Investor Sentiment and Stock Returns

by

Benjamin David Lee Brookins

Submitted to the Sloan School of Management, Department of Finance
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Abstract

Since Keynes coined the term animal spirits economists have been debating what the real impact human psychology is on economic variables. The major challenge in identifying these effects is the close ties between negative (positive) emotions and poor (good) future real outlook. I exploit a historical weighting anomoly in a widely cited US stock index to examine the impact of psychology on stock returns. I first argue this is a plausibly exogenous shock, and compare this measure to other measures found in the literature. I find that the measure doesn't seem to relate to previous proxies for investor sentiment, however, when I examine survey measures of interest rates and consumer confidence we find a relationship. I then examine how sentiment affects the cross section of stock returns, consistent with predictions I find that small stocks earn low subsequent returns when sentiment is low, and high returns when sentiment is high.

Thesis Supervisor: Adrien Verdelhan
Title: Associate Professor

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Chapter 1

Introduction

Economists have long debated the effect of investor sentiment on asset prices. Classical finance theory says there is no place for behavioral theories in asset prices. In contrast since at least Keynes (1936) coined the term "animal spirits" many authors have considered the possibility that if sentiment affects a critical mass of market participants than prices can depart from fundamentals. Classical finance theory argues that sentiment effects would be erased by fully rational traders arbitraging asset prices departures from fundamental value. If these traders are unable to exploit this arbitrage opportunity then sentiment effects are more likely to be observed.

The main empirical challenge of differentiating the behavioral and classical theories in asset pricing is the lack of exogenous variation. Our current proxies for investor sentiment are insufficient in this regard because, as it is unclear if what we are observing are changes in "animal spirits", which would be the behavioralists view, or changes in expectations of future cash flows, a classical finance theorists view. I aim to solve this empircal issue by proposing a new source of exogenous variation, which is derived from an anomalous weighting scheme in the Dow Jones Industrial

Average (DJIA).

In this paper I present evidence that sentiment significantly effects the cross-section of asset prices, and argue that this effect is due to "sentiment shocks" which are independent of news about future states of the world. I build on a concept that dates back to at least Miller (1977) who argues that even if there are a large number of rational participants in the market then if no one is willing to short sell there still may be pricing anomolies.

There are several papers which do similar exercises to my paper, the most prominent probably being Baker and Wurgler (2006) and Stambaugh, Yu, and Yuan (2012). My study differs from previous literature in one primary way, I propose a source of exogenous variation and argue this can be viewed as an exogenous shock to sentiment. In doing so I demonstrate the causal effect of sentiment on asset prices. In order to validate this as capturing a shock to sentiment, I show that it affects LIBOR rate (a survey based measure of interest rates), as well as consumer confidence. Interestingly I find that it does correlate with traditional measures of consumer confidence used in the literature. I then derive a trading strategy in the same spirit as Baker and Wurgler (2006) and Stambaugh, Yu, and Yuan (2012) and show I can generate significant excess returns. Finally I show these returns cannot be explained by a traditional factor models.

The rest of the paper is organized as follows: Section 2 describes the construction of the index and data used, Section 3 provides evidence of how this new shock relates to current measures of sentiment, Section 4 presents results and discussion, and Section 5 concludes.

Chapter 2

Shock Description

2.1 Dow Jones Industrial Average

The Dow Jones Industrial Average (DJIA) is a price-weighted index comprised of 30 of the largest American corporations. It is the oldest and most cited index in the United States. The DJIA is calculated as

$$Dow_t = \frac{\sum_i P_{it}}{Divisor_t}$$

The $Divisor_t$ is a time varying constant that adjusts everytime there is an stock split, extraordinary dividend, spinoff for any component of the DJIA, or if there is an addition or deletion from the index. The divisor is calculated such that the new prices divided by the new divisor is the same as the old prices divided by the old divisor. In math:

$$\frac{\sum_i P_{it-1}^{new}}{Divisor_t} = \frac{\sum_i P_{it-1}^{old}}{Divisor_{t-1}} \Longrightarrow Divisor_t = Divisor_{t-1}\frac{\sum_i P_{it-1}^{new}}{\sum_i P_{it-1}^{old}}$$

This way of calculating an index runs counter to the way virtually every other index in the world is calculated. The other two widely cited indeces in the US, the NASDAQ composite, and the S&P 500, are both weighted by market capitalization (value-weighted), as are most other indices economists reference. The reason that the DJIA is different is for historic technology constraints. When Charles Dow started calculating the DJIA in 1896, it was calculated by hand. His goal was to create an index that could be calculated quickly, and the easiest thing to do when you observe prices is simply to add them up. Since the advent of computers, it is obviously computationally simple to weight things by market capitalization, but Dow has resisted such changes. In their words:

> *With little to gain, except maybe a reduction in criticism, we have no reason to reweight the Dow to market capitalization. And there would be a lot to lose: all that history is in price-weighted terms.*

2.2 Value-weighted Index

I calculate the value weighted analog to the DJIA, a complete list of the stocks in the Historical DJIA is displayed in Table A.1. The value weightings are quite different from the price weightings as you can see in Figure A-1. For example at the end of 2012, even though IBM and General Electric have near identical market values, $214 billion and $218 billion respectively, IBM contributes more than nine times to the DJIA returns than General Electric does. In our value weighted calculation they both contribute the same amount to our value-weighted Dow. My calculation of the value-weighted Dow is completely analougous to the DJIA. I exclude ordinary dividends, and only include extraordinary dividends in the return calculation. I refer to this constructed index as $VWIndex_t$ and the returns as $VWRet_t$.

Table A.2 displays summary statistics for the two constructed indices over various time periods. In this analysis I will primarily focus on the time period from 1986-2012 for the LIBOR results since that is the period over which LIBOR is available. I will focus on results from 1963-2012 for the results on stock market and treasuries since that is when the better data becomes available. Additionally I will focus on the index which excludes ordinary dividends, in order to parellel the DJIA as closely as possible although all results are qualitatively similar when I use the index that includes ordinary dividends. As you can see in Table A.2 the value-weighted index and the price weighted index are very similar in terms of means, medians, and standard deviations from 1986-2012. Lastly, Figure ?? graphs the monthly deviations of our index. Visually, you can see that it looks very random, there is some time-varying heteroskedasticity and the dispersion seems to be greatest during recessions, but that isn't unexpected. Our deviation would mechanically be more disperse when the crossectional standard deviation of stock returns is higher, this is the case during recessions. The important thing to note is it doesn't seem that there are necessarily more good or bad signals during recessions, it is only the 2nd moment that increases, the distribution is still centered around zero.

All of these facts taken together tell us that the difference between the value-weighted and price-weighted index returns are plausibly exogenous. I construct variables of interest in our analysis is Dev_t,$GoodSignal_t$ and $BadSignal_t$. Dev_t is simply the deviations in returns from the value-weighted index and the DJIA. I define

$$Dev_t \equiv VWRet_t - DJIA_t$$

This tells us how much of the return is due to the unconventional weighting scheme. I further define variables in the spirit of trying to capture something like good and bad signals. The most crude way to do this is simply to define:

$$GoodSignal_t \equiv \mathbf{1}\left\{(DJIA_t > 0) \cap (VWRet_t < 0)\right\} \tag{2.1}$$

Similarly

$$BadSignal_t \equiv \mathbf{1}\left\{(DJIA_t < 0) \cap (VWRet_t > 0)\right\} \tag{2.2}$$

$GoodSignal_t$ simply means that when I observe a positive quoted return even though the return on wealth is negative, $BadSignal_t$ is analogous. Over the time period from 1982-2012 $GoodSignal_t$ occurs 5.1% of the time and $BadSignal_t$ occurs 4.4% of the time.

Chapter 3

Relationship to Sentiment

Although the majority of our discussion has focused this Dev_t the majority of our tests actually run the specification

$$\Delta y_t = \alpha + \beta_1 VWRet_{t-1} + \beta_2 PWRet_{t-1} + \delta X_t + \epsilon_t$$

The reason this is, is because I want to control for the value weighted return in our regressions. If I run the specification

$$\Delta y_t = \alpha^\star + \beta_1^\star VWRet_{t-1} + \beta_2^\star Dev_{t-1} + \delta X_t^\star + \epsilon_t$$

The coeffecient value becomes a little less natural to interpret. Our H_0 is that the price-weighted return conditional on the value weighted return shouldn't matter. Therefore I can test this directly with $H_0 : \beta_2 = 0$.

3.1 Interest Rates

Table A.3 presents estimates of with X_t being the possible conflicting states. I control for all 4 possible states in these regressions, even though the both the price and value weighted moving in the same direction are not presented. As you can see the coeffecients on the returns are significant especially at the longer horizons. This tells us that bankers when reporting LIBOR put weight on the price weighted index, especially at longer horizons. If you think of the DJIA as a type of "economic indicator", it also makes sense that these effects are primarily present at longer term horizons since we know better the economic conditions at the present, and therefore the DJIA is providing information about future economic conditions.

The most stark coeffecients in Table A.3 are β_3 and β_4. When a good signal is recieved, as manifested through the price-weighted being positive return when the value-weighted return was actually negative, LIBOR increases positively and significantly at the 3-month horizon onward. Furthermore these jumps are economically large ranging from .6 - 1.1 basis point. This estimates represents between 25 - 35% of the mean absolute daily change in LIBOR rates. Finally you see that the coeffecient on $\beta_4$is zero. This is surprising at first, since one may not expect people to behave assymetrically. However this result is consistent with previous ideas that people react positively to good signals and do not react to bad signals.

Table A.4 presents the same regressions except for treasury yields instead of LIBOR. The contrast is stark. There are essentially no significant coeffecients. One might be concerned that even though individually they are not significant, that is due to the large standard errors generated by the multicollinearity. Examining the F-stat for this regression we see that it is small and insignificant everwhere, telling us that the model is jointly insignificant. As robustness As a robustness check I ran regressions where we included dividends instead of excluding dividends, qualitatively the results from both the LIBOR and treasury yield analysis did not change. This is a surprising result in many ways considering the close relationship between LIBOR and treasury yields. However, given that we are trying to pick up the "human error" component of the surveys, it seems like I may have done just that.

3.2 Investor Sentiment and Consumer Confidence Indices

I convert our daily series to a monthly series by taking difference between the monthly returns of the DJIA and the value-weighted analog. I do this to examine a wider class of data including the commonly cited indicators of investor sentiment, and consumer confidence.

Table A.5 displays a regression of the monthly changes in consumer confidence on the monthly deviations of the DJIA. This is contemporaneous, since the surveys are completed at the end of the month, the timing matches pretty well. As you can see there is a relatively strong relationship and fairly robust to the inclusion of other possible variables. Additionally the F-stat is reasonably large in several of the regressions. I think this measure could be used as an instrument for consumer confidence in future research projects.

If we examine the relationship between our measure and the Baker-Wurgler index, in Table A.6,we essentially see no relationship. Additionally if we examine the relationship between our shock to sentiment and the components of the Baker-Wurgler index, again there is no consistent relationship. One thing that you might notice is that the F-stat is relatively higher for the flexible polynomial spacification. The primary significant coeffecients in that specification are the 2nd and 4th moments. I interpret this to have more to do with the correlation between the dispersion of the second moment of our index and the likelihood of recessions than having some exogenous relationship. The fact that there is no relationship between traditional measures used in the literature and my measure of shock would be more troubling if there wasn't a strong relationship to either consumer confidence or LIBOR. It does seem this measure affects people's feelings about the future, even if it doesn't effect traditional measures of investor sentiment. One possible explanation, is that while my measure is really capturing the "animal spirits" portion of sentiment, while previous measures are loading much more on changes in expectations about the future. Another possible explanation, is that this measure of sentiment is simply not affecting investors, it is only affecting the more general public. I think that argument is largely refuted by the LIBOR survey results, LIBOR survey takers are by all accounts sophisticated market participants, and Section ??'s results on stock returns.

3.3 Stock Returns

Figure A-3 plots percentile deviations agains the expected returns of Small-Big and Small-Medium Portfolios. There is clearly a strong relationship between these two variables, and it is not as if this only exists at the extremes of the distribution. It is fairly uniformly decreasing throughout the distribution. If you look at the same graph for Growth-Value or Growth-Core you don't see nearly as strong as a relationship. For the rest of the paper we focus on the Small-Big portfolio, although the same results are qualitatively the same if you focus on the Medium-Big portfolio.

Chapter 4

Cross-Section of Stock Returns

4.1 Trading Strategy Construction

I construct 6 different trading strategies, but they are all based off of the same idea. The basic idea is to invest in small stocks when sentiment is high (as proxied for by our measure) and invest in large stocks when sentiment is low. We construct two types of strategies, the first is a simple long strategy. In each period we either buy a portfolio of small stocks, or a portfolio of large stocks. The second strategy is a no-cost strategy, if sentiment is high we buy a portfolio of small stocks and concurrently short a portfolio of small stocks, then reverse the position when our measure of sentiment is low, shotrting small stocks and longing large stocks. For each type of strategy we examine 3 types of portfolios. The first is simply declaring zero to be the cutoff, we are net long small stocks in $Dev_t > 0$. The second strategy is doing the same simple strategy, but estimating at which point we should switch from buying small stocks by using the regression line in Figure A-3. Finally we apply a check function, to give more weight to those observations far away from the optimal cutoff.

Each strategy we are on average long one unit. In the first two weighting schemes we are always long one unit (and short one unit if we are using a no cost strategy). The weights are constructed that on average we are long one unit, and can be long anywhere from 0 to 2 units. The weighting kernel chosen in the weighting scheme is largely arbitrary and just trying to give deviations far away from the cutoff more weight. Figure A-5 displays graphically what these weighting schemes look like.

4.2 Returns and Risk

Table A.7 displays the moments of the trading strategy as well as the estimate of α and β from a simple CAPM model. The S&P 500 is used as the return on the market for comparison and in the regressions. As you can see the first two long strategies are very similar in terms of standard deviation, skewedness, and kurtosis but generate significantly higher returns that the S&P 500. The third strategy is more risky, but not incredibly so in terms of standard deviation. Your strategy has about 25% higher a standard deviation, but recieves almost 4x the return on the market. However there is much higher kurtosis than the market. The next three strategies are so called "no-cost" strategies. Notice first of all, that all three of their β is essentially zero. This means the theoretical return should be roughly in line with the risk free rate. However the returns far exceed this and even exceed the returns of the S&P 500. One might be worried about the large kurtosis involved in taking these strategies, but notice the skew of the distribution is positive, it suggests these tail events are actually very positive windfalls for you and not very negative events. Looking at Table A.8 we see this is indeed the case. Table A.9 show that these returns are also not due to loading on some other risk factorα is still very positive and significant. The results are robust to including momentum as a fourth factor.

Figure A-6 shows our returns through time. The vast majority of years our strategies outperform the market. The one exception to this is the naive no-cost strategy. On average it still outperforms the market, and it is a zero-beta asset, so comparing those to the S&P are unfair to begin with.

Chapter 5

Conclusion

My results are largely consistent with effecient markets, although it seems like we can construct this trading strategy of investor sentiment, when we actually go and attempt to implement it using liquid and large markets, the relationship dissappears. Likely the excess returns we are seeing are due to limits of arbitrage and/or transaction costs. My measure does effect large and important variables LIBOR and consumer confidence and could be used as an instrument for consumer confidence in the future.

Appendix A

Figures and Tables

Table A.1: Historical Components of DJIA 1939-Present

Current Components		Past Components		
Company Name	Entry Date	Company Name	Entry Date	Exit Date
Alcoa *	6/1/1959	Kraft Foods	9/22/2008	9/14/2012
American Express	8/30/1982	General Motors	3/4/1939	6/8/2009
Boeing	3/12/1987	American International Group	4/8/2004	9/22/2008
Bank of America	2/19/2008	Altria Group *	10/30/1985	2/19/2008
Caterpillar	5/6/1991	Honeywell International *	3/4/1939	2/19/2008
Cisco	6/8/2009	ATT Corp	3/4/1939	4/8/2004
Chevron *	2/19/2008	Eastman Kodak	3/4/1939	4/8/2004
Du Pont	3/4/1939	International Paper	7/3/1956	4/8/2004
Disney	5/6/1991	Goodyear	3/4/1939	11/1/1999
General Electric	3/4/1939	Union Carbide	3/4/1939	11/1/1999
Home Depot	11/1/1999	Sears	3/4/1939	11/1/1999
Hewlett-Packard	3/17/1997	Westinghouse Electric	3/4/1939	3/17/1997
IBM	6/29/1979	Texaco *	3/4/1939	3/17/1997
Intel	11/1/1999	Bethlehem Steel	3/4/1939	3/17/1997
Johnson and Johnson	3/17/1997	Woolworth	3/4/1939	3/17/1997
JPMorgan	5/6/1991	Navistar *	3/4/1939	5/6/1991
Coca Cola	3/12/1987	USX *	3/4/1939	5/6/1991
McDonalds	10/30/1985	Primerica *	12/16/1988	5/6/1991
3M *	8/9/1976	American Can Company *	3/4/1939	12/16/1988
Merck	6/29/1979	Inco LTD *	3/4/1939	3/12/1987
Microsoft	11/1/1999	Owen-Illinois	6/1/1959	3/12/1987
Pfizer	4/8/2004	General Foods	3/4/1939	10/30/1985
Procter and Gamble	3/4/1939	American Brands *	3/4/1939	10/30/1985
AT&T Inc *	11/1/1999	Chrysler	3/4/1939	6/29/1979
Traveler's Company *	3/17/1997	Esmark *	6/1/1959	6/29/1979
UnitedHealth Group	9/14/2013	Mansville Corporation	3/4/1939	8/30/1982
United Technologies *	3/4/1939	Anaconda Copper	6/1/1959	8/9/1976
Verizon	4/8/2004	American Smelting	3/4/1939	6/1/1959
Wal-Mart	3/17/1997	Corn Products	3/4/1939	6/1/1959
Exxon Mobil *	3/4/1939	National Steel	3/4/1939	6/1/1959
		National Distillers	3/4/1939	6/1/1959
		Loews Incorporated	3/4/1939	7/3/1956

Table A.2: Characteristics of Constructed Index

	Value-Weighted Index Excluding Dividends	Value-Weighted Index Including Dividends	DJIA
	Panel A: 1986-2012		
Mean	.0381	.0488	.0381
Median	.0455	.0554	.0519
Standard Deviation	1.200	1.200	1.162
$Corr\,(VW_t, DJIA_t)$	.97	.97	–
	Panel B: 1962-2012		
Mean	.0252	.0398	.0278
Median	.0218	.0348	.0343
Standard Deviation	1.046	1.045	1.024
$Corr\,(VW_t, DJIA_t)$	.97	.97	–
	Panel C: 1939-2012		
Mean	.0212	.0374	.0287
Median	.0229	.0407	.0392
Standard Deviation	.971	.970	.953
$Corr\,(VW_t, DJIA_t)$	.97	.97	–

Figure A-1: Dow Jones Price vs Value Weightings: December 31st, 2012

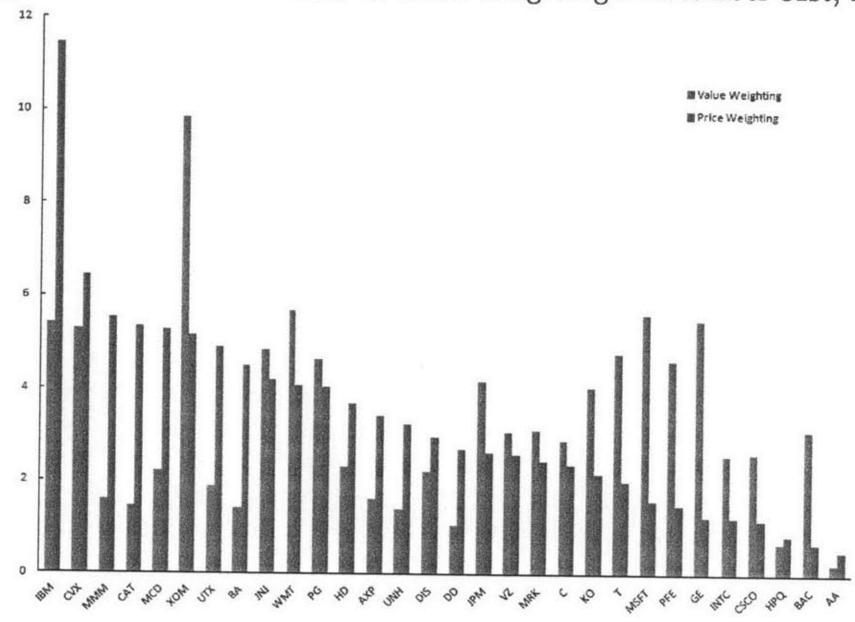


Figure A-2: Frequency Distribution of Signals

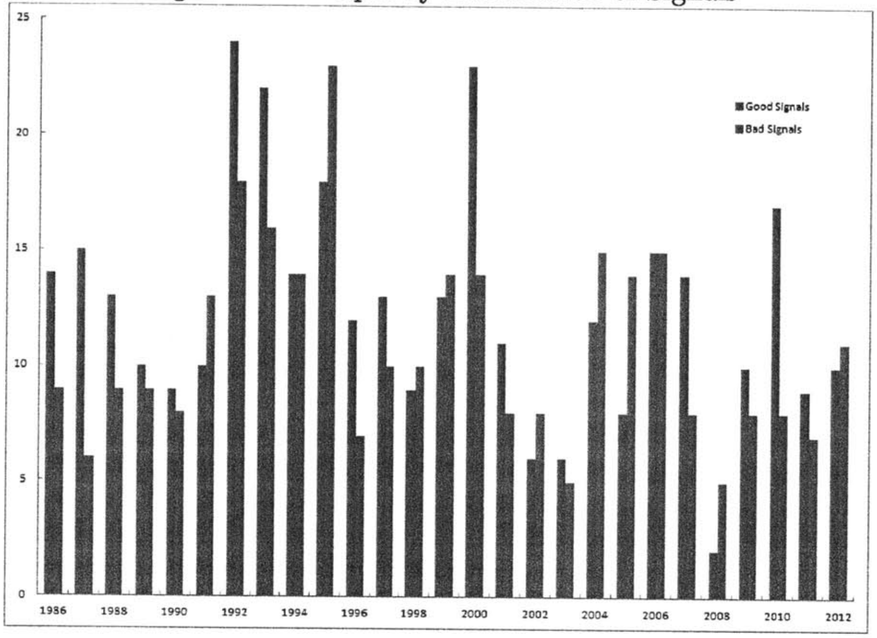


Table A.3: LIBOR and Misleading Signals

Maturity	1 month	3 month	6 month	9 month	12 month
$VWRet_t$	0.0025	0.0054*	0.0077**	0.0070**	0.0080**
$(t-stat)$	(0.80)	(1.86)	(2.40)	(2.13)	(2.19)
$PWRet_t$	-0.0029	-0.0046	-0.0073*	-0.0068*	-0.0085*
	(-0.84)	(-1.34)	(-1.86)	(-1.70)	(-1.91)
$GoodSignal_t$	0.0025	0.0056*	0.0082**	0.0078**	0.0111**
	(0.78)	(1.74)	(2.35)	(2.01)	(2.52)
$BadSignal_t$	0.0000	-0.0007	-0.0026	-0.0035	-0.0029
	(0.01)	(-0.28)	(-0.86)	(-1.04)	(-0.81)

*, **, and *** mean significant at the 10%, 5% and 1% level respectively.

Table A.4: Treasury Yield and Misleading Signals

Maturity	3 month	6 month	1 year	3 year	5 year	10 year
$VWRet_t$	-0.0069	-0.0052	-0.0033	-0.0013	-0.0015	-0.0014
$(t-stat)$	(-1.38)	(-1.20)	(-0.91)	(-0.35)	(-0.43)	(-0.40)
$PWRet_t$	0.0072	0.0050	0.0040	0.0011	0.0015	0.0008
	(1.34)	(1.13)	(1.07)	(0.31)	(0.45)	(0.25)
$GoodSignal_t$	-0.0024	-0.0003	-0.0070*	-0.0034	-0.0046	-0.0043
	(-0.53)	(-0.09)	(-1.70)	(-0.89)	(-1.31)	(-1.38)
$BadSignal_t$	0.0008	0.0015	-0.0035	-0.0032	-0.0033	-0.0023
	(0.17)	(0.37)	(-1.04)	(-1.04)	(-1.08)	(-0.80)
$F-stat$	0.82	0.66	1.57	1.27	1.28	1.04
$(p-value)$	(.53)	(.65)	(.17)	(.27)	(.27)	(.39)

*, **, and *** mean significant at the 10%, 5% and 1% level respectively.

Table A.5: Consumer Confidence

$$\Delta CC_t = \alpha + \beta_1 DJIA_t + \beta_2 VWRet_t + \delta X_t + \epsilon_t$$

Maturity	(1)	(2)	(3)	(4)	(5)
Dev_t	-1.5045***				
	(-3.07)				
$PWRet_t$		1.5728***	1.6481***	0.6552*	0.7419*
$(t - stat)$		(3.28)	(3.25)	(1.77)	(1.82)
$VWRet_t$		-1.2745***	-1.3241***	-0.5882*	-0.5991
		(-2.66)	(-2.67)	(-1.65)	(-1.62)
State Controls	No	No	Yes	No	Yes
Macro Controls	No	No	No	Yes	Yes
F-Stat	9.4197	6.5871	2.7477	16.0591	14.0092

*, **, and *** mean significant at the 10%, 5% and 1% level respectively.
Regressions are monthly from 1978-2012. State controls refer to the Good Signal State, Bad Signal State, both the Value-weighted and Price-weighted indices rising, and both the Value-weighted and price-weighted indices declining.

Table A.6: Baker-Wurgler Index and Components

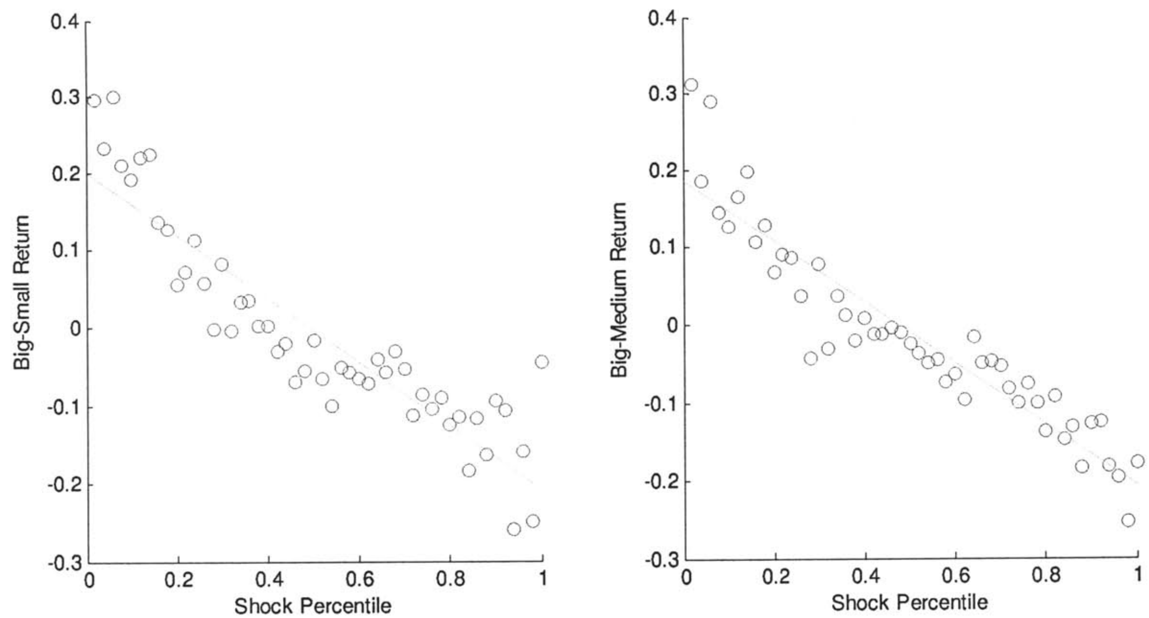
This model estimates the following specification

$$\Delta y_t = \alpha + \beta_1 DJIA_t + \beta_2 VWRet_t + \delta X_t + \epsilon_t$$

Controls		BW-Index	BW-Index$^{\perp}$	Div Prem	IPO Vol	IPO Ret	CEF Disc	SE	Tu 1
Baseline	β_1	0.0133	-0.0006	-0.7968	2.0448	-0.2454	-0.3491	-0.0288***	0.0 7
	F-Stat	0.0896	0.0049	2.6135	1.7722	4.248	1.3009	4.2044	5.0 3
State Controls	β_1	0.0116	-0.004	-0.9095	2.1144	0.1188	-0.3226	-0.0300***	0.0 1
	F-Stat	0.3041	0.26	1.041	1.6716	2.8251	1.4331	2.0637	3.8 9
Flexible Polynomial	β_1	0.0306	0.0333	-2.0158**	4.0686**	1.9506	-0.3868	-0.0212	-0.0 71
	F-Stat	11.2632	19.1952	3.7248	2.2356	9.4715	8.5107	3.4489	18.8 37
All	β_1	0.0334	0.0359	-2.1754**	3.8646*	1.8449	-0.3788	-0.0216	-0.0 75
	F-Stat	7.2505	11.971	2.0965	2.1778	7.2791	7.4628	2.4075	13. 7

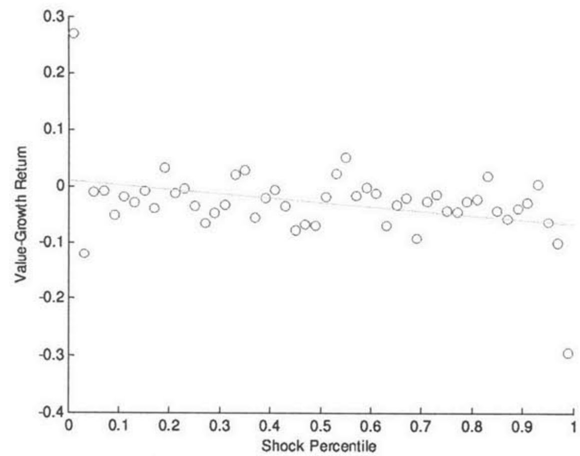
$^{\perp}$Index is orthogonalized to macro factors. State Controls means controlling for the four possible states of the world, DJIA increases and value-weighted index decreases, DJIA decreases and value-weighted index increases, both the DJIA and value-weighted indices decrease, and both the DJIA and value-weighted indices increase. The flexible polynomial is a 4th degree polynomial in Dev_t.

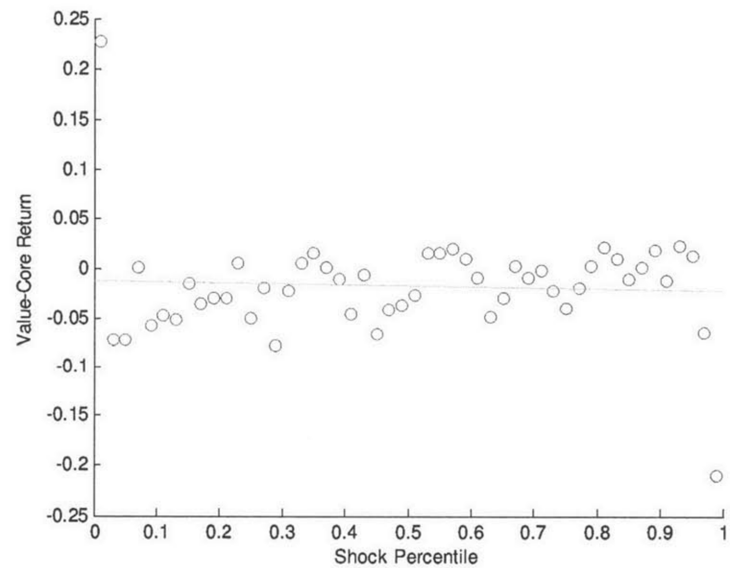
Figure A-3: Daily Returns on Size Sorted by Shock Percentile



This graph shows the Dev_{t-1} graphed against the returns of the Small minus Big portfolio, and the Small minus Medium portfolio in period t. The x-axis is shock percentiles with 0 being the DJIA underperforming the Value-weighted index, and 1 being the DJIA outperforming the value-weighted index. The data is split into 50 bins with the dots representing the average return for that day. The line is the regression line of a simple linear regression of $Ret_t = \alpha + \beta ShockPercentile_{t-1} + \epsilon_t$

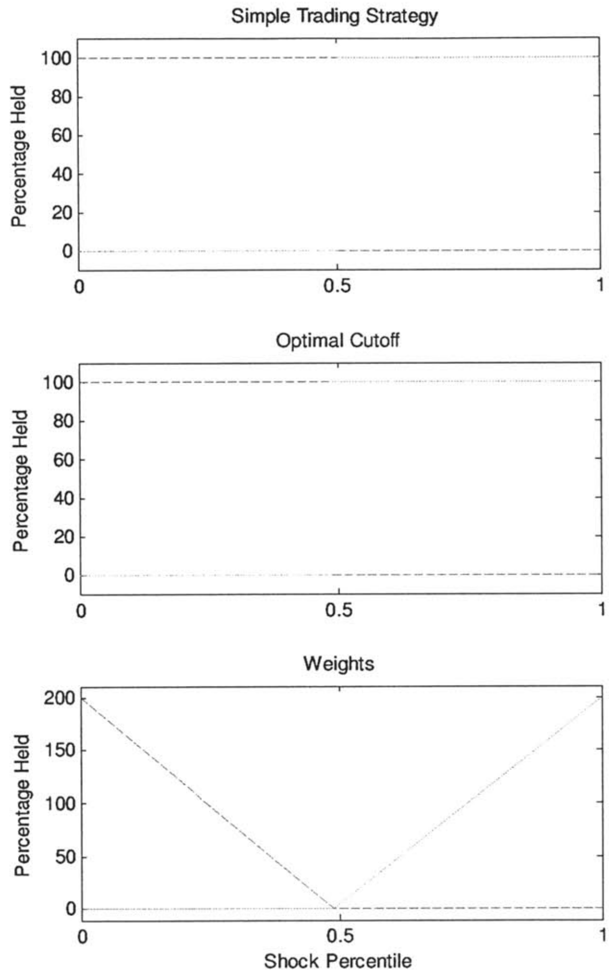
Figure A-4: Daily Returns on $\frac{B}{M}$ sorted on Shock Percentile





These are the same graphs of the previous page but sorting on B/M instead of size.

Figure A-5: Weighting Rules for Trading Strategy



The blue dashed line represents the percentage of the portfolio held in the large stocks as a function of the shock percentile. Likewise the redline dotted represents the percentage of the portfolio held in small stocks. In the case of zero cost portfolios, the blue dashed line represents the amount we hold in the Big - Small Portfolio, while the red dotted line represents the amount we hold in the Small - Big portfolio.

Table A.7: Daily Statistics - Summary of Moments

	α	β	Mean (bps)	Standard Deviation (%)	Skewness	Kurtosis
Market Baseline						
S&P 500	0.00%	1.00	3.08	1.03	-0.63	[illegible]
One-way Strategies						
Simple Long Strategy	4.04%	0.81	6.51	0.97	-0.15	[illegible]
Optimal Cutoff Long Strategy	6.94%	0.82	9.40	0.97	-0.78	[illegible]
Optimal Cutoff Long Strategy (w/weights)	9.34%	0.95	12.20	1.27	-1.88	[illegible]
No Cost Strategies						
Simple Long-Short Strategy	3.74%	0.02	3.72	0.75	1.16	[illegible]
Optimal Cutoff Long-Short	9.54%	0.04	9.49	0.74	0.70	[illegible]
Optimal Cutoff Long-Short (w/weights)	13.43%	0.08	13.47	1.01	2.06	10 6

The simple long strategy involves longing one dollar of large stocks if my measure of sentiment is low the previous day and longing one dollar of small stocks if my measure of sentiment is high. The simple long short strategy involves longing one dollar of the largest stocks and shorting one dollar of the small stocks if sentiment is low, and doing the opposite if sentiment is high. The optimal cutoff is estimated via regression at which point holding small stocks outperforms holding large stocks, at point I reverse the position then, instead of just at the 0 value. Optimal Cutoff with weights is when I put increasing weights on things away from the cutoff, taking bigger bets in more extreme events.

All info is from July 3rd, 1962 - December 31st, 2012.

Table A.8: Daily Statistics- Comparison of Tail Risk

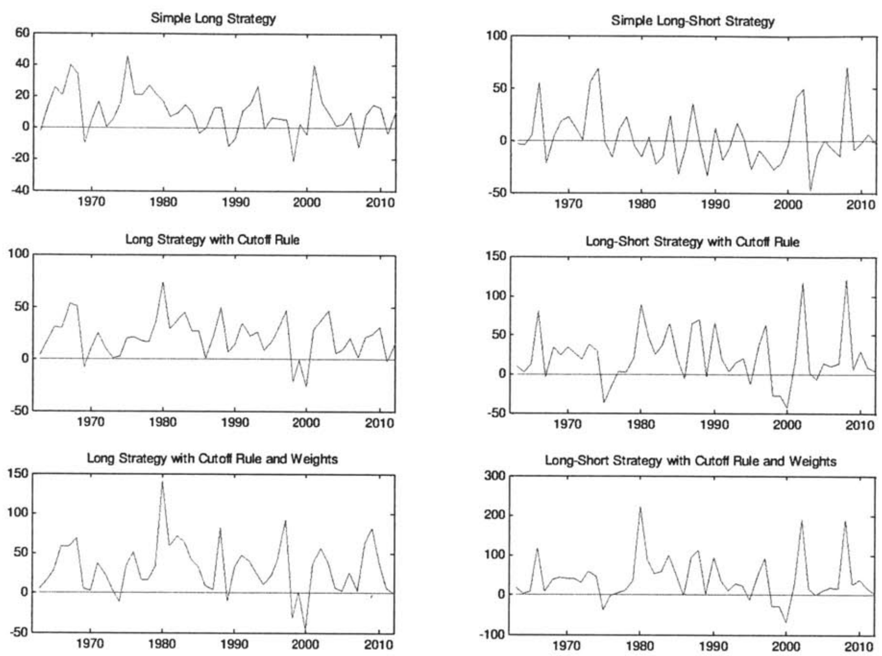
	Min	1%	5%	95%	99%	Max
Market Baseline						
S&P 500	-20.5	-2.70	-1.52	1.54	2.77	11.6
One-way Strategies						
Simple Long Strategy	-10.4	-2.67	-1.41	1.44	2.72	11.5
Optimal Cutoff Long Strategy	-19.7	-2.66	-1.37	1.46	2.66	10.5
Optimal Cutoff Long Strategy (w/weights)	-39.3	-3.44	-1.54	1.8	3.9	15.0
No Cost Strategies						
Simple Long-Short Strategy	-5.18	-1.82	-1.05	1.16	2.03	16.1
Optimal Cutoff Long-Short	-9.25	-1.78	-0.98	1.2	2.04	16.1
Optimal Cutoff Long-Short (w/weights)	-18.5	-2.34	-1.09	1.59	3.09	32.2

Table A.9: Fama-French 3-factor Model

	α	β_{Mkt}	β_{SMB}	β_{GMV}
One-way Strategies				
Simple Long Strategy	4.0995	0.8864	0.5571	0.2161
(Standard Error)	(1.4791)	(0.0783)	(0.0946)	(0.0965)
Optimal Cutoff Long Strategy	12.0287	1.0918	0.5774	0.372
	(2.2851)	(0.121)	(0.1462)	(0.1491)
Optimal Cutoff Long Strategy (w/weights)	19.5952	0.9937	0.7609	0.4955
	(4.4505)	(0.2357)	(0.2847)	(0.2904)
No Cost Strategies				
Simple Long-Short Strategy	7.9291	-0.3849	-0.0217	-0.0119
	(2.5142)	(0.1331)	(0.1609)	(0.1641)
Optimal Cutoff Long-Short	25.4946	-0.0604	-0.113	-0.2282
	(5.2085)	(0.2758)	(0.3332)	(0.3399)
Optimal Cutoff Long-Short (w/weights)	39.1664	-0.3335	-0.1057	0.0569
	(7.4645)	(0.3953)	(0.4776)	(0.4871)

The Fama-French 3 factor model is estimated at an annual frequency using returns and factor data from 1963-2012.

Figure A-6: Excess Returns above S&P 500

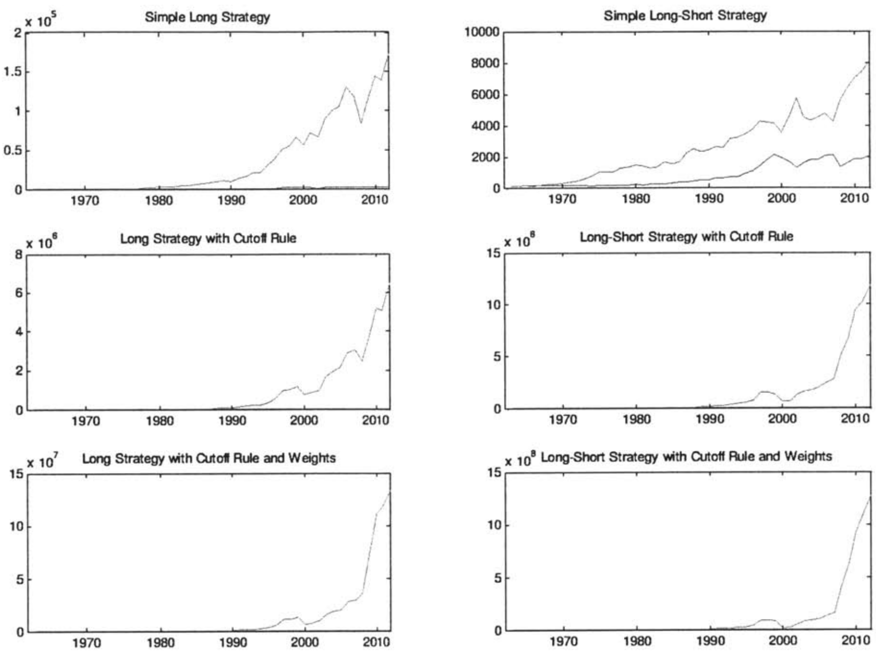


The excess returns displayed are those from following the strategies described in Table A.7 and Figure A-5. The strategies used are looking at the trading in the largest decile and smallest decile. All figures are qualitatively similar if we trade in the largest decile and median decile (and vice versa). Excess returns are defined as those above the S&P 500.

The results on the left hand side are little more difficult to interpret due to the fact that it is a long-short portfolio with a zero net position. On average (and everywhere for the top two panels) the weightings are such we are investing with no leverage.

None of the returns reflect the transaction costs associated with these strategies.

Figure A-7: Cumulative Returns- Strategy vs. S&P 500



The returns displayed are those from following the strategies described in Table A.7 and Figure A-5. The strategies used are looking at the trading in the largest decile and smallest decile. All figures are qualitatively similar if we trade in the largest decile and median decile (and vice versa). The returns are graphed against the returns on the S&P 500, the S&P 500 returns are in shown in blue.

The results on the left hand side are little more difficult to interpret due to the fact that it is a long-short portfolio with a zero net position. On average (and everywhere for the top two panels) the weightings are such we are investing with no leverage.

None of the returns reflect the transaction costs associated with these strategies.

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