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Abstract

This dissertation contains three essays in empirical finance which each use predictive statistics to analyze characteristics of firms, market conditions, or funds to anticipate future events.

In the first, I study the information content of flows of assets into leveraged exchange traded funds. Using daily flow and return data, I find that flows to leveraged ETFs predict subsequent benchmark index returns. These results remain significant to a lesser extent at the weekly level, but disappear for monthly returns. Separating ETFs into commodity, debt, domestic equity, foreign equity, and real estate sectors, I find that out-of-sample predictability is limited to foreign equity and junk bonds. A self funding strategy based on out-of-sample predictability earns over 5% per year, but the majority of this is negated by transaction costs. This suggests that although flows do not predict most market sectors, flows can anticipate movements in markets where there are higher transaction costs or less liquidity.

In the second study, I investigate the dynamics of equity and commodity market correlation. Unlike previous economic downturns where equity returns dropped but commodity futures returns largely stayed positive, following the financial crisis equity and commodity futures returns showed much higher than normal levels of co-movement. Using mean-variance spanning tests, I find that though diversification from a portfolio of solely equities into a portfolio of equities and commodities generally improves an investor's efficient frontier, it did not yield any significant improvement from 2008 to 2010 and little to no improvement in 2007 and 2011. Frontiers post crisis starting in 2012 are again benefited from diversification into commodities. Using quality of predictive power for several factors, I find that the levels of global supply and demand, and to a lesser extent commodity relevant hedge fund assets under management (AUM), and index investment aid in predicting future commodity-equity correlation leading into the financial crisis as well as during the subsequent recovery.

Finally, in the third study I examine the associations of various types of director expertise on a distressed firm's ability to avoid bankruptcy. Since the advent of the Sarbanes Oxley Act of 2002 there have been significant increases in the percentage of board members with accounting, investment banking and legal expertise. In a study of US firms during the period between 1996 and 2011, I find that the percentages of bankers and lawyers on boards are associated with significant changes in the likelihood that a firm will enter bankruptcy in the future. No similar effect is observed for board member accounting expertise. These results support the idea that bankers may aid distressed firms in renegotiating their debt, enabling them to avoid bankruptcy. Conversely, a board with more legal expertise may be instrumental in steering a firm through bankruptcy.

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Chapter 1

Do Fund Flows Anticipate Market Movements? Evidence from Leveraged ETFs

Abstract

Can fund flows be used to predict future market returns? Existing literature using long-horizon returns and flows concludes that they cannot; but using daily data, I find that flows to leveraged ETFs predict subsequent benchmark index returns. These results remain significant to a lesser extent at the weekly level, but disappear for monthly returns. Separating ETFs into commodity, debt, domestic equity, foreign equity, and real estate sectors, I find that out-of-sample predictability is limited to foreign equity and junk bonds. A self funding strategy based on out-of-sample predictability earns over 5% per year, but the majority of this is negated by transaction costs. This suggests that although flows do not predict most market sectors, flows can anticipate movements in markets where there are higher transaction costs or less liquidity.

Keywords: market anticipation, authorized participants, ETFs, fund flows, smart money, leveraged ETFs, inverse ETFs, efficient markets, transaction costs

JEL Classifications: G11, G14, G15, G17, G23

1.1 Introduction

Can investors anticipate market movements and funnel their money into funds that track those markets? Studies by Gruber (1996) and Zheng (1999) found evidence for this in mutual fund flows and termed it “smart money”. Yet subsequent investigations by Sapp and Tiwari (2004) and Frazzini and Lamont (2008) find more convincing evidence against investors’ ability to anticipate market movements. The current general consensus in the smart money mutual fund literature is that investors have no skill and exhibit naïve fund selection methods such as return chasing. These studies all used either monthly or quarterly return and flow data to analyze actively managed US equity mutual funds. In this study, I investigate flows in leveraged and inverse exchange traded funds at daily and weekly time frames and test their ability to predict future benchmark returns.

I use daily returns and flows for this analysis because they are readily available for ETFs. Additionally, it is plausible that a skilled investor may anticipate the movement of a market on a short-term basis. Daily data are better positioned to detect short-run market-timing investment flows than monthly data. A secondary, but nevertheless important reason to use ETFs for this study is that flows to ETFs differ from flows to open-ended mutual funds. ETF flows are arguably better suited for a search of smart money. ETF share prices are kept close to NAV by arbitrages transactions carried out by authorized parties(APs) and ETFs. Each day, ETFs define a redemption basket for which they are willing to exchange a given amount of ETF shares. The basket closely resembles the ETF’s holdings. When APs deliver the basket for ETF shares, there is positive flow to the ETF. On the other hand when APs deliver shares for the redemption basket, there is negative flow to the ETF. The flows to ETFs are more discrete and less noisy than mutual fund flows because the transactions between the ETF and the AP are limited to multiples of the redemption basket, which is typically 50,000 shares or more. In summary, daily ETF flows are better suited to detect market timing investments than monthly mutual fund flows because of their higher frequency and lower noise.

Among exchange traded funds, leveraged and inverse ETFs hold a unique position: they are possibly the least likely ETF candidates for buy-and-hold investments. Cheng and Madhavan (2009) concluded these funds were unsuitable for long-term investors, and in 2009, FINRA and the SEC "formally warned buy-and-hold investors of the extra risks associated with leveraged ETFs over the long term."[1] A search for smart money flows in leveraged ETFs stands a greater chance of avoiding obscurement by uninformed buy-and-hold investment flows, than in typical ETFs.

The term "smart money" is used with varying meaning in academic research. Depending on the source, smart money could be one or more of asset allocation, market timing, stock selection, and fund manager selection. For the purposes of this study, I define smart money as any flow exhibiting market timing skill. Because the majority of past studies in mutual fund smart money analyze investors' ability to select actively managed mutual funds, they are inherently two-layered. The first layer being whether investors can identify skilled fund managers. The second layer being whether those skilled managers subsequently performed well (possibly from a combination of asset allocation, market timing, and stock selection). In contrast, my study focuses on funds exclusively tied to benchmarks. If a smart investor puts money in a fund that follows a benchmark, it is reasonable to assume that the investor anticipates market movement, not fund manager skill. In essence, focusing on benchmarked funds as opposed to actively managed funds simplifies the search for smart money.

Leveraged ETFs are particularly well suited for this investigation for three reasons. First, an ETF's characteristics such as fund size, shares outstanding, price and return are widely available on a daily basis. Second, fund flows for ETFs only occur from action by an authorized participant (which in almost all cases is a very large investor with smart money potential). Lastly, leveraged and inverse ETFs tend to track their benchmarks closely as reported by Elston and Choi (2009) and Lu et al. (2009).

I find via in-sample OLS and GARCH regressions that fund flow as a percentage of

[1] Tang and Xu (2013);FINRA regulatory notices 09-31 of June 2009 and 09-53 of August 2009. Also investor alert jointly issued by the FINRA and SEC in August 2009

ETF size is significantly correlated with next period benchmark returns at daily, weekly, and monthly levels. More importantly, following Welch and Goyal (2008) and Campbell and Thompson (2008), I find that leveraged ETF flows have significant power to predict future benchmark returns. Fund flow predicts benchmark returns better than a wide array of market predictors used by Welch and Goyal to predict future risk premiums. The significantly positive out-of-sample R^2 values are strongest at the daily frequency, significant at a weekly frequency, but not significant or positive when viewed on a monthly basis. Similar to Campbell and Thompson (2008), I find that predictive power increases further with restricted-sign regressions.

Due to the wide variety of ETFs in my sample, I subdivide my the ETFs into five major sectors (commodities, debt, domestic equity, foreign equity, and real estate). I find that my results are driven primarily by the foreign equity sector. In fact, excluding the foreign equity sector, leveraged ETF flows show no significant ability to forecast future benchmark movements. Within the foreign equity sector, fund flows are predictive for both developed and emerging markets. The evidence suggests that these foreign equity smart money flows are possible due to the increased transaction costs for investing in international markets which leads to greater market inefficiency.

This study is novel and expands the existing body of research on smart money fund flows by presenting the first day-to-day analysis of fund flows. To my knowledge, this is the first smart money study done which addresses sectors outside of domestic equity, ETFs, or non-actively managed funds. Furthermore, there are only a handful of studies that focus on inverse and leveraged ETFs. This paper contributes to the growing number of studies in that field, as well as expanding the field beyond domestic equity leveraged ETFs. Lastly, I establish that smart money

The remainder of the paper is as follows: Section 1.2 summarizes pertinent scholarly literature, Section 1.3 outlines my data and empirical methodology, Section 1.4 presents the study's results, and Section 1.5 summarizes and concludes.

1.2 Background & Related Literature

In this section I outline some of the major work related to studies of “smart money” or in other words, investors’ ability to anticipate market movements. I will also address some of the fundamental differences of open-ended mutual funds and exchange traded funds and in particular how those differences come to play in smart money fund flows.

1.2.1 History of Mutual Funds and ETFs

Mutual funds and ETFs are investment vehicles that offer exposure to market segments that would be more costly to directly invest in independently. The first mutual funds in the world originated in the Netherlands in the late 1700s or early 1800s. These closed-end funds gained popularity in Western Europe and eventually came to America in the late 1800s. In the 1920s, the first open-ended mutual funds became available.

Closed-end mutual funds are distinguished by the fact that though their shares are traded on an exchange, there is no active primary market in which shares can be created or redeemed. This leads to situations where the net assets under management of the fund can differ from the market capitalization of its shares. These discounts or premiums are much more common than not because there is no mechanism to drive the two to equality. Suppose a closed-end fund held $100 million in net assets. There is no guarantee that its shares would have a market capitalization of $100 million.

Traditional open-end mutual funds (which greatly outnumber closed-end mutual funds) are not traded on an exchange. Only a primary market exists for these funds, thus investors seeking shares must deal directly with the mutual fund. Open-ended mutual fund transactions occur once per day at closing and the price is the fund’s NAV.

Exchange traded funds share similarities with both open-end and closed-end funds. Like a closed-end fund, the shares are traded in a secondary market (an exchange) freeing the investor from the necessity of dealing directly with the fund. Like open-ended funds, there is an ongoing primary market where shares can be purchased or redeemed. However, with ETFs this market is only available to designated parties called "Authorized Participants"(APs).

> "An authorized participant (AP) is typically a large financial institution that enters into a legal contract with an ETF distributor to create and redeem shares of the fund. In addition, APs are U.S.-registered, self-clearing broker-dealers that can process all required trade submission, clearance, and settlement transactions on their own account, as well as full participating members of the National Securities Clearing Corporation and the Depository Trust Company."[2]

APs keep the market capitalization and the total net assets of ETFs roughly equal by creating or redeeming shares.

1.2.2 Fund Flows

Though at first glance, mutual funds and exchange traded funds share many common traits, the concept of a fund flow is quite different between the two groups. In order for an investor to purchase shares in a mutual fund they conduct a transaction with the fund itself where they give money in return for shares of the fund. Later, when the investor seeks to exit their position, they redeem their shares for money with the mutual fund itself. These transactions typically only occur once a day at the close of trading and are transacted at the closing NAV for the mutual fund. The net transactions between investors and mutual funds can be classified as a primary market: net cash inflows to the mutual fund result in the creation of more fund shares, while outflows result in the redemption of shares for cash as illustrated in Figure **??**. There is no secondary market for mutual fund shares.

Exchange traded funds, on the other hand, are traded on an exchange and therefore can be traded at any time throughout the business day. The transactions occur between market participants holding shares in the fund seeking to sell and buyers seeking to purchase shares

[2] www.ici.org 2016 Fact Book

of the ETF. This is the ETF share secondary market. In this secondary market, identical to corporate equity on a stock exchange, these transactions do not involve the ETF directly. Also similar to corporate equity issuances or repurchases, ETFs also feature a restricted-access primary market where shares can be created or redeemed as illustrated in Figure **??**. Each ETF has designated "Authorized Participants"(APs) who can transact directly with the fund. However, the transactions between APs and ETFs differ from the primary markets for both corporate equity and mutual funds. The assets exchanged in ETF primary market transactions are ETF shares and a designated basket of assets. The key difference is that the transaction between APs and ETFs are in-kind exchanges, meaning shares of the ETF (a financial asset) is exchanged for the redemption basket (a group of assets) often with little or no cash involved. ETF inflows do not force turnover in the ETF holdings. In contrast when mutual funds experience net flows the managers often have to re-balance by either purchasing or selling a portion of their position because these flows are cash and not an in-kind exchange.

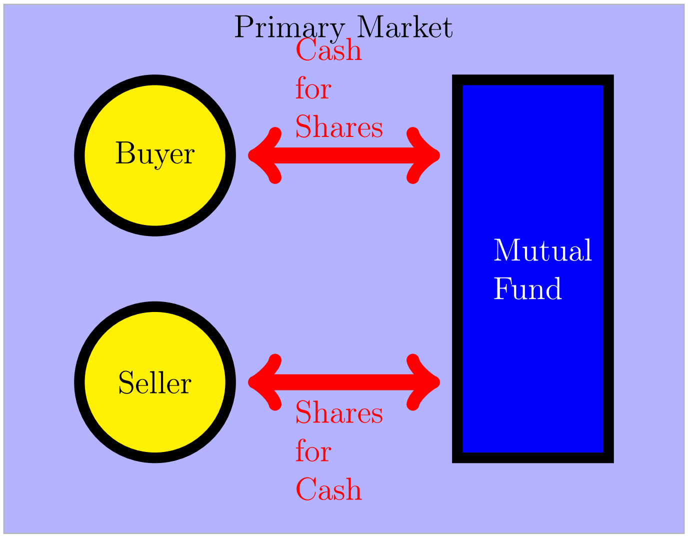

Figure 1.1a: Mutual Fund Primary Market

Due to the existence of a secondary market for ETF shares, flows to and from ETFs do not mechanically represent investor demand. It is a widely held view that APs initiate fund flows with ETFs when there are arbitrage opportunities available (see Ben-David et al. (2012)

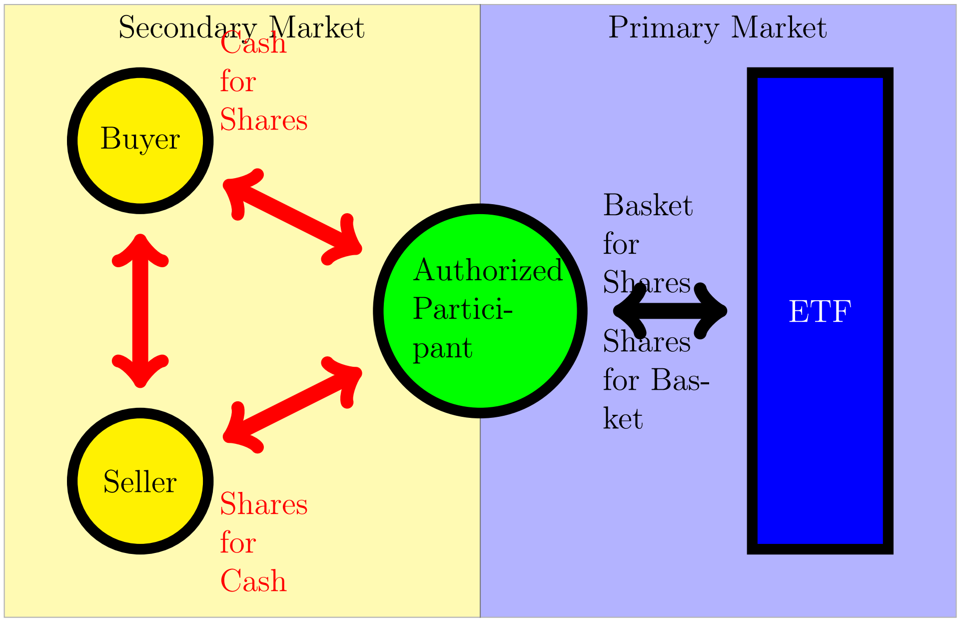

Figure 1.1b: Exchange Traded Fund Primary and Secondary Markets

and Marshall et al. (2013)). If the price of the ETF departs significantly from the value of the basket of assets held by the ETF then the AP can deliver the cheaper asset (either shares or the basket) to the ETF and reap an arbitrage profit. As in other arbitrage situations, these actions serve to drive the basket of goods and the ETF price towards each other, reducing the arbitrage opportunity. This arbitrage is limited to multiples of a "redemption" basket that is traded for a given number of ETF shares (typically 50000 shares).

1.2.3 Inverse and Leveraged Funds

Inverse and leveraged exchange traded funds are a relatively new style of fund introduced in June of 2006. Typically, their prospectus objective is to deliver a given multiple of the daily return of their target benchmark. Leveraged ETF multiples are greater than one while inverse ETF multiples are less than or equal to negative one. There are a few instances of inverse benchmarks, two of which are in my sample. I classify funds that have positive multipliers of inverse benchmarks as inverse funds. There are no ETFs benchmarked to inverse benchmarks with negative multipliers. There are inverse and leveraged funds that represent a wide variety of markets including domestic equity, debt, commodities, international equity, and real estate.

Inverse mutual funds have been available since before 2000. The first inverse ETFs came into being in the summer of 2006 and quickly gained market share. Since the beginning of 2008 inverse ETFs have held more than 90% of the inverse fund market share with aggregate fund size between 100 and 150 billion dollars. These funds are a small fraction of the mutual fund and ETF markets which were estimated to total 16 trillion and 2 trillion dollars respectively at the end of 2014[3]. Though there is a small fraction of the market that is made up of mutual funds, this paper will focus on exchange traded funds since they make up the large majority share of the market.

One might question the need for inverse funds in a market where futures and shorting allow for similar return strategies that avoid manager fees. Several drawbacks to shorting securities are eliminated when investing in an inverse fund. Elston and Choi (2009) list five reasons investors might opt for a bear fund over using futures or shorting. Namely: (1) Limited liability–the maximum loss to the inverse fund investor is 100%, while shorting can entail unlimited liability. (2) No shares need to be found by the broker to short when investing in an inverse fund. (3) Brokers have the right to terminate short positions at any time but not inverse fund positions. (4) Accounting for tax purposes can be more straightforward with inverse funds than shorting. (5) Inverse fund are admissible in retirement funds while short positions are not.

Similar to inverse funds, leveraged fund seek to provide a multiple of a given sector or index return on a daily basis. Common multiples are 2x, 3x, -2x, and -3x. These daily returns are most often achieved by use of equity swaps, derivatives and daily rebalancing. Leveraged funds are vulnerable to volatile markets. The arithmetic effect of an up movement one day followed by a down movement the next mechanically leads to a loss compared to the index for any fund levered greater than 1x.

[3]http://www.icifactbook.org/pdf/2015_factbook_1.pdf
https://www.ici.org/etf_resources/background/faqs_etfs_market

1.2.4 Smart Money

The term "smart money" is used to describe investments made by an investor that has ability to skillfully anticipate the movements of prices or markets. The earliest example of using this phrase in this context seems to come from Campbell and Kyle (1993) where they presented a theoretical framework for price movements in an environment of noise traders and "smart money" traders. Zheng (1999) described the work of Gruber (1996) as the first to study "the ability of investors to select funds" (pg. 902). Gruber concludes that there is rationality to investments in actively managed mutual funds due in part to the phenomenon that flows of money newly invested in the market outperform the stock of money already invested in those same mutual funds.

Zheng (1999) in part agrees with the with Gruber's findings, emphasizing that funds that receive money subsequently outperform those that lose money from investor flows. However, he acknowledges that this may in part be due to momentum, and concludes that there are still ways to choose funds such that positive abnormal returns are achieved.

Sapp and Tiwari (2004) find that the "smart money effect documented by Gruber (1996) and Zheng (1999)...is explained by the stock return momentum phenomenon documented by Jegadeesh and Titman (1993)." Sapp and Tiwari also conclude that "investors do not select funds based on a momentum investing style, but rather simply chase funds that were recent winners." Other later studies such as Frazzini and Lamont (2008) agree with Sapp and Tiwari that there is little to no actual "smart money" flows in mutual funds and that in some cases return chasing is actually wealth reducing in the long run.

The periodicity of each of these studies should be noted. Gruber uses monthly data mutual fund data, while Zheng and Sapp and Tiwari use quarterly data. Their conclusions may indicate that there is little to no smart money investments detectable at the monthly or quarterly timeframe, but they do not rule out its existence at a shorter time frame. In fact, it is not hard to imagine an instance where an large investor may be privy to some (possibly inside) information that will be apparent to the market within the next trading day but is not yet evident. This sort of short-term “smart money” investment would be difficult to identify using exclusively monthly or quarterly observations.

Previous studies did not identify possible smart money investors and then tailor their analyses to detect that type of investor’s behavior. Candidates for smart money investors could be manifold, but skilled retail investors stand little chance of making noticeable impacts at a fund or market level due to the size of their investments. The larger a “smart money” investors’ investment flows, the more easily they could be detected. A large investor such as an investment bank, pension fund, hedge fund, or other institutional investor stand the best chance of having “smart money” flows detected by a statistical analysis. When compared with mutual fund flows, ETF flows have characteristics that better position them to potentially identify and answer smart money questions. Whereas any mutual fund investor can cause flows to or from the mutual fund, only authorized participants (APs) can initiate flows to or from an ETF. APs are the only entities that can participate in the ETF primary market. All other ETF investors seeking to buy or sell ETF shares must go to the exchange, or ETF secondary market. APs are almost exclusively the largest actors in the markets, such as investment banks, hedge funds, pension funds and institutional investors. Authorized participants are some of the biggest market players and may be the best candidates for detectable smart money investors.

Since the goal of an investigation of smart money is to identify an investor’s ability to select funds that will subsequently outperform others, focusing on only actively managed funds addresses only a subset of the smart money question. It can also muddy the waters. For example, a savvy investor might put money in an actively managed fund because they anticipate that the manager is skilled. Yet the actively managed fund only does well if the manager also correctly anticipates market movements. Thus studies that exclusively look for smart money only in actively managed funds add a second layer to the game of anticipating future returns. It is equally likely that skilled investors might identify a sector or index that will do well in the future and opt to invest in an index fund linked to that sector or index. In this case, as long as the index fund tracks its benchmark, the skill is easily assignable to the investor's selection and not confounded with manager skill. Additionally, Warther (1995), Berk and Green (2002),Wermers (2003) and others find that fund flows affect actively managed fund managers' behavior and their subsequent performance; another reason why index tracking funds may be more promising territory in the search for smart money flows. For these reasons, I limit this investigation to passive funds that track a benchmark, eliminating the second layer present in most smart money investigations. Because all of the ETFs in my study track benchmarks, would not anticipate an investor of these ETFs to invest based on the manager's skill. Rather the money flows would be a reflection of the investor's anticipation of that fund's benchmark movements.

Flows of money into mutual funds and exchange traded funds have been found to be correlated with contemporaneous market returns. Gruber (1996) was among the first studies to report this. Many subsequent studies have sought to explain whether this correlation stems from "smart money"–investors anticipating future market movements–or some other phenomenon. Both Zheng (1999) and Sapp and Tiwari (2004) attribute most or all of this correlation to momentum a la Jegadeesh and Titman (1993). Frazzini and Lamont (2008) claim that the net effect of fund flows from return chasing is a reduction in subsequent returns due to the overweighting of sectors with higher than normal sentiment and lower than normal expected returns. Return chasing in ETF fund flows has also been documented by Clifford et al. (2014). Sirri and Tufano (1998) provide evidence that fund flows do not generally stem from "smart money" as much as from return chasing due to the difficulty of searching and finding skilled managers. Another example of flows not representing "smart money" is Cooper et al. (2005) where they find that simply changing a fund's name to a "hot investment style"–without changing its trading behavior–can induce significant flow (+28% abnormal flow) to the name-changed fund.

It is evident that a large portion of flows invested in mutual funds is not "smart money". However, there are still studies that indicate that there are informed investors in the market.

For instance two recent papers (Rapach et al. (2016) and Li and Zhu (2016)) on shorting both submit evidence of "smart money" flows.

Warther (1995), Goetzmann and Massa (1999), as well as Edelen and Warner (2001) find that fund flows and market returns are strongly contemporaneously correlated. More importantly, these flows when viewed on aggregate (ie. net flows into or out of mutual funds or ETFs) still show strong correlation with market movements. This phenomenon goes beyond the possible identification of the good money managers by smart investors because of the aggregate effect of the industry on the market. Goetzmann and Massa (1999) claim that this contemporaneous co-movement is evidence that the market movements are reactions to changes in demand.

1.2.5 Source of Flows

In pursuing this project, I was made aware of several anecdotes from practitioners and regulators where flows to ETFs did not come via the standard method of APs and ETFs exchanging the redemption basket and shares. Two types of deviation from the standard flow were noted; first, transactions where shares and cash (instead of the redemption basket) were exchanged, and second, transactions between the ETF and institutional investors that are not APs.

Table 1.1: Standard and Non-Standard ETF Flows

	Assets Exchanged	
Parties	**Shares and Redemption Basket**	**Shares and Cash**
ETF and AP	ETF and AP exchange shares and basket (standard flow)	ETF and AP exchange shares and cash (non-standard flow)
ETF and non-AP	ETF and non-AP exchange shares and basket (non-standard flow)	ETF and non-AP exchange shares and cash (non-standard flow)

Due to data limitations, there is no way to distinguish between these non-standard flows listed above and standard flows. This section analyzes theoretically each type of flow and then contrasts these flows with the standard situation where APs do exchange shares and the redemption basket with the ETF.

1.2.5.1 ETF and AP Exchange Shares and Cash

If an AP and an ETF exchange shares and cash in lieu of the redemption basket, the resultant flow would resemble the flows of an open-ended mutual fund. Rakowski (2010) and many others[4] address flow risk in mutual funds. Nondiscretionary trading driven by daily fund flows in mutual funds have been associated with reduced risk-adjusted performance. In other words, when a mutual funds has large flows of cash, the mutual fund's performance suffers and the poor performance is tied to the trades carried out in response to the inflows or outflows. This effect is among the reasons ETFs were designed to have flows in kind, which greatly reduce the funds need to trade in response to inflows or outflows. Theoretically an ETF experiencing a large flow of cash may be as susceptible to flow risk as a mutual fund. However, since the ETF is under no contractual obligation to perform this type of transaction, it would be surprising if ETFs carried out non-standard exchanges to their own detriment.

Leveraged and inverse ETFs share characteristics that tend to mitigate the negative effects of large cash flows. The majority of holdings for leveraged and inverse ETFs are in cash and swaps typically entered into with their APs (see Appendix A). Leveraged and inverse ETFs rebalance their holdings daily in order to meet their target levered return. This means that the notional value of the ETF swap positions is adjusted daily in order to achieve the ETF's target leveraged return. If there was a change in the size of the fund due to a cash flow, though it would affect the daily rebalance trade performed by the ETF, the rebalance would have occurred either way. Put another way, a cash flow to a levered ETF does not

[4] Notably Chordia (1996), Edelen (1999), and Dubofsky (2010) among others.

necessitate additional trades by the ETF, instead the cash flow just affects the size of the rebalancing trade that was already going to happen that day.

1.2.5.2 ETF and non-AP Exchange Shares and Redemption Basket

If a non-AP institutional investor seeks to exchange shares and the redemption basket with an ETF, it may be doing so to participate in arbitrage trading similar to an AP, or it may be seeking to minimize the price effects associated with gaining a large exposure to the ETF share price.

When an institutional investor exchanges shares and the redemption basket with an ETF, the exchange might, but won't necessarily mirror the typical exchange between APs and the ETF. Whether the trade mirrors the standard transaction between APs and ETFs depends on if the institutional investor is seeking exposure to the ETF or seeking arbitrage. APs typically have trading desks that monitor the wedge between ETF secondary market prices and the ETF's redemption basket. If the wedge grows beyond a threshold level, the AP trading desk will initiate an arbitrage trade where they lock in an arbitrage profit in the secondary market and unwind the position with an exchange with the ETF. For example if the secondary market share price is high, the desk would short the ETF shares and buy the redemption basket. Then at the close of trading for the day the AP would deliver the redemption basket to the ETF in exchange for ETF shares which they would use to unwind their short position. The AP has no net exposure following the exchange with the ETF. The AP's trades (both the shorting of the ETF shares and the purchasing of the redemption basket) tend to erode the wedge reducing further arbitrage profits.

If a non-AP institutional investor carries out the same transactions listed in the previous paragraph, the market forces would be identical and the non-AP would also gain an arbitrage profit (as long as the ETF agrees to the exchange) with no net position at the end of the day. The only difference between an AP and a non-AP carrying out such a transaction is that the ETF would have the ability to decline such a trade from a non-AP.

In contrast, if an institutional investor is seeking exposure to the ETF share price, the market forces would differ from the arbitrage trade outlined above. When seeking ETF share price exposure the institutional investor buys the redemption basket and exchanges it for ETF shares. In almost all cases the market for the assets in the redemption basket are much larger than the secondary market for ETF shares, thus the institutional investor may benefit by carrying out this exchange because it minimizes the price effects of taking a position in the ETF, since there are no transactions occurring in the ETF secondary market.

To summarize, an institutional investor who is not an AP may seek to exchange the redemption basket for ETF shares or vice versa either to participate in arbitrage trading, or to gain exposure with less price impact on the secondary ETF share price.

1.2.5.3 ETF and non-AP Exchange Shares and Cash

Though ETFs are not contractually required to exchange shares for cash at all, nor are ETFs required to interact with non-APs, it is possible that these exchanges may also take place. If so, the effects of both section 1.2.5.1 and section 1.2.5.2 would apply. Cash in lieu of assets will affect the size of the ETF. This will impact the daily rebalancing that occurs for leveraged ETFs, but it does not for the fund to perform additional non-discretionary trades as it would for a mutual fund. In terms of motivation for a non-AP institutional investor seeking to exchange shares and cash directly with an ETF, it is more likely to be for gaining exposure than for seeking arbitrage. Since a cash price the exchange would have to be negotiated for, it may prove more difficult for a non-AP to find arbitrage profits with an exchange of cash and shares. On the other hand, being able to enter a large position in an ETF without trading in either the ETF secondary market or redemption basket markets would likely be even more attractive to non-AP institutional investors if the opportunity afforded itself. The attraction to the institutional investor in trading in this manner lies in the fact that there would be no market pressure or price effects tipping their hand so to speak until after the transaction is complete.

1.3 Empirical Methodology and Data

1.3.1 Return and Flow Data

I use Morningstar Direct to obtain daily, weekly and monthly ETF size, share price, shares outstanding and returns. I select only inverse and leveraged funds domiciled in the US. The first leveraged and inverse ETFs came into being in June, 2006 which is when my sample starts. Running to June 2016, my data contains 362,204 fund size and daily return observations for 248 inverse or leveraged ETFs.

Using daily fund size and returns I calculate daily flows in dollars and flows as a percentage of fund size following Sirri and Tufano (1998) and many others[5]. In short, the fund flow in dollars is the change in fund size not attributable to fund returns and the percentage fund flow is fund flow in dollars scaled by the previous period's fund size.

$$PFF_{i,t} = \frac{FS_{i,t} - FS_{i,t-1}}{FS_{i,t-1}} - R_{i,t} \tag{1.1}$$

$$FF_{i,t} = PFF_{i,t} \times FS_{t-1} \tag{1.2}$$

where for each fund i on day t, $FS_{i,t}$ is fund size in dollars, $R_{i,t}$ is the daily return for the time period from $t-1$ to t, $FF_{i,t}$ is daily fund flow in dollars, and $PFF_{i,t}$ is the percentage daily fund flow as compared to the previous day's fund size (FS).

Fund flow and percentage fund flow were also measured as functions of each ETF's daily shares outstanding as a robustness check:

$$SF_{i,t} = (SO_{i,t} - SO_{i,t-1}) \times P_{i,t} \tag{1.3}$$

$$PSF_{i,t} = \frac{SF_{i,t}}{FS_{i,t-1}} \tag{1.4}$$

[5]Zheng (1999), Sapp and Tiwari (2004), Frazzini and Lamont (2008) to name three. Also of note, I do not include flows from fund mergers though several other researchers do because no fund mergers occurred within my sample.

again where for each fund i on day t, $SF_{i,t}$ is the flow in dollars in or out of the fund based on the change in shares outstanding and the share price, $SO_{i,t}$ is the number of shares outstanding for ETF i on day t, $P_{i,t}$ is the share price of ETF i at close on day t and $PSF_{i,t}$ is the percentage daily fund flow calculated from changes in shares outstanding (SO) as a percentage of the previous day's fund size (FS).

1.3.2 Benchmark Data

Each leveraged or inverse ETF has a specific benchmark and a leverage multiplier (such as -3x or 2x). Of these funds, 122 are inverse ETFs, while 126 are leveraged with multipliers including -3, -2, -1, 1, 1.25, 2, and 3. Though there is a slightly higher number of leveraged ETFs, inverse ETFs are slightly more represented since 53% of the sample of daily returns and flows is from inverse funds. Three funds in the sample have a positive one multiplier because the benchmark that they follow is itself an inverse benchmark. I classify those three funds as inverse funds.

Morningstar lists each ETF's benchmark. Among the 248 ETFs, there were 114 unique benchmark indexes of which 82 indexes' returns were also available from Morningstar. The remaining 32 benchmark indexes' returns were hand collected from the index websites or from Bloomberg. Each fund is classified into one of five broad categories based on prospectus objective: commodities, debt, domestic equity, foreign equity, or real estate. Domestic equity is the category most represented in the sample with 117 funds comprising 47.2% of the fund-day observations. Real estate is the smallest category with only 10 ETFs and 3.5% of the total observations. The list of benchmarks for each sector are found in Tables 1.2a for non-equity ETFs and in Table 1.2b for equity ETFs.

Table 1.2a: Leveraged ETF Benchmarks for Commodity, Debt, and Real Estate Sectors

Commodity	Debt	Real Estate
Alerian MLP Infrastructure PR	Barclays 10Y US Tr Fu Tar Exp TR	DJ Gbl Ex US Select RESI TR
Alerian MLP Infrastructure TR	Barclays 10Y US Tr Fu Tar Expo TR	DJ US Real Estate TR
Bloomberg Commodity TR	Barclays 2Y US Tr Fu Tar Expo TR	ISE Exclusively Homebuilders TR
Bloomberg Sub Natural Gas TR	Barclays 5Y US Tr Fu Tar Expo TR	MSCI US REIT
Bloomberg Sub WTI Crude Oil TR	Barclays Lo Bd US Tre Fu Tar Expo TR	MSCI US REIT GR
DB Liq Commo-Optimum Yld Agricult TR	Barclays US Agg Bond TR	MVIS Global Mortgage REITs NR
DB Liquid Commodity TR	Barclays US Treasury 20+ Yr TR	MVIS Global Mortgage REITs PR
DB Liquid Commodity-Light Crude TR	Barclays US Treasury 3-7 Yr TR	
DB Liquid Commodity-Optimum Yield TR	Barclays US Treasury 7-10 Yr TR	
DB Liquid Commo-Optimum Yld Gold TR	Barclays US Treasury US TIPS TR	
DBIQ Optimum Yield Indl Metals TR	DB Bund Futures	
DJ US Oil & Gas TR	DB Inverse JGB Futures	
ISE Revere Natural Gas PR	DB JGB Futures	
LBMA Gold Price PM	DB Long US Dollar TR	
LBMA Silver Price	DB Short US Dollar TR	
MVIS Global Junior Gold Miners NR	ICE U.S. Treasury 20+ Year Bond TR	
MVIS Global Junior Gold Miners PR	ICE U.S. Treasury 7-10 Year Bond TR	
NYSE Arca Gold Miners TR	Markit iBoxx Liquid High Yield TR	
S&P Energy Select Sector TR	Markit iBoxx Liquid IG TR	
S&P GSCI Crude Oil TR		
S&P GSCI Gold TR		
S&P GSCI Natural Gas ER		
S&P GSCI Silver ER		
S&P Oil & Gas Explor & Pro Sel Indust TR		
WTI Light Sweet Crude Oil PR		

NR: net return, dividends reinvested **TR:** total return **TR:** total return **GR:** gross return

Table 1.2b: Leveraged ETF Benchmarks for Domestic and Foreign Equity Sectors

Domestic Equity	**Domestic Equity (cont.)**	**Foreign Equity**
Barclays Inverse US Tr Fu Agg TR	Russell 1000 Financial Services TR	CSI 300 NR
DJ Industrial Average TR	Russell 1000 Growth TR	FTSE China 50 NR
DJ US Basic Materials TR	Russell 1000 TR	FTSE China 50 TR
DJ US Consumer Goods TR	Russell 1000/Retail TR	FTSE Developed Europe NR
DJ US Consumer Svcs TR	Russell 2000 TR	FTSE Developed Europe TR
DJ US Financial TR	S&P 500 TR	FTSE Developed ex North America NR
DJ US Health Care TR	S&P Biotechnology Select Industry TR	FTSE Emerging NR
DJ US Industrials TR	S&P Financial Select Sector TR	Indus India TR
DJ US Select Dividend PR	S&P Health Care Select Sector TR	MSCI Brazil 25-50 GR
DJ US Select Home Construction TR	S&P High Yield Dividend Aristcrts PR	MSCI Brazil 25-50 NR
DJ US Semiconductors TR	S&P MidCap 400 TR	MSCI EAFE GR
DJ US Technology TR	S&P MLP PR UBS	MSCI EAFE NR
DJ US Telecom TR	S&P Regional Banks Select Indust TR	MSCI EM GR
DJ US Utilities TR	S&P SmallCap 600 TR	MSCI EM NR
Dynamic Pharmaceutical Intellidex TR	S&P Technology Select Sector TR	MSCI Europe 100% Hdg NR
ISE Cyber Security TR	Solactive Regional Bank TR	MSCI Japan 100% hedged to NR
MSCI US Broad Market GR	Solactive US High Div Low Vol PR	MSCI Japan GR
NASDAQ 100 TR	Solactive US Small Cap High Div PR	MSCI Japan NR
NASDAQ Biotechnology TR	Well Fargo MLP Ex-Energy PR	MSCI Korea 25-50 NR
NYSE Diversified High Income PR	Wells Fargo Business Devlpm Cmpny TR	MSCI Mexico IMI 25-50 GR
PHLX Semiconductor Sector TR		MSCI Mexico IMI 25-50 NR
		MSCI Pacific Ex Japan GR
		MVIS Russia NR
		S&P Latin America 40 TR

NR: net return, dividends reinvested **TR:** total return **TR:** total return **GR:** gross return

One of the key variables I use in this study is multiplied benchmark returns. This is simply the product of fund i's leverage multiplier (m_i) and fund i's benchmark returns (BR_i).

$$mBR_{i,t} = m_i \times BR_{i,t} \tag{1.5}$$

1.3.3 Control Data

Following work by Welch and Goyal (2008) and Campbell and Thompson (2008) I include many controls suggested as good predictors of the equity premium. The majority of these controls I gather from Amit Goyal's website[6]. The data he kindly provided is monthly, so where possible I gathered daily data to supplement when using daily or weekly returns and flows. All variables I was unable to compile at a shorter time frame than monthly will not have viable daily or weekly out-of-sample prediction estimates. I collected S&P 500 Total Return Index SPXT price levels from Bloomberg, Secondary Market Rates for 3-Month Treasury Bills as well as the TED spread from the Federal Reserve Bank of St. Louis (FRED) website[7], consumer price index data for inflation from Bureau of labor and statistics[8] U.S. city average not seasonally adjusted and Daily VIX index data from Chicago Board of Options Exchange (CBOE) website[9].

Variance Risk Premium from Bollerslev et al. (2009) from Zhao Hao's website.[10] This was not available beyond December 31, 2015 and thus any tests I perform with the variance risk premium as a control is limited to observations before 2016. Similarly, the consumption wealth ratio (CAY) from Lettau and Ludvigson (2001) is only provided up until March of 2015, limiting my regressions with CAY as an explanatory variable to prior to the cutoff date. CAY data is available from Lettau's website [11].

[6] http://www.hec.unil.ch/agoyal/
[7] https://fred.stlouisfed.org/series/WTB3MS and https://fred.stlouisfed.org/series/TEDRATE
[8] http://www.bls.gov/cpi/
[9] http://www.cboe.com/micro/vix/historical.aspx
[10] https://sites.google.com/site/haozhouspersonalhomepage/
[11] http://faculty.haas.berkeley.edu/lettau/data/cay_current.txt

Table 1.3: Summary Statistics for Controls

Variable	**Abbreviation**	**Mean**	**Std. Dev.**	**N**
S&P 500 TR Price Level	SPXT	2819	788	358966
S&P 500 Return	SPXR	0.008	0.039	360236
S&P 500 Return ex Dividends	SPXX	0.006	0.039	360236
Stock Variance	SVAR	0.003	0.005	360236
Price-to-Dividend Ratio	SPXDR	32.526	7.35	360236
12-Month Earnings	E12	82.807	21.625	360236
Book to Market	B2M	0.329	0.039	360236
Net Equity Expansion	NTIS	-0.004	0.016	360236
Risk Free Rate	R_f	0	0.001	360236
Inflation	INFL	0.001	0.003	360236
Treasury Bills	T-BL	0.27	0.804	356705
Long Term Gov Bond	LTR	0.005	0.031	360236
Long Term Gov Bond Yield	LTY	0.031	0.008	360236
Long Term Corp Bond Return	CORPR	0.006	0.027	360236
AAA Bond Yield	DAAA	4.325	0.652	356705
BAA Bond Yield	DBAA	5.433	0.845	356705
TED Spread	TED	0.345	0.341	355282
CBOE Volatility Index	VIX	19.218	7.789	358952
Variance Risk Premium	VRP	13.089	20.71	329405

1.3.4 Summary Statistics

Summary statistics for the ETFs and benchmarks in the sample are found in Table 1.5. The average daily return for the benchmarks of the ETFs in my sample is 2.6 basis points. The average daily fund returns for the entire sample is -0.3 basis points. To compare this with the average benchmark return, each fund's benchmark must be multiplied by the funds leverage multiple. The average multiplied benchmark returns (mBR) are 0.1 basis points, thus the difference between the average fund returns and mBR is 0.4 basis points per day. Though there is a difference in sign between the fund returns and mBR, it is insignificant at the daily level. Both have comparable standard deviations and the difference of the average is roughly one thousandth of the sample standard deviation. A wald test for difference of means fails to reject that the means of mBR and ETF daily returns are equal with a p-value of 0.612. Similar tests for the difference in means of weekly and monthly returns yield p-values of 0.047 and 0.002 respectively. The results are marginally significant for weekly returns and significant for monthly returns.

Separating the inverse fund returns which average -6 BP/day from the positively leveraged fund returns that +6.1 BP/day and accounting for the fact that the sample is 53% inverse funds and 47% leveraged funds explains why on average ETF returns are negative. These results are straightforward considering that the mode multiplier for inverse funds is -2 and +2 for leveraged funds. Both averages are a factor of about 2.3 times the benchmark return, which is the average multiplier for leveraged funds.

1.3.5 In-Sample Methodology

I first establish that there is a link between multiplied benchmark returns and both concurrent returns and lagged fund flows using in-sample OLS regressions. I analyze the sample by multiplier and by sector. These regressions are meant to establish that there is a relationship between the variable of interest (benchmark returns) and the explanatory variable (ETF flows). Acknowledging that these are panel data (where autocorrelated errors violate

Table 1.4: Sample Divided by Sector and Leverage Multiplier

Sector	**Funds**	**Observations**	**Percentage**
Commodity	54	75303	20.8%
Debt	33	48347	13.3%
Domestic Equity	117	170975	47.2%
Foreign Equity	34	54817	15.1%
Real Estate	10	12762	3.5%
Total	**248**	**362204**	**100.0%**

Multiplier	**Funds**	**Observations**	**Percentage**
-3	34	45158	12.5%
-2	50	90341	24.9%
-1	35	54850	15.1%
1	3	3171	0.9%
1.25	4	1496	0.4%
2	74	102657	28.3%
3	48	64531	17.8%
Total	**248**	**362204**	**100.0%**

the assumptions of the OLS regression), I also run a panel regression clustering the standard errors on the fund-level.

As a further test of the relationship of multiplied benchmark returns and lagged fund flows, I perform a GARCH regression of lagged percentage fund flow on multiplied benchmark returns in the presence of the controls enumerated in Welch and Goyal (2008). I use a step-back GARCH model where the regression is run with up to five lags to see if these controls can substitute for all or part of the relationship found between lagged flows and benchmark returns. In practice, the most lags necessary was never more than three, and the results are not sensitive to selecting lags above three or to the distribution used in the GARCH regression.

Table 1.5: Summary Statistics for ETFs and Benchmarks

Variable	**Abbreviation**	**Mean**	**Std. Dev.**	**N**
Daily Returns				
Benchmark (%)	BR_D	0.026	1.455	360660
ETF (%)	R_D	-0.003	3.421	360660
Multiplied Benchmark (%)	mBR_D	0.001	3.267	360660
Leveraged ETFs (%)	R_D^{lev}	0.061	3.538	168599
Inverse ETFs (%)	R_D^{inv}	-0.060	3.235	192061
Weekly Returns				
Benchmark (%)	BR_W	0.147	2.966	86394
ETF (%)	R_W	-0.048	6.912	86394
Multiplied Benchmark (%)	mBR_W	0.017	6.7	86394
Leveraged ETFs (%)	R_W^{lev}	0.316	7.283	40220
Inverse ETFs (%)	R_W^{inv}	-0.365	6.556	46174
Monthly Returns				
Benchmark (%)	BR_M	0.504	5.848	17414
ETF (%)	R_M	-0.346	13.335	17414
Multiplied Benchmark (%)	mBR_W	0.062	13.325	17414
Leveraged ETFs (%)	R_M^{lev}	0.993	14.168	8090
Inverse ETFs (%)	R_M^{inv}	-1.507	12.452	9324
Fund Size ($1M)	FS	180.996	449.038	360660
Shares Outstanding (millions)	SO	6.35	24.8	360660
Fund Flow ($1M)	FF	6.92	1820.6	360660
Percentage Fund Flow (%)	PFF	0.007	3.378	360660

1.3.6 Out-Of-Sample Methodology

The key purpose of this study is to identify whether EFT flows are able to predict future benchmark returns. Welch and Goyal (2008) evaluated a wide array of variables "suggested by academic literature to be good predictors of the equity premium." They examine the in-sample and out-of-sample prediction performance of these variables and determine that the predictions are largely "unstable" (meaning the in-sample predictions worked to an extent, but out-of-sample predictions did not) and thus "would not have helped an investor... to profitably time the market." (pg. 1455) Errors for each prediction are used to calculate the adjusted R^2. A positive and significant adjusted R^2 indicates that the out-of-sample predictions are superior to a historical mean prediction strategy.

I follow Welch and Goyal (2008) and Campbell and Thompson (2008) to test whether ETF flows can predict future benchmark returns by performing forward-looking regressions and using the predictions from those regressions to calculate out-of-sample R^2 statistics.

The first step of this method is to regress a given lagged independent variable on multiplied benchmark returns for the prediction window. I use OLS regressions and only use data available at or before time t. Though in Equation 1.6 I use lagged percentage fund flows, realize that PFF is only one of the independent variables I tested for predictive power. An example of the prediction regression using PFF is:

$$mBR_{i,t} = \beta_{0,i,t} + \beta_{1,i,t} PFF_{i,t-1} + \varepsilon_{i,t} \tag{1.6}$$

where $mBR_{i,t}$ is the multiplied benchmark return for fund i at time t, $PFF_{i,t-1}$ is the lagged percentage fund flow, β_0 is the intercept coefficient and β_1 is the estimated PFF_{t-1} coefficient. The β coefficients are used in combination with time t percentage funds flows to predict time $t+1$ multiplied benchmark returns. The prediction residuals, or the errors between the predicted value and the observed mBR are used to calculate the out-of-sample R^2.

For daily returns I use a prediction window of 252 trading days (approximately one calendar year); but as a simple example, suppose today was Thursday immediately after the close of trading. Further suppose that the prediction window was three days. I would regress Monday through Wednesday's fund flows on Tuesday through Thursdays benchmark returns and get coefficient estimates. I would then use today's fund flows to predict tomorrow's benchmark returns. If on average those predictions were better than a prediction using the weekly mean benchmark return prior to Friday, the out-of-sample R^2 would be positive.

Campbell and Thompson (2008) addressed Welch and Goyal's study and proposed several ways to improve the out-of-sample predictions. Though most are not relevant to this study, I do implement one method: sign restrictions. Prior to performing predictive regressions, a training sample is used to determine the "proper" sign of the each coefficient. The training regression for PFF is:

$$mBR_{i,t+1} = \gamma_{0,i} + \gamma_{1,i} PFF_{i,t} + \varepsilon_{i,t} \qquad \text{for } t = 1...tw$$

where $\gamma_{0,i}$ and $\gamma_{1,i}$ are the training coefficients and tw is the training window size.

The training sample is not used subsequently. However, after each predictive regression is run the β coefficient(s) (in Equation 1.6) are set to zero if the signs of γ and β do not agree. I use a training window size of two years for my restricted sign method.

I calculate these out-of-sample R^2 values for each independent variable at each return periodicity and subsequently break the results down into sectors and individual funds.

1.4 Results

I first establish that there is a close relationship between concurrent ETF returns and benchmark returns. If a leveraged ETF perfectly tracked its benchmark by the its leverage multiplier, then the regression coefficient (β_i) for the following model would be one.

$$m_i \times BR_{i,t} = \alpha + \beta_i r_{i,t} + \varepsilon_{i,t} \tag{1.7}$$

OLS regressions using the model from Equation 1.7 of concurrent ETF return on multiplied benchmark return are reported in Tables **??** and **??**. These regressions provide evidence that leveraged and inverse funds track their benchmarks in large part but not perfectly. For each multiplier, in each sector, and at all return periodicities, the β coefficient is positive but less than one. Though many coefficients are significantly less than one, the mean daily coefficient is close to one. Possible explanations for these coefficients not equaling one could be management fees, tracking error, lack of liquidity or willing counter-parties during market downturns; see Elston and Choi (2009). These results agree with other studies on leveraged funds and are not the primary focus of this paper.

The final in-sample regressions I perform include the controls used in Welch and Goyal (2008). I perform the regressions on the fund-level using a GARCH five lag step-back method. The step back method uses a recursive algorithm to determine the number of lags to use in the GARCH regression. I selected five lags as a conservative starting point based on because results from Durbin-Watson tests of the OLS regression errors indicated zero, first, or second order autocorrelation. The reasoning behind performing fund-level regressions over a panel regression is that there is no need to estimate a single coefficient for the overall relationship of all funds flows and their benchmarks. It is more important to determine whether there are funds that have significant relationships and to determine the distribution of the coefficients for all the funds. Table 8 as well as Figures 2 and 3 present the results of these regressions. Nearly half of all funds have a significant coefficient for lagged percentage fund flow. The domestic equity sector is the only sector equally balanced around zero. Foreign equity has exclusively negative and significant beta coefficients, and the remaining 3 sectors have predominantly positive and significant betas.

Table 1.6: Panel Regression of mBR_t on PFF_{t-1} with Sector Indicator Variables and Interactions

	Daily Returns	**Weekly Returns**	**Monthly Returns**
Intercept	0.007	0.036	0.130
	(0.014)	(0.060)	(0.241)
PFF_{t-1}	0.053***	-0.069***	-0.059***
	(0.008)	(0.008)	(0.012)
Commodity	-0.010	-0.031	-0.218
	(0.019)	(0.089)	(0.334)
Debt	-0.012	-0.055	-0.219
	(0.017)	(0.067)	(0.339)
Foreign Equity	-0.006	-0.016	-0.190
	(0.015)	(0.091)	(0.313)
Real Estate	-0.004	0.016	-0.072
	(0.062)	(0.205)	(1.014)
PFF_{t-1}×Commodity	-0.014	-0.100***	0.041*
	(0.012)	(0.013)	(0.022)
PFF_{t-1}×Debt	-0.048***	0.056***	0.044***
	(0.009)	(0.012)	(0.013)
PFF_{t-1}×ForeignEquity	-0.295***	-0.059***	0.091***
	(0.015)	(0.016)	(0.020)
PFF_{t-1}×RealEstate	0.090***	0.025	0.070
	(0.032)	(0.017)	(0.060)

Panel regression of multiplied benchmark returns (mBR) on lagged percentage fund flow ($PFF_{i,t-1}$) and sector indicator variables ($sector_j$) and interactions. Errors are clustered by fund and the regressions are performed for daily, weekly and monthly returns. The intercept and PFF_{t-1} coefficients represent the domestic equity sector and the sector and interaction coefficients are the difference between the respective sector and domestic equity. The regression model is:

$$mBR_{i,t} = \beta_0 + \beta_1 PFF_{i,t-1} + \beta_{2,i} sector_i + \beta_{3,i} PFF_{i,t-1} \times sector_i + \varepsilon_{i,t}$$

where $mBR_{i,t}$ is fund i's time t multiplied benchmark return, $PFF_{i,t-1}$ is fund i's lagged percentage fund flow, and $sector_i$ is the sector indicator variable for fund i. Robust standard errors are reported in parentheses. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

Table 1.7: Panel Regressions of mBR_t on PFF_{t-1} by Sector

Sector	**Variable**	**Daily Returns**	**Weekly Returns**	**Monthly Returns**
Commodity	Intercept	-0.0021	0.0072	-0.0854
		(0.0156)	(0.0636)	(0.3056)
	PFF_{t-1}	0.0393***	-0.1699***	-0.0185
		(0.0072)	(0.0140)	(0.0172)
Debt	Intercept	-0.0049	-0.0198	-0.0895
		(0.0060)	(0.0250)	(0.1163)
	PFF_{t-1}	0.0050	-0.0137	-0.0147
		(0.0065)	(0.0093)	(0.0141)
Domestic Equity	Intercept	0.0061	0.0342	0.1283
		(0.0076)	(0.0323)	(0.1306)
	PFF_{t-1}	0.0529***	-0.0695***	-0.0591***
		(0.0052)	(0.0107)	(0.0116)
Foreign Equity	Intercept	0.0007	0.0195	-0.0599
		(0.0129)	(0.0598)	(0.2796)
	PFF_{t-1}	-0.2417***	-0.1287***	0.0318
		(0.0059)	(0.0146)	(0.0192)
Real Estate	Intercept	0.0023	0.0521	0.0576
		(0.0330)	(0.1297)	(0.5376)
	PFF_{t-1}	0.1433***	-0.0445	0.0112
		(0.0213)	(0.0399)	(0.0430)

Panel regression of multiplied benchmark returns (mBR) on lagged percentage fund flow ($PFF_{i,t-1}$) by sector. Errors are clustered by fund and the regressions are performed for daily, weekly and monthly returns. The regression model is:

$$mBR_{i,t} = \beta_0 + \beta_1 PFF_{i,t-1} + \varepsilon_{i,t}$$

where $mBR_{i,t}$ is fund i's time t multiplied benchmark return and $PFF_{i,t-1}$ is fund i's lagged percentage fund flow. Robust standard errors are reported in parentheses. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

Table 1.8: Fund-Level GARCH Regression β Coefficients for PFF_{t-1}

	Commodity	Debt	Domestic Equity	Foreign Equity	Real Estate
Positive, Significant	17	21	23	0	5
Not Significant	32	9	55	0	4
Negative, Significant	4	3	31	38	1

This table presents the distribution of GARCH regression of mBR on PFF_{t-1} coefficients broken down by sign and significance. There are significant β coefficients for both signs for all sectors except foreign equity. Also note that it is common for there to be a significant relationship between benchmark returns and lagged fund flows in all sectors. Figures 2 and 3 illustrate the distributions of the regression coefficients graphically.

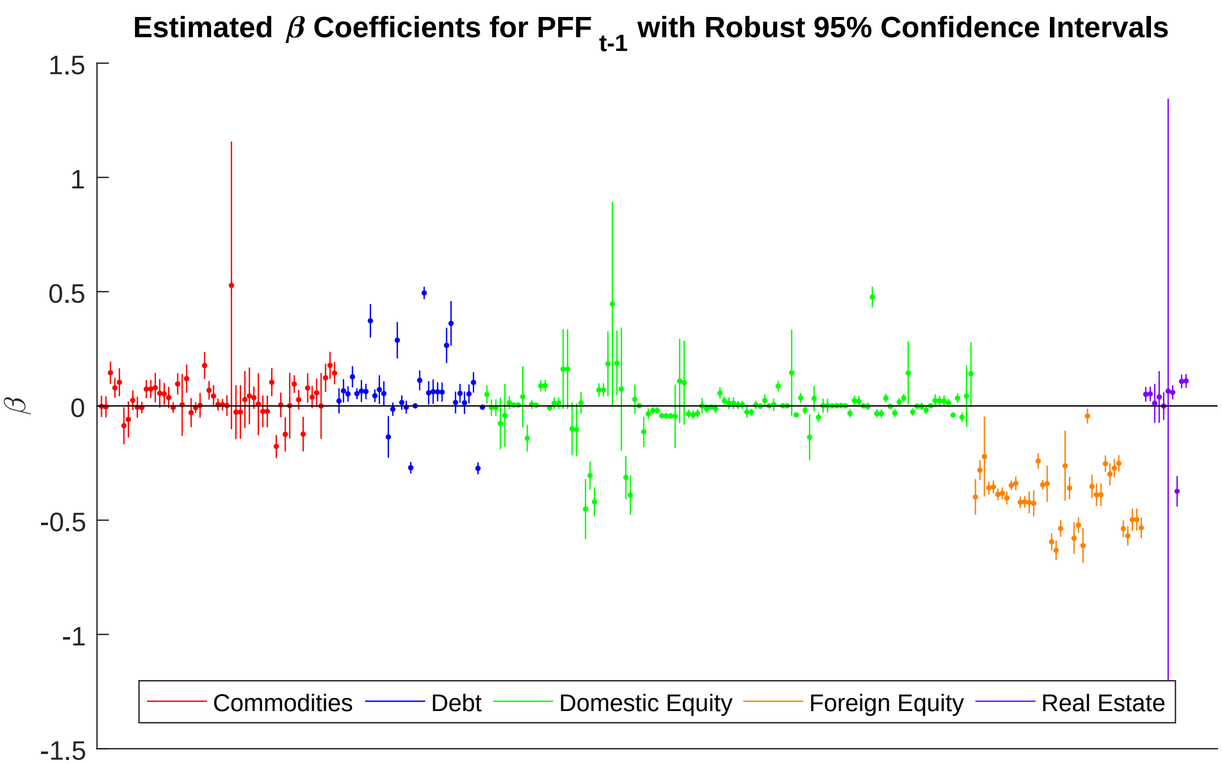

Figure 1.2: Estimated Coefficients for Fund-level GARCH Regressions of mBR on PFF_{t-1} with Controls

This shows the robust 95% confidence intervals for the lagged percentage fund flow coefficients for each fund. Table 1.8 tabulates this distribution.

All of the regressions presented in this paper to this point are in-sample regressions. Table 1.9 presents the results of predictive regressions and their out-of-sample R^2 statistics. Notably, no independent variable displays any predictive ability at the monthly return frequency. This agrees with the existing body of research on smart money. Yet percentage fund flow R^2 statistics are positive and significant for both daily and weekly frequencies. As noted by Campbell and Thompson (2008) the restricted sign method yields overall better predictions or higher R^2 values. I tested significance of these R^2 values using McCracken''s out-of-sample F-test (which was used by Welch and Goyal) as well as Diebold-Mariano tests using Newey-West standard errors. The results from either test yield the same results. Only lagged percentage fund flow (PFF_{t-1}), lagged S&P500 total returns ($SPXR_{t-1}$) and lagged S&P500 total returns ex-dividends ($SPXX_{t-1}$) showed significant predictive power. Table 1.9 presents the aggregate out-of-sample R^2 values for all leveraged and inverse ETFs. Weekly data shows no predictability in any of the variables with the exception of marginal significance for percentage fund flow using Campbell and Thompson's restricted sign method.

Separating these results into sectors, it is evident from Figure 1.4 that fund flows are not uniformly predictive of benchmark returns. The foreign equity ETFs are the sector that has the highest average R^2 by far. Though there are multiple outliers, all other sectors' interquartile ranges include zero. Yet every single foreign equity ETF has a positive out-of-sample R^2. Table 1.10 presents the sector out-of-sample R^2 statistics by sector. There is no significant predictive power on a sector level outside of foreign equity. Figure 1.5 presents the fund-level out-of-sample R^2 values and their significance. Two high yield bond funds show significant ability to predict their benchmark returns, as well as a majority of the foreign equity funds in my sample.

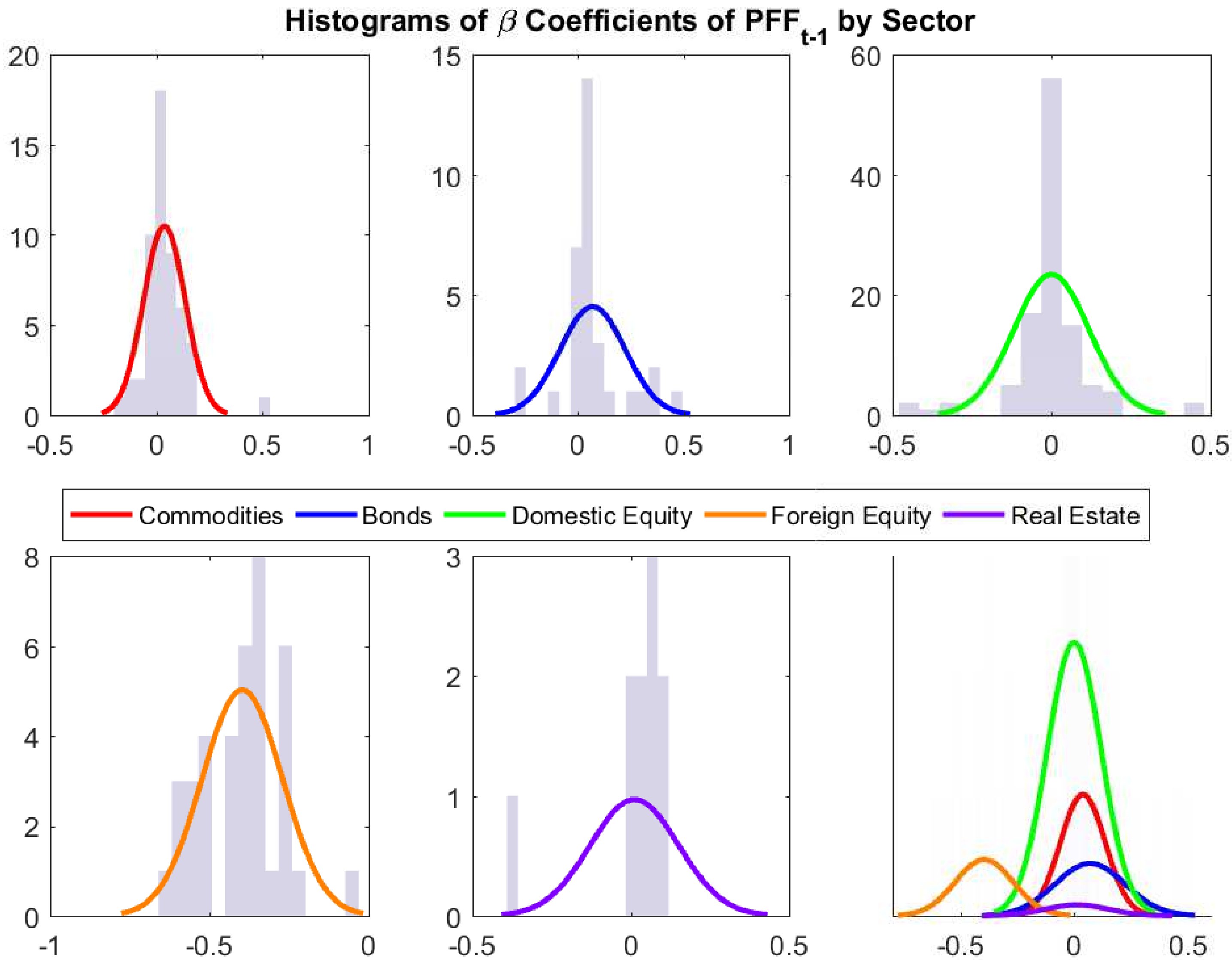

Figure 1.3: Histograms of Estimated Coefficients for Fund-level Regressions of mBR on PFF_{t-1} with Controls

Histograms illustrating the distribution of lagged percentage fund flow betas from a GARCH regression of multiplied benchmark returns on lagged percentage fund flows by sector. The bottom right figure is all five sectors combined. Table 1.8 tabulates this distribution.

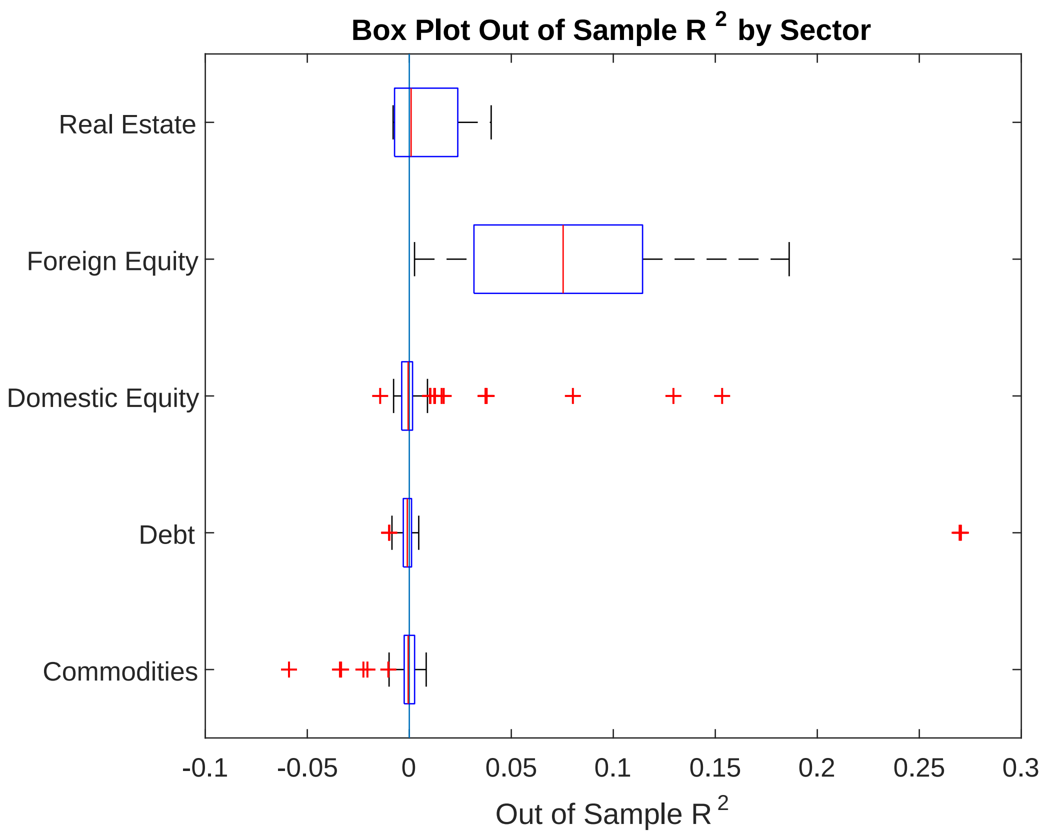

Figure 1.4: Box plots of the out-of-sample R^2 distributions by sector.

Table 1.9: Out of Sample R^2 for Predictions of mBR

	Daily		Weekly		Monthly	
	R^2	R^2_{rs}	R^2	R^2_{rs}	R^2	R^2_{rs}
PFF	**0.84*** **	**1.20*** **	-1.68	**0.31***	-15.19	-7.62
SPXT	-0.79	-25.56	-19.21	-50.58	-16.45	-1.40E+03
SPXR	**0.60*** **	**0.83*** **	-1.99	-0.03	-8.98	-3.45
SPXX	**0.60*** **	**0.82*** **	-1.99	-0.04	-9.13	-3.45
SVAR	-0.91	-0.86	-5	-20.25	-76.41	-44.4
SPXDR	-1.17	-2.12	-93.18	-241.09	-28.88	-343.27
E12					-32.75	-2.70E+03
B2M					-15.39	-929.73
NTIS					-29.77	-29.43
R_f					-52.57	-36.56
INFL					-20.35	-9.28
T-BL	-1.06	-0.55	-4.49	-3.08	-29.61	-17.16
LTY					-27.61	-169.43
LTR					-8.55	-1.46
CORPR					-8.8	-0.85
DAAA	-0.53	-3.88	-13.23	-52.54	-29.34	-368.31
DBAA	-0.53	-2.85	-9.55	-96.29	-33.62	-252
TED	-0.86	-4.6	-7.2	-22.69	-26.07	-76.66
VIX	-0.81	-3.01	-3.97	-16.04	-21.68	-40.08
VRP	-0.73	-0.43	-3.48	-0.69	-4.36	-2.08
Window	252	252	52	52	12	12
Training	504	504	104	104	24	24
Forecasts	197406	197406	51667	51667	9412	9412

Out of Sample Adjusted R^2 and Adjusted R^2_{rs} (restricted sign) for predictions of multiplied benchmark returns from lagged independent variables. The prediction regression equation is

$$mBR_{i,t+1} = \beta_{0,i} + \beta_{1,i}\text{variable}_{i,t} + \varepsilon_{i,t} \qquad \text{for } t = tw+1...tw+w$$

A predictive regression is run using observations from time $tw+1$ to $tw+w$ where w is the window size in order to estimate the coefficients used with the time $tw+w+1$ variable to estimate $mBR_{i,tw+w+2}$.
Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively based on bootstrap sampling distribution.

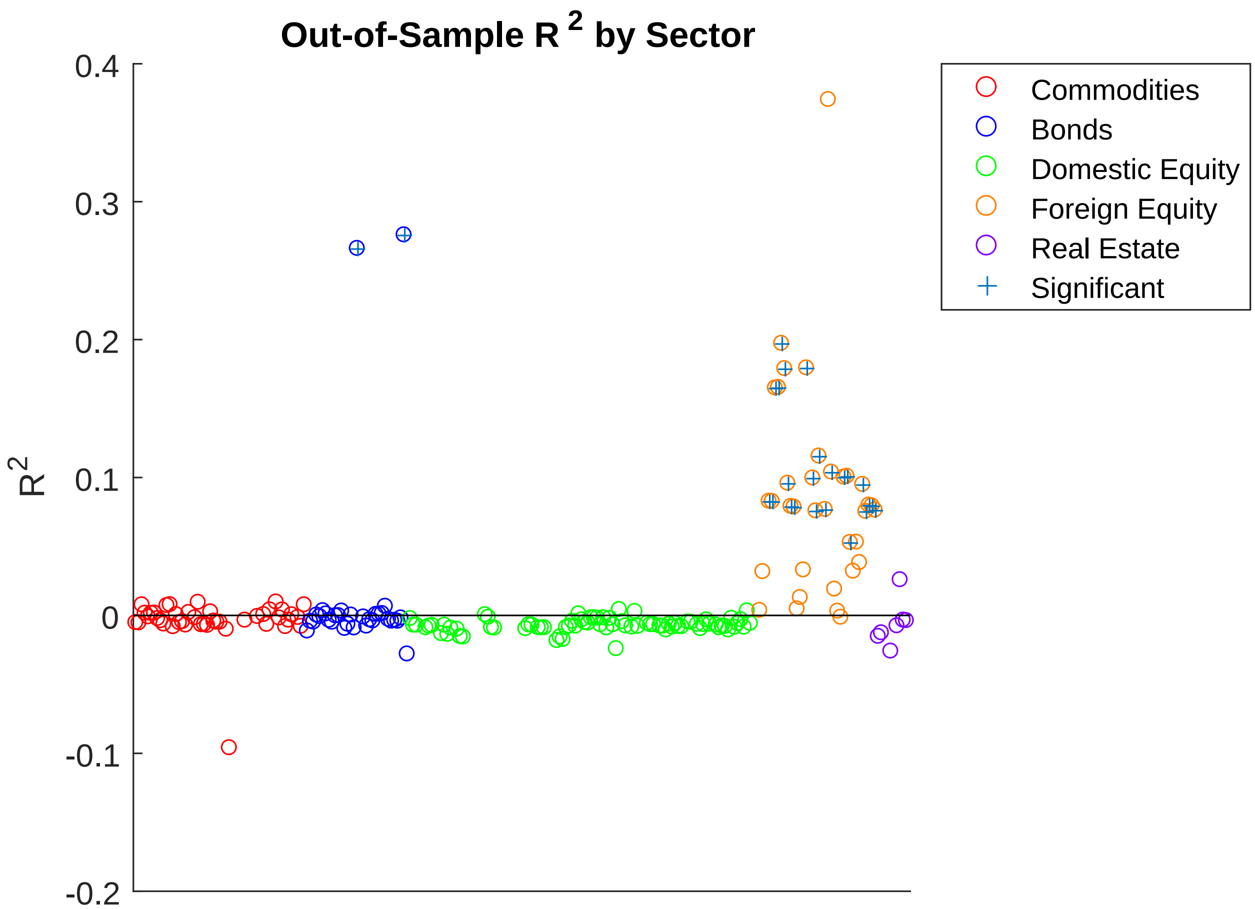

Figure 1.5: Out-of-Sample R^2 for All Leveraged Funds

Significant out-of-sample R^2 values at the 0.01 level are denoted by a + sign. All funds with significant predictive power are in the foreign equity sector except for two 'junk' bond levered ETFs.

Table 1.10a: Out-of-Sample R^2 by Sector

	Commodity	Debt	Domestic Equity	Foreign Equity	Real Estate
PFF	-0.90	-0.03	-0.72	**7.90*** **	-0.80
SPXT	-0.93	-1.01	-0.63	-0.87	-0.57
SPXR	-0.40	-0.29	-0.59	**6.67*** **	-0.61
SPXX	-0.39	-0.29	-0.59	**6.69*** **	-0.61
SVAR	-1.25	-0.85	-1.15	-1.29	-1.27
SPXDR	-1.11	-1.25	-1.21	-1.18	-1.33
T-BL	-1.25	-1.07	-1.01	-0.80	-1.01
DAAA	-0.40	-0.60	-0.59	-0.58	-1.00
DBAA	-0.30	-0.62	-0.69	-0.57	-1.04
TED	-0.46	-1.19	-1.33	-0.59	-1.35
VIX	-0.61	-0.83	-0.97	-0.78	-1.34
VRP	-0.33	-0.69	-1.11	-0.67	-1.06
Select	-2.51	0.43	-2.69	**7.52*** **	-2.39
Kitchen Sink	-30.63	-39.18	-23.67	-7.56	-28.32

The holding period for investors in leveraged ETFs is not necessarily one day. Though I test the ability of daily, weekly, and monthly flows on daily, weekly and monthly benchmark returns, in unreported results available upon request, I find that the predictability of subsequent market returns based on daily flows decreases monotonically as the holding period goes up from one day and is no longer significant by the four day holding period.

Possible explanations for foreign equity market predictability are market inefficiency or the time differences involved in foreign equity markets. The time difference argument cannot fully explain this phenomenon due to the fact that weekly lagged fund flows also demonstrate significant predictive power. Additionally, no time difference exists for the high yield bond funds. There is no stark difference between the predictability of developed versus emerging foreign markets as shown in Figure 1.6. The evidence from the high yield bond and foreign equity funds more strongly supports an argument that predictability is more easily achieved in less efficient markets, where there may be higher transaction costs, and less liquidity.

Table 1.10b: Out-of-Sample Restricted Sign R^2 by Sector

	Commodity	Debt	Domestic Equity	Foreign Equity	Real Estate
PFF	-0.60	0.32*	-0.24	**8.14*****	-0.40
SPXT	-4.41	-0.62	-17.80	-90.81	-0.56
SPXR	0.01	0.11	-0.26	**6.88*****	-0.51
SPXX	0.01	0.11	-0.26	**6.90*****	-0.50
SVAR	-2.97	-1.21	-2.20	-2.87	-1.32
SPXDR	-2.44	-0.79	-0.63	-4.85	-1.09
T-BL	-0.51	-0.76	-0.62	-0.20	-2.23
DAAA	-3.81	-0.07	-2.83	-0.23	-48.12
DBAA	-0.05	-8.07	-6.76	-0.09	-0.33
TED	-2.08	-2.06	-8.89	-1.71	-0.55
VIX	-3.50	-0.69	-2.99	-2.74	-0.42
VRP	-0.03	-0.35	-0.74	-0.52	-0.81
Select	-2.90	-46.35	-37.15	**6.08*****	-1.97
Kitchen Sink	-2.6E+4	-9.3E+4	-7.4E+4	-4.0E+4	-5.4E+4

The "Select" regression out-of-sample R^2 and R^2_{rs} values are for a prediction regression that uses lagged PFF, SPXT, and SPXX as the independent variables. The "Kitchen Sink"regression out-of-sample R^2_{rs} values are for a prediction regression that uses all the above listed independent variables. Notably, over-fitting is extreme in the Kitchen Sink regression. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively based on Diebold-Mariano tests using Newey-West standard errors.

Table 1.11: Diebold-Mariano Test of Lagged PFF versus Lagged S$P500 Returns

	MSE	**Diebold-Mariano Test**		
PFF	7.3994		DM	p-value
SPXR	7.5004	SPXR vs. PFF	2.401	0.0082
SPXX	7.4991	SPXX vs. PFF	2.371	0.0089

This table presents the mean squared prediction errors for lagged percentage fund flow (PFF_{t-1}), lagged S&P500 total returns ($SPXR_{t-1}$) and lagged S&P500 total returns ex dividends ($SPXX_{t-1}$). The Diebold-Mariano tests provide evidence that lagged fund flows are better predictors of future benchmark returns than either S&P500 total returns with or without dividends.

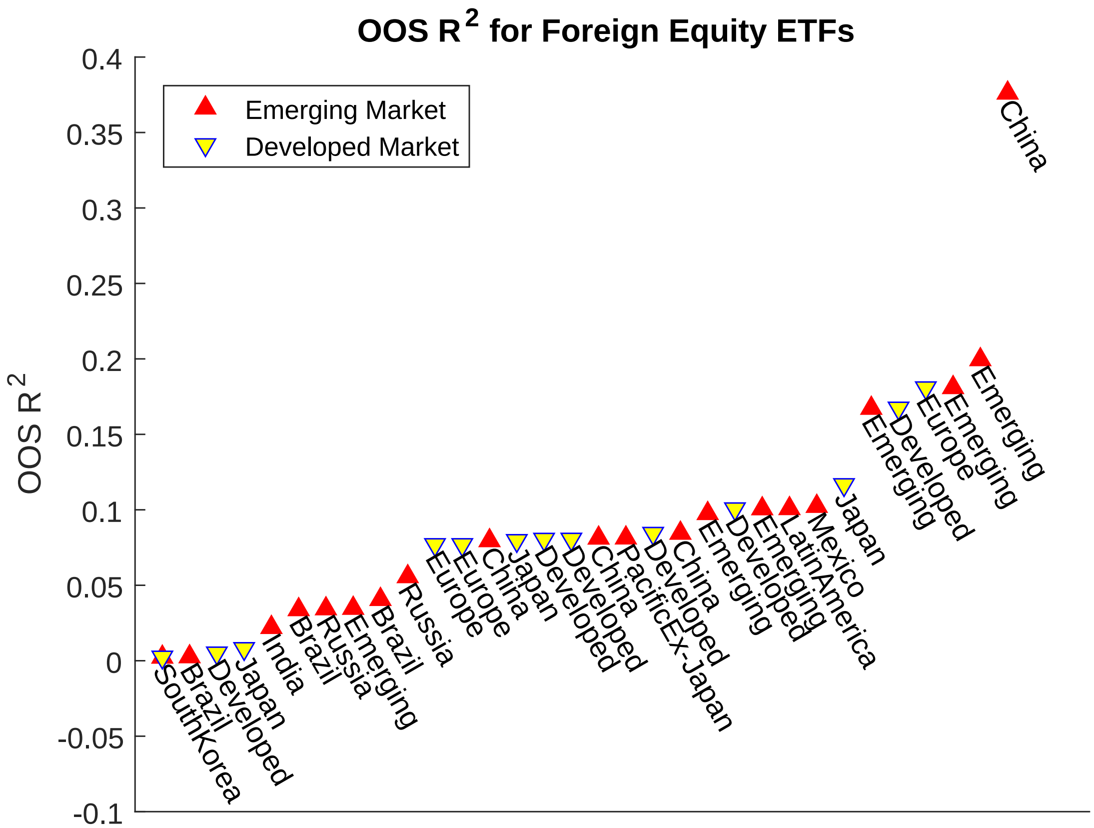

Figure 1.6: Sorted Fund Out-of-Sample R^2 for ETFs in the Foreign Equity Sector with Country or Region Labels

Emerging market countries and regions are identified by triangles pointing up, while developed countries are identified by triangles pointing down. South Korea is considered an emerging market by MSCI but a developed market by FTSE.

1.4.1 Self-Funding Portfolio

Using the predictions from the out-of-sample tests, I construct a self-funding portfolio of ETFs. I begin the strategy when there are more than five ETFs with statistically significant historical out-of-sample r-squared values at a 1% significance level. In other words, I start at the beginning of the data and analyze each fund using the predictions in the past to see if and when their prediction errors have predictive power. Once they are significant[12] they are added to the list of eligible funds. Once the list has at least five funds, I perform the following strategy on a daily basis: of the eligible funds, I select the top and bottom predicted benchmark return. I then select an unlevered ETF that is based on those two benchmarks and go long the fund that has the highest predicted return and short the ETF with the lowest predicted benchmark return. The position is entered into each day at the opening of trading and is liquidated the following open.

I chose to select unlevered ETFs to perform this strategy as a way of being more conservative. This way, the results are focused on the benchmark index movement instead of the level of leverage selected. Additionally, there are many ETFs available that can be traded commission-free, yet in my search I found none that were leveraged or inverse. Trading costs can easily eclipse gains from a trading strategy when done on a daily basis. Without taking into account trading costs, my strategy yields 1.98 basis points per day, but costs can easily be larger than this especially for a retail investor.

1.5 Conclusions

My study provides evidence that there is predictive power in shorter term exchange traded fund flows. Specifically, I find both contemporaneous and lagged relationships between ETF flows and the associated benchmark returns. More importantly, I find that lagged percentage fund flows can help predict future benchmark returns at a daily and weekly

[12] All funds that had statistically significant out of sample r-squared demonstrated this near the beginning of their time series. No fund that was significant at the 1% level ever dropped back into insignificance.

level. In agreement with existing literature, I find no such ability at the monthly level. The predictive power of these flows is concentrated in the foreign equity ETF sector, but is also present in some high-yield bond funds. The evidence supports market inefficiencies and not global timing effects as leading to predictive power in these funds. Those seeking leading indicators of market movements will not find them in domestic equity, commodity, or real estate ETF flows. Yet there is potential with foreign equity ETFs.

I intend to expand this study in several ways. First, though leveraged ETFs have attributes that lend them to be especially good to use to look for smart money, I plan on expanding this study to all ETFs that are tied to a benchmark. I plan on examining foreign holidays to determine if there is any change in the predictive power of the regressions around those events. Most importantly, I intend to obtain measures of market inefficiency or transaction costs to directly compare how the out-of-sample R^2 fund results change with these measures. I also intend to investigate measures for AP arbitrage opportunities. These may help to further classify flows into predictive flows and uninformative flows.

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Appendix

1.A Appendix A: Top Holdings For Foreign Equity ETFs With Predictable Benchmarks

In this appendix is listed the top ten holdings for all ETFs with predictable benchmark returns as characterized by positive and significant out-of-sample R^2. All the funds tend to have holdings similar to those characterized in previous research in this area (see Ivanov et al. (2014)). Specifically, the vast majority of holdings are in cash and in swaps initiated with the ETF's authorized participants.

Notably, there is no difference in the holding strategies of the funds that have predictable benchmarks compared to those that do not (see Appendix B).

Table 1.A.1: Top Ten Holdings for Funds With Significant OOS R^2

Fund Ticker	Holding Security Description	Shares (thousands)	Market Value ($1,000)
DPK	BANK OF NEW YORK CASH RESERVE	1,965.28	1965.28
DPK	DREYFUS TREAS PRIME CASH MGMT/INST	724.53	724.53
DPK	FIDELITY INSTITUTIONAL GOVERNMENT PORTFOLIO	1,174.54	1174.54
DPK	FIDELITY INSTITUTIONAL GOVERNMENT PORTFOLIO	626.42	626.42
DPK	GOLDMAN FINL SQ TRSRY INST 468	2,883.40	2883.40
DPK	ISHARES MSCI EAFE ETF SWAP	-164.30	-10198.29
DPK	ISHARES MSCI EAFE ETF SWAP	-30.87	-1916.29
DPK	ISHARES MSCI EAFE ETF SWAP	-44.93	-2788.56
DPK	ISHARES MSCI EAFE ETF SWAP	-75.77	-4703.29
DZK	BANK OF NEW YORK CASH RESERVE	8,257.07	8257.07
DZK	DREYFUS TREAS PRIME CASH MGMT/INST	2,264.37	2264.37
DZK	FIDELITY INSTITUTIONAL GOVERNMENT PORTFOLIO	3,272.95	3272.95
DZK	FIDELITY INSTITUTIONAL GOVERNMENT PORTFOLIO	4,688.40	4688.40
DZK	GOLDMAN FINL SQ TRSRY INST 468	632.18	632.18
DZK	ISHARES MSCI EAFE ETF	38.27	2375.29
DZK	ISHARES MSCI EAFE ETF SWAP	215.93	13403.02
DZK	ISHARES MSCI EAFE ETF SWAP	388.15	24092.72
DZK	ISHARES MSCI EAFE ETF SWAP	389.43	24171.80
DZK	ISHARES MSCI EAFE ETF SWAP	42.38	2630.28

Table 1.A.2: Top Ten Holdings for Funds With Significant OOS R^2 (Continued)

Fund Ticker	Holding Security Description	Shares (thousands)	Market Value ($1,000)
EDC	BANK OF NEW YORK CASH RESERVE	60,312.03	60312.03
EDC	DREYFUS TREAS PRIME CASH MGMT/INST	9,103.65	9103.65
EDC	ISHARES MSCI EMERGING MARKETS ETF	169.97	6723.97
EDC	FIDELITY INSTITUTIONAL GOVERNMENT PORTFOLIO	13,005.63	13005.63
EDC	GOLDMAN FINL SQ TRSRY INST 506	13,078.31	13078.31
EDC	ISHARES MSCI EMERGING MARKETS ETF SWAP	1,769.43	69998.65
EDC	ISHARES MSCI EMERGING MARKETS ETF SWAP	1,813.14	71727.70
EDC	GOLDMAN FINL SQ TRSRY INST 468	22,539.60	22539.60
EDC	ISHARES MSCI EMERGING MARKETS ETF SWAP	2,385.44	94367.97
EDC	GOLDMAN FINL SQ TRSRY INST 506	25,787.08	25787.08
EDC	ISHARES MSCI EMERGING MARKETS ETF SWAP	2,690.77	106446.86
EDC	ISHARES MSCI EMERGING MARKETS ETF SWAP	3,006.92	118953.83
EDZ	ISHARES MSCI EMERGING MARKETS ETF SWAP	-1,265.51	-50063.54
EDZ	ISHARES MSCI EMERGING MARKETS ETF SWAP	-1,709.67	-67634.39
EDZ	ISHARES MSCI EMERGING MARKETS ETF SWAP	-3,517.32	-139145.10
EDZ	ISHARES MSCI EMERGING MARKETS ETF SWAP	-400.00	-15824.00
EDZ	ISHARES MSCI EMERGING MARKETS ETF SWAP	-839.11	-33194.99
EDZ	ISHARES MSCI EMERGING MARKETS ETF SWAP	-880.11	-34817.27
EDZ	MORGAN STANLEY ILF/TREAS/INST	10,932.30	10932.30
EDZ	DREYFUS TREAS PRIME CASH MGMT/INST	12,225.25	12225.25
EDZ	FIDELITY INSTITUTIONAL GOVERNMENT PORTFOLIO	15,105.83	15105.83
EDZ	BANK OF NEW YORK CASH RESERVE	39,337.60	39337.60
EDZ	GOLDMAN FINL SQ TRSRY INST 468	4,404.71	4404.71
EDZ	GOLDMAN FINL SQ TRSRY INST 506	5,106.41	5106.41
EDZ	GOLDMAN FINL SQ TRSRY INST 506	51,462.95	51462.95

Table 1.A.3: Top Ten Holdings for Funds With Significant OOS R^2 (Continued)

Fund Ticker	**Holding Security Description**	**Shares (thousands)**	**Market Value ($1,000)**
YINN	BANK OF NEW YORK CASH RESERVE	31,825.53	31825.53
YINN	DREYFUS TREAS PRIME CASH MGMT/INST	13,819.55	13819.55
YINN	FIDELITY INSTITUTIONAL GOVERNMENT PORTFOLIO	20,427.37	20427.37
YINN	FIDELITY INSTITUTIONAL GOVERNMENT PORTFOLIO	4.15	4.15
YINN	GOLDMAN FINL SQ TRSRY INST 468	24.07	24.07
YINN	GOLDMAN FINL SQ TRSRY INST 506	5.16	5.16
YINN	GOLDMAN FINL SQ TRSRY INST 506	8,118.22	8118.22
YINN	ISHARES CHINA LARGE-CAP ETF	1,212.42	47696.48
YINN	ISHARES CHINA LARGECAP ETF SWAP	1,325.22	52134.08
YINN	ISHARES CHINA LARGECAP ETF SWAP	1,329.65	52308.31
YINN	ISHARES CHINA LARGECAP ETF SWAP	1,896.81	74620.43
YINN	ISHARES CHINA LARGECAP ETF SWAP	2,407.23	94700.39
YINN	ISHARES CHINA LARGECAP ETF SWAP	2,787.19	109648.13
YINN	MORGAN STANLEY ILF/TREAS/INST	11,242.27	11242.27
YANG	BANK OF NEW YORK CASH RESERVE	25,397.12	25397.12
YANG	DREYFUS TREAS PRIME CASH MGMT/INST	8,479.30	8479.30
YANG	FIDELITY INSTITUTIONAL GOVERNMENT PORTFOLIO	12,691.44	12691.44
YANG	FIDELITY INSTITUTIONAL GOVERNMENT PORTFOLIO	19,192.28	19192.28
YANG	GOLDMAN FINL SQ TRSRY INST 468	10.84	10.84
YANG	GOLDMAN FINL SQ TRSRY INST 506	3.46	3.46
YANG	GOLDMAN FINL SQ TRSRY INST 506	3,499.24	3499.24
YANG	ISHARES CHINA LARGECAP ETF SWAP	-1,480.26	-58233.23
YANG	ISHARES CHINA LARGECAP ETF SWAP	-2,306.83	-90750.53
YANG	ISHARES CHINA LARGECAP ETF SWAP	-742.86	-29224.19

Table 1.A.4: Top Ten Holdings for Funds With Significant OOS R^2 (Continued)

Fund Holding Ticker	Security Description	Shares (thousands)	Market Value ($1,000)
RUSL	BANK OF NEW YORK CASH RESERVE	20,481.86	20481.86
RUSL	DREYFUS TREAS PRIME CASH MGMT/INST	30,925.25	30925.25
RUSL	FIDELITY INSTITUTIONAL GOVERNMENT PORTFOLIO	3,613.96	3613.96
RUSL	FIDELITY INSTITUTIONAL GOVERNMENT PORTFOLIO	4,640.50	4640.50
RUSL	GOLDMAN FINL SQ TRSRY INST 468	14,847.51	14847.51
RUSL	GOLDMAN FINL SQ TRSRY INST 506	12,664.93	12664.93
RUSL	MARKET VECTORS RUSSIA ETF SWAP	2,581.84	52746.99
RUSL	MARKET VECTORS RUSSIA ETF SWAP	3,014.49	61585.93
RUSL	MARKET VECTORS RUSSIA ETF SWAP	4,166.69	85125.56
RUSL	MARKET VECTORS RUSSIA ETF SWAP	5,052.05	103213.40
RUSL	MARKET VECTORS RUSSIA ETF SWAP	5,910.58	120753.11
RUSL	VANECK VECTORS RUSSIA ETF	4,117.75	84125.53
RUSS	BANK OF NEW YORK CASH RESERVE	12,240.56	12240.56
RUSS	DREYFUS TREAS PRIME CASH MGMT/INST	8,302.59	8302.59
RUSS	FIDELITY INSTITUTIONAL GOVERNMENT PORTFOLIO	4,760.30	4760.30
RUSS	FIDELITY INSTITUTIONAL GOVERNMENT PORTFOLIO	8,884.56	8884.56
RUSS	GOLDMAN FINL SQ TRSRY INST 468	4,009.29	4009.29
RUSS	GOLDMAN FINL SQ TRSRY INST 506	8,284.42	8284.42
RUSS	MARKET VECTORS RUSSIA ETF SWAP	-1,178.80	-24082.90
RUSS	MARKET VECTORS RUSSIA ETF SWAP	-1,190.01	-24311.80
RUSS	MARKET VECTORS RUSSIA ETF SWAP	-1,477.03	-30175.70
RUSS	MARKET VECTORS RUSSIA ETF SWAP	-703.16	-14365.48
RUSS	MARKET VECTORS RUSSIA ETF SWAP	-713.27	-14572.07

Table 1.A.5: Top Ten Holdings for Funds With Significant OOS R^2 (Continued)

Fund Ticker	**Holding Security Description**	**Shares (thousands)**	**Market Value ($1,000)**
INDL	BANK OF NEW YORK CASH RESERVE	9,652.53	9652.53
INDL	DREYFUS TREAS PRIME CASH MGMT/INST	3,983.49	3983.49
INDL	FIDELITY INSTITUTIONAL GOVERNMENT PORTFOLIO	0.00	0.00
INDL	FIDELITY INSTITUTIONAL GOVERNMENT PORTFOLIO	27,665.71	27665.71
INDL	GOLDMAN FINL SQ TRSRY INST 468	0.01	0.01
INDL	GOLDMAN FINL SQ TRSRY INST 506	0.00	0.00
INDL	GOLDMAN FINL SQ TRSRY INST 506	10,873.28	10873.28
INDL	ISHARES MSCI INDIA ETF	1,702.18	53227.20
INDL	ISHARES MSCI INDIA ETF SWAP	2,480.46	77563.83
INDL	ISHARES MSCI INDIA ETF SWAP	4,389.75	137267.48
INDL	ISHARES MSCI INDIA ETF SWAP	843.97	26391.00
EEV	ISHARES MSCI EMERGING MARKETS (EEM) SWAP SOCIETE GENERALE	-0.79	-696.27
EEV	ISHARES MSCI EMERGING MARKETS (EEM) SWAP GOLDMAN SACHS	-2.13	-1878.14
EEV	ISHARES MSCI EMERGING MARKETS (EEM) SWAP CREDIT SUISSE	-10.58	-9326.09
EEV	ISHARES MSCI EMERGING MARKETS (EEM) SWAP UBS AG	-15.64	-13792.36
EEV	ISHARES MSCI EMERGING MARKETS (EEM) SWAP CITIBANK NA	-48.10	-42415.36
EEV	NET OTHER ASSETS / CASH	33,915.43	33915.43
EET	ISHARES MSCI EMERGING MARKETS (EEM) SWAP BANK OF AMERICA NA	3.34	2946.70
EET	ISHARES MSCI EMERGING MARKETS (EEM) SWAP CITIBANK NA	11.50	10138.59
EET	ISHARES MSCI EMERGING MARKETS (EEM) SWAP CREDIT SUISSE	6.93	6110.07
EET	ISHARES MSCI EMERGING MARKETS (EEM) SWAP GOLDMAN SACHS	0.85	748.24
EET	ISHARES MSCI EMERGING MARKETS (EEM) SWAP MORGAN STANLEY	5.55	4892.37
EET	ISHARES MSCI EMERGING MARKETS (EEM) SWAP SOCIETE GENERALE	1.66	1464.21
EET	ISHARES MSCI EMERGING MARKETS (EEM) SWAP UBS AG	25.87	22814.63
EET	NET OTHER ASSETS / CASH	24,584.75	24584.75

Table 1.A.6: Top Ten Holdings for Funds With Significant OOS R^2 (Continued)

Fund Ticker	**Holding Security Description**	**Shares (thousands)**	**Market Value ($1,000)**
SJB	MARKIT IBOXX $ LIQUID HIGH YIELD INDEX (HYG) SWAP CREDIT SUISSE	-18.96	-25864.63
SJB	MARKIT IBOXX $ LIQUID HIGH YIELD INDEX (HYG) SWAP GOLDMAN SACHS	-19.68	-26853.91
SJB	MARKIT IBOXX $ LIQUID HIGH YIELD INDEX (HYG) SWAP CITIBANK NA	-44.96	-61341.97
SJB	NET OTHER ASSETS / CASH	115,223.12	115223.12
UJB	ISHARES IBOXX $ HIGH YIELD CORPORATE BOND ETF	27.16	2364.54
UJB	MARKIT IBOXX $ LIQUID HIGH YIELD INDEX (HYG) SWAP CITIBANK NA	0.75	1025.41
UJB	MARKIT IBOXX $ LIQUID HIGH YIELD INDEX (HYG) SWAP CREDIT SUISSE	1.58	2151.48
UJB	MARKIT IBOXX $ LIQUID HIGH YIELD INDEX (HYG) SWAP GOLDMAN SACHS	0.50	684.97
UJB	NET OTHER ASSETS / CASH	740.84	740.84
EFO	ISHARES MSCI EAFE (EFA) SWAP CREDIT SUISSE	10.94	10957.56
EFO	ISHARES MSCI EAFE (EFA) SWAP UBS AG	4.05	4054.84
EFO	ISHARES MSCI EAFE (EFA) SWAP MORGAN STANLEY	2.53	2538.71
EFO	ISHARES MSCI EAFE (EFA) SWAP SOCIETE GENERALE	1.02	1018.12
EFO	ISHARES MSCI EAFE (EFA) SWAP MERRILL LYNCH	0.73	730.03
EFO	ISHARES MSCI EAFE (EFA) SWAP GOLDMAN SACHS	0.44	444.71
EFO	ISHARES MSCI EAFE (EFA) SWAP CITIBANK NA	0.39	387.12
EFO	NET OTHER ASSETS / CASH	10,054.91	10054.91
EFU	ISHARES MSCI EAFE (EFA) SWAP CITIBANK NA	-1.04	-1045.95
EFU	ISHARES MSCI EAFE (EFA) SWAP UBS AG	-1.14	-1140.95
EFU	ISHARES MSCI EAFE (EFA) SWAP CREDIT SUISSE	-1.73	-1733.00
EFU	ISHARES MSCI EAFE (EFA) SWAP SOCIETE GENERALE	-4.58	-4586.18
EFU	NET OTHER ASSETS / CASH	4,266.99	4266.99

Table 1.A.7: Top Ten Holdings for Funds With Significant OOS R^2 (Continued)

Fund Ticker	Holding Security Description	Shares (thousands)	Market Value ($1,000)
EFZ	ISHARES MSCI EAFE (EFA) SWAP CITIBANK NA	-6.79	-6803.45
EFZ	ISHARES MSCI EAFE (EFA) SWAP CREDIT SUISSE	-5.62	-5626.18
EFZ	ISHARES MSCI EAFE (EFA) SWAP GOLDMAN SACHS	-12.96	-12987.01
EFZ	ISHARES MSCI EAFE (EFA) SWAP SOCIETE GENERALE	-4.79	-4801.08
EFZ	ISHARES MSCI EAFE (EFA) SWAP UBS AG	-4.62	-4631.74
EFZ	NET OTHER ASSETS / CASH	34,807.85	34807.85

Table 1.A.8: Top Ten Holdings for Funds With Significant OOS R^2 (Continued)

Fund Ticker	**Holding Security Description**	**Shares (thousands)**	**Market Value ($1,000)**
EUM	ISHARES MSCI EMERGING MARKETS (EEM) SWAP GOLDMAN SACHS	-1.48	-1306.03
EUM	ISHARES MSCI EMERGING MARKETS (EEM) SWAP MORGAN STANLEY	-3.63	-3202.49
EUM	ISHARES MSCI EMERGING MARKETS (EEM) SWAP SOCIETE GENERALE	-9.94	-8762.10
EUM	ISHARES MSCI EMERGING MARKETS (EEM) SWAP CREDIT SUISSE	-19.61	-17286.85
EUM	ISHARES MSCI EMERGING MARKETS (EEM) SWAP UBS AG	-20.47	-18051.16
EUM	ISHARES MSCI EMERGING MARKETS (EEM) SWAP BANK OF AMERICA NA	-32.01	-28228.54
EUM	ISHARES MSCI EMERGING MARKETS (EEM) SWAP CITIBANK NA	-114.11	-100619.12
EUM	NET OTHER ASSETS / CASH	175,981.90	175981.90
EWV	ISHARES MSCI JAPAN (EWJ) SWAP BANK OF AMERICA NA	-0.32	-343.20
EWV	ISHARES MSCI JAPAN (EWJ) SWAP MORGAN STANLEY	-2.15	-2298.55
EWV	ISHARES MSCI JAPAN (EWJ) SWAP UBS AG	-3.01	-3213.47
EWV	ISHARES MSCI JAPAN (EWJ) SWAP SOCIETE GENERALE	-5.00	-5339.91
EWV	ISHARES MSCI JAPAN (EWJ) SWAP CREDIT SUISSE	-10.24	-10931.52
EWV	NET OTHER ASSETS / CASH	11,066.07	11066.07
EZJ	ISHARES MSCI JAPAN (EWJ) SWAP MORGAN STANLEY	10.42	11132.15
EZJ	ISHARES MSCI JAPAN (EWJ) SWAP BANK OF AMERICA NA	4.86	5186.22
EZJ	ISHARES MSCI JAPAN (EWJ) SWAP SOCIETE GENERALE	1.03	1102.98
EZJ	ISHARES MSCI JAPAN (EWJ) SWAP UBS AG	0.98	1042.54
EZJ	ISHARES MSCI JAPAN (EWJ) SWAP CREDIT SUISSE	0.94	1007.09
EZJ	NET OTHER ASSETS / CASH	9,721.12	9721.12
FXP	ISHARES FTSE CHINA LARGE-CAP (FXI) SWAP MORGAN STANLEY	-0.83	-617.36
FXP	ISHARES FTSE CHINA LARGE-CAP (FXI) SWAP GOLDMAN SACHS	-3.16	-2361.87
FXP	ISHARES FTSE CHINA LARGE-CAP (FXI) SWAP BANK OF AMERICA NA	-3.36	-2507.72
FXP	ISHARES FTSE CHINA LARGE-CAP (FXI) SWAP CREDIT SUISSE	-9.50	-7090.67
FXP	ISHARES FTSE CHINA LARGE-CAP (FXI) SWAP UBS AG	-19.71	-14712.60
FXP	ISHARES FTSE CHINA LARGE-CAP (FXI) SWAP SOCIETE GENERALE	-21.59	-16114.87
FXP	ISHARES FTSE CHINA LARGE-CAP (FXI) SWAP CITIBANK NA	-58.82	-43896.19
FXP	NET OTHER ASSETS / CASH	43,447.71	43447.71

Table 1.A.9: Top Ten Holdings for Funds With Significant OOS R^2 (Continued)

Fund Ticker	**Holding Security Description**	**Shares (thousands)**	**Market Value ($1,000)**
XPP	ISHARES FTSE CHINA LARGE-CAP (FXI) SWAP BANK OF AMERICA NA	0.01	8.12
XPP	ISHARES FTSE CHINA LARGE-CAP (FXI) SWAP CREDIT SUISSE	3.89	2902.65
XPP	ISHARES FTSE CHINA LARGE-CAP (FXI) SWAP GOLDMAN SACHS	34.82	25989.34
XPP	ISHARES FTSE CHINA LARGE-CAP (FXI) SWAP MORGAN STANLEY	2.44	1820.88
XPP	ISHARES FTSE CHINA LARGE-CAP (FXI) SWAP SOCIETE GENERALE	7.18	5360.04
XPP	ISHARES FTSE CHINA LARGE-CAP (FXI) SWAP UBS AG	31.25	23326.02
XPP	NET OTHER ASSETS / CASH	29,809.06	29809.06
YXI	ISHARES FTSE CHINA LARGE-CAP (FXI) SWAP BANK OF AMERICA NA	-0.87	-651.97
YXI	ISHARES FTSE CHINA LARGE-CAP (FXI) SWAP CITIBANK NA	-5.71	-4257.91
YXI	ISHARES FTSE CHINA LARGE-CAP (FXI) SWAP GOLDMAN SACHS	-0.43	-321.82
YXI	ISHARES FTSE CHINA LARGE-CAP (FXI) SWAP SOCIETE GENERALE	-2.47	-1842.31
YXI	ISHARES FTSE CHINA LARGE-CAP (FXI) SWAP UBS AG	-3.28	-2447.28
YXI	NET OTHER ASSETS / CASH	9,452.55	9452.55
SMK	ISHARES MSCI MEXICO CAPPED (EWW) SWAP CREDIT SUISSE	-0.41	-647.25
SMK	ISHARES MSCI MEXICO CAPPED (EWW) SWAP SOCIETE GENERALE	-1.54	-2415.47
SMK	ISHARES MSCI MEXICO CAPPED (EWW) SWAP UBS AG	-0.79	-1231.22
SMK	NET OTHER ASSETS / CASH	2,143.95	2143.95

1.B Appendix B: Top Holdings For Foreign Equity ETFs Without Predictable Benchmarks

In this appendix is listed the top ten holdings for all foreign equity ETFs that do not have predictable benchmark returns as characterized by positive and significant out-of-sample R^2. All the funds tend to have holdings similar to those characterized in previous research in this area (see Ivanov et al. (2014)). Specifically, the vast majority of holdings are in cash and in swaps initiated with the ETF's authorized participants.

Table 1.B.1: Top Ten Holdings for Funds Without Significant OOS R^2

Fund Ticker	Holding Security Description	Shares (thousands)	Market Value ($1,000)
CHAD	BANK OF NEW YORK CASH RESERVE	70271.5	70271.47
CHAD	DEUTSCHE X-TRACKERS HARVEST CSI 300 SWAP	-1759.3	-44720.92
CHAD	DEUTSCHE X-TRACKERS HARVEST CSI 300 SWAP	-596.7	-15168.50
CHAD	DEUTSCHE X-TRACKERS HARVEST CSI 300 SWAP	-62.9	-1598.64
CHAD	DEUTSCHE X-TRACKERS HARVEST CSI 300 SWAP	-892.8	-22695.94
CHAD	DREYFUS TREAS PRIME CASH MGMT/INST	488.1	488.06
CHAD	FIDELITY INSTITUTIONAL GOVERNMENT PORTFOLIO	0.0	0.00
CHAD	FIDELITY INSTITUTIONAL GOVERNMENT PORTFOLIO	4541.2	4541.23
CHAD	GOLDMAN FINL SQ TRSRY INST 468	6451.1	6451.06
CHAD	GOLDMAN FINL SQ TRSRY INST 506	10367.0	10367.04
CHAD	GOLDMAN FINL SQ TRSRY INST 506	4.8	4.79
BRZU	BANK OF NEW YORK CASH RESERVE	5581.7	5581.68
BRZU	DREYFUS TREAS PRIME CASH MGMT/INST	9533.6	9533.63
BRZU	FIDELITY INSTITUTIONAL GOVERNMENT PORTFOLIO	0.5	0.51
BRZU	GOLDMAN FINL SQ TRSRY INST 468	4879.0	4879.05
BRZU	GOLDMAN FINL SQ TRSRY INST 506	10149.0	10148.95
BRZU	GOLDMAN FINL SQ TRSRY INST 506	3643.4	3643.41
BRZU	ISHARES MSCI BRAZIL CAPPED ETF	1084.1	41031.63
BRZU	ISHARES MSCI BRAZIL CAPPED ETF SWAP	1046.4	39604.42
BRZU	ISHARES MSCI BRAZIL CAPPED ETF SWAP	1151.9	43600.70
BRZU	ISHARES MSCI BRAZIL CAPPED ETF SWAP	1260.1	47694.37
BRZU	ISHARES MSCI BRAZIL CAPPED ETF SWAP	453.8	17178.03
BRZU	ISHARES MSCI BRAZIL CAPPED ETF SWAP	557.2	21089.94
BRZU	ISHARES MSCI BRAZIL CAPPED ETF SWAP	758.2	28697.34
BRZU	MORGAN STANLEY ILF/TREAS/INST	2227.1	2227.06

Table 1.B.2: Top Ten Holdings for Funds Without Significant OOS R^2 (Continued)

Fund Ticker	**Holding Security Description**	**Shares (thousands)**	**Market Value ($1,000)**
EURL	BANK OF NEW YORK CASH RESERVE	2894.5	2894.49
EURL	DREYFUS TREAS PRIME CASH MGMT/INST	8.3	8.27
EURL	FIDELITY INSTITUTIONAL GOVERNMENT PORTFOLIO	0.8	0.80
EURL	GOLDMAN FINL SQ TRSRY INST 468	6230.9	6230.87
EURL	GOLDMAN FINL SQ TRSRY INST 506	0.0	0.00
EURL	GOLDMAN FINL SQ TRSRY INST 506	3573.5	3573.48
EURL	VANGUARD FTSE EUROPE ETF	226.2	11661.89
EURL	VANGUARD FTSE EUROPE ETF SWAP	237.8	12260.50
EURL	VANGUARD FTSE EUROPE ETF SWAP	509.5	26272.14
EURL	VANGUARD FTSE EUROPE ETF SWAP	528.1	27227.50
JPNL	BANK OF NEW YORK CASH RESERVE	695.5	695.46
JPNL	FIDELITY INSTITUTIONAL GOVERNMENT PORTFOLIO	2108.5	2108.46
JPNL	FIDELITY INSTITUTIONAL GOVERNMENT PORTFOLIO	0.1	0.10
JPNL	GOLDMAN FINL SQ TRSRY INST 506	191.8	191.77
JPNL	GOLDMAN FINL SQ TRSRY INST 506	760.8	760.82
JPNL	ISHARES MSCI JAPAN ETF	72.0	3719.52
JPNL	ISHARES MSCI JAPAN ETF SWAP	203.0	10488.27
JPNL	ISHARES MSCI JAPAN ETF SWAP	66.5	3435.24
JPNL	ISHARES MSCI JAPAN ETF SWAP	93.7	4842.82

Table 1.B.3: Top Ten Holdings for Funds Without Significant OOS R^2 (Continued)

Fund Ticker	**Holding Security Description**	**Shares (thousands)**	**Market Value ($1,000)**
KORU	BANK OF NEW YORK CASH RESERVE	1105.0	1105.01
KORU	DREYFUS TREAS PRIME CASH MGMT/INST	0.1	0.09
KORU	FIDELITY INSTITUTIONAL GOVERNMENT PORTFOLIO	842.9	842.93
KORU	ISHARES MSCI SOUTH KOREA CAP	48.0	2935.68
KORU	ISHARES MSCI SOUTH KOREA CAPPED ETF SWAP	212.5	12998.76
LBJ	BANK OF NEW YORK CASH RESERVE	3597.2	3597.17
LBJ	DREYFUS TREAS PRIME CASH MGMT/INST	2079.4	2079.38
LBJ	FIDELITY INSTITUTIONAL GOVERNMENT PORTFOLIO	190.1	190.10
LBJ	GOLDMAN FINL SQ TRSRY INST 506	1973.9	1973.90
LBJ	ISHARES LATIN AMERICA 40 ETF	288.2	9123.27
LBJ	ISHARES LATIN AMERICA 40 ETF SWAP	217.8	6895.93
LBJ	ISHARES LATIN AMERICA 40 ETF SWAP	260.0	8232.99
LBJ	ISHARES LATIN AMERICA 40 ETF SWAP	364.4	11538.27
LBJ	ISHARES LATIN AMERICA 40 ETF SWAP	465.2	14728.80
LBJ	ISHARES LATIN AMERICA 40 ETF SWAP	66.7	2112.39
LBJ	MORGAN STANLEY ILF/TREAS/INST	582.2	582.17
UBR	ISHARES MSCI BRAZIL CAPPED (EWZ) SWAP BANK OF AMERICA NA	4.4	4032.51
UBR	ISHARES MSCI BRAZIL CAPPED (EWZ) SWAP CREDIT SUISSE	20.6	18728.49
UBR	ISHARES MSCI BRAZIL CAPPED (EWZ) SWAP MORGAN STANLEY	2.1	1886.16
UBR	ISHARES MSCI BRAZIL CAPPED (EWZ) SWAP SOCIETE GENERALE	2.2	1964.72
UBR	ISHARES MSCI BRAZIL CAPPED (EWZ) SWAP UBS AG	13.5	12288.70
UBR	NET OTHER ASSETS / CASH	19436.7	19436.69

Table 1.B.4: Top Ten Holdings for Funds Without Significant OOS R^2 (Continued)

Fund Ticker	**Holding Security Description**	**Shares (thousands)**	**Market Value ($1,000)**
UMX	ISHARES MSCI MEXICO CAPPED (EWW) SWAP BANK OF AMERICA NA	0.5	802.29
UMX	ISHARES MSCI MEXICO CAPPED (EWW) SWAP CREDIT SUISSE	2.5	3986.33
UMX	ISHARES MSCI MEXICO CAPPED (EWW) SWAP GOLDMAN SACHS	0.1	95.91
UMX	ISHARES MSCI MEXICO CAPPED (EWW) SWAP MORGAN STANLEY	0.1	89.54
UMX	ISHARES MSCI MEXICO CAPPED (EWW) SWAP SOCIETE GENERALE	1.7	2706.66
UMX	ISHARES MSCI MEXICO CAPPED (EWW) SWAP UBS AG	6.1	9619.78
UMX	NET OTHER ASSETS / CASH	8662.4	8662.38
UPV	NET OTHER ASSETS / CASH	10691.2	10691.25
UPV	VANGUARD FTSE EUROPE (VGK) SWAP CITIBANK NA	0.2	362.49
UPV	VANGUARD FTSE EUROPE (VGK) SWAP CREDIT SUISSE	1.6	2750.62
UPV	VANGUARD FTSE EUROPE (VGK) SWAP GOLDMAN SACHS	0.5	918.85
UPV	VANGUARD FTSE EUROPE (VGK) SWAP MERRILL LYNCH	0.3	464.21
UPV	VANGUARD FTSE EUROPE (VGK) SWAP MORGAN STANLEY	4.0	6939.00
UPV	VANGUARD FTSE EUROPE (VGK) SWAP SOCIETE GENERALE	1.4	2466.46
UPV	VANGUARD FTSE EUROPE (VGK) SWAP UBS AG	4.3	7466.40

Table 1.B.5: Top Ten Holdings for Funds Without Significant OOS R^2 (Continued)

Fund Ticker	**Holding Security Description**	**Shares (thousands)**	**Market Value ($1,000)**
EPV	NET OTHER ASSETS / CASH	39099.8	39099.76
EPV	VANGUARD FTSE EUROPE (VGK) SWAP CITIBANK NA	-20.3	-35341.27
EPV	VANGUARD FTSE EUROPE (VGK) SWAP CREDIT SUISSE	-3.5	-6042.61
EPV	VANGUARD FTSE EUROPE (VGK) SWAP GOLDMAN SACHS	-2.9	-5092.65
EPV	VANGUARD FTSE EUROPE (VGK) SWAP MORGAN STANLEY	-0.8	-1347.69
EPV	VANGUARD FTSE EUROPE (VGK) SWAP SOCIETE GENERALE	-10.4	-18125.33
EPV	VANGUARD FTSE EUROPE (VGK) SWAP UBS AG	-7.0	-12200.74
BZQ	NET OTHER ASSETS / CASH	36954.1	36954.11
BZQ	ISHARES MSCI BRAZIL CAPPED (EWZ) SWAP UBS AG	-18.9	-17137.57
BZQ	ISHARES MSCI BRAZIL CAPPED (EWZ) SWAP SOCIETE GENERALE	-22.0	-19999.90
BZQ	ISHARES MSCI BRAZIL CAPPED (EWZ) SWAP MORGAN STANLEY	-32.3	-29305.50
BZQ	ISHARES MSCI BRAZIL CAPPED (EWZ) SWAP CREDIT SUISSE	-6.6	-5967.39
BZQ	ISHARES MSCI BRAZIL CAPPED (EWZ) SWAP BANK OF AMERICA NA	-1.8	-1651.65

1.C Appendix C: Top Ten Weightings of Foreign Equity Benchmark Indexes

In this appendix I investigate the major weighting of the foreign equity indexes which the leveraged ETFs in my sample use as benchmarks. As note, “It is not easy to determine which non-U.S. firms are cross-listed in the U.S., or when firms have initiated or ended their ADR programs, or the type of ADR.” A subsample of hand collecting data on firms in these indexes shows that the U.S. cross-listing rate is below 20%. Additionally, many of the listed firms are constituents of both predictable and non-predictable indexes (such as firms that make up the FTSE China 50 and the CSI 300, as well as firms in both the MSCI EAFE and the FTSE Developed Europe indexes).

Table 1.C.1: Top Ten Weighting of Predictable Benchmark Indices

Index	**Constituent**	**Weight**
FTSE China 50	China Construction Bank	9.52%
FTSE China 50	Tencent Holdings	9.46%
FTSE China 50	China Mobile	8.34%
FTSE China 50	Industrial and Commercial Bank of China	6.57%
FTSE China 50	Bank of China	5.27%
FTSE China 50	Ping An Insurance	4.30%
FTSE China 50	CNOOC	3.89%
FTSE China 50	China Petroleum & Chemical	3.79%
FTSE China 50	China Life Insurance	3.75%
FTSE China 50	Petrochina	3.54%
Indus India	Reliance Industries Ltd	10.00%
Indus India	Infosys Ltd	10.00%
Indus India	Housing Development Finance Corporation Ltd	5.43%
Indus India	Oil & Natural Gas Corpn Ltd	4.89%
Indus India	Hindustan Unilever Ltd	4.23%
Indus India	Sun Pharmaceuticals Industries Ltd	4.21%
Indus India	Indian Oil Corporation Ltd	3.44%
Indus India	Axis Bank Ltd	3.08%
Indus India	Coal India Ltd	3.02%
Indus India	Maruti Suzuki India Ltd	2.79%
MSCI EAFE	NESTLE	1.75%
MSCI EAFE	HSBC HOLDINGS (GB)	1.34%
MSCI EAFE	TOYOTA MOTOR CORP	1.32%
MSCI EAFE	ROCHE HOLDING GENUSS	1.30%
MSCI EAFE	NOVARTIS	1.28%
MSCI EAFE	ROYAL DUTCH SHELL A	0.96%
MSCI EAFE	BP	0.94%
MSCI EAFE	TOTAL	0.91%
MSCI EAFE	ROYAL DUTCH SHELL B	0.87%
MSCI EAFE	BRITISH AMERICAN TOBACCO	0.86%
MSCI EM	SAMSUNG ELECTRONICS CO	3.79%
MSCI EM	TENCENT HOLDINGS LI (CN)	3.63%
MSCI EM	TAIWAN SEMICONDUCTOR MFG	3.61%
MSCI EM	ALIBABA GROUP HLDG ADR	2.57%
MSCI EM	CHINA MOBILE	1.73%
MSCI EM	CHINA CONSTRUCTION BK H	1.62%
MSCI EM	NASPERS N	1.61%
MSCI EM	ICBC H	1.16%
MSCI EM	BAIDU ADR	1.13%
MSCI EM	HON HAI PRECISION IND CO	1.02%

Table 1.C.2: Top Ten Weighting of Predictable Benchmark Indices (Continued)

Index	**Constituent**	**Weight**
MSCI Pac ex-Japan	COMMONWEALTH BANK OF AUS	6.76%
MSCI Pac ex-Japan	WESTPAC BANKING	5.25%
MSCI Pac ex-Japan	AIA GROUP	4.87%
MSCI Pac ex-Japan	ANZ BANKING GROUP	4.16%
MSCI Pac ex-Japan	BHP BILLITON (AU)	4.08%
MSCI Pac ex-Japan	NATIONAL AUSTRALIA BANK	3.87%
MSCI Pac ex-Japan	WESFARMERS	2.32%
MSCI Pac ex-Japan	CSL	2.24%
MSCI Pac ex-Japan	CK HUTCHISON HOLDINGS	2.21%
MSCI Pac ex-Japan	HONGKONG EXCH & CLEARING	2.04%
MSCI Japan	TOYOTA MOTOR CORP	5.33%
MSCI Japan	MITSUBISHI UFJ FIN GRP	2.61%
MSCI Japan	SOFTBANK GROUP CORP	1.96%
MSCI Japan	SUMITOMO MITSUI FINL GRP	1.74%
MSCI Japan	HONDA MOTOR CO	1.65%
MSCI Japan	KDDI	1.63%
MSCI Japan	MIZUHO FINANCIAL GROUP	1.47%
MSCI Japan	JAPAN TOBACCO	1.29%
MSCI Japan	SONY CORP	1.22%
MSCI Japan	MITSUBISHI CORP	1.13%
MSCI Mexico	AMERICA MOVIL L	14.49%
MSCI Mexico	FEMSA UNIT UBD	10.29%
MSCI Mexico	GRUPO FIN BANORTE O	8.66%
MSCI Mexico	CEMEX CPO	7.96%
MSCI Mexico	GRUPO MEXICO B	7.77%
MSCI Mexico	GRUPO TELEVISA CPO	7.27%
MSCI Mexico	WALMART MEXICO V	6.97%
MSCI Mexico	FIBRA UNO ADMINISTRACION	2.86%
MSCI Mexico	GRUPO BIMBO A	2.73%
MSCI Mexico	ALFA	2.64%
MVIS Russia	SBERBANK-SPONSORED ADR	8.03%
MVIS Russia	GAZPROM OAO-SPON ADR	7.72%
MVIS Russia	LUKOIL OAO-SPON ADR	6.88%
MVIS Russia	MAGNIT OJSC-SPON GDR REGS	6.58%
MVIS Russia	NOVATEK PJSC	5.82%
MVIS Russia	MMC NORILSK NICKEL PJSC	5.51%
MVIS Russia	TATNEFT-SPONSORED ADR	4.94%
MVIS Russia	MOBILE TELESYSTEMS-SP ADR	4.92%
MVIS Russia	VTB BANK PJSC-GDR-REG S	4.52%
MVIS Russia	AK TRANSNEFT PJSC	4.46%

Table 1.C.3: Top Ten Weighting of Non-Predictable Benchmark Indices

Index	**Constituent**	**Weight**
CSI 300	Ping An Insurance	4.07%
CSI 300	China Minsheng Bank	2.54%
CSI 300	Industrial Bank	2.42%
CSI 300	China Merchants Bank	2.06%
CSI 300	Bank of Communications	1.81%
CSI 300	Kweichow Moutai	1.80%
CSI 300	Shanghai Pudong Development Bank	1.59%
CSI 300	China Vanke	1.56%
CSI 300	CITIC Securities	1.48%
CSI 300	Haitong Securities Company	1.43%
FTSE Developed Europe	Nestle	2.83%
FTSE Developed Europe	Novartis (REGD)	2.29%
FTSE Developed Europe	Roche Hldgs (GENUS)	2.12%
FTSE Developed Europe	HSBC Hldgs	1.99%
FTSE Developed Europe	British American Tobacco	1.46%
FTSE Developed Europe	Royal Dutch Shell A	1.40%
FTSE Developed Europe	Total France Oil & Gas Producers	1.34%
FTSE Developed Europe	BP	1.33%
FTSE Developed Europe	Royal Dutch Shell B	1.25%
FTSE Developed Europe	GlaxoSmithKline	1.23%
MSCI Brazil 25-50	ITAU UNIBANCO PN	11.26%
MSCI Brazil 25-50	AMBEV ON (NEW)	7.97%
MSCI Brazil 25-50	BANCO BRADESCO PN	7.93%
MSCI Brazil 25-50	PETROBRAS PN	6.15%
MSCI Brazil 25-50	PETROBRAS ON	5.50%
MSCI Brazil 25-50	ITAUSA PN	3.22%
MSCI Brazil 25-50	BRF ON	3.08%
MSCI Brazil 25-50	CIELO ON	3.07%
MSCI Brazil 25-50	VALE PN A	3.01%
MSCI Brazil 25-50	BM&F BOVESPA ON	2.96%
MSCI Korea 25-50	SAMSUNG ELECTRONICS CO	25.94%
MSCI Korea 25-50	SK HYNIX	3.85%
MSCI Korea 25-50	SAMSUNG ELECTRONICS PREF	3.59%
MSCI Korea 25-50	NAVER	3.20%
MSCI Korea 25-50	HYUNDAI MOTOR CO	3.04%
MSCI Korea 25-50	SHINHAN FINANCIAL GROUP	2.80%
MSCI Korea 25-50	POSCO	2.62%
MSCI Korea 25-50	HYUNDAI MOBIS	2.59%
MSCI Korea 25-50	KB FINANCIAL GROUP	2.49%
MSCI Korea 25-50	KT&G CORP(KOREA TOBACCO)	1.79%

Chapter 2

Commodity Diversification Around the Great Recession

Abstract

Commodity futures returns and equity returns correlation peaked at unprecedentedly high levels during the 2008 financial crisis. Unlike previous economic downturns where equity returns dropped but commodity futures returns largely stayed positive, following the financial crisis equity and commodity futures returns showed much higher than normal levels of co-movement. Using mean-variance spanning tests, I find that though diversification from a portfolio of solely equities into a portfolio of equities and commodities generally improves an investor's efficient frontier, it did not yield any significant improvement from 2008 to 2010 and little to no improvement in 2007 and 2011. Frontiers post crisis starting in 2012 are again benefited from diversification into commodities. Using quality of predictive power for several factors, I find that the levels of global supply and demand, and to a lesser extent commodity relevant hedge fund assets under management (AUM), and index investment aid in predicting future commodity-equity correlation leading into the financial crisis as well as during the subsequent recovery.

2.1 Introduction

Is diversification into commodities a worthwhile avenue for investors with equity portfolios seeking to minimize the portfolio variance for a given expected return? Historically, the answer has been yes, at least according to several papers including Jensen et al. (2000),(2002), Gorton and Rouwenhorst (2004), Erb and Harvey (2006), and Conover et al. (2010). In a classic Markowitz portfolio optimization, returns with minimum variance are more easily attainable with portfolios of assets that have low or negative correlation. Historically, the correlation between commodity futures returns and equity returns have been near zero and sometimes even negative (Gorton and Rouwenhorst (2004), Erb and Harvey (2006)). However, present commodity futures markets have changed in significant ways over the last decade since these articles were published.

Increasingly since the early 2000s there has been a large inflow of investor capital into the commodities market. Index investment in particular has grown more than twenty-fold since 2003. This phenomenon is widely referred to as the financialization of commodities. Since the mid 2000s, the commodity-equity correlation has increased and it peaked during the financial crisis of 2008.

In this paper I test whether efficient frontier improvements were possible from adding the Standard & Poors Goldman Sacs Commodity Index (GSCI) to I find that adding the to a portfolio of size-based equity quintiles for time periods before, during, and after the financial crisis of 2008. I also test the predictive power of several factors on future commodity-equity correlation.

I find that before and after the crisis an investor's efficient frontier was significantly improved by the addition of GSCI, but not during the crisis.

This paper's contribution to the literature is two-fold. First, though many papers identify the changes in commodity-equity correlation, none that I am aware of test whether it has significantly affected investors' diversification prospects by expanding from equities into commodities. Second, no papers have addressed the post crisis recovery of commodity-equity correlation.

In section 2.2, I introduce the historical trends of commodity-equity correlation as cover applicable research in this area. Section 2.3 tests whether the addition of a commodity index improves the efficient frontier of a portfolio of equity holdings for different time and holding periods. Section 2.4 outlines hypotheses that I test to evaluate the impact of several factors on the commodity-equity correlation. Section 2.5 outlines the data used in this paper and presents the results of a simple whole sample OLS regression. In section 2.6 I compare several factors based on their ability to predict commodity-equity correlation. I conclude in section 2.7.

2.2 Background

Historically, the correlation of commodity futures returns with the equity market has been close to zero. Before 2008, most commodity futures' equity correlation rarely if ever had absolute values of 0.5 or greater. The long term time trend of equity and commodity futures correlation is illustrated in figure 2.1. Five representative commodity futures (light crude, high grade copper, lean hogs, silver, and wheat) are shown. These commodities were selected because they each from different commodity sectors: energy, industrial metals, livestock, precious metals, and grain. Also included are the time trends of GSCI's correlation with the equity market. Since GSCI is heavily weighted in energy is not surprising that GSCI's correlation closely follows that of light crude.

Each of the commodities shown in figure 2.1 has a noticeable rise in correlation around October of 2008. Though any large regime shift is debatable for lean hogs and silver, light crude, copper, wheat, and the GSCI all behave with stark differences (higher average correlation and less correlation volatility) following 2008. All have consistently higher correlations with the equity market for a period of three to four years following the financial crisis of 2008. These trends are observable for each of the correlation period lengths shown

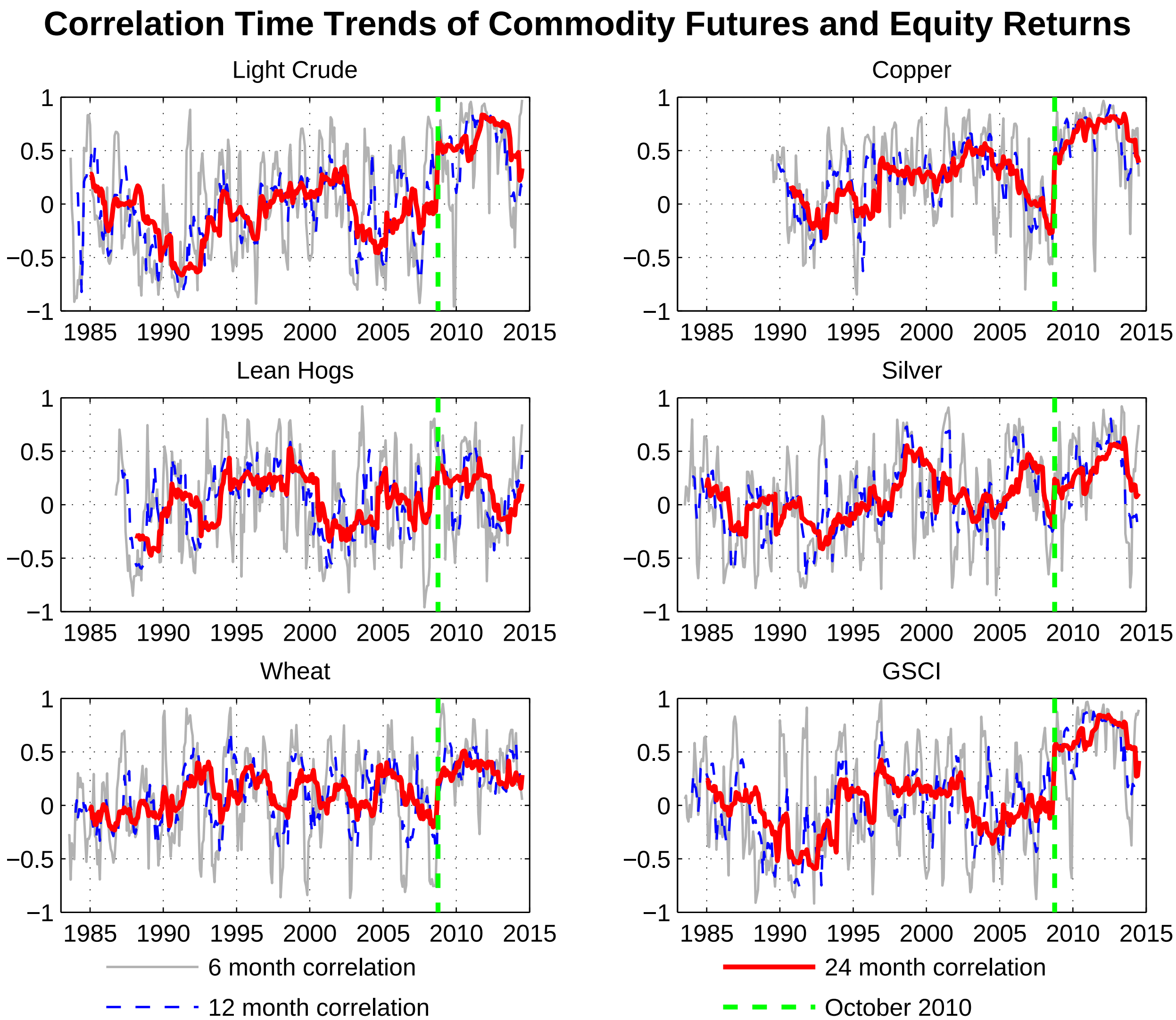

Figure 2.1: Correlation Time Trends of Commodity Futures and Equity Returns

This figure depicts 6, 12, and 24 month rolling correlations of equity market returns with 6 commodity returns. Light Crude is the CL contract traded on the NYMEX, Copper is the HG contract traded on COMEX, Lean Hogs is the LH contract traded on CME, Silver is the SI contract traded on COMEX, Wheat is the W_ contract traded on CBOT, and GSCI is the Standard & Poor's Goldman Sachs Commodity Index. All correlations are of monthly returns. The vertical dotted green line indicates the financial crisis of October of 2008.

in figure 2.1. Though there is more variation in shorter correlation periods, the time trends are still evident. I chose to use 24 month correlations as my dependent variable for my regression analyses owing to the lower apparent noise with longer time period correlations.

There is no previous precedent for this magnitude and duration of correlation behavior.

Several researchers have proposed possible explanations for this change in the covariance or correlation structure of equities and commodities. Most literature falls in one or both of the broad categories of financialization or global commodity supply or demand.

2.2.1 Commodity Financialization

Following the 'dot com' crash of equities in 2000, several researchers published findings touting the benefits of diversification gained when combining commodity and equity investments. Gorton and Rouwenhorst (2004) claim that commodity futures are effective at diversifying equity and bond holdings with increasing benefits with longer holding periods. They also report that during the most severe equity downturns, commodity futures returns are positive on average. Both Gorton and Rouwenhorst as well as Erb and Harvey (2006) find that commodities consistently have "equity-like" risk premia. Other papers touting the benefits of diversification of equity portfolios with the use of commodities include Jensen et al. (2000), (2002),Chong and Miffre (2010), Büyükşahin and Robe (2008), and Conover et al. (2010). Whether from heeding these recommendations or for other reasons, index investors have invested in commodities in unprecedented levels since 2000. According to CFTC (2008), index investment increased by more than an order of magnitude between 2003 and 2008 from $15 billion to more than $200 billion and currently estimates for 2014 are well above $300 billion (Henderson et al. (2014)). Index investment in commodities has experienced a more than twenty-fold increase in little more than a decade. At the same time, open interest in commodities in general has increased but at nowhere near the rate of index investment grown. Open interest trends for five representative commodities scaled to 100 in January of 2000 are illustrated in figure 2.2. All five commodities have had open interest more than double since 2000, but none of these commodities had open interest growth anywhere near the more than 2000% seen in index investment. With such a large growth in index investment, index investors now represent a much larger fraction of traders holding positions in commodities.

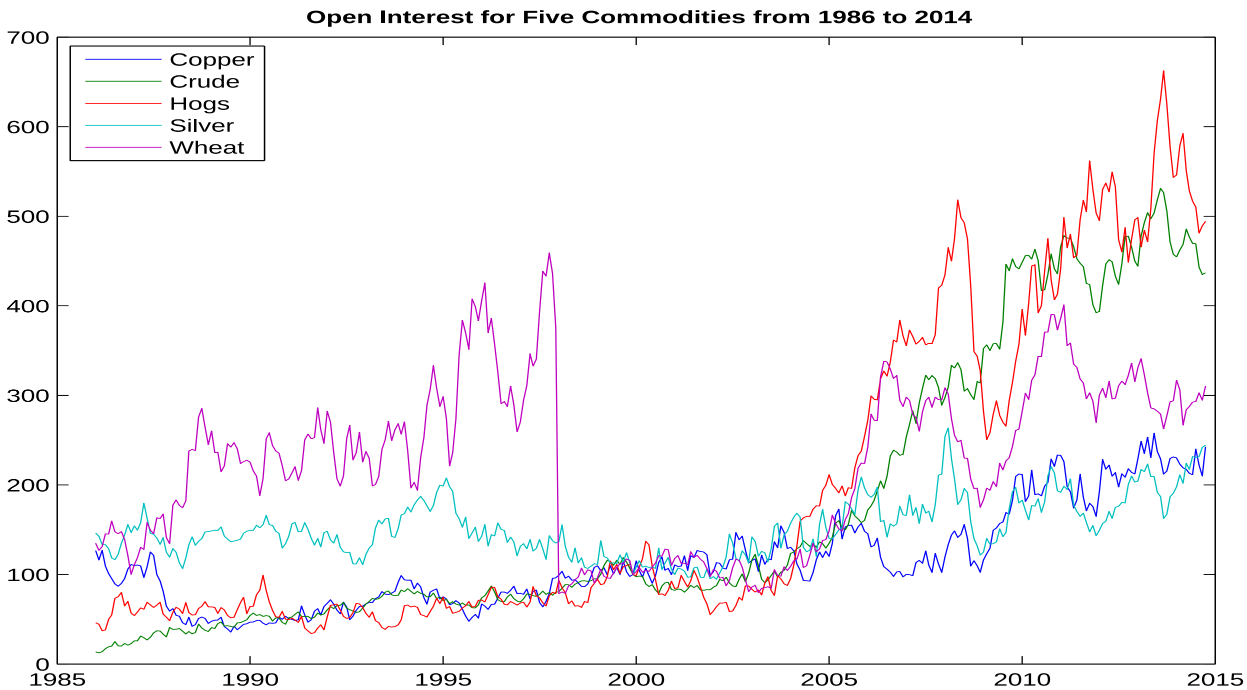

Figure 2.2: Open Interest for Five Commidities from 1986 to 2014

This figure shows open interest for five commodities normalized to 100 on January 2000. There has been a marked increase in open interest in all, but especially in crude, hogs and wheat. Open interest in hogs, wheat and silver all dropped significantly during the financial crisis of 2008.

The theoretical argument for index investment affecting commodity-equity correlation is manifold (Silvennoinen and Thorp (2013)). First, if equities and commodities are widely held by investors then state variables driving these investors' stochastic discount factors would become more similar leading to co-movements in pricing. Second, if poor performance in one market drives liquidation in the other (or if good performance drives purchases in the other market), then correlation would increase between the two markets. Third, if investors increasingly treat commodities as a unified group by favoring commodity indices, then demand for previously uncorrelated commodities would be tied through the index increasing inter-commodity correlation.

Though the growth in index investment in commodities is widely acknowledged, the effects of this shift in the commodity markets are widely debated. Singleton (2013) finds that there is a positive relation between crude oil futures prices and lagged investor flows. Henderson et al. (2014) show that large trades performed in response to the beginning and ending of over-the-counter Commodity-Linked Note contracts moved commodity market prices despite these contracts' lack of informativeness of futures market prices. (Brunetti and Reiffen (2011) find evidence that index traders have become an "important supply of price risk insurance", or in other words they now play an important role in the determination of market prices. Tang and Xiong (2010) claim that the correlation of commodity prices has increased more for indexed commodities than for those not on major commodity indices. Hamilton and Wu (2014b) conclude that risk premia for crude oil futures are no longer determined primarily by commercial hedging but increasingly by index investment. However in another paper, they find no evidence that index investment in agricultural commodities can help predict commodity futures returns (Hamilton and Wu (2014a)). Several other papers find little to no evidence of index investment having consistent or predictable effects on the price movements and returns of commodity futures. Büyükşahin and Robe (2008) find no change in the correlation structure of commodities and eguities during the increased financialization of the commodity market from 1993 to 2008. Stoll and Whaley (2010) find no evidence that index investment Granger causes futures returns. Büyükşahin and Robe (2014) using a non-public dataset of trader positions comprising approximately 70-90% of open interest from the CFTC find that speculator participation (especially hedge funds employing strategies in both equities and commodities) corresponds with higher equity-commodity correlation. They find no effects from increased index investment. Irwin and Sanders (2011) find no systematic link between the positions of index funds and commodity futures prices.

2.2.2 Global Supply and Demand

The argument that commodity futures prices are primarily driven by the demand for those contracts goes all the way back to Keynes (1923) and Hicks (1939). This theory proposes that hedgers seeking price insurance are willing to pay a premium to attract speculators on the opposite side (usually long). Many papers find evidence supporting this hedging pressure theory including Fama and French (1987), Hirshleifer (1988), Bessembinder (1992), and Gorton and Rouwenhorst (2004).

Several papers written after the beginning of commodity market financialization have found that global supply and demand (especially in developing countries) is much more relevant and helpful in predicting commodity returns and commodity-equity correlation than market participation by speculative investors including Domanski and Heath (2007), Krugman(2008), Stoll and Whaley (2010), Irwin and Sanders (2011), Fattouh et al. (2012), and Roache (2012).

2.3 Tests for Mean-Variance Spanning

Using mean-variance spanning as presented in Kan and Zhou (2012), as well as Huberman and Kandel (1987) I test whether there is a significant improvement to the mean-variance efficient frontier when a broad based commodity index is added to a portfolio of equity holdings. For equity holdings, I use the size quintiles available from Kenneth French's website. For the commodity index, I use the GSCI due to it being the longest established broad based commodity index and also due to it being one of the most widely established benchmarks for commodities. As discussed in Gibbons et al. (1989), using asymptotic tests–especially with small sample sizes–can lead to misleading results so I implement the small sample corrections found in Kan and Zhou (2012) which they refer to as "modified U tests".

Table 2.1: Modified U Tests for Mean-Variance Spanning of Monthly Returns for Equity Quintiles with the Addition of GSCI

Using holding periods of 12, 15, 18, 21, 24, 30, 60, and 90 months, with sample data beginning in February of 1983 and ending in July of 2014, the significance of the expansion of the minimum variance frontier from adding GSCI to a portfolio of size quintiles is tested. The beginning month of each holding period is listed as well as the corresponding p-value for the test. A rejection of the test (with low p-values) indicates that there was a significant improvement to the minimum variance efficient frontier with the addition of GSCI.

12 Months	
Date	p-value
198308	0.246
198408	0.038
198508	0.001
198608	0.039
198708	0.000
198808	0.011
198908	0.092
199008	0.155
199108	0.217
199208	0.167
199308	0.909
199408	0.053
199508	0.267
199608	0.061
199708	0.002
199808	0.250
199908	0.801
200008	0.170
200108	0.196
200208	0.014
200308	0.221
200408	0.077
200508	0.738
200608	0.014
200708	0.147
200808	0.996
200908	0.787
201008	0.865
201108	0.133
201208	0.090
201308	0.076

15 Months	
Date	p-value
198305	0.112
198408	0.218
198511	0.000
198702	0.000
198805	0.002
198908	0.014
199011	0.043
199202	0.008
199305	0.504
199408	0.012
199511	0.072
199702	0.006
199805	0.112
199908	0.263
200011	0.003
200202	0.013
200305	0.086
200408	0.046
200511	0.083
200702	0.073
200805	0.698
200908	0.839
201011	0.903
201202	0.009
201305	0.035

18 Months	
Date	p-value
198302	0.126
198408	0.006
198602	0.003
198708	0.000
198902	0.012
199008	0.015
199202	0.005
199308	0.312
199502	0.011
199608	0.039
199802	0.043
199908	0.009
200102	0.034
200208	0.001
200402	0.026
200508	0.162
200702	0.021
200808	0.896
201002	0.663
201108	0.023
201302	0.004

21 Months	
Date	p-value
198302	0.056
198411	0.000
198608	0.000
198805	0.001
199002	0.005
199111	0.001
199308	0.163
199505	0.012
199702	0.001
199811	0.061
200008	0.034
200205	0.000
200402	0.019
200511	0.007
200708	0.849
200905	0.468
201102	0.185
201211	0.001

24 Months	
Date	p-value
198408	0.000
198608	0.000
198808	0.000
199008	0.002
199208	0.119
199408	0.002
199608	0.003
199808	0.010
200008	0.011
200208	0.000
200408	0.033
200608	0.007
200808	0.879
201008	0.344
201208	0.003

30 Months	
Date	p-value
198408	0.000
198702	0.000
198908	0.001
199202	0.010
199408	0.001
199702	0.001
199908	0.001
200202	0.000
200408	0.003
200702	0.187
200908	0.913
201202	0.020

60 Months	
Date	p-value
198408	0.000
198908	0.000
199408	0.000
199908	0.000
200408	0.164
200908	0.067

90 Months	
Date	p-value
198408	0.000
199202	0.000
199908	0.000
200702	0.504

The null hypothesis of a mean-variance spanning modified U test is that the minimum variance frontier for a portfolio of A assets is the same as the minimum variance frontier for a portfolio of $A + B$ assets. In this case A is the group of five size quintiles of equity, while B is a single asset, GSCI. The results of mean-variance spanning tests for various holding periods ranging from 12 months to 90 months are presented in table 2.1.

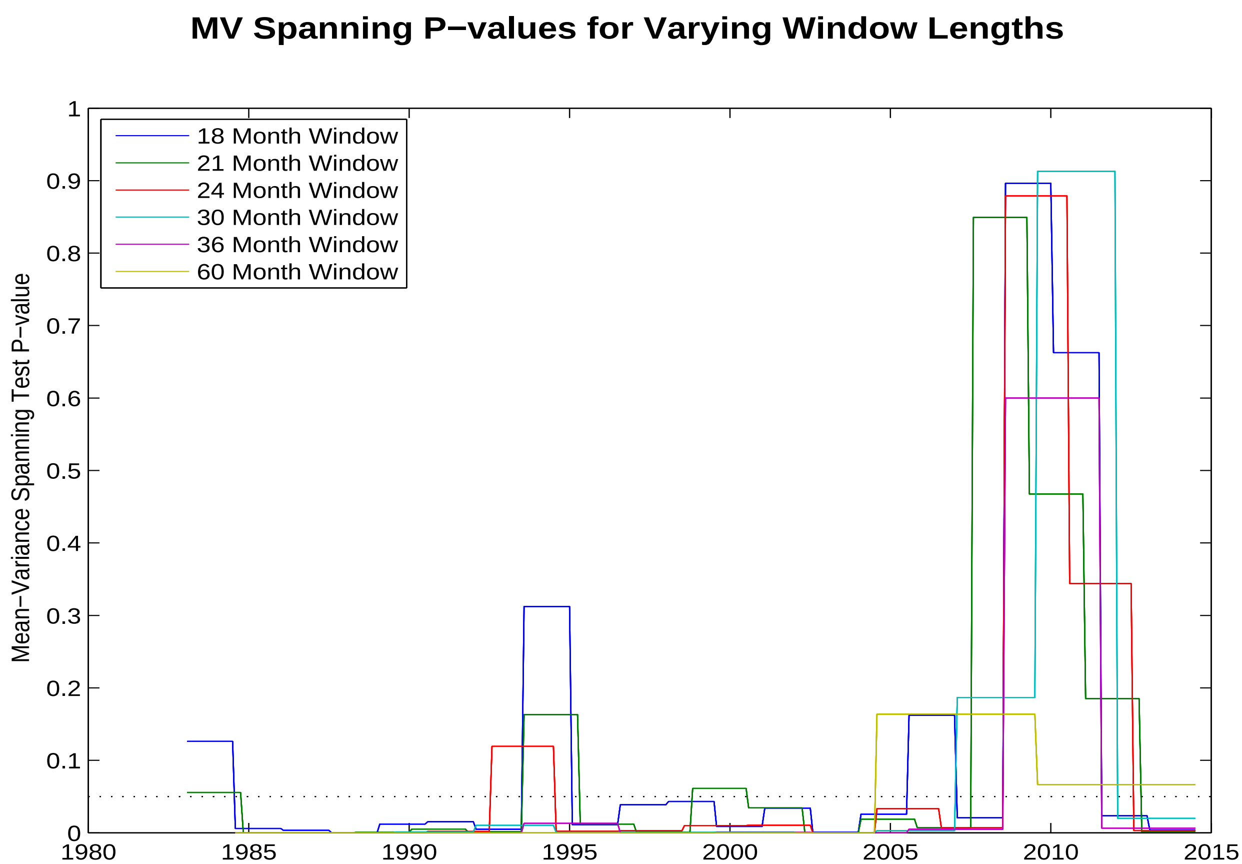

Figure 2.1: MV Spanning P-values for Varying Window Lengths

This figure shows the results of mean-variance spanning modified U tests for portfolios of equity size quintiles with the addition on GSCI holdings for holding periods between 18 and 60 months. The horizontal dotted line is at a p-value of 0.05. Three times (1984, 1994, and 2009-2001) between 1983 and 2014 failed to show significant improvements to the minimum variance frontier from adding GSCI for multiple holding periods. Most notably for all holding periods of lengths less than 60 months, the efficient frontier was not significantly expanded by the addition of GSCI between 2009 and 2011.

For horizons of longer duration (18 months or more), adding holdings in the GSCI to an equity portfolio bring a significant improvement in the mean-variance efficient frontier for the majority of the sample period between February 1983 and July 2014. I find that for time horizons of less than 15 months, adding GSCI to an equity portfolio is not reliably beneficial. In fact a majority of the periods for the 9 and 12 months do not significantly improve the minimum variance frontier by the addition of GSCI holdings (9 month holding period test results are not presented by available upon request). Regardless of holding period length, no frontier for holding periods beginning in 2008, 2009, or 2010 were significantly improved by holding the GSCI commodity index. Most–but not all–holding periods starting in 2007 and 2011 also showed no real improvement in minimum variance frontiers with the addition of GSCI.

Figure 2.1 graphically shows the p-values from the mean-variance spanning modified U tests for holding periods between 18 and 60 months. For instance, the 18 month window minimum variance frontiers were significantly improved (using a confidence level of 0.05) for 17 of 22 windows between 1983 and 2014. The insignificanly different frontiers of 18 month holding periods were in 1984, 1995, 2006, and the two consecutive windows going from August 2008 to July 2011. No holding periods of lengths less than 60 month showed significant benefits from holding GSCI between 2009 and 2011. A visual example of how the minimum variance frontiers changed in time is shown in figure 2.2.

Both table 2.1 and figures 2.1 and 2.2 present evidence that there was little to no frontier improvement around the period of the 2008 financial crisis. This is consistently evident for a wide range of window lengths. This is not a surprising result considering the large increase in correlation between equities and commodities during that same time period.

2.4 Hypotheses

Possible cross-market linkage stemming from traders participating in both the equity and the commodity market can be made for index investors, and hedge funds. If the level of investment by these parties is a factor driving changes in the correlation between equity

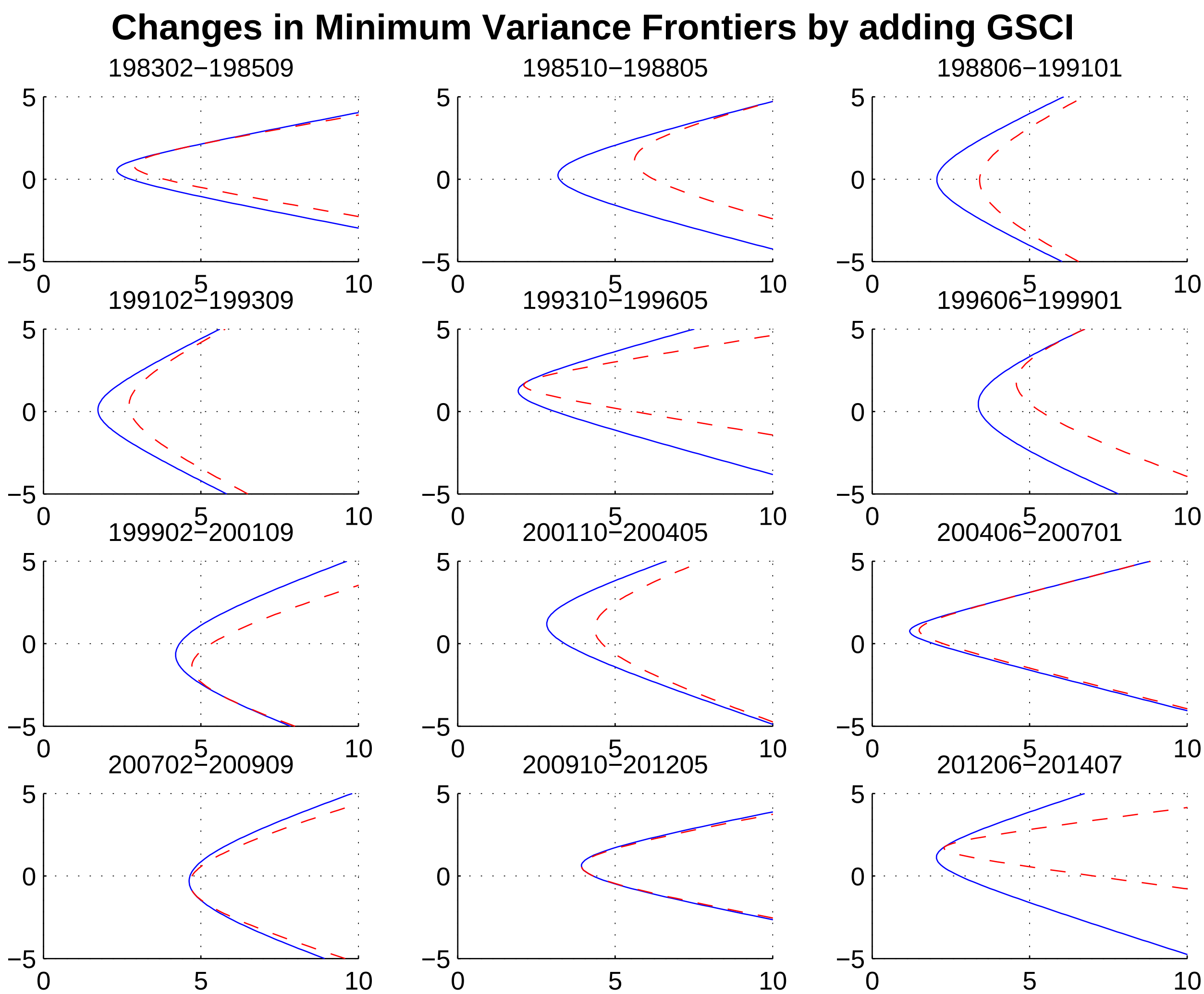

Figure 2.2: Changes in Minimum Variance Frontiers by Adding the GSCI Index

This figure depicts the expansion of the minimum variance efficient frontiers for 31 month holding periods of a portfolio of the five equity size quintiles (red dashed line) when the GSCI is added to the portfolio (blue solid line). The time period for each frontier is listed above the frontiers in YYYYMM format. Notably, the three frontiers with the smallest visual expansion correspond with holding periods from June of 2004 to May of 2012 which coincides with the financial crisis of 2008 and the period of unusually high correlation between equities and commodities. Refer to table 2.1 for the statistical tests of changes in minimum variance efficient frontiers.

returns and commodity futures returns, then that information should aid in anticipating future correlation between the two markets.

> **Hypothesis 1:** Factors influencing the correlation of commodity futures returns and equity market returns should covary significantly with the

correlation.

To test this, I perform an OLS regression of the correlation on commodity market measures, global supply and demand measures, seasonal measures, and measures of index fund and hedge fund participation in the commodity market.

Hypothesis 2: Factors influencing the correlation of commodity futures returns and equity market returns should significantly improve predictions of the commodity-equity correlation in the immediate future.

To test this, I perform rolling 60 month window regressions to generate coefficients used to predict future correlations. I use Diebold Mariano tests to determine whether the addition of various factors significantly improve the predictions of future correlation between commodities and equities.

2.5 Data & Methods

The dependent variable for my analyses is the correlation of the monthly returns of five commodity futures, the GSCI, and the equity market. For the independent variables, I used four classes of factors: global commodity production/demand measures, commodity market measures, seasonal measures, and investor measures.

2.5.1 Data Description

2.5.1.1 Commodity-Equity Correlation

I obtained monthly prices for GSCI and five representative commodities (light crude, high grade copper, lean hogs, silver, and wheat) from Bloomberg Terminal provided by Bloomberg L.P..

Returns from holding futures are inherently different from the returns from holding equity. Though futures contracts require collateral (margin), the price to enter into the contracts is zero by design. Additionally, the margin gains interest while it is held as collateral. Any return generated by changes in the futures price are properly considered excess returns because of the interest accrual of the collateral. In addition, because the nature of futures involves contracts with expiration dates, any strategy that involves the holding of futures for significant lengths of time must address the process of rolling a futures position from a nearer to further expiration contracts. The most common roll method for producing a long time series of futures returns consists of rolling the contract which is closest to expiring into the next closest contract shortly before the expiration month of the expiring contract is reached. This method keeps positions in the most liquid contracts in hopes of minimizing any transaction costs stemming from illiquid holdings.

Roll dates and ratio adjustment methodology for the Bloomberg data is available publicly and is beyond the scope of this paper. It is sufficient to note that the returns mirror the returns an investor would see if they invested in the specific commodity and rolled the position to the next nearest maturity contract approximately one to two weeks prior to the active contract maturing. Following Fama and French (1987) I calculate the returns each of the commodities resulting with return data from February of 1983 to July of 2014. Market equity excess returns were obtained from Kenneth French's website. Correlation between the equity market and the six commodity futures returns were then calculated.

2.5.1.2 Global Commodity Production and Demand

I used the Baltic Dry Index (BDI) as a measure of global demand for commodities. Specifically, BDI is an index that represents the prevailing costs of maritime shipping of dry goods around the world. BDI is a commonly accepted leading indicator of global commodity demand. However, it should be noted that though BDI does reflect trends in the global commodity market, it also is affected by other factors not directly linked to commodities such as the size and capacitiy of the global maritime shipping fleet, or changes in shipping costs due to geopolitical situations and piracy.

As a measure of the availability of capital for investment in both commodities and equities through borrowing I include the risk free rate obtained from Kenneth French's website. As another measure of commodity demand I use the United State's gross domestic product (GDP) and NBER recession data. I collected GDP data from the U.S. Department of Commerce's Bureau of Economic Analysis. GDP data on a quarterly basis are available beginning in 1947 and continue until the present. NBER recession data provides a simple binary variable for economic downturns.

> "The NBER does not define a recession in terms of two consecutive quarters of decline in real GDP. Rather, a recession is a significant decline in economic activity spread across the economy, lasting more than a few months, normally visible in real GDP, real income, employment, industrial production, and wholesale-retail sales."[1]

Though U.S. GDP and NBER recessions are not mechanically equivalent, they do measure similar economic states. For my entire time period regression I include both. However for subsequent regressions involving regressions on shorter windows of data, I omit the NBER recession data due to multicolinearity concerns. Instead of the level of the U.S. GDP, I use the change in GDP to more closely approximate the health of the economy at a given time. The Central Planning Board or Netherlands (CPB) publishes monthly measures of global economic data including world production. I use the CPB world production as a measure of global commodity supply and demand.

2.5.1.3 Commodity Market Measures

The U.S. Commodity Futures Trading Commission (CFTC) provides weekly reports called Commitment of Traders (COT) data which includes measures of total open interest, and open interest held by large investors of various broad categories. Originally, COT reports classified large traders in the categories of commercial and non-commercial traders. Large

[1] http://www.nber.org/cycles/cyclesmain.html

commercial traders were those who had ties to the production or consumption of that specific commodity (such as wheat farmers and flour mills in the case of wheat). Other traders without such ties are classified as non-commercial traders. The COT report provides the aggregate long and short positions for these large traders as well as the long and short positions for traders with positions smaller than the reporting threshold. The reporting threshold varies for each contract and can be found on the CFTC website as well as included in table 2.1.

Table 2.1: CFTC Large Trader Reporting Levels for Applicable Commodities

Commodity Futures	**Reporting Level (contracts)**
Live Cattle	100
Cocoa	100
Coffee	50
Copper	100
Corn	250
Cotton	100
Crud Oil, Light Sweet	350
Lean Hogs	100
Silver	150
Soybeans	150
Soybean Meal	200
Soybean Oil	200
Sugar	500
Wheat	150

This table shows the threshold holding levels for reportable positions. Traders with holdings above these levels must report their holdings on a weekly basis to the CFTC. Included in this table are the five representative commodity futures (light crude, copper, lean hogs, silver, and wheat) as well as those for which the CIT report covers.

Beginning in 2006, the COT reports changed format. The reportable trader (or large trader) position classifications changed to one of four new designations: first, producer/ merchant/processor/users, second, swap dealers, third, managed money, and fourth, others. In essence, the non-commercial traders are now broken down into swaps dealers, managed money, and other following the 2006 format change. The CFTC continues to provide COT reports in their legacy format of commercial and non-commercial large traders. For continuity of data, I use the legacy format throughout.

As market measures, I use the open interest, non-commercial long position and net hedging pressure for each of five commodities from five different sectors: light crude oil, high grade copper, lean hogs, silver, and wheat from the energy, industrial metals, livestock, precious metals and crop sectors respectively. Open interest is included as a measure of overall futures market usage for that commodity, non-commercial long position is used as a guage of speculation in that market, and net hedging pressure is used as a measure of the intensity of commodity producers and consumers' demand for futures as insurance against commodity price volatility.

Open interest and non-commercial long positions are both available directly from the COT reports. Hedging pressure is not. I calculate net hedging pressure similar to Bessembinder (1992) and following the approach of De Roon, Nijman, and Veld (2000). As Bessembinder and De Roon et al. do, I assume that hedgers are solely large commercial traders, and that non-commercial and non-reportable traders are speculators. Obviously this assumption is not wholly accurate and may degrade the informativeness of net hedging pressure as a measure of the commodity futures market.

2.5.1.4 Seasonal Measures

There are noticeable seasonal trends in many commodity prices and their futures. Several commodities do not have maturities in every month of the year. To capture possible calendar effects in commodity returns, I include month indicators in my regressions.

2.5.1.5 Measures of Hedge Fund and Index Fund Investments in Commodities

Using the TASS database, I generate a monthly measure of assets under management (AUM) for all hedge funds that use at least one commodity based strategy. In addition I generate a monthly measure of AUM for all hedge funds that use both equity based and commodity based strategies to compare results with Büyükşahin and Robe (2014).

In 2006 the CFTC began issuing an additional report called the *Supplemental Commitment of Traders* report which is widely referred to as the commitment of index traders (CIT) report. The CIT contains "aggregate futures and options positions for non-commercial, commercial, and index traders for 12 selected agricultural commodities"[2]. Table **??** outlines the contracts included in the CIT report as well as the number of weeks of data available. All contracts except soybean meal have 455 contract-week observations when exchange changes are taken into account. There were 4 contracts (cocoa, coffee, cotton, and sugar) that moved from the New York Board of Trade to The ICE Futures U.S. exchange. The Kansas City Board of Trade's wheat contract (which was for hard-red winter wheat) was moved to the Chicago Board of Trade and renamed HRW while the existing CBOT wheat contract was renamed SRW. Reporting of soybean meal began for the week ending April 2, 2013 thus there are only 77 weeks worth of observations for this contract. I omitted soybean meal to from this study to make a longer consitent time series of index trader investment from 2006 until 2014.

In an effort to include only a few representative independent variables for index investment in commodities, I aggregated the open interest and commodity index trader information for all contracts included in the CIT report except soybean meal to create one time series. I include the commodity index traders' long and short positions as well as the market fractions of these positions as calculated by the long and short positions divided by the open interest for that commodity.

2.5.1.6 Periodicity of Data

I obtained monthly commodity futures and GSCI returns from Bloomberg starting February of 1983. Monthly market returns and risk free rate are available on Kenneth

[2]http://www.cftc.gov/MarketReports/CommitmentsofTraders/index.htm

Table 2.2: Contracts Covered by the CIT Report

Contract	Exchange	Weeks
Cocoa	ICE	368
Cocoa	NYBOT	87
Columbian Coffee	ICE	368
Columbian Coffee	NYBOT	87
Corn	CBOT	455
Cotton No. 2	ICE	368
Cotton No. 2	NYBOT	87
Feeder Cattle	CME	455
Lean Hogs	CME	455
Live Cattle	CME	455
Soybean Meal	CBOT	77
Soybean Oil	CBOT	455
Soybeans	CBOT	455
Sugar No. 11	ICE	368
Sugar No. 11	NYBOT	87
Wheat	CBOT	415
Wheat	KCBOT	415
Wheat-HRW	CBOT	40
Wheat-SRW	CBOT	40

This table shows the commodity futures contracts for which the CIT report covers. Though not all columns show 455 weeks of data, all commodity contracts with the exception of soybean meal do have 455 weeks of CIT reports when exchange changes are taken into account.

Table 2.3: Summary Statistics

Variable	n	Mean	Standard Deviation	Minimum	Maximum
Correlations					
Light Crude	283	0.073	0.377	-0.666	0.833
Copper	283	0.296	0.292	-0.317	0.843
Lean Hogs	283	0.076	0.198	-0.343	0.528
Silver	283	0.125	0.234	-0.414	0.623
Wheat	283	0.173	0.159	-0.204	0.506
GSCI	283	0.140	0.361	-0.591	0.844
Independent Variables					
Risk Free Rate	283	0.240	0.177	0.000	0.560
Commodity Only HF AUM	283	99343	90070	2060	301000
Commodity Equity HF AUM	283	86413	76693	1810	270000
NBER Recessions	283	0.110	0.313	0.000	1.000
ΔGDP	283	25.478	27.063	-104.867	77.800
BDI	283	2252	1879	706	10814
OpenInterestcopper	283	86507	36974	32792	180848
NClongcopper	283	21732	15073	979	65681
HedgePresscopper	283	0.079	0.198	-0.345	0.631
OpenInterestcrude	283	1035910	814142	266423	2783050
NClongcrude	283	167179	187958	3657	703640
HedgePresscrude	283	0.029	0.065	-0.149	0.237
OpenInteresthogs	283	104051	87781	16610	323626
NClonghogs	283	28054	28691	1570	134875
HedgePresshogs	283	0.007	0.193	-0.521	0.452
OpenInterestsilver	283	106731	23468	65936	183619
NClongsilver	283	36276	11426	16243	72487
HedgePresssilver	283	0.450	0.164	0.042	0.828
OpenInterestwheat	283	473463	198571	161920	944796
NClongwheat	283	98682	57201	19255	228417
HedgePresswheat	283	0.048	0.107	-0.234	0.310
CPB World Production	283	92.694	17.994	66.000	126.300
Post 2005					
Light Crude Correlation	103	0.390	0.335	-0.270	0.833
Copper Correlation	103	0.462	0.334	-0.276	0.843
Lean Hogs Correlation	103	0.102	0.168	-0.256	0.431
Silver Correlation	103	0.285	0.176	-0.191	0.623
Wheat Correlation	103	0.219	0.180	-0.204	0.506
GSCI Correlation	103	0.430	0.337	-0.146	0.844
CIT Long	103	1578126	210673	1026181	1936108
CIT Short	103	174221	83035	23986	333438
Index Market Fraction Long	103	0.279	0.024	0.229	0.333
Index Market Fraction Short	103	0.024	0.011	0.004	0.041

French's website starting in 1927. Hedge fund data from TASS is monthly starting February of 1977. Monthly CPB global production estimates begin January 1991.

For my analyses, I converted all data that was not at a monthly periodicity into monthly observations. The Baltic Dry Index (BDI) is daily starting January 4th, 1985. I used the last observation for each month as the monthly observation for BDI.

COT from the CFTC is weekly data starting January of 1986, and CIT reports are weekly starting January of 2006. To convert these to monthly, I took the month average for positions as well as for hedging pressure.

US GDP and NBER recession data are quarterly starting the first quarter of 1947. In order to use this in a setting where everything else could be analyzed monthly, I assigned the month in the center of each quarter the reported GDP value for that quarter. I used a weighted average linear interpolation to assign GDP values for the remaining two months in the quarter. For example, US GDP for the fourth quarter of 1979 was 6503.9 and it grew by 21 to 6524.9 in the first quarter of 1980. This is an average GDP growth per month of 7. I assigned November 1979 the fourth quarter GDP of 6503.9, December a value of $6503.9 + 7 = 6510.9$, January seven higher at 6517.9 and February 1980 the first quarter GDP of 6524.9.

2.5.2 Full Period OLS Regression

Using OLS regression, I regressed the five sector representative commodity futures and GSCI return correlation with equity market returns on the four groups of independent variables outlined above. Due to the limited length of the CIT time series, I run separate regressions including and excluding the data which I will refer to as CIT and non-CIT regressions throughout this paper.

All independent variables beside the intercept and month indicators were standardized by subtracting the mean and dividing by the standard deviation. The interpretation of the coefficients in the regressions is the change in correlation of the given commodity and the equity market for a one standard deviation increase in the independent variable. Standard deviations are available in the summary statistics presented in table 2.3.

I find that global commodity supply and demand measures are significant in each regression. Notably, CPB world production and BDI are significant in every regression. Though production was significant, the sign of the coefficient was negative for hogs and wheat, while positive for crude, copper, silver and GSCI. The sign for the Baltic Dry index was consistently negative, indicating that when shipping prices are higher, we should expect lower commodity-equity correlation. The ΔGDP and NBER recession factors are not reliably significant across the six regressions. The risk-free rate was significant for copper, hogs, and silver, but not for crude, wheat and GSCI.

At least one futures market measure is significant for its related commodity correlation for all five individual commodities. Light crude correlation significantly covaried with all three of its own as well as all three of copper and silver's market measures. Copper-equity correlation had significant factors in copper, hogs and wheat, as well as open interest for crude. GSCI's equity correlation had all of copper and crude's market measures as well as two from hogs, and one from both silver and wheat. Crude hedging pressure was the only factor significant on at least the 0.1 level for all six regressions.

Seasonal effects measured by month indicators were not consistently significant across the six regressions. The GSCI index showed the most significant seasonal effects falling in the summer, where all the coefficients were significantly less than zero.

Hedge fund AUM was marginally significant in the regression for copper and GSCI, and significant only for hogs.

In the shorter time sample regression with CIT data (results found in tables 2.5, 2.5), less factors had coefficients significantly different than zero. The significance of global supply and demand measures drops, but remains significant for all but hogs. Hedging pressure for copper, silver and wheat seem to be the most significant commodity market factors for the reduced sample. No seasonal effect is evident for GSCI, though a slight seasonal effect may be present for hogs in the summer. The risk-free rate and the two hedge fund AUM factors were the only factors that rose in significance when going from the full sample to the shortened sample. Hedge fund factors were significant in all but the wheat correlation regression. Index investor measures showed to be significant for the metals copper and silver, and slightly so for hogs and GSCI.

Table 2.4: Whole Sample OLS Regression Without CIT

	Light Crude	Copper	Lean Hogs	Silver	Wheat	GSCI
Intercept	0.073***	0.296***	0.076***	0.125***	0.173***	0.140***
	(7.817)	(42.624)	(10.325)	(18.027)	(25.274)	(14.931)
Risk Free Rate	-0.005	-0.049***	0.158***	0.147***	-0.007	0.028
	(-0.225)	(-3.227)	(9.866)	(9.785)	(-0.494)	(1.372)
BDI	-0.144***	-0.104***	-0.056***	-0.084***	-0.065***	-0.138***
	(-8.510)	(-8.227)	(-4.145)	(-6.631)	(-5.200)	(-8.081)
ΔGDP	-0.009	0.021**	0.060***	0.040***	0.006	0.013
	(-0.676)	(2.010)	(5.442)	(3.820)	(0.565)	(0.955)
CPB World Production	0.204***	0.322***	-0.271***	0.287***	-0.123***	0.214***
	(3.897)	(8.223)	(-6.510)	(7.352)	(-3.182)	(4.052)
NBER Recessions	0.029**	-0.003	0.023**	0.018*	-0.016	0.034**
	(1.973)	(-0.244)	(1.992)	(1.653)	(-1.465)	(2.340)
OpenInterestcopper	0.318***	0.035	0.021	0.053	-0.005	0.259***
	(6.096)	(0.907)	(0.497)	(1.366)	(-0.136)	(4.912)
NClongcopper	-0.268***	0.034	-0.002	-0.035	0.074**	-0.237***
	(-6.908)	(1.170)	(-0.050)	(-1.199)	(2.581)	(-6.043)
HedgePresscopper	0.113***	0.023	0.054***	-0.019	-0.026*	0.143***
	(6.005)	(1.600)	(3.599)	(-1.348)	(-1.881)	(7.471)
OpenInterestcrude	0.574***	0.167***	0.225***	0.330***	0.060	0.581***
	(7.565)	(2.951)	(3.728)	(5.840)	(1.069)	(7.580)
NClongcrude	-0.472***	-0.225***	-0.135*	-0.364***	-0.090	-0.485***
	(-5.012)	(-3.189)	(-1.808)	(-5.188)	(-1.302)	(-5.100)
HedgePresscrude	0.087***	0.036**	0.064***	0.073***	0.026*	0.108***
	(4.610)	(2.562)	(4.250)	(5.173)	(1.876)	(5.665)
OpenInteresthogs	-0.103	-0.415***	-0.258***	-0.094	0.046	-0.300***
	(-1.106)	(-5.956)	(-3.480)	(-1.349)	(0.665)	(-3.190)
NClonghogs	0.033	0.211***	0.090*	0.113**	-0.042	0.115*
	(0.492)	(4.211)	(1.694)	(2.269)	(-0.858)	(1.697)
HedgePresshogs	-0.011	-0.040***	-0.002	-0.018*	0.027***	-0.016
	(-0.866)	(-4.093)	(-0.234)	(-1.808)	(2.787)	(-1.231)
OpenInterestsilver	-0.075***	-0.003	-0.034	0.018	-0.057***	-0.041
	(-2.784)	(-0.144)	(-1.567)	(0.898)	(-2.854)	(-1.496)
NClongsilver	0.050*	-0.023	0.019	-0.071***	0.002	0.021
	(1.804)	(-1.088)	(0.869)	(-3.425)	(0.086)	(0.765)
HedgePresssilver	-0.056**	0.003	-0.005	0.082***	0.020	-0.064***
	(-2.467)	(0.157)	(-0.282)	(4.844)	(1.192)	(-2.790)
OpenInterestwheat	-0.008	0.042**	-0.038*	-0.033*	0.011	0.006
	(-0.295)	(2.094)	(-1.809)	(-1.653)	(0.555)	(0.209)

***,**,* Significant at the 0.01, 0.05, 0.10 levels, respectively.

- table continued on next page -

Table 2.4: Whole Sample OLS Regression Without CIT (continued)

	Light Crude	Copper	Lean Hogs	Silver	Wheat	GSCI
NClongwheat	0.054	-0.071***	0.058**	-0.005	0.081***	0.073**
	(1.606)	(-2.835)	(2.172)	(-0.180)	(3.264)	(2.150)
HedgePresswheat	-0.006	0.029**	-0.036***	0.022*	-0.065***	-0.025
	(-0.398)	(2.430)	(-2.861)	(1.860)	(-5.666)	(-1.567)
Jan Dummy	-0.011	-0.003	0.001	-0.010	-0.005	-0.009
	(-0.866)	(-0.281)	(0.130)	(-0.986)	(-0.542)	(-0.724)
Feb Dummy	-0.017	-0.007	0.004	-0.005	-0.007	-0.018
	(-1.320)	(-0.738)	(0.361)	(-0.480)	(-0.697)	(-1.362)
Mar Dummy	-0.015	-0.007	-0.022**	-0.017*	-0.008	-0.024*
	(-1.112)	(-0.662)	(-2.034)	(-1.652)	(-0.833)	(-1.734)
Apr Dummy	-0.025*	-0.011	-0.014	-0.019*	-0.004	-0.033**
	(-1.828)	(-1.108)	(-1.292)	(-1.905)	(-0.426)	(-2.403)
May Dummy	-0.024*	-0.003	-0.014	-0.018*	-0.006	-0.029**
	(-1.754)	(-0.314)	(-1.255)	(-1.759)	(-0.612)	(-2.099)
Jun Dummy	-0.030**	-0.012	-0.016	-0.009	-0.005	-0.041***
	(-2.249)	(-1.250)	(-1.505)	(-0.894)	(-0.478)	(-3.040)
Jul Dummy	-0.025*	-0.021**	-0.014	-0.008	-0.005	-0.035***
	(-1.931)	(-2.131)	(-1.322)	(-0.780)	(-0.534)	(-2.632)
Aug Dummy	-0.028**	-0.018*	-0.022**	-0.013	0.001	-0.039***
	(-2.178)	(-1.869)	(-2.119)	(-1.362)	(0.094)	(-2.964)
Sep Dummy	-0.016	-0.017*	-0.018*	-0.018*	-0.003	-0.023*
	(-1.252)	(-1.738)	(-1.782)	(-1.894)	(-0.301)	(-1.756)
Oct Dummy	-0.016	-0.016*	-0.006	-0.016*	0.000	-0.020
	(-1.196)	(-1.697)	(-0.554)	(-1.695)	(0.025)	(-1.521)
Nov Dummy	-0.011	-0.004	0.001	-0.004	0.010	-0.014
	(-0.832)	(-0.393)	(0.078)	(-0.371)	(1.068)	(-1.072)
Commodity Only HF AUM	-0.384	0.537**	-1.425***	0.253	0.034	-0.615*
	(-1.174)	(2.194)	(-5.472)	(1.036)	(0.140)	(-1.862)
Commodity Equity HF AUM	0.325	-0.396*	1.877***	-0.245	0.049	0.674**
	(1.050)	(-1.708)	(7.608)	(-1.061)	(0.214)	(2.154)
Adjusted R^2	0.828	0.840	0.604	0.752	0.476	0.809
Number of Observations	283	283	283	283	283	283

***,**,* Significant at the 0.01, 0.05, 0.10 levels, respectively.

This table presents the ordinary least squares regression for the 24 month correlation of commodities with the equity market. This regression omits independent variables from the CFTC's CIT report so that the regression can be run over a larger time period beginning February 1985 and ending July 2014. Sample size and adjusted R squared values are presented on the second page.

Table 2.5: Whole Sample OLS Regression With CIT

	Light Crude	Copper	Lean Hogs	Silver	Wheat	GSCI
Intercept	0.390***	0.462***	0.102***	0.285***	0.219***	0.430***
	(51.310)	(69.409)	(14.450)	(37.631)	(33.399)	(67.529)
Risk Free Rate	-0.340***	-0.233***	-0.035	-0.010	-0.186***	-0.314***
	(-6.455)	(-5.051)	(-0.717)	(-0.198)	(-4.097)	(-7.111)
BDI	-0.065**	-0.072***	0.018	-0.036	-0.060***	-0.041*
	(-2.630)	(-3.302)	(0.759)	(-1.472)	(-2.783)	(-1.987)
ΔGDP	0.030*	0.012	-0.012	0.025	0.012	0.022
	(1.797)	(0.832)	(-0.761)	(1.473)	(0.838)	(1.550)
CPB World Production	0.173***	0.084*	-0.086*	0.225***	-0.040	0.152***
	(3.357)	(1.852)	(-1.776)	(4.366)	(-0.901)	(3.520)
NBER Recessions	-0.008	-0.034	-0.048*	0.032	-0.071***	-0.023
	(-0.278)	(-1.391)	(-1.846)	(1.170)	(-2.997)	(-1.011)
OpenInterestcopper	0.006	-0.000	-0.035	-0.093*	-0.069	-0.005
	(0.108)	(-0.008)	(-0.684)	(-1.676)	(-1.448)	(-0.104)
NClongcopper	-0.032	0.005	-0.008	0.043	0.042	-0.036
	(-0.561)	(0.104)	(-0.155)	(0.763)	(0.856)	(-0.742)
HedgePresscopper	-0.089***	-0.024	0.043*	-0.078***	-0.020	-0.055***
	(-3.648)	(-1.145)	(1.887)	(-3.205)	(-0.967)	(-2.700)
OpenInterestcrude	-0.074	-0.038	-0.071	0.035	-0.044	-0.023
	(-1.264)	(-0.745)	(-1.311)	(0.600)	(-0.881)	(-0.467)
NClongcrude	-0.040	-0.013	-0.052	-0.060	0.002	-0.047
	(-0.459)	(-0.178)	(-0.646)	(-0.698)	(0.023)	(-0.652)
HedgePresscrude	-0.064	-0.089*	0.053	-0.035	-0.081	-0.069
	(-1.065)	(-1.692)	(0.934)	(-0.590)	(-1.568)	(-1.375)
OpenInteresthogs	0.011	0.023	-0.046	0.002	0.058	0.028
	(0.222)	(0.524)	(-1.008)	(0.047)	(1.379)	(0.673)
NClonghogs	-0.067	0.083	0.090	-0.002	0.014	-0.049
	(-1.046)	(1.472)	(1.507)	(-0.035)	(0.249)	(-0.918)
HedgePresshogs	0.039	-0.025	0.004	-0.005	-0.006	0.018
	(1.620)	(-1.164)	(0.177)	(-0.193)	(-0.268)	(0.882)
OpenInterestsilver	-0.001	-0.005	-0.013	-0.014	0.005	0.010
	(-0.016)	(-0.145)	(-0.388)	(-0.371)	(0.156)	(0.310)
NClongsilver	-0.069*	-0.007	-0.006	0.009	-0.029	-0.075**
	(-1.671)	(-0.199)	(-0.149)	(0.225)	(-0.808)	(-2.178)
HedgePresssilver	0.129***	0.005	0.022	0.005	0.071*	0.113***
	(3.043)	(0.145)	(0.544)	(0.126)	(1.937)	(3.177)
OpenInterestwheat	0.039	0.127***	-0.030	0.117***	0.030	0.028
	(1.126)	(4.150)	(-0.919)	(3.371)	(0.993)	(0.959)
NClongwheat	0.095**	0.087**	-0.026	0.060	0.059	0.127***
	(2.267)	(2.377)	(-0.678)	(1.436)	(1.628)	(3.620)
HedgePresswheat	-0.109***	-0.061**	0.024	-0.064**	-0.042*	-0.099***
	(-4.002)	(-2.537)	(0.932)	(-2.367)	(-1.776)	(-4.326)

***,**,* Significant at the 0.01, 0.05, 0.10 levels, respectively.

- table continued on next page -

Table 2.5: Whole Sample OLS Regression With CIT (continued)

	Light Crude	Copper	Lean Hogs	Silver	Wheat	GSCI
Jan Dummy	-0.002	-0.003	-0.005	-0.000	-0.001	-0.001
	(-0.136)	(-0.296)	(-0.485)	(-0.003)	(-0.077)	(-0.085)
Feb Dummy	-0.016	-0.016	-0.005	-0.006	-0.009	-0.018*
	(-1.298)	(-1.480)	(-0.388)	(-0.517)	(-0.822)	(-1.706)
Mar Dummy	0.010	0.021*	-0.010	0.015	0.007	0.007
	(0.687)	(1.674)	(-0.769)	(1.049)	(0.574)	(0.578)
Apr Dummy	0.018	0.016	0.013	0.019	0.011	0.015
	(1.209)	(1.168)	(0.922)	(1.264)	(0.853)	(1.153)
May Dummy	0.006	0.015	0.021	0.006	0.009	-0.001
	(0.391)	(1.145)	(1.475)	(0.403)	(0.676)	(-0.042)
Jun Dummy	-0.011	-0.003	0.028**	-0.007	0.005	-0.014
	(-0.790)	(-0.258)	(2.167)	(-0.467)	(0.441)	(-1.187)
Jul Dummy	-0.011	-0.015	0.029**	-0.010	-0.006	-0.014
	(-0.830)	(-1.320)	(2.372)	(-0.744)	(-0.514)	(-1.298)
Aug Dummy	-0.006	-0.016	0.031**	-0.011	-0.007	-0.011
	(-0.431)	(-1.274)	(2.350)	(-0.764)	(-0.604)	(-0.944)
Sep Dummy	-0.008	-0.013	0.017	-0.008	-0.016	-0.015
	(-0.555)	(-1.019)	(1.319)	(-0.579)	(-1.326)	(-1.262)
Oct Dummy	-0.005	-0.008	0.002	0.001	-0.014	-0.013
	(-0.351)	(-0.625)	(0.144)	(0.050)	(-1.100)	(-1.094)
Nov Dummy	0.007	-0.008	-0.007	0.007	-0.007	-0.000
	(0.518)	(-0.666)	(-0.561)	(0.544)	(-0.586)	(-0.000)
Commodity Only HF AUM	0.617***	0.308***	-0.247**	0.704***	-0.041	0.501***
	(5.552)	(3.154)	(-2.378)	(6.347)	(-0.432)	(5.367)
Commodity Equity HF AUM	-0.579***	-0.293***	0.199*	-0.650***	0.023	-0.478***
	(-5.353)	(-3.089)	(1.965)	(-6.028)	(0.241)	(-5.264)
CIT Long	-0.056	-0.211***	0.069	-0.171***	-0.031	-0.081**
	(-1.179)	(-5.058)	(1.549)	(-3.609)	(-0.756)	(-2.031)
CIT Short	0.005	0.099*	-0.044	0.017	-0.021	-0.032
	(0.093)	(1.946)	(-0.811)	(0.289)	(-0.425)	(-0.660)
Index Market Fraction Long	-0.003	0.087***	-0.041	0.092***	-0.017	-0.001
	(-0.088)	(2.970)	(-1.293)	(2.753)	(-0.573)	(-0.052)
Index Market Fraction Short	0.008	-0.052	0.243***	-0.046	0.052	0.071
	(0.142)	(-1.016)	(4.470)	(-0.792)	(1.042)	(1.446)
Adjusted R^2	0.947	0.959	0.817	0.809	0.864	0.963
Number of Observations	103	103	103	103	103	103

***,**,* Significant at the 0.01, 0.05, 0.10 levels, respectively.

Table 2.5: Whole Sample OLS Regression With CIT (continued)

This table presents the ordinary least squares regression for the 24 month correlation of commodities with the equity market. This regression includes independent variables from the CFTC's CIT report limits the time period of the regression to be from January of 2008 to July of 2014. Sample size and adjusted R squared values are presented on the second page of the table.

2.6 Prediction of Future Correlation

To test my second hypothesis that factors affecting the commodity-equity correlation should significantly improve the forcast accuracy of future commodity equity I use a sequential regression approach. Beginning with an intercept term, I regress the commodity-equity correlation for a 24 month period and predict the next month's correlation using the final month's X values as the expected next month's expected X values.

$$y_t = x_t\beta + e \qquad \text{using } t = 1 \text{ through } 24 \tag{2.1}$$

$$\mathbb{E}\left[y_{25}\right] = \hat{y}_{25} = \mathbb{E}\left[x_{25}\right]\beta \tag{2.2}$$

$$pe = \hat{y}_{25} - y_{25} \tag{2.3}$$

This predicted correlation, $\hat{y}$ is then compared with the observed correlation for the next month to calculate the prediction error. This process is rolled forward one month and repeated to generate prediction errors for the remainder of the time series. The sum of squared error (SSPE) for the intercept only model is taken as the baseline predictive error. Then I test each factor individually by adding it to the intercept X matrix and calculating the SSPE for each intercept and single factor model. The factor with the greatest reduction in SSPE is selected, and this minimum SSPE becomes the new baseline. This process is then repeated with the remaining factors until all factors are added to the model. I perform sequential regressions on each of the six commodity-equity correlation for both the non-CIT and CIT time series resulting in 12 regressions. Figure 2.1 illustrates the improvement in SSPE as more factors are added to the model in sequential order for the non-CIT time series. The CIT time series improvement in SSPE is very similar and thus not presented. There is little to no gains in predictive power for adding more than four factors to the intercept. Using Diebold-Mariano tests (Diebold and Mariano (2002)), I find that no factors beyond the fourth significantly improve predictive accuracy in each of the twelve sequential regressions performed.

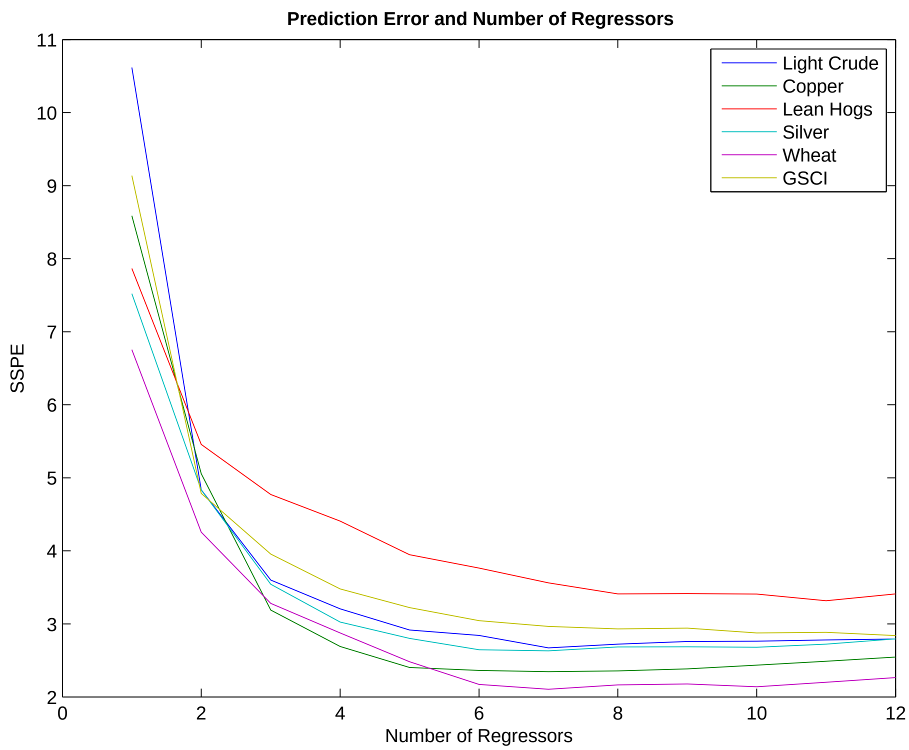

Figure 2.1: Prediction Error as a Function of Number of Regressors

This figure displays the change in sum of squared predicted error for adding independent variables. In all cases the first regressor is an intercept term. Subsequent factors are selected based on the independent variable that reduces the SSPE by the most when added as a single independent variable. Notably, a majority of prediction improvement is accomplished by the fifth variable (which is the fourth non-intercept factor).

Table 2.1 identifies the five factors for each commodity that sequentially minimized prediction errors for both non-CIT and CIT regressions. Looking first at the non-CIT regressions because of their higher number of observations. Light crude, copper, wheat and GSCI all have world production and the risk free rate as the two factors that improve predictive accuracy the most. Lean hogs and silver both have hedge fund AUM as the top two factors improving predictive accuracy. Light crude is the only other commodity showing that hedge fund AUM aids in the prediction of its correlation with the equity market. Commodity market factors such as open interest, non-Commercial long positions, and hedging pressures fill the fourth position in each of the six non-CIT sequential regressions. Seasonal effects are not significant in any of these regressions.

The CIT regressions span a much shorter time period since there is only sufficient data to begin predictions starting in early 2008. There is little substantive difference in the results of light crude, copper, and silver when comparing the non-CIT and CIT regressions. Light crude, copper, and GSCI still have global commodity production/demand factors as most important followed by futures market factors, while silver again gives the top two places to hedge fund AUM followed by a global demand and a futures market factor. Lean hogs changes the most in that no hedge fund factors load, but index market fraction of short positions loads first followed by two production/demand factors and a futures market factor. Wheat loses the risk free rate when comparing non-CIT to CIT regressions and gains CIT long in the forth position.

These results show most convincingly that global demand and production measures aid in the prediction of future equity-commodity correlation. Each of the 12 regressions performed had at least one global demand or production measure in the top three factors. The AUM for hedge funds using commodity based strategies seems to play an important roll in silver futures, lean hogs, and light crude to a lesser extent, but seems to take a secondary role to production and demand factors. There is also some evidence that the level of index investment can improve predictive accuracy for lean hogs futures and possibly wheat futures, but not as much as production and demand factors. Of note, the risk free rate which was present in four of six regressions for non-CIT regressions only appears once in the CIT regressions. This could possibly stem from the unusually low rates and low variation observed following the financial crisis of 2008. Though these sequential regressions fail to clearly reject any factors beyond seasonal indicator variables, there is more evidence supporting the role of market production and demand in predicting future commodity-equity correlation when compared to both hedge fund and index investor participation in the commodity futures market.

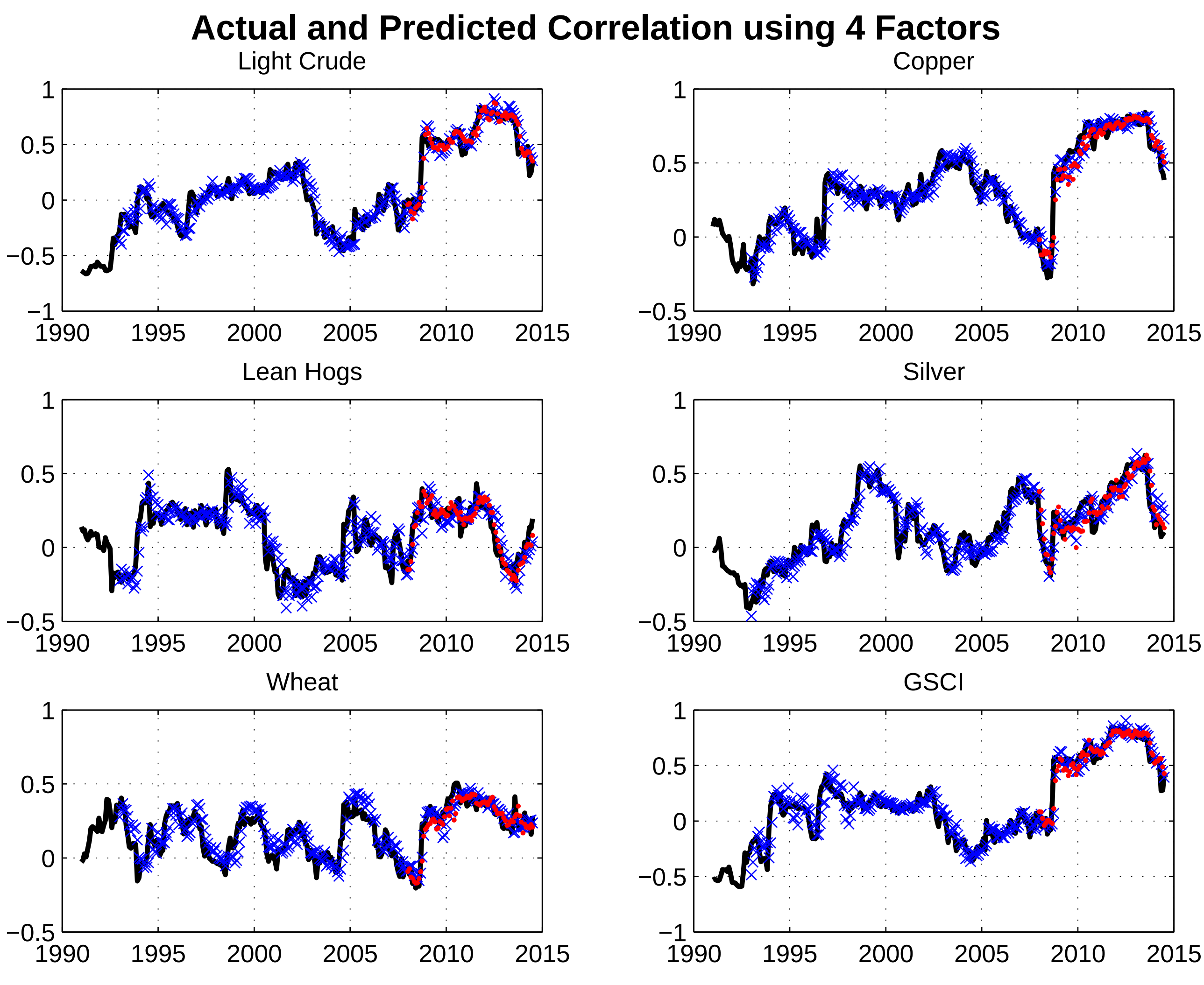

Figure 2.2: Actual and Predicted Correlation Using Four Factors

This figure shows the observed correlation of commodity futures returns and equity market returns (solid black line) with the predicted correlation including CIT data (red dots) and omitting CIT data (blue Xs). All predictions are using intercept and the 4 'best' independent variables specific to that commodity.

Table 2.1: Four Factors Showing the Greatest Sequential Improvement in Prediction Error

Non-CIT Regressions

	Light Crude	**Copper**	**Lean Hogs**
1	CPB World Production	CPB World Production	Commodity Equity HF AUM
2	Risk Free Rate	Risk Free Rate	Commodity Only HF AUM
3	Commodity Equity HF AUM	OpenInteresthogs	CPB World Production
4	HedgePresscopper	NClongcopper	OpenInterestcopper

	Silver	**Wheat**	**GSCI**
1	Commodity Only HF AUM	CPB World Production	CPB World Production
2	Commodity Equity HF AUM	Risk Free Rate	Risk Free Rate
3	BDI	OpenInterestcopper	OpenInteresthogs
4	NClongcopper	HedgePresshogs	HedgePresscopper

CIT Regressions

	Light Crude	**Copper**	**Lean Hogs**
1	CPB World Production	BDI	Index Market Fraction Short
2	Risk Free Rate	NClongcrude	CPB World Production
3	HedgePresscopper	CPB World Production	OpenInterestsilver
4	OpenInterestcrude	NClongsilver	NClongsilver

	Silver	**Wheat**	**GSCI**
1	Commodity Only HF AUM	BDI	BDI
2	Commodity Equity HF AUM	NClongcopper	CPB World Production
3	CPB World Production	OpenInterestsilver	GDP
4	OpenInterestcopper	CIT Long	OpenInterestsilver

This table presents the four factors that sequentially minimized SSPE when added to an intercept only model one at a time. The ordering of factors goes from most significant improvements in prediction errors as measured by both Diebold-Mariano test statistics and SSPE. The non-CIT regressions

2.7 Conclusion

The departure from historical norms of commodity-equity correlation made it such that it was not beneficial for equity investors seeking diversification to invest in commodities during the financial crisis of 2008. Since the end of 2011, commodity-equity correlation has returned to near-normal historic levels, and currently there is a benefit to equity investors adding exposure to commodity markets.

World commodity supply and demand measures such as the Baltic Dry Index or Netherland's CPB world production index are more consistently helpful in predicting future commodity-equity correlation than hedge fund AUM with commodity strategies or measures of index investment in commodity markets. However, hedge fund and index investment in commodities may still be important in commodity market price movements and correlation.

There are several subjects within this area of research that could be explored further. The prediction models in this paper are basic OLS regressions that could be improved by adjusting for nesting and by improving the expected values of the independent variables for the prediction. Regime shifting models would also be an interesting way of analyzing correlation trends in future work.

In my view, the most important unanswered question is whether or not commodity-equity correlation will return to high levels during a future downturn in equity markets.

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Chapter 3

Board Member Expertise and Distressed Firm Bankruptcy

Abstract

This paper examines the associations of various types of director expertise on a distressed firm's ability to avoid bankruptcy. Since the advent of the Sarbanes Oxley Act of 2002 there have been significant increases in the percentage of board members with accounting, investment banking and legal expertise. In a study of US firms during the period between 1996 and 2011, I find that the percentages of bankers and lawyers on boards are associated with significant changes in the likelihood that a firm will enter bankruptcy. No similar effect is observed for board member accounting expertise. These results support the idea that bankers may aid distressed firms in renegotiating their debt, enabling them to avoid bankruptcy.

3.1 Introduction

If a firm's poor performance is coupled with a sufficiently large debt load, the firm may be unable to pay its debt obligations. In this case it may have to choose between filing bankruptcy or restructuring its debt. In general, restructuring debt yields better returns to shareholders than going through bankruptcy. However, a distressed firm cannot unilaterally decide to restructure its debt. There must be a consensus among its debt holders. If a firm can negotiate new debt agreements that it can meet, the firm can avoid bankruptcy through negotiations with debt holders. These negotiations often involve debt holders trading a portion of their debt for equity interests in the firm. Although prior research on a distressed firms' ability to avoid bankruptcy through out-of-court negotiations of debt restructuring has mainly focused on firm operating performance and the characteristics of its existing debt.

The negotiation of new debt agreements is not based solely on a firm's operating performance or debt characteristics. The negotiation process involves key players within the firm as well as the major debt holders. Common major debt holders for typical firms usually include investment banks and institutional investors. Debt renegotiation is common. Roberts and Sufi (2009) show that over 90% of long term debt contracts are renegotiated prior to maturity. From a firm's perspective, debt renegotiation is likely to be uncommon, but from the banker's perspective it occurs often. Board members bankers, familiar with debt renegotiation could be well suited to aid a firm in offering new agreements to its debt holders. The board of directors has a role to monitor, but also to advise. A firm that has board members with an intimate familiarity of debt restructuring would hold an advantage in the renegotiations of debt agreements when a firm is in distress. Additionally, the banker's inside connections may also aid in debt negotiations. The Sarbanes-Oxley(SOX) Act of 2002 mandated that the audit committee of a firm's board of directors be made up entirely of independent directors and that there must be at least one 'financial expert' in the committee. Linck (2009) finds that between 2001 and

2005, the average percentage of financial experts on the board of directors grew significantly from 10.45% to 12.77%. The stated purpose of SOX was "To protect investors by improving the accuracy and reliability of corporate disclosures made pursuant to the securities laws, and for other purposes." Bédard (2004) and Krishnan (2011) find that accounting and legal expertise in a board's auditing committee is associated with less aggressive earnings management and improved financial reporting quality. Both these papers focus on audit committees and they tend to support the stated purpose of SOX by helping to improve the accuracy and reliability of disclosures. However, Güner (2006) questions some of the possibly unintended effects of SOX legislation. Specifically, the original wording in SOX defined a financial expert as essentially either a CPA or a CFO. However, by the time the bill was passed, the definition had been relaxed.

> "a key change between the proposed and final rules, allowed people who were several degrees removed from the actual issuance of financial statements, such as investment bankers, venture capitalists, and CEOs, to fill the role." (Stuart 2005)

Stuart's (2005) review of the designated financial experts of Fortune 500 companies in 2005 found only 16% were CFOs and 8% were public auditors. The sample used by Güner et al. found much lower numbers: 1% CFOs and 0.5% accountants. They both found that the vast majority of those who claimed the title financial expert were investment bankers often still having ties to a specific investment bank. It would not be expected that an experienced accountant would have similar ties and familiarity with debt restructuring that a banker would, though under SOX both accountants and bankers are classified "financial experts". An intent of SOX was in increase reporting accuracy by having more accountants and CFOs on boards, but it seems to have instead increased the prevalence of bankers onto boards.

Another demographic change in boards over the past decade is an increase in legal expertise found in the board of directors. Though this is not mandated in SOX, from 2001 to 2005 the percentage of lawyers on boards grew 4% from 5.55% to 9.69%, nearly doubling (Linck 2009) possibly due to the increased culpability of managers and directors resulting from SOX legislation. Again, like accountants, attorney directors would not have the same level of familiarity and experience with debt restructuring as bankers, but may be able to give quality advice regarding both restructuring negotiations as well as bankruptcy proceedings due to the inherent legal nature of each process.

The testable hypotheses of this paper are as follows. First, a higher percentage of banker directors on a firm's board should decrease the likelihood of a firm going bankrupt. Second, the percentage of accountants on the board should not affect the likelihood of a firm going bankrupt. Third, a higher percentage of attorney directors on a firm's board should decrease the likelihood of a firm going bankrupt.

In addition to testing hypotheses, I include a descriptive analysis of the changes in board size, composition, and expertise as event studies around Compustat delisting or dropping below an Altman-Z score of 1.8. The justification for choosing an Altman-Z score of 1.8 being that below that threshold, a firm is said to be in financial distress (Altman 1968). The descriptive analysis of board size helps to illustrate the cost benefit problem that individual directors face when weighing the decision to leave or stay a firm that may possibly go bankrupt.

The rest of this paper is outlined as follows. In the next section, I cover relevant background in this field. Section III describes the data and methods of analysis of the data. Results are presented in section IV and section V is the conclusion.

3.2 Background

3.2.1 Challenges Faced by Distressed Firms

There are many choices faced by a firm's top management and board of directors when the firm's performance flags and the likelihood of restructuring or bankruptcy is high.

3.2.1.1 Negotiations and Determinants of Bankruptcy

Though legal, it is rare for a firm to file for chapter 11 bankruptcy protection without ever contacting or negotiating with its debt holders. There is incentive for troubled firms to try to avoid bankruptcy through renegotiation of their debt contracts. Gilson (1990) find that returns to shareholders in general are lower for bankruptcy compared to private renegotiation of debt. In order for a firm to successfully renegotiate its debt obligations outside of bankruptcy court, it must negotiate with all its debt holders and each must agree on the new arrangement. Bankruptcy law allows for resolution without a full consensus, but is generally more costly for the firm. Chatterjee (1996) found that the ability of a firm to restructure its debt was dependent on the extent of the firm's creditors' coordination. Brunner (2008) found similar results in Germany when "bank pools" were created to aid in lender coordination during times of distress. Yost (2002) analyzed the determinants of operating performance on the likelihood of a firm going through chapter 11 bankruptcy, prepackaged bankruptcy, or out-of-court restructuring. He found that better performance and more long-term debt contracts pushed a firm's likelihood of bankruptcy down and increased its likelihood of successful renegotiation.

Distressed firms that have CEO duality and have more inside directors show markedly higher bankruptcy rates (Simpson 1999 and Daily 1994).

Legal experts may also affect a firm's likelihood of avoiding bankruptcy. Since the renegotiation of the contracts have a need for legal agreements between the firm and its creditors, a lawyer on the board may be beneficial. But the bankruptcy process is arguably also a domain where legal expertise is valuable since the duration and terms of the bankruptcy are often determined by judges and lawyers and can occur as long as a sufficient portion of the debt seniority classes agree (Gilson 2012). Additionally, firms with more legal expertise on the board may be more likely to file for bankruptcy based on strategic legal protection concerns instead of financial concerns as outlined in in Rose-Green and Dawkins (2002).

3.2.1.2 Leadership Exodus

Turnover in the upper echelons of a firm is a topic of much discussion. Individually, the directors and management face the decision to stay on board or flee a ship that might sink dragging them down with it. Gales and Kesner (1994) found that over the period of 4 years surrounding bankruptcies, both board size and the percentage of independent directors decrease. There is observably higher executive turnover rates for distressed firms and decreases in board size leading up to bankruptcy from the departure of outside managers. Any amount of exodus by the board or management may increase work load for the remaining management and board either due to efforts to replace losses, or simply from less managers and directors.

A turnover in management or the board of a distressed firm may help the firm recover or bring it closer to the brink of default or bankruptcy. However, loss of continuity in management or the board in some cases could be more costly than the potential benefits of hiring someone new. In a December 2000 Wall Street Journal article on Robert S. Miller, a 'turnaround specialist' and former CEO of Delphi Corp., Waste Management, Aetna, and Federal Mogul said "you don't have to fire the losing team in order to make [the company] a winner." However, Hotchkiss (1995) finds that lack of management turnover during a bankruptcy process is correlated with poor post-bankruptcy operating performance. Additionally, Hambrick and D'Aveni (1992) find that a bankrupt firm's top management team (CEO, president, and major department managers) deteriorates, often without external pressure, leading up to bankruptcy "through a combination of voluntary departure, scapegoating, and limited resources for attracting new executive talent." Whether departure is voluntary or forced, it is difficult to determine whether departure of directors and managers is caused by or causes poor performance. Denis and Denis (1995) show that forced resignations of top managers (though rare) are in general preceded by declines in operating performance and followed by improved operating performance, however no causality is proven.

First from the director in a distressed firm's point of view, there is the cost of leaving including seeking a new job, severing ties, forgoing notoriety from a possible turnaround, etcetera. This is offset by the potential benefit of leaving before the firm gets any worse off. Gilson (1989) analyzed distressed firms and found a high personal cost to top level managers. His study found a higher rate of turnover (52% of distressed firm-years had at least one top level management change, compared to 19% of non-distressed firm-year observations). Additionally, of the approximately 100 top level managers that left during distress in this study, *not even one of them* was later employed as a top level manager in any publicly traded firm for at least 3 years following their exit. This supports his argument that there is high personal cost to top level managers when firm distress reaches the point of bankruptcy, default, or debt restructuring. However, there can also be great rewards to individuals who can right the ship. Ellis (2011) finds that firms that hire a turnaround specialist CEO are significantly different than comparable firms that hire a non-turnaround specialist CEO. These turnaround specialists have a niche in the business world, and have been shown to make positive changes to companies in distress. Specifically, firms that hire a turnaround specialist have higher probability of distress, have lower profit rates, but also have 6% higher abnormal returns around the CEO hiring announcement, reduce their scales of operation, and improve operating performance more than firms that hire non-turnaround specialist CEOs. Turnaround specialists are not the only types entering on the scene when a firm becomes distressed. Hotchkiss and Mooradian (1997) find that firms in default who become controlled by a vulture investor show improved post-restructuring operating performance compared to other firms in default. Control can either be through appointment as CEO, chairman, or through ownership of a controlling portion of debt which can enable them to bargain in strength and influence the terms of restructuring. There are also positive abnormal returns associated with the announcement that a firm has been taken control of by a vulture investor, indicating probable value addition to the firm. Strömberg, Hotchkiss and Smith (2011) Find that private equity backed firms are no less likely to default than other firms, but when they are distressed take less time to complete a restructuring, and they are more likely to survive as an independent going concern compared to non-private equity backed firms. In any case, directors or managers that choose to stay with their firms "will have incentives to run their firms more efficiently to increase operating cash flows" as Gilson states. Staying with a distressed firm is only one of a few strategies the managers may select. Another would be to leave the firm prior to reaching a major negative event such as bankruptcy or forced restructuring. Several authors have found that many directors and managers do leave a firm around the period of distress. Daily and Dalton (1994) present the finding that in comparison to a matched group of survivor firms, bankrupt firms have a higher proportion of inside directors, and higher instances of CEO duality. Gales and Kesner (1994) agree with Daily and Dalton while extending Hambrick and D'Aveni's work to the board of directors. They analyze the size and composition of bankrupt firms' board of directors two years prior, at, and two years post bankruptcy. They find that consistent with Hambrick and D'Aveni, there is an exodus of outside directors at each time period and overall board size decreases. Interestingly here, their finding indicate that outside directors are still trying to leave even after the bankruptcy has past. In an analysis of banking firms, Simpson and Gleason (1999) found that only CEO duality seemed to have a significant effect on a firm's likelihood to be distressed. This partially agrees with the findings of Daily and Dalton, but doesn't show support for a change in board composition. However, this study was limited in scope to banking firms.

3.2.2 Director Expertise

Legal and financial expertise of a firm's board of directors have mainly been focused on financial reporting and operating performance. A few papers touching on financial reporting mainly focused on the audit committee; Bédard et al. (2004) found that aggressive earnings management is negatively associated with financial and governance expertise on a board's audit committee. Krishnan et al. (2011) found that legal, financial and the interaction between legal and financial expertise all help to increase financial reporting quality when present in a firm's audit committee. Güner et al. (2006) focused on financial expertise and distinguishes it into categories of investment bankers and accountants. They found that firms with investment banker directors tended to have more access to external funding, larger bond issues and worse acquisitions. They also find that in general, an investment banker director tends to benefit the associated investment bank more than the firm in terms of fees, operating performance, and share price.

3.3 Methods & Data

I obtained board of director information from Risk Metrics, combining the legacy Risk Metrics (1996 to 2006) and the newer Risk Metrics (2007-2011) information into one large set. Since there is an inherent difference between these two periods of data, I implemented a legacy indicator variable which was included in all regressions. The time frame of my study goes from 1996 to 2011. I used CRSP and compustat merged data to calculate altman-Z scores as well as delisting dates and reasons. The formula for Altman-Z is:

$$Z = 1.2\frac{(ca - cl)}{ta} + 1.4\frac{re}{ta} + 3.3\frac{(ni + int + tax)}{ta} + 0.6\frac{cso \times p}{lt} + 0.999\frac{s}{at}$$

Since the proceedings of bankruptcies involve outside decision making regarding the firms operations and hirings, I focused on periods before bankruptcy. This narrows the study to the firm's volitional changes (from shareholders, board, or managers themselves) associated with distress before any major intervention.

I used Compustat delisting codes 2 (chapter 11 bankruptcy) and 3 (chapter 7 bankruptcy) as bankruptcy. Additionally, I hand collected information on several firm's boards by reading SEC records of firms' DEF 14A form fillings. Hand collection augmented the data

Table 3.1: COMPUSTAT Variables Used for Calculating Altman Z

Variable	**Name**	**Compustat FTP Name**
ca	Current Assets	DATA4
cl	Current Liabilities	DATA5
ta	Total Assets	DATA6
s	Net Sales	DATA12
int	Interest Expense	DATA15
tax	Income Taxes - Total	DATA16
p	Stock Price	DATA24
cso	Common Shares Outstanding	DATA25
re	Retained Earnings	DATA36
ni	Net Income/Loss	DATA172
tl	Total Liabilities	DATA181

by adding 235 firm year observations of board expertise composition from 23 different firms. This brought the number of firms that went to bankruptcy in my data set up to 82 with a total of 466 firm-year observations of board composition. Firms not undergoing bankruptcy during 1996 to 2011 account for the majority of data: 3794 firms with 24528 firm-year observations for a total of bankrupt and non-bankrupt firm count of 3853 with 24759 firm-years. Due to data limitations, I do not have information on out-of-court debt negotiations, and thus I will treat not going bankrupt as indistinguishable from successful negotiations to avoid bankruptcy.

The fraction of independent board members, as well as the fraction of the board with specific experience were collected from both Risk Metrics as well as the hand collected firms. I classified the board member's experience into lawyer, banker, consultant, retired, accountant, and academic. An extension to the data collection that I intend to pursue in the future is analyzing board turnover. In the hand collected data, I was able to quantify how many members of the board left in a given year and how many newly joined the board. This may bear importance in the dynamics of a board in times of distress.

Using the Risk Metrics, I collapsed the individual director observations for each board meeting into a single observation that included board size and composition including a

Table 3.2: Summary Statistics for Bankrupt and Non-Bankrupt Firms

Non-Bankrupt Firms

Variable	Obs	Mean	Std. Dev.	Min	Max
Total Assets	539189	6047.9	59957.63	0	3879172
Market Cap	567134	2270.7	11991.82	0	604414.8
Sales	542198	547.25	2952.758	-25623	207307.3
Board Size	24524	9.494	2.8064	1	39

Bankrupt Firms

Variable	Obs	Mean	Std. Dev.	Min	Max
Total Assets	16309	518.34	2346.016	0	67260
Market Cap	18478	211.1	1232.406	0.064666	65416.54
Sales	16197	109.69	855.9007	-1783.76	50129
Board Size	235	8.668	2.2438	3	18

percentage of each expertise listed above in each board. Using the time series data from compustat I generated two variables *zdrop* and *delist* with which I created my event studies. The variable *zdrop* was assigned a value of zero in the first year a given firm had an Altman-z score below a threshold level of 1.8. This value was chosen based on Altman's (1968) classification that firms with scores below this level were "in distress" or in other words, in danger of default or bankruptcy.

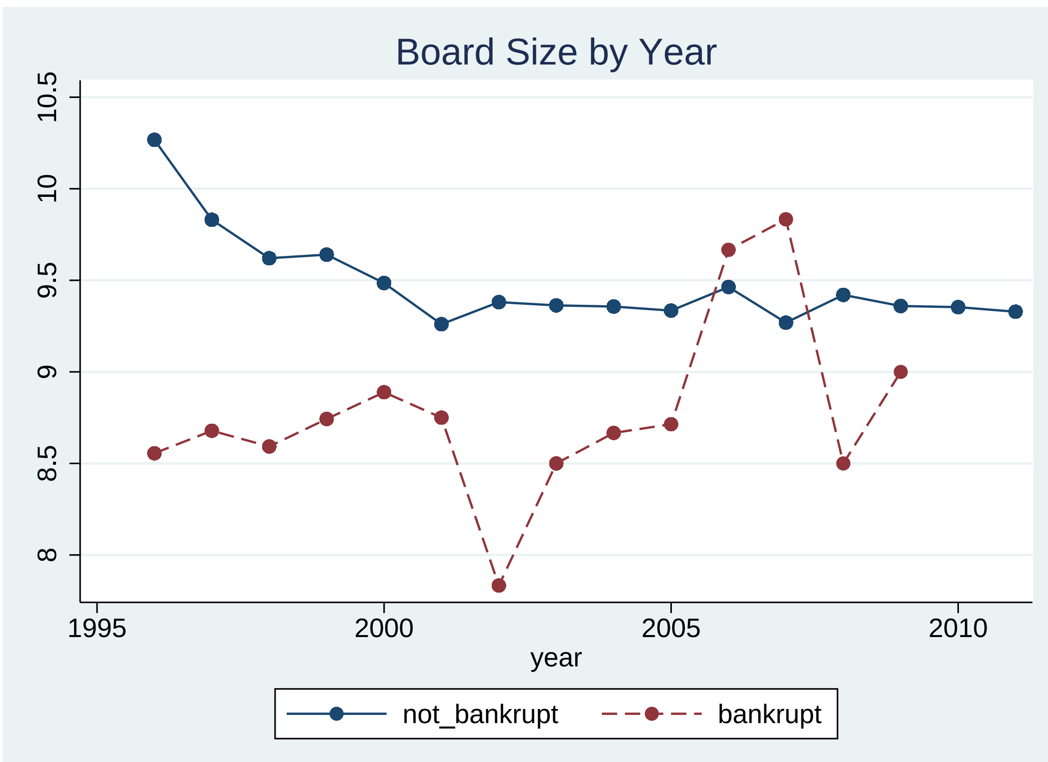
Since it is apparent that there is a large difference in the average bankrupt and non-bankrupt firm in the sample, I have included control variables in my regression including total assets, market capitalization, sales, and market to book. Additionally, the hand-collected and Risk Metrics data were not entirely comparable. The frequencies of lawyers, bankers, accountants, and academics were all significantly higher in the hand collected data. These differences could not be reconciled through going over the Risk Metrics data in a different way. Analyses without the hand collected data are presented in this paper, and the combined data analyses are included in the appendix for comparison.

3.4 Results

For the testable hypotheses, I used logistic regression of the likelihood of bankruptcy based on the percentage of board expertise in bankers, lawyers and accountants, while including the control variables mentioned above in the data and methods section.

In each regression that includes accountants, the effect is not even close to marginally significant, supporting my second hypothesis that the percentage of accountants on a board should not effect the likelihood of a firm going bankrupt. However, %Insider, %Lawyer, and %Banker each are, with lawyers being marginally so.

Figure 3.1: Firm Board Size By Year



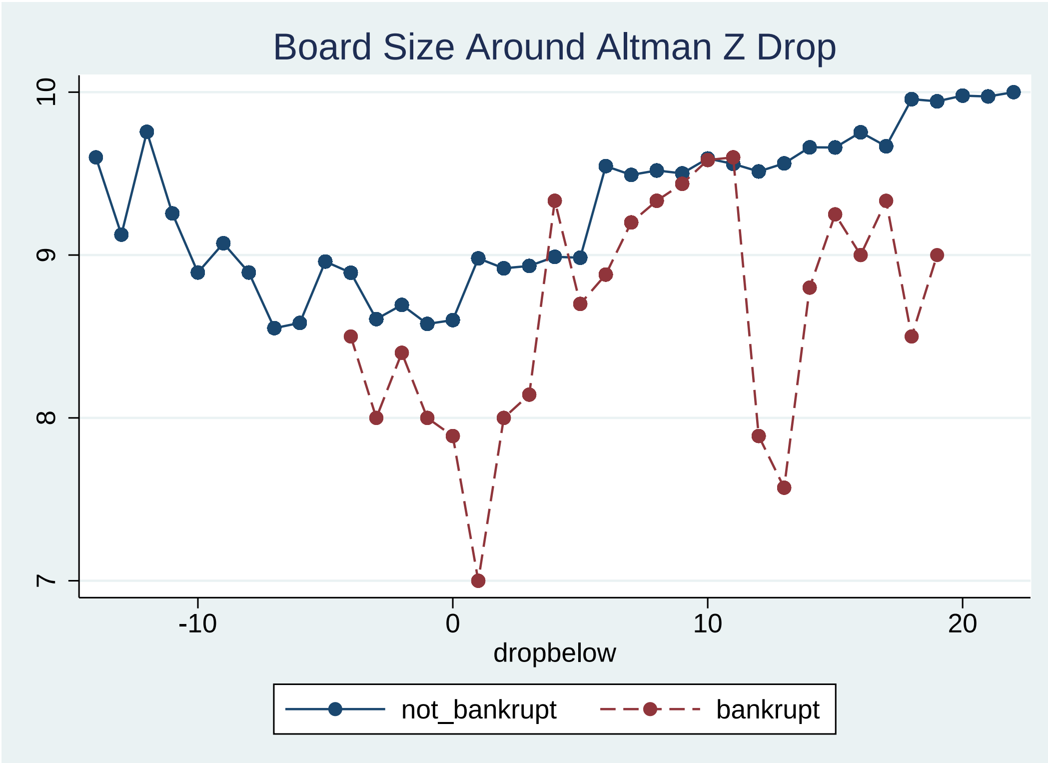
Average board size for firms that did not go bankrupt between 1996 and 2011 (solid line) and firms that did go bankrupt during that same period (dashed line)

Table 3.1: Logistic Regression of Bankruptcy on Board Composition

	I	II	III	IV
%Insider	0.312	0.461	0.467*	
	(0.335)	(0.101)	(0.096)	
%Lawyer	3.244*	2.835*	3.032*	3.815**
	(0.059)	(0.064)	(0.072)	(0.021)
%Banker	-3.161**	-3.783**	-3.213**	
	(0.019)	(0.001)	(0.012)	
%Consult	0.272			
	(0.852)			
%Retired	0.073			
	(0.942)			
%Accountant	-1.570	-2.170		-0.878
	(0.778)	(0.692)		(0.874)
%Academic	1.831			
	(0.298)			
Controls	Yes	Yes	Yes	Yes
n	12892	12892	12892	12892
Pseudo R^2	0.1409	0.1348	0.1402	0.1345

Logistic regression with independent indicator variable bankruptcy with percentage compositions of the board specialty, control variable and year fixed effects. P-values are in parentheses, ** significant at the 5% level and * significant at the 10% level. Column I is with all percentages, Column II is with only the percentage of insider directors, column III is with insider directors, lawyers and bankers and column IV is bankruptcy specialists alone.

Figure 3.2: Board Size Around Altman-Z Drop



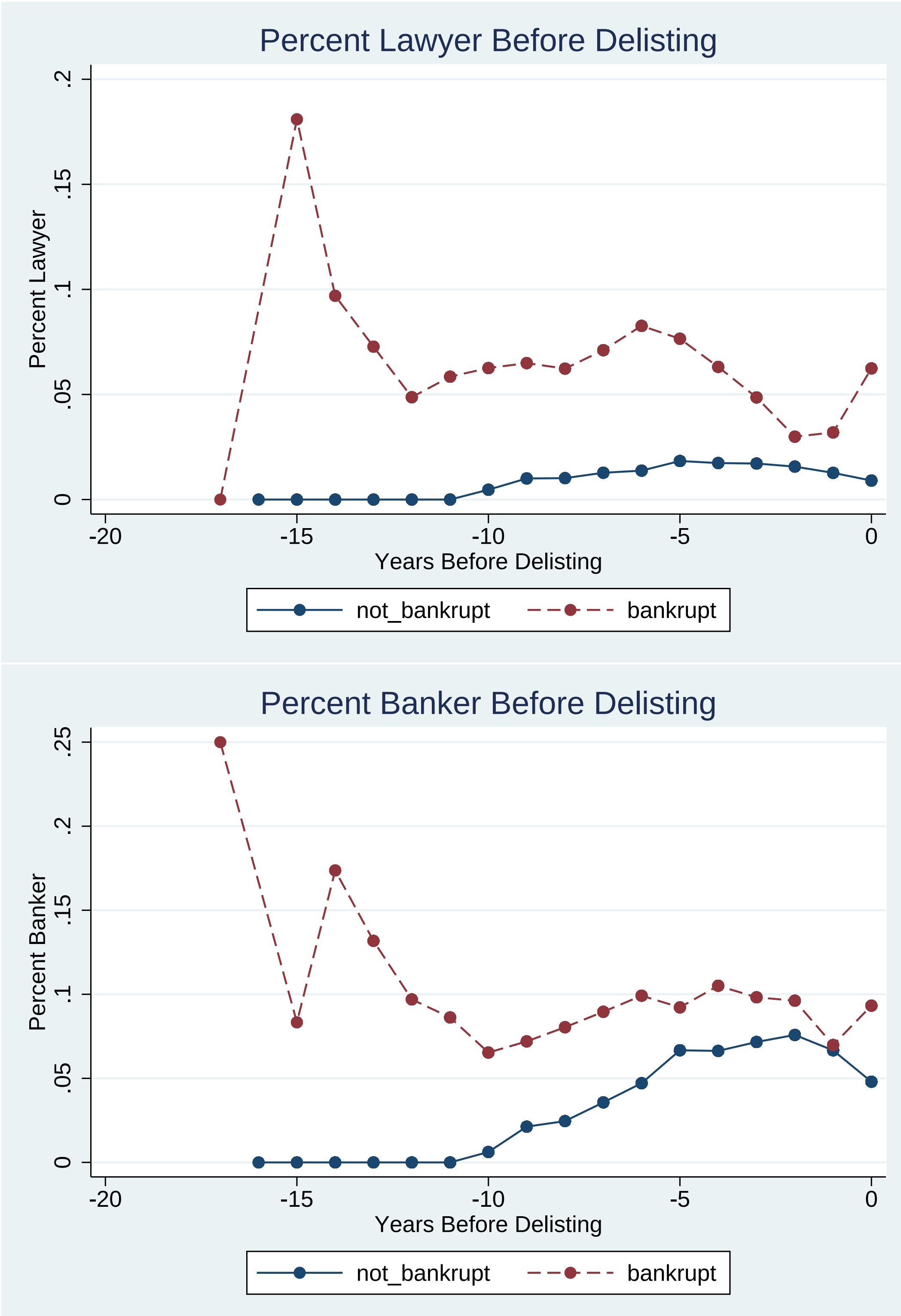
Average board size for firms that did not go bankrupt (solid line) and firms that did go bankrupt during that same period (dashed line) as an event study for firms that experienced a first time Altman-z score below 1.8 during the sample's time period from 1996 to 2011.

I generated a time plot of board size for the duration of the study. Of note, there is a decreasing trend in board size over the 25 years of data in this study. The majority of the reduction in board size happened in the late 90s. Subsequently, board size for the sampled firms has stayed relatively constant hovering right around an average of 9.5 board members. Figure 1 is a plot of board size with time.

I performed OLS regressions, on year, but also on the two events, *zdrop* and *delist*. Studying the behavior of board size around *zdrop* will help shows evidence against hypotheses 1.

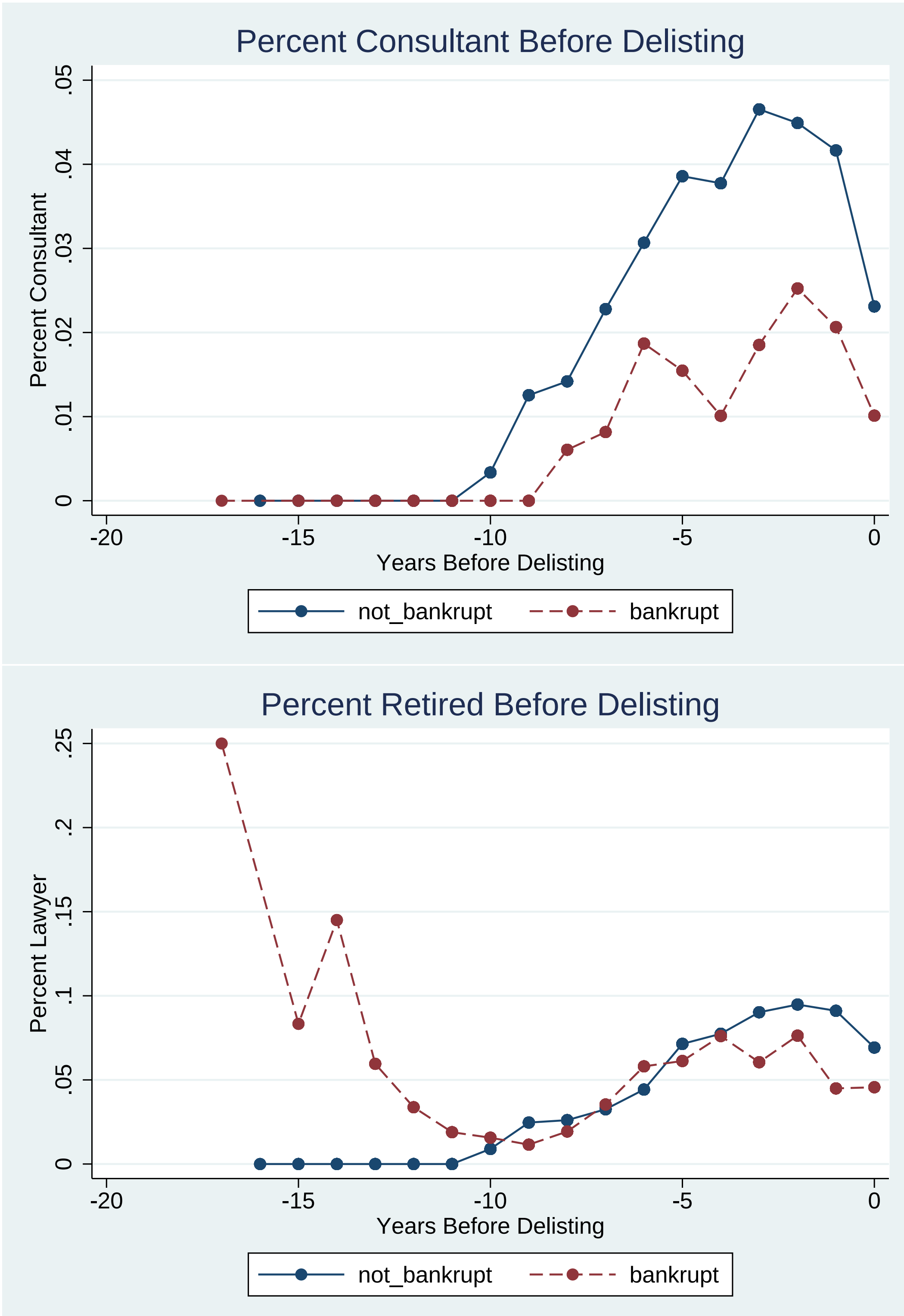
The evidence supports rejecting hypothesis 1. A reactionary executive exodus following a period of financial distress is not evident. If anything, a possibility could be that the drop

Figure 3.3: Event Studies Based on Board Expertise: Lawyer and Banker



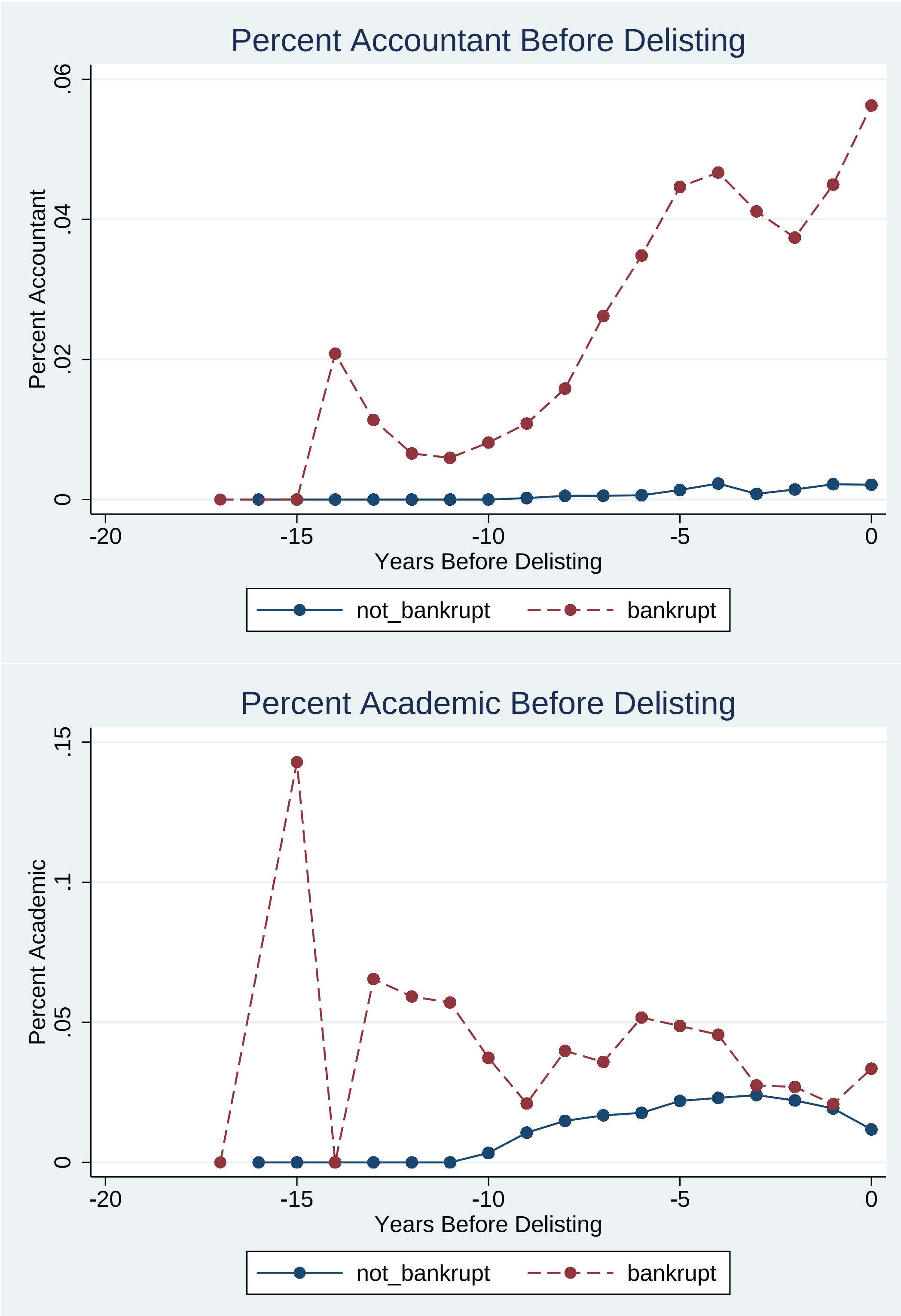
Event study plots comparing firms that went bankrupt to other firms that were delisted for non-bankruptcy reasons, such as going private or being acquired. In each plot the event is the point at which the firm was delisted and that year is labeled year zero.

Figure 3.4: Event Studies Based on Board Expertise: Consultant and Retired



Event study plots comparing firms that went bankrupt to other firms that were delisted for non-bankruptcy reasons, such as going private or being acquired. In each plot the event is the point at which the firm was delisted and that year is labeled year zero.

Figure 3.5: Event Studies Based on Board Expertise: Accountant and Academic



Event study plots comparing firms that went bankrupt to other firms that were delisted for non-bankruptcy reasons, such as going private or being acquired. In each plot the event is the point at which the firm was delisted and that year is labeled year zero.

in board size from almost 10 to below 9 may be a more likely cause for the distress than the other way around.

3.5 Conclusion

Board composition and makeup naturally varies with time. With the enactment of SOX, director expertise has changed. The specific makeup of the board of directors can contribute to swaying a firm toward or away from bankruptcy. The percentage of investment bankers on the board is negatively correlated with the likelihood of a firm to go bankrupt. Though in SOX, both accountants and bankers are classified as financial experts, the percentage of accountants in a board has no effect on the likelihood of a firm going bankrupt. These two findings combine to support the negotiation hypothesis that the familiarity of bankers with out-of-court debt restructuring aids firms in the negotiation process, whereas there is no comparable benefit in negotiation from accounting experience on boards. The percentage of lawyers on a board was also correlated with the likelihood for a firm to go bankrupt, but in this case it is positively correlated. This could be due to the fact that lawyers may be limited in effectiveness when advising the firm on debt restructuring, but may be more likely to advise the firm to go through bankruptcy possibly for strategic legal reasons.

Descriptive analysis of a firm's board size following a drop in Altman-Z below 1.8 shows a notable drop in board size for 1 to 2 years following, but then a subsequent recovery to normal board size when compared to non-bankrupt firms. This is in agreement with other research on changes in board size around bankruptcy.

In summary, there is a noticeable trend of director exodus following a drop in a firm's z-score below the threshold level of 1.8 but only in the first couple of years. In fact, after two years the trend is increasing. The expertise of a board can have significant effect on a firm's likelihood to go bankrupt. Bankers tend to aid a firm in avoiding bankruptcy by lending the firms advice beneficial in negotiating a restructuring of debt out-of-court, whereas lawyers tend to lead a distressed firm towards the court process of bankruptcy in order to bring about a debt restructuring.

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