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Do Daily Short Sales Forecast S&P 500 Sector Returns?

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Abstract

We examine the data for S&P 500 firms for 2009 to 2012 to determine whether daily short selling, aggregated at the industry sector level, forecasts relative returns. Prior research documents short sellers as skilled fundamental analysts and information processors at the individual security level and in aggregate as forecasters of short-term market direction. Intriguingly, we find not only that sector-aggregated daily short sale information does not correctly forecast the short-term relative performance of industry sectors but rather that some contrarian strategies that are *short* the least shorted sectors and *long* the most shorted sectors are profitable on average.

I. Introduction

A growing body of academic research suggests short sellers detect and trade on short-term opportunities. Engelberg, Reed, and Ringgenberg (2012) examine daily short sales around Dow Jones News Service and Wall Street Journal stories. They find that the negative relation between short selling and future stock return is substantially larger around news days, particularly days with negative news. They conclude that "the evidence suggests that public news provides valuable trading opportunities for short sellers who are skilled information processors" (p. 260). Blau and Tew (2014) analyze daily short selling around class-action lawsuits and conclude "short activity surges in the days before the filing." Lynch, Nikolic, Yan, and Yu (2014) conclude that short sellers are informed at the market-wide level and document that aggregate daily short selling forecasts market-level returns for the following 5 to 20 trading days.

Our research question is whether daily short selling of individual firms -- aggregated by *industry sector* -- provides a valuable signal of sector future performance relative to other sectors. A finding that daily short sales forecast the relative returns of industry sectors could be of particular interest to portfolio managers. A commonly-used performance measure for equity portfolio management is attribution analysis, which compares the active return generated by the manager's sector allocation decisions with the active return generated from the selection of individual securities (see Held, 2009; Stewart, Piros, and Heisler, 2011 pp. 444-447; Reilly and Brown, 2012 pp. 988-989; and Bodie, Kane and Marcus, 2011 pp. 850-851).

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The impact of sector weight decisions can dwarf the impact of individual stock selection for equity portfolio performance, but consistently forecasting relative sector performance is challenging. Reilly and Brown (2012, p.

560) write: "While there are impressive gains to be made in correctly timing the hottest (or the coldest) market sectors, a manager must be right substantially more than he or she is wrong. Because this is an extremely difficult thing to do consistently, many investors choose to interpret Exhibit 16.8 as ultimately extolling the virtue of asset and sector class diversification."

Short sellers as skilled information processors might be particularly adept at interpreting and synthesizing information that disproportionately impacts sectors. Examples of such information are the impact of OPEC announcements for the Energy sector (Watts and Sjolin, 2014), FOMC announcements for the Utilities sector (Lydon, 2017), and regulatory announcements for the Financials and Health Care sectors (Moreno, 2014). Investment practitioners have a keen appreciation for the importance of understanding the information that drives sector returns. The equity research function at large sell-side and buy-side firms is typically organized by sector (Boni and Womack, 2006; Vardharaj and Fabozzi, 2007; and De Franco, Hope, and Laroque, 2013).

Even if short sellers do not attempt to forecast relative sector performance, their short selling aggregated across the individual firms they target might forecast sector relative performance. A growing body of research documents informed short selling at the individual security level. Among those that conclude short sellers are skilled analysts who synthesize publicly available information are Dechow, Hutton, Meulbroek, and Sloan (2001), Desai, Krishnamurthy, and Venkataraman (2006), Boehmer, Jones, and Zhang (2008), Karpoff and Lou (2010), and Engelberg, Reed, and Ringgenberg (2012). Other researchers provide evidence consistent with short sellers trading on private information in advance of announcements (Christophe, Ferri, and Angel, 2004; Christophe, Ferri, and Hsieh, 2010; and Blau and Tew, 2014). Regardless whether the information used by short sellers of individual securities is public or private, when aggregated by sector, this short selling could translate to a valuable signal of the sector's future performance.

If aggregate daily short selling correctly forecasts relative sector performance, strategies that are long the least shorted sectors and short the most shorted sectors should earn abnormal positive returns. We analyze long-short sector strategies for a variety of daily short selling measures for the S&P 500 firms for September 2009 to December 2012. We examine our research question in the context of S&P 500 firms rather than all listed firms for several reasons. First, if aggregate daily short selling provides a reliable predictor, the sector selection strategies could be easily implemented using existing liquid sector ETFs (e.g., Select Sector SPDR ETFs). Second, Chan, Lakonishok, and Swaminathan (2007) find that the comovement of returns that results from industry-sector effects is more pronounced for large firms than for small firms.

Refuting our conjecture that aggregate daily short selling correctly forecasts future relative performance, our empirical findings are that *none* of the long-short strategies based on the various aggregate daily short selling measures earns average returns that are significantly positive. When means of returns are significantly different from zero, they are *negative.* Further analysis shows that contrarian strategies using some of the daily short selling measures may be profitable. These strategies are *short* the least shorted sectors and *long* the most shorted sectors. Separate probit analysis confirms that aggregate daily short selling does not correctly forecast future sector performance. Overall, our results are consistent with a hypothesis that the bulk of daily short selling is liquidity provision by market makers, high-frequency trading, or hedging, rather than the positioning of short sellers who correctly place bets on short-term overvaluation.

Our paper contributes to recent research that examines whether short selling, aggregated across individual short sellers, provides valuable investment signals. As in the previously referenced research by Lynch, Nikolic, Yan, and Yu (2014), we examine aggregated *daily short selling* data for U.S. stocks. While Lynch, et al (2014) focus on whether short selling predicts overall market direction, we focus on the relative performance of sectors. Our findings that contrarian strategies might be profitable extend the research of Mohamad, Jaafar, and Goddard (2016). They examine a measure of *daily short interest* for ETFs traded on the London Stock Exchange. They find a positive association between increases in short interest and abnormal returns. They note that their measure of daily short interest is not observable by researchers for ETFs in the U.S.

Our findings are in contrast to those of other researchers who examine *monthly short interest* data and longer-horizon investment strategies. Huszar, Tan, and Zhang (2017) examine monthly short interest data for U.S.-listed firms aggregated across a 24-industry group classification and find strategies that short heavily shorted industries might be profitable over a one-month to six-month horizon. Rapach, Ringgenberg, and Zhou (2016) conclude that short sellers correctly predict future cash flows and, as a result, aggregate short interest is the best predictor of overall market performance in the next one, three, six, and twelve months.

The remainder of the paper is organized as follows. Section 2 discusses the data, sector variables, and descriptive statistics. Section 3 provides a probit analysis of whether aggregate daily short selling forecasts sector winners or losers. Section 4 reports results for the weekly long-short portfolios constructed from short sale daily data. Section 5 discusses results for long-short portfolios formed at a daily frequency. Section 6 concludes.

II. Data, sector variables, and descriptive statistics

A. Data

As of September 2009, many of the U.S. self-regulatory organizations (SROs) provided free internet access to their daily total short sale share volume for each security after the close of trading.[1] Thus, since September 2009, daily short sale data have been available to the public for their use in next-day trading decisions. We download short sale data from each SRO's website for September 1, 2009 through December 31, 2012 and retain data for S&P 500 firms. Daily stock returns, share prices and volume, and shares outstanding are from CRSP.

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[1] SRO short sale data web links were reached through http://www.sec.gov/answers/shortsalevolume.htm. The SROs during the sample period are BATS Exchange, Inc.; Direct Edge Holdings, LLC; Financial Industry Regulatory Authority, Inc.; International Securities Exchange, LLC; NASDAQ Stock Market LLC; NASDAQ OMX BX, Inc.; National Stock Exchange, Inc.; New York Stock Exchange LLC; NYSE Amex LLC; and NYSE Arca, Inc. We purchased NYSE's data. NYSE was the only SRO that charged for their short sale data during the sample period.

We partition the S&P 500 firms by 2-digit Global Industry Classification Standard (GICS) classifications from Compustat (see Bhoraj, Lee, and Oler, 2003; Chan, Lakonishok, and Swaminthan, 2007). The GICS 2-digit classification consists of ten sectors: Consumer Discretionary, Consumer Staples, Energy, Financials, Health Care, Industrials, Information Technology, Materials, Telecommunications, and Utilities. Just two firms, AT&T and Verizon, dominate the Telecommunication sector. We include the Telecommunications sector firms in the Information Technology sector. This is consistent with how State Street Bank and Trust Company partitioned the S&P 500 firms during the time period to create nine very liquid Select Sector SPDR ETFs, which could be used in aggregate to replicate the S&P 500 index.

B. Sector variables

Our focus is whether daily short sale data for one week can be used to forecast sector relative return performance the following week. Although it might be possible for traders to aggregate short sale information after the close in time to implement trading strategies the following day prior to the close, our weekly trading strategies avoid possible day of the week or weekend effects documented for short selling by Christophe, Ferri, and Angel (2009), Blau, Van Ness, and Van Ness (2009), and Lynch, Nikolic, Yan, and Yu (2014).

We calculate weekly sector variables as follows. For each stock, we calculate two short sale measures each day. The first is the percentage of share volume shorted (sv_{it}), which is the number of shares shorted divided by the stock's share volume that day. The second measure is the percentage of outstanding shares shorted (ss_{it}), which is the number of shares shorted divided by the number of shares outstanding. Weekly measures are obtained for each weekday. For example consider a position initiated at closing prices for Friday, August 20, 2010, and liquidated on the close Friday, August 27, 2010.

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Friday, 8/13              Thursday, 8/19    Friday, 8/20                  Friday, 8/27
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We define week w as Friday's close August 20 through Friday's close August 27. The holding period return is Ret_w. The period for short sale measures (used for trading decisions for week w) is defined as week $w\text{-}1$, which consists of the trading days of Friday, August 13, through Thursday, August 19, in the example. The weekly $w\text{-}1$ short sale measures for each firm are the averages for the daily measures (sv_{it} and ss_{it}) for the days in week $w\text{-}1$. The weekly short sale measures for each sector (SV_{w-1} and SS_{w-1}) are the market capitalization weighted averages for the firms in the sector, where the market capitalization for each firm is the average of its daily market capitalizations for week $w\text{-}1$. In other words, short sale daily measures are averaged for Friday through the following Thursday to create the decision variable for forecasting returns for the next day Friday's close through the Friday close of the following week. Similarly, for positions initiated and liquidated on Monday closes, the average of daily short sale information for the prior week's Monday through Friday is used, etc. Because we want to analyze not only levels of short sale measures but also changes in levels week over week, we calculate the percentage change in the short sale variables (ΔSV_{w-1} andΔSS_{w-1}) as the percentage change in the weekly short sale measure for week $w\text{-}1$ relative to week $w\text{-}2$.

For ease of exposition, throughout the paper, we define "best" and "worst" short selling from the standpoint of the buy-and-hold investor, who likely prefers little or no short seller activity. Thus, a sector is the "best" ("worst") in terms of the short selling level measures (SV_{w-1} and SS_{w-1}) if it has the lowest (highest) value that week compared with the other sectors. For the percentage change measures (ΔSV_{w-1} and ΔSS_{w-1}), "best" means the sector has the largest percentage decrease in short selling level relative to the level the prior week (or has the least increase if all sectors' changes are positive). "Worst" means the sector has the largest increase (or has the least decrease if all sectors' changes are negative).

C. Descriptive statistics

Table I Panel A reports descriptive statistics for each of the nine sectors. There are 166 weeks in the sample period. *Weight* is the sector's weight in the S&P 500.

The mean of weekly return (*Ret*) for the sample period is slightly positive for each of the sectors, ranging from the low for Financials at 0.116% to the high of 0.385% for Consumer Discretionary. The means of short sale levels as a percentage of share volume (*SV*) range from 44.9% (Health Care) to 48.5% (Consumer Discretionary). These levels are higher for the sample period relative to levels reported by researchers using the 2005 to 2007 transaction-level data. For example, Diether, Lee, and Werner (2009) report a mean of 23.4% for large NYSE stocks and 37.8% for large Nasdaq stocks for January 3, 2005 to December 30, 2005. Lynch, et al (2014) report a mean of 24.2% for the value-weighted average across common stocks for January 3, 2005 to June 29, 2007. The means of short sales as a percentage of shares outstanding (*SS*) are also higher, ranging from 0.251% (Consumer Staples) to 0.658% (Materials) as compared with a mean of 0.182% for the value-weighted average across common stocks reported by Lynch, et al (2014). Changes from week to week are greater in magnitude for shorted shares as a percentage of shares outstanding (ΔSS) than as a percentage of daily share volume (ΔSV).

Correlations among the variables are reported in Panel B of Table I. Holding period returns for week *w* (Ret_w) are negatively correlated with week *w-1* holding period returns (Ret_{w-1}) and the week *w-1* percentage change in outstanding shares shorted (ΔSS_{w-1}). They are weakly positively correlated with the week *w-1* level of share volume shorted (SV_{w-1}). Contemporaneous levels of the two short selling measures (SV_{w-1} and SS_{w-1}) are positively correlated as are percentage changes (ΔSV_{w-1} and ΔSS_{w-1}).

Panel C of Table I reports the average number of firms per sector.[2] The 3 largest -- Consumer Discretionary, Financials, and Information Technology (including Telecommunication) -- average about 80 firms each and together account for almost half of the firms in the S&P 500. The smallest 2 sectors -- Materials and Utilities -- average about 30 firms each.

Chan, Lakonishok, and Swaminathan (2007) find the finer partition of the GICS 6-digit ("industry") classification is even better for explaining industry effects of return comovement than is our GICS 2-digit "sector" partition. Academic research highlights the value of forecasting future winners or losers at the industry level (e.g., Huszar, Tan, and Zhang, 2017;

[2] During the sample period, some firms were removed and others added to the S&P 500 index. We report the average number of firms for the Friday-basis weekly sector variables.

Kacperczyk, Sialm, and Zheng, 2005; Busse and Tong, 2012; Jame and Tong, 2014). It is reasonable to ask whether our analysis would be of more value if performed at the industry, rather than the sector, level.

To address this question, the last columns of Table I Panel C report the number of industries per sector and minimum and maximum number of firms by industry if we use the GICS 6-digit ("industry) classifications for the S&P 500 firms. Using the GICS 6-digit classifications greatly reduces the number of firms. Some of the industries in 6 of the sectors have just one firm. We conclude the finer GICS 6-digit classification is too fine for our analysis of S&P 500 firms.

Table I. Descriptive statistics

Panel A: Weekly sector variables

	Consumer Discretionary	Consumer Staples	Energy	Financials	Health Care	Industrials	Information Technology	Materials	Utilities
N	166	166	166	166	166	166	166	166	166
Weight	0.105	0.119	0.114	0.149	0.116	0.104	0.224	0.035	0.035
	(0.005)	(0.005)	(0.007)	(0.008)	(0.005)	(0.003)	(0.006)	(0.001)	(0.002)
Ret (%)	0.385	0.282	0.223	0.116	0.270	0.270	0.264	0.215	0.227
	(2.708)	(1.507)	(3.321)	(3.341)	(1.898)	(2.958)	(2.604)	(3.455)	(1.890)
SV	0.485	0.453	0.479	0.484	0.449	0.474	0.467	0.480	0.478
	(0.033)	(0.036)	(0.033)	(0.034)	(0.035)	(0.035)	(0.032)	(0.033)	(0.036)
ΔSV (%)	0.895	0.950	0.512	0.553	0.865	0.798	0.619	0.978	1.270
	(3.872)	(5.404)	(5.494)	(4.657)	(4.379)	(4.433)	(4.253)	(5.366)	(5.568)
SS (%)	0.583	0.251	0.397	0.502	0.323	0.370	0.517	0.658	0.332
	(0.115)	(0.054)	(0.097)	(0.151)	(0.075)	(0.095)	(0.112)	(0.184)	(0.083)
ΔSS (%)	6.205	5.274	4.134	5.522	6.229	5.283	5.519	5.194	5.999
	(18.495)	(18.696)	(18.686)	(22.109)	(19.728)	(19.708)	(19.187)	(19.019)	(21.002)

Panel A reports means (and standard deviations in parentheses) for sector variables used for Friday-initiated portfolios with one-week holding periods.

Panel B: Pearson correlation coefficients

	Ret_w		Ret_{w-1}		SV_{w-1}		ΔSV_{w-1}		SS_{w-1}	
Ret_{w-1}	-0.083	***								
SV_{w-1}	0.043	*	-0.032							
ΔSV_{w-1}	0.000		-0.129	***	0.302	***				
SS_{w-1}	-0.032		-0.105	***	0.330	***	0.043	*		
ΔSS_{w-1}	-0.067	***	-0.235	***	-0.028		0.149	***	0.197	***

***, **, and * are statistical significance at 1%, 5%, and 10%, respectively.

Panel C: Company and industry statistics

	Average number of companies per sector	Industries per sector	Average number of companies per industry: Minimum	Average number of companies per industry: Maximum
Consumer Discretionary	79.9	12	1.0	18.0
Consumer Staples	41.0	6	2.4	14.4
Energy	40.6	2	11.1	29.5
Financials	80.0	8	1.0	21.5
Health Care	51.6	6	1.0	15.8
Industrials	59.7	12	1.0	14.2
Information Technology	81.3	10	1.0	17.9
Materials	30.5	5	2.5	14.1
Utilities	33.2	4	1.0	15.0
All	500	65	1.0	29.5

III. Probit analysis of forecasting winners and losers

We first analyze whether short selling can be used to forecast the sectors that will have the best return (the "winner") or worst return (the "loser"). If the probability of being the sector with the best return is equal for all sectors, each of the nine sectors should have the best return in Panel A of Table II (column Ret_w) for 11.1% of the weeks. Using a chi-square test, we reject the null hypothesis at the 1% level that sectors are equally likely to have the best return. Similarly, the hypothesis of equal probability for having the best short selling is rejected for each of the four short selling measures at the 1% level. Chi-square tests also reject the null of equal probability of being the worst sector in terms of the return (Ret_w) and four short selling measures at the 1% level (Panel B).

Table II. Sector rankings by returns and short sale measures

Panel A: Best sectors	Ret_w		SV_{w-1}		ΔSV_{w-1}		SS_{w-1}		ΔSS_{w-1}	
	% of Weeks	Pr | Prior	% of Weeks	Pr | Prior	% of Weeks	Pr | Prior	% of Weeks	Pr | Prior	% of Weeks	Pr | Prior
Consumer Discretionary	9.0%	0.067	0.0%	-	3.1%	0.208	0.0%	-	6.2%	-
Consumer Staples	10.8%	0.168	34.3%	0.582	9.9%	-	98.8%	0.988	5.0%	0.130
Energy	15.7%	0.232	7.8%	0.387	18.6%	0.069	0.0%	-	14.9%	0.043
Financials	13.9%	-	1.2%	-	11.2%	0.058	0.0%	-	16.1%	0.080
Health Care	9.0%	0.134	44.0%	0.593	9.3%	-	0.0%	-	11.2%	-
Industrials	4.2%	-	1.2%	-	7.5%	-	0.0%	-	11.8%	0.055
Information Technology	6.6%	-	4.2%	-	7.5%	-	0.0%	-	9.3%	-
Materials	16.9%	0.036	3.0%	-	16.1%	0.120	0.0%	-	9.3%	-
Utilities	13.9%	0.131	4.2%	-	16.8%	-	1.2%	-	16.1%	0.040
All	11.1%	0.097	11.1%	0.491	11.1%	0.045	11.1%	0.976	11.1%	0.039
Memo: Best 3 Sectors	33.3%	0.321	33.3%	0.683	33.3%	0.224	33.3%	0.838	33.3%	0.234
Panel B: Worst sectors										
Consumer Discretionary	4.8%	-	16.9%	0.323	6.8%	0.094	22.3%	0.653	9.9%	-
Consumer Staples	10.2%	0.118	0.0%	-	14.9%	0.087	0.0%	-	8.1%	0.080
Energy	13.9%	0.131	24.1%	0.503	13.7%	0.189	0.0%	-	7.5%	-
Financials	18.7%	0.227	19.9%	0.213	9.9%	-	3.6%	0.168	19.3%	0.067
Health Care	6.0%	-	0.0%	-	9.3%	-	0.0%	-	11.8%	-
Industrials	6.6%	0.091	3.6%	-	8.1%	-	0.0%	-	10.6%	-
Information Technology	9.0%	0.201	0.6%	-	7.5%	-	6.6%	0.549	7.5%	-
Materials	13.3%	0.183	17.5%	0.243	9.9%	0.065	67.5%	0.880	9.9%	0.065
Utilities	17.5%	0.208	17.5%	0.208	19.9%	0.097	0.0%	-	15.5%	0.083
All	11.1%	0.158	11.1%	0.297	11.1%	0.071	11.1%	0.782	11.1%	0.039
Memo: Worst 3 Sectors	33.3%	0.319	33.3%	0.640	33.3%	0.224	33.3%	0.899	33.3%	0.241

The columns labeled "Pr|Prior" report for return (Ret_w) and each of the four short selling measures the probability the sector will be the best sector (Panel A) or worst sector (Panel B) conditional on being the best sector (Panel A) or worst sector (Panel B) for the prior week. If being the best (worst) one week has no impact on the probability of being the best (worst) the next week, "Pr|Prior" should be one in nine (11.1%). For example, Panel B reports, for all sectors combined, the probability of having the worst return (Ret_w), conditional on having the worst return the prior week, is 15.8%. This suggests using the prior week's relative return performance may help forecast losers.

To analyze whether short selling, possibly in combination with the prior week's relative return performance, can be used to forecast winners or losers, we estimate the following probit model specifications:

$$WINNER_{j,w} = \beta_0 + \beta_1 Ret_{j,w-1} + \beta_2 WINNER_{j,w-1} + \beta_3 LOSER_{j,w-1} + \beta_4 ShortMeasure\_rank_{j,w-1} + \varepsilon_{j,w} \quad (1)$$

$$LOSER_{j,w} = \beta_0 + \beta_1 Ret_{j,w-1} + \beta_2 WINNER_{j,w-1} + \beta_3 LOSER_{j,w-1} + \beta_4 ShortMeasure\_rank_{j,w-1} + \varepsilon_{j,w} \quad (2)$$

In model 1, the dependent variable *WINNER* equals 1 if sector *j* is the winner (the sector with the best return) in week *w*, and equals 0 otherwise. The independent variables include sector *j*'s return in the prior week ($Ret_{j,w-1}$). Including $Ret_{j,w-1}$ allows us to test whether having a positive return in the prior week increases the probability of being a winner, in which case we expect a positive estimate for β_1. The dummy variable $WINNER_{j,w-1}$ takes the value 1 if sector *j* is the winner in the prior week. A positive estimate for β_2 would be consistent with sector "repeat winners". Model 1 also includes a dummy variable $LOSER_{j,w-1}$, which takes the value 1 if sector *j* is the loser in the prior week. We include this dummy variable to allow for the possibility that sector relative volatility drives extreme winner and loser rankings. If the probability of winning and losing is related to extreme short-term volatility and sectors oscillate from having the best to worst relative returns from one week to the next, then the estimate for β_3 should be positive. For each of the 4 short selling measures, we determine $ShortMeasure\_rank_{j,w-1}$, which is the sector's rank from 1 (best) to 9 (worst) relative to the other sectors. If less short selling (relative to the other sectors) forecasts better relative returns, we expect β_4 to be negative for model 1.

For model 2, the dependent variable *LOSER* equals 1 if sector *j* is the loser (the sector with the worst return) in week *w*, and equals 0 otherwise. Consistent with the reasoning for model 1, $Ret_{j,w-1}$ allows us to test whether having a negative return in the prior week increases the probability of being a loser, in which case we expect a negative estimate for β_1. If the probability of winning and losing is related to extreme short-term volatility, the estimate for β_2 should be positive. A positive estimate for β_3 would be consistent with sector "repeat losers". If more short selling (relative to other sectors) forecasts worse relative returns, we expect β_4 to be positive for model 2.

We estimate the models for each of the four short selling measures. We cluster standard errors by sector. To avoid overlapping observations and to allow for possible day-of-the-week anomalies, we estimate the models separately for each of the "weekday-of-initiation" measures. For example, Table III reports the results for the estimates for the weekly measures for positions initiated on Fridays.

Panel A of Table III reports the results for the probit regressions for the probability of being the winner. The pseudo R^2 is extremely small for each regression. With the exception of the estimates for the coefficients for the short selling measure rankings for SV_{w-1} and ΔSV_{w-1}, none of the estimates are statistically significant at conventional levels. Interestingly, the significant estimates for SV_{w-1} and ΔSV_{w-1} are positive, which is the opposite of the sign we expect if less short selling forecasts better relative returns. Having lower short selling relative to the other sectors, measured as either the level or percentage change of share volume shorted (SV_{w-1}), *reduces* the probability of being the next week's winner. Evaluated at the mean of $Ret_{j,w-}$

$_1$ and values of 0 for the $WINNER_{w-1}$ and $LOSER_{w-1}$ dummy variables, being the sector with the least (versus the most) short selling reduces the probability of being the winner by 3.7% for the SV_{w-1} measure and by 5.8% for the ΔSV_{w-1} measure.

Table III. Probit regressions of forecasting sector winners and losers

Panel A: Probability that sector will be the winner	(1)	(2)	(3)	(4)
Intercept	-1.3497 ***	-1.4232 ***	-1.3044 ***	-1.2293 ***
	(0.000)	(0.000)	(0.000)	(0.000)
Ret_{w-1}	-0.6599	-1.0047	-0.5380	-0.7011
	(0.751)	(0.618)	(0.802)	(0.749)
$WINNER_{w-1}$	-0.0756	-0.0574	-0.0711	-0.0497
	(0.716)	(0.783)	(0.733)	(0.817)
$LOSER_{w-1}$	0.1028	0.1022	0.0970	0.0902
	(0.410)	(0.411)	(0.408)	(0.475)
SV_rank_{w-1}	0.0249 **			
	(0.037)			
ΔSV_rank_{w-1}		0.0386 ***		
		(0.000)		
SS_rank_{w-1}			0.0161	
			(0.413)	
ΔSS_rank_{w-1}				0.0010
				(0.955)
Pseudo R^2	0.0033	0.0061	0.0021	0.0010
N	1,493	1,449	1,493	1,449

Panel B: Probability that sector will be the loser	(1)	(2)	(3)	(4)
Intercept	-1.3046 ***	-1.1755 ***	-1.2177 ***	-1.0279 ***
	(0.000)	(0.000)	(0.000)	(0.000)
Ret_{w-1}	0.5571	0.6995	0.6449	0.6295
	(0.778)	(0.708)	(0.741)	(0.739)
$WINNER_{w-1}$	0.1144	0.0693	0.1192	0.0888
	(0.505)	(0.714)	(0.490)	(0.641)
$LOSER_{w-1}$	0.2676 ***	0.2517 ***	0.2726 ***	0.2764 ***
	(0.001)	(0.004)	(0.001)	(0.002)
SV_rank_{w-1}	0.0071			
	(0.759)			
ΔSV_rank_{w-1}		-0.0175		
		(0.243)		
SS_rank_{w-1}			-0.0106	
			(0.677)	
ΔSS_rank_{w-1}				-0.0496 ***
				(0.000)
Pseudo R^2	0.0045	0.0047	0.0047	0.0121
N	1,493	1,449	1,493	1,449

P-values in parentheses. ***, **, and * statistical significance at 1%, 5%, and 10%, respectively.

The results for the probit regressions for the probability of being the loser are reported in Panel B of Table III. Being the loser for the prior week provides help in forecasting whether the sector will be a "repeat loser". As in model 1, the pseudo R^2 is again extremely small for each regression, however. The only other estimate that is significantly different from 0 is the estimate for the percentage change in outstanding shares shorted measure (ΔSS_{w-1}). Similar to what we observed for forecasting the probability of winning, the estimate has the opposite sign we expect if short selling forecasts relative returns. The estimate is negative, meaning that a higher percentage change in outstanding shares shorted reduces the probability of being the next week's loser.

Untabulated results of the probit regressions for the weekly measures for positions initiated on the other days of the week tell a consistent story as to the potential for using sector short selling to forecast winners and losers. Results are available by request. Summarizing the results of the analysis reported in this section, we find no evidence that sector-aggregated short sale information correctly forecasts sector winners or losers.

IV. Long-short portfolio analysis

A. Long-short strategies

We next analyze whether long-short portfolio strategies based on the aggregate daily short selling measures are profitable. We concluded in the previous section that the short selling measures did little to help us correctly forecast *which* sectors would have the best or worst returns. And interestingly, estimates for the short measures, when significant, had the opposite of the sign we expected. It is possible, however, that the sectors with more short selling have lower *returns* the following week *on average* than the sectors with less short selling.

To analyze this, we construct weekly long-short portfolios that are long the firms of the least shorted sector and are short the firms of the most shorted sector. We examine the long-short strategy separately for each of the weekly short sale measures (SV_{w-1}, ΔSV_{w-1}, SS_{w-1}, and ΔSS_{w-1}) and for each weekday of initiation. We also analyze portfolios long the firms of the three sectors with the least short sales and short the firms of the three sectors with the most short sales, with the three sectors equally weighted in the long and short portfolios. For comparison, we report returns for two additional long-short portfolio strategies. The first is the strategy that assumes perfect foresight. In other words, it assumes we know the best and worst performers one week in advance. The returns from this strategy are reported to indicate the maximum return from picking sector winners and losers (excluding transaction costs). The other strategy is a return momentum-based strategy, which uses sector rankings based on week *w-1* holding period returns (Ret_{w-1}).

Returns for the long-short portfolios are reported in Table IV. Average weekly returns for the long-short strategies which are long the best sector and short the worst sector are reported in Panel A. The first column provides the results for the strategy that assumes perfect foresight. Labeled Ret_w, it shows there are substantial opportunities for gains from picking the best and worst sectors. The mean of weekly returns ranges from a low of 3.60% for weekly portfolios formed on Wednesdays to a high of 3.82% for portfolios formed on Fridays. In stark contrast, the means of returns for the long-short strategy based on forming portfolios using their returns for the prior week (Ret_{w-1}) are sometimes negative, and never significantly different from zero.

For the short selling strategies, the means of the returns are rarely significantly different from zero; but when they are significant, they are negative. Specifically, the means of returns are negative and significant for the portfolios formed on Tuesdays and Fridays using the change in short volume measure. The means of returns are also negative and significant for the portfolios formed on Mondays and Fridays using the change in short shares outstanding measure.

Table IV. Long-short portfolio returns

Panel A: Weekly returns for "best sector - worst sector" strategies						
	Ret_w	Ret_{w-1}	SV_{w-1}	ΔSV_{w-1}	SS_{w-1}	ΔSS_{w-1}
Mondays	3.72% ***	0.27%	-0.06%	-0.12%	-0.16%	-0.28% *
Tuesdays	3.71% ***	-0.05%	0.03%	-0.32% **	-0.01%	0.00%
Wednesdays	3.60% ***	-0.11%	-0.06%	-0.13%	-0.08%	0.04%
Thursdays	3.63% ***	-0.10%	-0.05%	-0.19%	-0.17%	-0.26%
Fridays	3.82% ***	0.14%	0.00%	-0.31% *	-0.22%	-0.29% *

Panel B: Weekly returns for "best 3 sectors - worst 3 sectors" strategies						
	Ret_w	Ret_{w-1}	SV_{w-1}	ΔSV_{w-1}	SS_{w-1}	ΔSS_{w-1}
Mondays	2.51% ***	0.08%	-0.15%	-0.09%	-0.16% *	0.03%
Tuesdays	2.45% ***	-0.07%	-0.06%	-0.21% **	0.00%	-0.03%
Wednesdays	2.46% ***	-0.09%	-0.06%	-0.18% **	-0.01%	-0.10%
Thursdays	2.51% ***	-0.08%	-0.07%	-0.30% ***	-0.06%	-0.11%
Fridays	2.59% ***	-0.03%	-0.10%	-0.26% ***	-0.07%	-0.22% **

***, **, and * are statistical significance at 1%, 5%, and 10%, respectively.

Panel B reports the returns for the long-short portfolios formed using the best 3 sectors and the worst 3 sectors. Returns are similar to those we observed in Panel A. The means of weekly returns for picking the best 3 and worst 3 sectors with perfect foresight are large, ranging from a low of 2.45% for the Tuesday portfolios to a high of 2.59% for those formed on Fridays. Returns based on returns for the prior week are never significantly different from zero. For the short selling strategies, when the means of the weekly returns are significantly different from zero, they are negative.

In summary, we conclude that none of the sector-aggregated short sale measures result in long-short portfolios that earn mean returns that are significantly positive.

B. Contrarian strategies

The results in the last section suggest that contrarian weekly strategies, which are *short* the least shorted sectors and *long* the most shorted sectors, might be profitable on average, prior to transaction costs, for some of the short selling measures. In this section, we examine the risk characteristics of these contrarian strategies and whether they are stable over time. We focus on the portfolios formed on Fridays and use the two *change* in short selling measures.

Annualized return, annualized volatility, and Sharpe ratio for the sample period are shown in the upper panel of Table V. For all four of the contrarian strategies, Sharpe ratios (prior to transaction costs and assuming 0.25% for the annualized risk-free rate) are almost 0.9 or higher. Although both of the "Best 3 – Worst 3" strategies have annualized returns that are less than either of "Best – Worst" strategies, the "Best 3 – Worst 3" strategies have less volatility and better Sharpe ratios.

Table V. Return performance and risk of contrarian strategies

Panel A: Annualized performance of weekly strategies	Annualized Return	Annualized Volatility	Sharpe Ratio
Best - Worst Strategies			
Change in Short Shares Outstanding	14.88%	16.46%	0.889
Change in Short Volume	14.06%	15.32%	0.901
Best 3 - Worst 3 Strategies			
Change in Short Shares Outstanding	13.15%	9.26%	1.393
Change in Short Volume	10.86%	8.63%	1.229

Panel B: Fama-French three risk factor model plus Carhart [1997] momentum	Alpha	Excess Market	Size (SMB)	Value (HML)	Momentum (WML)	Annualized Alpha
Best - Worst Strategies						
Change in Short Shares Outstanding	0.0035 *	-0.116	0.054	-0.149	-0.079	18.18%
Change in Short Volume	0.0031 *	-0.096	0.063	0.031	0.070	16.04%
Best 3 - Worst 3 Strategies						
Change in Short Shares Outstanding	0.0029 ***	-0.043	0.006	-0.039	-0.101	14.95%
Change in Short Volume	0.0022 **	-0.002	0.004	-0.067	-0.011	11.19%

***, **, and * are statistical significance at 1%, 5%, and 10%, respectively.

The lower panel in Table V reports the coefficient estimates for the Fama-French three risk factor model plus Carhart (1997) momentum. All four strategies have alpha (weekly basis) returns that are significant at the 10% level, ranging from 0.22% to 0.35%. None of the three Fama-French risk factors or momentum coefficient load at the 10% level.

Table VI reports the means of weekly returns for each contrarian strategy by year and overall for the entire sample period. Means are positive each year with the exception of the change in short volume strategies for 2010. Standard deviations of weekly returns are reported under the means in parentheses. Returns are sufficiently volatile to prevent weekly returns from being statistically different from zero at the 10% level for most years.

While the results presented here are intriguing, it is worth emphasizing that the results are for portfolios formed on Friday closes only and for the *changes* in short selling strategies only. Our results suffer from hindsight bias in that we intentionally selected the strategies and formation day which we expected to have the greatest potential given the results of their non-contrarian counterparts. Nor have we been able to obtain and analyze daily short sale data and strategy performance for the period after December 31, 2012.

Table VI. Contrarian strategy performance by calendar year.

	Sept. - Dec. 2009		2010	2011	2012		Sept. 2009 - Dec. 2012	
Best - Worst Strategies								
Change in Short Shares Outstanding	0.57%		0.45%	0.22%	0.21%		0.31%	*
	(1.84%)		(2.63%)	(2.64%)	(1.61%)		(2.28%)	
Change in Short Volume	0.37%		-0.07%	0.45%	0.46%	**	0.29%	*
	(2.17%)		(1.97%)	(2.71%)	(1.51%)		(2.12%)	
Best 3 - Worst 3 Strategies								
Change in Short Shares Outstanding	0.20%		0.31%	0.44%	0.07%		0.26%	***
	(1.11%)		(1.29%)	(1.48%)	(1.10%)		(1.28%)	
Change in Short Volume	0.57%	**	-0.01%	0.19%	0.37%	***	0.22%	**
	(0.84%)		(1.07%)	(1.57%)	(0.93%)		(1.20%)	

This table reports means of weekly returns with standard deviations in parentheses.
***, **, and * are statistical significance of 2-sided *t*-tests of means at 1%, 5%, and 10%, respectively.

V. Long-short portfolios formed daily

We check whether daily short selling forecasts sector performance when long-short portfolios are formed daily. We initiate the long-short positions on the close each day using short sale data from the prior day. The portfolio positions are liquidated on the close of the following trading day. We form portfolios for each of the four short sale measures.

Similar to what we document for the weekly portfolios, the potential gain from placing daily long-short portfolio "sector bets" with perfect foresight is high. Before transaction costs, the means of the daily raw returns and four-factor adjusted returns for the "perfect foresight" portfolios are 1.7% for the Best – Worst portfolios and 1.1% for the Best 3 – Worst 3 portfolios. However, the means of the raw returns and four-factor adjusted returns from the daily long-short portfolios using the short sale measures are not significantly different from 0.

VI. Concluding remarks

We use daily short selling data from September 2009 through December 2012 to examine whether short selling, aggregated at the sector level, forecasts the relative performance of sectors for S&P 500 firms. Using a probit analysis, we find that more heavily shorted sectors do *not* underperform the following week. The means of returns of long-short portfolios constructed each week – short the sector(s) with most short selling (aggregated across firms) and long the sector(s) with least short selling -- are not significantly different from 0 for most of the cases we examine. More interestingly, when the means of returns for the strategies are significantly different from 0, they are negative suggesting a contrarian strategy could be profitable. Average returns for long-short portfolios formed daily are not significantly different from 0.

Our main contribution is to the area of recent research on whether short sellers are skilled at forecasting market direction overall and industry sector relative performance in particular. Lynch, Nikolic, Yan, and Yu (2014) conclude that aggregate daily short selling forecasts *market-*

level returns for the following 5 to 20 trading days. We document that aggregate short selling does not correctly forecast *relative sector performance*. Our findings offer an important extension to those of Mohamad, Jaafar, and Goddard (2016) who use a measure of daily short interest for ETFs traded on the London Stock Exchange. They find that aggregate short interest does not correctly forecast future ETF abnormal returns and suggest a contrarian strategy of taking long positions in heavily shorted ETFs. Our findings for short-term investment strategies are in contrast to those of Huszar, Tan, and Zhang (2017) and Rapach, Ringgenberg, and Zhou (2016) who examine *monthly short interest* data. They respectively conclude that short sellers correctly predict relative industry performance and overall market direction, thus providing valuable signals for longer-horizon investment strategies.

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Bank Dividend-cuts and the Stock Market Reaction around the Great Recession

Mujtaba Zia and Mucahit Kochan

Abstract:

We study investors' reaction to dividend decreases and omissions in the US banking industry during the Great Recession of 2007 and 2008 and compare it to the reaction in the years before and after the crisis. Conducting standard event study approach, we find that investors didn't react negatively to dividend-cuts in the years preceding the financial crisis and during the crisis as they did in the years following the crisis. Our results imply a shift in the perception of dividend cuts during the financial crisis. Dividend cuts were not perceived as a negative signal about the financial health of the banking firms during the Great Recession.

I. Introduction

Dividend increases or decreases have traditionally served as signals about the financial health of firms when explicit information is unavailable. Miller and Rock (1985) develop the signaling theory of dividends under asymmetric information between managers and investors and conclude that managers initiate dividends to signal firm's future earnings. Empirical studies of the signaling theory of dividends reveal that investors react positively to dividend initiations and increases and react negatively to dividend omission and decreases, i.e. dividend cuts. During market downturns information about financial health of firms becomes more important. Investors may wonder if the firms they have invested in are financially sound. At the same time, firms may limit the release of negative explicit information about their financials. During such times, asymmetry of information may increase, and dividend cuts may signal financial trouble in firm.

Asymmetry of information in the banking industry has been more pronounced than in other industries due to the opaque nature of the banking firms and their vulnerability to runs. During a credit crunch and downturn financial markets, banks become more prone to runs and hence managers become more hesitant to reveal explicit information about the financial health of their firms in fear of "runs" on their deposits or being cut off from credit markets by other financial institutions. During such market condition, investors may rely more on implicit signals such as dividend increases or cuts in the market.

The commencement or increase of dividends has been perceived as a positive signal about future earnings of the firm. Dividend cuts, on the other hand, have been indicative of a negative outlook of firm's future earnings or financial health. Empirical research supports this

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signaling effect of dividend initiation and omissions. A dividend initiation or increase has traditionally been accompanied by a positive stock market reaction, and dividend cuts have been accompanied by a negative stock market reaction.

Banking firms finance a greater amount of their assets with liability compared to other industries. During a financial turmoil, banking firms become more vulnerable to risks as credit markets tighten up and default rates on loans increase. When a bank cuts dividends, it means one of the two things. Either the bank cannot sustain the dividend payout policy due to deteriorated financial health, or it retains more of the internally generated funds to weather the financial turmoil. If the dividend cut is due to the first case, then the stock market reaction should be negative as it has traditionally been in empirical studies on other industries. If the dividend cut, however, is due to the second case, then the stock market reaction shouldn't be negative as retaining more of the internally generated funds is not a negative sign of financial health. In fact, it can be considered a risk-reducing decision as it makes banks more solvent and thus, a positive sign.

During the Great Recession of 2007 and 2008, many US banks cut dividends. We investigate the stock market reaction to dividend cuts during the crisis and compare it to the reaction in the preceding years and post-crisis years. We also shed light on dividend-cut trends in the banking industry and the financial ratios that can explain investor reactions to dividends over the study period of 2003 to 2013.[1]

This research serves to fill an existing research gap; a possible change in the stock market reaction to dividend cuts during the recent financial crisis of 2007 and 2008. The rest of the paper is organized as follows. In part II, we review previous studies; in part III we present data and methodology; in part IV we discuss results, and in part V, we summarize with concluding remarks.

II. Previous Studies

Boldin and Leggett (1995) study bank dividend policy as a signal of bank quality and argue that well-managed banks have an incentive to signal their asset quality through dividend policy to differentiate themselves from other institutions with poor asset qualities. Their argument is consistent with the literature on dividend as a signal. In their study, Boldin and Leggett (1995) find a positive relationship between bank dividends per share and bank quality ratings. Their study supports the dividend signaling argument.

[1] While the stock market reaction to dividend initiation and increases during the same period would complement this study, we couldn't identify enough numbers of dividend initiations or increases during the financial crisis of 2007 and 2008 to conduct the analysis. We identified a total of 6 dividend increases during the financial crisis period. Because of the small number of dividend initiations or increases, any statistical analysis would be unreliable. Therefore, we limit our study to dividend-cuts only.

Bessler and Nohel (1996) conduct an empirical test of Boldin and Leggett (1995) and study the stock market reaction to dividend cuts and omissions in the US banking industry. Their study of 17 banks over the period of 1975 to 1991 reveals that the announcement effect of a dividend cut is more severe for banking firms than for non-bank firms. Their results support the notion that the signaling impact of dividends is more pronounced in the banking industry than in other industries.

If the stock market reaction to dividend cuts is severe in the banking industry, then we would expect banks to be reluctant to cut dividends to avoid emitting a negative signal about their perspective earnings, especially during a financial turmoil. Acharya et al. (2011) empirically tests this assertion and study dividend pay-out policy of US banks during the 2007 and 2008 financial crisis. They find that banks hesitated to cut dividends despite financial hardship and regulatory pressure; banks persisted paying out dividends.

Abreu and Gulamhussen (2013) addresses why banks persistently paid dividends during the recent financial crisis as evidenced in the Acharya et al. (2011) study. They analyze the dividend payouts of 462 US bank holding companies before and during the recent financial crisis. They study the determinants of bank dividend payouts from four different angles, firm characteristics, agency cost hypothesis, signaling hypothesis, and regulatory pressure. They find that firm characteristic, agency cost hypothesis and signaling hypothesis explain bank dividend payouts but regulatory pressure has been ineffective in limiting bank dividend payouts during the financial crisis. It is worth to note that Abreu and Gulamhussen (2013) do not test the signaling effect of dividend increases or decreases, but study the determinants of paying dividends.

Floyd, LI, and Skinner (2014) compare payout policies of US industrials firms and banks over the past three decades including the financial crisis period and find that the declining trends in dividend payouts as studied by Fama and French (2001)[2] largely reverses after 2002. They find that banks paid higher and more stable dividends after 2002; large banks resisted cutting dividends as the crisis began but then cut dividends aggressively while industrial firm dividends were largely unaffected. They assert that banks continue to use dividend to signal financial strength.

While the valuable studies above address various aspects of dividends and their determinants, they don't address how the stock market reacted to dividend-cuts in the banking industry round the recent financial crisis or whether there is a shift in the market perception of dividend-cuts during the financial turmoil from the investor perspective. We attempt to fill this gap in the banking research literature.

III. Data and Methodology

A. Data

[2] Fama and French (2001) find a general decreasing of dividends in the US from 1960 to 1990's.

We collect data on U.S. bank holding companies (BHC) on the NYSE/AMEX or NASDAQ listed in COMPUSTAT from 2003 to 2013 that had dividend cuts data for the period in the Center for Research in Security Prices (CRSP). We identify a potential dividend omission when a firm has not paid a dividend within one-quarter, six months or one year from the previous payment if the firm used to pay quarterly, semi-annual or annual dividends, respectively. We define a dividend cut as a reduction in a firm's regular cash dividend per share in a particular fiscal year. A dividend cut of 100% would be considered a complete omission. We also refer to omission as cuts throughout the paper.

To determine the exact date of a dividend cut or omission announcement, we use Lexis-Nexis database. If the same company has a dividend cut or omission within 90 days of a previous dividend cut, we exclude the observation.[3] Excluding these observations would reduce information contamination of dividend cuts. Using the filtering system, we identified 90 dividend-cuts announcement over the study period for which cross-sectional data for the issuing bank was available. Figure 1 shows the number of dividend cuts in in each year.

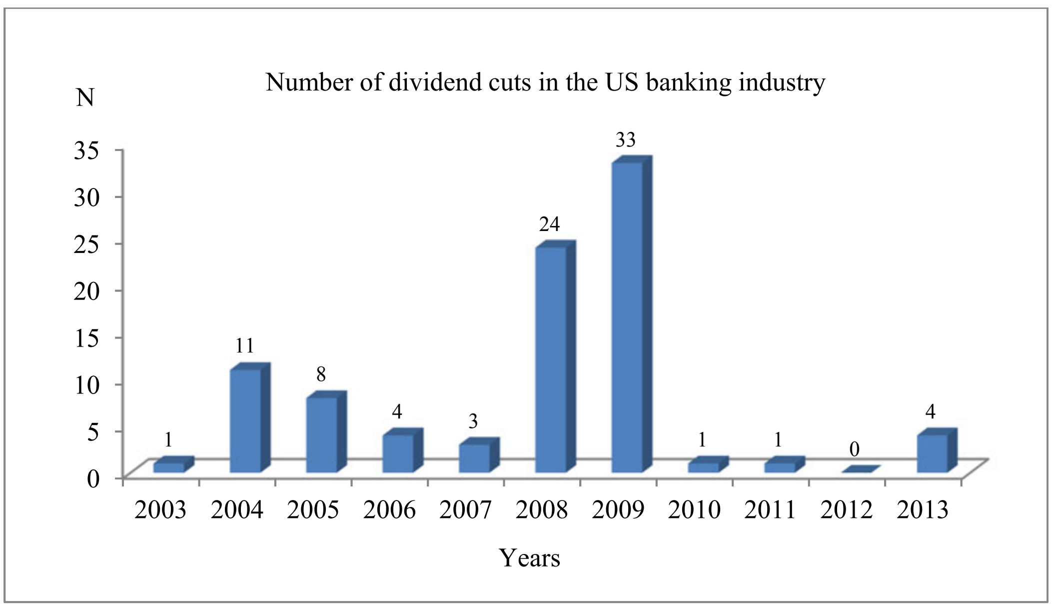

Figure I. The number of dividend cuts in the US banking industry from 2003 to 2013.

B. Methodology

i. Estimating Stock Market Reaction to Dividend Cuts

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[3] Since regular dividend payments are quarterly, semiannually or annually, it is very unlikely for a firm to announce more than one dividend-cut during a 90-day period. Nonetheless, we took the possibility into account and identified three banks that had more than one dividend cut announcements within a 90-day period. We included the initial cut and excluded the second dividend cut announcement that happened within 90 days of the first cut.

To estimate the stock market reaction to dividend cuts, we conduct standard event study approach and consider the estimation period of 254 to 45 days before the event. We estimate cumulative abnormal returns (CARs) for various days around the event date. To test the significance of estimates, we employ the test methodology of Boehmer, Musumeci and Poulsen (1991), hence denoted as BMP. This method allows for the possibility of event-induced variance when determining the statistical significance of abnormal returns. The BMP test is powerful and gives the proper rejection rate accounting for possible serial correlation among prediction errors as could be expected among firms in the same industry.

To test how dividend-cuts were perceived by investors in the banking industry before, during and after the recent financial crisis, we study the stock market reaction to dividend cuts in three periods, the pre-crisis, crisis, and post-crisis periods. We define the pre-crisis period from the first quarter of 2003 to the second quarter of 2007, the crisis period from the fourth quarter of 2007 to the fourth quarter of 2008 and the post-crisis period from the first quarter of 2009 to the last quarter of 2013. For robustness purposes, we also report the stock market reaction in the year immediately following the financial crisis, i.e. 2009[4], as well as for the entire study period of 2007 to 2013. We report CARs and BMP test statistics for various event windows around the event date in Table I.

Table I. Market reaction to dividend cuts and omissions

The table summarizes cumulative abnormal returns (CARs) for various event windows (days around the event date of the dividend cut or omission announcement) for different periods.

Panel A: pre-crisis period: 2003 q1 to 2007 q2, inclusive.

Days	Number of Observations	Mean CAR	BMP Test Statistics
(-1,+1)	26	-0.09%	-0.109
(-7,+1)	26	-1.05%	-1.22
(-2,+2)	26	-0.09%	-0.373
(-3,+3)	26	0.39%	0.098
(0,+3)	26	0.12%	-0.209
(+3,+5)	26	-0.26%	-1.23

Panel B: crisis period: 2007 q4 to 2008 q4, inclusive.

Days	Number of Observations	Mean CAR	BMP Test Statistics
(-1,+1)	25	-0.49%	-0.03
(-7,+1)	25	-0.04%	-0.312
(-2,+2)	25	1.04%	0.422
(-3,+3)	25	1.02%	0.34
(0,+3)	25	-2.01%	-0.294
(+3,+5)	25	2.17%	1.332

Panel C: immediate post-crisis period: 2009

Days	Number of Observations	Mean CAR	BMP Test Statistics
(-1,+1)	33	-2.41%	-1.281
(-7,+1)	33	-11.21%	-2.819**
(-2,+2)	33	-3.42%	-1.283
(-3,+3)	33	-5.36%	-1.717*
(0,+3)	33	-3.74%	-1.597
(+3,+5)	33	1.64%	0.881

Panel D: Post-crisis period: 2009-2013, inclusive.

Days	Number of Observations	Mean CAR	BMP Test Statistics
(-1,+1)	39	-2.30%	-1.247
(-7,+1)	39	-9.13%	-3.005**
(-2,+2)	39	-2.82%	-1.115
(-3,+3)	39	-5.06%	-1.86*
(0,+3)	39	-3.75%	-1.672*
(+3,+5)	39	1.25%	1.094

[4] While the economy was still struggling to recover in 2009, banks had already passed stress tests and were re-capitalized and the term-structure of interest rates which concerns banks more than other industries were indicating recovery from the financial crisis.

Table I. continued

Panel E. For all the periods: 2003-2013			
Days	Number of Observations	Mean CAR	BMP Test Statistics
(-1,+1)	90	-1.11%	-0.763
(-7,+1)	90	-4.27%	-2.523**
(-2,+2)	90	-0.96%	-0.534
(-3,+3)	90	-1.80%	-0.825
(0,+3)	90	-2.15%	-1.317
(+3,+5)	90	1.07%	1.25

Legend: * 5% significance, ** 1% significance, and *** 0.1% significance.

ii. Cross-Sectional Analysis of Market Reaction to Dividend Cuts

To understand what explains the abnormal returns, we conduct cross-sectional analysis of bank ratios that could explain the market reaction. The set of relevant explanatory variables we use in our study and their descriptive statistics are summarized in Table II and Table III, respectively.

Table II. Explanatory variables in cross-sectional analysis of CARs.

Variables	Abbreviation	Description
Size of dividend-cuts	Divchange	Percentage change in dividends from regularly paid previous dividend amount to measure the size of dividend-cut
Bank Tier-1 capital	Tier1	Tier1 capital of banks to measure bank capital as ratio of total assets
Return on Assets	ROA	measured as the ratio of net income to total assets in the quarter preceding the dividend-cut announcement
Bank Size	SIZE	measured as the natural log of total assets in the last quarter of 2007
Marketable Securities	SECASS	measured as the total of marketable securities which includes mortgage backed securities (MBS) divided by the total assets in the last quarter of 2007
Noninterest Income	NONINT	measured as the ratio of non-interest income divided by total revenue in the quarter preceding the dividend-cut announcement
Real Estate Loan	RE_LOAN	Bank's real estate loan held in the quarter preceding the dividend-cut
Market-to-Book Value	MVBV	Ratio of market-to-book value as a proxy for growth opportunities

Notes:
We use Tier-1 capital as a measure of bank capital rather than total capital. From the regulatory perspective Tier-1 capital is the most loss-absorbing measure of capital. Regulatory Capital Rule of the Office of the Comptroller of the Currency, the banking regulatory unit of the U.S. Department of Treasury. October 11, 2013 Final Rulemaking. Accessed from http://www.occ.gov/news-issuances/bulletins/2013/bulletin-2013-23.html on February 14, 2017.

Table III: Descriptive statistics

Variables	Observations	Mean	Standard Deviation	Min	Max
CAR(-1,1)	90	-0.0111	0.1713	-0.8804	0.4173
CAR(-7,1)	90	-0.0427	0.1079	-0.4160	0.3721
Divchange	90	-0.5637	0.2456	-1.0000	-0.0909
Tier1	90	11.1469	2.5854	5.7800	20.3000
ROA	90	-0.0012	0.0180	-0.0600	0.0369
SIZE	90	9.8471	1.4647	6.9126	14.5245
SECASS	90	0.0503	0.0678	0.0000	0.2763
NONINT	90	0.1187	0.1259	0.0082	1.2915
RE_LOAN	90	0.0028	0.0032	0.0000	0.0231
MVBV	90	1.2650	0.8151	0.1751	4.4501

IV. Results and Discussion

A. Stock Market Reaction Results

Panel A and B of Table I show that the stock market reaction to dividend-cut announcements for the pre-crisis and the crisis period is insignificant for all event windows, i.e. days around the announcement. Panel C and D in Table I show that the stock market reaction to dividend cut announcements in the year immediately following the crisis, i.e. 2009, and the period 2009-2013[5] was negative and significant for the (-7,+1) days window and remained insignificant for the (-1,+1) days window. While the negative reaction for the (-1,+1) days window remained insignificant from the pre-crisis and crisis periods to the post-crisis periods, it became worse. The reaction changed from a -0.09% and -0.49% from the pre-crisis and crisis periods in Panel A and B in Table I to -2.41% and -2.3% in 2009 and in 2009-2013, respectively. The reaction for (-7,+1) window significantly changed from and insignificant -1.05% and 0.04% from the pre-crisis and crisis periods to a significant -11.21% in 2009 and -9.13% in the 2009-2013 period.

The insignificant results in the pre-crisis and crisis indicate that investors didn't perceive dividend-cuts in the banking industry a surprisingly negative signal. Perhaps they were expecting banks to have financial difficulty and cut dividends to retain more of the internally generated funds to weather the financial turmoil. We can't say with certainty that banks cut dividends during the financial crisis for precautionary reasons to build up more financial cushion or whether investors believed banks did so, but the possibility exists and requires a comprehensive

[5] 33 of the 39 dividend-cuts between 2009 and 2013 happened in 2009 alone, making the results for the 2009 as the immediate year after the crisis very similar to the results for the whole post-crisis period of 2009-2013. We report both to provide better insight and clarity.

study beyond the scope of our paper. Perhaps a survey of bank managers and investors will provide us more insight. If bank managers did cut dividends due to this precautionary reason, it would be consistent with the (Miller and Rock 1985) assertion that dividends are part of the investment decisions.

The significant results for the (-7,+1) window for the 2009 and 209-2013 periods imply that investors perceived dividend cuts as negative signals about the firms. Since the market reaction to the dividend-cut announcements for the (-1,+1) days window is still insignificant, it implies that news of dividend-cuts leaked to the market over 7 days preceding the actual announcement date. It may also indicate that investors adjusted their decisions such that when the announcements were actually made, they had insignificant effects on stock prices.

Our finding of insignificant CARs for the (-1,+1) days around the event is different from all previous studies of dividend cuts and market reaction in the banking industry for which the results are significant. For instance, (Bessler and Nohel 1996) report that on average banks experienced a negative excess return of negative 4.64% on the day of the dividend cut announcement and negative 3.38% one day after the event. Both test statistics are significant at 1% level. Their results imply a -8.02% abnormal return. In our tests, while the market reactions are still negative for the 1-day around the event date, they are insignificant for all periods, pre-crisis, crisis, and post-crisis.

The insignificant CARs for the (-7,+1) days window during the financial crisis in Panel B of Table I has two important implications.

Implication I: Investors cannot discern information about dividend cuts during the financial crisis, i.e. dividend cuts do not emit the implicit strong negative signal during financial crisis.

Implication II: Investors understand that there is a credit crunch and banks cutting dividends are not necessarily in adverse financial situation; banks may hold on to more internally generated funds for perhaps precautionary reasons to weather a financial turmoil.[6]

Our test results support the first implication. The mean CARs for the (-7,+1) window during the financial crisis as reported in Panel B of Table I is -0.04%, the lowest among all CARs for all other windows and periods and statistically indifferent from zero. Investors may have had difficulty interpreting what a dividend-cut by a bank during the financial crisis meant. On one hand, it could mean that the dividend-cutting bank is unable to continue paying dividends and thus a negative signal about financial health. On the other hand, it could mean that the bank is cutting dividends to retain more funds to reduce liquidity risk during such financial turmoil. If the second reason for dividend cuts is true, then rational investors would perceive it as a positive

[6] A third implication may be thought as investors anticipated the dividend cut announcements at earlier dates, i.e. at least 8 days prior to the announcement day, and adjusted their investment decision accordingly such that in the period 7 days prior to the announcement to 1 day after, their decision didn't change. We tested for the possibility of this implication by estimating CARs for different windows such as (-14, -8) days and (-30,-8), the tests yielded insignificant results.

sign of good management decision reducing risk and, therefore, market reaction should be positive.

To check for robustness of our results and insure that the significant negative CARs in the immediate post-crisis year of 2009 and the post-crisis period of 2009-2013 are not due to a random stock market down-turn, we generated random dates, set them as event dates and tested for significance of CARs. None of the results were statistically significant which increase our confidence in our methodology.

B. Cross-Sectional Analysis of Cumulative Abnormal Returns

Since we are measuring the stock market reaction to dividend-cut announcements, the CARs on (-1,+1) days and (-7,+1) days around the event is of greater interest as they measure market reaction one day around the event and the gradual reaction from seven days prior to the event to 1 day after the event. We found insignificant CARs on (-1,+1) window, hence, there is not much value in discussion cross-sectional analysis to determine what explains the insignificant CARs on (-1,+1) event window. We shall focus our results and discussion on the cross-sectional analysis of CARs for the (-7,+1) event window. Nonetheless, we report our analysis on both event windows in Panel A and B in Table IV, respectively.

Table IV. Cross-sectional analysis of the stock market reaction to dividend-cuts
The dependent variable is the cumulative abnormal returns (CARs). Panel A summarizes the results of CARs over (-1,+1) around the event date of dividend-cut announcement and Panel B summarizes CARs over (-7,+1) days around the event date.

Panel A. Regression analysis of CARs (-1,+1) over periods between 2003-2013					
Periods	2003-2013	2003-2007	2007q4-2008	2009	2009-2013
CARs (-1,+1)	Coefficients	Coefficients	Coefficients	Coefficients	Coefficients
Divchange	0.1893	-0.0370	0.3783	0.2427	0.2268
Tier1	0.0010	0.013*	0.0136*	-0.0084**	-0.0118**
ROA	0.6895	-2.5499*	-4.3564*	7.1515**	6.9792*
SIZE	0.0039	-0.0103	-0.0574	0.0273	0.0236
SECASS	0.4671	0.3972	0.6603	1.0247	0.9164
NONINT	0.0015	0.0040	0.0094	0.0007	0.0009
RE_LOAN	8.2710	21.7317	-5.3824	20.5106	20.0409
MVBV	0.0281	0.0184	-0.0614	-0.0139	-0.0173
Intercept	-0.0673	-0.1023	0.6369	-0.2221	-0.1419
N	90	25	26	33	39
Prob>F	0.0747	0.0107	0.0413	0.0002	0.0002
Adjusted R-squared	0.1472	0.4403	0.3515	0.3144	0.3151

Table IV. Continued

Panel B. Regression analysis of CARs (-7,+1) over periods between 2003-2013					
Periods	2003-2013	2003-2007	2007q4-2008	2009	2009-2013
CARs (-7,+1)	Coefficients	Coefficients	Coefficients	Coefficients	Coefficients
Divchange	0.0714	-0.0810	0.2658	0.1355	0.1358
Tier1	0.0012	0.0045**	0.0035*	-0.0046**	-0.0045**
ROA	0.2574	-2.7118*	-2.3623*	2.4569*	2.3521*
SIZE	-0.0077	-0.0146	-0.0456	0.0028	0.0024
SECASS	0.3126**	0.0526	0.4112	0.5311	0.4887
NONINT	0.0008	-0.0005	0.0077	0.0005	0.0005
RE_LOAN	1.9073	30.6307*	-6.6883	18.5722*	18.1040*
MVBV	0.0007	-0.0015	-0.0780	-0.0694	-0.0657
Intercept	0.0703	0.0858	0.6146	0.0589	0.0627
N	90	25	26	33	39
Prob>F	0.0007	0.0010	0.0030	0.0001	0.0001
Adjusted R-squared	0.0740	0.4295	0.2799	0.1516	0.1475

Legend: * 5% significance, ** 1% significance, and *** 0.1% significance.

The results in Panel B of Table IV suggest that investors' negative reaction to dividend-cuts were inversely related to the tier-1 capital ratio of banks in the pre-crisis and crisis periods. Investors reacted less to dividend cut announcements by well-capitalized banks during the pre-crisis and crisis periods. The coefficients are 0.0045 and 0.0035, statistically significant at 1% and 5% levels, respectively. Interestingly, the coefficients change signs for the 2009 and 2009-2013 periods. They become -0.0046 and -0.0045, both significant at 1% level. These results suggest that investors perceived dividend-cuts by better-capitalized banks as a positive signal before and during the crisis periods and as a negative signal in the post-crisis periods.

Contrary to tier-1 ratio, returns on assets (ROA) is positively related to the negative reaction to dividend cuts in the pre-crisis and crisis periods and inversely related in the post-crisis periods. Investors reacted more negatively to dividend-cuts by profitable banks in the pre-crisis and crisis periods and less negatively in the post-crisis periods. The coefficients are -2.71, -2.3, 2.46 and 2.35 for pre-crisis, crisis, 2009, and post-crisis periods, respectively. They are all significant at 5% level. They imply that dividend cut announcements by profitable banks were a more severe negative signal in the pre-crisis and crisis periods than in 2009 and beyond. It implies that investors value the maintaining profitability more than dividends in the banking industry.

Banks with more real estate loans on their balance sheet as measured by RE_LOAN experienced less negative reaction to their dividend cut announcements both for the pre-crisis and post-crisis periods, which suggests investors either expected these banks to cut-dividends or found dividend-cuts as a positive move to build up funds and reduce insolvency risk. Contrary to our expectations, investors didn't react significantly to dividend cuts by banks with larger real estate loans on their balance sheets during the crisis period. The result is negative, meaning dividend cuts were perceived a negative signal, but not statistically significant.

Another interesting result is the size of dividend cuts as measured by Divchange. The signaling theory of dividend cuts suggests that investors would react more to larger dividend cuts than to smaller ones. However, the size of dividend cuts did not impact market reaction to dividend cut announcements. The coefficient is not significant for any periods. It implies that investors did not differentiate between a dividend cut of, say, 20% and 80%, or a complete omission. A dividend-cut announcement of any size was sufficient enough to be considered a negative signal. Other ratios unrelated to the stock market reactions to dividend-cut announcements were bank-size, amount of marketable securities, non-interest income and market-to-book ratios. These ratios were independent of the stock market reaction to dividend cut announcements.

For the entire study period of 2003 to 2013, only tier-1 capital ratio significantly explains stock market reaction to dividend-cuts, all other ratios fail to explain abnormal returns. The failure of ratios to explain the stock market reaction to dividend cuts in the banking industry for the entire study period suggests that certain bank ratios have different importance during different time periods, i.e. pre-crisis, crisis, and post-crisis periods.

V. Summary and Conclusion

The signaling theory of dividends suggests that dividends signal about the financial health and earning potential of firms. In the banking industry, this signaling effect of dividends is more pronounced, attributed to the opaque nature of the banking industry. During the Great Recession of 2007 and 2008, many financial firms, in particular banks, experienced financial difficulty. At the same time, banks wouldn't release explicit negative information about their financials and asset quality in fear of being subject to runs or being cut from credit markets. During the recession, investors may have relied more on implicit signals, such as a dividend-cut, about bank financials. While investor reactions to dividend-cuts have been extensively investigated during normal times, they have not been examined during the 2007 and 2008 financial crisis. We attempted to fill this gap by investigating dividend-cut announcements around the financial crisis.

We studied the stock market reaction to bank dividend-cuts in three periods around the Great Recession; the pre-crisis period, 2003-quarter 1 to 2007-quarter 2; the crisis period, 2007-quarter 4 to 2008-quarter 4; and the post-crisis period, 2009-quarter 1 to 2013-quarter 4. Using event-study methodology and BMP test-statistics, we found that during the pre-crisis and the crisis periods, investors' reaction to dividend cuts was statistically insignificant, although negative. Investors' reaction to dividend cuts was negative and statistically significant in the year immediately following the crisis, i.e. 2009, and in the post-crisis period of 2009-2013. For the event-window of (-7,+1) days around the dividend-cut announcements in 2009, the stock market reaction (CARs) was negative 11.21%, significant at 1% level. We also found that the size of dividend-cuts, whether a partial cut or a complete omission, had no impact on the size of the market reaction.

Contrary to our expectations, investors didn't react to bank dividend-cuts during the financial crisis. In all other studies of dividend-cut announcements, the stock market reaction has been negative and statistically significant. The insignificant result during the crisis period is a departure from prior results of event studies on dividend-cut. This may imply that investors' perception of dividend-cuts as a signal changed during the Great Recession. Investor's perception of dividend-cuts as a negative signal resumed immediately in the aftermath of the Great Recession and became even more robust.

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Reputation as a Selection Criteria: A "Golden Egg" or just an "Egg?"

Thomas M. Krueger and Mark A. Wrolstad

Abstract

The semi-strong level of the Efficient Market Hypothesis (EMH) asserts that current prices reflect all of the publically available information about a firm. Harris Interactive, Inc. has done extensive polling and data analysis of public perceptions to produce a credible numerical indicator of corporate reputations for which they have coined the term "Reputation Quotient" (RQ). Using RQ information, this research analyzes corporate annualized returns of highly visible firms with very good reputations and compares their performance with firms with very poor reputations. Portfolios of the ten firms with the best reputations have higher raw returns than portfolios of the ten firms with the worst reputations but the difference is not statistically significant. However, reputations appear to parallel risk, with firms possessing better reputations having lower return standard deviations and less sensitivity to market conditions. As a consequence, firms with good reputations have significantly higher Sharpe, Treynor, and Jensen's alpha measures. This observed outperformance was found to be more significant during the second half of the fourteen year period studied which includes the 2008 financial crisis and its' aftermath.

I. Introduction

In an informationally-efficient securities market, investors continuously price securities on the basis of current information that is expected to provide insight to the future performance of companies (Fama, 1970). This research looks carefully at the potential value of publically available information regarding a firm's reputation using a measure called the Reputation Quotient (RQ). RQs were developed by the collaborative efforts of Harris Interactive Inc. and Charles Fombrun, Professor of Management at New York University's Stern School of Business and Executive Director of the Reputation Institute (Fombrun & Shanley, 1990). Professor Fombrun (1996) also wrote the first academic textbook on corporate reputation. Others (i.e., Aneosun and Ganiyu, 2013) view the quantifying of reputations as the starting point in the development of reputation management as a separate academic discipline and research field. The RQ is a comprehensive metric that quantifies information collected from a large number of respondents and condenses it into a single number that reflects the favorableness of corporation's reputation. The RQ measures are calculated using proprietary methodology

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from data received by Harris Poll Online which has a global database of over 4.2 million cooperative respondents. The instrument enables research on the drivers of a company's reputation as well as comparisons of reputations both within and across industries.

The asserted advantages of strong reputations are powerful and visible according to Professor Fombrun (Fombrun, 1999). He contends that a strong reputation means greater consumer trust and the ability to command premium pricing. The better the reputation, the greater the company's opportunity to create new products and to lower marketing costs. It also helps companies attract the best employee talent. A good reputation means stronger word of mouth endorsement, a barrier against imitation, and faster recovery from economic recessions. "A good reputation can be a decisive source of competitive advantage in markets where companies find it hard to differentiate via the traditional means of price and quality. The bottom line," says Fombrun, "is that good reputations are valuable strategic assets that help strengthen corporate profitability". (Fombrun, 1999) Good corporate reputations are critical not only because of their potential for value creation, but also because their intangible character makes replication by competing firms considerably more difficult, according to Adeosun and Ganiyu (2013). Given the apparent current value of a good reputation and likelihood that this competitive advantage persists into the future, this study examines the predictive power of RQ announcements.

II. Literature Review

One of the most popular measures of corporate reputation is *Fortune Magazine's* annual listing of the most admired companies in the United States. Anderson and Smith (2006) report that admired firms outperformed the S&P 500. The 22 *Fortune* portfolios created from 1983-2004 achieved, on average, a 16.51 percent increase in value 250 trading days after the publication date, whereas the S&P 500 showed an average increase of only 10.27 percent increase. The differences in average wealth grew increasingly pronounced and statistically significant as the horizon lengthens. The use of the 250 trading days was necessary because like RQs Fortune's listing is not released on a fixed annual basis.

A similar study is the listing of Britain's Most Admired Companies, which was studied by UK researchers Cole, Brown and Sturgess (2014). Reputation is determined in this list's case through queries of corporate executives in the various industries. Cole, Brown, and Sturgess conclude that the optimal investment strategy was a two-step process of selecting companies with excellent reputations and then look for companies that they determined to be undervalued in the market. They reasoned that excellent reputation companies have a high likelihood of having a management that is equipped and capable to turn around whatever problems the organization was experiencing.

An interesting insight into the performance of companies with good reputations is found in research done by Grahame Dowling and Peter Moran (2012). They distinguished between companies with good reputations earned by supporting worthy causes or other social responsibility gestures versus companies that earned good reputations from actions like producing superior products/services that were grounded in the strategy of the organization. Their conclusion is that reputations based upon corporate strategies are far more likely to reward the company with a sustainable competitive advantage. However, Raithel and Schwaiger (2015) disclosed that those reputation perceptions that are driven by nonfinancial aspects of a small sample of German firms over a seven year period were more highly correlated with future firm values than reputation perceptions that were primarily driven by previous financial performance.

In their summary of prior reputation research, Adeosun and Ganiyu (2013), struggle with defining the asset-value of a good reputation in an accounting sense. They observe that a reputation "is not a fixed asset or depreciable and a figure cannot be put on it. Adeonsun and Ganiyu (2013, p. 222) view reputation as an intangible asset that necessitates the use of complex and controversial valuation metrics. According to Hutton et al (2001), reputations are generally something that cannot be managed directly, but are a general response to a firm's behavior. In fact, we typically do not refer to reputation in rational number terms, but with ordinal measures such as the possession of a "good," "neutral," or "bad" reputation. In order to benchmark behavior, Fombrun and van Riel (1998) assert that reputation is an aggregate assessment of a firm's actions relative to the perceived norms in an industry. Indeed, Genasi (2002) asserts that the value of a corporation's reputation arises from it being a touchstone to the future in a world full of unknowns. Fombrun's Reputation Quotient (RQ) metric is an attempt to quantify this elusive asset.

Even if reputation can be described and measured, one still has to identify what constitutes a "good" versus a "bad" reputation. Harris Interactive has identified a RQ hurdle above which it considers firms to have an "excellent" reputation. In a recent study, Gonzales and Krueger (2015) used this information to compare the stock price performance of firms with excellent reputations relative to the Standard & Poor's 500. In years with at least two firms in the "excellent" reputation category, equal investment in the "excellent reputation" firms provided a significantly higher rate of return relative to the Standard & Poor's 500 Index.

This is not the only study comparing the performance of firms with high RQs to those with low RQs. Prior research (e.g., Krueger and Wrolstad (2007), Krueger, Wrolstad, and Van Dalsem (2009) and Krueger, Wrolstad, and Van Dalsem (2010)) however assume an investment horizon of one year, regardless of the duration of the intervening period between the publication of RQ values. As shown in Table 2, the time between public announcements has in fact ranged from 256 to 507 days. The artificial assumption that the RQ's impact lasts for exactly 365 days has the potential to confound the results. When the interval between RQ announcements is short, there is likely to be an understatement of the impact of a given RQ announcement. At the opposite extreme, when the interval between RQ announcements is long, the impact of a given RQ announcement is likely to be overstated. For instance, if either the TOP10 or BOT10 portfolio consistently earned a 0.25 percent monthly excess return, an eight-month interval would find a 2.0 percent rate of excess performance, while a 17-month interval would be assigned a 4.25 percent rate of excess performance. The variation in excess performance is likely to diminish the statistical significance of RQ measure. Although one could argue that an investor using the RQ methodology could shift to cash twelve months after an RQ announcement, it is more probable that a typical investor would leave their funds in an RQ-based portfolio awaiting the next RQ press release.

For this research, we recast the holding period returns into annualized return streams for the Top 10 and Bottom Ten RQ portfolios and we have completed a detailed investigation of return, risk, and risk-adjusted return performance of the stock portfolios. An additional change from previous work done by Krueger, et al. is the seventy-five percent increase in available observations, which is achieved by the passage of the years since the previous research was completed.

III. Methodology

Sample

Harris Interactive began reporting Reputation Quotients in 1999. On February 3, 2014 Harris Interactive was acquired by Nielson Holdings N.V. to reportedly bolster the proprietary information Nielson supplies to manufacturers and retailers (Feltner, 2014). This analysis is based upon a total of fourteen Reputation Quotient (RQ) reports made prior to the acquisition of Harris Interactive by Nielson Holdings.

In this research two portfolios are created, one consists of the covered firms with the ten highest reputations (Top 10 Portfolio) and the other consists of the ten firms with the lowest reputations (Bottom 10 Portfolio), as measured by Harris Interactive's RQ measure. Equal investment in all 10 companies in each portfolio is assumed. A larger sample would dilute the potential impact of the RQ measure while a smaller sample would increase the likelihood that unique events at individual companies would confound results. Given that RQs are publically reported for a total of 60 companies each year, our investigation captures the performance of one-third of the firms, with an equal initial number selected at both extremes. Portfolio membership is updated on the day a new RQ article is published by Harris Interactive. This analysis could be theoretically based on 280 firms (i.e., 20 RQ firms taken from each of the 14 surveys), consisting of 140 firms with outstanding reputations and 140 with poor reputations. However, Harris Interactive periodically includes a company in its survey, which has never been publicly-traded (i.e., S.C. Johnson), has been acquired (i.e., Bridgestone), or either goes bankrupt or is acquired before the next RQ survey is released (i.e., Merrill Lynch and Chrysler, respectively). A complete listing of all companies with extreme RQ ratings that are not in the sample for these reasons is presented in Table 1. Information on only one company with a high RQ rating (i.e., S.C. Johnson) is not available, resulting in this segment of the investigation being based on a total of 139 observations of performance by firms with widely accepted favorable reputations.

As depicted by Table 1, most of the missing data exists within the low RQ segment of the empirical sample. After adjusting for the number of instances without complete information among the set of firms with low RQ measures, the impact of low reputations is being estimated using 122 observations, or 87 percent of the relevant population. Although additional firms with low RQ measures could be added, their inclusion would add firms with less extreme reputations, which is likely to confound the results. To the extent that ow RQ firms listed in Table 1 earn lower returns than other firms in the Bottom 10 portfolio when they file for bankruptcy, the impact of the missing values is a bias in favor of finding less of a difference between the return performance of the Top 10 Portfolio and Bottom 10 Portfolio. Although the asymmetric distribution of missing values leads to the warning that these results should be viewed with caution, excluding firms that provide total losses to investors results in a more conservative analysis of the importance of corporate reputations. It is not possible to include the bankrupt firms by assigning a complete loss to such investments, because trading has frequently halted prior to inclusion in the RQ announcement.

This study addresses the predictive nature of firm reputations. The prediction hypothesis postulates a causal relationship running from company reputation to share prices. As a consequence, it implicitly assumes that the market is inefficiently pricing the reputation metric as measured using Reputation Quotients. In order to seek evidence of market inefficiency, we analyze share price performance during the period after the release of RQ survey results. This study expands upon the research done in Krueger, Wrolstad, and Van Dalsem (2009) in two ways. Firstly, we have included additional RQ announcements that were not available to the previous researchers and secondly, by employing annualized returns as our measure of investment performance.

Justification for Annualizing Returns

Unlike quarterly or year-end financial reports, an exogenously fixed time schedule does not exist for the release of information on firm reputations. Reputation quotients (RQs) are also not as highly anticipated or widely reported as Harris Interactive’s political surveys. Consequently, RQs are not reported on a fixed periodic schedule. As shown in the first row of Table 2 the average time between the releases of RQs is slightly over a year, coming in at 1.04 years or 379 days. If you were to take the total number days from the very first 1999 RQ announcement to the 2014 RQ announcement and divide by 14, you would end up with a value of 1.03. The extra 0.01 is tied to leap years, which occurred in 2000, 2004, 2008, and 2012. The extent to which this number exceeds 365 is the difference between the calendar date when the first Reputation Quotient report was released in 1999 and one year after the last pre-acquisition RQ announcement in 2013. Of course this is an extensive process that frequently begins in the prior year with identification of the sixty most prominent firms. For example, the 2013 announcement is based upon information for which the survey process began in 2012.

The median time between observations is an almost identical 1.02 years or 371 days. A similar mean and median suggests that the distribution of announcement periods exhibits little skewness. However, one should not take this similarity as a guarantee that there has been little variation in the length of time between announcements. Simple comparison of the average and median can hide the actual amount of variation in announcements. The actual average difference between 379 days and the actual announcement date is 0.15 years, or 55 days, as shown in the third row of Table 2. In this case the median is noticeably shorter, at 0.11 years, or 40 days. The higher average suggests that we are dealing with "fat tail" distribution of actual reporting periods around the mean.

Ideally, one would prefer no absolute difference in in the days on which RQ information is released. Stated another way, it would be ideal if the announcements were all on the same day of the year. Annualizing returns would not be necessary in such a case. However, the one instance of this occurring is a statistical artifact, created by ending the final forecast period one year before the last announcement. The maximum time between announcements was the 507 days between the initial announcement and the second RQ report publication on February 7, 2001. The minimum time lapse between RQ announcements was 0.70 years, as reported in the bottom row of Table 2. In 2004, RQ-related press releases occurred on February 19 and November 15 of the same year.

Performance Measures

Returns based only on prices and total returns (based on both prices and dividends) are computed for individual firms. Firm returns are equally weighted to create portfolio returns. Both return streams were identified in order to detect any ability of dividends to impact firm reputation beyond that which would arise from stock price-based returns alone. Firms with worse reputations may offer a higher dividend yield in order to attract investors. For instance, near the end of the empirical sample, dividend yields in the tobacco industry ranged from 5.46% at Lorillard to 3.92% at Philip Morris (Maurer, 2012). Philip Morris showed up frequently in the Bottom 10 portfolio, while the less well-known Lorillard seldom made the list of 60 firm RQ ratings reported by Harris Interactive.

Mean, median, and geometric means are computed with the latter two being measured due to the limited sample and large difference in return volatility, respectively. Risk-adjusted returns were estimated using Sharpe ratios to estimate returns in excess of the risk-free rate per unit of total risk, which is estimated using standard deviation. Treynor ratios measure returns in excess of the risk-free rate per unit of systematic risk, while Jensen's alphas measures are estimates of return in excess of what is required based upon the risk-free rate, market return, and systematic risk. The three measures were computed in the traditional way using the following equations. .

Sharpe ratio = $(R_i – R_f) / \sigma$

Treynor ratio = $(R_i – R_f) / \beta$

Jensen's alpha = $R_i – R_f – \beta\ (R_m\text{-}R_f)$

Where,

β = a measure of systematic risk, using five years of data and the Standard & Poor's 500 as the measure of market returns.

R_f = annualized combination of rolling three-month Treasury bill yields during the period between HQ announcements, weighted for the date when the RQ announcement is made

R_i = annualized portfolio return between RQ announcement dates which may include dividends when R_i is a total return measure

R_m = annualized return on the Standard and Poor's 500, with and without the dividend yield, depending upon the form of the R_i term

σ_i = standard deviation of the portfolio return

Pairwise t-tests are run to compare the mean return and estimated risk-adjusted return measure for the two independent Top 10 Portfolio and Bottom 10 Portfolio investments in a manner similar to the research method followed in prior research (i.e., Krueger and Wrolstad (2009) and Krueger Wrolstad and Van Dalsem (2010)). The null hypothesis is that the high RQ and low RQ portfolios earned the same rate of return. The tables below present t-statistic p-values, giving the reader insight to the probability of rejecting a correct null hypothesis that share prices are independent of the RQ measure of firm reputation. If no significance is found the stock market are informationally efficient preventing investors from using the RQ information as a means to earn abnormal rates of return.

IV. Findings

Returns and Risk

Means annualized returns are presented in the first row of Table 3. Price-based returns and total returns are presented in the left and right columns, respectively. Subtraction of the priced-based value from the total return value reveals the average annual dividend payment. The Top 10 Portfolio, consisting of firms with the highest RQ values had the highest subsequent returns, regardless of whether returns are defined in terms of share prices or total returns. Although the difference in price-based returns and total returns exceeds four percent, the difference is not statistically significant suggesting the RQs are poor predictors of subsequent returns.

An interesting revelation arising from Table 3's first row of data is that firms with the worst reputation had a higher dividend yield in the subsequent year. The Top 10 Portfolio had a dividend yield of 2.15 percent (i.e., 11.65% - 9.5%), while the dividend yield of Bottom 10 Portfolio was 3.51 percent (i.e., 7.64% - 4.14%). The 1.36 percent difference was able to offset about one fourth of the 5.36 percent (i.e., 9.50% - 4.14%) difference in price-based returns.

In every column, the geometric mean return was lower than the mean return, while the median return was higher. The reason for the consistency of this pattern in is revealed by information exhibited in the remaining three rows of Table 3, where we see that there is a large difference between the single highest annualized return and the lowest annualized return following RQ announcements. The larger return standard deviation found in the Bottom 10 Portfolio columns explain the larger difference between geometric and median values found earlier in Table 3. In summary, Table 3 documents the higher annualized returns of the Top 10 Portfolio, though post-announcement returns are quite variable.

In light of the creation of portfolios of firms with extreme levels on the Reputation Quotient metric, systematic risk is a relevant risk measure. Portfolio betas presented in Table 4 are an equally weighted average of the portfolios of the firms in each extreme cluster. Investor aversion to systematic risk is evidenced by these values, with the Top 10 Portfolio's average beta being less than 1.0, or "defensive" in nature. By comparison, the Bottom 10 Portfolio's beta values are consistently higher and greater than 1.0, which is commonly referred to as being "aggressive." In fact, the average Bottom 10 Portfolio beta, given in the first row of Table 4, is a whopping 68 percent larger.

The similarity of average and median values in each column of Table 4 delineates stability in the RQ values across time. However, the Top 10 Portfolio's beta range from 0.688 to 1.068, with the latter value representing only a slight level of "aggressiveness," the Bottom 10 Portfolio's beta ranges from 0.987, or about unity, to 2.257. The relatively high beta standard deviation value reflects the wide range of Bottom 10 Portfolio beta values across time. In summary, Table 4 reports that firms with higher Reputation Quotients tend to have lower levels of systematic risk.

Risk-adjusted Return Estimates

Given the Top 10 Portfolio's lower level of risk in terms of standard deviation and systematic risk, as exhibited in Table 3 and Table 4, respectively, risk-adjusted returns of the Top 10 Portfolio and Bottom 10 Portfolio were computed and contrasted. Table 5 contrasts risk-adjusted performance when standard deviation is used as the measure of risk. The Sharpe values of both portfolios are greater than zero, as shown in Panel A, indicating that both portfolios provide a return in excess of Treasury yields. In both instances the Top 10 Portfolio's Sharpe values are significantly larger at the 0.05 level. With almost a ninety-nine percent level of confidence, we can say that the Top10 Portfolio outperformed the Bottom10 Portfolio in terms of return in excess of the Treasury yield per unit of standard deviation.

Results for the first and second seven-year periods within the fourteen-year sample period are reported in Panel B of Table 5. For instance, in the first column, the full sample period's 0.459 Sharpe value of the Top10 Portfolio's price-based returns arises from a 0.258 Sharpe value in the first seven years and a 0.605 level in the second seven years. A lack of significance despite the large difference in sub-period Sharpe values is not surprising given the limited number of observations.

Comparison of the Top10 Portfolio's Sharpe values and Bottom10 Portfolio's Sharpe values reveals a consistent level of higher performance for the Top10 Portfolio which helps to make the t-statistic p values more significant for the entire period than the individual periods separately. Despite the limited number of observations, during the most recent 7-year period, the Sharpe value of the Top10 Portfolio is significantly higher at the 0.05 level. Higher Sharpe values exist whether returns are based on price or both price and dividends. In summary, firms with higher reputations earned higher risk-adjusted returns, in terms of Sharpe values, with the predictive power of firm reputations being most dramatic in recent years.

Given that portfolio performance relative to the stock market overall is an appropriate comparison, Table 6 reports beta-adjusted portfolio-excess returns, or Treynor values.

Given the wider disparity in betas than standard deviations, it is not a surprise to see the Top10 Portfolio registering much higher Treynor values. Being defensive, Top10 Portfolio betas actually accentuate the difference between portfolio returns and the Treasury yield. Conversely, the highly aggressive Bottom10 Portfolio's beta diminishes the difference between this portfolio's return and the Treasury yield. One can say with a ninety-nine percent level of confidence that the Top10 Portfolio's Treynor measures are higher using price-based returns. Inclusion of the higher dividend yield posted by Bottom10 Portfolios has a limited impact, diminishing the relative value of the Top10 portfolio from 8.86 percent (i.e., 9.65% - 0.79%), to 8.79 percent (i.e., 12.16% - 3.37%). The level of confidence falls to being just slightly lower than ninety-nine percent.

In all but one instance, the Treynor values are higher in the second seven-year sub-period. The exception to this rule is that the Bottom10 Portfolio's Treynor measure is higher during the first sub-period when considering total returns. Nonetheless, the difference between the first and second sub-period is not significant for any return series. A comparison of Top10 Portfolio Treynor measures and Bottom10 Portfolio Treynor values reveals that the former is always higher. In fact, during the most recent sub-period the performance difference is significant at about the ninety-nine percent level. In summary, selection of firms with higher RQs resulted in better portfolio performance when measured using Treynor values, and this better performance has grown in more recent years.

While investors consider returns in terms of percentages and excess returns relative to required returns, the Treynor statistic measures performance in terms of return per unit of systematic risk. Consequently, Jensen's alpha measures were also estimated, because these statistics measure the extent to which returns exceed required returns in light of Treasury yields, market returns, and the level of systematic risk. Two measures of market returns were captured, one being the annualized changes in the Standard & Poor's 500 Index. The other market measured added the dividend yield on the S&P 500 Index during the period to changes in the index itself. The first set of columns presented in Table 7 include only the change in the Standard & Poor's 500 as an input to the capital asset pricing model (CAPM) upon which Jensen's alpha is based. Jensen's alpha estimates using total market return are presented in Table 7's second set of columns.

Whether considering price-based or total returns, the Top10 Portfolio's Jensen's alpha measures exceed the Bottom10 Portfolio's alpha estimates. In fact, the Top10 Portfolio provides positive alpha values, while the Bottom10 Portfolio's alpha values are negative, with the difference being over ten percent whether you include or exclude dividends. Careful comparison of each set of columns provides additional insight. Comparing the Top10 Portfolio columns (i.e. 5.62% and 6.16%), we can conclude that the defensive betas of the Top10 Portfolio were sufficient to offset its lower dividend yield relative to the market. The Bottom 10 Portfolio's Jensen alpha improves when dividends are added, suggesting that this portfolio's higher dividend payment is more than sufficient to offset the larger amount required as a consequence of this portfolio's higher beta. Nonetheless, The Bottom 10 Portfolio's total return's alpha value indicates that it underperforms required returns by over four percent annually. The measures of statistical significance both indicate that we can say with a ninety-five percent level of confidence that the Top10 Portfolio outperformed the Bottom10 Portfolio when using Jensen's alpha as a benchmark.

Unlike sub-period results presented in Table 5 and Table 6, there was a statistically significant change in the alpha measures across sub-periods for each portfolio. Top10 Portfolio alpha values doubled, which was significant at the 0.10 level when either price-based or total returns are considered. By contrast, Bottom10 Portfolio alpha values dropped, with the drop being significant at the 0.10 level when total returns are under consideration. During the latter seven-year period, the Bottom 10 portfolio underperformed the market by over eleven percent, per the Jensen's alpha statistic. During this latter period, the difference in Jensen's alphas between the Top10 Portfolio and Bottom 10 Portfolio was significant at the 0.05 level with or without consideration of dividend payments. In summary, firms with high reputations earn a return in excess of the required return based on the CAPM- founded Jensen's alpha measure, while the dismal performance of the firms with poor reputations is well below the required return and worst in the recent time period.

V. Conclusion

The importance of corporate reputation is widely perceived as being a key to firm success, as attested to repeatedly by Federal Reserve Board Chairman Alan Greenspan (1999, 2004). Several recent studies examined the importance of firm reputation in selecting firms. Although one might argue that firms with better reputations should perform well in the future, in an efficient market their current share price should already reflect reputation as well as all other aspects of a firm. Hence, firms with good reputations should subsequently only earn the risk-adjusted market return. A corollary to this efficient market hypothesis reasoning is that those firms with poor reputations should be priced at relatively low values for the market to be in equilibrium, resulting in market matching subsequent performance.

A popular, widely disseminated measure of firm reputation is Harris Interactive's Reputation Quotient (RQ) value, which first became available in 1999. Past research has estimated firm return between RQ announcements. This return measurement process however does not consider difference in the timing of RQ announcements, which we found to run from 256 to 507 days. Differences in interval length will impact returns and return measurements. Treating these varying time periods similarly has the unintended impact of understating the RQ selection during short intervals and overstating RQ selection during longer intervals. The research method will have a confounding impact limiting the statistical significance of the RQ metric. In order to adjust for this methodological error, we computed annualized returns.

Our results are consistent with those found elsewhere. A portfolio of ten firms with the best reputations has higher raw returns than a portfolio of firms with the worst reputations although the result is not statistically significant. However, reputation appears to have an inverse relationship with risk. Firms possessing better reputations have lower return standard deviation and less sensitivity to market conditions. As a consequence, firms with good reputations have significantly higher Sharpe, Treynor, and Jensen's alpha measures. Outperformance was more significant during the more recent period, which included the 2008 financial crisis. As noted in the discussion of the data, this study excludes firms that went bankrupt or were acquired by other firms at rock-bottom prices during the year following RQ announcement release. Hence, these findings probably overstate the performance of firms with poor reputations. Future research might consider the RQ and other measures of firm reputation across a variety of economic conditions to evaluate the importance of market conditions on the investment value of information regarding firm reputation.

Table 1. Firms with Reputation Quotients not included in Study

Firm	*RQ Year*	*Why Excluded*	*Year of Event*
Top 10 Portfolio Firms			
SC Johnson	*2010*	*Always private*	*not applicable*
Bottom 10 Portfolio Firms			
MCI Communications (WorldCom)	*2002,2006*	*Bankrupt*	*2002*
Bridgestone Tire	*2003*	*Acquired by Firestone*	*1988*
Adelphia Communications	*2003, 2005, 2006*	*Bankrupt*	*2002*
Global Crossing	*2004*	*Bankrupt*	*2002*
Enron	*2006*	*Bankrupt*	*2001*
Northwest Airlines	*2008*	*Acquired by Delta*	*2005*
Citgo Petroleum	*2008,2009*	*Acquired by Petroleos de Venezuela*	*1990*
Chrysler	*2008, 2009, 2010, 2011*	*Acquired by Cerberus*	*2008*
Merrill Lynch	*2009*	*Acquired by Bank of America*	*2009*
General Motors	*2009, 2010*	*Bankrupt*	*2009*

Table 2. Analysis of Variation in Reputation Quotient Announcement Dates

Average Time Period Between RQ Announcements	1.04 years	379 days
Median Time Period Between RQ Announcements	1.02 years	371 days
Average Absolute Excess Sample Period Length	0.15 years	55 days
Median Absolute Excess Sample Period Length	0.11 years	40 days
Minimum Absolute Excess Sample Period Length	0.00 years	0 days
Maximum Time Between RQ Announcements	1.39 years	507 days
Minimum Time Between RQ Announcements	0.70 years	256 days

Table 3. Contemporaneous Return Characteristics

	Price-based Returns		Total Returns	
	Top 10 Portfolio	Bottom 10 Portfolio	Top 10 Portfolio	Bottom 10 Portfolio
Mean Return	9.50%	4.14%	11.65%	7.64%
t-statistic p values	0.1117		0.198	
Geometric Return	8.28%	0.32%	10.43%	3.83%
Median Return	10.15%	4.77%	12.24%	8.03%
Maximum Return	45.07%	42.47%	46.93%	52.32%
Minimum Return	-22.43%	-42,.14%	-20.63%	-41.03%
Return Standard Deviation	16.70%	27.82%	16.81%	28.50%

Table 4. Detailed Analysis of Portfolio Beta

	Top 10 Portfolio	Bottom 10 Portfolio
Average	0.861	1.449
Median	0.838	1.411
Maximum	1.068	2.257
Minimum	0.688	0.987
Standard Deviation	0.101	0.338

Table 5. Sharpe Measure Estimates of Total Risk Adjusted Contemporaneous Returns

	Price-Based Returns			Total Returns		
Panel A. Entire Sample Period	Top 10 Portfolio	Bottom 10 Portfolio	t-statistic p values Across Portfolios	Top 10 Portfolio	Bottom 10 Portfolio	t-statistic p values Across Portfolios
	0.459	0.091	0.012**	0.582	0.211	0.015**
Panel B. Sub-period						
First 7 Years	0.258	0.081	0.182	0.425	0.282	0.256
Second 7 Years	0.605	0.093	0.020**	0.698	0.140	0.017**
t-statistic p values Across Time Periods	0.206	0.481	na	0.4820.223	0.437	na

*, **, *** indicates significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table 6. Treynor Measure Estimates of Systematic Risk Adjusted Contemporaneous Returns

	Price-Based Returns			Total Returns		
Panel A: Entire Sample Period	Top 10 Portfolio	Bottom 10 Portfolio	t-statistic p values Across Portfolios	Top 10 Portfolio	Bottom 10 Portfolio	t-statistic p values Across Portfolios
	9.65%	0.79%	0.007***	12.16%	3.37%	0.011**
Panel B: Sub-period						
First 7 Years	4.18%	0.51%	0.170	6.86%	4.61%	0.257
Second 7 Years	15.11%	1.07%	0.011**	17.46%	2.13%	0.009***
t-statistic p values Across Time Periods	0.195	0.483	na	0.203	0.422	na

*, **, *** indicates significance at the 0.10, 0.05, and 0.01 levels, respectively

Table 7. Jensen's alpha Measures of Systematic Risk-Adjusted Contemporaneous Returns

	Price-Based Returns			Total Returns		
Panel A. Entire Sample Period	Top 10 Portfolio	Bottom 10 Portfolio	t-statistic p values Across Portfolios	Top 10 Portfolio	Bottom 10 Portfolio	t-statistic p values Across Portfolios
	5.62%	-4.80%	0.041**	6.16%	-4.08%	0.029**
Panel B. Sub-period						
First 7 Years	3.07%	-0.53%	0.199	4.06%	2.88%	0.377
Second 7 Years	8.17%	-9.07%	0.031**	8.25%	-11.04%	0.021**
t-statistic p values Across Time Periods	0.060*	0.113	na	0.098*	0.059*	na

*, **, *** indicates significance at the 0.10, 0.05, and 0.01 levels, respectively.

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TGIF? The Weekend Effect in Energy Commodities

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Abstract

While there exists today ample evidence of the weekend effect in the equity and currency markets, similar evidence in the commodities market remains sparse. In this paper, we investigate the presence of the weekend effect in crude oil and natural gas markets. The sample uses daily spot returns in crude oil (WTI and Brent) and natural gas markets from the U.S. Energy Information Administration for periods beginning as early as data is available (1986, 1987, and 1997 respectively) through May 2017. We estimate robust OLS and median regression models across the entire sample period and three approximately equal subperiods for each of the commodities. We find evidence of the weekend effect for WTI and Brent commodities while documenting a "reverse" weekend effect in natural gas returns.

I. Introduction and Literature Review

Observed patterns in asset prices which contradict the efficient market hypothesis are commonly referred to as market anomalies. An important example is the "calendar anomaly," which is understood to be systematic asset price behaviors which are inconsistent with the notion of market efficiency and routinely observed at different times of the year. Examples of calendar effects documented in the asset pricing literature include the weekend effect (e.g., Alt, Fortin, and Weinberger, 2011; Blau, Van Ness, and Van Ness, 2009; Christophe, Ferri, and Angel, 2009), the intramonth and turn-of-the-month effects (e.g., Compton, Kunkel, and Kuhlemeyer, 2013; Jalonen, Vähämaa, and Äijö, 2010; Kunkel, Compton, and Beyer, 2003; Wiley and Zumpano, 2009), the day of the week effect (e.g., Seif, Docherty, and Shamsuddin, 2017), the January effect (e.g., Agnani and Aray, 2011; Easterday, Sen, and Stephan, 2009; Sun and Tong, 2010), the Daylight Saving Effect (e.g., Gerlach (2010); Gregory-Allen, Jacobsen, and Marquering, 2010; Kamstra, Kramer, and Levi, 2000), the lucky numbered days (e.g., Haggard, 2015), the Halloween effect (e.g., Andrade, Chhaochharia, and Fuerst, 2013; Haggard, Jones, and Witte, 2015; Jacobsen and Visaltanachoti, 2009), and the holiday effect (e.g., Gama and Vieira, 2013; Yatrakis and Williams, 2010; Yuan and Gupta, 2014). The vast research literature concerning the existence of calendar effects provides support for the continued investigation of such anomalies.

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The research cited above shows that various forms of the calendar anomaly, including the weekend effect, exist in equity and currency markets. Corroborative evidence from commodities markets remains sparse. This is noteworthy given the increased popularity and usage of commodities as an asset class for institutional investors. The U.S. Commodity Futures Trading Commission (CFTC hereafter) (2008) cites in a recent report the increase of commodity-related investments from an estimated $15 billion in 2003 to at least $200 billion in 2008 held by institutional investors. Moreover, the CME Group (2017) recently released a report highlighting the leading products traded on their platform for the first quarter of 2017. Among commodities, the West Texas Intermediate Crude Oil (WTI) was the most actively traded followed by Gas with an average daily volume of 1,118,945 and 429,548 contracts traded, respectively. Collectively, this increase in institutional investment in commodities and the recent volume of energy commodities trading make the absence of academic research on the likely cyclicality of returns in energy commodities perhaps more puzzling.

Among the limited body of academic research on the weekend effect in commodities are studies by Ball, Torous, and Tschoegl (1982) and Ma (1986) who find evidence in support of the weekend effect in the gold market.[1] However, the study of petroleum and natural gas markets is largely absent from the literature. In one exception, Kohli (2014) studies the day-of-the-week and month effects in sweet crude oil using a sample from 1983 to 2012 and finds marginal evidence of positive Friday returns for sweet crude. Moreover, evidence initially reported by Connolly (1989) and Chang, Pinegar, and Ravichandran (1993) and later supported by the findings of Kamara (1997) and Chen and Singal (2003) suggest that the weekend effect disappears in equity markets post-1980. Therefore, the important question of whether the weekend effect exists in energy commodities post-1980 remains unanswered.

We study a specific days-of-the-week effect termed the "weekend effect" in the petroleum and natural gas markets. Early evidence of the weekend effect, first reported by Fields (1931), builds on the intuition that risk-averse investors are more likely to close out their positions on Friday afternoon and open those positions back up on Monday morning. Consistent with the proposition of Fields (1931), Cross (1973) reports evidence that Friday returns tend to be higher than Monday returns for the S&P Composite. French (1980) documents a similar behavior for U.S equity returns: equity returns tend to be higher than average on the last trading day of the week (Friday) and lower on the first (Monday).

This study seeks to provide an answer to this question for two benchmark crude oil commodities, West Texas Intermediate Crude Oil (WTI) and Brent Sweet Crude Oil (Brent), and for Henry Hub Natural Gas (Gas). Our study builds on five different model estimation techniques, four being robust estimations (3 OLS and 1 median) to account for outliers within the

[1] For a recent study investigating calendar effects in metal commodity markets please see Borowski and Lukasik (2015).

data. All models are estimated using a parsimonious regression equation to investigate the existence of a potential weekend effect in petroleum and natural gas. In general, we find that a weekend effect for WTI and Brent exists over our entire sample period using robust OLS techniques. That is, the mean Monday returns on both commodities are negative and significant whereas mean Friday returns tend to be flat, statistically indifferent from zero relative to the returns during the middle of the week. However, when we focus on the median regression analysis, the weekend effect is present in the WTI sample and not evident in the Brent sample.

Alternatively, our strong and consistent findings across all estimations for Gas suggest the existence of a "reverse" weekend effect, whereas mean and median Friday returns are negative and strongly significant while mean and median Monday returns are positive and significant regardless of regression estimation contributes to the growing calendar effect literature. Brusa, Liu, and Schulman (2000) are among the first to document the presence of a "reverse" weekend effect in U.S. indices. To the best of our knowledge, this study is the first to document such a calendar anomaly for natural gas.

To investigate whether the weekend effect is persistent or period driven post-1980, we segregate our sample into three approximately equal subperiods. We then replicate our analysis over the various subperiods separately. Using the subperiods, we find that (1) the weekend effect we document for the OLS estimations for WTI is largely driven by the 1997-2006 subperiod, (2) evidence of the weekend effect for WTI using median regression estimation for the two subperiods of 1997-2006 and 2007-2017, (3) the weekend effect found for the Brent robust OLS estimation is primarily driven by the 2007-2017 subperiod, and (4) the "reverse" weekend effect we document for natural gas persists within each of the subperiods and across all estimations.

Data and methodology are presented in the following section. In section III, we present our results and discuss our findings. A summary and concluding remarks are offered in section IV.

II. Data and Methodology

Daily closing spot prices on all three energy commodities (WTI, Brent, and Gas) are obtained from the United States Energy Information Administration (hereafter EIA) website.[2] The EIA reports data for WTI starting January 1986, the data on Brent is available beginning May 1987, and the data for Gas starting in January 1997. The sample period for all data concludes with the last trading day of May 2017.

[2] The EIA data for petroleum is available at the following address: https://www.eia.gov/petroleum/data.php and EIA data for natural gas is available at the following address: https://www.eia.gov/naturalgas/data.php.

Figure 1 plots the daily closing spot prices for all three commodities. Panels A and B of Figure 1 suggest that WTI and Brent prices are positively correlated, as expected, over our sample period. However, we also note that Gas spot prices are not as highly, positively correlated with the two crude oil commodities (See Panel C of Figure 1).

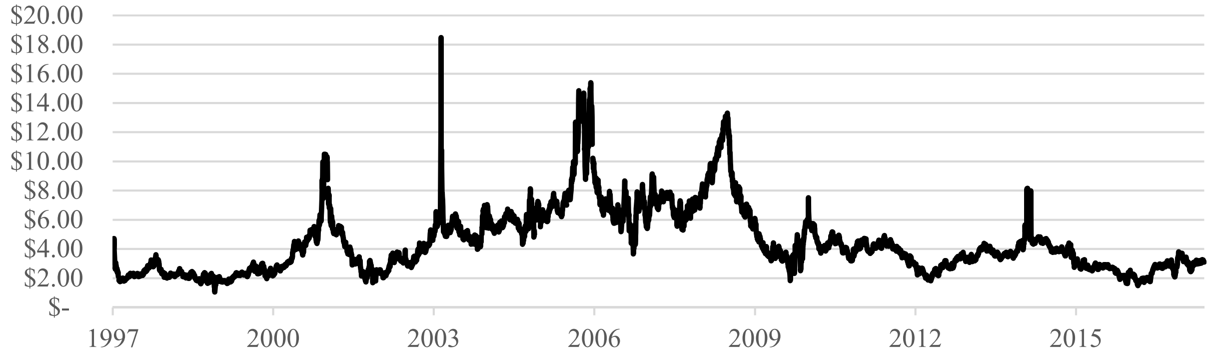
Figure 1: Daily WTI, Gas, and Brent Prices over Sample Period

The figure in Panel A illustrates the time series of the daily spot price (USD per barrel) for WTI (crude oil; Cushing, OK) covering the sample period from January 2, 1986 through May 30, 2017. The figure in Panel B displays the time series of the daily spot price (USD per barrel) for Brent (crude oil; Europe) covering the sample period from May 20, 1987 through May 30, 2017. The figure in Panel C depicts the time series of the daily spot price (USD per MBTU) for Gas (Henry Hub Natural Gas) covering the sample period from January 7, 1997 through May 30, 2017. The data was collected from the U.S. Energy Information Administration (EIA).

Panel A: Daily WTI (USD per barrel) Prices (January 2, 1986 - May 30, 2017)

Panel B: Daily Brent (USD per barrel) Prices (May 20, 1987 - May 30, 2017)

Panel C: Daily Gas (USD per MBTU) Prices (January 7, 1997 - May 30, 2017)



Commodities returns are calculated from each price series as:

$$R_{i,t} = \frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}} \tag{1}$$

where $i = \{\text{WTI, Brent, Gas}\}$, $P_{i,t}$ represents commodity *i's* price at time *t* and $P_{i,t-1}$ the commodity's price on the previous trading day. Returns that occur over a holiday and the day following a holiday are excluded, allowing for the return series to represent "normal daily returns."[3] The final sample includes 7,667, 7,441, and 4,945 observations for WTI, Brent, and Gas, respectively. Table 1 presents summary statistics of our daily return series for crude oil and natural gas.

Panel A of Table 1 describes centrality, range, and distribution of our series. We find average daily returns on Gas to be 6.54 basis points (Bps), approximately twice as high as average daily returns on WTI (3.04 Bps) and Brent (3.45 Bps). This pattern of returns is replicated in the second, third, and fourth moments of our return series. However, median returns are positive for WTI (3.13 Bps) while being 0.00 Bps for both Brent and Gas. Panel B shows the correlations for each of the days of our return series.

We report Pearson (below the diagonal) and Spearman (above the diagonal) correlation coefficients for each trading day of the week. Not surprisingly, we find the correlation between WTI and Brent to be much stronger than the correlation between either type of crude oil and Gas. For example, the Pearson correlation coefficient on Monday between WTI and Brent is about 65.39% while the correlation between WTI (Brent) and Gas is 11.00% (16.04%). Of note is the finding that Wednesday and Friday returns for WTI and Gas are not significantly correlated. Levene's test statistics for the returns for the day of the week are reported in Panel C and provide evidence against the null hypothesis of equal variances across days for each commodity. The number of return observations for each day of the week differ due to our data cleaning requirement of two consecutive trading days and excluding dates corresponding with holidays.

[3] To be included in the sample, we require two consecutive trading days for the computation of returns and exclude trading days that correspond to calendar holidays from our sample to reduce any potential bias.

Table 1: Summary Statistics

This table reports the summary statistics for the daily returns of the spot price (USD per barrel) for WTI (crude oil; Cushing, OK) covering the sample period from January 2, 1986 through May 30, 2017, the daily returns of the spot price (USD per barrel) for Brent (crude oil; Europe) covering the sample period from May 20, 1987 through May 30, 2017, and the daily returns of the spot price (USD per MBTU) for Gas (Henry Hub Natural Gas) covering the sample period from January 7, 1997 through May 30, 2017. This data is used throughout the analysis. Panel A reports descriptive statistics of relevant daily return variables. Panel B contains correlation matrices and coefficients for each of the three commodities (WTI, Brent, and Gas) for each day of the week used in the analysis. Correlations reported above the diagonal are Spearman correlations whereas those reported below the diagonal are Pearson correlations. P-values (two-tailed tests) for the coefficients that are less than 1 percent are in bold, less than 5 percent are in bold italics, and less than 10 percent are in italics. Panel C provides the results from the Levene's test of equal variances centered around the means and medians for WTI, Brent, and Gas, respectively. In Panel C, the symbols *, **, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively, using a 2-tailed test. The data in the table was collected from the U.S. Energy Information Administration (EIA).

Panel A: Sample Daily Return Descriptive Statistics

Variable	*N*	Mean	S.D.	Skewness	Kurtosis	Min	0.25	Median	0.75	Max
WTI	7,667	0.0304	2.4934	-0.1794	12.9496	-33.3953	-1.2048	0.0313	1.2750	21.1073
Brent	7,441	0.0345	2.2640	-0.1524	12.7051	-30.3170	-1.1192	0.0000	1.1863	18.9262
Gas	4,945	0.0654	4.4577	2.1943	37.8954	-43.3442	-2.0253	0.0000	1.8617	78.0089

Panel B: Correlation Matrix by Day Returns

Monday	**WTI**	**Brent**	**Gas**
WTI		**0.6090**	**0.0915**
Brent	**0.6539**		**0.1945**
Gas	**0.1100**	**0.1604**	

Tuesday	**WTI**	**Brent**	**Gas**
WTI		**0.5155**	**0.1073**
Brent	**0.5274**		**0.2198**
Gas	***0.0717***	**0.1955**	

Wednesday	**WTI**	**Brent**	**Gas**
WTI		**0.5883**	0.0267
Brent	**0.6051**		**0.0811**
Gas	0.0163	***0.0623***	

Thursday	**WTI**	**Brent**	**Gas**
WTI		**0.5383**	*0.0607*
Brent	**0.5801**		**0.1537**
Gas	**0.0902**	**0.1314**	

Friday	**WTI**	**Brent**	**Gas**
WTI		**0.5212**	0.0411
Brent	**0.5580**		**0.1562**
Gas	0.0271	**0.1530**	

Table 1 – *continued*

Panel C: Levene's Test Statistic (Null: Equal Variances)

WTI Daily Returns

Day	Mean	S.D.	*N*
Monday	-0.0973	2.8567	1,433
Tuesday	-0.0609	2.3337	1,495
Wednesday	0.0651	2.5238	1,613
Thursday	0.1397	2.5189	1,585
Friday	0.0892	2.2003	1,541
Total	0.0304	2.4934	7,667
Mean Statistic	**8.1207**	***	
Median Statistic	**8.1114**	***	

Brent Daily Returns

Day	Mean	S.D.	*N*
Monday	-0.0568	2.4988	1,429
Tuesday	-0.0896	2.1175	1,444
Wednesday	0.0128	2.1689	1,531
Thursday	0.2132	2.3686	1,536
Friday	0.0801	2.1372	1,501
Total	0.0345	2.2640	7,441
Mean Statistic	**3.9400**	***	
Median Statistic	**3.9247**	***	

Gas Daily Returns

Day	Mean	S.D.	*N*
Monday	1.0052	5.6247	916
Tuesday	0.5787	4.4540	962
Wednesday	0.3154	3.9488	1,047
Thursday	-0.3348	3.6899	1,027
Friday	-1.1484	4.1632	993
Total	0.0654	4.4577	4,945
Mean Statistic	**10.1965**	***	
Median Statistic	**9.1038**	***	

We follow Lucey and Zhao (2008) and Haggard and Witte (2010) for our analytical investigation of the weekend effect in energy markets. We generally estimate the following parsimonious OLS model:

$$R_{i,t} = \alpha + \beta_1 M_t + \beta_2 F_t + \varepsilon_{i,t} \quad (2)$$

where $R_{i,t}$ is the return on commodity i at time t, M_t and F_t are indicator variables taking the value of "1" for Monday and Friday respectively, and "0" otherwise. Following Haggard and Witte (2010), who show that outliers can account for a significant proportion of calendar anomalies, we consider the effect of outliers and perform Huber (1964) and Hampel (1974) *M-estimation* techniques. For robustness, we perform an additional robust OLS regression estimation that eliminates observations with Cook's distance greater than one prior to iterating with Huber and biweights consecutively as recommended by Li (1985).

Even after attempting to adjust outliers or extreme data observations, we may still find evidence of a weekend anomaly in our data due to OLS regressions estimating the conditional mean function. Therefore, we estimate median (least-absolute-residual) regressions with robust standard errors as described by Koenker and Hallock (2001) and following Haggard, Jones, and Witte (2015). Median regressions are robust to outliers as the regression estimates the conditional median function, resulting in the minimization of absolute deviations from the estimated median. This estimation technique diminishes the impact of any single outlier and the impact of a few outliers is greatly reduced.

III. Empirical Results

Our empirical investigation of the weekend effect in energy markets starts with univariate estimations of equation (2) above where we restrict the parameters β_2 or β_1 to zero. We then allow both parameters to be estimated freely as per the specification of equation (2). This approach allows us to observe the commodities Monday and Friday returns independently before pooling them to investigate the weekend effect in crude oil and natural gas.

Table 2 presents the results of our analyses for WTI over the entire sample period. In Panel A, we report results of our estimations after restricting the parameters β_2 to zero. We find $\beta_1$to be negative and strongly significant across our models. For example, in Model (3), estimated using the Hampel (1974) M-Estimation technique, we find that the average Monday return for WTI is negative and approximately 17.04 Bps lower than other daily returns throughout the week with an approximate t-statistic of about 2.77. The sign and significance of this average Monday return is replicated in models (1), (2), (4), and (5) as well. In Panel B, we restrict the parameter β_1 to zero in estimating equation (2) for WTI. We find across all our estimation methods that, while the mean return on Friday over the sample period generally carries a positive sign, it is also not statistically different from zero.

Lastly, when allowing the parameters in equation (2) to be freely estimated, we find the Monday and Friday return behaviors to replicate those obtained when investigated independently. Specifically, as shown in Panel C of Table 2, we find that, while the mean and median Monday returns over our entire sample remain negative and strongly significant across our estimation methods, that of Friday returns also retains its positive sign and remains insignificant. For instance, in model (5) estimated using the median regression method with robust standard errors, we find that the median Monday return for WTI is negative and significantly 19.89 Bps (t-stat ≈ 2.86) lower than the middle of the week daily returns. Friday returns continue to be flat, statically indifferent from zero (approximately 2.91 Bps; t-stat ≈ 0.51) relative to the returns during the middle of the week.

Table 2: Weekend Effect WTI Regression Analysis

This table contains the results of regression specifications conducted to analyze the weekend effect for WTI (crude oil; Cushing, OK) covering the sample period from January 2, 1986 through May 30, 2017. Panel A and Panel B contain univariate estimations of equation (2) by restricting the parameters β_2 and β_1 to zero, respectively. Panel C provides the results from equation model (2); all equation models are described in the paper. Column 1 is an OLS regression that corrects for heteroskedasticity using White-Huber standard errors. Column 2 is a robust M-Estimation regression using Huber (1964) weight with $c = 1.345$. Column 3 is a robust M-Estimation regression using Hampel (1974) weights with $a = 2$, $b = 4$, and $c = 8$. Column 4 is a robust regression that eliminates gross outliers with a Cook's distance greater than 1 and then performs Huber iterations followed by biweight iterations. Column 5 is a median regression estimation with robust standard errors. In all specifications, the dependent variable is the daily return for WTI and expressed in percentage terms (e.g., 1.45 = 1.45%). Monday and Friday are binary variables that take the value of "1" for Monday and Friday returns, respectively. t-statistics are presented in brackets below the respective coefficients. The symbols *, **, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively, using a 2-tailed test.

Panel A: Monday Effect

	(1)	(2)	(3)	(4)	(5)
Monday	-0.1571*	-0.1645***	-0.1704***	-0.1640***	-0.2081***
	[-1.9310]	[-2.7740]	[-2.7707]	[-2.7743]	[-3.1274]
Intercept	0.0598**	0.0690***	0.0631**	0.0678***	0.0813***
	[1.9657]	[2.6953]	[2.3722]	[2.6549]	[3.0667]
N	7,667	7,667	7,667	7,667	7,667
R^2	0.0006	0.0007	0.0001	0.0010	
adj. R^2	0.0005	0.0006	-0.0001	0.0009	
pseudo R^2					0.0008

Panel B: Friday Effect

	(1)	(2)	(3)	(4)	(5)
Friday	0.0735	0.0690	0.0601	0.0642	0.1012*
	[1.1326]	[1.1958]	[1.005]	[1.1167]	[1.873]
Intercept	0.0157	0.0248	0.0197	0.025	0.0000
	[0.4782]	[0.9575]	[0.7351]	[0.9702]	[0.0000]
N	7,667	7,667	7,667	7,667	7,667
R^2	0.0001	0.0001	0.0000	0.0002	
adj. R^2	0.0000	-0.0001	-0.0002	0.0001	
pseudo R^2					0.0002

Panel C: Monday and Friday Effect (Weekend Effect)

	(1)	(2)	(3)	(4)	(5)
Monday	-0.1474*	-0.1561**	-0.1647***	-0.1565**	-0.1989***
	[-1.7639]	[-2.5548]	[-2.6019]	[-2.5706]	[-2.8688]
Friday	0.0390	0.0335	0.0223	0.0291	0.0291
	[0.5859]	[0.564]	[0.362]	[0.4907]	[0.5181]
Intercept	0.0501	0.0605**	0.0575*	0.0605**	0.0720**
	[1.394]	[2.0508]	[1.8791]	[2.0525]	[2.1923]
N	7,667	7,667	7,667	7,667	7,667
R^2	0.0006	0.0007	0.0001	0.0010	
adj. R^2	0.0004	0.0005	-0.0002	0.0008	
pseudo R^2					0.0008

Overall the evidence reported in Table 2 suggests the existence of a weekend effect in the WTI crude-oil market. The signs of our estimated parameters are consistent with Kohli (2014). Table 2 brings credence to the notion of controlling for outliers as there is only marginal significance with a basic OLS estimation (Model 1). Using robust OLS techniques and the median estimation, we find strong evidence of the weekend effect for WTI.

Next, we repeat the analysis above for Brent and Gas. Table 3 reports the results of this exercise over the entire sample period for Brent, and Table 4 for Gas. We find that the behavior of Brent's mean returns on Monday and Friday, relative to the daily returns during the middle of the week, as shown in Table 3 closely replicate that of WTI reported in Table 2. Brent's Friday mean returns are not statistically different from zero across our estimation techniques (See Panels B and C of Table 3), whereas Monday mean returns are negative and statistically significant in six out of ten models estimated (See Panels A and C of Table 3). The evidence in Table 3 indicates that one would not have found any evidence of a weekend effect for Brent simply by estimating a basic OLS regression. However, once we perform robust OLS techniques to account for outliers in the conditional mean, we find evidence of the weekend effect in the Brent market. Interestingly, this finding is not conclusive as the median regression estimation fails to find evidence of the anomaly. While we find similar evidence using the conditional mean regressions (OLS), this lack of evidence highlights the differences in the data distributions as WTI had an approximate daily median return of 3.13 Bps and Brent's median return was 0.00 Bps.

Table 3: Weekend Effect Brent Regression Analysis

This table contains the results of regression specifications conducted to analyze the weekend effect for Brent (crude oil; Europe) covering the sample period from May 20, 1987 through May 30, 2017. Panel A and Panel B contain univariate estimations of equation (2) by restricting the parameters β_2 and β_1 to zero, respectively. Panel C provides the results from equation model (2); all equation models are described in the paper. Column 1 is an OLS regression that corrects for heteroskedasticity using White-Huber standard errors. Column 2 is a robust M-Estimation regression using Huber (1964) weight with c = 1.345. Column 3 is a robust M-Estimation regression using Hampel (1974) weights with a = 2, b = 4, and c = 8. Column 4 is a robust regression that eliminates gross outliers with a Cook's distance greater than 1 and then performs Huber iterations followed by biweight iterations. Column 5 is a median regression estimation with robust standard errors. In all specifications, the dependent variable is the daily return for Brent and expressed in percentage terms (e.g., 1.45 = 1.45%). Monday and Friday are binary variables that take the value of "1" for Monday and Friday returns, respectively. t-statistics are presented in brackets below the respective coefficients. The symbols *, **, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively, using a 2-tailed test.

Panel A: Monday Effect

	(1)	(2)	(3)	(4)	(5)
Monday	-0.1130	-0.1225**	-0.1289**	-0.1245**	-0.0215
	[-1.5703]	[-2.2032]	[-2.2301]	[-2.2294]	[-0.3642]
Intercept	0.0562**	0.0503**	0.0447*	0.0418*	0.0215
	[1.9773]	[2.0615]	[1.7598]	[1.7067]	[0.8803]
N	7,441	7,441	7,441	7,441	7,441
R^2	0.0004	0.0005	0.0005	0.0007	
adj. R^2	0.0003	0.0004	0.0004	0.0006	
pseudo R^2					0.0000

Panel B: Friday Effect

	(1)	(2)	(3)	(4)	(5)
Friday	0.0572	0.0523	0.0571	0.0512	0.0483
	[0.9118]	[0.9561]	[1.0053]	[0.9345]	[0.9127]
Intercept	0.0230	0.0168	0.0091	0.0082	0.0000
	[0.772]	[0.6829]	[0.3569]	[0.3336]	[0.0000]
N	7,441	7,441	7,441	7,441	7,441
R^2	0.0001	0.0001	0.0000	0.0001	
adj. R^2	-0.0001	-0.0001	-0.0002	-0.0001	
pseudo R^2					0.0001

Panel C: Monday and Friday Effect (Weekend Effect)

	(1)	(2)	(3)	(4)	(5)
Monday	-0.1050	-0.1161**	-0.1217**	-0.1184**	-0.0104
	[-1.4202]	[-2.0191]	[-2.0385]	[-2.0559]	[-0.1726]
Friday	0.0319	0.0251	0.0285	0.0237	0.0379
	[0.4956]	[0.4450]	[0.4863]	[0.4197]	[0.6930]
Intercept	0.0482	0.0439	0.0375	0.0357	0.0104
	[1.4556]	[1.5567]	[1.2799]	[1.2627]	[0.3805]
N	7,441	7,441	7,441	7,441	7,441
R^2	0.0004	0.0005	0.0005	0.0007	
adj. R^2	0.0002	0.0003	0.0003	0.0005	
pseudo R^2					0.0001

Perhaps more interesting is our finding of a "reverse" weekend effect for Gas returns. We generally find that Friday mean returns on Gas are negative and strongly significant while the Monday mean returns are positive and strongly significant relative to daily returns from the rest of the week. Specifically, we find in all estimated models including the Monday variable that Monday mean returns are positively significant at the one percent level of confidence. The mean Monday return coefficients vary between 38.63 Bps and 115.34 Bps across our estimated OLS models and the median Monday return coefficient is approximately 37.17 Bps (See Panels A and C of Table 4). Similarly, all the estimated models including the Friday variable show that the Friday returns on Gas are significantly negative relative to the rest of the week. Estimated Friday mean return coefficients vary between -151.88 Bps and -102.00 Bps and the median Friday return coefficient is approximately -90.09 Bps (See Panels B and C of Table 4) lower relative to the middle of the week.

Table 4: Weekend Effect Gas Regression Analysis

This table contains the results of regression specifications conducted to analyze the weekend effect for Gas (Henry Hub Natural Gas) covering the sample period from January 7, 1997 through May 30, 2017. Panel A and Panel B contain univariate estimations of equation (2) by restricting the parameters β_2 and β_1 to zero, respectively. Panel C provides the results from equation model (2); all equation models are described in the paper. Column 1 is an OLS regression that corrects for heteroskedasticity using White-Huber standard errors. Column 2 is a robust M-Estimation regression using Huber (1964) weight with c = 1.345. Column 3 is a robust M-Estimation regression using Hampel (1974) weights with a = 2, b = 4, and c = 8. Column 4 is a robust regression that eliminates gross outliers with a Cook's distance greater than 1 and then performs Huber iterations followed by biweight iterations. Column 5 is a median regression estimation with robust standard errors. In all specifications, the dependent variable is the daily return for Gas and expressed in percentage terms (e.g., 1.45 = 1.45%). Monday and Friday are binary variables that take the value of "1" for Monday and Friday returns, respectively. t-statistics are presented in brackets below the respective coefficients. The symbols *, **, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively, using a 2-tailed test.

Panel A: Monday Effect

	(1)	(2)	(3)	(4)	(5)
Monday	1.1534***	0.7191***	0.7436***	0.6286***	0.3717***
	[5.8614]	[6.0684]	[6.1151]	[5.3913]	[2.8029]
Intercept	-0.1483**	-0.1674***	-0.1738***	-0.1666***	0.0000
	[-2.2851]	[-3.2824]	[-3.3231]	[-3.3208]	[0.0000]
N	4,945	4,945	4,945	4,945	4,945
R^2	0.0101	0.0048	0.0019	0.0058	
adj. R^2	0.0099	0.0046	0.0017	0.0056	
pseudo R^2					0.0007

Table 4 – *continued*

Panel B: Friday Effect

	(1)	(2)	(3)	(4)	(5)
Friday	-1.5188***	-1.2091***	-1.2306***	-1.1038***	-0.9009***
	[-10.1215]	[-10.6155]	[-10.5179]	[-9.8397]	[-6.5345]
Intercept	0.3704***	0.1942***	0.2012***	0.1534***	0.0000
	[5.1998]	[3.8078]	[3.8397]	[3.0516]	[0.0000]
N	4,945	4,945	4,945	4,945	4,945
R^2	0.0186	0.0149	0.0043	0.0192	
adj. R^2	0.0185	0.0148	0.0041	0.0191	
pseudo R^2					0.0059

Panel C: Monday and Friday Effect (Weekend Effect)

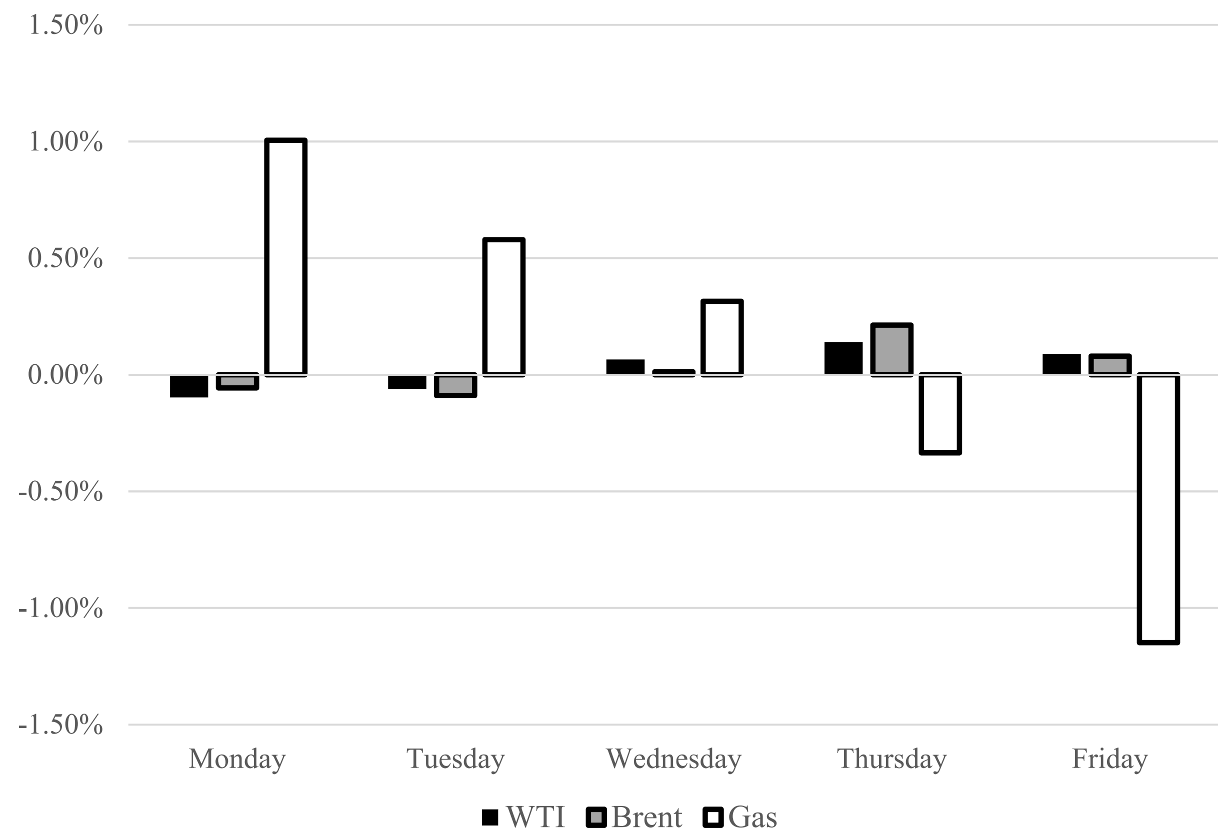
	(1)	(2)	(3)	(4)	(5)
Monday	0.8263***	0.4543***	0.4681***	0.3863***	0.3717***
	[4.1353]	[3.7514]	[3.7750]	[3.2440]	[2.7899]
Friday	-1.3273***	-1.1101***	-1.1255***	-1.0200***	-0.9009***
	[-8.7803]	[-9.4557]	[-9.3558]	[-8.8318]	[-6.4634]
Intercept	0.1789**	0.0952	0.0972	0.0706	0.0000
	[2.4331]	[1.6329]	[1.6281]	[1.2306]	[0.0000]
N	4,945	4,945	4,945	4,945	4,945
R^2	0.0235	0.0167	0.0054	0.0215	
adj. R^2	0.0232	0.0164	0.0050	0.0212	
pseudo R^2					0.0066

Overall, the evidence reported in Table 4 suggests the existence of a “reverse” weekend effect in natural gas returns. Unlike the weekend effect of Fields (1931) or French (1980), where Monday returns are shown to be negative and significant and Friday returns are generally positive, we find that Friday returns for Gas tend to be negative and strongly significant while Monday returns carry positive signs and are statistically different from zero. This finding is consistent with Brusa, Liu, and Schulman (2000) whom document the presence of a “reverse” weekend effect in U.S. indices

Figure 2 presents average returns for each day of the week for each commodity. Consistent with our earlier findings, this figure shows negative Monday and positive Friday mean returns for WTI and Brent. The Monday and Friday mean returns on Gas are positive and negative, respectively. More evident in this figure are the differences in magnitudes of daily returns across the commodities, an observation consistent with the differences in price volatilities reported in Table 1.

Figure 2: Daily WTI, Gas, and Brent Returns in Percent by Day

This figure displays the average daily return data for the following: 1) The average daily return by day for WTI (crude oil; Cushing, OK) covering the sample period from January 2, 1986 through May 30, 2017, 2) the average daily return by day for Brent (crude oil; Europe) covering the sample period from May 20, 1987 through May 30, 2017, and 3) the mean daily return by day for Gas (Henry Hub Natural Gas) covering the sample period from January 7, 1997 through May 30, 2017. The data was collected from the U.S. Energy Information Administration (EIA).



Evidence reported by Connolly (1989) and Chang et al. (1993) and later supported by the findings of Kamara (1997) and Chen and Singal (2003) suggest that the weekend effect disappears in equity markets post-1980. However, our results for a post-1980 sample period show that the weekend effect exists in crude oil in general, and unique to natural gas, there is evidence of a "reverse" weekend. Nevertheless, the question of whether the weekend effect we document in this study disappears sometime post-1980 remains open. To address this concern, we split our sample into three equal subperiods and replicate our analysis for each of the subperiods. We report the results of our estimations of equation (2) above when both parameters β_2 and β_1 are estimated freely.

Table 5 shows the subperiod results for WTI. There is no evidence of any weekend effect for the first subperiod of 1986 through 1996 (Panel A). Subsequently, for WTI, the weekend effect we document using robust OLS techniques in this study is largely driven by the behavior of WTI prices during the 1997-2006 subperiod. However, if we shift focus from the conditional mean to the conditional median, we find evidence of the weekend for both the subperiods of 1997-2006 and 2007-2017 using the median regression estimation. Collectively, without the median estimation, we might have incorrectly claimed to find no weekend effect for the last subperiod. In Panel C, only the median estimation provides negative (-23.62 Bps) and significant (t-stat ≈ -2.21) median Monday returns. However, the corresponding mean Friday return is also negative (-2.84 Bps) and insignificant (t-stat ≈ -0.26). On the other hand, when investigating the subperiod of 1997 to 2006, we find robust evidence of a weekend effect. Four out of five models (all robust OLS and median regression techniques) estimated report significantly negative mean and median Monday returns while five out of five models estimated report positively significant mean and median Friday returns (See Panel B of Table 5).

Table 5: Weekend Effect WTI Regression Analysis Subperiods

This table contains the results of regression specifications conducted to analyze the weekend effect for WTI (crude oil; Cushing, OK) covering three sample subperiods from January 2, 1986 through May 30, 2017. Panels A, B, and C provide the results from equation model (2) as described in the paper. Panel A covers the period of January 2, 1986 through December 31, 1996, Panel B includes the period of January 2, 1997 through December 29, 2006, and Panel C comprises the period of January 2, 2007 through May 30, 2017. Column 1 is an OLS regression that corrects for heteroskedasticity using White-Huber standard errors. Column 2 is a robust M-Estimation regression using Huber (1964) weight with c = 1.345. Column 3 is a robust M-Estimation regression using Hampel (1974) weights with a = 2, b = 4, and c = 8. Column 4 is a robust regression that eliminates gross outliers with a Cook's distance greater than 1 and then performs Huber iterations followed by biweight iterations. Column 5 is a median regression estimation with robust standard errors. In all specifications, the dependent variable is the daily return for WTI and expressed in percentage terms (e.g., 1.45 = 1.45%). Monday and Friday are binary variables that take the value of "1" for Monday and Friday returns, respectively. t-statistics are presented in brackets below the respective coefficients. The symbols *, **, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively, using a 2-tailed test.

Panel A: Monday and Friday Effect (Weekend Effect; 1986-1996)

	(1)	(2)	(3)	(4)	(5)
Monday	-0.0283	-0.0126	-0.0132	-0.0078	-0.0530
	[-0.1856]	[-0.1348]	[-0.1352]	[-0.0849]	[-0.4823]
Friday	-0.1102	-0.0398	-0.0852	-0.0303	-0.0530
	[-1.0031]	[-0.4336]	[-0.8894]	[-0.3342]	[-0.5601]
Intercept	0.0510	0.0553	0.0580	0.0499	0.0530
	[0.8576]	[1.2101]	[1.2159]	[1.1048]	[1.1039]
N	2,725	2,725	2,725	2,725	2,725
R^2	0.0003	0.0000	0.0011	0.0000	
adj. R^2	-0.0005	-0.0008	0.0004	-0.0008	
pseudo R^2					0.0002

Table 5 – *continued*

Panel B: Monday and Friday Effect (Weekend Effect; 1997-2006)

	(1)	(2)	(3)	(4)	(5)
Monday	-0.2027	-0.3192***	-0.3179***	-0.3611***	-0.3623**
	[-1.3641]	[-2.638]	[-2.6382]	[-3.0222]	[-2.2166]
Friday	0.2884**	0.2582**	0.2517**	0.2438**	0.2024*
	[2.4747]	[2.2182]	[2.1717]	[2.1206]	[1.8208]
Intercept	0.0262	0.0735	0.0702	0.0899	0.0858
	[0.4107]	[1.2716]	[1.2188]	[1.5738]	[1.2838]
N	2,413	2,413	2,413	2,413	2,413
R2	0.0039	0.0051	0.0000	0.0073	
adj. R^2	0.0031	0.0043	-0.0009	0.0065	
pseudo R^2					0.0041

Panel C: Monday and Friday Effect (Weekend Effect; 2007-2017)

	(1)	(2)	(3)	(4)	(5)
Monday	-0.2278*	-0.1556	-0.1631	-0.1259	-0.2362**
	[-1.7481]	[-1.4638]	[-1.4747]	[-1.1901]	[-2.2192]
Friday	-0.0397	-0.0694	-0.0677	-0.0906	-0.0284
	[-0.3322]	[-0.6712]	[-0.6292]	[-0.8799]	[-0.2637]
Intercept	0.0722	0.0499	0.0383	0.0412	0.0702
	[1.1292]	[0.9708]	[0.7159]	[0.8057]	[1.1845]
N	2,529	2,529	2,529	2,529	2,529
R2	0.0012	0.0006	0.0001	0.0007	
adj. R^2	0.0005	-0.0002	-0.0007	-0.0001	
pseudo R^2					0.0008

Shifting our focus to the Brent sample, we find no apparent evidence of the weekend effect for returns during subperiod of 1987 through 1996. There is marginal evidence of positive Friday returns during the second subperiod (1997-2006) in Models 3 through 5. In the final subperiod (2007-2017), there is marginal evidence of negative Monday and Friday returns. Collectively, even though we found evidence of a weekend effect for the conditional means over the entire sample period, there is little to no evidence consistent with the existence of a weekend effect when splitting our sample period (See Panels A, B, and C of Table 6).

Remarkably, our results from this exercise with Gas over the sub-sample periods closely resemble our findings using the entire sample. That is, over the period from 1997 to 2006, four out of five models report evidence consistent with our "reverse" weekend effect. Over the final period from 2007 through 2017, all estimated models suggest the existence of the "reverse" weekend effect. The evidence for Gas provided in Table 7 is robust across different estimation techniques and does not appear to be driven by any return outliers in the data.

Table 6: Weekend Effect Brent Regression Analysis Subperiods

This table contains the results of regression specifications conducted to analyze the weekend effect for Brent (crude oil; Europe) covering the sample period from May 20, 1987 through May 30, 2017. Panels A, B, and C provide the results from equation model (2) as described in the paper. Panel A covers the period of May 20, 1987 through December 31, 1996, Panel B includes the period of January 2, 1997 through December 29, 2006, and Panel C comprises the period of January 2, 2007 through May 30, 2017. Column 1 is an OLS regression that corrects for heteroskedasticity using White-Huber standard errors. Column 2 is a robust M-Estimation regression using Huber (1964) weight with $c = 1.345$. Column 3 is a robust M-Estimation regression using Hampel (1974) weights with $a = 2$, $b = 4$, and $c = 8$. Column 4 is a robust regression that eliminates gross outliers with a Cook's distance greater than 1 and then performs Huber iterations followed by biweight iterations. Column 5 is a median regression estimation with robust standard errors. In all specifications, the dependent variable is the daily return for Brent and expressed in percentage terms (e.g., 1.45 = 1.45%). Monday and Friday are binary variables that take the value of "1" for Monday and Friday returns, respectively. t-statistics are presented in brackets below the respective coefficients. The symbols *, **, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively, using a 2-tailed test.

Panel A: Monday and Friday Effect (Weekend Effect; 1987-1996)

	(1)	(2)	(3)	(4)	(5)
Monday	0.0061	-0.0409	-0.0383	-0.0494	0.0000
	[0.0457]	[-0.4767]	[-0.4299]	[-0.5795]	[0.0000]
Friday	0.0630	0.0727	0.0746	0.0829	0.1760*
	[0.6018]	[0.8634]	[0.8535]	[0.9914]	[1.9101]
Intercept	0.0140	0.0206	0.0103	0.0128	0.0000
	[0.2472]	[0.4882]	[0.2352]	[0.3042]	[0.0000]
N	2,402	2,402	2,402	2,402	2,402
R2	0.0001	0.0003	0.0001	0.0007	
adj. R^2	-0.0008	-0.0006	-0.0008	-0.0002	
pseudo R^2					0.0008

Panel B: Monday and Friday Effect (Weekend Effect; 1997-2006)

	(1)	(2)	(3)	(4)	(5)
Monday	-0.1832	-0.1435	-0.1473	-0.1316	-0.0742
	[-1.3578]	[-1.2265]	[-1.2644]	[-1.1270]	[-0.5672]
Friday	0.1898	0.1894	0.1898*	0.1933*	0.2232*
	[1.6388]	[1.6412]	[1.6519]	[1.6782]	[1.8435]
Intercept	0.0571	0.0539	0.0457	0.0507	0.0188
	[0.9267]	[0.9341]	[0.7948]	[0.8795]	[0.2931]
N	2,499	2,499	2,499	2,499	2,499
R2	0.0024	0.0019	0.0005	0.0021	
adj. R^2	0.0017	0.0012	-0.0004	0.0014	
pseudo R^2					0.0016

Panel C: Monday and Friday Effect (Weekend Effect; 2007-2017)

	(1)	(2)	(3)	(4)	(5)
Monday	-0.1324	-0.1672*	-0.1841*	-0.1879**	-0.1193
	[-1.1474]	[-1.7712]	[-1.8447]	[-1.9769]	[-1.3018]
Friday	-0.1534	-0.1705*	-0.1776*	-0.1781*	-0.1390*
	[-1.3603]	[-1.8472]	[-1.8215]	[-1.9181]	[-1.8541]
Intercept	0.0717	0.0641	0.0528	0.0474	0.0652
	[1.3283]	[1.3965]	[1.0887]	[1.0260]	[1.5305]
N	2,540	2,540	2,540	2,540	2,540
R2	0.0010	0.0015	0.0004	0.0024	

adj. R^2	0.0003	0.0008	-0.0004	0.0017	
pseudo R^2					0.0009

Table 7: Weekend Effect Gas Regression Analysis Subperiods

This table contains the results of regression specifications conducted to analyze the weekend effect for Gas (Henry Hub Natural Gas) covering two sample subperiods from January 7, 1997 through May 30, 2017. Panels A and B provide the results from equation model (2) as described in the paper. Panel A covers the period of January 7, 1997 through December 29, 2006 and Panel B includes the period of January 2, 2007 through May 30, 2017. Column 1 is an OLS regression that corrects for heteroskedasticity using White-Huber standard errors. Column 2 is a robust M-Estimation regression using Huber (1964) weight with $c = 1.345$. Column 3 is a robust M-Estimation regression using Hampel (1974) weights with $a = 2$, $b = 4$, and $c = 8$. Column 4 is a robust regression that eliminates gross outliers with a Cook's distance greater than 1 and then performs Huber iterations followed by biweight iterations. Column 5 is a median regression estimation with robust standard errors. In all specifications, the dependent variable is the daily return for Gas and expressed in percentage terms (e.g., 1.45 = 1.45%). Monday and Friday are binary variables that take the value of "1" for Monday and Friday returns, respectively. t-statistics are presented in brackets below the respective coefficients. The symbols *, **, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively, using a 2-tailed test.

Panel A: Monday and Friday Effect (Weekend Effect; 1997-2006)

	(1)	(2)	(3)	(4)	(5)
Monday	0.7994**	0.3866**	0.4319**	0.2866	0.3106*
	[2.4747]	[1.9836]	[2.1606]	[1.4912]	[1.7117]
Friday	-1.2302***	-0.9969***	-1.0385***	-0.8911***	-0.9009***
	[-5.1063]	[-5.3196]	[-5.4032]	[-4.8218]	[-3.8208]
Intercept	0.2100*	0.1057	0.1065	0.0765	0.0000
	[1.7720]	[1.1378]	[1.1175]	[0.8348]	[0.0000]
N	2,396	2,396	2,396	2,396	2,396
R2	0.0167	0.0110	0.0059	0.0126	
adj. R^2	0.0159	0.0102	0.0051	0.0118	
pseudo R^2					0.0049

Panel B: Monday and Friday Effect (Weekend Effect; 2007-2017)

	(1)	(2)	(3)	(4)	(5)
Monday	0.8520***	0.5188***	0.5140***	0.4628***	0.4329**
	[3.4987]	[3.4842]	[3.3204]	[3.123]	[2.5051]
Friday	-1.4187***	-1.2034***	-1.2117***	-1.1296***	-0.9042***
	[-7.6257]	[-8.2651]	[-8.0086]	[-7.8004]	[-4.9027]
Intercept	0.1493*	0.0879	0.0902	0.067	0.0000
	[1.6812]	[1.2141]	[1.1995]	[0.9302]	[0.0000]
N	2,549	2,549	2,549	2,549	2,549
R2	0.0341	0.0247	0.0088	0.0332	
adj. R^2	0.0334	0.0240	0.0081	0.0325	
pseudo R^2					0.0087

IV. Conclusion

While researchers have increasingly sought to document and understand calendar anomalies in the equity market, little attention has been paid to documenting similar evidence in the commodities markets. This study makes several contributions to the body of the literature on the weekend effect in commodities. First, using five different regression estimation techniques and data from the United States Energy Information Administration website, we provide robust evidence of the existence of the weekend effect for two major benchmark crude oil commodities (WTI and Brent). While our analyses suggest that the weekend effect for WTI is largely driven by the 1997-2006 subperiod, there is only marginal evidence of the weekend effect for Brent across subperiods.

Second, we document the existence of a “reverse” weekend effect for Gas. Specifically, we find mean and median Friday returns to be negative and strongly significant while mean and median Monday returns are positive and significant. We show with subperiod analyses that the “reverse” weekend effect we document persists over time, suggesting that further investigation on the behavior of natural gas returns could be a fruitful avenue for future research. Finally, we add to prior studies demonstrating the importance of accounting for outliers in return data.

Overall, our study reveals that the calendar anomaly we investigate for the commodities market manifests itself in a variety of ways depending on the underlying commodity. Our results also present a challenge for the validity of the efficient market hypothesis in the commodities market. We suggest that the following questions remain open and warrant further research: (1) Do explanations of calendar anomalies in equity markets carry over to commodities markets? (2) What underlying characteristic of the commodities yields the observed disparity in the manifestation of the weekend effect documented in this study? And perhaps more interestingly, why do these anomalies persist in the commodities market?

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