers portfolio (decile 0) and shorting the winners portfolio (decile 9). The *t*-statistics is reported in parentheses. *, **, and *** denote two-tailed significance at the 10, 5, and 1 percent levels, respectively.

should be higher in stocks with high arbitrage costs. The test results are reported in Table 6.

Model 1 of Table 6 includes only idiosyncratic volatility (*IDIO*) as a proxy of arbitrage cost. Although the coefficient on *IDIO* is not significant on average, the coefficient on the interaction between the loser stocks dummy and *IDIO* is positive and significant. This suggests that in the same year within loser stocks, the higher the idiosyncratic volatility, the higher the January returns. In other words, idiosyncratic volatility seems to deter arbitrage activity so that arbitrageurs are not able to eliminate the January effect mispricing. Similarly, Models 2 and 3 include two measures of transaction cost, illiquidity (*ILLI*) and the frequency of zero return days (*Zerofreq*), respectively. An interaction term between the loser stocks dummy and *ILLI* or *Zerofreq* is also included. The results shown in Table 6 indicate that the higher the transaction costs, the higher the January returns within loser stocks in the same year.

Table 6 Cross-sectional Regressions of January Returns with Arbitrage Cost Variables

	Model 1	**Model 2**	**Model 3**	**Model 4**
Intercept	1.22***	1.27***	.88***	.60***
	(13.45)	(10.50)	(7.08)	(5.92)
Size	–.16***	–.17***	–.12***	–.10***
	(–12.90)	(–11.95)	(–9.95)	(–8.47)
BEME	–.17***	–.18***	–.21***	–.20***
	(–4.73)	(–4.71)	(–6.16)	(–5.16)
Loser	.04	.31***	–.19***	–.97*
	(.28)	(4.87)	(–2.64)	(–1.84)
IDIO	–.25			.66
	(–.36)			(.97)
*Loser*IDIO*	1.89**			1.32**
	(2.16)			(1.98)
ILLI		0		0
		(1.00)		(.28)
*Loser*ILLI*		1.03***		.83
		(3.29)		(1.08)
Zerofreq			.01***	.01***

(*To be continued*)

(*Continued*)

	Model 1	Model 2	Model 3	Model 4
			(3.88)	(3.45)
*Loser*Zerofreq*			.01***	.01***
			(7.02)	(6.25)

Notes. This table reports Fama-MacBeth cross-sectional regressions of daily returns for January 1–15 on various firm characteristics over the period 1927 to 2013. The dependent variable is daily stock returns for the first fifteen days of January (January 1–15) between 1927 and 2013. *Size* is the natural logarithm of the market value of equity of the stock as of each December. Variable *BEME* is defined as in Kayhan and Titman (2007) where the market value is of December of each year and the book value of equity is defined as the following equation. *Book Equity = Total Assets–*[*Total Liabilities + Preferred Stock*] *+ Deferred Taxes + Conv. Debt. Loser* is a dummy variable, which equals 1 if the stock is in groups 0 and 1 of the *Loser/winner* decile and 0 otherwise. *Loser/winner* is measured as compounded monthly returns from February to November. Then we rank the stocks according to the measure and put them into 10 groups, where decile 0 is the lowest return group, i.e., losers, and decile 9 is the highest return group, i.e., winners. *IDIO* is a proxy of idiosyncratic volatility, which is the standard deviation of residuals from regressing an individual stock's monthly return against the Fama-French three factors and the momentum factor over the previous 60 months. It is measured each December. *ILLI* is a measure of illiquidity, following Amihud (2002), which is the average ratio of the absolute value of daily returns by daily dollar volume (in thousands) over December. *Zerofreq* is a comprehensive measure of transaction costs, following Lesmond, Ogden, and Trzcinka (1999) and Ali, Hwang, and Trombley (2003), which is the frequency of zero return days within the past 12 months. Interactions of some variables are also included. The coefficients are time series averages of cross-sectional regression coefficients, obtained from daily regressions. *T*-statistics are reported in parenthesis, which are adjusted for autocorrelation by Newy-West corrections. *, **, and *** denote two-tailed significance at the 10, 5, and 1 percent levels, respectively.

Model 4 of Table 6 includes both holding cost measures (*IDIO*) and transaction cost measures (*ILLI* and *Zerofreq*), as well as the interaction terms between the loser stocks dummy and arbitrage cost measures. The results imply that for losing stocks in the same year, the higher the arbitrage costs, the higher the January returns. When we include both *ILLI* and *Zerofreq* in the model, the coefficient on *Loser*ILLI* is no longer significant. However, the coefficient on *Loser*Zerofreq* does remain positive and significant. This result suggests that transaction costs are mainly captured by the *Zerofreq* measure, while *ILLI* seems to be a relatively small component in the transaction costs for arbitrageurs.

In sum, the results in Table 6 support Hypothesis 2, which suggests that losing stocks with high arbitrage costs tend to have higher January returns relative to

losing stocks with low arbitrage costs.

5 Conclusion

In this study, we examine the relation between market performance and the January effect to answer one puzzling question. Why has the January effect existed for more than three decades in spite of the fact that it has been well documented by researchers and well recognized by practitioners? We find that arbitrageurs appear to exploit the January effect if they can easily identify the losing stocks that have the most tax-loss-sellers, i.e., in good market years, and if the arbitrage costs associated with trading on those losing stocks are not high enough to deter the arbitrage.

In particular, we find that the extreme losers have relatively lower January returns in good years than in bad years, because the arbitrageurs' trading activities are more concentrated on the few losers in good years. After taking arbitrage costs into consideration, we find that the January effect is stronger for losing stocks with high arbitrage costs than for those with low arbitrage costs.

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