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THE MOTIVES OF CORPORATE SPINOFFS: EVIDENCE FROM EX-ANTE MISVALUATION

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ABSTRACT

This study examines whether ex-ante misvaluation can explain motive differences between focus-increasing and non-focus-increasing spinoffs. In this study, a spinoff is defined as focus-increasing if the parent firm and the spun-off subsidiary operate in different industries. Otherwise, a spinoff is classified as a non-focus-increasing spinoff. The empirical results show that firms are more likely to conduct non-focus-increasing (focus-increasing) spinoffs if their valuation errors are larger (smaller). Also, short-term firm-specific overvaluation and overvalued long-run growth opportunities increase the probability of conducting a non-focus-increasing spinoff. The probability of conducting a focus-increasing spinoff increases when long-run growth opportunities are undervalued. The results suggest that motives underlying non-focus-increasing spinoffs are likely related to the exploitation of investors, whereas the motives underlying focus-increasing spinoffs are more likely beneficial to investors. An examination of investor reactions to spinoff announcements suggests that investors can see through the motives underlying corporate spinoffs.

JEL: G14, G32, G34

KEYWORDS: Corporate Spinoff, Divestiture, Focus, Misvaluation

INTRODUCTION

Prior studies suggest that deciphering spinoff motivation is a difficult task (Kurtaran, 2009). Despite this, many have hypothesized that the motivation for corporate spinoffs is to improve firm focus, significant conflicting results have been reported in the literature (Slovin et al. 1995). The issue is further complicated by the fact that a considerable number of spinoffs are non-focus-increasing (Harris and Madura, 2011; Lin and Yung, 2014). Other suggested motivations for spinoffs include reduction of information asymmetry (Krishnaswami and Subramaniam 1999; Bergh et al. 2008), removal of regulatory constraints (Schipper and Smith, 1983), and reduction of agency costs (Allen, 1998). Nevertheless, their empirical supports have also been inconclusive. The issue of spinoff motivation is also made complex by the insignificant or negative abnormal returns associated with many spinoff announcements (Veld and Veld-Merkoulova 2008; Lin and Yung 2014). Existing empirical evidence is unable to clearly distinguish among the hypothesized motivations for spinoffs, probably due to the simultaneous existence of multiple motives in any sample of spinoffs. Researchers have emphasized the value creation effect of corporate spinoffs. Surprisingly, none has directly examined the impact of firm misvaluation on spinoff decisions even though undervaluation is considered by many as related to the motives underlying spinoffs (Siddiqi and Warganegara 2003; Ahn and Denis 2004; Ahn and Walker 2007).

In this study, the ex-ante misvaluation of the parent firm is proposed to identify spinoff motivation. The idea that pre-announcement share prices influence corporate restructuring activity has gained much attention in recent years. Many have focused on the assumption that the deviation of share price from fundamental value can explain major firm investment decisions (Baker et al. 2003, Campello and Graham 2013). Specifically, a sizeable stream of research has argued that mergers are driven by market values that are excessively high as compared with fundamental values (Shleifer and Vishny 2003; Rhodes-Kropf and

Viswanathan 2004; Dong et al. 2006). This line of research is extended in this study to examine motivations for corporate spinoffs. The approach adopted in this paper is based on the Rhodes-Kropf, Robinson, and Viswanathan (2005, henceforth RKRV) methodology to decompose a firm's misvaluation into three components: short-term firm-specific valuation error, industry-wide valuation error, and long-term growth opportunities valuation error. This approach offers a unique advantage over methodologies adopted in prior spinoff studies because different motives of spinoffs are assessed simultaneously in the same model; it removes the issue of comparability as different methods are not used to examine different types of spinoff motivations. In addition, this approach's focus on firm misvaluation explores directly the commonly offered explanation by firms announcing spinoffs that the objective is to correct valuation problems in the market. To my knowledge, no published research on corporate spinoffs has analyzed the relation between firm misvaluation and spinoff motivations. The RKRV approach also has an advantage over conventional event study methodologies in understanding motivations for spinoffs as event study methodologies, in general, require the assumption that the underlying asset-return generating process is correctly specified.

Several interesting observations are found from the empirical results. First, firms contemplating non-focus-increasing spinoffs have significantly larger misvaluation errors than firms contemplating focus-increasing spinoffs. Second, overvaluation increases (decreases) the probability of conducting a non-focus-increasing (focus-increasing) spinoff. The result implies that the motives underlying non-focus-increasing spinoffs are likely related to exploiting investors because non-focus-increasing spinoffs aggravate the problem of information asymmetry. On the other hand, the motives underlying focus-increasing spinoffs are more likely beneficial to investors because improving firm focus when the firm value is less mispriced suggests that the firm wants to be informed or knowledgeable investors to know more about the future of the company. Third, higher levels of short-term firm-specific misvaluation and long-run growth misvaluation increase the probability of conducting a non-focus-increasing spinoff. Fourth, overvalued long-run growth opportunities increases (decreases) the likelihood of conducting a non-focus-increasing (focus-increasing) spinoff. Fifth, investors react more positively to spinoff announcements when valuation errors are smaller. Sixth, investor reactions to non-focus-increasing spinoff announcements are non-positive or insignificant when valuation errors are significant. Seventh, investors react positively to focus-increasing spinoff announcements, and the size of misvaluation has no impact on the reaction of investors. Eighth, overvaluation has a significant negative effect on investor reactions to non-focus-increasing spinoff announcements. Ninth, undervaluation has a significant positive impact on investor reactions to focus-increasing spinoff announcements. In sum, my findings suggest that the motives underlying non-focus-increasing spinoffs are unlikely related to improving firm efficiency, valuation accuracy, and information asymmetry. Vice versa, the motivations underlying focus-increasing spinoffs are likely related to improving valuation accuracy, information asymmetry, and firm efficiency.

This paper contributes to the literature on corporate spinoffs in several ways. It is the first study to examine the effect of firm misvaluation on corporate spinoff decisions. It is also the first paper to evaluate motives for corporate spinoffs by examining the ex-ante misvaluation of the parent firm. This approach has garnered much attention in recent years as researchers find that the deviation of share price from fundamental value can explain critical corporate decisions (Baker et al. 2003, Campello and Graham 2013). This paper also contributes to the literature by explicitly showing that the motives underlying non-focus-increasing are different from those underlying focus-increasing spinoffs. There is no existing study on the motivations underlying non-focus-increasing spinoffs. Another vital contribution in this paper to the literature is that my results are consistent with the implication that there could be multiple motives underlying a spinoff decision. For example, the motives underlying focus-increasing spinoffs seem more likely related to improving firm efficiency, information asymmetry, and valuation accuracy. This observation of the possible existence of multiple motives is particularly important because prior studies on spinoff motivation have frequently encountered conflicting results. Previous studies are unable to clearly distinguish among the hypothesized motivations for spinoffs, probably due to the simultaneous existence of multiple motivations in any sample of spinoffs. The rest of the paper is organized as follows. Section 2 summarizes related literature and testing hypotheses. Section 3 describes the sample collection process and provides descriptive statistics of the sample. Section 4 reports and discusses the results of this study. Section 5 concludes the paper.

LITERATURE REVIEW AND HYPOTHESES

Literature Review

A firm is split into separately traded entities when a spinoff takes place. Shareholders of the parent firm are given shares of the spun-off subsidiary on a pro-rata basis. Spinoffs differ from other forms of divestitures in that they do not involve any cash. Thus, spinoffs are unlikely motivated by a desire to generate cash to pay off debt, as is often the case with other forms of divestitures. Corporate spinoffs could be either focus-increasing or non-focus-increasing. In a focus-increasing spinoff, assets unrelated to the core business of the parent company are spun off to form a subsidiary. In a non-focus-increasing spinoff, the assets spun off are related to the core business of the parent firm.

A frequently mentioned spinoff motivation is corporate focus improvement. John and Ofek (1995) use the term 'removal of negative synergies' to describe the improvement of corporate focus through spinoffs as managers are freed from operations unrelated to the core business. Chen and Guo (2005) find that highly diversified firms are more likely to divest units when suffering from low operating efficiency. Comment and Jarrell (1995) suggest that firm performance is positively related to corporate focus because managerial efficiency improves when they are not distracted by non-core issues. Related to these arguments is the extensive evidence that the equity of diversified firms is traded at a discount compared with single-business firms. Thus, underlying the motivation to increase corporate focus and firm efficiency is the incentive to improve firm valuation. Although empirical findings are supporting the corporate focus explanation, Slovin et al. (1995) find contradictory results by examining how the share prices of competitors respond to spinoff announcements. Specifically, they find the positive share price reactions of competing firms opposite to the predictions of the corporate focus explanation of corporate spinoffs. They argue that if improved firm focus and better managerial incentives do indeed enhance firm performance, share prices of competitors are expected to react negatively to a spinoff announcement. Based on the finding of Solvin et al. (1995), Habib et al. (1997) posit that the corporate focus explanation may be viewed as having some limitations.

Another frequently mentioned motivation for the corporate spinoff is the reduction of agency costs. The agency costs explanation views spinoffs as a way to enhance firm performance as the alignment of incentives between managers and shareholders is improved (Allen, 1998). Specifically, the creation of a subsidiary with publicly traded securities enables shareholders to motivate and monitor the subsidiary managers in ways that may not have been feasible when the subsidiary was not publicly traded. Seward and Walsh (1996) and Daley et al. (1997) do not find evidence supporting the incentive alignment explanation. The third motivation for corporate spinoff discussed in the literature is the removal of tax or regulatory constraints. It is suggested that through a spinoff, either the parent or the subsidiary can escape constraints imposed by external regulatory bodies. For example, contracts with labor unions or rate regulators that presume the existence of one firm are altered upon a spinoff. Schipper and Smith (1983) study 93 voluntary spinoffs between 1963 and 1981, but they do not find evidence supporting the regulatory constraints argument. Lastly, the reduction of information asymmetry is another commonly mentioned motivation for the corporate spinoff. The explanation argues that spinoffs enable investors to value the parent firm more correctly and thus avoid the firm's value discount typically suffered by diversified firms. Habib et al. (1997) argue that spinoffs increase the number of securities that are traded on the market, and this makes the price system more informative. Krishnaswami and Subramaniam (1999) postulate that spinoffs improve the accuracy of information about the parent firm and its spun-off assets and thus enhance the total firm value. Chen and Zhang (2007) suggest that firms divest to improve information availability and enhance valuation accuracy. Tracking the Motives for Corporate Spinoffs and Hypothesis Development The methodology developed by RKRV is applied to identify spinoff motivation from ex-ante market valuation data. According to RKRV, the market-to-book (M/B) ratio of a firm can be decomposed into three misvaluation components: short-term firm-specific misvaluation, time-series sector misvaluation, and long-run growth opportunities misvaluation. The decomposition equation is stated as:

$$m - b = (m - v_1) + (v_1 - v_2) + (v_2 - b) \tag{1}$$

where *m* and *b* are the market and book values of shares in logarithmic forms, respectively. The first component, $(m - v_1)$, is the difference between market value and the fundamental value implied by industry averages at time *t*. This component measures firm-specific pricing deviations from short-run industry pricing, and it exists when the firm is experiencing short-run irrational mispricing in the market. The second component, $(v_1 - v_2)$, is the difference between the firm's fundamental value implied by industry averages at time *t* and the firm's fundamental value implied by long-run industry averages. This component arises when contemporaneous multiples differ from long-run multiples. The component reflects that firms in the same industry could encounter common misvaluation factors temporarily. The third component, $(v_2 - b)$, is the difference between the firm's fundamental value implied by long-run industry averages and the book value of the firm. According to RKRV, the third component captures the misvaluation of the long-run growth opportunities of the firm. Positive errors imply overvaluation, whereas negative errors imply undervaluation. For straightforward interpretation of the multivariate regression results, negative errors are multiplied by -1. Following RKRV (2005, Eq. 15), a firm's fundamental value is estimated as follow:

$$m_{it} = \alpha_{0jt} + \alpha_{1jt} b_{it} + \alpha_{2jt} \ln(NI)^+_{it} + \alpha_{3jt} I_{(<0)} \ln(NI)^+_{it} + \alpha_{4jt} LEV_{it} + \varepsilon_{it} \tag{2}$$

where m_{it} is the natural logarithm of the market value of equity of firm i in year t, bit is the natural logarithm of the firm's book value of equity in year t. NI is net income, and LEV is book leverage ratio. $(NI)^+$ is the absolute value of its net income in year t. $I_{(<0)}$ is an indicator when its net income in year t is negative. To calculate the short-run contemporaneous industry average multiples, $\alpha_{jt,}$ each year, all the firms in the same industry are grouped to run annual cross-sectional regressions to generate estimated industry multiples. The industry multiples, α_{jt}, are then used to compute the short-run fundamental value (v_1) of each firm in year *t*. To calculate the long-run industry multiples, α_j, the short-run yearly estimates (α_{jt}) is averaged. The long-run industry multiples are used to compute the long-run fundamental value (v_2) of each firm.

RKRV compare the three M/B ratio components between acquirers and target firms to evaluate merger motivation. For example, RKRV conclude that for many acquirers, the motivation is to use overvalued equities to acquire assets because acquirers have significantly higher short-term valuation errors than target firms. RKRV also suggest that the motivation of many acquirers is to buy growth because acquirers have long-term growth opportunities valuation errors that are significantly lower than those of target companies. Based on the result of RKRV, an acquisition could be driven by multiple motives if the acquirer exhibits different types of valuation errors simultaneously. In this study, the RKRV methodology is extended to relate the three misvaluation components to spinoff decisions to decipher the motives underlying corporate spinoffs. The first component of the decomposed M/B ratio, short-term firm-specific valuation error, likely occurs when investors are affected by the problem of information asymmetry. When investors lack sufficient information, they miscalculate firm value, and they tend to overreact or underreact to market news. It implies that if a non-focus-increasing spinoff decision is related to positive short-term firm-specific misvaluation (that is, overvaluation), then the motivation of the spinoff is likely associated with the exploitation of investors by compounding the problem of information asymmetry. Consistent with this view, some researchers find that assets divested through spinoffs are less than desirable. Michaely and Shaw (1995) find no evidence supporting the hypothesis that parent firms attempt to leave undervalued assets in the hands of current shareholders. Desai and Jain (1999) conclude that parent firms that undertake non-focus-increasing spinoffs are merely divesting the poorly performing subsidiaries and that efficiency is not the motive in these spinoffs. On the other hand, if a focus-increasing spinoff decision is related to negative short-term firm-specific misvaluation (that is, undervaluation), then the motivation is likely related to improving valuation accuracy by reducing information asymmetry in the market. Thus, the hypotheses are:

H1a: The motives underlying non-focus-increasing spinoffs are likely related to exploiting investors if the spinoffs are related to positive short-term misvaluation.

H1b: The motives underlying focus-increasing spinoffs are likely beneficial to investors if the spinoffs are related to negative short-term misvaluation.

The second component of the decomposed M/B ratio, time-series sector-wide valuation error, exists when firm value deviates from the long-run industry average. This error likely occurs when there are temporal regulatory changes or industry-wide structural problems. It implies that spinoff firms experiencing this misvaluation are facing some temporary industry-wide valuation adjustments. Thus, it is argued that a significant relationship between a spinoff decision and the second component of the M/B ratio can be used to infer motives that represent responses to industry-wide fundamental shocks. Thus, the hypothesis as:

H2: The motives underlying corporate spinoffs are likely related to reducing regulatory constraints in the industry if the spinoffs are related to sector-wide valuation errors.

The last component of the decomposed M/B ratio measures the misvaluation of long-run growth opportunities. It is argued that this component is suitable for tracking spinoff motivations that are related to concerns of agency problems or firm efficiency. Specifically, if long-run growth opportunities are undervalued, the motives underlying focus-increasing spinoffs are likely related to the improvement of valuation accuracy and firm efficiency. Moreover, if long-run growth opportunities are overvalued, the motives of focus-increasing spinoffs are likely related to the reduction of agency problems. Prior studies suggest that overvalued firms are more likely to have significant agency problems as managers use overvalued equities to pursue personal objectives (Jensen, 2005; Kothari et al. 2006). Divesting non-core assets when the firm is overvalued may discourage managers from abusing its resources for personal interests. On the other hand, one can argue that if long-run growth opportunities are misvalued (overvalued or undervalued), the motives underlying non-focus-increasing spinoffs are likely unrelated to the improvement of firm efficiency or valuation accuracy. It is because non-focus increasing spinoffs keep the firms diversified and make the valuation of growth opportunities difficult by complicating the issue of information asymmetry. Non-focus-increasing spinoffs also allow managers to extract benefits from the firm more easily. Thus, my hypotheses are:

H3a: The motives underlying focus-increasing spinoffs for firms that experienced negative long-run valuation errors are likely related to the improvement of firm efficiency and/or valuation accuracy.

H3b: The motives underlying focus-increasing spinoffs for firms that experienced positive long-run valuation errors are likely related to the reduction of agency problems.

H3c: The motives underlying non-focus-increasing spinoffs for firms that experienced (positive or negative) long-run valuation errors are likely unrelated to the improvement of firm value or efficiency.

DATA AND METHODOLOGY

Sample Selection

A sample of U.S. publicly traded firms that completed a spinoff transaction between 1980 and 2008 are collected from the Thomas ONE Banker's Mergers and Acquisitions database. The data does not extend beyond 2008 is to avoid the significant negative market reactions on corporate events caused by the financial crisis. Following RKRV (2005) and Hertzel and Li (2010), the fiscal year-end accounting data from Compustat is collected and matched with the Center for Research in Security Prices (CRSP) market value data three months after the fiscal year-end to calculate and decompose M/B ratio. If a spinoff is announced between the fiscal year-end and one month after the CRSP market value measured, the spinoff is matched with data from fiscal year *t-1*. To be included in the final sample, a spinoff must be a voluntary tax-free deal. It means spinoffs engaged in anti-trust regulations, taxable distribution, liquidation, bankruptcy, carve-out, and merger process are excluded. Firms in financial and regulated industries (SIC codes 4900-4949 and 6000-6999) are also excluded. A sample is dropped if the spinoff announcement date and the effective date (completion of a spinoff) of a firm cannot be verified in news releases or articles from Factiva. Finally, to remain in the sample, a spinoff parent firm must have enough Compustat and CRSP data to calculate the three components of the M/B ratio. The financial analysts' forecast data is from the Institutional Brokers Estimate System (IBES) through Thomas ONE Banker and segment data from Compustat and Compact Disclosure. My final sample consists of 307 completed spinoff transactions over the period 1980-2008. Consistent with the existing literature, a spinoff is classified as focus-increasing if the parent firm and the spun-off subsidiary have different 2-digit SIC codes. Otherwise, a spinoff is labeled as a non-focus-increasing spinoff.

<u>Descriptive Statistics</u>

Table 1 presents the distribution of the sample by year. There are at least five spinoffs in each year of the sample period except between 1980 and 1983. More than half of the spinoffs occurred during the decade between 1990 and 2000. Of the 307 spinoffs examined, 205 are focus-increasing, and 102 are non-focus-increasing. The 307 spinoffs involved 286 parent firms. Among the 286 parent firms, one divested four subsidiaries, one divested three subsidiaries, and sixteen divested two subsidiaries in the same year. The distribution of the parent firms of spinoffs by industry is analyzed (non-tabulated). The industry that has the largest number of spinoffs is manufacturing (52), followed by electronics (28) and services (27)

Table 1: Sample Distribution of Spinoffs

Year	Number of Spinoffs	Focus-Increasing Spinoffs	Non-Focus-Increasing Spinoffs	Year	Number of Spinoffs	Focus-Increasing Spinoffs	Non-Focus-Increasing Spinoffs
1980	0	0	0	1995	13	9	4
1981	1	1	0	1996	28	16	12
1982	0	0	0	1997	22	17	5
1983	1	1	0	1998	14	9	5
1984	6	5	1	1999	23	9	14
1985	9	8	1	2000	17	11	6
1986	12	12	0	2001	10	7	3
1987	7	4	3	2002	11	5	6
1988	13	10	3	2003	10	5	5
1989	7	4	3	2004	8	5	3
1990	10	5	5	2005	7	4	3
1991	8	8	0	2006	5	4	1
1992	11	6	5	2007	9	5	4
1993	17	13	4	2008	14	11	3
1994	14	11	3				

Notes: The number of spinoffs is the number of completed spinoffs per year. A spinoff is classified as focus-increasing if the parent firm and the spun-off subsidiary have the same 2-digit SIC code; otherwise, it is classified as non-focus-increasing.

Table 2 presents basic descriptive statistics of the parent firms and information regarding the spinoff transactions. All ratios are calculated in the fiscal year-end preceding the announcement year. The financial characteristics of the parent firms are reported in Panel A. The mean (median) sales revenue of the entire sample is $4,657 million ($1,279 million), and the mean (median) book assets are $6,198 million ($1,394 million). The sales and total assets of my sample of parent firms are higher than those in previous studies (Desai and Jain 1999; Krishnaswami and Subramaniam 1999), implying that spinoffs have become more commonly used by larger firms to restructure their organizations in recent years. The mean (median) market value of all the parent firms prior to the announcement is $6,358 million ($1,233) million. The mean (median) market-to-book ratio (M/B) of the entire sample is 3.36 (2.15), and non-focus-increasing firms have significantly higher M/B ratios compared to focus-increasing firms. The numbers suggest that non-focus-increasing firms have a higher degree of misvaluation before the spinoff. The mean (median) leverage of the entire sample is 0.55 (0.57), and this ratio is comparable between non-focus increasing and focus-increasing firms. Regarding operating performances, the mean (median) return on assets (ROA), return on equity (ROE), and cash-adjusted return on assets (ROA_cash_adj) are 12.60% (13.68%), 34.04% (32.81%) and 12.69% (15.05%), respectively.

Relative to focus-increasing firms, non-focus-increasing firms have poorer performance ratios across all the measures, which is consistent with the findings of Krishnaswami and Subramaniam (1999) and Michaely and Shaw (1995) that firms involved in non-focus spinoffs have lower levels of operating performance. Prior to the split, spinoff firms, on average, have 3 subsidiaries. The mean (median) Herfindahl index (HERF) of the entire sample is 0.59 (0.54); it is comparable to the finding of Harris and Madura (2011). Panel B of Table 2 presents spinoff transaction characteristics. Transaction value is measured by the market value of the spun-off subsidiary at the end of the first trading day, and spinoff size is the ratio of the transaction value to the market value of the parent firm one day prior to the ex-date. The mean (median) transaction value for the entire sample is $867.84 million ($176.3 million), and the mean (median) transaction value for focus-increasing and non-focus-increasing spinoffs is $895.61 million ($176.3 million) and $815 million ($178.30 million), respectively. The mean (median) spinoff size for all spinoffs is equal to 34.76 % (17.07%) of the value of the parent firm's capitalization. These numbers are comparable to 29% in Vijh (1994) and 30.7% in Krishnaswami and Subramaniam (1999). On average, parent firms in my sample took approximately seven months to complete their spinoffs, and non-focus-increasing deals are completed slightly quicker than focus-increasing deals.

Table 2: Descriptive Statistics for Spinoff Firms

Panel A: Characteristics of Spinoff Firms			
Measure	**All Spinoffs**	**Focus-increasing**	**Non-focus-increasing**
Sales($MM)	4,657.05 [1,279.13]	4,595.93 [1,512.95]	4,770.73 [790.33]
Total Assets ($MM)	6,198.48 [1,394.89]	5,435.85 [1,424.15]	7,616.96[1,357.15]
Market Value($MM)	6,358.68 [1,233.02]	6,804.65 [1,174.45]	5,529.18 [1,490.30]
M/B	3.36 [2.15]	2.68 [1.92]	4.63 [2.70]
LEVERAGE	0.55 [0.57]	0.55 [0.57]	0.54 [0.56]
ROA (%)	12.60 [13.68]	13.20 [13.80]	11.49 [13.25]
ROE (%)	34.04 [32.81]	35.73 [33.11]	30.87 [31.36]
ROA_ cash_adj (%)	12.69 [15.05]	13.43 [16.06]	11.31 [15.02]
Current Ratio (%)	225.81 [169.67]	218.38 [171.96]	239.53 [163.71]
N_SEG	2.92 [3.00]	3.09[3.00]	2.58[3.00]
HERF	0.59 [0.54]	0.55 [0.52]	0.67 [0.61]

Panel B: Deal Characteristics		
Transaction Value ($MM)	867.84 [176.30]	895.61 [176.30]
Spinoff Size (%)	34.76 [17.07]	35.41 [17.91]
Duration (Days)	208.51 [190.00]	216.03 [194.50]

Notes: Panel A represents the characteristics of spinoff parent firms. All ratios are calculated in the fiscal year-end preceding the announcement year. The first value of each variable represents the mean, and the second value represents the median. Sales are sales revenue. Total assets are the total book value of assets. Market capitalization is market value of equity of a firm. M/B is measured as the market value of equity divided by the book value of equity. Leverage is measured as the ratio of long-term and short-term debt to book assets. ROA is the ratio of operating income before depreciation to total book assets. ROE is the ratio of operating income before depreciation to total book equity. ROA_cash_adj is the ratio of operating income before depreciation scaled by book value of total assets minus cash and marketable securities. The current ratio is the ratio of current assets to current liabilities. N_SEG is the number of segments of the spinoff firm. HERF is the sales-based Herfindahl index. Panel B reports deal characteristics of the spinoffs. The transaction value is the market value of a spun-off subsidiary at the end of the first trading day. Spinoff size is the ratio of the transaction value to the market value of a parent firm one day prior to the ex-date. Duration is calculated as the number of days between spinoff announcement and ex-date.

RESULTS AND DISCUSSIONS

Univariate Analysis

The valuation errors of firms in the year prior to their corporate spinoff announcements are examined using the equation (2) developed by RKRVand reported in Table 3. The result shows that firms contemplating spinoffs have significant valuation errors. For example, firms contemplating focus-increasing spinoffs have a mean total misvaluation (TOTALMISV) of 0.718 and a median total misvaluation of 0.651. Firms contemplating non-focus-increasing spinoffs have a mean total misvaluation of 0.989 and a median total misvaluation of 0.994. Of the three misvaluation components, both focus-increasing and non-focus-increasing firms have experienced only short-term firm-specific (FSE) and long-run growth opportunities (LRVTB) valuation errors. Interestingly, industry-wide valuation (TSSE) errors are not found among firms contemplating spinoffs. An important result shown in Table 3 is that non-focus-increasing firms have valuation errors that are significantly higher than those of focus-increasing firms. As shown in the last column of Table 3, the mean (median) difference in total misvaluation is significant at the 1 percent and 5 percent levels, respectively; the mean (median) difference in long-run growth opportunities misvaluation is significant at the 5 percent level. The association between higher valuation errors and non-focus-increasing spinoffs implies that the motives underlying non-focus-increasing spinoffs are likely unrelated to improving valuation accuracy because such spinoffs typically aggravate the problem of asymmetric information (Krishnaswami and Subramaniam, 1999). On the other hand, the association between focus-increasing spinoffs and lower valuation errors suggest that the motives underlying focus-increasing spinoffs are likely related to improving firm efficiency and/or valuation accuracy as the parent firms want knowledgeable investors to know more about the future of the company.

Table 3: Ex-ante Firm Misvaluation before the Spinoff

	Focus-Increasing (n=186)		**Non-Focus-Increasing (n=100)**		**Difference**	
Component	**Mean**	**Median**	**Mean**	**Median**	**t(diff)**	**z(diff)**
TOTALMISV	0.718***	0.651***	0.989***	0.994***	-2.68***	-2.23**
FSE	0.336***	0.350***	0.402***	0.438***	-0.82	-0.74
TSSE	0.019	0.014	0.037	0.036	-0.52	- 0.74
LRVTB	0.357***	0.394***	0.552***	0.639***	-2.24**	-2.48**

Notes: This table reports information on the ex-ante misvaluation of focus-increasing and non-focus-increasing spinoff firms over the period 1980-2008. Three valuation errors are computed using the Rhodes-Kropf, Robinson, and Viswanathan (2005) methodology as follow: $m_{it} = \alpha_{0,jt} + \alpha_{1,jt} b_{it} + \alpha_{2,jt}\ ln(NI)^{+}_{it} + \alpha_{3,jt} I_{(<0)}\ ln(NI)^{+}_{it} + \alpha_{4,jt} LEV_{it} + \varepsilon_{it}$ *. FSE is short-term firm-specific misvaluation, TSSE is time-series sector-wide misvaluation, and LRVTB is long-run growth opportunities misvaluation. TOTALMISV is the sum of the three valuation errors. ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.*

Probit Analysis on Motives of Underlying Spinoffs

Probit regression is adopted to examine the effect of market misvaluation on spinoff decisions in a multivariate framework. The first testing model is expressed as follow:

$$Prob(Non\_Focus\_Increasing\ Spinoff_{it}) = \alpha + \beta_1 MISVALUATION_{\ it-1} + \gamma\ Control_{it-1} + \varphi Year\ dummies + \theta Industry\ Dummies + \varepsilon_{it-1} \quad (3)$$

where the dependent variable is a dummy variable with a value of 1 if the spinoff is non-focus-increasing, and 0 otherwise. A group of control variables, including leverage, firm size, profitability, level of diversification, and proxies of information asymmetry from previous literature, is included in the model to control the potential motivations of spinoffs. The year and industry dummies are also included in the model to capture the influence of time-series trends and industry effects. In Panel A of Table 4, the misvaluation is defined as total misvaluation (TOTALMISV). In Panel B of Table 4, the misvaluation is separated into positive total misvaluation (POS_TOTALMISV) and negative total misvaluation (TOTALMISV).

Panel A of Table 4 shows that the coefficient on TOTALMISV is positive and significant in all the models. The results suggest that firms with higher levels of misvaluation are more likely to conduct non-focus-increasing spinoffs. When TOTALMISV is separated into POS_TOTALMISV and NEG_TOTALMIS, the significant positive coefficient on POS_TOTALMISV reported in Panel B of Table 4 implies that overvaluation is more likely to result in non-focus-increasing spinoffs. Vice versa, firms are more likely to conduct focus-increasing spinoffs when they are less overvalued. Those findings above provide several interesting implications. On the one hand, the higher levels of market misvaluation among non-focus-increasing firms imply that the problem of asymmetric information facing investors is likely significant for these firms. Thus, if firms with high levels of misvaluation decide to pursue non-focus-increasing spinoffs, the problem of asymmetric information is further aggravated; the motive is, therefore, likely to take advantage of investors' asymmetric information problems rather than improving firm efficiency or valuation accuracy. On the other hand, the lower levels of market misvaluation among focus-increasing firms imply that the problem of asymmetric information is less significant for these firms. Thus, if firms with lower levels of misvaluation conduct focus-increasing spinoffs, it suggests that the firms appreciate the presence of informed investors and want to send credible signals about the firm's true potential to the investors. Thus, the likely motive of focus-increasing spinoffs when misvaluation is low is to improve firm efficiency or valuation accuracy. The findings support hypotheses 1a and 1b.

Table 4: Estimates of the Probability of Spinoffs and the Effect of Total Misevaluation

Panel A: Estimates of the Probability of Non-Focus-Increasing Spinoffs and the Effect of Total Misevaluation

	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	-0.642***	-0.468	-0.371	-1.820**	-1.806***
	(-2.82)	(-0.12)	(-0.81)	(-2.39)	(-2.70)
TOTALMISV	0.223**	0.254**	0.139$^{\#}$	0.245**	0.263*
	(2.18)	(2.31)	(1.61)	(2.15)	(1.88)
LEVERAGE		-0.374	-0.102	-0.413	-0.387
		(-0.75)	(-0.18)	(-0.78)	(-0.57)
SIZE		0.017	0.055	0.073$^{\#}$	0.117*
		(0.38)	(0.95)	(1.36)	(1.76)
ROA		-0.007	-0.003	-0.006	-0.013
		(-0.97)	(-0.34)	(-0.81)	(-1.03)
N_SEG			-0.156**	0.031	
			(-2.33)	(0.32)	
HERF				1.336**	1.111***
				(2.35)	(2.67)
SPIN_SIZE			-0.001		
			(-0.03)		
SPREAD			-0.991	-0.689	
			(-0.39)	(-0.26)	
ANA_ERROR					-0.031
					(-0.33)
Pseudo R^2	0.087	0.091	0.101	0.131	0.101
Wald X^2 Statistic	24.754***	25.807**	25.434*	35.280***	21.011*
N	286	286	257	276	215

Panel B: Estimates of the Probability of Non-Focus-Increasing Spinoffs and the Effects of Positive and Negative Total Misvaluation

	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	-0.711***	-0.424	-0.274	-1.440**	-1.630***
	(-5.32)	(-1.38)	(-0.77)	(-2.18)	(-2.77)
POS_ TOTALMISV	0.349***	0.398***	0.298**	0.360***	0.356**
	(3.09)	(3.32)	(2.23)	(2.90)	(2.51)
NEG_ TOTALMISV	-0.382	-0.377	-0.444	-0.277	-0.993
	(-0.78)	(-0.08)	(-0.82)	(-0.52)	(-1.23)
LEVERAGE		-0.727$^{\#}$	-0.517	-0.639$^{\#}$	-0.507
		(-1.57)	(-0.99)	(-1.32)	(-0.84)
SIZE		0.023	0.061	0.070$^{\#}$	0.096
		(0.53)	(1.09)	(1.35)	(1.50)
ROA		-0.007	-0.004	-0.005	-0.008
		(-0.99)	(-0.42)	(-0.69)	(-0.69)
N_SEG			-0.173***	-0.015	
			(-2.68)	(-0.16)	
HERF				1.120**	0.962**
				(2.09)	(2.46)
SPIN_SIZE			-0.001		
			(-0.36)		
SPREAD			-1.097	-1.179	
			(-0.43)	(-0.39)	
ANA_ERROR					-0.061
					(-0.58)
Pseudo R^2	0.034	0.046	0.052	0.086	0.069
Wald X^2 Statistic	9.621***	12.471**	13.063*	23.261***	14.069**
N	286	286	257	276	215

Notes: This table reports the results of probit regressions on the likelihood of conducting a non-focus-increasing spinoff: $Prob(Non\_Focus\_Increasing\ Spinoff_{it}) = \alpha + \beta_1 MISVALUATION_{it-1} + \gamma\ Control_{it-1} + \varphi Year\ dummies + \theta Industry\ Dummies + \varepsilon_{it-1}$ *.The dependent variable is a dummy variable with a value of 1 if the spinoff is non-focus-increasing, and 0 otherwise. TOTALMISV is the total misvaluation of the firm. POS_TOTALMISV (NEG_TOTALMISV) represents positive (negative) total misevaluation. LVERAGE is measured as the ratio of book leverage to book assets. SIZE is the natural log of the book assets. ROA is the ratio of operating income before depreciation to total book assets. N_SEG is the number of segments of the spinoff firm. HERF is the sales-based Herfindahl index. SPIN_SIZE is the log of the transaction value. SPREAD is bid-ask spread calculated as the average 100 days bid-ask spread scaled by the average of the bid-ask prices before the spinoff announcement. ANA_ERROR is financial analysts' forecast error and is measured as the ratio of the absolute value of the difference between actual earnings and forecast earnings to the price per share in the last month of the fiscal year before the spinoff announcement. Robust z-statistics are reported in parentheses.* ***, **, *and* * *indicate statistical significance at the 1%, 5%, and 10% levels, respectively (two-tailed t-test).*

To further understand the impact of misvaluation on spinoff decisions, TOTALMISV is separated into short-term firm-specific error (FSE), industry-wide error (TSSE), and long-run growth misvaluation (LRTVB) in the probit models. The probit model, therefore, is expressed as follow:

$$Prob(Non\_Focus\_Increasing\ Spinoff_{it}) = \alpha + \beta_1 FSE_{it-1} + \beta_2 TSSE_{it-1} + \beta_3 LRVTR_{it-1} + \gamma\ Control_{it-1} + \varphi Year\ dummies + \theta Industry\ Dummies + \varepsilon_{it-1} \quad (4)$$

Table 5 reports the probability of non-focus-increasing spinoffs and the effects of those three misvaluation components using the equation above. The coefficients of FSE in Table 5 is positive and significant in columns (1) through (4), implying that short-term firm-specific misvaluation increases the probability of conducting a non-focus-increasing spinoff. The result is consistent with the implication that the motive for conducting non-focus-increasing spinoffs is to exploit the short-term misunderstanding of investors rather than improving information asymmetry or firm efficiency. If the intention is to reduce information asymmetry or improve firm efficiency, focus-increasing spinoffs should have been conducted instead. The coefficient on TSSE is insignificant in all the columns. The coefficient on LRVTB, however, is positive and significant in four of the five columns, implying that firms are more likely to conduct non-focus-increasing spinoffs when investors do not fully understand the value of the long-run growth opportunities. The motive, again, is likely to exploit the misunderstanding of investors rather than correcting the misevaluation.

Table 5: Estimates of the Probability of Non-Focus-Increasing Spinoffs and the Effects of the Misvaluation Components

	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	-0.675***	-0.206	-0.309	-1.552*	-2.386***
	(-2.92)	(-0.38)	(-0.50)	(-1.77)	(-2.74)
FSE	0.253**	0.425**	0.249#	0.402*	0.157
	(1.99)	(1.96)	(1.51)	(1.80)	(0.62)
TSSE	-0.066	0.005	-0.389	-0.115	-0.525
	(-0.18)	(0.01)	(-0.89)	(-0.29)	(-1.15)
LRVTB	0.258*	0.233*	0.166	0.245*	0.519**
	(1.93)	(1.82)	(1.02)	(1.73)	(2.32)
LEVERAGE		-0.822	-0.327	-0.795	0.172
		(-1.11)	(-0.38)	(-1.02)	(0.17)
SIZE		0.003	0.053	0.063	0.150**
		(0.06)	(0.87)	(1.09)	(2.07)
ROA		-0.007	-0.002	-0.006	-0.019
		(-0.88)	(-0.25)	(-1.09)	(-1.45)
N_SEG			-0.158**	0.022	
			(-2.35)	(0.22)	
HERF				1.278**	1.193***
				(2.23)	(2.81)
SPIN_SIZE			-0.001		
			(-0.54)		
SPREAD			-1.257	-0.882	
			(-0.49)	(-0.33)	
ANA_ERROR					-0.045
					(-0.44)
Pseudo R^2	0.089	0.096	0.109	0.136	0.115
Wald X^2 Statistic	25.350**	27.047**	27.225*	36.498***	23.627*
N	286	286	257	276	215

Notes: This table reports the results of probit regression on the likelihood of non-focus-increasing spinoffs and the effect of the three RKRV misvaluation components. The testing model is expressed as follow: $Prob(Non\_Focus\_Increasing\ Spinoff_{it}) = \alpha + \beta_1 FSE_{it-1} + \beta_2 TSSE_{it-1} + \beta_3 LRVTR_{it-1} + \gamma\ Control_{it-1} + \varphi Year\ dummies + \theta Industry\ Dummies + \varepsilon_{it-1}$. *The three components are: firm-specific error (FSE), time-series sector error (TSSE), and the long-run value-to-book (LRVTB).The dependent variable is a dummy variable with a value of 1 if the firm is a non-focus-increasing spinoff and 0 otherwise. All other variables definitions can be found in the notes of Table 4. Robust z-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively (two-tailed t-test).*

Three misvaluation errors in are also separated into their respective positive and negative components to examine the impacts of individual misvaluation components in detail. The probit model is expressed as follow:

$$Prob(Non\_Focus\_Increasing\ Spinoff_{it}) = \alpha + \beta_1 POS\_FSE_{it-1} + \beta_2 NEG\_FSE_{it-1} + \beta_3 POS\_TSSE_{it-1} + \beta_4 NEG\_TSSE_{it-1} + \beta_5 POS\_LRVTR_{it-1} + \beta_6 NEG\_LRVTR_{it-1} + \gamma\ Control_{it-1} + \varphi Year\ dummies + \theta Industry\ Dummies + \varepsilon_{it-1} \quad (5)$$

The results of the probit model above are reported in Table 6. It is found that only the coefficient on POS_LRVTB is significant. The positive coefficient on POS_LRVTB implies that firms are more likely to conduct non-focus-increasing spinoffs when their long-run growth opportunities are overvalued in the market. Thus, the result further confirms that the motive is likely not to improve valuation accuracy because the problem of information asymmetry is made more complicated by non-focus-increasing spinoffs. Similarly, the significant positive coefficient on POS_LRVTB also implies that the motive for conducting non-focus-increasing spinoffs in the presence of overvalued long-run growth opportunities is unlikely related to improving firm efficiency. Vice versa, the result in Table 6 also implies firms are more likely to conduct focus-increasing spinoffs if their long-run growth opportunities are less overvalued. That is, when investors are more capable of understanding a firm's long-run growth opportunities, firms are more inclined to pursue focus-increasing spinoffs as if trying to signal the firm's future to investors. The finding is consistent with the view that the motive of conducting focus-increasing spinoffs is to improve valuation accuracy and/or efficiency. The findings support hypothesis 3a and 3c.

Do Investors See Through the Motives Underlying Spinoffs? The results in Tables 3 to 6 suggest that the motives for conducting non-focus-increasing spinoffs are likely related to exploiting investors, whereas the motives for conducting focus-increasing spinoffs are possibly related to helping investors. It would be interesting to know if investors were capable of understanding the motivations underlying spinoffs. Therefore, I calculate abnormal returns around spinoff announcements measured by the market model as the proxy of market reaction. Then, the spinoff sample is divided into quantities based on the degree of pre-spinoff misvaluation to examine investors' reactions. Quintile 1 are spinoffs that have the lowest misvaluation, and Quintile 5 are spinoffs that have the highest misvaluation.

Table 7 reports the relationship between the degree of pre-spinoff misvaluation and investor reactions around spinoff announcements for all spinoffs. The findings in Table 7 indicate that investors react positively to spinoff announcements when valuation errors are small. For example, the announcement period return has a mean of 4.49% and a median of 2.46% for firms that are in the lowest quintile of TOTALMISV; the announcement period return has a mean of 1.00% and a median of 1.26% for firms that are in the highest quintile of TOTALMISV. The difference in the mean is significant at the one percent level, and the difference in the median is significant at the 10 percent level. Similarly, firms in the lowest quintile of FSE also have a more positive announcement period return (the mean is 3.96%, and the median is 2.48%) than firms in the highest quintile of FSE (the mean is 2.46% and the median is 1.87%). A similar observation can also be made for firms in the lowest and highest quintiles of LRVTB. Specifically, the announcement period return has a mean of 4.22% and a median of 2.12% for firms that are in the lowest quintile of LRVTB; the announcement period return has a mean of 1.84% and a median of 2.03% for firms that are in the highest quintile of LRVTB. The difference in the mean is significant at the 10 percent level. In sum, investors react more positively to spinoff announcements when valuation errors are smaller.

Table 6: Estimates of the Probability of Non-Focus-Increasing Spinoffs and the Effects of Positive and Negative Misvaluation Components

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Intercept	-0.906***	-0.719	-0.710	-1.793**	-2.180***
	(-5.01)	(-1.36)	(-1.21)	(-2.19)	(-2.80)
POS_FSE	0.193	0.276	0.276$^{\#}$	0.220	0.118
	(1.05)	(1.18)	(1.38)	(0.90)	(0.43)
NEG_FSE	-0.217	-0.312	0.169	-0.313	0.029
	(-0.58)	(-1.73)	(0.35)	(-0.71)	(0.06)
POS_TSSE	0.188	0.099	0.087	0.169	0.083
	(0.33)	(0.17)	(0.13)	(0.28)	(0.13)
NEG_TSSE	0.525	0.334	0.685	0.527	0.816
	(0.72)	(0.44)	(0.83)	(0.65)	(0.90)
POS_LRVTB	0.652***	0.634***	0.455**	0.561***	0.582**
	(3.47)	(3.04)	(1.97)	(2.65)	(2.06)
NEG_LRVTB	0.389	0.367	0.129	0.216	-0.144
	(1.15)	(1.07)	(0.50)	(0.60)	(-0.28)
LEVERAGE		-0.543	-0.176	-0.388	0.217
		(-0.79)	(-0.22)	(-0.54)	(0.25)
SIZE		0.029	0.066	0.072$^{\#}$	0.121*
		(0.79)	(1.12)	(1.30)	(1.74)
ROA		-0.007	-0.004	-0.004	-0.017$^{\#}$
		(-0.85)	(-0.49)	(-0.56)	(-1.29)
N_SEG			-0.164**	0.002	
			(-2.53)	(0.02)	
HERF				1.162**	1.000**
				(2.14)	(2.48)
SPIN_SIZE			-0.001		
			(-0.12)		
SPREAD			-1.652	-1.261	
			(-0.60)	(-0.46)	
ANA_ERROR					-0.054
					(-0.54)
Pseudo R^2	0.053	0.059	0.062	0.095	0.071
Wald X^2 Statistic	14.633**	15.627*	15.623	25.385**	14.559
N	286	286	257	276	215

Notes: This table reports the results of probit regression on the likelihood of non-focus-increasing spinoffs and the effect of the three positive and negative RKRV misvaluation components. The testing model is expressed as follows:
$Prob(Non - Focus - Increasing\ Spinoff_{it}) = \alpha + \beta_1 POS\_FSE_{it-1} + \beta_2 NEG\_FSE_{it-1} + \beta_3 POS\_TSSE_{it-1} + \beta_4 NEG\_TSSE_{it-1} + \beta_5 POS\_LRVTR_{it-1} + \beta_6 NGG_{LRVTR_{it-1}} + \gamma\ Control_{it-1} + \varphi Year\ dummies + \theta Industry\ Dummies + \varepsilon_{it-1}$ *The dependent variable is a dummy variable with a value of 1 if the firm is a non-focus-increasing spinoff and 0 otherwise. POS_FSE (NEG_FSE) is the positive (negative) firm-specific error. POS_TSSE (NEG_TSSE) is the positive (negative) time-series sector error. POS_LRVTB (NEG_LRVTB) is the positive (negative) long-run value-to-book. All other variables definitions can be found in the notes of Table 4. Robust z-statistics are reported in parentheses.* ***, **, *and* * *indicate statistical significance at the 1%, 5%, and 10% levels, respectively (two-tailed t-test).*

Table 7**:** Degree of Pre-Spinoff Misvaluation and Investor Reactions to Spinoff Announcements

Component		**Quintile 1 Lowest**	**Quintile 2**	**Quintile 3**	**Quintile 4**	**Quintile 5 Highest**	**Difference Q1 – Q5**
TOTALMISV	Mean	4.49%***	2.44%***	2.61%***	3.06%***	1.00%	3.39%***
	Median	2.46%***	1.81%***	1.91%***	2.64%***	1.26%	1.20%*
	N	57	57	58	57	57	
FSE	Mean	3.96%***	3.58%***	1.56%**	2.37%***	2.46%***	1.50%
	Median	2.48%***	1.59%***	1.42%***	1.94%***	1.81%***	0.67%
	N	57	57	58	57	57	
TSSE	Mean	2.15%***	3.15%***	3.28%***	3.14%***	2.12%**	0.03%
	Median	0.84%***	3.14%***	3.02%***	2.20%***	2.05%**	-1.21%
	N	57	57	58	57	57	
LRVTB	Mean	4.22%***	2.61%***	2.38%***	2.88%***	1.84%**	2.38%*
	Median	2.12%***	2.40%***	1.76%***	2.20%***	2.03%**	0.09%
	N	57	57	58	57	57	

Notes: This table reports the mean and median of 2-day (-1, 0) cumulative abnormal returns estimated by market model for a sample of spinoff firms around the spinoff announcement period, sorted based on the degree of misvaluation. The abnormal returns are calculated using the market model parameters estimated over 255 days ending five days (Day -5) before the announcement date (Day 0). The CRSP value-weighted index is used in the market model to compute betas. N represents the number of observations in each quintile. The difference is the mean and median differences between Quintile 1 and Quintile 5. The t-test is used for the mean difference, and the Wilcoxon signed-rank test is applied for the median difference. ***, **, * *denote significance at the 1%, 5%, and 10% levels, respectively.*

Panel A of Table 8 reports the results on the effect of misvaluation on investor reactions to spinoff announcements among non-focus-increasing spinoffs only. The result shows that investors react positively to non-focus-increasing spinoff announcements when valuation errors are small; the result also indicates that investor reactions to non-focus-increasing spinoff announcements are non-positive and insignificant when valuation errors are large. For example, the announcement period return has a mean of 4.28% and a median of 1.95% for firms that are in the lowest quintile of TOTALMISV; the announcement period return has a mean of -0.210% and a median of -0.50% for firms that are in the highest quintile of TOTALMISV. The difference in the mean is significant at the 10 percent level, and the difference in the median is significant at the one percent level. A similar pattern is found between firms in the lowest and highest quintiles of LRVTB. Thus, the result in Panel A suggests that investors are concerned about the motives underlying non-focus-increasing spinoffs when misvaluation is large. Investors are less worrisome about the motives underlying non-focus-increasing spinoffs when misvaluation is small. Such finding is consistent with the results of the probit models in Tables 3-5 that the motives of non-focus-increasing spinoffs are likely related to exploiting investors.

Panel B of Table 8 reports results on the effect of misvaluation on investor reactions to spinoff announcements among focus-increasing spinoffs only. The result shows investors react positively to focus-increasing spinoff announcements, and the size of misvaluation has no impact on the reaction of investors. For example, the announcement period return has a mean of 4.86% and a median of 3.77% for firms that are in the lowest quintile of TOTALMISV; the announcement period return has a mean of 3.02% and a median of 3.07% for firms that are in the highest quintile of TOTALMISV. The difference in mean and the difference in the median are insignificant. A similar pattern can be observed between firms in the lowest and highest quintiles of FSE, TSSE, and LRVTB, respectively. Thus, the result in Panel B suggests that investors are not concerned about the magnitude of misvaluation when focus-increasing spinoffs are carried out. The result implies that investors consider the motives underlying focus-increasing spinoffs likely advantageous. This is consistent with the finding of the probit models in Tables 3-6 that the motives of focus-increasing spinoffs are likely related to improving valuation and efficiency. Overall, both Tables 7 and 8 show the univariate results on the effect of misvaluation on investor reactions to spinoff announcements.

The results of multivariate regressions on the impact of misvaluation on investor reactions to non-focus-increasing and focus-increasing spinoff announcements are reported in Table 9 and Table 10. The testing model adopted in those two tables is expressed as follow:

$$CAR = \beta_0 + \beta_1\, POS\_FSE + \beta_2\, NEG\_FSE + \beta_3\, POS\_TSSE + \beta_4\, NEG\_TSSE + \beta_5\, POS\_LRVTB + \beta_6\, NEG\_LRVTB + +\gamma\, Control_{it-1} + \varphi Year\ dummies + \theta Industry\ Dummies + \varepsilon \tag{6}$$

where CAR is the mean 2-day cumulative abnormal returns generated over the interval (-1, 0) by using the market model with the CRSP value-weighted index as the benchmark of the market portfolio; POS_FSE (NEG_FSE) is the positive (negative) firm-specific error; POS_TSSE (NEG_TSSE) is the positive (negative) time-series sector error; POS_LRVTB (NEG_LRVTB) is the positive (negative) long-run value-to-book. Table 9 reports the relationship between the market reaction and the degree of misvaluation components of non-focus-increasing spinoffs. A major observation in the table is that overvaluation has a significant negative effect on investor reactions to non-focus-increasing spinoff announcements. For example, the coefficient on POS_FSE is negative and significant in columns (1) to (4); the coefficient on POS_TSSE is negative and significant in columns (1), (2), and (5); the coefficient on POS_LRVTB is negative and significant in columns (1), (3), and (4). Thus, investors are concerned about the motives underlying non-focus-increasing spinoffs when firms are overvalued. On the other hand, undervaluation does not affect investor reactions to non-focus-increasing spinoff announcements.

Table 8: Degree of Pre-Spinoff Misvaluation And Investor Reactions to Spinoff Announcements by Non-Focus-Increasing and Focus-Increasing Spinoffs

Panel A: Degree of Pre-Spinoff Misvaluation and Investor Reactions to Spinoff Announcements of Non-Focus-Increasing Spinoffs							
Component		**Quintile 1 Lowest**	**Quintile 2**	**Quintile 3**	**Quintile 4**	**Quintile 5 Highest**	**Difference Q1 – Q5**
TOTALMISV	Mean	4.28%**	2.40%**	1.72%	1.90%*	-0.21%	4.49%***
	Median	1.95%**	1.72%**	2.20%	1.87%	-0.50%	2.45%*
	N	20	20	20	20	20	
FSE	Mean	3.21%**	2.62%*	1.17%	1.11%	0.61%	2.60%
	Median	2.71%**	1.46%	2.70%	1.10%	0.56%	2.15%
	N	20	20	20	20	20	
TSSE	Mean	1.53%	1.77%	1.63%	3.07%**	0.05%	1.48%
	Median	0.43%	1.53%	2.14%*	2.21%**	-0.01%	0.44%
	N	20	20	20	20	20	
LRVTB	Mean	5.36%***	0.55%	1.81%**	2.43%*	-1.12%	6.48%***
	Median	2.79%***	-0.29%	1.17%*	1.79%*	-1.12%	3.91%*
	N	20	20	20	20	20	
Panel B: Degree of Pre-Spinoff Misvaluation and Investor Reactions to Announcements of Focus-Increasing Spinoffs							
TOTALMISV	Mean	4.86%***	3.22%***	1.52%*	4.43%***	3.02%***	1.84%
	Median	3.77%***	1.83%***	0.86%**	2.92%***	3.07%***	0.70%
	N	37	37	38	37	37	
FSE	Mean	4.23%***	4.18%***	2.65%***	2.13%**	3.84%***	0.39%
	Median	2.48%***	1.86%***	2.14%***	1.95%***	3.07%***	-0.59%
	N	37	37	38	37	37	
TSSE	Mean	2.61%***	2.94%***	4.36%***	3.24%***	3.68%***	-1.07%
	Media	0.98%***	3.01%***	4.63%***	2.20%***	2.48%***	-1.50%
	N	37	37	38	37	37	
LRVTB	Mean	4.05%***	2.48%***	3.26%***	3.54%***	3.33%***	0.72%
	Median	1.83%***	2.40%***	2.96%***	2.60%***	2.48%***	-0.65%
	N	37	37	38	37	37	

Notes: This table reports the mean and median of 2-day (-1, 0) cumulative abnormal returns estimated by market model for a sample of non-focus-increasing (focus-increasing) firms around the spinoff announcement period, sorted based on the degree of misvaluation components. The abnormal returns are calculated using the market model parameters estimated over 255 days ending 5 days (Day -5) before the announcement date (Day 0). The CRSP value-weighted index is used in the market model to compute betas. N represents the number of observations in each quintile. The difference is the mean and median differences between Quintile 1 and Quintile 5. The t-test is used for the mean difference, and the Wilcoxon signed-rank test is applied for the median difference. ***, **, * *denote significance at the 1%, 5%, and 10% levels, respectively.*

Table 9: Relation between Investor Reactions and Misvaluation Components of Non-Focus-Increasing Spinoffs

	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	0.012	-0.019	-0.006	-0.030	-0.022
	(0.40)	(-0.40)	(-0.12)	(-0.45)	(-0.18)
POS_FSE	-0.027*	-0.036**	-0.046**	-0.046**	-0.029
	(-1.84)	(-2.09)	(-2.48)	(-2.45)	(-1.17)
NEG_FSE	0.029	0.042	0.013	0.009	-0.040
	(0.85)	(1.17)	(0.33)	(0.22)	(-0.72)
POS_TSSE	-0.082#	-0.082#	-0.065	-0.071	-0.134#
	(-1.60)	(-1.55)	(-1.03)	(-1.08)	(-1.59)
NEG_TSSE	0.059	0.065	0.074	0.070	-0.086
	(0.91)	(1.00)	(1.02)	(0.94)	(-0.78)
POS_LRVTB	-0.019*	-0.017	-0.024*	-0.022#	-0.018
	(-1.75)	(-1.26)	(-1.73)	(-1.41)	(-0.70)
NEG_LRVTB	0.003	0.028	0.026	0.026	0.053
	(1.22)	(1.13)	(0.90)	(0.90)	(0.67)
LEVERAGE		0.054	0.056	0.056	0.033
		(1.24)	(1.20)	(1.19)	(0.39)
SIZE		-0.001	-0.002	0.001	-0.001
		(-0.01)	(-0.46)	(0.07)	(-0.02)
N_SEG			0.001		
			(0.21)		
HERF				0.017	0.057#
				(0.59)	(1.39)
SPREAD				0.443	
				(0.33)	
ANA_ERROR					0.066**
					(2.29)
N	100	100	93	93	73
Adj. R^2	0.238	0.232	0.166	0.155	0.194

The abnormal returns on the misvaluation component of non-focus-increasing spinoffs.The testing model is expressed as follow: $CAR = \beta_0 + \beta_1\ POS\_FSE + \beta_2\ NEG\_FSE + \beta_3\ POS\_TSSE + \beta_4\ NEG\_TSSE + \beta_5\ POS\_LRVTB + \beta_6\ NEG\_LRVTB + +\gamma\ Control_{it-1}\ \varphi Year\ dummies + \theta Industry\ Dummies + \varepsilon$ *.The dependent variable CAR is the mean 2-day cumulative abnormal returns generated over the interval (-1, 0) by using the market model with the CRSP value-weighted index as the benchmark of the market portfolio. POS_FSE (NEG_FSE) is the positive (negative) firm-specific error. POS_TSSE (NEG_TSSE) is the positive (negative) time-series sector error. POS_LRVTB (NEG_LRVTB) is the positive (negative) long-run value-to-book. All other variables definitions can be found in the notes of Table 4. Two-tail heteroskedasticity-adjusted t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively (two-tailed t-test). # indicates statistical significance at the 10% levels (one-tailed t-test).*

Table 10 reports the results of multivariate regressions on the effect of misvaluation on investor reactions to focus-increasing spinoff announcements. The results in this table are opposite to those in Table 9. The major observation in Table 10 is that undervaluation has a significant positive effect on investor reactions to focus-increasing spinoff announcements. For example, the coefficient on NEG_FSE is positive and significant in columns (1) to (5); the coefficient on NEG_TSSE is positive and significant in column (5); the coefficient on NEG_LRVTB is positive and significant in columns (1) and (5). Thus, the results imply that investors consider the motives underlying focus-increasing spinoffs likely related to improve valuation and efficiency when the firm is undervalued. Interestingly, the coefficients on POS_FSE, POS_TSSE, and POS_LRVTB are all insignificant. It appears that investors are less concerned about firm overvaluation when they consider the motives underlying focus-increasing spinoffs are likely beneficial. In sum, the reaction of investors to focus-increasing and non-focus-increasing spinoffs confirm the results of the probit regression models that the motives underlying non-focus-increasing spinoffs are likely related to exploiting investors whereas the motives underlying focus-increasing spinoffs are likely advantageous to investors.

Table 10: Relation Between Investor Reactions and Misvaluation Components of Focus-Increasing Spinoffs

	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	0.060	0.015	0.001	0.004	0.038
	(0.88)	(0.18)	(0.01)	(0.05)	(0.48)
POS_FSE	0.010	-0.004	-0.005	-0.004	0.002
	(0.81)	(-0.21)	(-0.27)	(-0.23)	(0.09)
NEG_FSE	0.046**	0.062**	0.067**	0.066**	0.055*
	(1.98)	(2.19)	(2.30)	(2.25)	(1.90)
POS_TSSE	0.019	0.024	0.024	0.025	0.036
	(0.36)	(0.47)	(0.47)	(0.48)	(0.70)
NEG_TSSE	0.032	0.063	0.074	0.067	0.103#
	(0.52)	(0.95)	(1.09)	(0.91)	(1.31)
POS_LRVTB	-0.001	0.001	0.001	0.001	0.017
	(-0.06)	(0.06)	(0.06)	(0.05)	(1.08)
NEG_LRVTB	0.003#	0.027	0.028	0.029	0.006**
	(1.37)	(1.08)	(1.13)	(1.14)	(2.09)
LEVERAGE		0.086*	0.099*	0.094*	0.070
		(1.72)	(1.80)	(1.75)	(1.12)
SIZE		-0.003	-0.003	-0.003	-0.006#
		(-0.93)	(-0.85)	(-0.77)	(-1.38)
N_SEG			-0.001		
			(-0.14)		
HERF				-0.003	-0.036#
				(-0.11)	(-1.32)
SPREAD				0.030	
				(0.28)	
ANA_ERROR					-0.001#
					(-1.58)
N	186	186	183	183	142
Adj. R^2	0.035	0.049	0.042	0.035	0.164

This table reports the abnormal returns on the misvaluation component of focus-increasing spinoffs. The testing model is expressed as follow: $CAR = \beta_0 + \beta_1\ POS\_FSE + \beta_2\ NEG\_FSE + \beta_3\ POS\_TSSE + \beta_4\ NEG\_TSSE + \beta_5\ POS\_LRVTB + \beta_6\ NEG\_LRVTB + +\gamma\ Control_{it-1} + \varphi Year\ dummies + \theta Industry\ Dummies + \varepsilon$ *. The dependent variable is the mean 2-day cumulative abnormal returns generated over the interval (-1, 0) by using the market model with the CRSP value-weighted index as the benchmark of the market portfolio. POS_FSE (NEG_FSE) is the positive (negative) firm-specific error. POS_TSSE (NEG_TSSE) is the positive (negative) time-series sector error. POS_LRVTB (NEG_LRVTB) is the positive (negative) long-run value-to-book. All other variables definitions can be found in the notes of Table 4. Two-tail heteroskedasticity-adjusted t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively (two-tailed t-test). # indicates statistical significance at the 10% levels (one-tailed t-test).*

CONCLUDING COMMENTS

Understanding the motives underlying corporate spinoffs is besieged by conflicting empirical results in the existing literature. The issue is further complicated by the firm's choice between non-focus-increasing and focus-increasing spinoffs. This study is the first one to use ex-ante misvaluation of the parent firm to identify spinoff motivation. Based on the results of studies on merger motivation, this study argues that the deviation of share price from fundamental value can explain corporate spinoff decisions. By adopting the methodology of Rhodes-Kropf et al. (2005) to decompose a firm's misvaluation into three components that include short-term firm-specific valuation error, industry-wide valuation error, and long-term growth valuation error, I find that firms contemplating non-focus-increasing spinoffs have significantly larger valuation errors than firms contemplating focus-increasing spinoffs. My results show that short-term firm-specific overvaluation and long-run growth opportunities overvaluation increases the likelihood of conducting non-focus-increasing spinoffs. The finding suggests that the motives underlying non-focus-increasing spinoffs are likely related to the exploitation of investors because non-focus-increasing spinoffs aggravate the problem of asymmetric information.

My results also show that firms are more likely to conduct focus-increasing spinoffs when they have smaller valuation errors, and when long-run growth opportunities are less overvalued. The finding suggests that when investors are more informed or knowledgeable, firms use focus-increasing spinoffs to signal the future of the firm to investors. In other words, the motives underlying focus-increasing spinoffs are likely related to improving valuation and/or firm efficiency. My investigation of investor reactions to spinoff announcements suggests that investors can see through the motives underlying the spinoff decisions. The results show that investor reactions to non-focus-increasing spinoff announcements are non-positive and insignificant when valuation errors are large. In addition, overvaluation has a significant negative effect on investor reactions to non-focus-increasing spinoff announcements. On the other hand, univariate results show that investors react positively to focus-increasing spinoff announcements, and the size of misvaluation has no impact on the reaction of investors. Multivariate regressions show that investors respond favorably to focus-increasing spinoffs is long-run growth opportunities are undervalued. The findings in this study shed light on the investment strategies to practitioners who consider investing in spinoff companies. According to recent research by Willis Towers Watson (2019), over half of the companies engaging in divestments since 2010 have lost shareholder value. Such evidence supports the hypotheses addressed in this study that not all spin-offs create value for shareholders. Investors, therefore, must study the motive of a spinoff carefully to avoid being exploited by managers due to information asymmetry problems prior to spinoffs. Due to the significant adverse market reactions during the recent global financial market crash, this study only examines the pre-crash sample. Future studies might want to include recent spin-off cases to determine whether the relationship between misvaluation of spinoffs and the market reactions holds due to the significant market microstructure and regulations change after the crisis.

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POLITICAL PARTIES IN POWER AND U.S. ECONOMIC PERFORMANCE

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ABSTRACT

This study examines the simultaneous interaction between political control of the White House and both chambers of Congress and the impact of those combinations on various measures of economic activity in the U.S. Past economic growth is not significantly different under Republican and Democratic presidential administrations. Nor does the party that controls the House of Representatives appear to have a significant impact on economic growth. However, growth has been strongest when Republicans control the Senate. Non-farm payrolls and industrial production grow faster under Democratic Presidents, while higher inflation and unemployment are generally observed when Democrats control the Senate or House. Republican Presidents are in office for a significantly greater number of months when the economy is in a recession. The same is true when Democrats are in charge of the Senate or House. The U.S. economy appears to have the strongest performance under the combination of a Democratic President with a Republican controlled Senate and House, and the weakest economic performance is generally under a Republican President with a Senate controlled by Democrats and a Republican controlled House.

JEL: D72, E32, N12

KEYWORDS: Political Business Cycle, Leading Indicators, Economic History

INTRODUCTION

The phrase "It's the economy, stupid" was coined by James Carville during the 1992 presidential race to try and tie President G.H.W. Bush's re-election chances to the 1990-1991 recession (Brown, 1992). Right or wrong, U.S. presidents have been given credit for strong economies and the blame for economic weakness. Johnson, Chittenden, and Jensen (1999), among others, have examined the relationship between stock and bond returns and which political party controls the White House. Others, like Hibbs (1977) and Blinder and Watson (2016) have compared macroeconomic performance in a similar manner. Beyer, Jensen, and Johnson (2006) consider the impact of political gridlock. This paper expands on previous research by separately comparing the changes in macroeconomic variables across which political party controls the presidency, the Senate, and the House of Representatives (the House). In addition, the simultaneous interaction between political control of the White House, the Senate, and the House is considered. The remainder of the paper is organized as follows. In the next section, the literature on economic performance under different political parties is surveyed. The data and methodology used in the study are discussed next. The results and discussion, including limitations of the study, are presented in the following section. The paper closes with some concluding comments and suggestions for future research.

LITERATURE REVIEW

Numerous studies have examined the relationship between the political party of the President with the performance of financial assets. Johnson, Chittenden, and Jensen (1999) find that small-cap stock returns are higher during Democratic presidential administrations while bond returns are higher during Republican administrations. Santa-Clara and Valkanov (2003), Liston, Chong, and Bayram (2014), and others, report comparable findings. Abidin, Old, and Martin (2010) observe analogous effects in New Zealand. However, Jones and Banning (2009) find no significant difference in stock returns during Democratic and Republican administrations. Sy and Al Zaman (2011) suggest higher stock returns during Democratic administrations can be attributed to higher market and default risk premiums. Herbst and Slinkman (1984) conclude that the stock market follows a cycle that corresponds to U.S. presidential elections. Beyer, Jensen, and Johnson (2008), Wong and McAleer (2009), and Kräussl, Lucas, Rijsbergen, van der Sluis, and Vrugt (2014) come to similar conclusions. Sturm (2016) finds that firms' book-to-market ratios are related to the presidential election cycle. Belo, Gala, and Li (2013) conclude that the presidential cycle is strongest for firms with high exposure to government spending. Lamb, Ma, Pace, and Kennedy (1997) state that average daily stock market returns "when Congress is not meeting are almost thirteen times greater than when Congress is in session." Liston, et al. (2014) find that investor sentiment is higher during Democratic administrations while Adjei and Adjei (2017) find that investor sentiment starts low and rises during Democratic administrations and starts high but falls during Republican administrations. See Wisniewski (2016) for a more extensive review of the literature that examines politics and stock returns.

Rather than focusing on the financial markets, others have examined the impact of political party control and the performance of macroeconomic variables. Fair (1978, 1982, 1988) models how macroeconomic variables can predict presidential outcomes. Blinder and Watson (2016) find that real GDP grew 1.79 percentage points faster under Democratic administrations compared to Republican administrations. They attribute the positive difference in economic growth during Democratic administrations to favorable oil price shocks, higher growth in defense spending, and higher productivity shocks compared to Republican administrations. Most of the literature in this area focuses exclusively on the political party of the president. Some, like Beyer, Jensen, and Johnson (2006) and Blinder and Watson (2016) include measures for which political party controls Congress. Beyer, et al. (2006) conclude that stock market returns are generally higher "during periods of political harmony" and poor during periods of gridlock. Political harmony is defined as when the same political party controls the presidency, the Senate, and the House. Blinder and Watson (2016) take a similar approach. These studies treat Congress as a single entity rather than two distinct chambers. This paper extends the current literature by examining the individual and joint impact of which political party controls the presidency, the Senate, and the House.

DATA AND METHODOLOGY

This study uses quarterly and monthly data from 1977 through 2016. This period is chosen for several reasons. During this period, all presidents served their entire term. Extending to a longer period would necessitate including the time periods of political uncertainty after the deaths of presidents Franklin Roosevelt and John Kennedy and the resignation of Richard Nixon. In addition, the time period is long enough that there are a large number of both quarterly and monthly observations, but not so long that there are major structural changes (for example, the collapse of Bretton Woods or the establishment of the Treasury-Fed Accord.) Also, this period coincidently is evenly split between Democratic and Republican presidential administrations. Quarterly data for 160 quarters was obtained from FRED (Federal Reserve Economic Data) at the Federal Reserve Bank of St. Louis. This data includes the annualized percent change from the preceding quarter in real GDP (seasonally adjusted), annualized percent change from the quarter one year prior in real GDP (seasonally adjusted), the annualized percent change in Nonfarm Business Sector Real Output, and the annualized percent change in Business Sector Real Output. Monthly data for 480 months comes from two sources. Monthly data for the Coincident Economic Index (CEI) were obtained from The Conference Board. Monthly data for Total Nonfarm Payrolls (TNFP), Industrial Production (INDPRO), the Consumer Price Index for All Urban Consumers: All Items (CPI), the Producer Price Index for All Commodities (PPI), the unemployment rate, and the NBER based Recession Indicator for the United States from the Period following the Peak through the Trough were retrieved from FRED. The monthly percent change for the CEI, TNFP, INDPRO, CPI, and PPI was calculated as:

$$\%\Delta X = \frac{X_t}{X_{t-1}} - 1 \qquad (1)$$

where X is the variable and t is the time period. The parametric Welch's (1951) unequal variances t-test is used to compare the means of the variables during Democratic and Republican control. Ruxton (2006) states "the unequal variance t-test performs as well as, or better than, the Student's t-test in terms of control of both Type I and Type II error rates whenever the underlying distributions are normal." In addition, the non-parametric Mann-Whitney test is used to compare the means. Conover (1999) demonstrates that this test is consistent and unbiased regardless if the underlying data are normally distributed or not. The related one-way chi square approximation is used to evaluate the difference in the number of months of recession under each political party.

RESULTS AND DISCUSSION

During the period examined, January 1977 through December 2016, Democrats and Republicans each controlled the presidency fifty percent of the time. As shown in Table 1, Democrats and Republicans each held the White House for 80 quarters (240 months). Democrats had a majority in the Senate for 86 quarters (259 months) versus 74 quarters (221 months) for the Republicans. In the House, Democrats led for 88 quarters (264 months) while Republicans had control for 72 quarters (216 months).

Table 1: Political Party in Control 1977-2016

Quarters			
	President	**Senate**	**House**
Democrat	80	86	88
Republican	80	74	72
Total	160	160	160
Months			
	President	**Senate**	**House**
Democrat	240	259	264
Republican	240	221	216
Total	480	480	480

This table shows the number of quarters and months that Democrats and Republicans were in control of the presidency, the Senate, and the House of Representatives. Note that between January and May 2001, the Senate was split with 50 Democrats and 50 Republicans and the Republican Vice-President cast any tie-breaking vote. For these months, Republicans were counted as having control of the Senate. In June 2001, a Republican Senator switched to Independent and caucused with the Democrats, giving Democrats the majority.

Blinder and Watson (2016) found that GDP grew faster under Democratic presidential administrations versus Republican administrations between 1949 – 2012. They observe "that a sizeable share of the overall D-R gap comes from the Truman and Kennedy-Johnson years." During the forty years examined in this study, economic growth is also higher during Democratic presidencies as compared to Republican presidencies. As shown in Table 2, GDP growth (measured as the annualized percent change from the previous quarter) was on average 0.3175% faster each year under a Democratic president. When GDP is measured as the percent change from one year prior, the difference falls to 0.1287%. In both cases, the difference is not statistically significant. When economic growth is measured as the percent change in Nonfarm Business Sector Real Output (percent change in Business Sector Real Output), the difference is 0.1727% (0.1707%) in favor of the Democrats. As with GDP, these differences are not statistically significant. Generally speaking, economic growth is not significantly different under Democratic presidents than Republican presidents.

Table 2: Mean Difference Analysis for Economic Growth by Presidential Political Party

	Party	Mean	Difference		
Qtrly Real GDP, %Δ from Preceding Period	Democratic	2.9600%	0.3175%	Prob >|t|	0.5183
	Republican	2.6425%		Prob>|Z|	0.9823
Qtrly Real GDP, %Δ from Qtr. One Year Ago	Democratic	2.8487%	0.1287%	Prob >|t|	0.6964
	Republican	2.7200%		Prob>|Z|	0.4547
%Δ in Nonfarm Business Sector Real Output	Democratic	0.8451%	0.1727%	Prob >|t|	0.2535
	Republican	0.6724%		Prob>|Z|	0.3983
%Δ in Business Sector Real Output	Democratic	0.8507%	0.1707%	Prob >|t|	0.2758
	Republican	0.6800%		Prob>|Z|	0.4885

*This table shows mean difference analysis for GDP growth measured as the annualized percent change from the previous quarter, GDP growth measured as the percent change from one year prior, the percent change in Nonfarm Business Sector Real Output and the percent change in Business Sector Real Output. The last column reports the p-value associated with a two-tailed test for the parametric t-test (Prob >|t|) and the non-parametric Mann-Whitney test (Prob>|Z|) for differences in means. ***, **, and * indicate significance at the 1, 5 and 10 percent levels, respectively. The number of observations in each sample is the same number of quarters as indicated in Table 1.*

When economic growth is compared to when Democrats versus Republicans control the Senate, growth is slower under Democratic Senates. As documented in Table 3, GDP growth (measured as the annualized percent change from the previous quarter) was 1.0335% faster on average each year under a Republican Senate. This difference is statistically significant at the 5% level using both the parametric t-test (Prob >|t|) and the non-parametric Mann-Whitney test (Prob>|Z|). When GDP is measured as the percent change from one year prior, the Republican advantage increases to 1.1554%, which is significant at the 1% level. Using the percent change in Nonfarm Business Sector Real Output (percent change in Business Sector Real Output) to compare economic activity, the difference is 0.3160% (0.3156%) in favor of the Republicans. These differences are statistically significant at the 5% level. Economic growth is stronger when the Senate is controlled by Republicans. The differences in economic growth based on the political party controlling the House is similar to the results found for the presidency. As shown in Table 4, economic growth is weaker when Democrats control the House, but these differences are not statistically significant. GDP growth (measured as the annualized

Table 3: Mean Difference Analysis for Economic Growth by Senate Political Party

	Party	Mean	Difference		
Qtrly Real GDP, %Δ from Preceding Period	Democratic	2.3233%	-1.0335%	Prob >|t|	0.0328**
	Republican	3.3568%		Prob>|Z|	0.0152**
Qtrly Real GDP, %Δ from Qtr One Year Ago	Democratic	2.2500%	-1.1554%	Prob >|t|	0.0004***
	Republican	3.4054%		Prob>|Z|	0.0001***
%Δ in Nonfarm Business Sector Real Output	Democratic	0.6171%	-0.3160%	Prob >|t|	0.0439**
	Republican	0.9331%		Prob>|Z|	0.0295**
%Δ in Business Sector Real Output	Democratic	0.6180%	-0.3156%	Prob >|t|	0.0392**
	Republican	0.9336%		Prob>|Z|	0.0248**

*This table shows mean difference analysis for GDP growth measured as the annualized percent change from the previous quarter, GDP growth measured as the percent change from one year prior, the percent change in Nonfarm Business Sector Real Output and the percent change in Business Sector Real Output. The last column reports the p-value associated with a two-tailed test for the parametric t-test (Prob >|t|) and the non-parametric Mann-Whitney test (Prob>|Z|) for differences in means. ***, **, and * indicate significance at the 1, 5 and 10 percent levels, respectively. The number of observations in each sample is the same number of quarters as indicated in Table 1.*

percent change from the previous quarter) was 0.1619% slower on average each year under a Democratic House. When GDP is measured as the percent change from one year prior, the difference is 0.2733% in favor of the Republicans. The difference in the percent change in Nonfarm Business Sector Real Output (percent change in Business Sector Real Output) is even smaller in magnitude. Although the differences are not statistically significant, economic growth is slightly stronger when Republicans control the House. In summary, economic growth is strongest when a Democrat is in the White House and when Republicans control the Senate or House.

Table 4: Mean Difference Analysis for Economic Growth by House Political Party

	Party	Mean	Difference		
Qtrly Real GDP, %Δ from Preceding Period	Democratic	2.7284%	-0.1619%	Prob >|t|	0.7294
	Republican	2.8903%		Prob>|Z|	0.9385
Qtrly Real GDP, %Δ from Qtr One Year Ago	Democratic	2.6614%	-0.2733%	Prob >|t|	0.3804
	Republican	2.9347%		Prob>|Z|	0.8115
%Δ in Nonfarm Business Sector Real Output	Democratic	0.7081%	-0.1225%	Prob >|t|	0.4196
	Republican	0.8306%		Prob>|Z|	0.6105
%Δ in Business Sector Real Output	Democratic	0.7122%	-0.1181%	Prob >|t|	0.4289
	Republican	0.8303%		Prob>|Z|	0.6681

*This table shows mean difference analysis for GDP growth measured as the annualized percent change from the previous quarter, GDP growth measured as the percent change from one year prior, the percent change in Nonfarm Business Sector Real Output and the percent change in Business Sector Real Output. The last column reports the p-value associated with a two-tailed test for the parametric t-test (Prob >|t|) and the non-parametric Mann-Whitney test (Prob>|Z|) for differences in means. ***, **, and * indicate significance at the 1, 5 and 10 percent levels, respectively. The number of observations in each sample is the same number of quarters as indicated in Table 1.*

In addition to economic growth, several additional monthly economic time series are examined. Comparing the political parties that occupy the White House in Table 5, the monthly percent change in the Coincident Economic Index (CEI), Total Nonfarm Payrolls (TNFP), and Industrial Production (INDPRO) are statistically significantly higher under Democratic control versus Republican control. The changes in the Consumer Price Index (CPI) and the Producer Price Index (PPI) are also higher under Democratic administrations, while the unemployment rate is lower. However, these last three differences are generally not statistically significant. Overall, Democratic presidencies tend to see a stronger economy, higher job growth, and higher increases in productivity.

Table 6 considers the same variables but controls for which party has a majority in the Senate. The monthly percent changes in the CEI and TNFP are higher when Republicans control the Senate and these differences are generally statistically significant. INDPRO is lower when Democrats control the Senate, but the difference is not significant. Inflation, as measured by the monthly change in the CPI and PPI and the unemployment rate are all statistically significantly higher, generally at the 1% level, when Democrats control the Senate. A similar pattern is observed when the party in charge of the House is considered. As reported in Table 7, the monthly percent change in the CEI, TNFP, and INDPRO is higher when Republicans control the House, although these differences are not statistically significant. However, the level of inflation (as measured by changes in the CPI and PPI) and the unemployment rate are higher when Democrats control the House and this difference is statistically significant. In summary, changes in the Coincident Economic Index, Total Nonfarm Payrolls, and Industrial Production are generally stronger under Democratic presidents but lower under a Democratic House or Senate. Inflation and unemployment tend to be higher when Democrats control either the Senate or the House.

Table 5: Mean Difference Analysis for Economic Variables by Presidential Political Party

	Party	Mean	Difference		
%Δ in CEI	Democratic	0.2036%	0.0884%	Prob >|t|	0.0027***
	Republican	0.1152%		Prob>|Z|	0.0020***
%Δ in TNFP	Democratic	0.1630%	0.0787%	Prob >|t|	0.0001***
	Republican	0.0843%		Prob>|Z|	0.0001***
%Δ in INDPRO	Democratic	0.2416%	0.1525%	Prob >|t|	0.0140**
	Republican	0.0891%		Prob>|Z|	0.0096***
%Δ in CPI	Democratic	0.3071%	0.0186%	Prob >|t|	0.5136
	Republican	0.2885%		Prob>|Z|	0.0458**
%Δ in PPI	Democratic	0.2736%	0.0792%	Prob >|t|	0.3408
	Republican	0.1944%		Prob>|Z|	0.4203
Unemployment Rate	Democratic	6.3671%	-0.0167%	Prob >|t|	0.9074
	Republican	6.3838%		Prob>|Z|	0.7445

*This table shows mean difference analysis for the percent change in the Coincident Economic Index (CEI), the percent change in Total Nonfarm Payrolls (TNFP), the percent change in Industrial Production (INDPRO), the percent change in Consumer Price Index (CPI), the percent change in the Producer Price Index (PPI), and the unemployment rate. The last column reports the p-value associated with a two-tailed test for the parametric t-test (Prob >|t|) and the non-parametric Mann-Whitney test (Prob>|Z|) for differences in means. ***, **, and * indicate significance at the 1, 5 and 10 percent levels, respectively. The number of observations in each sample is the same number of months as indicated in Table 1.*

Table 6: Mean Difference Analysis for Economic Variables by Senate Political Party

	Party	Mean	Difference		
%Δ in CEI	Democratic	0.1306%	-0.0623%	Prob >|t|	0.0317**
	Republican	0.1929%		Prob>|Z|	0.0909*
%Δ in TNFP	Democratic	0.1073%	-0.0353%	Prob >|t|	0.0448**
	Republican	0.1426%		Prob>|Z|	0.1014
%Δ in INDPRO	Democratic	0.1547%	-0.0231%	Prob >|t|	0.7084
	Republican	0.1778%		Prob>|Z|	0.6176
%Δ in CPI	Democratic	0.3381%	0.0872%	Prob >|t|	0.0027***
	Republican	0.2509%		Prob>|Z|	0.0027***
%Δ in PPI	Democratic	0.3005%	0.1437%	Prob >|t|	0.0795*
	Republican	0.1568%		Prob>|Z|	0.0052***
Unemployment Rate	Democratic	6.7085%	0.7202%	Prob >|t|	0.0001***
	Republican	5.9883%		Prob>|Z|	0.0001***

*This table shows mean difference analysis for the percent change in the Coincident Economic Index (CEI), the percent change in Total Nonfarm Payrolls (TNFP), the percent change in Industrial Production (INDPRO), the percent change in Consumer Price Index (CPI), the percent change in the Producer Price Index (PPI), and the unemployment rate. The last column reports the p-value associated with a two-tailed test for the parametric t-test (Prob >|t|) and the non-parametric Mann-Whitney test (Prob>|Z|) for differences in means. ***, **, and * indicate significance at the 1, 5 and 10 percent levels, respectively. The number of observations in each sample is the same number of months as indicated in Table 1.*

Although the number of months each party controlled the presidency is equal, the number of months the U.S. economy was in a recession is quite unbalanced. As Table 8 illustrates, during the 480 months between 1977 and 2016, inclusive, the National Bureau of Economic Research determined the U.S. economy was in a recession for 56 of those months, or about 11.67% of the time. The economy was in a recession only 5% of the time (12 months) while a Democrat was president as compared to 18.33% of the time (44 months) when a Republican was president. These differences are statistically significant at the 1% level. Thus, recessions occurred significantly more often when Republicans controlled the presidency.

However, the opposite is true when Republicans control the Senate or House. In the case of a Republican controlled Senate, the U.S. economy was in a recession for only 18 months versus 38 months for a Democratic controlled Senate. The difference is even more striking when Republicans control the House, during which the U.S. economy was in a recession for only 8 months versus 48 months for a Democratic House. The differences for the Senate and House are both statistically different at the 1% level. In summary, the economy generally does better with a Democratic President, a Republican Senate, or a Republican House. Up to this point, the impact of Democratic or Republican control of the presidency, the Senate, and the House has been considered in isolation. Tables 9, 10, and 11 examine the pairwise comparisons of all the combinations of the controlling parties of the presidency, the Senate, and the House (PSH). For example, DDD represents those times when Democrats controlled all three while RRD represents the periods when there was a Republican President, a Republican Senate, and a Democratic House. Table 9 lists the number of periods for all the combinations alphabetically. DDD and RDD each account for 20% of the period examined while RDR makes up less than 4%. During the period examined, there was not a time when there was a Democratic President, a Republican Senate, and a Democratic House (DRD).

Table 7: Mean Difference Analysis for Economic Variables by House Political Party

	Party	Mean	Difference		
%Δ in CEI	Democratic	0.1424%	-0.0379%	Prob >|t|	0.1836
	Republican	0.1803%		Prob>|Z|	0.4419
%Δ in TNFP	Democratic	0.1214%	-0.0050%	Prob >|t|	0.7667
	Republican	0.1264%		Prob>|Z|	0.3270
%Δ in INDPRO	Democratic	0.1443%	-0.0468%	Prob >|t|	0.4354
	Republican	0.1911%		Prob>|Z|	0.9404
%Δ in CPI	Democratic	0.3900%	0.2049%	Prob >|t|	0.0001***
	Republican	0.1851%		Prob>|Z|	0.0001***
%Δ in PPI	Democratic	0.3092%	0.1670%	Prob >|t|	0.0447**
	Republican	0.1422%		Prob>|Z|	0.0123**
Unemployment Rate	Democratic	6.9985%	1.3846%	Prob >|t|	0.0001***
	Republican	5.6139%		Prob>|Z|	0.0001***

*This table shows mean difference analysis for the percent change in the Coincident Economic Index (CEI), the percent change in Total Nonfarm Payrolls (TNFP), the percent change in Industrial Production (INDPRO), the percent change in Consumer Price Index (CPI), the percent change in the Producer Price Index (PPI), and the unemployment rate. The last column reports the p-value associated with a two-tailed test for the parametric t-test (Prob >|t|) and the non-parametric Mann-Whitney test (Prob>|Z|) for differences in means. ***, **, and * indicate significance at the 1, 5 and 10 percent levels, respectively. The number of observations in each sample is the same number of months as indicated in Table 1.*

Table 10 details the mean percent growth in the economy using the same measures used earlier: mean GDP growth, measured both as the annualized percent change from the previous quarter and as the percent change from one year prior, the mean percent change in Nonfarm Business Sector Real Output and the mean percent change in Business Sector Real Output. Each PSH combination is listed from largest to smallest mean. The Levels columns indicate if the PSH combinations are statistically significantly different from each other using Tukey's HSD test. Levels connected by the same letter are not significantly different from each other and levels not connected by the same letter are significantly different at the 5% level. For all four measures of economic growth, a Democratic President with a Republican House and Senate (DRR) have the highest mean growth rate while a Republican President with a Democratic House and Republican Senate (RDR) have the lowest average economic growth rate. However, none of the differences in means are statistically significant at the 5% level. It is interesting to note that when the same party controls the presidency, the Senate, and the House, (DDD and RRR), the mean growth rate is ranked somewhere in the middle. By all four measures, the mean growth rate in the economy is slightly higher under RRR compared to DDD, although the differences are not statistically significant. From this, one could anecdotally conclude that some political gridlock is good for economic growth in the United States.

Table 8: Months in Recession

		# of Months in Recession	Mean % of Months in Recession	Difference		
President	Democratic	12	5.00%	(13.33%)	Prob >ChiSqr	0.0001***
	Republican	44	18.33%			
Senate	Democratic	38	14.67%	6.53%	Prob >ChiSqr	0.0266**
	Republican	18	8.14%			
House	Democratic	48	18.18%	14.48%	Prob >ChiSqr	0.0001***
	Republican	8	3.70%			

*This table shows mean difference analysis for the mean percent of months the U.S. economy was in a recession during Democratic and Republican control of the presidency, Senate, and House of Representatives (House) between 1977 and 2016, inclusive. The last column reports the p-value associated with the non-parametric Friedman Rank test (Prob>|ChiSqr|) for differences in means. ***, **, and * indicate significance at the 1, 5 and 10 percent levels, respectively.*

Table 9: Combinations of Parties in Control

	# of Quarters	# of Months
DDD	32	96
DDR	16	48
DRR	32	96
RDD	32	96
RDR	6	19
RRD	24	72
RRR	18	53

This table shows the number of quarters and months for each of the possible combinations of the controlling party of the presidency, the Senate, and the House. For example, RRD represents periods with a Republican President, a Republican Senate, and a Democratic House. Between 1977 – 2016 inclusive, there was not a time when there was a Democratic President, a Republican Senate, and a Democratic House (DRD).

The monthly percent change in the Coincident Economic Index (CEI), Total Nonfarm Payrolls (TNFP), Industrial Production (INDPRO), the Consumer Price Index (CPI), the Producer Price Index (PPI) and the unemployment rate are compared for all PSH combinations in Panel A of Table 11. For both the percent change in the Coincident Economic Index and the Total Nonfarm Payrolls, a Democratic President with a Republican Senate and House (DRR) has the highest (best) mean while a Republican President with a Democratic Senate and a Republican House (RDR) has the lowest (worst).

These differences are significant at the 5% level. When examining Industrial Production, RDR still has the worst growth rate while DDD has the best. However, these differences are not statistically significant. In Panel B of Table 11, the highest (worst) mean inflation rate, as measured by the percent change in the Consumer Price Index and the Producer Price Index, occurred when Democrats controlled the presidency, the Senate, and the House (DDD), while the lowest inflation rates were during the periods with a Republican President, a Democratic Senate, and a Republican House (RDR.) These differences are significant at the 5% level. During the time with a Democrat in the White House and Republicans controlling both chambers of Congress (DRR), the United States had the lowest average unemployment rate (4.8469%) while a Republican President with a Republican Senate and a Democratic House (RRD) had the highest average unemployment rate (8.1042%).

Table 10: Economic Growth and Pairwise Comparison of Party in Control of the Presidency, Senate and House

	Party of Pres/Sen/House	Mean	Level
Qtrly Real GDP, %Δ from Preceding Period	DRR	3.4656%	A
	RRD	3.4417%	A
	RRR	3.0500%	A
	DDD	2.8531%	A
	DDR	2.1625%	A
	RDD	2.0688%	A
	RDR	1.2833%	A
Qtrly Real GDP, %Δ from QTR One Year Ago	DRR	3.6063%	A
	RRD	3.3750%	A
	RRR	3.0889%	A
	DDD	2.4938%	A
	RDD	2.2938%	A
	DDR	2.0438%	A
	RDR	1.2667%	A
%Δ in Nonfarm Business Sector Real Output	DRR	0.9980%	A
	RRD	0.8998%	A
	RRR	0.8621%	A
	DDD	0.8008%	A
	DDR	0.6728%	A
	RDD	0.4718%	A
	RDR	0.2637%	A
%Δ in Business Sector Real Output	DRR	0.9973%	A
	RRD	0.9218%	A
	RRR	0.8482%	A
	DDD	0.7916%	A
	DDR	0.6757%	A
	RDD	0.4757%	A
	RDR	0.2975%	A

This table shows mean difference analysis for GDP growth measured as the annualized percent change from the previous quarter, GDP growth measured as the percent change from one year prior, the percent change in Nonfarm Business Sector Real Output and the percent change in Business Sector Real Output for each of the possible combinations of the controlling party of the presidency, the Senate, and the House. For example, RRD represents periods with a Republican President, a Republican Senate, and a Democratic House. The number of observations in each sample is the same number of quarters as indicated in Table 9. Levels connected by the same letter in the Level column are not significantly different from each other and levels not connected by the same letter are significantly different at the 5% level using the Tukey-Kramer test.

In summary, the economy appears to do best with a Democrat in the White House while Republicans control both the Senate and House (DRR.) A Republican President with Democrats controlling the Senate and Republicans in charge of the House (RDR) seem to be the worst combination for the economy. Table 12 shows the number of months and the mean percent of months the United States was in a recession for each PSH combination, ranked by the mean percent months in a recession. On average, the U.S. economy has been in a recession 11.67% of the time. The greatest percentage of months in a recession occurred with a Republican President, a Democratic Senate, and a Republican House (RDR). This PSH combination accounted for 19 months of the total period examined and the economy was in a recession for 6 of those months, or 31.58% of the time. The period with a Republican President and a Democratic House and Senate (RDD) accounts for the greatest number of months in a recession with 20 out of 96 total months, or 20.83%

of the time. There were no recessions during periods with a Democratic President and Senate with a Republican House (DDR) or a Democratic President with Republicans controlling both the Senate and House (DRR) even though these two PSH combinations made up 144 months, or 30%, of the 40-year period examined. The mean percentage of months in a recession for both RDR and RRD are statistically higher than the mean percentage of months in a recession for DDR and DRR. As demonstrated earlier, the PSH combination of DDR appears to be better for the U.S. economy than RDR.

Table 11 Panel A: Economic Variables and Pairwise Comparison of Party in Control of President, Senate and House

	Party of Pres/Sen/House	Mean	Level		
%Δ in CEI	DRR	0.2337%	A		
	DDR	0.1895%	A	B	
	DDD	0.1806%	A	B	
	RRD	0.1754%	A	B	
	RRR	0.1527%	A	B	
	RDD	0.0794%		B	
	RDR	-0.0363%		B	
%Δ in TNFP	DRR	0.1757%	A		
	DDD	0.1583%	A		
	DDR	0.1470%	A	B	
	RRD	0.1393%	A	B	
	RRR	0.0915%	A	B	
	RDD	0.0710%		B	
	RDR	-0.0775%			C
%Δ in INDPRO	DDD	0.2579%	A		
	DRR	0.2382%	A		
	DDR	0.2160%	A		
	RRR	0.1468%	A		
	RRD	0.1309%	A		
	RDD	0.0407%	A		
	RDR	0.0145%	A		

This table shows mean difference analysis for the percent change in the Coincident Economic Index (CEI), the percent change in Total Nonfarm Payrolls (TNFP), and the percent change in Industrial Production (INDPRO) for each of the possible combinations of the controlling party of the presidency, the Senate, and the House. For example, RRD represents periods with a Republican President, a Republican Senate, and a Democratic House. The number of observations in each sample is the same number of months as indicated in Table 9. Levels connected by the same letter in the Level column are not significantly different from each other and levels not connected by the same letter are significantly different at the 5% level using the Tukey-Kramer test.

Table 11 Panel B: Economic Variables and Pairwise Comparison of Party in Control of President, Senate and House

	Party of Pres/Sen/House	Mean	Level			
%Δ in CPI	DDD	0.5094%	A			
	RRD	0.3465%		B		
	RDD	0.3034%		B	C	
	RRR	0.2388%		B	C	D
	DRR	0.1862%			C	D
	DDR	0.1443%				D
	RDR	0.1323%		B	C	D
%Δ in PPI	DDD	0.5728%	A			
	RRR	0.4313%	A	B		
	RDD	0.2131%	A	B		
	RRD	0.0858%		B		
	DDR	0.0823%		B		
	DRR	0.0702%		B		
	RDR	-0.1489%		B		
Unemployment Rate	RRD	8.1042%	A			
	DDR	7.6313%	A	B		
	DDD	7.2552%		B		
	RDD	5.9125%			C	
	RDR	5.5211%			C	D
	RRR	5.2094%				D
	DRR	4.8469%				D

This table shows mean difference analysis for the percent change in the Consumer Price Index (CPI), the percent change in Produce Price Index (PPI), and the unemployment rate for each of the possible combinations of the controlling party of the presidency, the Senate, and the House. For example, RRD represents periods with a Republican President, a Republican Senate, and a Democratic House. The number of observations in each sample is the same number of months as indicated in Table 9. Levels connected by the same letter in the Level column are not significantly different from each other and levels not connected by the same letter are significantly different at the 5% level using the Tukey-Kramer test.

As an additional analysis, the impact of the political party in control of the presidency, Senate, and House are examined by estimating the multivariate regression model:

$$X_i = \beta_0 + \beta_1 President[D]_i + \beta_2 Senate[D]_i + \beta_3 House[D]_i + \varepsilon_i, \quad (2)$$

where X is the variable of interest, President[D] is set to 1 when the President is a Democrat and 0 otherwise, Senate[D] is set to 1 when the Senate is controlled by the Democrats and 0 otherwise, and House[D] is set to 1 when the House of Representatives is controlled by the Democrats and 0 otherwise. As shown in Table 13, the results are consistent with those found in Tables 2, 3, and 4. Economic growth is statistically weaker when the Senate is controlled by the Democrats, while the political party of the President and House do not appear to have a statistically significant impact on economic growth.

Table 12: Pairwise Comparison of Months in Recession by Party in Control of the Presidency, Senate, and House

	# of Months of Combination of P/S/H	# of Months in Recession	Mean % of Months in Recession	Levels	
RDR	19	6	31.58%	A	
RRD	72	16	22.22%	A	
RDD	96	20	20.83%	A	
DDD	96	12	12.50%	A	B
RRR	53	2	3.77%		B
DDR	48	0	0.00%		B
DRR	96	0	0.00%		B
Total	480	56	11.67%		

This table shows mean difference analysis for the mean percent of months the U.S. economy was in a recession for each of the possible combinations of the controlling party of the presidency, the Senate, and the House. For example, RRD represents periods with a Republican President, a Republican Senate, and a Democratic House. Levels connected by the same letter in the Level column are not significantly different from each other and levels not connected by the same letter are significantly different at the 5% level using the Tukey-Kramer test.

The results in Table 14 are similar to those found in Tables 5, 6, and 7. The percent change in the Coincident Economic Index, the percent change in Total Nonfarm Payrolls, and the percent change in Industrial Production are each statistically greater under Democratic Presidents while the CEI, and TNFP are statistically lower under Democratic Senates. The party in charge of the House does not appear to have a significant impact on the change in these variables. Table 14 also contains evidence that inflation and unemployment are generally higher under Democratic Presidencies and Democratic Houses, while the political party in charge of the Senate does not appear to have a significant impact on these variables.
Table 15 reports the results of logistic regression model:

$$\text{Recession Indicator}_i = \beta_0 + \beta_1\text{President[D]}_i + \beta_2\text{Senate[D]}_i + \beta_3\text{House[D]}_i + \varepsilon_i, \quad (3)$$

where the Recession Indicator is 1 for months when the U.S. economy is in a recession and 0 otherwise. President[D] is 1 when the President is a Democrat and 0 otherwise, Senate[D] is 1 when the Senate is controlled by Democrats and 0 otherwise, and House[D] is 1 when Democrats control the House of Representatives and 0 otherwise. The economy appears to be less likely to be in a recession when a Democrat is President but more likely to be in a recession when Democrats control the House. The results are consistent with those of Table 12, which showed that during the 40-year period examined, a Democrat was President for all the months the economy was not in a recession. However, Table 12 also showed that Democrats controlled the House for 48 of the 56 months the economy was in a recession.

Table 13: Regression Results for Economic Growth on President, Senate, and House Political Party

Dependent Variable (X_i)	Independent Variables	Coefficient	Prob >|t|
Qtrly Real GDP, %Δ from Preceding Period	Intercept (β_0)	0.0280	0.0001***
	President[D] (β_1)	0.0034	0.2059
	Senate[D] (β_2)	-0.0062	0.0321**
	House[D] (β_3)	0.0030	0.3136
Qtrly Real GDP, %Δ from Qtr One Year Ago	Intercept (β_0)	0.0279	0.0001***
	President[D] (β_1)	0.0023	0.1986
	Senate[D] (β_2)	-0.0065	0.0008***
	House[D] (β_3)	0.0022	0.2564
%Δ in Nonfarm Business Sector Real Output	Intercept (β_0)	0.0077	0.0001***
	President[D] (β_1)	0.0014	0.1241
	Senate[D] (β_2)	-0.0018	0.0586**
	House[D] (β_3)	0.0006	0.5386
%Δ in Business Sector Real Output	Intercept (β_0)	0.0077	0.0001***
	President[D] (β_1)	0.0013	0.1299
	Senate[D] (β_2)	-0.0018	0.0501*
	House[D] (β_3)	0.0006	0.5151

*This table shows regression results based on equation (2). President[D]is 1 when the President is a Democrat and 0 otherwise, Senate[D] is 1 when the Senate is controlled by Democrats and 0 otherwise, and House[D] is 1 when Democrats control the House of Representatives and 0 otherwise. The last column reports the p-value. ***, **, and * indicate significance at the 1, 5 and 10 percent levels, respectively. The number of observations in each regression is the same number of quarters as indicated in Table 1.*

Table 14: Regression Results for Economic Variables on President, Senate, and House Political Party

Dependent Variable (X_i)	Independent Variables	Coefficient	Prob >|T|
%Δ in CEI	Intercept (β_0)	0.0016	0.0001***
	President[D] (β_1)	0.0006	0.0006***
	Senate[D] (β_2)	-0.0005	0.005***
	House[D] (β_3)	0.0002	0.3178
%Δ in TNFP	Intercept (β_0)	0.0012	0.0001***
	President[D] (β_1)	0.0005	0.0001***
	Senate[D] (β_2)	-0.0004	0.0002***
	House[D] (β_3)	0.0003	0.0057
%Δ in INPRO	Intercept (β_0)	0.0017	0.0001***
	President[D] (β_1)	0.0008	0.0128**
	Senate[D] (β_2)	-0.0003	0.3784
	House[D] (β_3)	0.0002	0.6800
%Δ in CPI	Intercept (β_0)	0.0029	0.0001***
	President[D] (β_1)	0.0005	0.0019***
	Senate[D] (β_2)	-0.0001	0.4055
	House[D] (β_3)	0.0012	0.0001***
%Δ in PPI	Intercept (β_0)	0.0022	0.0001***
	President[D] (β_1)	0.0007	0.1458
	Senate[D] (β_2)	0.0002	0.6868
	House[D] (β_3)	0.0010	0.0551*
Unemployment Rate	Intercept (β_0)	0.0630	0.0001***
	President[D] (β_1)	0.0022	0.0021***
	Senate[D] (β_2)	0.0001	0.8499
	House[D] (β_3)	0.0075	0.0001***

*This table shows regression results based on equation (2). President[D]is a dummy variable of 1 when the President is a Democrat and 0 otherwise, Senate[D] is 1 when the Senate is controlled by Democrats and 0 otherwise, and House[D] is 1 when Democrats control the House of Representatives and 0 otherwise. The last column reports the p-value. ***, **, and * indicate significance at the 1, 5 and 10 percent levels, respectively. The number of observations in each regression is the same number of months as indicated in Table 1.*

The above analysis is limited in some ways. One limitation is due to policy lags. Each first term president inherits the economy of their predecessor. Any policy changes a new president implements to affect the economy may take time to have an impact. Thus, it is difficult to disentangle the lingering impact of the previous administration's economic policies from the effects of the policies of the new administration. For example, President Obama took office while the economy was in a recession. According to the NBER, the recession officially ended 6 months later in June 2009. Did the recession end due to President Obama's economic policies? Or would the recession have ended anyway because of policies put in place during the George W. Bush administration? Or did the policies of both administrations help stabilize the economy? It is impossible to truly know. Another limitation is due to the issue of data synchronization. The economic data used in this study are either month- or quarter-end. However, every four years a President's term typically begins on January 20th. Thus, economic results for the first month of a president's term are "credited" to the political affiliation of the person taking office on January 20th. This is less of an issue in the Senate and House as both generally begin their terms on January 3rd every other year.

CONCLUDING COMMENTS

Earlier studies have examined the relationship between the President's political party and the performance of financial and economic variables. Some have also examined the impact of having the same political party controlling the presidency, the Senate, and the House of Representatives. This paper extends the current literature by examining the impact of all combinations of the political party in control of the White House and both chambers of Congress. Past economic growth is not significantly different under Republican and Democratic presidential administrations. Nor does the party that controls the House of Representatives appear to have a significant impact on economic growth. However, growth has been strongest when Republicans control the Senate.

Table 15: Logistic Regression Results for Recession Indicator on President, Senate, and House Political Party

Dependent Variable (X_i)	Independent Variables	Coefficient	Prob >|T|
Recession Indicator	Intercept (β_0)	-2.5149	0.0001***
	President[D] (β_1)	-0.6379	0.0005***
	Senate[D] (β_2)	0.2501	0.1392
	House[D] (β_3)	0.6298	0.0029***

*This table shows regression results based on equation (2). The Recession Indicator is 1 for months when the U.S. economy is in a recession and 0 otherwise. President[D]is a dummy variable of 1 when the President is a Democrat and 0 otherwise, Senate[D] is 1 when the Senate is controlled by Democrats and 0 otherwise, and House[D] is 1 when Democrats control the House of Representatives and 0 otherwise. The last column reports the p-value. ***, **, and * indicate significance at the 1, 5 and 10 percent levels, respectively. The number of observations in each regression is the same number of months as indicated in Table 1.*

Other economic measures, such as the Coincident Economic Index, Total Nonfarm Payrolls, and Industrial Production grow faster under Democratic Presidents while higher inflation and unemployment are observed when Democrats control the Senate or House. Republicans occupy the White House during a significantly greater number of months when the economy is in a recession. The same is true when Democrats have a majority in the Senate or House of Representatives. The U.S. economy has the strongest performance under the combination of a Democratic President with a Republican controlled Senate and House of Representatives. During the months this combination was in power, the United States did not experience a recession. At the other extreme, economic performance is generally the poorest under a Republican President with a Senate controlled by the Democrats and a House controlled by Republicans. When the same party controls the presidency, the Senate, and the House, the economic results are average. It can be concluded that certain types of political gridlock are beneficial to the U.S. economy. As discussed previously, this study has some limitations due to data synchronization issues and policy lags. Future research could address these issues. Future research can also examine the impact of the degree of control in the Senate and House. For example, during the 95th Congress (1977 – 1979), the Senate was split between 61 Democrats, 38 Republicans, and 1 Independent that caucused with the Democrats. This level of control may have a different impact on economic growth than when the Senate is more closely split, like the 115th Congress (2017-2019) when Republicans in the Senate held 51 seats. Finally, although much research has been done on the impact of the political party of the President on financial market returns, few have looked at the role of Congress. Previous studies that have generally treat Congress as a single entity rather than two distinct chambers. None appear to have taken the approach in this study and examined all the combinations of the political parties in control of the White House, the Senate, and the House and the impact of those combinations on various financial market returns in the U.S.

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MOMENTUM MARKET STATES AND CAPITAL STRUCTURE ADJUSTMENT SPEED

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ABSTRACT

It is well established in the momentum literature that market states affect momentum profit. Moreover, the market state variables employed in the momentum literature are distinctive in that they are constructed to be ex-ante observable by the investor. This study shows that these momentum market state variables also significantly affect a company's capital structure adjustment speed. Our results provide a plausible explanation of how the momentum market state variables lead to momentum profit by affecting the capital structure. Additional findings show that low leveraged firms adjust their leverage toward target capital structure faster than high leveraged firms. We also show that producer linked variables such as total industry capacity utilization and producer price index significantly affect capital structure adjustment speeds, more so than standard macroeconomic variables.

JEL: G30, G32

KEYWORDS: Momentum, Market State Indicators, Dynamic Capital Structure, Speed of Adjustment, Macroeconomic Conditions, Industry Capacity Utilization, Producer Price Index

INTRODUCTION

In the momentum literature, it is well established that past market states affect momentum profit. Examples of research documenting the relationship between momentum profits and market states. Cooper et al., (2004) provide the seminal paper concerning this effect. The authors show that momentum profits depend on the past market state where the mean monthly momentum profit following the UP market state is 0.93%, but the mean profit following the DOWN market state is -0.37%. Moreover, their results are robust to the conditioning information in macroeconomic factors.

Asem and Tian (2010) study the effects of market transitions on momentum profits following both UP and DOWN market states. They found that when the market state changes to the opposite in successive market conditions, there will be large momentum profits (gain or loss). Li and Galvani (2018) show that momentum profits for corporate bonds also depend on the market state. They find that for corporate bonds, momentum gains exclusively follow UP market state periods; in contrast, DOWN market states predict momentum losses. Huang (2006) examines the effect of past market states on momentum profits in an international context. He defined three different periods. In these periods, market return is non-negative (negative), then the market state is defined as UP (DOWN). His results show that for international data, momentum profits associate with the UP market. His study confirms, using international data, the notion that different momentum profits are associated with specific values of the market state indicator.

What is notable concerning this strand of momentum research is that the market state indicator variable used in these studies is constructed to be observable ex-ante by the investor. Cooper et al., (2004), for example, defined the UP market state as when the previous three-year market return is non-negative, and the DOWN market state as when the previous three-year market return is negative. Thus, the investor at any particular time t can observe whether he currently belongs in the UP or DOWN market state using this type of market state indicator variable specification.

The studies described above are only representative. There are now a large number of studies documenting that the returns of applying the momentum strategy on assets such as stocks and corporate bonds are state-dependent and predictable ex-ante by these types of UP, DOWN ex-ante market state indicator variables. Less is known on the effect of time variations of these momentum market states indicators on capital structure dynamics. The present study aims to fill this gap by applying the momentum market states indicators to investigate their effects on capital structure dynamics. The hypothesis is that corporate decision-makers, like investors, can also observe and make use of these ex-ante market state indicators, and this information can influence their capital structure decisions moving forward.

Our main contribution is to show that capital structure adjustment speed is considerably state-dependent, that these momentum market state variables significantly affect a company's capital structure adjustment speed. That capital structure adjustment speed is state-dependent on observable past market states is consistent with an adapted version of the behavioral theory by Daniel et al. (1998) in that aggregate market gains can induce manager overconfidence and therefore influence their capital structure decisions. Given the variety of market state indicators applied in the existing momentum literature, a market-state effect on capital structure is also consistent with the bounded rationality theory by Hong and Stein (1999), where heterogeneity in the types of information structure available to decision-makers yields gradual information diffusion.

In as much as capital structure affects a company's value, our results provide a plausible pathway of how the momentum market state variables can lead to momentum profit by first affecting a company's capital structure. The remainder of the paper is organized as follows. In the following section, we describe the relevant literature. Next, we discuss the methodology and model. This is followed by a description of the data source. Statistical analysis is presented in the test results section. The results are presented in the following section. The paper closes with some concluding comments and suggestions for future research.

LITERATURE REVIEW

The well-known MM theory holds that the value of the company has nothing to do with the capital structure but makes strong assumptions such as the absence of taxes and transaction costs (Modigliani and Miller, 1958). Subsequent research suggests the idea of joining corporate tax, personal tax, and trade-off theory. The modified MM theory describes a tax-based model that allows capital structure decisions to influence company value. When considering corporate income tax, since the interest of the liability can offset the tax expenditure, the capital cost can be reduced, and the value of the enterprise can be increased. Therefore, as long as the company's financial leverage benefits continue to increase, the company will continue to reduce its capital cost.

According to Modigliani and Miller (1963), the more liabilities, the more obvious the leverage, the higher the company's value. Kraus and Litzenberger (1973) describe a trade-off model in which companies can use debt spending to offset taxes, and companies increase their value by increasing debt. However, as the debt rises, the possibility of a company falling into financial crisis increases, and may even lead to bankruptcy. If the company goes bankrupt, bankruptcy costs will inevitably occur. It will bring additional costs to the enterprise.

According to the trade-off theory, the value of a liability enterprise equals the value of a debt-free enterprise plus tax-saving benefits, minus the present value of the expected financial constraints cost. There also exist many empirical studies showing a relation between capital structure and profitability. The studies by Roden and Lewellen (1995), Ghosh et al. (2000), Abor (2005) and Berger and Bonaccorsi di Patti (2006) are examples of research that show capital structure to be correlated with profitability.

More recently, Danis et al. (2014) propose a relationship between profitability and capital structure when firms are at or near their optimal leverage. In short, the empirical literature shows that the capital structure decision is a relevant factor explaining value created to shareholders, thus providing a link between momentum market states, firms' capital structure adjustment decisions, and momentum strategy return. This study extends the literature by analyzing the relationship between past market states and capital structure adjustment speeds, whether the ex-ante market state variables used in the momentum literature are useful in further delineating capital structure adjustment speed.

Our results support our hypothesis. We find that the capital structure adjustment speed associated with the UP market states exceeds its corresponding adjustment speed in the DOWN market states, the difference statistically significant. This study also performs analysis on the variables that can affect a company's capital structure adjustment speed. Past research on capital structure shows that firm characteristics relate to leverage ratios (e.g., Rajan and Zingales, 1995; Graham, 1996; Hovakimian et al., 2001; Harford et al., 2008). Studies have also shown that companies tend to revert faster toward the target leverage during good economic periods (e.g., Korajczyk and Levy, 2003).

There is also evidence that companies revert to a target capital structure after perturbations (e.g., Fama and French, 2002; Leary and Roberts, 2005; Flannery and Rangan, 2006; Kayhan and Titman, 2007). Researchers have also explored whether capital structure might be affected by macroeconomic conditions. Their research analyzed leverage variation under different macroeconomic conditions (e.g., Fama and French, 1989; Hackbarth et al., 2006; Levy and Hennessy, 2007).

None of these studies, however, analyze the effect of the observable ex-ante momentum market states on capital structure behavior. When the general macroeconomic conditions improve, not all industries or companies will experience better profitability at the same time, and be willing to change the company's capital structure. These studies mainly focused on the analysis of the traditional theory of capital structure but ignored the impact of the market environment on the adjustment speed of capital structure. The results of these studies show that "standard macroeconomic factors" (such as Gross Domestic Product, GDP) can have an impact on the capital structure.

Other plausible variables that can affect the company's capital structure such as Earnings Per Share (EPS) or Book to Market ratio (BM), industry characteristics such as total industry capacity utilization (TCU) and producer price index (PPI) have been largely ignored. A prominent study is Franz and Gordon (1993), and Garner (1994) provides evidence showing that the relationship between capacity utilization and inflation is stable and that capacity utilization remains a reliable indicator of future changes in inflation.

This study hypothesizes that variables such as TCU and PPI by their construction have a closer relationship with producers than the other more commonly used macroeconomic variables and thus, should also be useful in describing capital structure adjustment speed. According to the Federal Reserve Bank, "PPI is an index that characterizes the average change in selling prices from production over time. It measures price movements from the company's point of view. In other words, this index tracks changes in the costs of production for the company" (Board of Governors of Federal Reserve, 2019). The other index, "TCU represents the percentage of resources used by firms to produce goods in manufacturing, mining, and utilities. The index can be thought of as how much capacity is being used from the total available capacity to produce demanded finished products. The capacity utilization rate can describe how efficiently the factors of production (inputs in the production process) are being used" (Board of Governors of Federal Reserve, 2019).

It can be seen by the above definitions, compared to standard macroeconomic variables that have been used in the existing capital structure research; PPI and TCU, by construction, are more forward-looking and tied more closely to the actualities facing the producer. Rather than basing their capital structure decisions on measures of general economic conditions, managers may choose to make use of the information conveyed by PPI and TCU in deciding whether to adjust their company's capital structure. Also, when the input price of a manufacturer rises, this information is captured by the PPI.

In this scenario, the company will spend more on production costs, but the price of the products will also rise and, thus, increase profits. In this way, the company gains more profits and can pay off its liabilities, and managers may decide to adjust its capital structure to optimize the situation. Our results support our hypothesis and give evidence showing that TCU and PPI are indeed useful in explaining capital structure adjustment speeds.

EMPIRICAL METHODOLOGY AND MODEL

Definitions of Leverage

This paper focuses on describing changes in the capital structure. In the capital structure literature, some studies use book leverage while others use market leverage ratios. Fama and French (2002) and Thies and Klock (1992), for example, argue that book leverage should be used because book leverage ratios are independent of factors that are not under the direct control of firms. Welch (2004), on the other hand, argues that market leverage can better reflect possible agency problems between equity holders and creditors. For this study, we use both the book leverage and market leverage to do our tests and define these variables as in previous studies (e.g., Leary and Roberts, 2005; Flannery and Rangan, 2006; Cook and Tang, 2010). Precisely, the book leverage ratio is defined as:

$$BD_{i,t} = \frac{SD_{i,t}}{TA_{i,t}} \tag{1}$$

Alternatively, the market leverage ratio is defined as:

$$MD_{i,t} = \frac{(LD_{i,t} + SD_{i,t})}{(S_{i,t} * P_{i,t} + LD_{i,t} + SD_{i,t})} \tag{2}$$

$LD_{i,t} + SD_{i,t}$ denotes the sum of firm i's long- and short-term book value of interest-bearing debt at time t, $TA_{i,t}$ is the book value of the total assets. $S_{i,t} * P_{i,t}$ represents the number of common shares outstanding times the stock price per share at time t, which is equal to the market value of firm i's equity.

Dynamic Partial Adjustment Capital Structure Model

The recent literature discusses two main types of partial adjustment models, the two-stage partial adjustment model and the integrated dynamic partial adjustment capital structure model (Hovakimian et al., 2001; Flannery and Rangan, 2006; and Cook and Tang, 2010). The equations for the two-stage partial adjustment model are as follows:

Stage1:

$$D_{i,t}^{*} = \gamma Macro_{t-1} + \beta X_{i,t-1} \tag{3}$$

Stage 2:

$$D_{i,t} - D_{i,t-1} = \delta\left(D^{*}_{i,t} - D_{i,t-1}\right) + \varepsilon_{i,t} \tag{4}$$

In Stage1, it defines $D_{i,t}{}^{*}$as target leverage, which is a function of prior period macroeconomic variables and firm characteristic variables. It measures how quickly the company adjusts back toward target leverage from a position of deviation from its target leverage in Stage 2.

According to Flannery and Rangan (2006), the partial adjustment speed (the coefficient of the target leverage of the first stage regressions) is substantially smaller than predicted by theory. They advocated the use of the one-stage integrated dynamic partial adjustment capital structure model that includes the partial adjustment and firm fixed effects in one integrated capital structure model. Cook and Tang (2010) follow Flannery and Rangan (2006) and use the one-stage integrated dynamic partial adjustment capital structure model in their estimations of the impact of macroeconomic conditions on the capital structure adjustment speed.

In this study, we follow the framework of Flannery and Rangan (2006) and Cook and Tang (2010) and combine the partial adjustment and firm fixed effects into an integrated capital structure model in the calculation of the impact of macroeconomic conditions on capital structure adjustment speed. To do so, we substituting Stage1 for Stage 2 and rearrange, resulting in the following:

$$D_{i,t} = (1-\delta)D_{i,t-1} + \delta\beta X_{i,t-1} + \delta\gamma Macro_{t-1} + \varepsilon_{i,t} \tag{5}$$

$D_{i,t}$, and $D_{i,t-1}$ represent leverage for firm i in period's t and t−1, and δ represents the proportion of leverage deviation away from the firm's next period target leverage made by the firm from time t−1 to time t. δ=1 indicates that the firm fully adjusts for any deviation away from its target leverage. In the presence of adjustment costs, as in this study, we expect δ to be less than 1. We estimate capital structure adjustment using this equation across favorable and unfavorable macroeconomic conditions.

Macroeconomic Conditions and Market States

This study used the macroeconomic variables of term spread, default spread, GDP growth rate, and market dividend yield. Term spread is the difference between the 10-year Treasury-bill rate series and the 3-month g bond yield rate series. Default spread is the difference between the average yield of bonds rated Baa and the average yield of bonds rated AAA, each rated by Moody's based on bonds with maturities 20 years and above. GDP growth rate is the real GDP quarterly growth rate. Real interest rate is obtained from DataStream. It is the lending interest rate adjusted for inflation as measured by the GDP deflator.

In addition to the four macroeconomic indicators, we added three additional indicators; namely, NYSE stock index returns, TCU and PPI. We use the rolling windows calculation method to calculate the stock price index return beginning from 1987 Q1, and every five years as a cycle. We obtain the data for TCU and PPI from FRED. The PPI is the Producer Price Index for All Commodities (the value of the Index in 1982 is set equal to 100). TCU is the Total Industry Capacity Utilization, which refers to the percentage of resources used use for manufacturing, mining, and electric and gas utilities for all facilities located in the United States.

Cooper et al., (2004) and Asem and Tian (2010) examine whether conditioning on the state of the market is important to the profitability of momentum strategies. They define two market states: “UP” and “DOWN,” based only information that an investor can observe in the current time and does not require the assumption that the investor can look into the future and see information that is unknown in the present moment.

In this study, we employ ex-ante versions of macroeconomic market state variables. Specifically: "UP" is when the past 12-month Center for Research in Security Prices (CRSP) value-weighted (VW) return is nonnegative, and "DOWN" is when the past 12-month CRSP VW return is negative. For robustness, we also use the Quantile method to distinguish leverage into ten quantiles for both book-leverage and market-leverage. The quantile regression methodology allows us to examine what magnitude of leverage (book and market) is most sensitive to the economic boom.

DATA DESCRIPTION

We obtain the primary data from DataStream over the period 1986 Q1 to 2012 Q4. In the estimations, we employ moving windows of 60 quarters, so that the first actual equation that can be estimated starts from 1992 Q1 and the last is in 2012 Q4, a total of 80 quarters. There are 39,186 records per quarter. Following earlier related studies, we exclude financial firms and utilities from the sample because they are usually regulated, and unique factors might need to be considered in their capital structure decisions. To minimize possible bias in the estimations, our sample did not exclude companies that went bankrupt or became private companies during our sample period.

For the stock price index variable, we use the NYSE stock index from 1986 Q1 to 2012 Q4 and calculate quarterly stock index returns using the previous five years of data. We retrieve the stock price index from 1992 Q1 to 2012 Q4 to match the sample period. We determine whether the market situation is good or bad using each of the macroeconomic variables discussed previously; the decision rule being the economy is categorized as good (bad) if the indicator variable exhibits three consecutive quarters of growth.

Following the literature, we incorporate several company-specific characteristic variables that influence leverage into our estimation model (e.g., Rajan and Zingales, 1995; Hovakimian et al., 2001; Fama and French, 2002; Flannery and Rangan, 2006). These variables include EBIT (Earnings Before Interest and Tax), BM ratio (ratio of the book value of equity to the market value of equity), EPS (earnings per share), TA (total assets), DY (dividend yield), and AD (accumulated depreciation).

EMPIRICAL RESULTS

Summary Statistics

Table 1 provides the summary statistics for default spread, term spread, change in GDP (percentage change), real interest rate, NYSE index value, PPI, and TCU over the sample period, 1987 Q1 to 2012Q4. Such as, the average value for the default spread is 0.99 and its standard deviation is 0.409. In our estimations, the NYSE stock price index data span from 1992 Q1 to 2012 Q4 which corresponds to 84 quarters. We use the formula $\text{return} = \ln(\text{index}_t / \text{index}_{t-1})$ to calculate the stock index returns. Negative returns are concentrated near 2001Q1 ~ 2003Q2 following dot-com bubble of 2000 and the financial crisis in 2008 to 2009.

Table 1: Descriptive Statistics of the Economic Variables Used in the Estimations (1992/Q1-2012/Q4)

	Default Spread	**Term Spread**	**GDP Change**	**Real Interest**	**NYSE**	**PPI**	**TCU**
max	3.370	3.776	0.622	6.920	9903.855	203.800	85.000
min	0.560	-0.625	-0.606	0.505	1513.357	100.900	67.100
median	0.910	1.811	-0.031	4.741	5725.429	128.700	80.550
avg.	0.990	1.835	0.043	4.310	5176.181	141.132	79.737
std.	0.409	1.153	0.307	1.985	463.261	29.208	3.892

This table provides the summary statistics for default spread, term spread, change in GDP (percentage change), real interest rate, NYSE index value, PPI, and TCU over the sample period, 1987 Q1 to 2012Q4. Default spread is the difference between the average yield of bonds rated Baa and the average yield of bonds rated AAA. Term spread is the difference between the 10-year Treasury-bill rate series and the 3-month g bond yield rate series. GDP change is the real GDP quarterly growth rate. Real interest rate is obtained from DataStream. It is the lending interest rate adjusted for inflation as measured by the GDP deflator. NYSE is NYSE stock index returns. We obtain the data for TCU and PPI from FRED. The PPI is the Producer Price Index for All Commodities. TCU is the Total Industry Capacity Utilization.

Analysis of Adjustment Speed

Table 2 shows the computed adjustment speed of capital structure estimated by the integrated dynamic partial adjustment capital structure model using each of the seven macroeconomic variables, using quarterly data. Panel 2A gives the results for book-leverage, we find that the average value of δ estimated using TCU is the largest. Panel 2B presents the results for market-leverage. The results show that the computed δ's for all macroeconomic variables is significantly smaller than those calculated from book-leverage. However, similar to the results for book-leverage, the average computed δ for TCU is the largest.

Table 2: The Computed Adjustment Speed of Capital Structure Estimated by the Integrated Dynamic Partial Adjustment Capital Structure Model from Each of the Seven Macroeconomic Variables Using Quarterly Data

Variables	**Default Spread**	**Term Spread**	**GDP Change**	**Real Interest**	**NYSE**	**PPI**	**TCU**
Panel 2A: Book-Leverage							
max	0.9622	0.9566	0.9520	0.9624	0.9638	0.9637	0.9639
min	0.0012	0.0012	0.0012	0.0012	0.0012	0.0012	0.0012
median	0.2393	0.2300	0.2294	0.2388	0.2383	0.2447	0.2475
avg.	0.2726	0.2607	0.2428	0.2728	0.2753	0.2772	0.2774
std.	0.1578	0.1629	0.1741	0.1570	0.1570	0.1560	0.1560
p-value	<0.0001***	<0.0001***	<0.0001***	<0.0001***	<0.0001***	<0.0001***	<0.0001***
Panel 2B: Market-Leverage							
max	0.0482	0.0336	0.0525	0.0575	0.0563	0.0536	0.0482
min	0.0062	0.0006	0.0102	0.0156	0.0259	0.0211	0.0062
median	0.0224	0.0126	0.0366	0.0347	0.0371	0.0373	0.0224
avg.	0.0225	0.0149	0.0349	0.0355	0.0382	0.0383	0.0225
std.	0.0098	0.0077	0.0082	0.0088	0.0076	0.0076	0.0098
p-value	<0.0001***	<0.0001***	<0.0001***	<0.0001***	<0.0001***	<0.0001***	<0.0001***

We compile all the variables into quarterly data and calculate the speed of capital-structure adjustment coefficient δ for each quarter from 1992Q1 to 2012Q4. Panel A gives the results for book-leverage, and Panel B presents the corresponding results for market-leverage. The estimated p-values of all variables are significant at the 1% level. We define all variables in the note of the table 1 and in the text of the document.

Table 3 shows the computed values for δ after controlling for market states. Panel 3A presents the results for book-leverage. The panel shows that when the market state is "good," the computed δ from PPI is the highest. The table also presents the p-values for testing whether the δ's calculated for the "good" market states are significantly different from the δ's estimated for the "bad" market states. For PPI, the δ calculated in the good market states exceeds its value for the bad market states by 0.0495 with a p-value less than 0.0001, showing that the difference is statistically significant.

Panel 3B presents the results for market-leverage. Here when the market state is good, the average δ of the TCU regressions is the highest. The average δ associated with bad market states are also shown in the table. For the TCU regressions, the average δ in the good market states exceeds the corresponding average δ in the bad market states by 0.0029. All of the reported p-values are statistically significant.

Table 3: Estimated Values for δ After Controlling for Market States

Variables	**Default Spread**		**Term Spread**		**GDP Change**		**Real Interest**		**NYSE**		**PPI**		**TCU**	
States	**Good**	**Bad**	**Good**	**Bad**	**Good**	**Bad**	**Good**	**Bad**	**Good**	**Bad**	**Good**	**Bad**	**Good**	**Bad**
Panel 3A: Book-Leverage														
max	0.9622	0.5750	0.9566	0.5711	0.3972	0.4944	0.5749	0.5165	0.9638	0.3534	0.9637	0.5539	0.9639	0.3710
min	0.0023	0.0012	0.0603	0.0012	0.0731	0.0012	0.0012	0.1136	0.0832	0.0023	0.0608	0.0012	0.0608	0.0023
avg.	0.2912	0.2640	0.2596	0.2568	0.2457	0.1717	0.2529	0.2322	0.2708	0.2703	0.2928	0.2433	0.2879	0.2346
G vs. B	0.0272		0.0028		0.0740		0.0206		0.0005		0.0495		0.0533	
p-value	<0.0001***		<0.0001***		<0.0001***		<0.0001***		<0.0001***		<0.0001***		<0.0001***	
Panel 3B: Market-Leverage														
max	0.0525	0.0476	0.0398	0.0377	0.0244	0.0284	0.0525	0.0508	0.0506	0.0443	0.0563	0.0524	0.0532	0.0536
min	0.0125	0.0142	0.0073	0.0062	0.0046	0.0006	0.0174	0.0102	0.0254	0.0226	0.0273	0.0259	0.0288	0.0211
avg	0.0322	0.0305	0.0223	0.0209	0.0131	0.0153	0.0366	0.0325	0.0358	0.0338	0.0392	0.0370	0.0398	0.0369
G vs. B	0.0017		0.0014		-0.0022		0.0041		0.0020		0.0022		0.0029	
p-value	<0.0001***		<0.0001***		<0.0001***		<0.0001***		<0.0001***		<0.0001***		<0.0001***	

This table presents the estimated values for δ under different market states. The market state indicators are constructed following the ideas presented in Cooper, Gutierrez, and Hameed (2004) and Asem and Tian (2010). Panel A presents the results for book-leverage. Panel B gives the results for market-leverage. The p-values shown test whether the δ's calculated for the "good" market states are significantly different from the δ's estimated for the "bad" market states. We define all variables in the note of the table 1 and in the text of the document. G vs. B means the δ of good state minus the δ of bad state. G denotes good state, and B denotes bad state.

For all of the macroeconomic variables, the average δ is higher during good market states and lower during bad market states. The only exception is the results for GDP_change, where they are reversed. This estimate, however, only provides a preliminary picture of the overall behavior of δ and does show the effect of the magnitude (size) of leverage on the relation between the macroeconomic variables and the adjustment speed parameter δ. To model the impact of the size of leverage on δ, we use the quantile regression method and partition the dataset into ten quantiles according to the size of leverage.

The results show that the capital structure adjustment speed associated with the UP market states exceeds its corresponding adjustment speed in the DOWN market states, and the difference is statistically significant. The results also show that producer linked variables such as TCU and PPI significantly affects capital structure adjustment speeds, more so than standard macroeconomic variables.

Table 4 shows the results of the quantile regressions. The results show that the average adjustment speed of the capital structure decreases with the increase in leverage and changes from a positive to a negative number as we go from the least leveraged quantile (10%) to the most leveraged quantile (90%). Regardless of whether it is book-leverage or market leverage, the average capital structure adjustment speed is significantly faster in the 10% quantile than in the 90% quantile where it becomes negative.

For the 10% book-leverage quantile, the δ for TCU is the fastest, followed by δ for PPI. The results for market-leverage is different. For the 10% market-leverage quantile, the δ for GDP change is the fastest, followed by δ for term spread. The results suggest that companies with higher leverage appear to have more difficulty in adjusting their capital structure compared to companies with low amounts of leverage. We find that the firms' capital structure adjustment speed is faster for firms' with low leverage and slower for firms with high leverage.

Table 4: Estimated Values for δ Using Quantile Regressions

Variables	**Default Spread**		**Term Spread**		**GDP Change**		**Real Interest**		**NYSE**		**PPI**		**TCU**	
quantile	**10%**	**90%**	**10%**	**90%**	**10%**	**90%**	**10%**	**90%**	**10%**	**90%**	**10%**	**90%**	**10%**	**90%**
Panel 4A: Book-Leverage														
avg.	0.3881	-0.0762	0.3630	-0.0818	0.3266	-0.0841	0.3832	-0.0814	0.3898	-0.0798	0.3946	-0.0787	0.3956	-0.0789
std.	0.2559	0.1603	0.2486	0.1641	0.2387	0.1454	0.2591	0.1591	0.2598	0.1704	0.2601	0.1713	0.2603	0.1714
10% vs. 90%	0.4644		0.4448		0.4107		0.4646		0.4695		0.4733		0.4745	
p-value	<0.0001***		<0.0001***		<0.0001***		<0.0001***		<0.0001***		<0.0001***		<0.0001***	
Panel 4B: Market-Leverage														
avg.	0.1277	-0.0441	0.1488	-0.1067	0.1639	-0.1465	0.1371	-0.0519	0.1321	-0.0449	0.1298	-0.0319	0.1303	-0.0321
std.	0.0244	0.0238	0.0242	0.0316	0.0218	0.0349	0.0268	0.0370	0.0246	0.0236	0.0239	0.0140	0.0236	0.0184
10% vs. 90%	0.1718		0.2555		0.3104		0.1890		0.1770		0.1617		0.1624	
p-value	<0.0001***		<0.0001***		<0.0001***		<0.0001***		<0.0001***		<0.0001***		<0.0001***	

In this table, we divide the leverage into ten quantiles from small to large. 10% denotes the least leveraged quantile, and 90% indicates the most leveraged quantile. The p-value tests for whether the average δ estimated from the least leveraged quantile is significantly different from the average δ estimated from the most leveraged quantile. Panel A presents the results for book-leverage. Panel B shows the results for market-leverage. We define all variables in the note of the table 1 and in the text of the document.

Table 5 compares whether the δ's estimated from low leverage quantile firms (least leveraged 10% quantile) are significantly different from other firms not in this quantile. The results in this table show this to be true. Regardless of whether it is book-leverage or market-leverage, the δ for low leverage quantile firms are significantly larger than the δ for firms not included in this quantile. In sum, we can conclude that companies with low levels of leverage can respond more quickly to changes in the economic environment and adjust their capital structure.

Table 5: Comparison of Whether the δ's Estimated from the Least Leveraged 10% Quantile Firms Are Significantly Different from Other Firms Not in this Quantile

Variables	**Default Spread**		**Treasure Spread**		**GDP Change**		**Real Interest**		**NYSE**		**PPI**		**TCU**	
quantile	**non-**	**10%**	**non-**	**10%**	**non-**	**10%**	**non-**	**10%**	**non-**	**10%**	**non-**	**10%**	**non-**	**10%**
Panel 5A: Book-Leverage														
avg.	0.2726	0.3881	0.2607	0.3630	0.2429	0.3266	0.2728	0.3832	0.2753	0.3898	0.2772	0.3946	0.2774	0.3956
difference	-0.11552		-0.10237		-0.08378		-0.11042		-0.11443		-0.11746		-0.11821	
p-value	<0.0001***		<0.0001***		<0.0001***		<0.0001***		<0.0001***		<0.0001***		<0.0001***	
Panel 5B: Market-Leverage														
avg.	0.0326	0.1277	0.0225	0.1288	0.0149	0.1139	0.0349	0.1271	0.0355	0.1221	0.0382	0.1298	0.0383	0.1303
difference	-0.09507		-0.10626		-0.09905		-0.09217		-0.08661		-0.09169		-0.09203	
p-value	<0.0001***		<0.0001***		<0.0001***		<0.0001***		<0.0001***		<0.0001***		<0.0001***	

This table compares whether the δ's estimated from the least leveraged 10% quantile firms are significantly different from other companies not in this quantile. The non-quantile columns show the average δ's estimated from firms, not in the least leveraged 10% quantile. The quantile columns in this table show the average δ's estimated from companies in the least leveraged 10% quantile. Panel A presents the results for book-leverage. Panel B shows the results for market-leverage. We define all variables in the note of the table 1 and in the text of the document.

CONCLUSION

The main purpose of this study is to test the impact of non-macroeconomic factors on the adjustment of capital structure. We use the factors related to production and production to test it. TCU and PPI are used in the tests. We use the Dynamic partial adjustment capital structure model. Data used during the test 1986 Q1 to 2012 Q4. There are 39,186 records per quarter. Our findings show that low leveraged firms adjust their leverage toward target capital structure faster than high leveraged firms. We also show that producer linked variables such as total industry capacity utilization and producer price index significantly affect capital structure adjustment speeds, more so than standard macroeconomic variables.

This study analyzes the effect of the ex-ante market state indicators used in the momentum literature on capital structure adjustment speeds. The UP, DOWN market state indicators used in the momentum literature are defined to be functions of past market returns. As such, they are observable by the investor at time t. In the momentum literature, it is well established that past market states affect momentum profit. A large number of studies have documented that the returns of applying the momentum strategy on stocks and corporate bonds are state-dependent and predictable ex-ante these types of UP, DOWN market state indicator variables.

The effects of time variations of past market states on capital structure dynamics have not yet been researched. This study fills this gap by investigating the effects of the momentum market state indicators on capital structure dynamics. The hypothesis is that corporate decision-makers, like investors, can also observe and make use of these ex-ante market state indicators, and this information can influence their capital structure decisions moving forward.

Our results show that capital structure adjustment speed is considerably state-dependent, that these momentum market state variables significantly affect a company's capital structure adjustment speed. The results support the behavioral theory of Daniel et al. (1998) in that aggregate market gains can induce manager overconfidence and therefore influence their capital structure decisions. The finding of a market-state effect on capital structure is also consistent with the bounded rationality theory by Hong and Stein (1999), where heterogeneity in the types of information structure available to decision-makers yields gradual information diffusion.

In as much as there exists much empirical literature showing that capital structure affects a company's value, our results provide a plausible pathway of how the momentum market state variables lead to momentum profit by providing empirical evidence that they also affect capital structure adjustment speeds. Specifically, the empirical literature shows that the capital structure decision is a relevant factor explaining value created to shareholders, thus providing a link between momentum market states, firms' capital structure adjustment decisions, and momentum strategy return. This study extends the literature by analyzing the relationship between past market states and capital structure adjustment speeds, whether the ex-ante market state variables used in the momentum literature are useful in further delineating capital structure adjustment speed.

Our results support our hypothesis. We find that the capital structure adjustment speed associated with the UP market states exceeds its corresponding adjustment speed in the DOWN market states, the difference statistically significant. Our results also show that TCU and PPI are indeed useful in explaining capital structure adjustment speed.

This study further uncovers several new results. First, regressions that use TCU and PPI provide the most reliable results for the relation between the capital structure adjustment speed and macroeconomic indicators. The results are the same for both book-leverage or market-leverage. For example, the average adjustment speeds δ associated with TCU and PPI regressions are ranked first and second by magnitude, respectively in nearly all regressions. We also find that firms adjust capital structure faster when the economic state is good. Second, when we put companies into ten quantiles according to the magnitude of leverage, we find that the firms' capital structure adjustment speed is faster for firms' with low leverage and slower for firms with high leverage. Third, when we incorporated TCU and PPI into our regression specifications, the resulting δ of other macroeconomic indicators were not as discernible (both magnitude and significance).

From this, we can conclude that managers adjust their capital structure more in line with the information captured in these two (producer related) indicator variables than with the information proxied by the more commonly used (general) macroeconomic variables. Our results show the importance of factors related to the firms' production capacity in capital structure adjustment. This result shows that composite measures of the economy, such as GDP do not reflect entirely the information that goes into manager decision to adjust the capital structure. Instead, producer related indicator variables such as TCU and PPI are found to give more tangible results in the regressions.

From this study, we suggest that managers and investors should focus on the fundamentals of the company rather than commit to macroeconomic information. Most mainstream research focuses on macroeconomic factors. There is very little research on production factors, and there are great restrictions on the choice of production factors, such as the frequency of information or the degree of relevance. Subsequent research can analyze other choices for non-macroeconomic factors.

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EQUITY MARKET INTEGRATION AND DIVERSIFICATION: EVIDENCE FROM EMERGING AND DEVELOPED COUNTRIES

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ABSTRACT

This study examined the role of the US market on the portfolio of emerging stock markets in Asia, Europe, and S. America from the foreign investors' perspectives. The Lambda is used to separate impacts of exchange rates from stock returns in local currencies. Notable findings are as follows. First, there is no additional diversification gain for the portfolio of six emerging regional markets when the US market is added as a representative of developed markets. Second, there are some potential diversification benefits (lower risk) to be exploited in the portfolio of regional emerging markets if the US market is added: the US market seems to play an important role in reducing risk in the portfolio of regional emerging markets. The results could be of value to advance risk management for portfolio managers and individuals alike in emerging markets.

JEL: G110, G140, G150

KEYWORDS: Lambda, Integration, Diversification, Contagion, Emerging Markets, and Crisis

INTRODUCTION

In recent years, financial markets around the world became more integrated because of gradual abolition of regulations, advancement of new technology, fast flow of information, and increase of cross-border investments. Financial market integration and openness may discipline domestic financial sector and increase market efficiency. The benefits of market integration lie in a more efficient way of allocating assets and sharing investment risks thereof. Such benefits depend on the degree of interdependence between the economies concerned because the integrated economic/financial system results in a series of interdependencies that make contagion inevitable during financial crises. The additional risks beyond any fundamental economic ties have long been of great concern to fund managers and policymakers alike due mainly to serious impacts on investment activities and risk sharing. There has been substantial literature on the benefits of international diversification. Asset managers, when constructing portfolios, have employed such strategies as the mean-variance efficient portfolios (Markowitz 1952), dividend-weighted portfolios (Hsu and Campollo 2006), and equally-weighted portfolios (DeMiguel et al. 2009).

In empirical tests, it has long been debated how any innovation (or "shock"), originated from some economic/financial events in one economy, affects others in the integrated system. Since the fully integrated financial markets tend to co-move more closely, innovations in one market are likely to be fast transmitted to other markets. This would accentuate the market volatility, spillovers, and financial contagion during financial crises. Thus, empirical studies focus on the impacts of economic/financial events on stock market volatility and the co-movements of national stock markets. The objective of this study is to examine the impacts of the US market, as one of developed markets, on portfolios of regional emerging markets. Empirical studies thus far indirectly examine the benefits of diversification by using pair-wise inter-market correlations. In reality, correlation is only one of the elements, which affect the portfolio risk. If foreign stocks are added, the portfolio return depends not only on the intermarket correlations but also on the total risk of foreign stocks which would be compounded with additional risk from exchange-rate changes. This study uses Lambda (λ) (Fooladi and Rumsey 2006) to separate impacts of exchange-rate changes from stock returns (local currencies). This study will provide answers to the question if adding the US market to a portfolio of emerging market stocks could affect portfolio risk. Empirical findings will be of some value to advance risk management practices and the application of various hedging strategies for portfolio managers, individual investors, and policymakers alike. This paper is organized as follows. Section II reviews empirical literature, and Section III discusses data and methodology. Section IV discusses empirical results, and Section IV concludes this study with suggestions for future studies.

LITERATURE REVIEW

In the integrated financial system, financial markets are highly interdependent, and extensive networks link financial markets across national borders. Especially, the 2008 global financial crisis hit many economies by squeezing credit, falling house prices and stock markets, a slump in consumer confidence, and investments thereof. Sectors dependent on consumer credit (e.g., construction, auto industry) have seen their markets sharply deteriorate. Investments and consumer purchases had been put off, followed by a vicious cycle of falling demand, downsized business plans, and job cuts. In the end, high volatility and correlations breakdown thereof resulted in the unstable transmission of volatility spillover, comovements, and financial contagion. Empirical studies on market interdependency have been pursued in four different ways. The first group examined diversification benefits across financial markets; the second group tested for intermarket linkages and dynamic comovements; the third group analyzed volatility spillovers across equity markets and industries; and the fourth group checked the role of developed markets on volatility spillovers of emerging markets.

In the first group, Roca et al (1998) note that ASEAN-5 markets are closely linked each other in the short run but not in the long run. Cifarelli and Giannopoulos (2002) provide evidence of strong intermarket relationships between Asia and Europe, and of the pivotal role of the US market in the transmission of innovations (“news”) among major stock markets in the 1990s. Aquino et al. (2005) find that 1) a US domestic portfolio with either ADRs or their underlying shares provide superior return and lower risk than a US domestic portfolio, and 2) portfolios with ADRs do not provide any significant advantage over portfolios diversified with underlying foreign shares in sense of the mean-variance efficiency. Yan and Zhao (2013) note that for a global equity portfolio with country's indices, the simple allocation strategies deliver better out-of-sample performance even with short-sale and over-weighting constraints by providing higher risk-adjusted returns than the portfolio optimization. Thus, it is suggested to keep portfolio construction strategies simple. Najeeb et al. (2015) provide evidence of effective diversification opportunities for short holding periods (less than one year), but for longer investment horizons the markets appear to be highly correlated with minimal portfolio diversification benefits.

In the second group, Eun and Sim (1989) note that the US market had significant impacts on foreign markets, innovations in the US markets were rapidly transmitted to other markets, but foreign markets had no impact on the US market. Lau and McInish (1993) find a big increase in international stock market comovements after the 1987 US crash. Parhizgari et al. (1994) show that the NYSE is dominant, and the uni-directional causality is strong from the NYSE to other markets. Forbes and Rigobon (2002) find strong inter-market comovements after the 1994 Mexican peso crisis and the 1997 Asian crisis. Worthington et al. (2003) report that Asian markets became more integrated during the Asian crisis (1997), but developed and emerging markets became less integrated. Yang et al. (2003) note that the short-run causal linkages and the long-run cointegration became stronger during the Asian crisis (1997), and the US market had significant impacts on Asian markets. Hsin (2004) finds strong information-transmission effects among major developed markets in terms of returns and volatility, and the US market is the leading market with persistent and significant impacts. Darrat and Zhong (2005) show long-run strong relationships among Asian markets before the North-America Free Trade Agreement (NAFTA), but not after the NAFTA implementation. Fooladi and Rumsey (2006) report that strong co-movement and integration between stock markets had been counterbalanced by additional exchange-rate changes, but there are still diversification benefits (in US dollars) to be exploited. Haque and Kouki (2010) provide evidences of strong comovements in returns, volatility and stock-markets correlations in both developed and emerging markets and of increased comovements for a short term (i.e., 3 months for developed markets and 6 months for emerging markets). The comovements are mainly influenced by three factors, namely the global, economic, and geographical factors. Machuga and Wahab (2011) report that Asia-Pacific stock markets display asymmetry, and Asia-Pacific markets highly co-move with the US when the US returns are positive. Bekaert et al. (2014) find that: 1) countries with high political risk, large current account deficits, large unemployment, and a high government budget deficit, experienced a high degree of contagion, but financially integrated countries experienced less contagion from the US market.

In the third group, Huang and Yang (2002) note that after the 1997 Asian crisis, the volatility of the London and New York markets leads that of Tokyo, and New York market leads London market. Rim and Setaputra (2012) show that the US market became less integrated with Asian markets during the 2008 US crisis, suggesting the existence of more diversification benefits. Rim et al. (2012) find strong uni-directional volatility spillovers from the US market to Asian markets. Li and Giles (2015) provide strong evidences of 1) uni-directional volatility spillovers from the US to the Japanese and other markets but bi-directional volatility spillovers between the US and Asian markets during the 1997 Asian crisis; 2) uni-directional spillovers from the US market to the Japanese and other Asian markets during the 2007 US crisis; and 3) strong bi-directional volatility spillovers between the Japanese and other Asian markets. Jebran et al. (2017) find significant bi-directional volatility spillover between stock markets in India and Sri Lanka, Hong Kong and India, and Pakistan and India before the 2007 US crisis.

The fourth group examined the role of emerging markets on global investments. Heston and Rouwenhorst (1995) suggest investors pay more attention to the geographical, rather than industrial, composition. If emerging markets are not fully integrated with developed markets, external shocks might have limited impacts on emerging markets. Then investors in developed markets may gain additional benefits by adding emerging market stocks to their portfolios. If both emerging and developed markets are highly integrated, low volatilities of developed markets could reduce the volatility of emerging markets, and investors in emerging markets may gain more benefits from reduced volatility and risk (Goetzmann et al. 2005; Worthington and Higgs 2004). Bae et al. (2019) show that accessing emerging economies through investments in developed markets delivers the best of both worlds with emerging market-like returns and developed market volatility due to fewer challenges and lower investing costs in emerging markets.

DATA AND METHODOLOGY

This study uses six emerging market indexes for China and India (Asia); Spain and Turkey (Europe); and Argentina and Brazil (S. America) in addition to the US as a representative of developed markets. The data are collected from the Bloomberg Market Data for a period of 2006 and January 2018 because of several economic/financial crises such as the 2008 sub-prime mortgage crisis in the US, the 2009 Greek sovereign debt crisis, and European debt crises (2011, 2016). To better account for these impacts, this period is divided into four sub-periods: Period 1(P_1: 2006.1-2008.6); Period 2 (P_2: 2008.7–2010.7); Period 3 (P_3: 2010.8–2012.6); Period 4 (P_4: 2012.7–2014.10); and Period 5 (P_5: 2014.11–2018.1). First, stock market indexes are tested for unit roots by following the spirit of the Augmented Dickey-Fuller test (1981). Empirical tests show that all the index series have unit roots, but the first-differenced series are stationary: Daily returns are expressed in the first difference of a logarithm of closing indexes. Nelson and Plosser (1982) note that most financial time series (including stock prices) contain unit roots, dominated by stochastic trends. Thus, economic variables need to be measured in changes rather than absolute values. First, differencing facilitates comparison with stock returns. Second, first-differencing is applied to render the series stationary (Eun and Shim 1989). Second, Lambda (λ) is calculated as follows. The first step is to form a portfolio of equally-weighted indices (in local currency) for a portfolio of market indexes for every ten days. The second step is to compute Lambda as a ratio of the standard deviation (STD) of an equal-weight global portfolio to the STD average of all market indexes (Eq. (2), p. 228, Fooladi and Rumsey (2006)) as follow:

$$\lambda_{SD,T} = S_{p,t}/\acute{S}_T \tag{1}$$

where $S_{p,t}$ is the STD of the portfolio, and $\acute{S}_T$ is the average of STD of the m-market indexes for a period from T to T+n.

In empirical tests, it is easier to use Lambda (λ) values rather than many pair-wise correlations (i.e., N(N-1)/2) in previous studies. As financial markets become more integrated, Lambda (λ) increases in value up to 1. If financial markets are fully integrated, Lambda gradually increases to one as the STD of equal-weight portfolio approaches to the average STD of the indexes. If financial markets are integrated with a less degree, the Lambda value declines to below one. The benefits of diversification can be measured by the extent how small the Lambda (λ) becomes: The smaller the Lambda ($0 < \lambda < 1$) becomes, the more diversification benefits to investors are guaranteed.

From foreign investors' perspectives, Lambda (λ) is calculated for the following four scenarios:
Scenario 1: Invest in six emerging regional markets without the US market (λ_{11}) and with the US (λ_{12});
Scenario 2: Invest in Argentina-Brazil markets without the US market (λ_{21}) and with the US (λ_{22});
Scenario 3: Invest in China-India markets without the US market (λ_{31}) and with the US (λ_{32}); and
Scenario 4: Invest in Spain-Turkey markets without the US market (λ_{41}) and with the US (λ_{42}).

RESULTS AND DISCUSSION

Table 1 provides the means of Lambda, and Table 2 shows p-values to test for mean differences of Lambdas for various scenarios. For Scenario 1, the means of λ_{11} and λ_{12} are not significantly different, which is supported by the p-values in Table 2. The results suggest that adding the US market to the portfolio of six emerging regional markets has no impact on portfolio risk for the whole period. This is further supported by the graph in Figure 1 (Appendix). This result is very interesting in the sense that investors could have reduced enough portfolio risk by investing in the regional emerging markets across three continents without making investments in the US market as a representative of developed markets.

Table 1: Mean Values for Lambdas

Mean	λ_{11}	λ_{21}	λ_{31}	λ_{41}	$\lambda_{(1,1)}$	λ_{12}	λ_{22}	λ_{32}	λ_{42}	$\lambda_{(1,2)}$
P_1	0.634	0.912	0.774	0.875	0.799	0.628	0.879	0.667	0.789	0.741
P_2	0.703	0.925	0.816	0.892	0.834	0.702	0.894	0.706	0.827	0.782
P_3	0.641	0.884	0.784	0.843	0.788	0.654	0.865	0.682	0.805	0.752
P_4	0.584	0.82	0.784	0.816	0.751	0.586	0.778	0.671	0.763	0.700
P_5	0.607	0.877	0.79	0.793	0.767	0.603	0.824	0.679	0.746	0.713

(Note) The mean is the average of Lambdas for every 10-day returns. Lambda is computed for: λ_{11}&λ_{12}: Lambdas for six emerging regional markets without and with the US market; λ_{21}&λ_{22}: Lambdas for Argentina-Brazil portfolio without and with the US market; λ_{31}&λ_{32}: Lambdas for China-India portfolio without and with the US market; λ_{41}&λ_{42}: Lambdas for Spain -Turkey portfolio without and with the US market. The sub-periods are as follow: P_1: 2006.1~ 2008.6; P_2: 2008.7~2010.7; P_3: 2010.8~2012.6; P_4: 2012.7~ 2014.10; and P_5: 2014.11~2018.1.

Table 2: P-Values for Mean-Difference Tests

P-values	λ_{11} vs λ_{12}	λ_{21} vs λ_{22}	λ_{31} vs λ_{32}	λ_{41} vs λ_{42}
P_1	0.7435	0.0038**	0.0000**	0.0000**
P_2	0.9878	0.0138*	0.0000**	0.0000**
P_3	0.5416	0.2379	0.0000**	0.0357*
P_4	0.9347	0.0060**	0.0000**	0.0121*
P_5	0.8638	0.0003**	0.0000**	0.0191*

*(Note) Superscripts ** and * denote the significance at the 1% and 5% levels, respectively.*

For Scenario 2, the means of λ_{21} and λ_{22} are significantly different except Period 3, which is during the 2008 US financial crisis. During Period 3, investors could cut or avoid losses without making any investments in the US market. The results suggest that in other sub-periods, investors could gain more diversification benefits in the Argentina-Brazil portfolio by adding the US market. Similar results have been observed for Scenarios 3 and 4 because the means of Lambdas are significantly different from each other for the whole period. The results support the existence of additional benefits of diversifications to be exploited by adding the US market to the portfolios of regional emerging markets. These results are strongly supported by the graphs in Figures 2, 3, and 4 (Appendix). Table 3 provides the STDs of Lambdas with p-values, testing differences between standard deviations in Table 4. For Scenario 1, the STDs of λ_{11} and λ_{12} are not significantly different with insignificant p-values in Table 4. These results suggest that adding the US market to the portfolio of six regional emerging markets has no impact on the portfolio risk for the whole period. However, investors could reduce portfolio risk with only regional emerging stocks by adding the US market. Interestingly, the standard deviations of Lambdas gradually increase over time. (Other tables are available upon request.)

Table 3: Standard Deviations (STD) for Lambdas

STD	λ_{11}	λ_{21}	λ_{31}	λ_{41}	$\lambda_{(1,1)}$	λ_{12}	λ_{22}	λ_{32}	λ_{42}	$\lambda_{(1,2)}$
P_1	0.101	0.058	0.117	0.075	0.088	0.099	0.068	0.111	0.088	0.092
P_2	0.106	0.053	0.097	0.075	0.083	0.111	0.074	0.113	0.082	0.095
P_3	0.113	0.076	0.118	0.086	0.098	0.106	0.085	0.114	0.094	0.100
P_4	0.129	0.080	0.101	0.118	0.107	0.127	0.087	0.106	0.115	0.109
P_5	0.131	0.086	0.117	0.125	0.115	0.130	0.100	0.124	0.131	0.121

(Note) $\lambda_{(1,1)}$ and $\lambda_{(1,2)}$ denote the average of Lambdas without and with the US market, respectively.

Table 4: P-Values for Testing STD-Differences

P-values	λ_{11} vs λ_{12}	λ_{21} vs λ_{22}	λ_{31} vs λ_{32}	λ_{41} vs λ_{42}
P_1	0.7435	0.0038**	0.0000**	0.0000**
P_2	0.9878	0.0138*	0.0000**	0.0000**
P_3	0.5416	0.2379	0.0000**	0.0357*
P_4	0.9347	0.0060**	0.0000**	0.0121*
P_5	0.8638	0.0003**	0.0000**	0.0191*

*(Note) Superscripts ** and * denote the significance at the 1% and 5% levels, respectively.*

CONCLUDING COMMENTS

In this study, Lambda (λ) is used to examine diversification benefits on portfolios of regional emerging stock indexes from foreign investors' perspectives. Some of the important empirical findings are as follows. First, the US market has minimal impact on the portfolio of regional emerging markets. That is, there is no additional benefit of diversifications even if the US market is added to the portfolio of all six regional emerging market stocks across three continents. Second, investors in specific region(s) could reduce the portfolio risk by adding the US market to the portfolios of regional (e.g., Asia) emerging market stocks. The results suggest that the US market, a representative of developed markets, plays an important role in managing portfolio risk for specific regional emerging markets. These findings are of good use to advance risk management for portfolio managers and individuals alike. Finally, it is suggested that future studies need to further investigate the role of other developed markets (e.g., Germany, France, Japan, and Canada) on portfolio risk for the periods with different economic and/or financial crises.

APPENDIX: FIGURES FOR EMPIRICAL RESULTS

Figure 1: Values of λ_{11} (—) and λ_{12} (—) (Period 1)

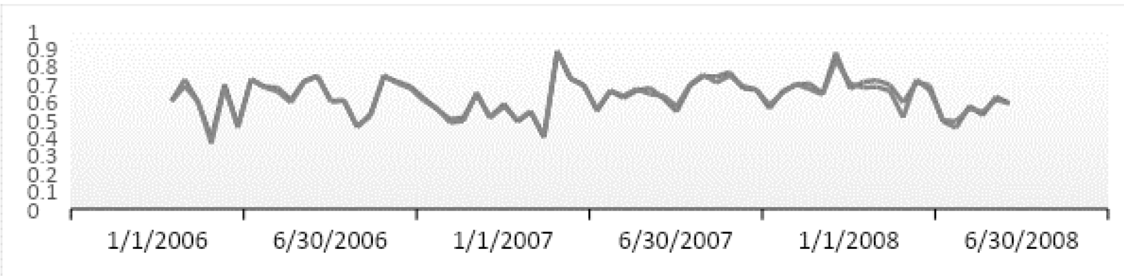


Figure 2: Values of λ_{31} (—) and λ_{32} (—) (Period 1)

Figure 3: Values of λ_{31} (—) and λ_{32} (—) (Period 2)

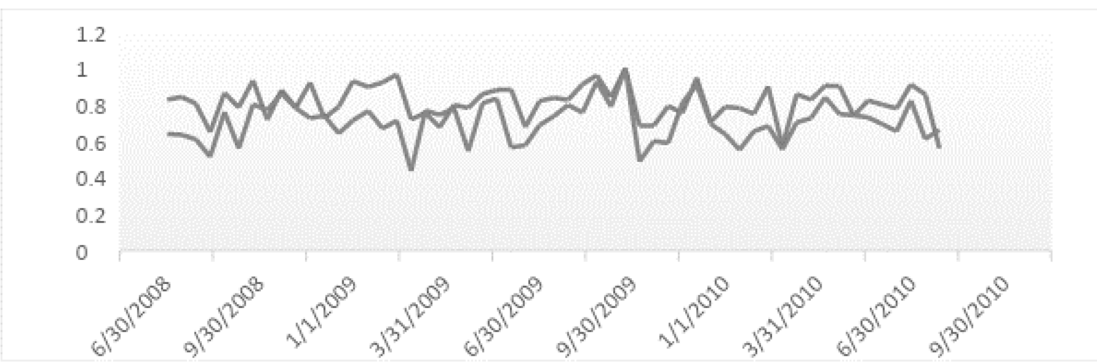
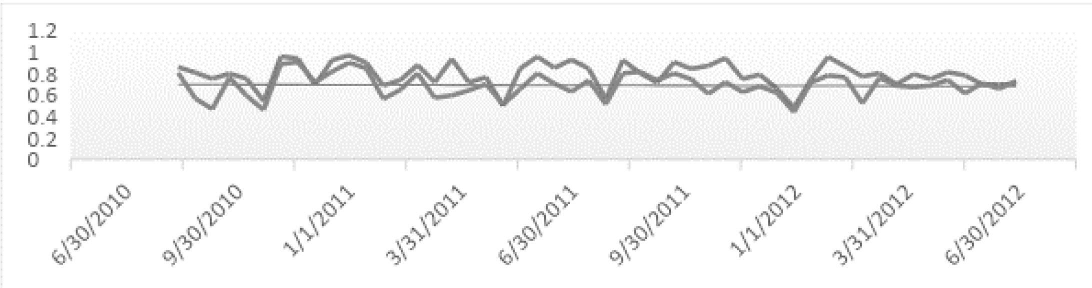


Figure 4: Values of λ_{31} (——) and λ_{32} ((——) (Period 3)



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LIMITS OF ARBITRAGE, RISK-NEUTRAL SKEWNESS, AND INVESTOR SENTIMENT

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ABSTRACT

This paper uses individual stock options to examine the effect of limits of arbitrage on the relations between risk-neutral skewness and investor sentiment for the underlying stocks. Empirical results show that the risk-neutral skewness tends to be more (less) negative under bearish (bullish) investor sentiment, and the significant relations become stronger especially when there are more impediments to arbitrage in stock options. In addition, the empirical results show that increased bearishness among market investors who dominate the use of index options increases the extent to which risk-neutral skewness is affected by fluctuations in investor sentiment for the underlying stocks. Empirical results show that the limits of arbitrage have important implications for the role of investor sentiment in explaining risk-neutral skewness.

JEL: G12, G14

KEYWORDS: Risk-Neutral Skewness; Investor Sentiment; Limits of Arbitrage

INTRODUCTION

Options are priced on the basis of the market's view of the distribution of future stock returns. Empirical studies show that the implied risk-neutral distribution extracted from observed option prices tends to be more negatively skewed than the assumptions of the Black–Scholes Model (e.g., Bakshi *et al.*, 1997). Realizing that the skewness of the stock return distribution is important in pricing securities, previous studies have demonstrated that several factors can help explain risk-neutral skewness, including firm-specific variables, such as the level of stock liquidity and firm implied volatility, along with market-wide variables, such as the skewness of the S&P500 and the volatility of market indexes. However, a sufficient explanation for the source of skewness is still lacking to support the development and improvement of option pricing models (e.g., Dennis and Mayhew, 2002; Friesen *et al.*, 2012).

The development of financial markets attracts a broader range of investors to participate in stock markets, resulting in many financial anomalies that do not conform to classical financial theories. A growing body of evidence suggests that investors are not fully rational, and investor sentiment has significant effects on stock returns (e.g., Baker and Wurgler, 2006). This raises an issue of whether investor sentiment may be a potential factor influencing option-implied risk-neutral skewness. Many papers have examined the role of investor sentiment in affecting index option prices. For example, Han (2008) and Coakley *et al.* (2014) provide evidence to show a significant relation between investor sentiment for broad stock market and risk-neutral skewness for index options. They indicate that small investor sentiment is not important in explaining risk-neutral skewness for index options, as they are not main participants in the index options market. However, for individual stock options, empirical studies testing the role of investor sentiment in explaining risk-neutral skewness have produced mixed results. This inconsistency within the extant literature has motivated us to focus on individual stock options to test whether a wave of investor sentiment for the underlying stocks has a significant effect on option-implied risk-neutral skewness. Moreover, this paper examines the impact of impediments to arbitrage on the role of investor sentiment about individual stocks in explaining risk-neutral skewness. And we also examine whether market-wide investor sentiment affects the relations between firm-specific investor sentiment and risk-neutral skewness.

This paper differs from previous studies in two important respects. First, we examine the effect of arbitrage limitations on the role of investor sentiment for individual stocks in explaining the firm-level option-implied risk-neutral skewness. Specifically, we examine whether firms that have higher restrictions on short sales and/or a higher default likelihood and/or a smaller firm size may produce a stronger relationship between investor sentiment and risk-neutral skewness. Firm-level stock options data enables us to examine the impact of individual investors on option prices.

Mispricing of a stock creates an arbitrage opportunity that attracts rational investors to trade accordingly and earn their profit from the subsequent convergence of the market price to fundamentals. However, certain types of arbitrage limits make the arbitrage process risky and costly in reality. Examples of arbitrage limits include trading constraints, information uncertainty and transaction costs. Trading constraints, including short sales restrictions, limit arbitrage in options and prevent arbitrageurs from exploiting market mispricing opportunities. Pessimistic investors who perceive stocks as being overvalued but are unable to sell short because of restrictions will resort to trading in the options market. These investors tend to buy out-of-the-money (OTM) put options, and the sentiment-based demand for OTM puts drives up the prices of low-strike price options (e.g., Buraschi and Jiltsov, 2006). Thus, the pricing impact of investor sentiment increases with impediments to arbitrage; that is, firms that have higher restrictions on short sales are expected to be associated with a stronger relationship between investor sentiment and risk-neutral skewness.

Several empirical studies have shown that arbitrage for small, young, or distressed stocks tends to be particularly risky and costly. Investors trading in such firms rely on scant information and imprecise earnings reports to determine correct stock values, leading to errors in evaluating the fair price for the option and hedge ratio. In addition, investors trade with less liquidity and a higher transaction cost when firms have a higher likelihood of default (e.g., Vassalou and Xing, 2004). Thus, arbitrage in options tends to be particularly risky and costly for firms with a higher likelihood of default. We argue that the pricing impact of investor sentiment is higher under significant impediments to arbitrage. We therefore expect a stronger relationship between investor sentiment for underlying stocks and option-implied risk-neutral skewness when firms are more likely to default.

Second, this paper examines whether the risk-neutral return distribution is more negatively skewed when investor sentiment turns more bearish, particularly in the case of increased bearishness among market investors who dominate the use of index options. Empirical evidence show a significant relation between investor sentiment for broad stock market and risk-neutral skewness for index options (e.g., Han, 2008). Risk-neutral skewness for index options is an important determinant of risk-neutral skewness for individual stocks (e.g., Dennis and Mayhew, 2002). Thus, we would expect market-wide sentiment common to all firms might affect firm-specific investor sentiment as well as the relations between firm-specific investor sentiment and firm-specific risk-neutral skewness.

Empirically, we use the stock and option prices for S&P500 component stocks from January 1, 2003 to December 31, 2012. We compute weekly risk-neutral skewness using the methodology proposed by Bakshi *et al.* (2003) and follow the empirical implications presented by Dennis and Mayhew (2002). The measure of skewness proposed by Bakshi *et al.* (2003) is easy to compute and has the advantage of not relying on any particular option pricing model. We utilize two commonly used proxies for investor sentiment based on trading activity in the options market. The first proxy for investor sentiment is defined as the average open interest of puts divided by the average open interest of all options for each week. A higher open interest ratio of puts to all options suggests that investors are generally more pessimistic. The second proxy for investor sentiment is defined as the average trading volume of puts divided by the average trading volume of all options for each week. Open interest and trading volume capture different types of information; open interest represents the total number of outstanding option contracts that have not been settled, whereas trading volume refers to the total number of trading transactions. Intuitively, investors seek to optimize their portfolios based on their outlook for specific stocks, and they have different demands for puts or calls option because of their various expectations of firm fundamentals. Therefore, we expect that investor sentiment for the underlying stocks affects option-implied risk-neutral skewness. In addition, the sentiment proxy regarding broad stock market is derived from trading activity in S&P500 index options. The measures of market-wide investor sentiment using S&P500 index options are consistent with the measures of firm-specific investor sentiment.

We begin our analysis of risk-neutral skewness by examining the relationship between investor sentiment and risk-neutral skewness. To clarify the robustness of the relation between risk-neutral skewness and investor sentiment, several control variables are included in the model such as logged stock trading volume, option implied volatility and book-to-market ratio. Stock trading volume is used as a proxy for the liquidity of individual stocks, while the option implied volatility is used to measure the volatility of a firm's stock return. The empirical results show that the option-implied risk-neutral distribution is more negatively skewed when investor sentiment for the underlying stocks turns bearish. Furthermore, we construct various portfolios with different levels in terms of short sales restrictions, a firm's default risk, and a firm's market capitalization at the end of each week. The empirical results show that when there are more impediments to arbitrage in stock options, a stronger relationship exists between investor sentiment for the underlying stocks and risk-neutral skewness. In addition, institutional investors tend to buy index put options as portfolio insurance against stock market declines due to hedging demands (e.g., Bollen and Whaley, 2004). The empirical results show that increased bearishness among market investors who dominate the use of index options increases the extent to which risk-neutral skewness is affected by fluctuations in investor sentiment for the underlying stocks.

The remainder of this paper is organized as follows. We first review the related literature, and then describe our data and how our model measures risk-neutral skewness, followed by a description of the proxies for important explanatory variables. Finally, we present the empirical results and conclusions.

LITERATURE REVIEW

The role of investor sentiment in affecting index option prices has been examined in numerous papers. For example, Han (2008) uses S&P500 options to show that investor sentiment about the broad stock market is an important determinant of index risk-neutral skewness. Coakley *et al.* (2014) provide evidence to show the significant relationship between investor sentiment and risk-neutral skewness for seven stock index options comprising either growth or value stocks. However, for individual stock options, empirical studies testing the role of investor sentiment in explaining risk-neutral skewness have produced mixed results. For example, Dennis and Mayhew (2002) do not find evidence to support that investor sentiment about the underlying stocks can explain the movement of risk-neutral skewness. The subsequent work of Taylor *et al.* (2009) finds a negative relationship between investor sentiment for the underlying stocks and risk-neutral skewness. This inconsistency within the extant literature has motivated us to focus on individual stock options to test whether a wave of investor sentiment for the underlying stocks has a significant effect on option-implied risk-neutral skewness.

Bollen and Whaley (2004) state that most trading in S&P500 index options involves puts, whereas most trading in stock options involves calls. Because of hedging demands, institutional investors buy index put options as portfolio insurance against stock market declines. Lakonishok *et al.* (2007) show that hedging trading strategies account for a small fraction of stock option activity. Unsophisticated investors actively trade options on individual stocks to speculate on stock price movements. Empirical work has provided evidence to show that different types of options serve different purposes and are likely to attract different types of traders. Han (2008) examined whether investor sentiment concerning the level of stock market index affects S&P500 option prices. By contrast, firm-level stock options data enables this paper to examine the impact of individual investors on option prices.

Arbitrage is defined as the simultaneous purchase and sale of the same, or essentially similar, securities in two different markets to take advantage of a price gap, thus bringing prices into convergence with fundamental values. Examples of arbitrage limits include trading constraints, information uncertainty and transaction cost (e.g., Gu *et al.*, 2018). Trading constraints, including short sales restrictions, make arbitrage in options more limited (e.g., Ofek *et al.*, 2004), preventing arbitrageurs from exploiting market mispricing opportunities. We take institutional ownership of the stock as the proxy for the market supply of short sales because firms with more institutional holdings are less costly to borrow and sell short. Short sales restrictions are likely to have a greater impact as the value of one minus the fraction of institutional ownership increases (e.g., Hu, 2014). In addition, several empirical studies have shown that arbitrage for small, young, or distressed stocks tends to be particularly risky and costly (e.g., Baker and Wurgler, 2006). Investors trading such firms rely on scant information and imprecise earnings reports to determine the correct stock values. Previous studies of the effect of default risk on equity focused on different default measures as a proxy for default risk. For example, Garlappi, Shu, and Yan (2008) use the expected default frequency of Moody's KMV to show that higher default probability is not related to higher stock returns. Vassalou and Xing (2004) developed a default likelihood indicator to calculate default measures for individual firms. However, their measures require a complicated equation that must be solved by implementing an iterative procedure. This paper uses Bharath and Shumway's (2008) naïve distance to default model to calculate the default likelihood for our target firms.

DATA AND METHODOLOGY

We select component stocks from the S&P500 index for our empirical data. The daily records of options and stocks are from the beginning of January 2003 through the end of December 2012. Market prices for the options written on the stocks of the S&P500 component stocks, and the market information of the corresponding stocks is obtained from Ivy DB OptionMetrics. We define the option prices as the averages of the last bid and ask prices for each option. The filters used to construct our empirical option data were set to the following exclusion criteria: (i) options with price quotes lower than $0.5, the bid or offer price is missing, or the bid price is zero; (ii) options with prices that violate general no-arbitrage constraints; (iii) option contracts that have zero open interests; (iv) options with maturities of less than 7 days or greater than 365 days; and (v) underlying stocks have zero trading volume.

Calculation of Risk-Neutral Skewness

This paper calculates the weekly estimates of risk-neutral skewness for each underlying stock by using the results of Bakshi and Madan (2000) and Bakshi *et al*. (2003). Following Dennis and Mayhew (2002), we calculate the risk-neutral skewness each day for the two different maturities that are greater than one week but closest to 22 trading days. The data have at least two calls and two puts for each maturity. The moneyness is defined as the ratio of the strike price to the stock price. A put option is defined as OTM when the moneyness is between 0.8 and 0.95, while a call option is defined as OTM when the moneyness is between 1.05 and 1.2. In estimating risk-neutral skewness, we use equal numbers of OTM calls and puts for each stock on each day. If there are n OTM puts on day t and $N > n$ OTM calls, we use the n OTM calls that have the most similar distance from stock to strike as the OTM puts for which we have data. In addition, following Conrad *et al.* (2013), we exclude stocks with highly illiquid options by discarding those with fewer than 10 quotes per month.

Bakshi *et al.* (2003) show that the moments of risk-neutral density can be expressed as the time t price of a quadratic, cubic, and quartic payoff received at time $t+\tau$. Let Q denote the probability distribution function under the risk-neutral measure. The τ period's continuously compounded return on the underlying asset $S_{i,t}$ is $R(t,\tau) \equiv ln\,[(S(t+\tau))/(S(t))]$. The time t price of a quadratic, cubic, and quartic payoff received at time $t+\tau$ can be respectively expressed $V(t+\tau) \equiv E^{Q}[e^{-r\tau}R(t+\tau)^2]$,

$W(t+\tau) \equiv E^Q[e^{-r\tau}R(t+\tau)^3]$, and $X(t+\tau) \equiv E^Q[e^{-r\tau}R(t+\tau)^4]$. Bakshi and Madan (2000) demonstrate that any payoff function for the stock price with bounded expectations can be constructed using a set of OTM calls and puts with different strike prices. The risk-neutral moments can be calculated as:

$$Skew_{i,t}^Q(\tau) = \frac{e^{r\tau}W_{i,t}(\tau) - 3\mu_{i,t}(\tau)e^{r\tau}V_{i,t}(\tau) + 2\mu_{i,t}(\tau)^3}{\left(e^{r\tau}V_{i,t}(\tau) - \mu_{i,t}(\tau)^2\right)^{3/2}} \quad (1)$$

Where,

$$V_{i,t}(\tau) = \int_{S_{i,t}}^{\infty} \frac{2\left(1 - ln\left(\frac{K_i}{S_{i,t}}\right)\right)}{K_i^2} C_{i,t}(\tau; K_i)dK_i + \int_0^{S_{i,t}} \frac{2\left(1 + ln\left(\frac{S_{i,t}}{K_i}\right)\right)}{K_i^2} P_{i,t}(\tau; K_i)dK_i \quad (2)$$

$$W_{i,t}(\tau) = \int_{S_{i,t}}^{\infty} \frac{6\,ln\left(\frac{K_i}{S_{i,t}}\right) - 3\left(ln\left(\frac{K_i}{S_{i,t}}\right)\right)^2}{K_i^2} C_{i,t}(\tau; K_i)dK_i - \int_0^{S_{i,t}} \frac{6\,ln\left(\frac{S_{i,t}}{K_i}\right) + 3\left(ln\left(\frac{S_{i,t}}{K_i}\right)\right)^2}{K_i^2} P_{i,t}(\tau; K_i)dK_i \quad (3)$$

$$X_{i,t}(\tau) = \int_{S_{i,t}}^{\infty} \frac{12\left(ln\left(\frac{K_i}{S_{i,t}}\right)\right)^2 - 4\left(ln\,(\frac{K_i}{S_{i,t}})^3\right)}{K_i^2} C_{i,t}(\tau; K_i)dK_i + \int_0^{S_{i,t}} \frac{12\left(ln\left(\frac{S_{i,t}}{K_i}\right)\right)^2 + 4\left(ln\,(\frac{S_{i,t}}{K_i})^3\right)}{K_i^2} P_{i,t}(\tau; K_i)dK_i \quad (4)$$

$$\mu_{i,t}(\tau) = e^{r\tau} - 1 - \frac{e^{r\tau}}{2}V_{i,t}(\tau) - \frac{e^{r\tau}}{6}W_{i,t}(\tau) - \frac{e^{r\tau}}{24}X_{i,t}(\tau). \quad (5)$$

To empirically estimate risk-neutral skewness, we need to approximate the integrals in Eqs. (2), (3), and (4), which are based on the weighted integrals of the OTM call and puts prices. The integrals are taken over all OTM strike prices, but a continuum of strike prices is not available. Thus, we use the trapezoidal approximation proposed by Dennis and Mayhew (2002) and Conrad *et al.* (2013) to construct the skewness measure with discrete option data. A hypothetical option with 22 trading days to maturity is constructed using linear interpolation or extrapolation. Table 1 reports the descriptive statistics for the sample estimates of risk-neutral skewness for the underlying stock. The results show that some individual stocks are negatively skewed. As Bakshi *et al.* (2003) indicate, a skewed risk-neutral distribution implies that the physical distribution is also skewed.

Table 1: Summary Statistics of Risk-Neutral Skewness for the Underlying Stocks

Variable	Mean	SD	Percentile		
			P5	**P50**	**P95**
Skewness	-0.910	0.613	−2.470	−0.883	0.729

Table 1 presents the summary statistics of firm-specific risk-neutral skewness. The sample period is from January 1, 2003 to December 31, 2012.

<u>Measures of a Firm's Likelihood of Default</u>

This paper applies Bharath and Shumway (2008) naïve distance to the default model to calculate the default likelihood for our target firms. The naïve distance to default is defined as follows:

$$naiveDD = \frac{ln\left(\frac{M+F}{F}\right) + (r_{i,t-1} - 0.5naive\sigma_v^2)T}{naive\sigma_v\sqrt{T}} \quad (6)$$

where $naive\sigma_v = \frac{M}{M+F}\sigma_s + \frac{F}{M+F}(0.05 + 0.25\sigma_s)$. M is each firm's market capitalization, calculated as the product of the stock price at the end of the month and the number of shares outstanding. F denotes the face value of the firm's debt, computed as the debt in current liabilities plus one-half of the long-term debt. σ_s is the volatility of stock returns which is estimated from the previous year's stock return, and $r_{i,t-1}$ is the stock return of firm i over the previous year. The naive probability estimate is defined as $\pi_{naive} = N(-naiveDD)$, where $N(.)$ is the cumulative standard normal distribution function.

EMPIRICAL RESULTS

Relationship between Risk-Neutral Skewness and Investor Sentiment

We first examine the relationship between risk-neutral skewness and investor sentiment for each investor sentiment proxy about the underlying stocks. The results of Bakshi and Madan (2000) and Bakshi *et al.* (2003) was applied to obtain weekly estimates of risk-neutral skewness for each underlying stock. We use the Fama–MacBeth (1973) type of approach to regress risk-neutral skewness for firm i on investor sentiment for each week in our sample period. These regressions investigate the cross-sectional relations between the dependent and the independent variables for each week and the significance of the time-series estimated coefficients is tested based on Newey-West (1987). The control variables include logged stock trading volume, option implied volatility and book-to-market ratio. The stock trading volume is calculated as the average of daily trading volume in the underlying stock for each week, which proxies the liquidity of the individual stocks. The weekly option implied volatility is calculated by averaging the daily mean option implied volatility over a week, and is used to measure the volatility of a firm's stock return.

Panel A of Table 2 documents the results of regressions on the investor sentiment proxy measured as the open interest of puts options divided by the open interest of all options. As expected, the estimated coefficient of investor sentiment is negative and significant, indicating that the risk-neutral distribution is more negatively skewed when investor sentiment turns bearish. Panel B of Table 2 examines the relationship between risk-neutral skewness and the investor sentiment proxy measured by the trading volume ratio of OTM puts to all options. Similarly, the coefficient of investor sentiment is negative and significant.

Table 2: Relationship between Risk-Neutral Skewness and Investor Sentiment

	Investor Sentiment	**Control**	**Adj R^2**
Panel A: Open Interest of Puts Divided by the Open Interest of all Options			
Coeff.	−0.151	Yes	0.14
t-stat	−4.572 ***		
Panel B: Trading Volume of Puts Divided by the Trading Volume of all Options			
Coeff.	−0.161	Yes	0.14
t-stat	−7.423***		

*Table 2 presents the empirical results of Fama-MacBeth (1973) regression to examine the relationship between risk-neutral skewness and investor sentiment about the underlying stocks. The sample period is from January 1, 2003 to December 31, 2012. ***, ** and * respectively indicate significance at 1%, 5% and 10% levels.*

Short Sales Restrictions, Firm Default Likelihood and Firm Size

Table 3 examines whether firms that have higher restrictions on short sales exhibit an increased correlation between option-implied skewness and investor sentiment for the underlying stocks. We define the proxy for short sales restrictions as one minus the fraction of institutional ownership for stock i at time t. Short sales restrictions are more likely to have an increased impact as one minus the fraction of institutional ownership increases. For each investor sentiment measure, we first construct two different portfolios, sorting all stocks into two portfolios based on the level of short sales restrictions at the end of each week. Portfolio 1 has the highest level of short sales restrictions, ranking in the top 30%, whereas Portfolio 2 constitutes the remaining stocks. For each portfolio, we run the Fama–MacBeth (1973) regression to regress the risk-neutral skewness on each investor sentiment proxy and the control variables for each week and the significance of the time-series estimated coefficients is tested based using Newey-West (1987).

As expected, the risk-neutral distribution is more negatively skewed when investor sentiment turns bearish, that is, the coefficient of investor sentiment is negative and significant. In addition, when firms have a higher level of short sales restrictions, the absolute estimated coefficient of investor sentiment tends to be greater. The empirical results show that stocks that have higher restrictions on short sales are expected to produce a stronger relationship between investor sentiment for the underlying stocks and risk-neutral skewness, regardless of the investor sentiment proxy used.

Table 3: Investor Sentiment and Short-Sales Restrictions

	Investor Sentiment	**Control**	**Adj R^2**
Panel A: Open Interest of Puts Divided by the Open Interest of all Options			
Portfolio 1			
Coeff.	−0.111	Yes	0.22
t-stat	−1.513		
Portfolio 2			
Coeff.	−0.111	Yes	0.15
t-stat	−3.023 ***		
Panel B: Trading Volume of Puts Divided by the Trading Volume of all Options			
Portfolio 1			
Coeff.	−0.186	Yes	0.22
t-stat	−3.845***		
Portfolio 2			
Coeff.	−0.162	Yes	0.15
t-stat	−6.412***		

*Table 3 presents the results of Fama-MacBeth (1973) regression for each portfolio. Portfolio 1 has the highest level of short sales restrictions, ranking in the top 30%, whereas Portfolio 2 constitutes the remaining stocks. The sample period is from January 1, 2003 to December 31, 2012. ** and * respectively ndicate significance at 5% and 10% levels.*

Table 4 presents the results of the relationship between risk-neutral skewness and investor sentiment in the context of likelihood of firm default. We construct two different levels of default risk portfolios. First, we sort all stocks into two portfolios based on the level of the firm's default likelihood at the end of each week. Portfolio 1 comprises stocks with the highest level of default risk, ranked in the top 30%, whereas Portfolio 2 comprises the remaining stocks. For each portfolio, we run the Fama–MacBeth (1973) regression and the *t*-statistics are estimated based on the Newey-West (1987) estimation for each portfolio. As expected, when firms have a higher default likelihood, the absolute estimated coefficient of investor sentiment tends to be greater for both investor sentiment measures. The empirical results show that for firms with a higher default risk, skewness is affected to a greater extent by fluctuations in investor sentiment about the underlying stocks, regardless for the investor sentiment proxy used.

Table 4: Investor Sentiment and a Firm's Default Likelihood

	Investor Sentiment	Control	Adj R^2
Panel A: Open Interest of Puts Divided by the Open Interest of all Options			
Portfolio 1			
Coeff.	−0.216	Yes	0.20
t-stat	−3.579***		
Portfolio 2			
Coeff.	−0.103	Yes	0.14
t-stat	−2.417**		
Panel B: Trading Volume of Puts Divided by the Trading Volume of all Options			
Portfolio 1			
Coeff.	−0.199	Yes	0.20
t-stat	−4.835***		
Portfolio 2			
Coeff.	−0.129	Yes	0.14
t-stat	−4.642***		

*Table 4 presents the results of Fama-MacBeth (1973) regression for each portfolio. Portfolio 1 comprises stocks with the highest level of default risk, ranked in the top 30%, whereas Portfolio 2 comprises the remaining stocks. The sample period is from January 1, 2003 to December 31, 2012. ***,** and * respectively indicate significance at1%, 5% and 10% levels.*

Table 5 shows the effect of firm size on the relation between option-implied skewness and investor sentiment for the underlying stocks. We first sort all stocks into two portfolios based on the level of the logged firm market capitalization at the end of each week. Portfolio 1 comprises stocks with the smallest level of logged firm market capitalization, ranked in the top 30%, whereas Portfolio 2 comprises the remaining stocks. For each portfolio, we run the Fama–MacBeth (1973) regression and the *t*-statistics are estimated based on the Newey-West (1987) estimation for each portfolio. As expected, the empirical results show that stocks for smaller firms are expected to produce a stronger relationship between risk-neutral skewness and investor sentiment for the underlying stocks, regardless of the investor sentiment proxy used.

Table 5: Investor Sentiment and a Firm's Size

	Investor Sentiment	Control	Adj R^2
Panel A: Open Interest of Puts Divided by the Open Interest of all Options			
Portfolio 1			
Coeff.	-0.208	Yes	0.22
t-stat	-3.837***		
Portfolio 2			
Coeff.	-0.171	Yes	0.15
t-stat	-3.910***		
Panel B: Trading Volume of Puts Divided by the Trading Volume of all Options			
Portfolio 1			
Coeff.	-0.175	Yes	0.22
t-stat	-4.506***		
Portfolio 2			
Coeff.	-0.156	Yes	0.15
t-stat	-5.398***		

*Table 5 presents the results of Fama-MacBeth (1973) regression for each portfolio. Portfolio 1 comprises stocks with the smallest level of logged firm market capitalization, ranked in the top 30%, whereas Portfolio 2 comprises the remaining stocks. The sample period is from January 1, 2003 to December 31, 2012. ***,** and * respectively indicate significance at1%, 5% and 10% levels.*

Investor Sentiment Regarding Broad Stock Market

Empirical works provide evidence to show the significant relation between investor sentiment for broad stock market and risk-neutral skewness for index options (e.g., Han, 2008). In addition, risk-neutral skewness for index options is an important determinant of risk-neutral skewness for individual stocks (e.g., Dennis and Mayhew, 2002). Thus, we would expect market-wide sentiment common to all firms might affect firm-specific investor sentiment as well as the relations between firm-specific investor sentiment and firm-specific risk-neutral skewness. Following Dennis and Mayhew (2002), we estimated a pooled time-series cross-sectional regression to test whether the relations between firm-specific investor sentiment and firm-specific risk-neutral skewness are related to the market-wide sentiment. We added an interaction terms of the firm-specific investor sentiment with a dummy variable, set to 1 if the market-wide sentiment proxy is greater than 0.6 and otherwise 0. The sentiment proxy regarding the broad stock market is derived from trading activity in S&P500 index options. Consistent with the definition of firm-specific investor sentiment, one proxy of investor sentiment regarding the broad stock market is the average open interest ratio of puts on an index stock to all index options for each week, while the other is the average trading volume ratio of puts on an index stock to all index options for each week. A higher open interest ratio or higher trading volume ratio suggests that investors are generally more pessimistic.

Table 6: Effect of Sentiment Regarding Broad Stock Market on the Relationship between Risk-Neutral Skewness and Investor Sentiment

	Firm-Specific Sentiment	Firm-Specific Sentiment x Dummy m	Control	Adj R^2
Panel A: Open Interest of Puts Divided by the Open Interest of all Options				
Coeff.	−0.153	-0.172	Yes	0.05
t-stat	−3.233***	-1.965**		
Panel B: Trading Volume of Puts Divided by the Trading Volume of all Options				
Coeff.	−0.047	-0.189	Yes	0.06
t-stat	−1.732*	-3.961***		

*Table 6 presents pooled time-series cross-sectional regression results with the risk-neutral skewness as the dependent variable. Dummy_m is a dummy variable which takes the value of 1 if the market-wide sentiment proxy is greater than 0.6 and otherwise 0.The sample period is from January 1, 2003 to December 31, 2012. Newey-West corrected estimates and t-statistics are reported. ***, ** and * respectively indicate significance at 1%, 5% and 10% levels.*

Table 6 shows the results. The coefficient of the investor sentiment is negative and significant, indicating that the risk-neutral density is more negatively skewed when investor sentiment turns more bearish. It should be noted that the coefficient of the interaction terms of the firm-specific investor sentiment with market-wide sentiment is negative and significant. The empirical results show that increased bearishness among market investors who dominate the use of index options will increase the extent to which risk-neutral skewness is affected by fluctuations in investor sentiment for the underlying stocks, regardless of the investor sentiment proxy used.

CONCLUSION

This paper focuses on individual stock options to test whether a wave of investor sentiment about the underlying stocks has a significant effect on risk-neutral skewness. It attempts to determine whether more impediments to arbitrage in the options market have important implications for the role of investor sentiment for the underlying stocks in explaining option-implied risk-neutral skewness. Specifically, this paper examines whether firms that have higher restrictions on short sales and/or a higher default likelihood and/or a smaller firm size may produce a stronger relationship between investor sentiment and option-implied risk-neutral skewness. In addition, we also examine whether market-wide investor sentiment affects the relations between firm-specific investor sentiment and firm-specific risk-neutral skewness.

Empirically, we use the stock and option prices for S&P500 component stocks from January 1, 2003 to December 31, 2012. We compute weekly risk-neutral skewness using the methodology proposed by Bakshi *et al.* (2003) and follow the empirical implications presented by Dennis and Mayhew (2002). The empirical results support that risk-neutral skewness is more negative under bearish investor sentiment for each investor sentiment proxy. The empirical results show that when firms have a higher level of short sales restrictions, a higher default likelihood or smaller size, the absolute estimated coefficient of investor sentiment tends to be greater for both investor sentiment measures. In addition, the pricing impact of investor sentiment for the underlying stocks on risk-neutral skewness is higher given increased bearishness among market investors who dominate the use of index options. The empirical results highlight that when there are more impediments to arbitrage in the option market, there is a stronger relationship between investor sentiment and risk-neutral skewness, indicating that risk-neutral skewness is affected to a greater extent by fluctuations in investor sentiment about the underlying stocks.

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BIOGRAPHY

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TRIMMING EFFECTS AND MOMENTUM INVESTING

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ABSTRACT

This study tests the effects of outlier trimming (or truncation) on the performance of momentum portfolios. We test the hypothesis that outliers are essential and possess carry-over effects applicable to momentum investing. Our results support the hypothesis. We find momentum portfolios formed using untrimmed data produce higher returns than those formed using outlier trimmed data. Risk-adjusted results show the same results. Moreover, we find that the less the data are trimmed, the larger the resulting spread between the winner and loser portfolios formed from momentum. Finally, our results show that the trimming effect continues to exist even after distinguishing between UP and DOWN market states.

JEL: G11, G12, G14, G17

KEYWORDS: Trimming Level,Trading Strategies, Investment Strategies

INTRODUCTION

Momentum is one of the strongest factors among the myriad of factors presented in the recent finance literature. In the vast majority of studies, momentum portfolios are formed using data from the previous year, which longs a winner portfolio and contemporaneously shorts a loser portfolio. The seminal paper by Jegadeesh and Titman (1993, JT hereafter) demonstrate the presence of momentum in stock returns over intermediate horizons. Their conclusions show that the self-financed portfolio that buys the winner 10% and sells the loser 10% of stocks ranked by past six months returns and holds the portfolios for six months generates an average performance of approximately 1% per month.

The effects of outlier trimming on momentum portfolio performance have not been thoroughly investigated. A review of the momentum literature shows that nearly all previous studies deal with outliers in an ad-hoc fashion without much explanation. Many studies, simply remove outliers from their dataset by an ad-hoc trimming level before momentum portfolio formation but without any justification.

Asness at al. (2013), for example, exclude stock prices less than $1 at the beginning of each month. Chuang and Ho (2014) exclude stocks with prices less than $1 during the formation period. Adrian at al. (2014) excludes the smallest decile of firms based on market capitalization on the formation date. Hwang and Rubesam (2015) exclude all stocks with prices below $5 at the portfolio formation date and all stocks whose sizes would place them in the smallest NYSE decile. Chen and Yang (2016) investigate the echo effect on momentum. They employ the entire sample of stocks (which means trimmed at 0% level) for their dataset. Daniel and Titman (1997) exclude firms with book-to-market values below zero. Fama and French (2012) show the results of excluding microcap portfolios. Menkhoff at al. (2012) exclude many smaller emerging markets from their sample. Kelly and Pruitt (2013) form their own data sets which exclude dividend nonpayers. None of these papers analyze the trimming effect on momentum investing described in this study.

Methodologically, we use monthly data and form momentum portfolios using the traditional JT strategy based on different levels of outlier trimming. Translated to the framework of the trimming effect; our hypothesis is then, the momentum portfolios formed from higher percentage outlier trimming may inadvertently also removed the outlier stocks with the most trimming effect and thus will underperform momentum portfolios formed from lower percentage outlier trimming or no outlier trimming. The methodology section will provide more details of the testing methodology. Our main results show that the performance proxy associated with a portfolio formed from stocks using the untrimmed momentum strategy is about 38% better than that of the different trimmed strategies investigated in this study.

The results, moreover, are robust to different subsamples and testing methodologies. Our study shows that the untrimmed strategy leads to higher performance, and captures more overreaction to previous information from investors when new information substantiates. To sum up, the momentum portfolio formed from untrimmed data outperforms those formed from trimmed data.

Our results show several additional details. First, the performance of the winner portfolios will reduce when the trimming level is increased. Second, the performance of the loser portfolios will increase when the trimming level is increased. Third, the winner minus loser (self-financed) portfolios' performance will also reduce when the trimming level is raised. Finally, our results show that the trimming effect continues to exist even after distinguishing between UP and DOWN market states.

The rest of this paper is organized as follows. In the next section, literature on the relative trimming are presented. In the following section, we provide a discussion of the data and methodology applied in the study. Analysis of Profit from Trimmed Strategies are provided in the results section. The final section, this study closes with some concluding comments and suggestions for future research.

LITERATURE REVIEW

Ledolter (1989) finds an additive outlier through the carryover effect affects the forecasts. Chen and Liu (1993) find Outliers in time series may have a mild to significant impact on the effectiveness for time series analysis. Daniel and Titman (1997) exclude firms with book-to-market values below zero. Their evidence show that the return premia on small size stocks and high book-to-market stocks does not arise because of the comovement of these stocks with common factors. Fama and French (2012) show the results of excluding microcap portfolios. They show that empirical asset pricing models capture the value and momentum patterns in international average returns. They further find the asset pricing seems to be integrated across North America, Europe, and Japan. Menkhoff at al. (2012) exclude many smaller emerging markets from their sample. They find excess returns of up to 10% per annum significantly between past self-financing currencies momentum portfolios. This spread in excess returns partially is explained by transaction costs and shows behavior consistent with investor under-reaction and over-reaction. Kelly and Pruitt (2013) form their own data sets which exclude dividend nonpayers. They construct forecasts of returns and cash flow growth rates both in-sample and out-of-sample by extracting information from disaggregate valuation ratios. Their results imply that discount rates are much less persistent, and their shocks more volatile, than previous literature suggests.

A review of the momentum literature shows that nearly all previous studies deal with outliers in an ad-hoc fashion without much explanation. Asness at al. (2013), for example, exclude stock prices less than \$1 at the beginning of each month. Their result find that the significant performance to value and momentum portfolios in every asset class with a linkage strongly. Chuang and Ho (2014) exclude stocks with prices less than \$1 during the formation period. They form an implied price risk (IPR) momentum strategy. They find IPR-momentum strategy is nearly orthogonal to the value investing strategy. They conclude that the performance of IPR-momentum strategy do not come from the value investing strategy because if the both strategies are similar, then their portfolio returns present a positive correlation. Adrian at al. (2014) excludes the smallest decile of firms based on market capitalization on the formation date. They find that the broker-dealer leverage factor can interpret the average excess returns on a wide variety assets, including equity portfolios sorted by size, book-to-market, momentum, and the Treasury bond portfolios sorted by maturity. Hwang and Rubesam (2015) exclude all stocks with prices below $5 at the portfolio formation date and all stocks whose sizes would place them in the smallest NYSE decile. They show that momentum has disappeared since the late 1990s, and the risk-adjusted momentum premium is only during certain periods in the past, notably from 1940 to 1960 and from 1970 to 1990. Chen and Yang (2016) investigate the echo effect on momentum. They employ the entire sample of stocks (which means trimmed at 0% level) for their dataset. They show the length of the skip-period in the 52-week high portfolios differs from the length of the skip- period in JT (Jegadeesh and Titman, 1993) momentum portfolios that found by Novy-Marx (2012).

None of these papers analyze the trimming effect on momentum investing described in this study. This study investigates the effects of outlier trimming on momentum profits. The effects of outlier trimming on momentum portfolio performance have not been thoroughly investigated.

DATA AND METHODOLOGY

This study uses monthly data. The data includes 23802 firms of all NYSE, AMEX, and NASDAQ stocks' prices (share codes 10 and 11) listed in the Center for Research in Securities Prices (CRSP) monthly file and contains all such stocks from December 1927 through December 2013. We compute the momentum portfolio following the procedures described by Jegadeesh and Titman (1993, JT hereafter) based on past 12-month return. Stocks are ranked using their past 12-month return. We then adopt various approaches of trimming level to the past return of the formation period. We use 10% cutoff to distinguish winner and loser portfolios in the analyses and hold positions for one month. Trimming removes outliers from samples. For instance, samples in the formation period that are trimmed 1% mean that we remove stocks with the largest 1% returns in the prior 12 months and also stocks with the smallest 1% returns in the prior 12 months. We denote this as T1%. Trimmed 0.5% level means removing stocks with the largest 0.5% returns in the prior 12 months and stocks with the smallest 0.5% returns in the prior 12 months. We denote this as T0.5% in this paper.

In this study, we examine the trimming effect on the JT momentum portfolio by varying trimming, from 0% to 1% level. This method produces eleven different formation patterns. We skip one month between portfolio formation and portfolios purchase to avoid lagged reaction effects, price pressure, and bid-ask spread by as in Jegadeesh (1990) and Lehmann (1990). We then hold the portfolios for one month. The resulting profits are calculated as the equally weighted average returns of the portfolios established one month ago.

For clarity of illustration, in the remainder of this paper, we denote momentum portfolios formed from the various trimming analyzed in this study using the Tx% notation. The "T" refers to trimming. Tx% denotes that the sample is trimmed at x% and 1-x% levels. The no-trimmed momentum strategy is denoted as T0% strategy using this notation. The 1%-trimmed momentum strategy is denoted as T1% strategy.

RESULTS

Analysis of Profit from Trimmed Strategies

In this section, we describe the monthly returns of the trimming strategies discussed in the last section — the analyzed period spans from 1927 to 2013 which covers most contemporary financial crises. Table 1 displays the average monthly raw returns of equally weighted decile portfolios and self-financed decile portfolios of eleven different trimmed JT (Jegadeesh and Titman, 1993) strategies over the one month holding period, with winners (the top decile) and losers (the bottom decile) identified using 10% cutoffs. The first row lists the eleven trimmed strategies. Table 1 also shows the results for self-financed portfolios, decile-based, long the top decile and short the bottom decile portfolios. Consistent with Jegadeesh and Titman (1993), our results show strong evidence of momentum based past 12-month return.

The second row shows the return of winner portfolios. It exhibits a descending pattern as the trimming level is raised. The T0% winner portfolio generates a return of 0.76% per month. The winner returns of the T0.5% and the T1% strategies reduce its return to 0.74% and 0.71%, respectively. It can be seen that the performance of the winner portfolios will reduce when the trimming level is raised.

The second to the last row expresses the return of loser portfolios. These portfolios exhibit an ascending pattern as the trimming level is raised. The T0% loser portfolio generates a return of -0.19% per month. The loser return of the T0.5% strategy has a higher return of -0.05%, and the loser returns of the T1% strategy gives an even higher return of positive 0.03%. It can be seen that after increases in trimming, a loser is not similar to a loser anymore and the performance of the loser portfolios will appreciate when the trimming level is raised.

The last row shows results of decile-based self-financed portfolios of eleven different trimmed strategies. The results also exhibit a descending pattern as the trimming level is raised. For the various trimmed strategies, the T0% self-financed portfolio provides the best returns, a positive monthly return of 0.95%, statistically significant with a t-statistic of 3.43 which is similar to Jegadeesh and Titman (1993). The T0.5% and the T1% self-financed portfolios reduce its returns to 0.8% and 0.69%, statistically significant with t-statistic of 2.94 and 2.56, respectively. The results show that performance will reduce when the trimming level is raised. Most notably, we find that the return of the T0% self-financed portfolio which is 38% greater than that of the T1% self-financed portfolio.

Table 1: Returns of Portfolios with Various Levels of Outlier Trimming

	Trimming										
Portfolios	**T0%**	**T0.1%**	**T0.2%**	**T0.3%**	**T0.4%**	**T0.5%**	**T0.6%**	**T0.7%**	**T0.8%**	**T0.9%**	**T1%**
Winner	0.76	0.76	0.75	0.74	0.74	0.74	0.74	0.73	0.72	0.72	0.71
2	0.69	0.69	0.69	0.70	0.70	0.70	0.71	0.71	0.72	0.72	0.72
3	0.74	0.74	0.74	0.73	0.74	0.73	0.73	0.74	0.73	0.73	0.73
4	0.68	0.68	0.68	0.69	0.68	0.69	0.69	0.68	0.68	0.68	0.67
5	0.73	0.72	0.73	0.72	0.73	0.72	0.72	0.73	0.72	0.72	0.73
6	0.60	0.59	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.59
7	0.61	0.61	0.61	0.62	0.62	0.62	0.62	0.62	0.62	0.62	0.62
8	0.49	0.48	0.48	0.47	0.47	0.47	0.47	0.47	0.47	0.47	0.47
9	0.40	0.40	0.41	0.42	0.43	0.44	0.44	0.44	0.44	0.45	0.45
Loser	-0.19	-0.15	-0.12	-0.09	-0.08	-0.05	-0.03	-0.01	0.00	0.02	0.03
Winner-Loser	0.95***	0.91***	0.87***	0.83***	0.82***	0.80***	0.77***	0.74***	0.71***	0.70***	0.69**
	(3.43)	(3.25)	(3.14)	(3.03)	(3.02)	(2.94)	(2.85)	(2.73)	(2.64)	(2.59)	(2.56)

*This table reports the average monthly returns from March 1927 through December 2013 for eleven momentum strategies of various trimming. Momentum portfolios are formed based on past 12-month return. Stocks are sorted into ten portfolios. The winner (loser) portfolio in momentum strategy is the equally weighted portfolio of 10% of stocks with the highest (lowest) past 12-month return. All portfolios are held for one month. The Trimming denotes that the portfolio is formed from a sample that is trimmed at T percent. Momentum strategy of T1% corresponds to portfolios formed from the sample of stocks that are trimmed each month at the top 1% and bottom 99% during the observation period. The sample includes all stocks on CRSP and t-statistics are in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% level, respectively.*

To summarize, Table 1 shows three notable aspects. First, the performance of the winner portfolios will reduce when the trimming level is raised. Second, the performance of the loser portfolios will appreciate when the trimming level is raised. Finally, the winner minus loser (self-financed) portfolio's performance will reduce when the trimming level is raised.

Risk-adjusted Returns

We next run time series regression of the average monthly excess returns on the Fama-French three factors to hedge out the effects of these factors. The dependent variable, R_(Td,t), in these regressions is the month t excess return corresponding to the various trimmed Tx% strategies. The independent variables are Fama-French three factors. The constant term in the regressions will then be the risk-adjusted performance measure which will allow us to compare the performance of the different trimming strategies from the following regression:

$$R_{Td,t} = b_{0,Td,t} + b_{1,Td,t} X_{FF3F,t-1} + e_{Td,t} \tag{1}$$

b_(0,Td,t) is risk-adjusted performance can be interpreted as the return of outliers to a neutral portfolio that has hedged out the Fama-French three factors identified by one of the eleven strategies. X_(FF3F,t-1) is Fama-French three factors in month t-1 include risk premium factor, size factor and book-to-market factor. In our regression, there is no overlapping effect because the portfolios are held for only one month.

Table 2 shows the estimated results for risk-adjusted performances and the associated t-statistics from the time series regressions. The sample period for Table 2 is from March 1927 to December 2013. The second row shows that the risk-adjusted performance of winner portfolios exhibits a descending pattern as the trimming level is raised. The risk-adjusted performance of T0% winner portfolio is 0.54% per month, statistically significant with a t-statistic of 2.24. The winner risk-adjusted performances of the T0.5% and the T1% winner portfolios are reduced to 0.53% and 0.51%, statistically significant with t-statistic of 2.24 and 2.16, respectively. It can be seen that the risk-adjusted performance of the winner portfolios is reduced when the trimming level is raised.

The second to the last row shows the risk-adjusted performance of loser portfolios. It shows an ascending pattern as the trimming level is raised. The T0% the loser portfolio generates a risk-adjusted performance of -0.64% per month, statistically significant with a t-statistic of -1.72. On the other hand, the loser risk-adjusted performances of the T0.5% and the T1% loser portfolios are higher, -0.05% and -0.42%, but not statistically significant. Overall pattern shows that the loser portfolios' the risk-adjusted performance tend to increase when the trimming level is raised.

The last row shows that the self-financed portfolios display a descending pattern in performance as the trimming level is raised. For the various trimmed strategies, the T0% self-financed portfolio provides the best risk-adjusted performances, a positive monthly risk-adjusted performance of 1.16%, statistically significant with a t-statistic of 4.24 which is 29% (15%) greater than that of T1% (T0.5%) self-financed portfolios (9% (1.01%)). The T0.5% and the T1% strategies exhibit lower risk-adjusted performances of 1.01% and 0.9%, statistically significant with t-statistics of 3.76 and 3.42, respectively. In short, the risk-adjusted performance of the self-financed portfolios will also reduce when the trimming level is raised.

Table 2: Comparison of Risk-adjusted performances of Momentum Portfolios with Various Trimming

	Trimming					
Portfolios	**T0%**	**T0.1%**	**T0.2%**	**T0.3%**	**T0.4%**	**T0.5%**
Winner	0.54**	0.55**	0.54**	0.54**	0.53**	0.53**
	(2.24)	(2.27)	(2.27)	(2.25)	(2.24)	(2.24)
2	0.49**	0.49**	0.49**	0.49**	0.49**	0.49**
	(2.35)	(2.34)	(2.33)	(2.36)	(2.36)	(2.36)
3	0.53***	0.53***	0.53***	0.53***	0.54***	0.53***
	(2.73)	(2.72)	(2.72)	(2.71)	(2.74)	(2.72)
4	0.47**	0.48**	0.48**	0.48**	0.47**	0.48**
	(2.34)	(2.35)	(2.34)	(2.37)	(2.33)	(2.36)
5	0.48**	0.48**	0.48**	0.47**	0.48**	0.47**
	(2.29)	(2.27)	(2.28)	(2.26)	(2.28)	(2.26)
6	0.35	0.35	0.35	0.35	0.35	0.35
	(1.63)	(1.62)	(1.63)	(1.63)	(1.64)	(1.64)
7	0.32	0.32	0.32	0.32	0.32	0.32
	(1.35)	(1.36)	(1.37)	(1.38)	(1.38)	(1.39)
8	0.21	0.21	0.21	0.20	0.20	0.20
	(0.85)	(0.85)	(0.84)	(0.81)	(0.80)	(0.78)
9	0.07	0.08	0.09	0.10	0.11	0.11
	(0.24)	(0.27)	(0.30)	(0.34)	(0.38)	(0.39)
Loser	-0.64*	-0.60	-0.57	-0.54	-0.53	-0.50
	(-1.72)	(-1.62)	(-1.53)	(-1.45)	(-1.43)	(-1.36)
Winner-Loser	1.16***	1.13***	1.09***	1.05***	1.04***	1.01***
	(4.24)	(4.09)	(3.99)	(3.88)	(3.87)	(3.76)

This table reports the average monthly risk-adjusted performances from March 1927 through December 2013 for eleven momentum strategies of various trimming. In each month t, common stocks listed on NYSE, AMEX, and Nasdaq are sorted into portfolios based on their returns over the past one year. Portfolios are obtained using 10% cutoff and then divide it into to ten trimming portfolios. $R_{Td,t} = b_{0,Td,t} + b_{1,Td,t}X_{FF3F,t-1} + e_{Td,t}$ *where* $R_{Td,t}$ *is the return of portfolio d decile in month t.* $X_{FF3F,t-1}$ *is the Fama-French three factors in month t-1. To obtain risk-adjusted performances, we run the times series regressions of portfolios averages (one for each average) on the Fama-French factor realizations to hedge out the factor predictability. The numbers reported for risk-adjusted performances are the constant from these time-series regressions. The sample includes all stocks on CRSP and t-statistics are in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% level, respectively.*

The last two columns provide the difference of risk-adjusted results for the difference between two portfolios of different trimming levels. The T0%-T0.5% and T0%-T1% loser portfolios generate risk-adjusted performances of -0.17% and -0.25% per month, statistically significant with t-statistic of -6.95 and -7.23, respectively. The difference in the risk-adjusted performance of the T0%-T0.5% and T0%-T1% self-financed portfolios generate 0.13% and 0.24% per month, statistically significant with t-statistic of 4.58 and 6.04, respectively. Results again show that the risk-adjusted performance of the T0% self-financed portfolio is greater than the risk-adjusted performance associated with all other trimmed self-financed portfolios. Indeed, the T0% strategy dominates the T0.5% and the T1% strategies as well.

To summarize, Table 2 denotes three notable aspects. First, the risk-adjusted performance of the winner portfolios and self-financed portfolios will reduce when the trimming level is raised. Second, the risk-adjusted performance of the loser portfolios will increase when the trimming level rises. Finally, the difference in the risk-adjusted performance of the self-financed portfolios indicates the T0% strategy dominates those of the T0.5% and the T1% strategies.

Table 2: Comparison of Risk-adjusted performances of Momentum Portfolios with Various Trimming (Continued)

	Trimming						
Portfolios	**T0.6%**	**T0.7%**	**T0.8%**	**T0.9%**	**T1%**	**T0%-T0.5%**	**T0%-T1%**
Winner	0.52**	0.52**	0.51**	0.51**	0.51**	-0.01	0.01
	(2.21)	(2.19)	(2.15)	(2.15)	(2.16)	(-0.73)	(0.58)
2	0.50**	0.50**	0.50**	0.51**	0.51**	-0.03***	-0.04***
	(2.40)	(2.41)	(2.41)	(2.44)	(2.43)	(-2.95)	(-2.92)
3	0.53***	0.54***	0.53***	0.53***	0.54***	-0.02***	-0.03***
	(2.71)	(2.74)	(2.74)	(2.74)	(2.76)	(-3.51)	(-2.95)
4	0.48**	0.47**	0.47**	0.47**	0.46**	-0.03***	-0.01*
	(2.36)	(2.31)	(2.31)	(2.31)	(2.28)	(-6.06)	(-1.88)
5	0.47**	0.48**	0.48**	0.47**	0.48**	-0.02***	-0.02***
	(2.27)	(2.28)	(2.27)	(2.26)	(2.28)	(-5.64)	(-4.35)
6	0.35	0.35	0.35	0.35	0.35	-0.03***	-0.02***
	(1.63)	(1.64)	(1.63)	(1.63)	(1.61)	(-8.09)	(-4.14)
7	0.33	0.33	0.32	0.33	0.33	-0.03***	-0.04***
	(1.40)	(1.40)	(1.39)	(1.40)	(1.44)	(-5.30)	(-4.87)
8	0.19	0.19	0.20	0.20	0.20	-0.01	-0.01
	(0.77)	(0.78)	(0.79)	(0.79)	(0.79)	(-0.67)	(-0.69)
9	0.11	0.12	0.12	0.13	0.13	-0.07***	-0.09***
	(0.39)	(0.42)	(0.44)	(0.47)	(0.47)	(-5.78)	(-5.26)
Loser	-0.48	-0.46	-0.45	-0.44	-0.42	-0.17***	-0.25***
	(-1.32)	(-1.26)	(-1.23)	(-1.20)	(-1.16)	(-6.95)	(-7.23)
Winner-Loser	0.98***	0.95***	0.93***	0.92***	0.90***	0.13***	0.24***
	(3.68)	(3.57)	(3.49)	(3.45)	(3.42)	(4.58)	(6.04)

This table reports the average monthly risk-adjusted performances from March 1927 through December 2013 for eleven momentum strategies of various trimming. In each month t, common stocks listed on NYSE, AMEX, and Nasdaq are sorted into portfolios based on their returns over the past one year. Portfolios are obtained using 10% cutoff and then divide it into to ten trimming portfolios. $R_{Td,t} = b_{0,Td,t} + b_{1,Td,t}X_{FF3F,t-1} + e_{Td,t}$ *where* $R_{Td,t}$ *is the return of portfolio d decile in month t.* $X_{FF3F,t-1}$ *is the Fama-French three factors in month t-1. To obtain risk-adjusted performances, we run the times series regressions of portfolios averages (one for each average) on the Fama-French factor realizations to hedge out the factor predictability. The numbers reported for risk-adjusted performances are the constant from these time-series regressions. The sample includes all stocks on CRSP and t-statistics are in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% level, respectively.*

Analysis Risk-adjusted Performance across Different Market States

To test the robustness of the effect of outlier trimming on momentum returns, we test to see if market states affect the results. Methodologically, we separate the whole sample period into two groups by market states using the market states definitions in Cooper et al. (2004). This market state definition is relevant to this study because Cooper et al. (2004) show market states when defined as such significantly influence momentum returns. In particular, they find positive average monthly momentum return is more likely to associate with UP market, and the negative average monthly momentum return is more likely to be associated with DOWN market. Following Cooper et al. (2004), we distinguish states of the market at the beginning of holding period of each portfolio. We employ the Dow Jones Industrial Average over the three years prior to the beginning of the strategy's holding period. Specifically, the returns on the Dow Jones Industrial Average are computed over the period t-36 to t-1, then non-negative (negative) returns of the Dow Jones Industrial Average index will define the UP (DOWN) market states. We also proffer a one-year definition of the market's state.

Table 3 presents the average monthly risk-adjust returns from March 1927 through December 2013 for various outlier trimmed momentum strategies in UP and DOWN markets, respectively. We employ the prior three-year return of the market as the market state proxy in Panel A and Panel B. In Panel C and Panel D; we employ the prior one-year return of the market as the market state proxy.

Panel A shows the results corresponding to UP markets based on three-year return. The Panel shows that the risk-adjusted performance of the winner portfolios exhibits a descending pattern as the outlier trimming level is increased. The risk-adjusted performance of T0% winner portfolio is 0.84% per month, statistically significant with a t-statistic of 3.43. The risk-adjusted performance of the T0.5% and the T1% winner portfolios are lower than the T0% winner portfolio (0.82% and 0.79%, statistically significant with t-statistic of 3.43 and 3.36, respectively). The results show that as the trimming level increases, the winner portfolio behaves less and less like a winner portfolio. Moreover, the risk-adjusted performance of the winner portfolios also reduces when the trimming level is increased. In comparison, the risk-adjusted performances of the loser portfolios exhibit an ascending pattern. The T0% loser portfolio generates a risk-adjusted performance of -0.78% per month, statistically significant with a t-statistic of -2.46. The loser risk-adjusted performances of the T0.5% and the T1% strategies show an increasing risk-adjusted performance of -0.61% and -0.53%, statistically significant with t-statistic of -1.98 and -1.75, respectively. The results show that as the trimming level increases, the loser becomes less like a loser, and its risk-adjusted performance will increase.

Table 3 Panel A: Comparison of Risk-Adjusted Performances in the Different Market State-Results for 3 Years UP Market

Panel A: 3 Years UP Market	**Trimming**				
Portfolios	**T0%**	**T0.5%**	**T1%**	**T0%-T0.5%**	**T0%-T1%**
Winner	0.84***	0.82***	0.79***	-0.01	0.02
	(3.43)	(3.43)	(3.36)	(-0.45)	(0.78)
2	0.73***	0.74***	0.76***	-0.04***	-0.06***
	(3.71)	(3.77)	(3.89)	(-3.83)	(-3.75)
3	0.77***	0.76***	0.77***	-0.01**	-0.02**
	(4.22)	(4.17)	(4.21)	(-2.02)	(-2.27)
4	0.70***	0.71***	0.69***	-0.03***	-0.02**
	(3.98)	(4.01)	(3.92)	(-6.60)	(-2.19)
5	0.69***	0.68***	0.68***	-0.02***	-0.02***
	(3.92)	(3.90)	(3.89)	(-6.26)	(-3.60)
6	0.58***	0.58***	0.58***	-0.03***	-0.02***
	(3.22)	(3.24)	(3.21)	(-8.56)	(-4.47)
7	0.47**	0.48**	0.49**	-0.04***	-0.04***
	(2.46)	(2.51)	(2.56)	(-6.38)	(-4.81)
8	0.28	0.27	0.28	-0.01*	-0.02*
	(1.39)	(1.33)	(1.37)	(-1.74)	(-1.94)
9	0.11	0.14	0.16	-0.05***	-0.07***
	(0.48)	(0.60)	(0.69)	(-4.39)	(-4.35)
Loser	-0.78**	-0.61**	-0.53*	-0.19***	-0.28***
	(-2.46)	(-1.98)	(-1.75)	(-7.11)	(-7.18)
Winner-Loser	1.60***	1.41***	1.30***	0.16***	0.27***
	(6.57)	(6.03)	(5.70)	(5.18)	(6.39)

This table reports the average monthly risk-adjusted performances from March 1927 through December 2013 for various trimmed momentum strategies in UP and DOWN markets. Returns on the Dow Jones Industrial Average are computed over the period t-m to t-1 (where m=36 or 12), and non-negative (negative) returns of the Dow Jones Industrial Average indicate UP (DOWN) market. Panel A shows the results for 3 years UP market. In each month t, common stocks listed on NYSE, AMEX, and Nasdaq are sorted into portfolios based on their returns over the past one year. Portfolios are obtained using 10% cutoff and then divide it into to ten trimming portfolios. $R_{Td,t} = b_{0,Td,t} + b_{1,Td,t}X_{FF3F,t-1} + e_{Td,t}$ *where* $R_{Td,t}$ *is the return of portfolio d decile in month t.* $X_{FF3F,t-1}$ *is the Fama-French three factors in month t-1. To obtain risk-adjusted performances, we run the times series regressions of portfolios averages (one for each average) on the Fama-French factor realizations to hedge out factors. The numbers reported for risk-adjusted performances are the constant from these time-series regressions. The sample includes all stocks on CRSP and t-statistics are in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% level, respectively.*

The last row shows the results of self-financed portfolios of three different outlier-trimmed portfolios. They show a descending pattern. Of the various trimmed strategies, the T0% strategy provides the best risk-adjusted performance; a positive monthly risk-adjusted performance of 1.6%, statistically significant with a t-statistic of 6.57 which is 23% (13%) higher than the 1.3% (1.41%) of the T1% (T0.5%) strategy. The T0.5% and the T1% strategies both show lower risk-adjusted performance than the T0% strategy; they provide 1.41% and 1.3%, statistically significant with t-statistic of 6.03 and 5.7, respectively. Overall, it can be seen that the risk-adjusted performance of strategies will reduce when the trimming level is raised. The last two columns in Panel A show the difference between the loser portfolios T0%-T0.5% and T0%-T1% correspond to risk-adjusted performances of -0.19% and -0.28% per month, statistically significant with t-statistic of -7.11 and -7.18, respectively. These results show that risk-adjusted performance of T0% loser portfolio behaves more like a loser compared to the T0.5% and the T1% portfolios. The difference between the risk-adjusted performance of the T0%-T0.5% and T0%-T1% portfolios yield 0.16% and 0.27% per month, statistically significant with t-statistics of 5.18 and 6.39, respectively. Here again, the risk-adjusted performance of the T0% strategy is higher than the risk-adjusted performance associated with the other two different trimmed strategies. We find the T0% strategy dominates the T0.5% and the T1% strategies as well.

In short, Table 3 Panel A shows five main patterns result when the UP market is defined from previous three-year market returns. First, the risk-adjusted performance of the winner portfolios will reduce when the trimming level is increased. Second, the risk-adjusted performance of the loser portfolios will appreciate when the trimming level is increased. Third, the zero investment strategy's risk-adjusted performance will reduce when the trimming level is increased. Fourth, the difference between the risk-adjusted performance of the various loser portfolios indicates that the T0% loser portfolio performs significantly worse than the T0.5% and the T1% loser portfolios. Finally, the difference in the risk-adjusted performance of the strategies indicates the T0% self-financed portfolio dominates the other T0.5% and the T1% self-financed portfolios as well.

Panel B shows that there is no evidence of significant risk-adjusted performance for the various momentum strategies following DOWN states. The last two columns in Panel B, show the difference in the risk-adjusted performance of different outlier trimmed strategies. The difference of the loser portfolios T0%-T0.5% and T0%-T1% strategies generate risk-adjusted performances of -0.12% and -0.19% per month, statistically significant with t-statistic of -2.09 and -2.55, respectively. The difference indicates that the risk-adjusted performance of T0% loser portfolio behaves more like a loser than the T0.5% and the T1% loser portfolios. The risk-adjusted performance of the T0%-T1% self-financed portfolio generates 0.18% per month, statistically significant with a t-statistic of 1.97. Here, the risk-adjusted performance of the T0% self-financed portfolio is higher than the risk-adjusted performance associated with T1% self-financed portfolio.

Table 3 Panel B shows three main patterns result when the DOWN market is defined from previous three-year market returns. First, there is no evidence of significant risk-adjusted performance from any of the decile portfolios and self-financed portfolios following DOWN states. Second, the difference between the risk-adjusted performances of the loser portfolios indicates that the T0% loser portfolio is significantly worse than the T0.5% and the T1% loser portfolios. Finally, the risk-adjusted performance of the T0%-T1% self-financed portfolio indicates that the T0% self-financed portfolio dominates the T1% self-financed portfolio.

To further check the robustness of the results, we evaluate the risk-adjusted performance of our portfolios when the market state indicator is based on the previous one-year return. Panel C shows the results following UP markets based on previous one-year return. The panel shows that the risk-adjusted performance of the winner portfolios still exhibits a descending pattern. The risk-adjusted performance of T0% winner portfolio is 1.56% per month, statistically significant with a t-statistic of 5.31. The winner risk-adjusted performances of the T0.5% and the T1% strategies are lower than this, 1.52% and 1.47%, statistically significant with t-statistic of 5.33 and 5.24, respectively. It can be seen that outlier trimming causes the winner portfolio to behave less and less like a winner. In short, the risk-adjusted performance of the winner portfolios will reduce when the trimming level is increased.

Table 3 Panel B: Comparison of Risk-adjusted Performances in the Different Market State-Results for 3 Years DOWN Market

Panel B: 3 Years DOWN Market			**Trimming**		
Portfolios	**T0%**	**T0.5%**	**T1%**	**T0%-T0.5%**	**T0%-T1%**
Winner	-0.04	-0.05	-0.08	-0.01	0.02
	(-0.06)	(-0.09)	(-0.12)	(-0.11)	(0.23)
2	0.05	0.04	0.07	-0.01	-0.04
	(0.09)	(0.07)	(0.11)	(-0.44)	(-1.13)
3	0.14	0.17	0.14	-0.04**	-0.02
	(0.25)	(0.29)	(0.24)	(-2.48)	(-0.59)
4	0.14	0.15	0.14	-0.03**	-0.02
	(0.23)	(0.25)	(0.22)	(-2.32)	(-0.91)
5	0.32	0.31	0.33	-0.01	-0.03***
	(0.48)	(0.47)	(0.50)	(-1.26)	(-2.88)
6	0.18	0.18	0.17	-0.02**	-0.01
	(0.27)	(0.27)	(0.25)	(-2.12)	(-0.68)
7	0.37	0.35	0.38	-0.01	-0.04
	(0.49)	(0.47)	(0.51)	(-0.41)	(-1.61)
8	0.54	0.52	0.51	0.00	0.01
	(0.68)	(0.65)	(0.63)	(0.03)	(0.30)
9	0.67	0.73	0.70	-0.09***	-0.06
	(0.73)	(0.81)	(0.79)	(-2.91)	(-1.42)
Loser	0.86	0.96	1.03	-0.12**	-0.19**
	(0.75)	(0.85)	(0.92)	(-2.09)	(-2.55)
Winner-Loser	-0.92	-1.04	-1.13	0.09	0.18**
	(-1.15)	(-1.31)	(-1.43)	(1.28)	(1.97)

This table reports the average monthly risk-adjusted performances from March 1927 through December 2013 for various trimmed momentum strategies in UP and DOWN markets. Returns on the Dow Jones Industrial Average are computed over the period t-m to t-1 (where m=36 or 12), and non-negative (negative) returns of the Dow Jones Industrial Average indicate UP (DOWN) market. Panel B shows the results for 3 years DOWN market. In each month t, common stocks listed on NYSE, AMEX, and Nasdaq are sorted into portfolios based on their returns over the past one year. Portfolios are obtained using 10% cutoff and then divide it into to ten trimming portfolios. $R_{Td,t} = b_{0,Td,t} + b_{1,Td,t}X_{FF3F,t-1} + e_{Td,t}$ *where* $R_{Td,t}$ *is the return of portfolio d decile in month t.* $X_{FF3F,t-1}$ *is the Fama-French three factors in month t-1. To obtain risk-adjusted performances, we run the times series regressions of portfolios averages (one for each average) on the Fama-French factor realizations to hedge out factors. The numbers reported for risk-adjusted performances are the constant from these time-series regressions. The sample includes all stocks on CRSP and t-statistics are in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% level, respectively*

The last row shows of Panel C shows the results of self-financed portfolios of three different outlier trimmed strategies. It can be seen that they exhibit a descending pattern. Compared to the other trimmed strategies, the T0% self-financed portfolio provides the best risk-adjusted performances, a positive monthly risk-adjusted return of 1.79%, statistically significant with a t-statistic of 6.83 which is 25% (12%) higher than 1.43% (1.6%) of the T1% (T0.5%) self-financed portfolio. In comparison, the T0.5% and the T1% strategies exhibit lower risk-adjusted returns of 1.6% and 1.43%, statistically significant with t-statistic of 6.35 and 5.78, respectively. Again, the results continue to show that the risk-adjusted performance of strategies will reduce when the trimming level is increased.

The last two columns in Panel C, show the difference in the risk-adjusted performance between different outlier trimmed strategies. The difference between the winner portfolios T0%-T1% generates a risk-adjusted performance of 0.06% per month, statistically significant with a t-statistic of 1.82. The results show that T0% winner portfolio behaves more like a winner than the T1% winner portfolio.

Table 3 Panel C: Comparison of Risk-adjusted Performances in the Different Market State- Results for 1 Years UP Market

Panel C: 1 Years UP Market	**Trimming**				
Portfolios	**T0%**	**T0.5%**	**T1%**	**T0%-T0.5%**	**T0%-T1%**
Winner	1.56***	1.52***	1.47***	0.02	0.06*
	(5.31)	(5.33)	(5.24)	(0.66)	(1.82)
2	1.28***	1.27***	1.29***	-0.02*	-0.04**
	(5.27)	(5.27)	(5.34)	(-1.71)	(-2.13)
3	1.25***	1.25***	1.26***	-0.02***	-0.04***
	(5.61)	(5.60)	(5.69)	(-3.01)	(-2.90)
4	1.26***	1.26***	1.24***	-0.03***	-0.01
	(5.69)	(5.69)	(5.58)	(-4.65)	(-0.62)
5	1.20***	1.20***	1.20***	-0.02***	-0.02***
	(5.59)	(5.57)	(5.58)	(-4.24)	(-2.80)
6	1.06***	1.06***	1.05***	-0.02***	-0.02***
	(4.84)	(4.84)	(4.83)	(-5.93)	(-4.49)
7	0.95***	0.97***	0.97***	-0.04***	-0.04***
	(4.11)	(4.19)	(4.18)	(-5.40)	(-3.83)
8	0.86***	0.84***	0.84***	-0.01	-0.01
	(3.38)	(3.31)	(3.32)	(-0.90)	(-0.92)
9	0.73***	0.79***	0.80***	-0.08***	-0.10***
	(2.61)	(2.84)	(2.93)	(-5.75)	(-5.03)
Loser	-0.25	-0.10	0.02	-0.18***	-0.30***
	(-0.69)	(-0.29)	(0.06)	(-5.84)	(-7.24)
Winner-Loser	1.79***	1.60***	1.43***	0.17***	0.34***
	(6.83)	(6.35)	(5.78)	(4.50)	(6.65)

This table reports the average monthly risk-adjusted performances from March 1927 through December 2013 for various trimmed momentum strategies in UP and DOWN markets. Returns on the Dow Jones Industrial Average are computed over the period t-m to t-1 (where m=36 or 12), and non-negative (negative) returns of the Dow Jones Industrial Average indicate UP (DOWN) market. Panel C shows the results for 1 years UP market. In each month t, common stocks listed on NYSE, AMEX, and Nasdaq are sorted into portfolios based on their returns over the past one year. Portfolios are obtained using 10% cutoff and then divide it into to ten trimming portfolios. $R_{Td,t} = b_{0,Td,t} + b_{1,Td,t}X_{FF3F,t-1} + e_{Td,t}$ *where* $R_{Td,t}$ *is the return of portfolio d decile in month t.* $X_{FF3F,t-1}$ *is the Fama-French three factors in month t-1. To obtain risk-adjusted performances, we run the times series regressions of portfolios averages (one for each average) on the Fama-French factor realizations to hedge out factors. The numbers reported for risk-adjusted performances are the constant from these time-series regressions. The sample includes all stocks on CRSP and t-statistics are in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% level, respectively.*

The difference between the loser portfolios T0%-T0.5% and T0%-T1% generate risk-adjusted performances of -0.18% and -0.3% per month, statistically significant with t-statistic of -5.84 and -7.24, respectively. These results show that T0% loser portfolio behaves more like a loser compared to the T0.5% and the T1% loser portfolios.

The risk-adjusted performance of the T0%-T0.5% and T0%-T1% self-financed portfolios generate 0.17% and 0.34% per month, statistically significant with t-statistic of 4.5 and 6.65, respectively. Here, the risk-adjusted performance of the T0% self-financed portfolio is higher than the risk-adjusted performance associated with the other two outlier trimmed self-financed portfolios. The T0% strategy dominates T0.5% and T1% strategies.

When the UP market is defined from previous one-year market returns, the results of Table 3 Panel C show five main patterns. First, the risk-adjusted performance of the winner portfolios will reduce when the trimming level is increased. Second, the zero investment strategy's risk-adjusted performance will reduce when the trimming level is increased. Third, the difference between the risk-adjusted performance of different loser portfolios indicates that the T0% loser portfolio performs significantly worse than the T0.5% and the T1% loser portfolios. Forth, the difference between the risk-adjusted performances of the various winner portfolios indicates that the T0% winner portfolio performs significantly better than the T1% winner portfolio. Finally, the difference between the risk-adjusted performances of the various self-financed portfolios indicate that the T0% self-financed portfolio dominates the corresponding T0.5% and the T1% self-financed portfolios.

Panel D shows the risk-adjusted performance of the winner portfolios following DOWN markets calculated using previous one-year return. The results exhibit an ascending pattern. The risk-adjusted performance of the T0% winner portfolio is -1.75% per month, statistically significant with a t-statistic of -3.83. The risk-adjusted performances of the T0.5% and the T1% winner portfolios are higher than it, both -1.71%, statistically significant with t-statistic of -3.79 and -3.85, respectively. Following DOWN market states increasing outlier trimming levels makes the winner portfolios' performance less negative compared to the untrimmed counterpart.

Table 3 Panel D: Comparison of Risk-adjusted Performances in the Different Market State- Results for 1 Years DOWN Market

Panel D: 1 Years DOWN Market	**Trimming**				
Portfolios	**T0%**	**T0.5%**	**T1%**	**T0%-T0.5%**	**T0%-T1%**
Winner	-1.75***	-1.71***	-1.71***	-0.07**	-0.07*
	(-3.83)	(-3.79)	(-3.85)	(-2.47)	(-1.76)
2	-1.39***	-1.38***	-1.36***	-0.03**	-0.05**
	(-3.32)	(-3.31)	(-3.27)	(-2.29)	(-2.36)
3	-1.03**	-1.03**	-1.03**	-0.02	-0.03
	(-2.55)	(-2.55)	(-2.54)	(-1.58)	(-1.49)
4	-1.18***	-1.17***	-1.19***	-0.03***	-0.02
	(-2.70)	(-2.67)	(-2.70)	(-3.25)	(-1.39)
5	-0.97**	-0.98**	-0.97**	-0.02***	-0.02***
	(-2.02)	(-2.03)	(-2.02)	(-3.98)	(-3.32)
6	-1.13**	-1.13**	-1.14**	-0.03***	-0.01
	(-2.24)	(-2.24)	(-2.27)	(-4.07)	(-0.87)
7	-1.15**	-1.14**	-1.11**	-0.03**	-0.06***
	(-2.07)	(-2.06)	(-2.00)	(-2.41)	(-3.20)
8	-1.19**	-1.21**	-1.21**	-0.01	0.00
	(-2.02)	(-2.05)	(-2.06)	(-0.29)	(-0.02)
9	-1.29*	-1.25*	-1.26*	-0.06***	-0.05
	(-1.84)	(-1.79)	(-1.83)	(-2.61)	(-1.61)
Loser	-1.47	-1.35	-1.29	-0.14***	-0.20***
	(-1.63)	(-1.53)	(-1.47)	(-2.98)	(-3.01)
Winner-Loser	-0.31	-0.38	-0.44	0.05	0.11
	(-0.47)	(-0.58)	(-0.68)	(0.92)	(1.62)

This table reports the average monthly risk-adjusted performances from March 1927 through December 2013 for various trimmed momentum strategies in UP and DOWN markets. Returns on the Dow Jones Industrial Average are computed over the period t-m to t-1 (where m=36 or 12), and non-negative (negative) returns of the Dow Jones Industrial Average indicate UP (DOWN) market. Panel D shows the results for 1 years DOWN market. In each month t, common stocks listed on NYSE, AMEX, and Nasdaq are sorted into portfolios based on their returns over the past one year. Portfolios are obtained using 10% cutoff and then divide it into to ten trimming portfolios. $R_{Td,t} = b_{0,Td,t} + b_{1,Td,t}X_{FF3F,t-1} + e_{Td,t}$ *where* $R_{Td,t}$ *is the return of portfolio d decile in month t.* $X_{FF3F,t-1}$ *is the Fama-French three factors in month t-1. To obtain risk-adjusted performances, we run the times series regressions of portfolios averages (one for each average) on the Fama-French factor realizations to hedge out factors. The numbers reported for risk-adjusted performances are the constant from these time-series regressions. The sample includes all stocks on CRSP and t-statistics are in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% level, respectively.*

The risk-adjusted performance of the loser portfolios also exhibits an ascending pattern following DOWN markets calculated using previous one-year return. The T0% loser portfolio generates a risk-adjusted performance of -1.47% per month, marginally significant with a t-statistic of -1.63. The loser risk-adjusted performances of the T0.5% and the T1% strategies show higher risk-adjusted performance, -1.35% and -1.29%, insignificantly different from zero. It can be seen that a loser behaves less like a loser, and the risk-adjusted performance of the loser portfolios will increase when the trimming level is increased. The last row of this Panel shows that there is no evidence significant returns for the self-financed portfolios corresponding to the three differently trimmed strategies following DOWN states.

The last two columns in Panel D show the difference in the risk-adjusted performance between the different outlier-trimmed portfolios and the untrimmed portfolio. For the winner portfolios, the T0%-T0.5% and T0%-T1% strategies generate risk-adjusted performances both of -0.07% per month, statistically significant with t-statistic of -2.47 and -1.76. These results indicate that the risk-adjusted performance of T0% winner portfolio now behaves less like a winner compared with the other two outlier trimmed portfolios.

The difference between the loser portfolios T0%-T0.5% and T0%-T1% strategies generate a risk-adjusted performance of -0.14% and -0.2% per month, statistically significant with t-statistic of -2.98 and -3.01, respectively. The results indicate that the risk-adjusted performance of T0% loser portfolio behaves more in line with a lower portfolio compared to the other two outlier-trimmed portfolios. The difference in the risk-adjusted performance of the T0%-T1% self-financed portfolio is 0.11% per month, marginally significant with a t-statistic of 1.62. Here, the risk-adjusted performance of the T0% strategy is higher than the risk-adjusted performance associated with T1% self-financed portfolio.

When the DOWN market state is calculated from previous one-year market returns, the results of Table 3 Panel D show five main patterns. First, the risk-adjusted performance of the winner portfolios increases with the outlier trimming level. Second, the risk-adjusted performance of the loser portfolios also increases when the trimming level is increased. Third, the difference between the risk-adjusted performance of the winner portfolios indicates that the T0% winner portfolio performs significantly worse than the T0.5% and the T1% strategies following the DOWN market state. Forth, the difference between the risk-adjusted performance of various pairs of loser portfolios indicates that the T0% loser portfolio performs significantly worse than the T0.5% and the T1% loser portfolios. Finally, the difference in the risk-adjusted performance of the self-financed portfolios indicates the T0% self-financed portfolio outperforms the T1% self-financed portfolio.

As a whole, Table 3 shows the effect of outlier trimming for a spectrum of momentum strategies in different two market states. In the UP market state, the risk-adjusted performances of the T0%-T0.5% and T0%-T1% self-financed portfolios are both positive and statistically significant. In the DOWN market state, the difference between the T0%-T1% self-financed portfolios' risk-adjusted performance is positive but marginally significant.

CONCLUDING COMMENTS

The seminal paper by Jegadeesh and Titman (1993, JT hereafter) reveals the presence of momentum in stock returns over intermediate horizons. Their conclusions show that the self-financed portfolio that buys the winner 10% and sells the loser 10% of stocks ranked by past six months returns and holds the portfolios for six months generates an average performance of approximately 1% per month. This study tests the hypothesis that in momentum investing, outliers are essential and may possess carryover effects. We compare the performances of momentum portfolios under different levels of outlier trimming. The effects of outlier trimming are tested using empirical results from momentum investing. We compare the performances of portfolios constructed using the standard JT methodology with those constructed using our proposed Tx% measure. This comparison permits us to explore whether there is a "trimming effect" under the framework of momentum investing.

Previous research on momentum almost always excludes outliers from their analysis without much discussion. For example, Asness at al. (2013) exclude stock prices inferior to $1 at the beginning of each month. Chuang and Ho (2014) exclude stocks with prices less than $1 during the formation period. Adrian at al. (2014) exclude the smallest decile of firms based on market capitalization on the formation date. Hwang and Rubesam (2015) exclude all stocks with prices below $5 at the portfolio formation date and all stocks whose sizes would place them in the smallest NYSE decile. There is no previous literature that analyzes the effects of outlier trimming on momentum returns. This study shows that outliers are important in momentum investing. We find that momentum portfolios formed from outlier trimmed data perform worse than momentum portfolios formed from the original untrimmed data that includes the outlier observations. Moreover, the performance decreases monotonically as a higher percentage of outliers are trimmed from the dataset.

Our results show that the no-trimmed (including outlier) momentum strategies lead to higher performance, captures more under-reaction and over-reaction to previous information from investors when new information substantiates. The portfolios constructed using untrimmed data are shown to outperform those from alternative trimming strategies. The performance of momentum strategies will reduce when the trimming level is raised. Outliers are important and possess trimming effects. In sum, the empirical findings of this study provide evidence of the existence of the trimming effect in stocks that manifests as the subsets of JT momentum strategy. The performance results show that the no-trimmed momentum self-financed portfolio provides the most robust performance, outperforming other trimmed self-financed portfolios.

For robustness, we additionally test whether the outlier trimming effect continues to exist under different market states. Our results show that the trimming effect continues to exist, even after controlling for the different market states. In the UP market state, the difference between the risk-adjusted performance of the T0%-T0.5% and T0%-T1% self-financed portfolios are both positive and statistically significant. In the DOWN market state, the difference between the T0%-T1% self-financed portfolio's risk-adjusted performance is positive but only marginally significant. The results suggest that outliers are somewhat more important for momentum investing in UP market states compared to DOWN market states.

The document of this study does not allow us to discriminate between under-reaction and over-reaction about investor behavior. In addition, these results may have other interpretations. In the light of our results suggest further research that attempts to determine interpretations for these empirical phenomena will be of interest.

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