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How Much Does Nominal Share Price Matter?

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Abstract

The paper examines the relation between nominal share price and price momentum, explicitly controlling for nominal share price levels. The results show that very high/low nominal share price stocks lack price momentum and utilize more systemic risk which remains even controlling for stock splits. While splitting a stock allows firm managers to keep the nominal share price constant, thereby increasing firm value and attracting more investors, it also increases the likelihood of uninformed trading by those with limited budgets and risk share capacity. As a result, splitting a stock causes stock information to diffuse more slowly, leading to higher price momentum.

Keywords: Price Risk; Momentum Crash; Stock Split/Dividend

JEL Codes: G11, G12, G14

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1 Introduction

Finance theory has suggested that, in a frictionless market, a firm's nominal share price should have no impact on its corporate value. Since a firm's nominal share price, strictly speaking, is merely the ratio of a firm's market capitalization over its number of shares outstanding which should have no relation to its corporate value. However, previous empirical studies (Dyl and Elliott (2006) and Weld, Michaely, Thaler, and Benartzi (2009)) have shown that corporate financial managers apply strategies to maintain investor perceptions of an optimal trading range for a firm's stock to ensure their average nominal share price rests within a narrow and roughly constant range over time. This phenomenon, though common, is not easily explained by standard economic theories such as marketability, pay-to-play, or signaling.[1]

There has been a great deal of research on the nominal share price strategy. However, much of this research examines the strategy from the firm manager's point of view. By contrast, this study contributes to the nominal share price literature by examining the nominal share price puzzle from the investor's perspective. Specifically, we examine the impact of a firm's share price on investor trading under the various circumstances of price levels. In this paper, we study the use of stock splitting as a means of maintaining a consistent nominal share price and the impact of this practice on a firm's price momentum.

Figure 1 illustrates our idea through examining the case of General Electric (GE). From 1926 to 2018, we see that GE split its stock seven times (red fonts) and provided stock dividends twice (blue fonts) resulting in a cumulative split of 4705.61:1. GE has contained its nominal share price around average \$57.23 since the Great Depression. Furthermore, if we mark the time of GE being selected into the "BUY" and "SELL" portfolios of momentum strategy[2] in green and red dots, respectively. GE was chosen into the 'BUY" portfolio of the momentum strategy when its nominal price was at a typically high status occurring before

[1]See Weld, Michaely, Thaler, and Benartzi (2009) for a discussion of these respective hypotheses in the context of stock splitting.

[2]See definitions of "BUY" and "SELL" portfolios of momentum strategy in the Section 2.4

a stock split in 1954.

[Place Figure 1 about here]

To assess the impact of the nominal share price on price momentum, we conduct an empirical study of a sample of stocks obtained from the Center for Research in Security Prices (CRSP). For our sample, we select all primary domestic stocks listed on the New York Stock Exchange (NYSE) from 1926-2013, the American Stock Exchange (AMEX) from 1962-2013, and the Nasdaq (NASDAQ) from 1972-2013. In our study, we examine not only how a stock split can affect the nominal share price and price momentum, but also how a stock dividend affects these. This approach differs from that of most previous empirical studies that focus on only the effect of the stock split. However, as we can see in Figure 1, GE's stock splits and stock dividends both impact its nominal share price levels and momentum. Consequently, we examine both stock split and dividend effects to make our empirical evidence more fruitful and address the gap in the literature.

Examining the effects of stock splits and dividends, we first find that the number of firms choosing each strategy varies considerably over both time and stock exchanges, as seen in Table 1. From 1926 to 2013, we find that around 32% (42%) of firms choose stock splits (dividends) on the NYSE and AMEX while 35% (23%) of NASDAQ firms choose stock splits (dividends). Regarding the effect of each choice on subsequent stock prices, we find a 3% (7%) reduction in stock price after a stock split (dividend) on the NYSE and AMEX; by contrast, we find a 125% increase (7% decrease) in stock price after a stock split (dividend) on the NASDAQ. These findings are consistent with the results of Minnick and Raman (2014) who argue that a subsequent price reduction on the NYSE and AMEX may reflect the increase over time in household wealth and institutional trading vehicles, such as mutual funds, which allow small investors to diversify without relying on low-priced stocks.

Our mixed results for the impact on price levels in the tech-heavy NASDAQ may reflect the unique stock split motivation of technology firms. That is, these firms may choose stock splits as a means of reforming outstanding shares and increasing the nominal share price to sustain firm growth.

Next, examine the effect of stock splits and dividends on price momentum. Specifically, we examine whether stock splits allow firms to lower their low nominal share price to attract more investors but also with an impact on price momentum. Following the previous momentum literature, we utilize only the returns on common shares for the firms in our sample. We then assign stocks that meet the data criteria stated in Section 3 into ten equally-weighted portfolios on the ending day of each formation month. To reduce any micro-structure effect associated with low-priced stocks, we include stocks with a price below we didn't exclude those stocks with a price below \$1, i.e., penny stocks, during in our portfolio formation. Doing so allows us to investigate the momentum effect for a general framework explicitly controlling for price levels. It also mitigates concerns related to sample selection bias. Including these low-priced stocks during the formation period, we construct momentum portfolios considering different nominal price levels according to a stock's nominal share price in $[0,1),[1,50),[50,100),[100,150),[150,\infty)$, and denote these portfolios by levels I to V, respectively.

Table 4 presents the main results for our study of the effect of nominal share prices on price momentum. From Table 4, we see that momentum portfolios formed by stocks with a very low/high (I and V, respectively) nominal share price significantly underperform compared to those with a nominal share price level in the normal range of $[1,150)$, which show promising momentum effects. Charting the momentum strategy from the year 1927 forward, we see from Figure 8 that momentum portfolios formed by stocks with a very low/high nominal share price range lose momentum over time.

This result reinforces the conclusion of Barberis, Huang, and Santos (2001)), who posit that a representative agent derives direct utility from both consumption and anticipation. As such, an agent who is wealth constrained considers nominal share price levels in assessing investment risk. For this agent, holding higher nominal share price stocks tends to be riskier than holding lower ones. Similarly, holding higher-priced stocks entails greater wealth volatility. These patterns mean investors are conscious, even speculative, in their investment decisions.

By contrast, we argue that investors in penny stocks cannot implement a long-short strategy as they cannot identify when a stock is spiking. Recent studies support this argument by showing that unsophisticated investors are attracted to lower-priced stocks as they believe the lower price limits potential loss while allowing for tremendous gains should the stock increase in price. These investors care about the short-term profits of their investment. This speculative mindset makes a low price stock portfolio more volatile, which in turn reduces the momentum effect.

The remainder of this paper is organized as follows. Section 2 describes our data and methodology and provides summary statistics of our sample. Section 3 presents the main findings and discusses the empirical results for our hypothesis. Sections 4 concludes.

2 Data and methodology

To determine our sample, we obtain CRSP monthly price data for all stocks traded on the NYSE and AMEX as well as the NASDAQ from 1926 to 2013. Only common shares with a 10 or 11 CRSP share-code are selected for our analysis. For our measure, we use company-level market capitalization (in $million), which reflects the firm's adjusted price times its adjusted total shares outstanding. The 48-industry classification scheme adapted from the definitions of Fama and French (1997) is applied to the CRSP data.

2.1 Stock splits and stock dividends

As mentioned, most previous studies on the effect of nominal share price focus on only the strategy of a stock split. However, as we argue in Figure 1, GE's share price momentum reflects the effects of both stock splits and dividends. Consequently, for every stock in our sample, we calculate their split ratio to quantify the price changes induced by a stock split/dividend. Split ratio is inferred by the change in the cumulative factor to adjust prices, i.e.,

$$\text{Split Ratio (SR)} \equiv \frac{\text{CFACPR}_t - \text{CFACPR}_{t-1}}{\text{CFACPR}_{t-1}} \tag{1}$$

where CFACPR is denoted as the cumulative factor to adjust prices.

Table 1 summarizes the sample statistics for the firms in our sample, including stock splits (with a CRSP distribution code of 5523), post-split prices, stock dividends (with a CRSP distribution code of 5533), and post-dividend prices. The top panel presents the results for stocks listed on the NYSE and AMEX while the bottom panel presents the results for stocks listed on the NASDAQ. Columns one and two reports the total number of stocks traded in the different sample year periods. Columns three to six represent the total number of stock splits, the average pre-split price, the average post-split price for splitters, and the average split ratio, respectively. Columns seven to ten represent the same data for stock dividends.

[**Place Table 1 about here**]

Examining the statistics in Table 1, we first find the fraction of firms that choose issue a stock split/stock dividend shows a relatively recent decrease across our sample period. Specifically, we find that stock splits/stock dividends reach their peak in the early 20th century and decline from there. To illustrate, from 1926 to 2013, we find that around 32% (42%) of firms choose stock splits (dividends)on the NYSE and AMEX. We further find that their stock price decreases by -3% (7%) after the stock split (dividend). Our results are consistent with the results of Minnick and Raman (2014) who show that stock splits have declined over time. They explain this finding as to the result of an increase in both household wealth and institutional trading vehicles, such as mutual funds, which allow small investors to diversify without relying on low-priced stocks.

By contrast, the statistics in Table 1 show that 35% (23%) of our NASDAQ firms choose stock splits (dividends). These results may reflect the predominance of technology growth firms on the NASDAQ. These firms often need to retain a greater proportion of their earnings to reinvest in the company. An interesting feature of stock splits on the NASDAQ is that these stocks show a 125% increase in price after the split, a finding which counters the argument in the stock split literature that splits cause a decline in the subsequent price. In this case, we conjecture that NASDAQ firms choose stock splits to reform their outstanding shares, increasing the nominal share price.

2.2 Stock splits and stock dividends by industry

We then examine whether our stock split and stock dividend statistics vary across industries. Industry differences are important as previous research as far back as King (1966) and, later, Fama and French (1997) and Moskowitz and Grinblatt (1999) has demonstrated an industry effect on stock price movements. To classify each firm in our sample, we follow Fama-French's 48-industry classification scheme. Table 2 shows the percentages of stock split and stock dividend by industries on the NYSE and AMEX and NASDAQ in our sample period.

[**Place Table 2 about here**]

From Table 2, we see that the top five industries with the greatest percentage of stock splits on the NYSE and AMEX are Retail (8.21%), Machinery (5.11%), Utilities (4.90%), Petroleum and Natural Gas (4.83%), and Banking (4.58%). The top five industries with the greatest percentage of stock dividends on the NYSE and AMEX are Retail (7.83%), Construction Materials (5.50%), Petroleum and Natural Gas (5.06%), Machinery (4.97%), and Banking (4.80%) for firms on the NYSE and AMEX. For the firms on the NASDAQ, the top five industries with the greatest percentage of stock splits are to have stock split are Banking (15.17%), Business Services (12.46%), Trading (7.72%), Electronic Equipment (5.75%), and Retail (5.29%), while the top five industries with the greatest percentage of stock dividends are Banking (35.30%), Trading (15.95%), Insurance (4.66%), Wholesale (4.28%), and Retail (4.19%).

Figures 2 & 3 further examine the time-varying distributions of stock splits and stock dividends through our sample years on NYSE and AMEX and NASDAQ, respectively. These figures show that firms in the Banking industry have more stock dividends than those in other industries, reinforcing the above findings from Table 2.

[Place Figures 2 & 3 about here]

2.3 Nominal share price, firm size, and returns

Numerous studies (such as Banz (1981); Reinganum (1983); Keim (1983); Lamoureux and Sanger (1989); Fama and French (1993); Heston, Rouwenhorst, and Wessels (1999)) have found that nominal share price and firm size are highly correlated, and that firm size and stock returns are negatively related. Consequently, we are interested in how firm size impacts our findings related to the nominal share price. Specifically, we are interested in whether our share price effect remains after controlling for firm size.

Previous research suggests it is possible that firm size may cause our observed share price to be either negatively related or unrelated to future returns. This conjecture is in contrast to the positive price-return relationship predicted in the lottery stock literature. Figure 4 depicts our findings regarding price, based on firm size deciles determined by NYSE market capitalization breakpoints. The results in Figure 4 demonstrate that, after the 1990s, our largest quantile starts to deviate from the norm by aiming for overly high prices. These high stock price levels create barriers for uninformed investors to enter the market because of budget constraints and limited risk-sharing capacity.

As mentioned, recent studies show that unsophisticated investors are attracted to lower-priced stocks as they believe the lower price limits potential loss while allowing for tremendous gains should the stock increase in price. For instance, Kumar and Lee (2006) find support for investor sentiment in the formation of returns and report co-movement in stocks with high retail concentration; Kumar (2009) documents negative returns for lottery stocks which are preferred by individual investors and are characterized by low prices; and Birru and Wang (2016) find direct evidence that investors overestimate the skewness of low-priced stocks, especially around share splits, resulting in future negative returns for these stocks.

In Figure 4, we expand this stream of literature by exploring the intersection of share price and stock returns across different market capitalizations. Since price and firm size are highly correlated, and size and returns are negatively related, it follows that price should be either negatively related or, at best, unrelated to future returns, which is contrary to the low price – low return (positive price-return relationship) documented in the lottery stock literature.

[**Place Figure 4 about here**]

The left panel of Figure 4 shows that the large firms in our sample have consistently higher share prices than the small firms. Examining the price trend over time by firm size quartile, we find that, after the 90s, the largest quantile starts to deviate from the norm by aiming for overly high prices. One explanation for this trend could be attributed to the aspiration of large-capitalization companies to belong to the "$1,000 club."

Examining this phenomenon more closely, we consider the case of one tech giant, Google, with a nominal stock price well outside the usual narrow band. On October 18, 2013, Google's stock surged to $1,011.41 a share, a feat recognized as a milestone in its remarkable ascent from its $85 public offering price on August 19, 2004, when a total of 19,605,052 shares were offered. Indeed, investors view companies like Google as members of the "$1,000 stock club," a type of trophy or achievement that signals success, domination, and growth. Although a share price of $1,000 has little bearing on the future performance of either the firm or the exchange, a soaring stock price captures market attention, even that of index funds.

2.4 Momentum portfolio

The momentum effect is a widely-documented phenomenon both in the US stock market and other financial assets and stock markets. For example, Okunev and White (2003) find a momentum effect in currencies; Erb and Harvey (2006) find a momentum effect in commodities; and Moskowitz, Ooi and Pedersen (2012) find a momentum effect in exchange-traded futures contracts. Further research documents a momentum effect in both developed (Rouwenhorst (1998)) and emerging (Rouwenhorst (1999)) markets. This anomaly contradicts the efficient market hypothesis, the weak-form of which says that past stock price movements should provide no information about future stock price changes. In other words, investors should have no logical reason to prefer recently rising stocks to recently falling ones. Researchers continue to conjecture over the profit from the momentum effect, which cannot be explained by controlling for other risk factors such as firm size or book-to-market ratio or by higher-risk or trading costs for high-performance stocks.

To construct our momentum portfolio, we use all stock returns from the CRSP database for our sample firms listed on the NYSE (starting in 1962), AMEX (1963), and NASDAQ (1973). We utilize only the returns on common shares with a 10 or 11 CRSP share code. Close-end funds, real estate investment trusts (REITs), unit trusts, American depository receipts (ADRs), and foreign stocks are excluded from the analysis.

Following the previous literature, we assign stocks that meet the data criteria mentioned above into ten equally-weighted portfolios, P1 to P10, based on their cumulative returns on the ending day of each formation month. We first rank the stocks based on their past J-month returns, excluding the most recent month. The 10% of firms with the highest-ranking period returns are grouped into portfolio P10, which we designate as the "BUY"-decile portfolio, and those with the lowest 10% ranking period returns are grouped into portfolio P1, which is the "SELL"-decile portfolio. The return on a zero-investment "BUY-SELL" portfolio is the difference between the returns on the BUY- and SELL-decile portfolios in each period. Each portfolio is held for one month following the formation month. We calculate the holding monthly returns of "BUY-SELL" portfolios using the equally-weighted returns. Firms do not change deciles within a month, except in the case of delisting. To provide greater confidence in our approach, in further analyses, we categorize firms using an overlapping portfolio that holds a series of portfolios selected in the current month and the previous month and finds similar results.

To construct our momentum portfolios, we assume $J = 12$ and denote by (12-1) to indicate momentum. In Section 3.2, we provide results using different settings of J=3, 6, 9, and 12 as a robustness check. The selection of 12-month returns is currently the most broadly used definition of momentum and these returns are available through the PR1YR factor of Carhart (1997). Moreover, as Benartzi and Thaler (1995) note, since tax filings and mutual fund reports occur once a year, most individual investors use a 12-month period for sincerely evaluating their investment performance. Finally, institutional investors typically conduct annual reviews of their money managers' performance. These reasons suggest a 12-month return is an appropriate selection for our momentum analysis.

Figure 5 plots the time series of (12-1) momentum portfolio returns. From Figure 5, we see that the highly-skewed returns of the momentum strategies suggest that the market under-reacts to public information in "normal" environments, resulting in consistent price momentum. However, in extreme market environments, stocks with previous sharp losses embody a very high premium, and investors who implement a momentum strategy would experience strings of negative returns, especially after a market collapse. For example, a momentum investor would have lost 41.89% in the US stock market at the turning-point occurrence in April 2009. These momentum crashes can even cluster across a span of several months. Daniel and Moskowitz (2016) characterize the strong momentum reversals that are caused by the significant negative skewness of the (12-1) momentum portfolio.

[Place Figure 5 about here]

3 Momentum under various nominal share price levels

This section presents our main empirical findings related to nominal share price levels and price momentum patterns.

3.1 Very low/high nominal share price stocks

Our momentum portfolios are constructed according to nominal share prices across different levels from $[0, 1), [1, 50), [50, 100), [100, 150), [150, \infty)$, labeled from I to V, respectively. At each price level, as in Section 2.4, we follow the same method to construct the momentum strategy and hold for one month (i.e., $K = 1$) following the formation month for each portfolio. Here we present the results for K=1 case, in Section 3.2, we use a different set of K=3, 6, 9, and 12 as a robustness check. Figure 6 presents the portfolio returns of implementing a momentum strategy in the nominal share price levels I and V (i.e., $[0, 1)$ and $[150, \infty)$), with low-priced (high-priced) stocks in the top (bottom) panel.

[Place Figure 6 about here]

From Figure 6, we see that momentum portfolios constructed with extreme nominal share price stocks yield an upside-down return pattern in economic recession periods such as the oil crisis in 1973 and the Dot-com Bubble in 2000. In comparison, Figure 7 provides the returns for portfolios constructed with nominal share price stocks from levels II to IV (i.e., $[1, 50), [50, 100)$, and $[100, 150)$) where the top (middle, bottom) panel is for II (III, IV) stocks, respectively.

[Place Figure 7 about here]

To compare all categories of nominal price levels, we list the average portfolio returns for "BUY"-decile, "SELL"-decile, and "B-S"-decile portfolios in Table 3.

[Place Table 3 about here]

Figure 8 provides the cumulative returns from momentum portfolios for stocks with nominal share price levels I to V, from 1927 to 2013, a total of 1,044 months. The cumulative return on an implementable strategy is based on investing at time zero and fully reinvesting at each subsequent time point. During the investment period, no cash is put in or taken out. From time t to T, the cumulative return is computed as:

$$\sum_{s=t+1}^{T} (1 + r_s), \tag{2}$$

where r_s is the s-period portfolio return. On the right side of the plot, we show the final values for each of the five portfolios: -26.12 (I), 13.34 (II), 10.09 (III), 12.00 (IV), and -1.30 (V). Overall, these results show that using a momentum strategy for stocks with nominal share price levels I, II, and III yields significantly high returns.

[Place Table 8 about here]

3.2 Robustness check for (J, K) momentum portfolios

As a robustness check, we extend the above analysis by constructing investment portfolios where J varies from 3, 6, 9, to 12, and K varies from 1, 3, 6, 9, to 12. All the stocks in these analyses satisfy the criteria prescribed in Section 2.

[Place Table 4 about here]

The results in Table 4 show penny stocks momentum portfolio returns are all significantly negative while the portfolio returns for stocks with a nominal share price in $[150, \infty)$ are slightly positive, albeit insignificantly so. Again, we find that momentum portfolios comprised of stocks with nominal share prices between \$1 to \$150 yield significantly positive returns. In particular, a momentum portfolio consisting of stocks with nominal share prices between \$100 to \$150 yields a portfolio return for $(J = 12, K = 1)$ of 2.377%, on average.

4 Conclusions

This study examines how nominal share price levels achieved through stock splits or stock dividends impact momentum investors. We investigate the possibility that the representation of a very low/high nominal share price may lead to a low degree of cognitive availability, as stated in Tversky and Kahneman (1973), which may reduce the informational-processing demands, as well as Chuang and Ho (2014), find the momentum effect can be substantial if low-price-risk stocks form the portfolio. Specifically, we investigate whether a very low/high nominal share price impacts subsequent investor choices and price momentum.

Understanding the role of the price is important in research on investor behavior and finance, which has recently focused on many aspects of the psychology of pricing: price awareness, the formation and use of reference prices, price acceptability, price partitioning, and willingness to pay. Similarly, recent marketing research has studied how price presentation impacts deal perception and behavior. Therefore, an understanding of price presentation effects is insightful for retailers as well as for brand managers.

Price presentation in the market relates to investor perceptions, as investors construct their own internal price for a given firm. This internal price reference then impacts that investor's subsequent investment decisions. Overall, our findings inspire additional research given the central role played by price in the field of finance. In addition, they shed light on the usefulness for researchers in studying the price risks of stocks.

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Tables

Table 1: Summary of nominal share prices, stock splits, and stock dividends

Stocks on the NYSE and AMEX

		Stock split (DISTCD = 5523)				Stock dividend (DISTCD = 5533)			
Years	Stocks	$\bar{p}^s_t$	$\bar{p}^s_{t-1}$	Splits	SR	$\bar{p}^s_t$	$\bar{p}^s_{t-1}$	Splits	SR
1926-1933	834	$52.93	$115.23	96	36%	$68.15	$82.11	428	-8%
1934-1943	902	$20.63	$41.16	71	88%	$48.00	$56.16	93	-12%
1944-1953	1089	$30.93	$63.73	233	-8%	$32.95	$40.18	655	-13%
1954-1963	2201	$38.17	$72.06	575	-34%	$34.03	$35.78	1,943	-5%
1964-1973	3379	$32.44	$56.88	1,418	-25%	$24.17	$26.41	2,669	-7%
1974-1983	3204	$23.60	$38.80	1,862	-31%	$13.86	$14.47	1,704	-6%
1984-1993	3498	$24.98	$42.17	1,833	6%	$17.01	$17.40	687	-5%
1994-2003	3869	$30.59	$52.63	1,690	-3%	$21.93	$23.87	531	-8%
2004-2013	2796	$32.28	$58.72	623	113%	$43.52	$45.74	142	-5%
	Mean	**$28.95**	**$50.69**	**95.47**	**-3%**	**$27.00**	**$29.62**	**100.59**	**-7%**

Stocks on the NASDAQ

		Stock split (DISTCD = 5523)				Stock dividend (DISTCD = 5533)			
Years	Stocks	$\bar{p}^s_t$	$\bar{p}^s_{t-1}$	Splits	SR	$\bar{p}^s_t$	$\bar{p}^s_{t-1}$	Splits	SR
1973-1983	5710	$16.73	$25.90	2,083	-7%	$13.24	$14.55	2,342	-9%
1984-1993	8721	$16.58	$25.60	3,324	163%	$15.20	$15.78	1,576	-6%
1994-2003	8724	$23.17	$38.50	3,601	120%	$17.89	$18.89	1,938	-6%
2004-2013	4070	$17.77	$27.82	1,030	282%	$17.09	$18.35	458	-4%
	Mean	**$19.10**	**$30.53**	**114.07**	**125%**	**$15.21**	**$16.24**	**71.75**	**-7%**

This table represents the summary statistics of stock splits (CRSP code=5523) and stock dividends (CRSP code=5533) for stocks listed on the NYSE and AMEX (top panel), from 1923 to 2013, and on the NASDAQ (bottom panel), from 1973 to 2013. SR is defined as equation (1)

Table 2: Stock split and stock dividend by industries

	NYSE and AMEX				NASDAQ			
	Split		Dividend		Split		Dividend	
Agric	21	0.25%	28	0.32%	20	0.20%	5	0.09%
Food	214	2.55%	253	2.86%	136	1.35%	73	1.26%
Soda	56	0.67%	63	0.71%	10	0.10%	8	0.14%
Beer	42	0.50%	39	0.44%	9	0.09%	4	0.07%
Smoke	40	0.48%	41	0.46%	2	0.02%	1	0.02%
Toys	80	0.95%	141	1.59%	65	0.65%	36	0.62%
Fun	77	0.92%	165	1.86%	145	1.44%	42	0.73%
Books	111	1.32%	85	0.96%	71	0.71%	25	0.43%
Hshld	268	3.19%	285	3.22%	179	1.78%	80	1.39%
Clths	165	1.96%	249	2.81%	72	0.72%	33	0.57%
Hlth	128	1.52%	49	0.55%	241	2.40%	53	0.92%
MedEq	132	1.57%	39	0.44%	247	2.46%	41	0.71%
Drugs	199	2.37%	106	1.20%	330	3.29%	44	0.76%
Chems	252	3.00%	380	4.29%	111	1.11%	61	1.06%
Rubbr	89	1.06%	165	1.86%	76	0.76%	36	0.62%
Txtls	111	1.32%	172	1.94%	31	0.31%	7	0.12%
BldMt	313	3.73%	487	5.50%	170	1.69%	153	2.65%
Cnstr	121	1.44%	75	0.85%	55	0.55%	36	0.62%
Steel	210	2.50%	317	3.58%	72	0.72%	29	0.50%
FabPr	45	0.54%	112	1.27%	26	0.26%	14	0.24%
Mach	429	5.11%	440	4.97%	265	2.64%	81	1.40%
ElcEq	132	1.57%	207	2.34%	220	2.19%	71	1.23%
Autos	232	2.76%	309	3.49%	83	0.83%	77	1.33%
Aero	101	1.20%	138	1.56%	19	0.19%	7	0.12%
Ships	33	0.39%	20	0.23%	2	0.02%	2	0.03%
Guns	29	0.35%	36	0.41%	11	0.11%	2	0.03%
Gold	35	0.42%	61	0.69%	29	0.29%	11	0.19%
Mines	72	0.86%	62	0.70%	12	0.12%	12	0.21%
Coal	16	0.19%	20	0.23%	8	0.08%	6	0.10%
Oil	406	4.83%	448	5.06%	257	2.56%	129	2.23%
Util	412	4.90%	348	3.93%	96	0.96%	137	2.37%
Telcm	185	2.20%	74	0.84%	272	2.71%	43	0.74%
PerSv	61	0.73%	61	0.69%	136	1.35%	56	0.97%
BusSv	369	4.39%	176	1.99%	1251	12.46%	157	2.72%
Comps	154	1.83%	103	1.16%	306	3.05%	39	0.68%
Chips	292	3.48%	303	3.42%	577	5.75%	163	2.82%
LabEq	149	1.77%	118	1.33%	168	1.67%	54	0.94%
Paper	166	1.98%	178	2.01%	94	0.94%	52	0.90%
Boxes	74	0.88%	101	1.14%	36	0.36%	15	0.26%
Trans	203	2.42%	301	3.40%	186	1.85%	36	0.62%
Whlsl	279	3.32%	329	3.72%	412	4.10%	247	4.28%
Rtail	690	8.21%	693	7.83%	531	5.29%	242	4.19%
Meals	152	1.81%	176	1.99%	279	2.78%	73	1.26%
Banks	385	4.58%	425	4.80%	1523	15.17%	2038	35.30%
Insur	251	2.99%	121	1.37%	322	3.21%	269	4.66%
RlEst	56	0.67%	97	1.10%	61	0.61%	41	0.71%
Fin	334	3.98%	256	2.89%	775	7.72%	921	15.95%
Other	30	0.36%	0	0.00%	39	0.39%	12	0.21%
Total	8401	100.00%	8852	100.00%	10038	100.00%	5774	100.00%

This table represents the percentages of stock splits and stock dividends on the NYSE and AMEX (left panel) and NASDAQ (right panel). The 48-industry classification scheme was extracted from Kenneth French's web site.

Table 3: K=1, 1965-2013

		K=1					
	Portfolios	SELL		BUY		B-S	
$p \in [1, \infty)$	1044/1044	0.005%		1.756%	***	1.273%	***
		(0.003)		(0.003)		(0.002)	
$p \in [0, 1)$	633/640	8.281%	***	4.101%	***	-4.139%	***
		(0.012)		(0.010)		(0.011)	
$p \in [1, 50)$	1044/1044	0.474%		1.752%	***	1.278%	***
		(0.003)		(0.003)		(0.002)	
$p \in [50, 100)$	1044/1044	0.454%	**	1.420%	***	0.966%	***
		(0.002)		(0.002)		(0.002)	
$p \in [100, 150)$	512/570	-0.491%		1.585%	***	2.377%	***
		(0.003)		(0.005)		(0.006)	
$p \in [150, \infty)$	279/294	1.268%	***	1.001%		-0.470%	
		(0.005)		(0.009)		(0.010)	

This table reports the monthly portfolio returns of the momentum strategy from January 1965 to December 2013. The portfolios are constructed by assigning the stocks into one of the ten portfolios based on their cumulative returns over the previous 12 months (J=12) with the most recent month excluded, as described in Section 2.4. During the formation periods, the momentum portfolios are also constructed according to the nominal share price levels in $[0, 1), [1, 50), [50, 100), [100, 150), [150, \infty)$, labeled from I to V, respectively. The 10% of firms with the highest-ranking period returns are assigned to the "BUY"-decile portfolio and the 10% of firms with the lowest-ranking period returns are assigned to the "SELL"-decile portfolio. The one-month holding period return on a zero-investment "B-S" portfolio is the difference between the returns on the "BUY"-decile portfolio and those on the "SELL"-decile portfolio in each period. Standard errors are given in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%.

Table 4: $(J = 12, K = 1, 3, 6, 9, \text{and } 12)$ Portfolios, 1965-2013

$p \in [0, 1)$		K=1		3		6		9		12	
J=	3	-4.329%	***	-3.370%	***	-2.359%	***	-1.622%	***	-1.418%	***
		(0.008)		(0.006)		(0.005)		(0.005)		(0.004)	
	6	-4.840%	***	-3.913%	***	-2.838%	***	-2.230%	***	-1.906%	***
		(0.010)		(0.008)		(0.007)		(0.007)		(0.007)	
	9	-4.602%	***	-3.623%	***	-2.304%	**	-2.051%	**	-1.942%	***
		(0.011)		(0.010)		(0.009)		(0.008)		(0.007)	
	12	-4.139%	***	-2.949%	***	-2.052%	**	-2.132%	***	-2.085%	***
		(0.011)		(0.010)		(0.009)		(0.008)		(0.007)	
$p \in [1, 50)$		K=1		3		6		9		12	
J=	3	0.619%	***	0.487%	***	0.498%	***	0.459%	***	0.408%	***
		(0.002)		(0.001)		(0.001)		(0.001)		(0.001)	
	6	0.705%	***	0.749%	***	0.760%	***	0.713%	***	0.487%	***
		(0.002)		(0.002)		(0.002)		(0.001)		(0.001)	
	9	0.886%	***	0.934%	***	0.907%	***	0.675%	***	0.402%	***
		(0.002)		(0.002)		(0.002)		(0.002)		(0.001)	
	12	1.278%	***	1.048%	***	0.773%	***	0.507%	***	0.221%	
		(0.002)		(0.002)		(0.002)		(0.002)		(0.001)	
$p \in [50, 100)$		K=1		3		6		9		12	
J=	3	0.499%	**	0.490%	***	0.508%	***	0.501%	***	0.475%	***
		(0.002)		(0.002)		(0.001)		(0.001)		(0.001)	
	6	0.691%	***	0.795%	***	0.834%	***	0.775%	***	0.639%	***
		(0.002)		(0.002)		(0.002)		(0.002)		(0.001)	
	9	0.848%	***	1.026%	***	0.914%	***	0.786%	***	0.612%	***
		(0.002)		(0.002)		(0.002)		(0.002)		(0.002)	
	12	0.966%	***	1.016%	***	0.886%	***	0.656%	***	0.487%	***
		(0.002)		(0.002)		(0.002)		(0.002)		(0.002)	
$p \in [100, 150)$		K=1		3		6		9		12	
J=	3	1.434%	***	0.543%	*	0.424%		0.272%		0.199%	
		(0.004)		(0.003)		(0.003)		(0.002)		(0.002)	
	6	1.250%	**	0.938%	**	1.008%	***	0.663%	**	0.590%	**
		(0.005)		(0.004)		(0.004)		(0.003)		(0.003)	
	9	1.964%	***	1.324%	***	1.178%	***	0.896%	**	0.645%	**
		(0.005)		(0.004)		(0.004)		(0.003)		(0.003)	
	12	2.377%	***	1.568%	***	1.144%	***	0.765%	**	0.800%	**
		(0.006)		(0.005)		(0.004)		(0.004)		(0.003)	
$p \in [150, \infty)$		K=1		3		6		9		12	
J=	3	0.281%		0.487%		0.574%		0.490%		0.241%	
		(0.009)		(0.006)		(0.004)		(0.004)		(0.004)	
	6	0.763%		0.889%		0.388%		0.424%		0.099%	
		(0.010)		(0.008)		(0.006)		(0.005)		(0.005)	
	9	0.932%		1.262%		0.762%		0.658%		0.546%	
		(0.010)		(0.009)		(0.007)		(0.006)		(0.006)	
	12	-0.470%		0.657%		0.395%		0.424%		0.259%	
		(0.010)		(0.009)		(0.007)		(0.007)		(0.006)	

This table reports the monthly portfolio returns of the momentum strategy by considering different combinations of (J, K), where J varies from 3, 6, 9, to 12 and the holding months of K vary from 1, 3, 6, 9, and 12 from January 1965 to December 2013. All the stocks examined to satisfy the criteria prescribed in Table 3. The one-month holding period return reported is the difference between the returns on the "BUY"-decile portfolio and those on the "SELL"-decile portfolio, i.e., on a zero-investment "B-S" portfolio in each period. Standard errors are given in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%.

Figures

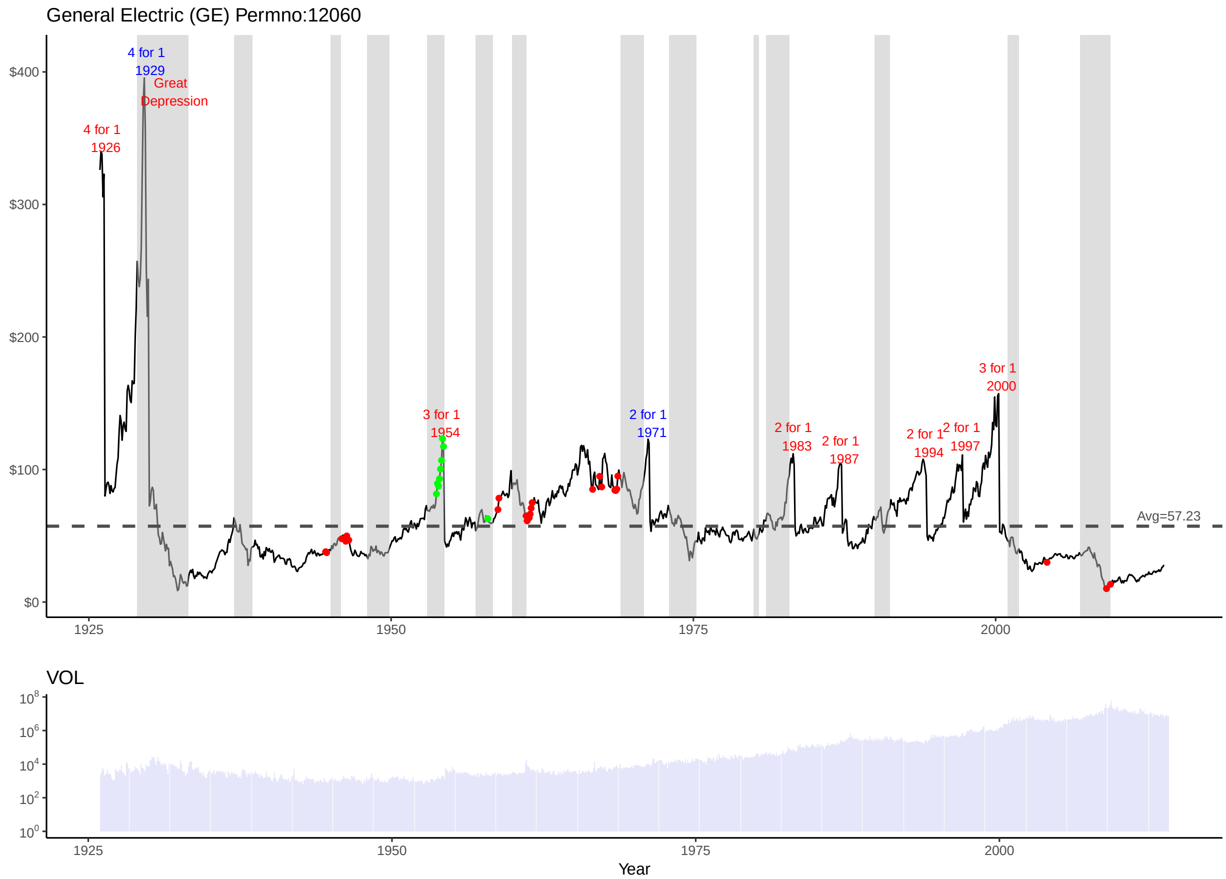

Figure 1: The nominal share price, stock splits (red font), and stock dividends (blue font) of General Electric, from 1926 to 2018 (green dots represent GE being selected in the "BUY"-decile portfolio of the momentum strategy while red dots are in the "SELL"-decile portfolio)

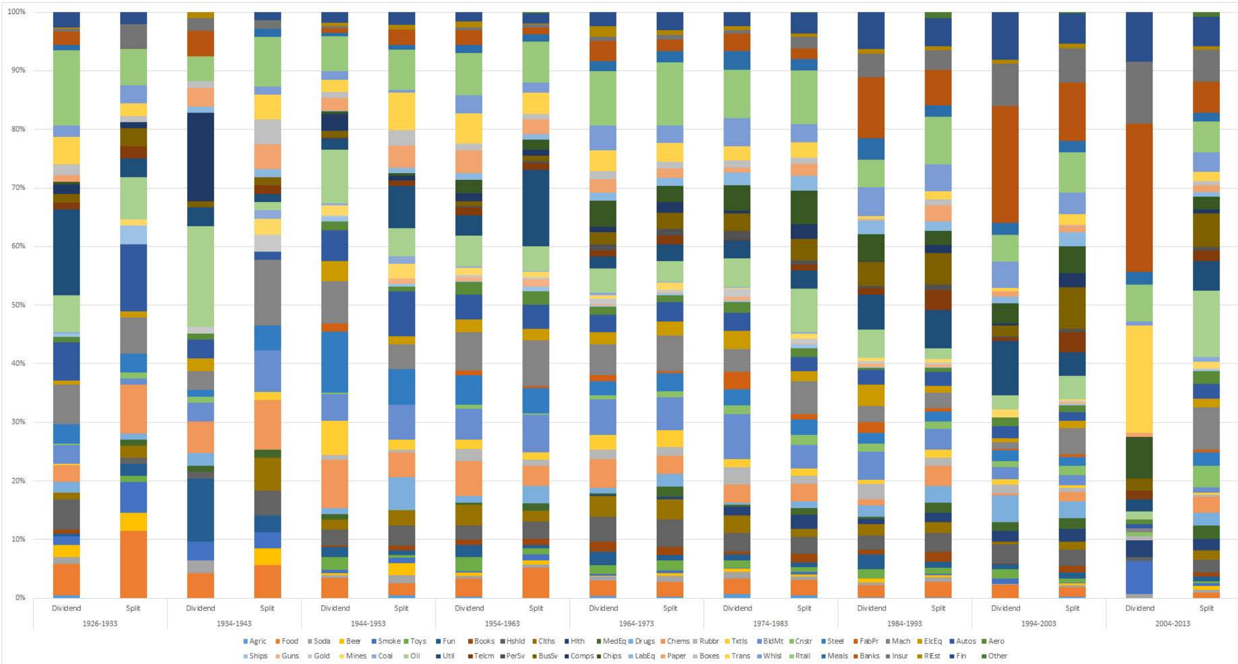

Figure 2: Stock splits (DISTCD=5523) and stock dividends (DISTCD=5533) on the NYSE and AMEX by industries, from 1926 to 2013

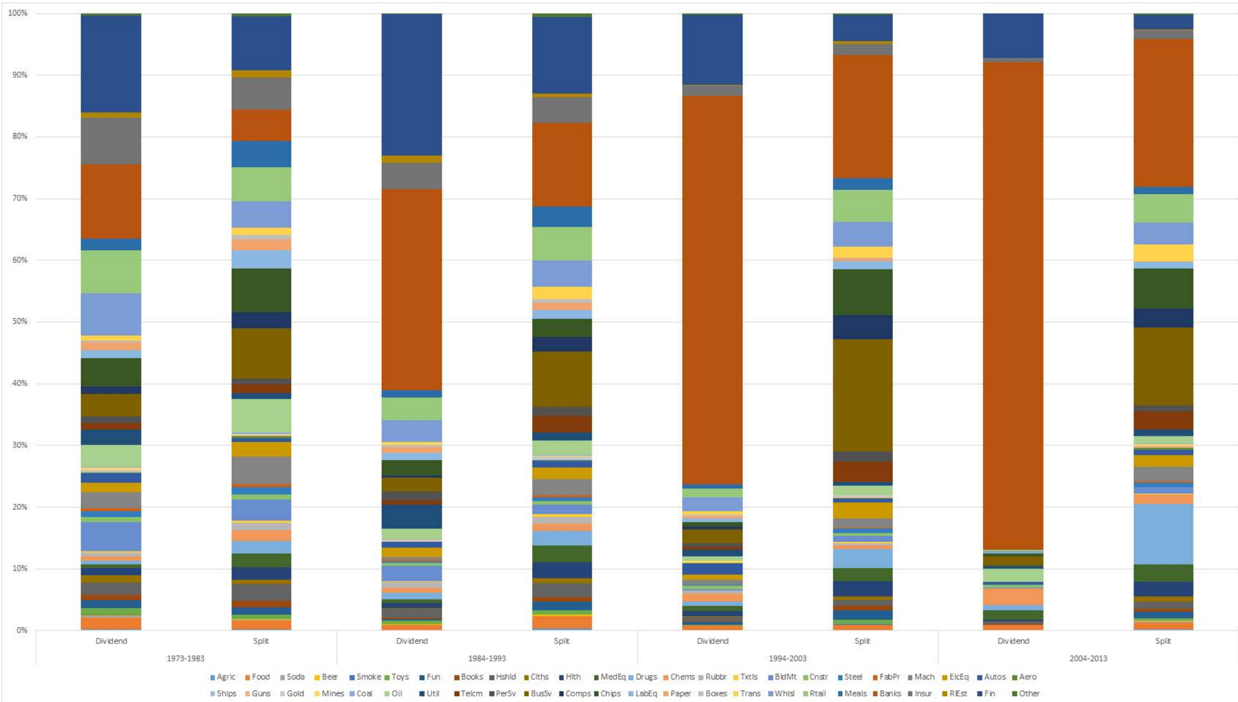

Figure 3: Stock splits (DISTCD=5523) and stock dividends (DISTCD=5533) on the NASDAQ by industries, from 1973 to 2013

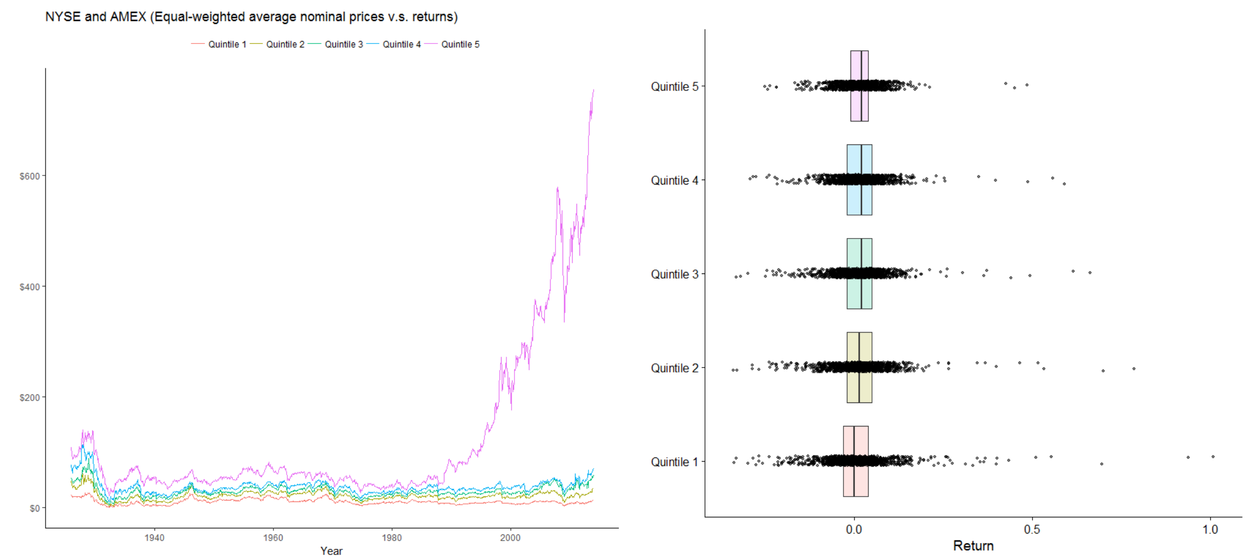

Figure 4: Average prices and returns by frim size quantiles on the NYSE and AMEX and the NASDAQ, from 1926 to 2013

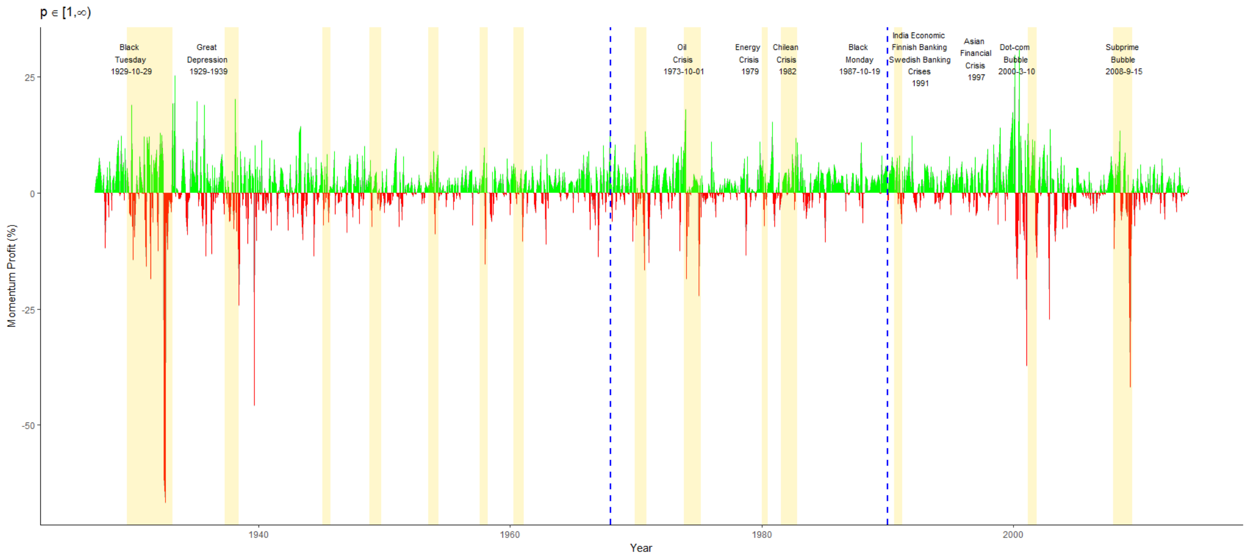

Figure 5: Momentum portfolio returns for stocks with nominal share prices in $[1, \infty)$, from 1927 to 2013 (dashed blue lines are the sample period of Jegadeesh and Titman (1993))

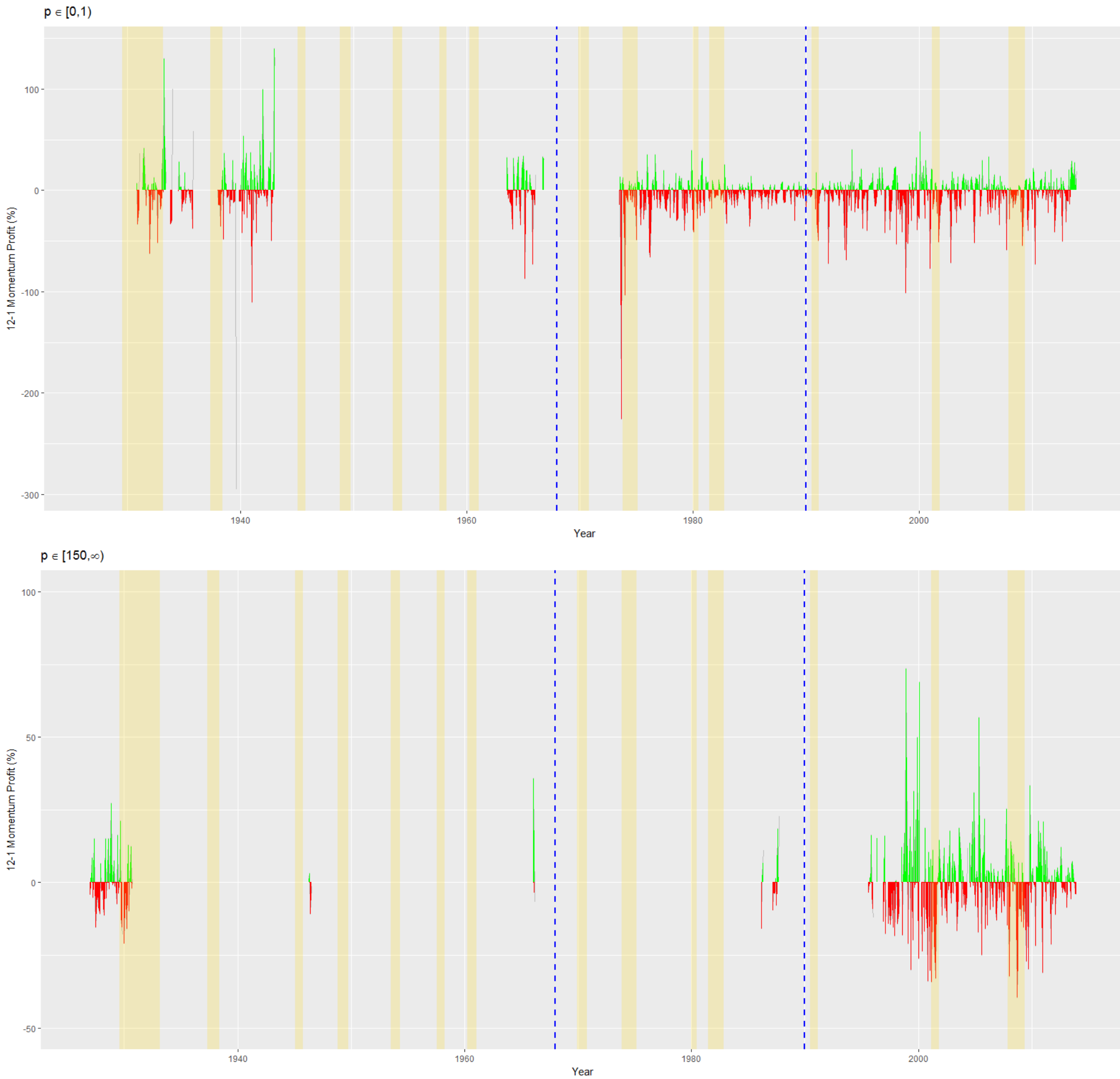

Figure 6: Momentum portfolio returns for stocks with nominal share prices in [0, 1) (top) and [150, ∞) (bottom), from 1927 to 2013 (dashed blue lines are the sample period of Jegadeesh and Titman (1993))

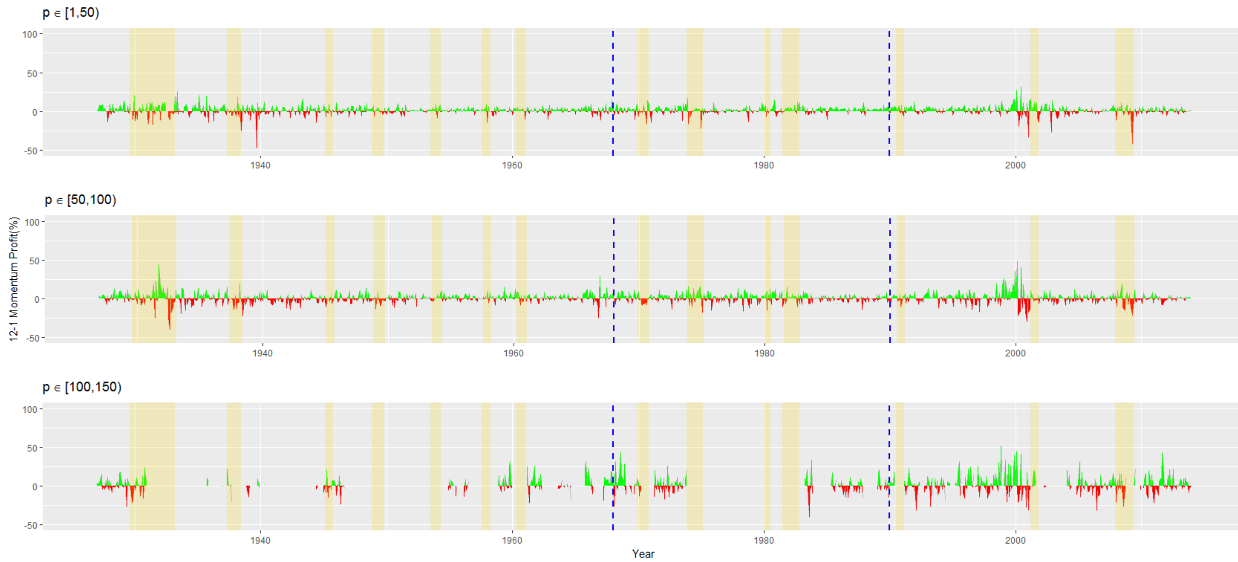

Figure 7: Momentum portfolio returns for stocks with nominal share prices in [1, 50) (top), [50, 100) (middle), and [100, 150) (bottom), from 1927 to 2013 (dashed blue lines are the sample period of Jegadeesh and Titman (1993))

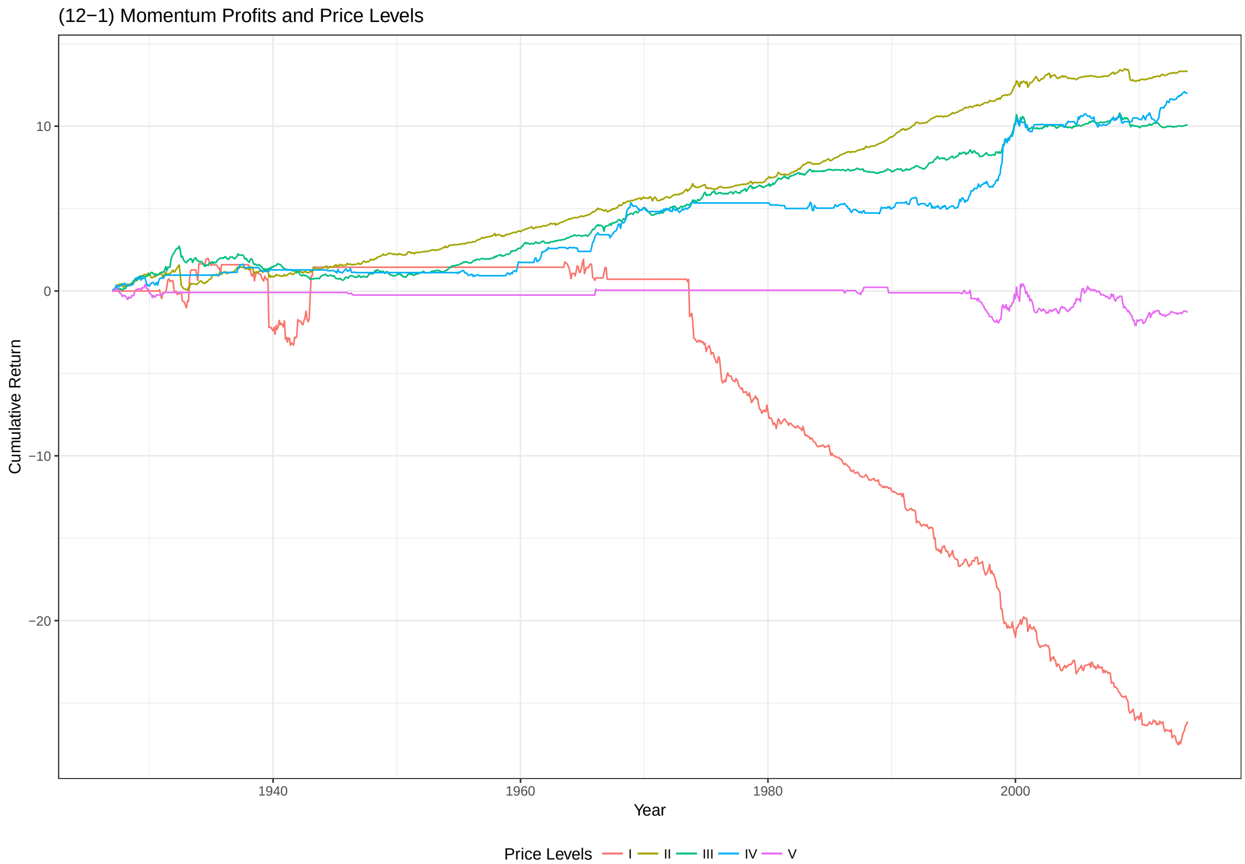

Figure 8: Cumulative returns of equation (2) of momentum profits by different nominal share price levels in $[0,1), [1,50), [50,100), [100,150), [150,\infty)$, labeled from I to V, from 1927 to 2013