Three Essays on Idiosyncratic Volatility

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Abstract

Three Essays on Idiosyncratic Volatility

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This thesis consists of three essays. The first essay (chapter two) examines the relationship between idiosyncratic volatility and future returns in the Canadian market. The negative relationship between realized idiosyncratic volatility (*RIvol*) and future returns uncovered by Ang et al. (2006) for the US market has been attributed to return reversals. For the Canadian market where return reversals have considerably less importance, we find that *RIvol* is positively related to future returns, even after controlling for risk loadings, illiquidity and reversals. Unlike the findings of Bali et al. (2011) for the US market, we find for the Canadian market that the relationship between extreme positive returns and future returns is positive and that idiosyncratic volatility is consistently positively related to future returns.

The second essay (chapter three) discusses the relationship between closed end fund discounts and the level of uncertainty about its holdings. Our trade-off model states that the intrinsic premium of a closed-end fund (CEF) is equal to the CEF's price minus both its NAVPS (net asset value per share) and the net present value (NPV) of its future benefits from liquidity, managerial abilities and leverage minus its managerial costs. Any additional premium will persist to the extent that arbitrage between these two price series is both costly and risky. We find that arbitrage incompleteness due to the uncertainties about this NPV and the CEF's holdings, as captured by idiosyncratic risk and other proxies, explains over two-thirds of the variation in CEF premiums or their changes. As expected, we find that the CEF premium is negatively related to gross leverage, management fees, cash and bond holdings, and positively related to liquidity enhancement, CEF performance and net leverage. These results are consistent with our finding that changes in CEF prices and NAVPS are more integrated than segmented using the Kappa test of Kapadia and Pu (2012).

The third essay (chapter four) investigates the information content of idiosyncratic volatility around the public release of M&A rumors. We examine the releases of hand-collected initial rumors about potential M&A for 2250 firms. Unlike previous research, we find that a strategy of investing in firms with rumors of lower (greater) credibility yields negative (positive) changes in idiosyncratic volatilities around the rumor dates and subsequent returns. We argue that this asymmetric effect on idiosyncratic volatilities is linked to asymmetric changes in the heterogeneity of the probabilities of actual M&A when conditioned on rumor credibility. Changes in idiosyncratic volatilities are positively related to

the market implicit probabilities of M&A as measured by the ratio of the market values at the M&A announcement and rumor dates.

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CHAPTER ONE

INTRODUCTION

Following the seminal work of Sharpe (1964), Lintner (1965) and Black (1972) on the CAPM, many financial economists and practitioners maintain that only systematic risk is priced under the assumption that investors are rational and returns are mean-variance efficient. Subsequent asset pricing models also generally assume that idiosyncratic risk (*Ivol*) is not priced. Goetzmann and Kumar (2008), among others, find that investors are not nearly as diversified as they should be. If investors do not hold diversified portfolios, are they compensated for their exposure to *Ivol*? Various asset-pricing models for imperfect markets (e.g., Merton 1987) predict a positive relationship between the incremental risks from holding not fully diversified portfolios and expected returns. In turn, this implies that expected returns are positively related to *Ivol*. In contrast, Ang *et al.* (2006, 2009) report a negative relationship between lagged *Ivol* and future returns. Since this finding is counter to expectations, it is dubbed the "idiosyncratic volatility puzzle". The role of idiosyncratic volatility increased over the past decade to reflect the limitations of asset pricing models in explaining expected returns. In this thesis, we investigate the role of idiosyncratic volatility in financial markets.

In the first essay (chapter 2), we investigate the relationship between *Ivol* and the future returns of individual stocks in the Canadian market. The use of the Canadian market is motivated by the evidence of much weaker return reversals in Canada than that documented in the US and the industrial composition of the Canadian market which differs markedly from that in the US. Our findings suggest that unlike the anomalous findings of Ang *et al.* (2006, 2009), there is a positive relationship between *Ivol* and future returns. Our findings are analogous to the findings of Huang *et al.* (2010) who argue that after controlling for return reversals in the US, the negative relationship between *Ivol* and future returns disappears. Our findings are consistent with the theory and are robust to risk loadings, return reversals, skewness and illiquidity.

We further investigate the relationship between extreme daily returns in a month with the future returns. Bali *et al.* (2011) uncover a negative relationship between extreme within-the-month positive returns and future returns and conjecture that this relationship is what is mistakenly explained by Ang *et al.* (2006) as the *Ivol* effect. Bali *et al.* (2011) argue that investors distort their beliefs and overweight stocks with extreme lagged daily returns. We hypothesize that this relationship might be a manifestation of the return reversion process in the US market. For the Canadian market, we find no sharp reversals in extreme returns. We find that the relationship between lagged *Ivol* and returns does not disappear after controlling for extreme positive returns in the prior months. Our results are confirmed using Fama-MacBeth equally and value weighted two stage regressions and Brennan *et al.* (1998) two stage risk-adjusted regressions.

In the second essay (chapter 3), we propose a tradeoff model that uses *Ivol*, among other variables, to explain the well documented anomalous negative closed end fund (CEF) premium. Many financial academics find the existence of this negative premium inconsistent with the market efficiency hypothesis (Cherkes 2012). The market efficiency hypothesis and the law of one price imply that the price of a share of the CEF and the CEF's net asset value per share (NAVPS) should be equal in frictionless markets. We investigate this phenomenon from an arbitrageur's perspective and we provide evidence that at least a significant portion of the gap of a CEF's price from its fundamental value is due to limits to arbitrage. It reflects the compensation that an arbitrageur would require for the hedgeable and non-hedgeable risks arising from the fund's portfolio composition and its uncertainty. Using the idiosyncratic volatility (*Ivol*) of the net position return obtained from a long/short position in the CEF price and its NAVPS, we identify a significant relationship between CEF premiums and *Ivol* differences only when the fund has positive returns in the previous period.

Our tradeoff model relates the benefits from holding the fund which the literature identifies as enhanced liquidity, managerial abilities and leverage, to costs such as management fees. The difference between the liquidities of the CEF and its holdings capture the liquidity benefit, Jensen's alpha captures managerial ability benefits and the ratio of non-common equity to assets (less the cash-to-asset ratio) captures the gross (net) leverage benefit. Our findings support the hypotheses that state that CEF premiums are positively related to these benefits (net but not gross leverage) and negatively related to management fees. We find that the premium not captured by our model is related to the unhedged systematic and idiosyncratic risk exposures associated with the net position from risk arbitrage between the CEF and its equivalent NAVPS. For the other proxies for the uncertainty of holdings, we find that CEF premiums are related negatively to idiosyncratic skewness but not related to options holdings.

The third essay (chapter 4) investigates the information content of idiosyncratic volatility around the release of rumors of M&A. Unlike earnings announcements, merger and acquisition (M&A) announcements are less frequent and more unpredictable events with a considerable impact on stock prices, especially for the acquired firms. Thus, being able to assess the credibility of rumors about potential M&As could be profitable. Under a rational expectations model with normally distributed returns, the absolute expected return conditional on the sign of the return increases with return volatility. All else equal, a (positive) negative relationship is expected between return volatilities and expected returns conditional on (good) bad news (Diamond and Verrecchia 1987). Around M&A rumor dates, buyers (sellers) of the potential targets over-weight (under-weight) the probabilities of subsequent M&A announcements and/or their values.

Consequently, buying rumored target firms does not always lead to a negative performance, as previously documented (Gao and Oler 2012; Zivney *et al.* 1997). Target firm performance after an M&A rumor depends on its credibility. We use a proprietary hand-collected database from different sources and with different characteristics to test the level of the credibility of types of M&A rumors. We find that good (bad) quality rumors lead to a positive (negative) performance. We also find that daily changes in idiosyncratic volatilities around initial rumor dates are positively related to the performance of the target firm after the rumor release date.

If the M&A rumors are from more credible sources, then the increased trading for the target firms leads to increased *Ivol*. If rumors increase expectations that actual M&A announcements will subsequently follow, this should lead to increased prices for the targets. If rumors lack credibility, market participants may diverge in their expectations about future M&A announcements, leading to increased idiosyncratic volatilities and possibly decreased target prices. We find that idiosyncratic volatilities are positively (negatively) related to the performances of the target firms for more- (less-) credible M&A rumors. This relationship is further supported by the finding that idiosyncratic volatility is positively related to the market-implied probability of a M&A using the run-up to markup price ratio as discussed in Betton *et al.* (2014). This relationship is robust to various firm-specific controls (such as size, book to market, long-term growth expectations), and firm- and sector-specific misvaluations.

CHAPTER TWO

IDIOSYNCRATIC VOLATILITIES AND INDIVIDUAL STOCK RETURNS

2.1. INTRODUCTION

Following the seminal work of Sharpe (1964), Lintner (1965) and Black (1972) on the CAPM, many financial economists and practitioners maintain that only systematic risk is priced under the assumption that investors are rational and returns are mean-variance efficient. Subsequent asset pricing models also generally assume that idiosyncratic risk (*Ivol*) is not priced. Goetzmann and Kumar (2008), among others, find that investors are not nearly as diversified as they should be. If investors do not hold diversified portfolios, are they compensated for their exposure to *Ivol*?

Various asset-pricing models for imperfect markets (e.g., Merton, 1987) predict a positive relationship between the incremental risks from holding not fully diversified portfolios and expected returns. In turn, this implies that expected returns are positively related to *Ivol*. However, empirical results on the nature of this relationship are mixed and range from a significant negative to no to a significant positive relationship. Furthermore, the empirical evidence on whether or not there is a trend in *Ivol* varies from upwards at least during the 1990's in Campbell *et al.* (2001) to no time trend but rather episodic phenomena associated partially with retail investors in Brandt *et al.* (2010).

Many studies explain the results of Ang *et al.* (2006, 2009) that realized *Ivol* (*RIvol*) and future returns are negatively related due to return reversals (Huang *et al.* 2010; Fu 2009). These studies argue that the negative relationship disappears after controlling for the prior month's return. Venezia *et al.* (2011) show that investor-herding, Granger-causes *RIvol*, which leads to lower returns in subsequent periods. The over- and under-reaction of investors in some markets is a well-documented phenomenon that has received much interest from practitioners and academics. Academic interest for the U.S. market include studies by De Bondt and Thaler (1985, 1987) who find overreaction over periods of a few years, Jegadeesh and Titman (1993, 2001) who find under-reaction over periods of a few months, and Jegadeesh (1990) and Lehmann (1990) who find overreaction over periods of between one week and a month. A large number of investors follow contrarian and momentum strategies in the US (Goetzmann and Massa 2002) that can lead to risk-adjusted excess returns when investors overreact or underreact to news, respectively (Eggins and Hill 2010). Grinblatt *et al.* (1995) find that over three-quarters of their mutual fund sample engage in momentum investing. The pervasiveness of longer-term momentum and shorter-term contrarian trading rules (e.g. 6-12 and one month respectively) is demonstrated by the so-called 'quant meltdown' of August 2007, when a large number of quantitative managers using such strategies experienced significant losses (Khandania and Lob 2007).

Herein, we examine the relationship between *RIvol* and future returns for a non-US (Canadian) market where there is evidence of considerably weaker return reversals than those documented in the US. Assoe and Sy (2003) find that the returns of a contrarian strategy consisting of buying (selling) low (high) return stocks are driven by small stocks and January effects. Using a longer non-overlapping period with a minimum of 12 months, Kryzanowski and Zhang (1992) find that a contrarian strategy does not yield positive and significant returns as was found in the US.

The industrial composition of the Canadian market differs markedly from that in the US. According to the TSX group, the Canadian market is the global leader in both the mining and oil & gas sectors. It has the highest market capitalization of mining stocks in the world with a total market capitalization of 6.9 Billion Canadian dollars where the combined capitalization of both the Australian Stock Exchange (ASX) and NYSE for this sector is 5.7 Billion Canadian dollars. The Canadian market is the leading global market for the number of mining companies with a total of 1,618 listed mining companies followed by the ASE with 782.[1] The Canadian market is also the leader in oil & gas listings with 369 such listings which is more than the combined total for both the ASX and NYSE. Furthermore, Boyer and Fillion (2006) report that commodity prices are more important than the domestic Canadian exchange rate and interest rates in explaining the overall performance of the Canadian stock market.

Our results are interestingly different for the Canadian versus the US market. First, we are unable to confirm for the Canadian market the negative relationship between *RIvol* and subsequent returns documented by Ang *et al.* for the US market. While Ang *et al.* (2009) included Canada in their international sample, they only included firms available in DataStream. In contrast, our sample is more inclusive since it includes all firms that have ever been listed on the Toronto Stock Exchange (TSX). Using quintiles and deciles based on

[1] All the numbers are calculated as of December 31, 2013. See: http://www.tmx.com/en/pdf/Mining_Sector_Sheet.pdf; and http://www.tmx.com/en/pdf/OilGas_Sector_Profile.pdf

different measures of *RIvol* (with and without adjustments for serial correlation) we find that the differences between the value-weighted (VW) portfolios based on high and low lagged *RIvol* tend to have positive and statistically significant returns, even after controlling for size, risk loadings, short- and long-term return reversals, return skewness and illiquidity.

Bali *et al.* (2011) for the U.S. market and Annaert *et al.* (2013) for the European market find that portfolios formed based on lagged extreme returns yield a statistically negative performance in the following month due to sharp return reversals. We find that the absence of such return reversals in the Canadian market changes their findings of a negative relationship between returns and *RIvol* to a positive one that is robust to the inclusion of extreme returns. Using both double-sorted portfolios to control for the effect of extreme returns on *RIvol* and cross-sectional regressions, we find that the estimated coefficients for *RIvol* are consistently positive and statistically significant.

Thus, this essay makes three contributions to the literature of *Ivol*. The first is to use an alternative market to test if the sign of the negative relationship between *RIvol* and future returns changes when one moves from the U.S. to the Canadian market. Our findings confirm the theoretical expectation of a positive relationship between *RIvol* and expected returns (Merton 1987) in a market characterized by the relative absence of short-term return reversals. Thus, our findings may provide an alternative confirmation of the return-reversal explanation for the puzzling results of Ang *et al.* (2006, 2009). Huang *et al.* (2010) explain that studies supporting the negative relationship between *RIvol* are omitting lagged returns to account for the negative first-order autocorrelation in monthly returns. In a weak to non-existent return reversal market, the relationship between lagged *RIvol* and returns should be positive. We confirm these findings in the Canadian market and show a positive relationship between lagged *RIvol* and monthly returns.

Our second contribution relates to the relationship between extreme returns and future returns in the Canadian market. Bali *et al.* (2011) and Annaret *et al.* (2013) report that stocks with extreme positive returns tend to decline in price in the following month leading to negative returns. The argument of these studies is focused on the behavioral explanation that investors chose to distort their beliefs about future probabilities and overweight stocks with small probabilities of large returns (i.e., lottery-like stocks). Conversely, we find that a strategy consisting of a long (short) position in lagged high (low) daily extreme positive returns yield a positive and significant return. The behavioral explanation proposed by Bali *et* *al.* (2011) is based on the anchoring hypothesis where investors change their subjective reference point to form their expectations. According to Shiller (1999), if people are not independent of each other in forming overconfident judgments about investments, and if these judgments change collectively through time, then these “noisy" judgments will tend to cause prices of some assets to deviate from their true investment value. In such a setting, investing in assets that are currently out of favor and shorting the highly sought after assets by most investors should be advantageous. There is evidence that such contrarian investment strategies do pay off in the US (De Bondt and Thaler 1985; Fama and French 1992; Lakonishok *et al.* 1994) as smart money does not eliminate these opportunities in the US market (Shleifer and Vishny 1997, amongst others). In contrast to the US market, Kryzanowski and Zhang (1992) and ourselves in this study provide evidence that a contrarian strategy does not yield positive returns in the Canadian market.

Our third contribution is to provide an alternative explanation to the relationship between *RIvol,* future returns and extreme returns. By isolating the interaction effect of extreme returns on *RIvol*, we are able to assess the relationship between the two. Our findings suggest that highly extreme returns and *RIvol* have opposite effects on future monthly returns. The theory inspired positive relationship between *RIvol* and future returns is consistently positive and significant, where stocks in the highest extreme return decile tend to have a negative effect on future returns even after controlling for possible return reversals. These results show that when some (mostly small) stocks are subject to the negative relationship outlined in Bali *et al.* (2011), this relationship is not sufficiently strong to affect the whole market.

The remainder of this essay is organized in eight sections. Section 2.2 discusses the so-called idiosyncratic volatility puzzle. Section 2.3 addresses our dataset, the formation of Fama-French factors for the Canadian market and the continuation behavior of the Canadian market. Section 2.4 describes the different measures of realized idiosyncratic volatilities (*RIvol*) and extreme returns for individual stocks used herein. Sections 2.5 and 2.6 report and discuss the results for tests of the relationship between returns and *RIvol* and extreme returns based on the portfolio approach. Section 2.7 reports and discusses the results of time series cross sectional regressions of returns on different measures of *RIvol* and extreme returns. Section 2.8 provides a robustness check of the relationship between EGARCH estimated *Ivol* and future returns. Section 2.9 concludes the essay.

2.2. THE IDIOSYNCRATIC VOLATILITY PUZZLE

Modern financial theory has long stressed the idea that only systematic risk is priced, and that unsystematic risk should be compensated positively by the market if it is priced. Consistent with the theoretical models for imperfect markets (e.g., Mao 1971; Levy 1978; Kryzanowski and To 1982; Merton 1987),[2] various authors report that the cross-sectional variations in expected returns are positively related to contemporaneous *RIvol*.[3] Goyal and Santa Clara (2003) find a positive and significant difference in returns between high and low *RIvol* portfolios. In contrast, Ang *et al.* (2006) report a negative relationship between lagged *RIvol* and future returns for value-weighted portfolios based on sorts of the previous month's *RIvol*. Since this finding is identified in other markets (e.g., Ang *et al.* 2009 for the G7 countries) and is counter to expectations, it is dubbed the "idiosyncratic volatility puzzle". Guo and Savikas (2008) find that the value-weighted *RIvol* and aggregate stock market volatility jointly exhibit strong predictive power for excess stock market returns.

The near consensus that a positive relationship exists between contemporaneous *RIvol* and returns (e.g., Fu 2009; Duffee 1995) is expected since monthly returns are the sum of the returns used to calculate *RIvol*. However, the diversion of opinions is mainly focused on studies that assume that $RIvol_{t-1}$ is a good proxy for $E(RIvol_t)$. However, the value of $RIvol_{t-1}$ depends upon the choice of interval over which it is measured, the frequency of returns used and whether it is based on (non-) overlapping periods. The most widely used method is within-month, where $RIvol_{t-1}$ is the standard deviation of the error terms from the regression of the daily returns on different factors for that month. Its major drawback is its inability to provide a forecast unless the lagged value is an unbiased expectation of its future value.

When Fu (2009) uses the best fit from nine estimated EGARCH models as an alternative measure to using $RIvol_{t-1}$ as a forecast for $EIvol_t$, he finds a positive contemporaneous relationship between future returns and the *EIvol* estimate after controlling for size and liquidity. Guo *et al.* (2014) argue that these results arise from a spurious correlation caused by the use of the return of month *t* in the *EIvol* estimates. Fink *et al.* (2012) test various methodologies for estimating *EIvol* and conclude that no contemporaneous relationship exists between *EIvol* estimates and contemporaneous stock returns after controlling for return reversals and the spurious relationship in the *EIvol* estimates caused by look-ahead bias. Brockman *et al.* (2009) find a positive relation between stock returns and conditional (EGARCH) *EIvol* for international data. Chua *et al.* (2010) propose another *EIvol* measure

[2] Kryzanowski and To (1982) compare and reconcile the Mao and Levy models and propose a clinical model.
[3] Examples include Tinic and West (1986), Lehmann (1990) and Spiegel and Wang (2005).

which uses the forecasts from modeling *RIvol* as an AR(2) model to forecast expected *Ivol* and the difference between these forecasts and the actual *RIvol* as the unexpected *Ivol*. They find that returns are significantly and positively related to both expected and unexpected *Ivol*.

Regardless of the methodology used to estimate future *Ivol*, various arguments are advanced in the literature to refute the existence of this negative relationship. After re-examining the portfolio methodology adopted by Goyal and Santa Clara (2003) using weighted averages, Bali *et al.* (2005) conclude that the negative relationship is due to small firm effects. Similarly, Bali and Cakici (2008) find that the findings of Ang *et al*. (2006) are sensitive to the methodology used to calculate *RIvol* (monthly versus daily), portfolio weightings (equally versus value weighted) and breakpoints (CRSP versus NYSE).

Boehme *et al.* (2009) connect the findings of Merton (1987) and Miller (1977) by differentiating between the dispersion of beliefs, high-level volatility according to Diether *et al.* (2002), and short sale constraints. Boehme *et al.* (2009) conjecture that these two confounding events influence the estimated relationship between expected returns and lagged *RIvol*. When they condition on visibility and the level of short interest, they find that lagged *RIvol* is positively related to expected returns for stocks that have a limited level of investor recognition and limited short selling.[4] Brav *et al.* (2010) empirically investigate the relation between limits of arbitrage, particularly *RIvol*, and stock return anomalies. They find that *RIvol* is associated with overvaluation anomalies, such as portfolios of small growth stocks and 6-months loser stocks, but not undervaluation anomalies, such as value stocks and 6-months winner stocks.

Some studies explain any negative relationship between *Ivol* and returns as being due to return reversals. Cao and Xu (2010) argue that return reversals are a byproduct of overpricing. While investors expect a positive return from *Ivol* due to their holdings of not fully diversified portfolios, limitations to arbitrage (Shleifer and Vishny 1997) and short-selling constraints lead to stock overpricing (Miller 1977; Jones and Lamont 2002). Together, they result in the low returns on the difference between high and low *RIvol* portfolios documented by Ang *et al.* (2006, 2009). Huang *et al.* (2010) also argue that sharp reversals of returns for stocks with extreme returns lead to a negative relationship between *RIvol* and

[4] *RIvol* is measured as the ratio of the standard deviations of the weekly returns for the firm and the CRSP value-weighted index, and also by the standard deviation of residuals of the Carhart (1997) model using weekly returns.

future returns.[5] They argue that the negative relation between *RIvol* and future stock returns identified in Ang *et al.* (2006) is non-monotonic and driven mostly by the highest *RIvol* portfolio.

2.3. SAMPLE, DATA AND FACTORS

The data used herein are drawn primarily from the CFMRC database, which contains daily (monthly) data on all the stocks listed on the Toronto Stock Exchange (TSX) since January 1975 (1950). The database is survivorship-bias free and comprehensive because it contains delisted companies. Until the end of 2012, this covers 9570 trade days for 5787 companies. Risk-free rates are collected from the Bank of Canada website.

Since the Fama-French and momentum factors are not available daily for Canada, we construct the SMB and HML factors as in Fama and French (1992, 1993), and the momentum (WML) factor using the methodology outlined on the website of Kenneth French.[6] The databases used to obtain (or cross check) the book values used to calculate the HML factor in decreasing order of priority are the Financial Post database, Compustat (Canadian edition), Mergent Online, Stockguide (especially for defunct and delisted firms) and Capital IQ.

2.4. RETURN BEHAVIOR OF CANADIAN STOCKS: SHORT-TERM CONTINUATIONS OR REVERSALS?

As noted earlier, Huang *et al.* (2010) and Fu (2009) attribute the negative relation between *Ivol* and future returns found by Ang *et al.* (2006, 2009) to short-term return reversals in the U.S. market. Thus, we begin by examining if the Canadian market is characterized by short-term return reversals. As such, we revisit the findings of Assoe and Sy (2003) who find that the positive performance of a contrarian strategy in the Canadian market is driven by small stocks and the January effect over the time period (1964-1998). After forming decile portfolios of stocks based on each stock's monthly return ranking, we follow their procedure of tracking the performance of these deciles over the following month. We replicate their

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[5] They also find that a significant positive relationship between *EIvol* and returns persists after controlling for return reversals as conjectured by Fu (2009).

[6] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_factors.html

formation and test procedure first for the whole sample and then for large and small stock subsamples based on each stock's median market value in the portfolio formation month.

Table 2.1 reports the results for all the deciles formed based on value and equal weightings of its constituent stocks. Consistent with Assoe and Sy (2003), we observe that the positive returns from a contrarian strategy as reported in the "10 – 1" row is driven by small stocks. The small stock sample shows very sharp return reversals that cannot be found in large stocks. The negative returns of the all stocks sample when equally weighted are due to the overweighting of small stocks. In untabulated results, we also examine the returns from longer term contrarian investment strategies for non-overlapping investment horizons of 12 to 60 months. We consistently find that portfolios formed from the highest 10% (decile) of market-adjusted returns (winners) outperform those formed from the lowest 10% (decile) of market-adjusted returns (losers) confirming the results found earlier by Kryzanowski and Zhang (1992). All of these results are robust to an examination of the CAPM and Carhart 4-factor alphas for these decile portfolios.

[Please place table 2.1 about here.]

2.5. RELATION BETWEEN *RIVOL* AND FUTURE PORTFOLIO RETURNS

Most of the literature on volatility distinguishes between the days-within-the-month *RIvol* and *EIvol* measures that use a form of conditional forecasting of volatility such as GARCH or ARCH. We have two justifications for beginning our investigation with *RIvol*. First, we initially are interested in *RIvol* pricing in the Canadian market using the same methodology outlined in Huang *et al.* (2010) and Ang *et al.* (2006), amongst others. Second, we are interested in the time-series characteristics of *RIvol* and its forecasting abilities for expected returns, as shown by Fu (2009), amongst others.

2.5.1 *RIVOL* Measures

To obtain *RIvol*, we first estimate the following Carhart (1997) model for the excess return r_{i,d_t} for each stock *i* for each of the days *d* in month *t*:

$$r_{i,d_t} = \alpha + \beta r_{M,d_t} + sSMB_{d_t} + hHML_{d_t} + \gamma WML_{d_t} + \varepsilon_{i,d_t} \tag{2.1}$$

Where r_{M,d_t} is the excess return of the market portfolio, SMB_{d_t} and HML_{d_t} are the two additional Fama-French factors, WML_{d_t} is the momentum factor, and ε_{i,d_t} is the error term. [7]

The standard deviation of the error terms at a monthly frequency is obtained by multiplying the within-month daily standard deviation $\sigma(\varepsilon_{i,d_t})$ by the square root of the number of trading days in the month (T):

$$RIvol_{\,i,t} = \sqrt{\sum_{t=1}^{T} \varepsilon_{i,d_t}^2} \quad \text{only for T} \geq 15 \text{ days} \tag{2.2}$$

We also obtain a *RIvol* adjusted for daily autocorrelations as in Goyal and Santa Clara (2003). We first use the approach developed by French *et al.* (1987) to obtain the variance of stock *i* for month *t* given by:

$$V_{i,t} = \sum_{d_t \in t} r_{d_t}^2 + \sum_{d_t \in t} 2 r_{d_{t-1}} r_{d_{t-1}} \tag{2.3}$$

Decomposing $V_{i,t}$ into its systematic and non-systematic components yields:

$$\begin{aligned} V_{i,t} &= \sum\nolimits_{d_t \in t} (\gamma^2 r_{f,d_t}^2 + \varepsilon_{i,d_t}^2) + \sum\nolimits_{d_t \in M} 2(\gamma r_{f,d_t} + \varepsilon_{i,d_t})(\gamma r_{f,d_{t-1}} + \varepsilon_{i,d_t-1}) = \\ &\underbrace{(\sum\nolimits_{d_t \in t} (\gamma^2 r_{f,d_t}^2 + 2\gamma r_{f,d_t} \gamma r_{f,d_t-1})}_{Systematic} + \underbrace{\sum\nolimits_{d_t \in t} \varepsilon_{i,d_t}^2 + 2\sum\nolimits_{d_t \in t} \varepsilon_{i,d_t} \varepsilon_{i,d_t-1}}_{Unsystematic} \end{aligned} \tag{2.4}$$

where γ is the factor loading of stock *i* on factor f, and r_{f,d_t} is the return of factor f in day d_t within month t. The first term of (2.4) is the stock's systematic risk adjusted for the inter-month autocorrelation of the factor returns and the second term is the unsystematic risk similarly adjusted. Hence, the daily adjusted *RIvol* becomes:

$$RIvol_{\,i,t}^{\,adj} = \sqrt{\sum_{t=1}^{T} \varepsilon_{i,d_t}^2 + 2\sum_{t=2}^{T} \varepsilon_{i,d_t} \varepsilon_{i,d_{t-1}}} \tag{2.5}$$

where all the terms are as defined earlier.

Descriptive statistics for both *RIvol* measures are reported in table 2.2, where the total number of firm months in the pooled sample is 325,648. The average number of within-month days used in the calculation of *RIvol* is 20.2, and about 75% of the *RIvol* values are based on at least 20 daily returns. The mean and median *RIvol* are 14.59% and 11.14%, respectively, and the mean and median-adjusted *RIvol* are higher at 16.94% and 11.95%,

[7] The construction of the daily factors are discussed in section 2.3.

respectively. The average (particularly, adjusted) *RIvol* is very close to the average *RIvol* of 16.87% found by Fu (2009) for the US for the period 1963 to 2006.

[Please place table 2.2 about here.]

The time-series properties of the *RIvol* series provide insight into the ability of this variable to predict stock returns. Based on the last column of table 2.2, we find that the autocorrelations of the unadjusted *RIvol* persist across stocks for at least 12 lags. The first-order autocorrelation of 0.244 is highly significant and higher orders decay slowly. The magnitudes of the autocorrelation coefficients imply a high level of dependency in the time series. Fu (2009) reports similar results for US data. To further investigate the process generating the *RIvol*s, we calculate the first differences in the natural log of the *RIvol* and re-estimate the autocorrelation coefficients for the same lags for both measures of *RIvol*. From the third and fourth rows of table 2.2, we observe that these new series have an average first-order autocorrelation coefficient of -0.36 and -0.39 for the natural log of the first-order differenced *RIvol* and adjusted *RIvol*, respectively. The magnitude of the average autocorrelation drops more than 90% from the first to the second order, which implies that the natural log of first differenced *RIvol* becomes an MA (1). We also perform a unit root test for the *RIvol* series for the individual stocks using the Augmented Dickey Fuller test. We are able to reject the existence of a unit root for about 70% of the stocks that have at least 30 monthly observations.

Although Ang *et al.* (2006) implicitly assume that the time-series of idiosyncratic volatilities can be approximated by a random walk, Fu (2009) argues that the implications of their results are associated more with a non-random walk series since they form their portfolios based on *RIvol* lagged one month. The implication is that temporal dependency in the *RIvol* series is important when predicting the expected return for the following period. If $RIvol_{t-1}$ is positively related to $RIvol_t$ and the relationship between contemporaneous *RIvol* and returns is positive as Fu finds, then the relationship between lagged *RIvol* and returns should be positive and not negative as found by Ang *et al.* (2006).

We further test the autocorrelation characteristics of our *RIvol* measures for various subsamples of large and small stocks delineated by the median market values in a given month, and of short- and long-term winners and losers to reflect the expected impact of return reversals on the estimated relation between *RIvol* and returns. As discussed in Fu (2009), Huang *et al.* (2010) and Li (2013), return reversals are responsible for changing the relationship between *RIvol* and returns from positive to negative. Like the undifferentiated sample, all of these subsamples exhibit a positive (not negative) and statistically significant autocorrelation in their first lags and a slow decay in subsequent lags.[8]

2.5.2 Relation between Portfolio Returns and their Lagged *RIvol*

We begin this section by examining the return performances of ten (decile) portfolios based on their one-month lagged *RIvol* as measured by either equation (2.2) or (2.5). Based on the results reported in table 2.3, we find that the returns of the value-weighted portfolios monotonically increase with increasing values of lagged *RIvol*, and that this observation persists when the sample is split into small and big stocks. A strategy consisting of buying high *RIvol* stocks and shorting low *RIvol* stocks yields statistically significant returns over the subsequent month of 2.87%, 1.78% and 2.88% for the full sample, and the subsamples of only big and only small stocks, respectively. However, when the portfolios are formed using equal weights, the significantly positive long/short returns become statistically insignificant and negative. These findings are robust to an examination of portfolios based on the adjusted *RIvol*. For example, the average return on the long/short value-weighted portfolio based on the lagged adjusted *RIvol* is 2.34%, 1.52% and 1.89% for the full sample, and the big and small firm subsamples, respectively.

[Please place table 2.3 about here.]

However, the long/short position is not risk free since its constituent decile portfolios hold different stocks. To adjust for their different exposures to systematic risks, we examine the alpha estimates after running the difference between the returns of high and low *RIvol* decile portfolios first against the market portfolio and then against the four factors in the Carhart model. Based on the results reported in table 2.3 for the ten value-weighted decile portfolios, the long/short position yields CAPM and Carhart-adjusted alphas of 1.40% and 1.18% for the whole sample, 0.65% and 0.49% for big stocks and 1.01% and 0.82% for small stocks, respectively. In contrast, all alphas are negative for the corresponding equally weighted decile portfolios. This implies that overweighting small stocks increases the risk profile of these portfolios and leads to a negative risk-adjusted performance.

We now control for factor loadings, return reversals, momentum, skewness and illiquidity by first sorting the samples on each of these controls and then lagged *RIvol* to form 100 (i.e.,

[8] Autocorrelation results for the subsamples are available from the authors.

10 x 10) value and equally weighted portfolios. Table 2.4 reports the results for the value weighted portfolios. Factor loadings are the sensitivities of the individual stock returns to the Market, SMB, and HML factors using daily returns over the prior month. Return reversal (short term) is the return of a stock over the prior month, and momentum (long term) is the cumulative monthly return over the period *t*-11 to *t*-2 to capture the argument of Li (2013) that reversals could be long or short term. Skewness is used to capture one aspect of lottery-like stocks which are defined as low priced stocks with high idiosyncratic volatility and skewness (Kumar 2009). The last control variable is the Amihud (2002) illiquidity measure.

[Please place table 2.4 about here.]

Instead of reporting the results for all of the 100 value-weighted portfolios in table 4 for each control, we report the returns of the 10 portfolios sorted according to lagged *RIvol* for firms with their intersection with the highest and the lowest control variable deciles. All the value weighted portfolios show that a long (short) position in the portfolio with the highest (lowest) lagged *RIvol* decile yields a positive raw return that is statistically significant after controlling for risk loadings, return reversals, momentum, skewness and illiquidity. The risk-adjusted alphas using the CAPM model or the 4-factor Carhart model confirm the positive performances of the portfolios after accounting for the controls, with statistical significance for 11 and 9 out of 14 for the CAPM and 4-factor models, respectively.

The results for the equally weighted double-sorted lagged *RIvol* portfolios are reported in table 2.5. The returns are statistically significant for portfolios that control for high reversals, high momentums and low skewness where the raw returns are positive for the first two controls and negative for the third. The same 10 out of 14 risk-adjusted returns are significant for each factor model, and all of the significant risk-adjusted returns are negative. Since these results are somewhat similar to those of Bali and Cakici (2008), they are consistent with their conjecture that the contradictory results reported in Ang *et al.* (2006) are not robust to weighting schemes. Bali and Cakici (2008) find that changing the weighting scheme from equal to value weighted changes the results and using the breakpoints from all CRSP versus the breakpoints from NYSE only cancels out the negative relationship documented in Ang *et al.* (2006).

[Please place table 2.5 about here.]

2.6. IS THE RELATION BETWEEN *RIVOL* AND FUTURE RETURNS ROBUST TO THE INCLUSION OF EXTREME POSITIVE RETURNS?

2.6.1 Literature

Bali *et al.* (2011) conclude that the relationship between *RIvol* and future returns dissipates after controlling for extreme positive returns in the prior month. They argue that the highest daily positive return in the lagged month (*MAX*) explains future cross-sectional returns. They explain this finding based on the cumulative prospect theory (Tversky and Kahneman 1992) where investors overweight assets with a small probability of a large positive return. Kumar (2009) shows that certain groups of individual investors appear to exhibit a preference for lottery-type stocks defined as low-priced stocks with high idiosyncratic volatilities and skewnesses.

Bali *et al.* (2011) sort US stocks using daily extreme positive returns into different deciles, and then calculate their market-weighted returns in the subsequent months. They find that a strategy consisting of buying (selling) stocks with the highest (lowest) extreme daily positive returns yields a negative risk-adjusted alpha return of -1.18%. The authors argue that the robust negative relationship between *MAX* and cross-sectional returns is not analogous to the negative relationship uncovered by Ang *et al.* (2006, 2009). Bali *et al.* (2011) acknowledge that *RIvol* and *MAX* are correlated by design since *RIvol* is based on the squared residuals of the excess returns. Hence, if *MAX* captures market-participant overreaction, it would lead to an increase in *RIvol*. Hence, Bali *et al.* (2011) conclude that idiosyncratic volatility is not priced in the US market and that the negative relationship uncovered by Ang *et al.* (2006, 2009) is just a proxy for *MAX*. Bali *et al.* (2011) explicitly argue that under diversified investors holding a high level of *RIvol* should be compensated positively. Annaert *et al.* (2013) report similar results for the European markets over a period of 30 years. They also argue that stocks with high returns tend to be overpriced leading to subsequently lower returns.

In order to put the explanation put forward by Bali *et al.* (2011) into perspective, we use a simple example to illustrate it. Let us assume that we have two stocks “A” and “B” with the same expected return and standard deviation. Unlike stock “B”, stock “A” experiences one day with an extreme positive return. A long (short) position in stock “B” (stock “A”) would yield a positive risk adjusted return. The authors argue that this result is robust to skewness in both of its forms (systematic and idiosyncratic). Hence, few extreme movements in the right tail of the daily return distribution would lead to a future low expected return. If these movements are part of the risk profile of the stock, they would be part of the second or third moments of the stock distribution. There should be a direct link between *RIvol* and *MAX*, if extreme values have enough weight to impact the risk profile of the stock.

Behavioral finance might provide some insight into explaining this phenomenon. Two of the most prominent concepts in behavioral finance are anchoring and mental compartmentalizing. Shiller (1999) explains that the anchoring and framing phenomena are human tendencies to place particular events into mental compartments based on superficial attributes. Instead of looking at the big picture, as would be implied by expected utility theory, individuals look at individual small decisions separately. Hence, individuals may tend to place their investments into arbitrarily separate mental compartments, and react separately to the investments based on which compartment they are in. Shefrin and Statman (1994) argue that individual investors think naturally in terms of having a "safe" part of their portfolio that is protected from downside risk and a risky part that is designed for a chance of getting rich. Consequently, investors would tend to react differently towards extreme movements. In turn, this could subsequently affect future returns.

Given the evidence of the various differences between the Canadian and US markets, we further analyze the relationship between the *RIvol* and future returns after controlling for extreme returns. Thus, in the remainder of this section, we first test if there is a relation between extreme returns and future returns, and then test if the positive relationship between *RIvol* and future returns identified earlier persists after controlling for extreme returns. Before doing so, we examine the time-series of extreme returns in the Canadian market.

2.6.2 Persistence in Extreme Returns

We examine the level of persistence in extreme positive returns by calculating a transition matrix that reports the probabilities of movement between deciles from one month to the next. Based on table 2.6, we find that a stock in the highest *MAX* decile in month t has a 36.28% probability of remaining there in month t+1, and a 70.24% probability of being in one of the highest 3 deciles in month t+1. Similarly, a stock in the lowest decile in month t has a 41.33% probability of remaining there in month t+1, and a 76.5% probability of being in one of the lowest 3 deciles in month t+1.

[Please place table 2.6 about here.]

To assess if persistence is exclusive to the *MAX* series, we calculate the transition matrices for two more measures of extreme returns; namely, *MIN* and *MAXDEV*. $MIN_{i,t}$ is defined as the minimum daily return in the month multiplied by -1 (i.e., $MIN_{i,t}$=-min($r_{d,t}$) where $r_{d,t}$ are the daily returns for a certain stock *i* in month *t*). We multiply the minimum by -1 to allow us to compare the effect of extreme returns (positive or negative) regardless of the sign. *MAXDEV* is the difference between the daily maximum and minimum returns during the month where the latter is not multiplied by -1. Like *MAX*, the *MIN* and *MAXDEV* series exhibit persistence from one month to another. To illustrate, the transition matrix for *MIN* reported in table 2.6 shows that a stock in the highest decile (the highest of the lowest returns) has a 41.28% chance of being in the same decile in the following month and a 75.36% probability of being in one of the lowest 3 deciles in the following month. Similarly, a stock in the lowest decile (the lowest of the lowest) has a 41.96% probability of being in the same decile in the following month and a 77.65% probability of being in one of the highest three deciles in the next month. These results imply that extreme-value variables do not follow a random walk and might contain information about future returns. These results further support our previous findings against return reversals in the Canadian market.

To examine the level of time-series predictability for each of these series, we calculate the autocorrelations for lags of 1 to 12 months for *MAX*, *MIN* and *MAXDEV* for all of the stocks in our sample. Similar to the time series properties of *RIvol*, we observe a considerable level of persistence in the autocorrelations of the *MAX*, *MIN* and *MAXDEV* series. The first-order cross-sectional autocorrelations of 0.14, 0.19 and 0.21 for *MAX*, *MIN* and *MAXDEV*, respectively, are highly significant and decay slowly with higher orders. The magnitudes of the autocorrelation coefficients imply a high level of dependency in the time series for each extreme-return measure.

We also perform a unit root test for the *MAX*, *MIN* and *MAXDEV* series for individual stocks using the Augmented Dickey Fuller test. We are able to reject the existence of a unit root in 86.9%, 77.88% and 74.63% of the cases for respectively the *MAX*, *MIN* and *MAXDEV* series of the stocks that have at least 30 monthly observations. The average autocorrelations coefficients are 0.74, 0.81 and 0.8264 for *MAX*, *MIN* and *MAXDEV* respectively. These results are very similar to our findings for *RIvol*. At this point, we conclude that extreme returns do not follow a random walk as they exhibit a considerable level of persistence.

2.6.3 Relation between Portfolio and Extreme Returns

2.6.3.1 Single extreme-return sorts

Based on the findings reported above, we expect that hedge portfolios (long high / short low) formed based on the extreme return deciles will yield positive returns for both *MAX* and *MIN*. To test this expectation, we examine hedge portfolios formed from the same samples as we examined earlier (all, big and small stocks).

We report the results for the ten deciles formed from the whole sample based on *MAX*, *MIN* and *MAXDEV* for the full, big and small stock samples in table 2.7. Consistent with expectations, we observe that returns and their risk-adjusted counterparts for all value weighted hedge portfolios are positive and statistically significant when sorted using *MAX, MIN* and *MAXDEV*. These results are consistent with the expectation that the relationship between extreme returns and future returns is different in the Canadian versus the US market.

[Please place table 2.7 about here.]

2.6.3.2 Extreme returns portfolios based on double sorts

To isolate the possible effect of return reversals from the performance of the extreme return hedge portfolio, we form portfolios for stocks with the highest and lowest lagged monthly returns. The columns labeled “high” and “low” in table 2.8 report the returns of portfolios of stocks with the highest and lowest lagged monthly returns. Stocks with high positive extreme returns do not necessarily have positive monthly returns. A positive return jump for one or more days in a month could be offset by one or more daily jumps in returns in the opposite direction, which in turn could lead to a negative cumulative performance over the month. In the absence of clear evidence of return reversals, it is not clear what the expectation is for future monthly returns. However, our findings when using *MAX, MIN and MAXDEV* suggest that high (low) lagged monthly returns lead to positive (negative) future returns, which could be explained as some support for the continuation hypothesis. According to these results, we can deduce that the predictability of returns is more important than one extreme event in the preceding month.

[Please place table 2.8 about here.]

Bali *et al.* (2011) report that the negative relationship between *RIvol* and future returns disappears after controlling for extreme positive returns. We start by testing if *RIvol* affects our uncovered positive relationship between extreme values and future returns. We first sort our sample into deciles according to the level of *RIvol* in the lagged month and then sort the highest and lowest deciles into deciles according to the level of extreme returns in the lagged month. The results reported earlier in table 2.4 on the relationship between lagged *RIvol* and monthly returns identified a positive return even after controlling for different variables. The high level of autocorrelation in *RIvol* would suggest the existence of a positive relationship between lagged *RIvol* and returns regardless of the level of extreme values. Based on table 2.9, we observe that the raw and adjusted returns of the value weighted hedge portfolio based on extreme returns when *RIvol* is high are positive and statistically significant. The raw and adjusted returns of the value weighted hedge portfolio based on extreme returns when *RIvol* is low are either statistically insignificant or negative if statistically significant. Hence, the explanatory power of extreme returns loses power for stocks with low *RIvol*. The difference in performance between equally and value weighted hedge portfolios results captures the impact of placing more weight on small stocks which have a different relationship than large stock with *RIvol* after controlling for extreme returns.

[Please place table 2.9 about here.]

We further examine the relationship between *RIvol* and future returns after controlling for extreme returns by sorting the sample according to ranked extreme returns and then sort the highest and lowest deciles into ranked lagged *RIvol* deciles. We report the results of these portfolios in table 2.10. The raw and adjusted returns for the value weighted hedge portfolio based on lagged *RIvol* returns for all extreme values are positive and statistically significant except for the value weighted portfolio of low *MAX*. These results are in accordance with our findings in table 4, where we find that the relationship between *RIvol* and future returns is robust to the inclusion of other control variables. These results are also partially in accordance with Bali *et al.* (2011) who report that the relationship between lagged *RIvol* and returns turns (insignificantly) positive when they control for *MAX*. The equally weighted hedge portfolios for *RIvol,* after controlling for *MAX* and *MAXDEV,* are all negative.

[Please place table 2.10 about here.]

In summary, the results from using the portfolio methodology show that extreme values are positively related to future monthly returns even after we control for return reversals. We also find that controlling for extreme returns does not materially change the positive relationship between *RIvol* and future returns.

2.7. EMPIRICAL FINDINGS BASED ON CROSS-SECTIONAL REGRESSIONS

In this section, we investigate the relationship between average cross sectional returns and different measures of *RIvol* using the Fama-MacBeth (1973) methodology. The standard error used to calculate each reported t-statistics is the standard error of the intercept of the sixth-order autoregressive process that captures all of the serial dependence in the coefficient's time series. According to Pontiff (1996), these standard errors are not biased by serial or cross-sectional correlations.

2.7.1 Fama-MacBeth Methodology

We start by implementing the Fama-MacBeth (1973) estimation procedure similar to that in Fu (2009) and Huang *et al.* (2010). The cross sectional regression model is as follow:

$$r_{i,t} = \alpha + \sum_j \gamma_{j,i,t} X_{j,i,t} + \xi_{i,t} \quad \textbf{(2.6)}$$

where $r_{i,t}$ is the monthly excess return of stock i in month t, $X_{j,i,t}$ are possible explanatory variables of cross-sectional expected returns such as beta, size, book-to-market ratio, and idiosyncratic volatility.

To obtain the conditional beta, we first run a conditional market model over time horizons of 60 months with a minimum of 24 months for each stock to obtain betas for each month and each stock. These stocks are ranked first by beta and then by size to form 100 (10×10) beta/size portfolios. We then run the excess returns of these equally weighted portfolios against the contemporaneous and lagged market excess returns. Each portfolio's beta is defined as the sum of the slopes of the current and lagged market returns to adjust for the effects of non-synchronous trading (Dimson 1979). The beta used in the cross-sectional regressions of individual stock returns for each stock is the beta of the portfolio to which it belongs. The mean beta of all stocks used in the cross sectional regressions is 1.04 and its median is 0.94. Fama and French (1992) use both the log of the market value calculated as the price of a firm's stock multiplied by the number of outstanding shares and the log of the ratio of book to market to control for growth. We calculate book to market ratio based on the definition provided in the construction of the Fama and French factors and discussed earlier in this essay.

Fu (2009) uses two control variables: liquidity and momentum. Huang *et al.* (2010) augment the model and add the prior month's return to control for return reversals. They measure liquidity by the log of average stock turnover and the log of its coefficient of variation. Average turnover is the average share turnover during the past 36 months, constructed as in Chordia *et al.* (2001). The motivation for using the coefficient of variation of turnover as an additional control variable is based on the finding that both the level and the volatility of trading activity are related to average returns in the cross-section. Easley *et al.* (2002) use the same variables to control for the effects of liquidity. We extend the return horizon of the momentum measure to include 10 months prior to t-2 as per Huang *et al.* (2010).

As an alternative test of liquidity, we use the modified Amihud (2002) illiquidity measure discussed in Brennan *et al.* (2013). The Amihud (2002) illiquidity measure is given by the absolute market return divided by traded dollar share volume over a monthly frequency. Brennan *et al.* (2013) decompose the Amihud measure into elements that correspond to positive (up) and negative (down) return days, and find that in general, only the down-day element commands a return premium. Further analysis of the up- and down-day elements using order flows shows that a sidedness variable, which captures the tendency for orders to cluster on the sell side on down days, is associated with a more significant return premium than the other component of the Amihud measure. The expected sign of the half Amihud (for down return days) is positive.

Another control variable that we use is Synchronicity, which measures co-movements (Morck *et al.* 2000) by controlling for the level of firm-specific information incorporated into stock prices. Since R^2 is bounded within the interval [0, 1], Morck *et al.* (2000) propose the use of the following logistic transformation for synchronicity:

$$SYNC_{i,t} = Ln\left(R_{i,t}^2/\left(1 - R_{i,t}^2\right)\right) \tag{2.7}$$

where the R^2 for stock i is obtained from regression (1) using the days-within-each-month. Higher values of R^2 imply an increase in the co-movements of the stock with the risk factors, and thus an increase in synchronicity (Durnev *et al.* 2003). Also, higher R^2 values may imply a decline in firm-specific variation or noise (Jin and Myers 2006), which leads to lower *Ivol* because firm-specific information is already embedded in stock prices. However, some inconsistencies occur with synchronicity as Asbaugh-Skaife *et al.* (2006) find that non-fundamental factors influence stock price synchronicity but the variation in firm-specific information flows or fundamentals is not consistently captured by R^2. Thus, the expected coefficient for *SYNC* is indeterminate if the findings of Asbaugh-Skaife *et al.* (2006) apply to the Canadian market. We calculate the average cross sectional correlations of all the control variables discussed earlier and the measures of idiosyncratic volatility. All average correlations are low implying the absence of multicollinearity problems in the cross sectional regressions.

Table 11, columns (1-8) report the average (equally weighted) coefficients of the cross sectional regressions of betas, log market value and log book to market value with contemporaneous or lagged *RIvol*, momentum and different liquidity measures. Columns (1-4) report the average coefficients of regressions using the same liquidity measures as reported in Fu (2009). Columns (5-8) report the average coefficients of regressions using the half Amihud measure and synchronicity as control variables. We find that the average stock returns are not related to its beta, is negatively related to firm size, and positively related to log(BE/ME) so that value firms tend to have higher returns than growth firms. In all regressions, we observe a positive and highly significant relationship between the contemporaneous *RIvol*s and cross sectional returns. These results are consistent with the theoretical models of Mao (1971), Levy (1978), Merton (1987) and Malkiel and Xu (2002), and the empirical findings of Lehmann (1990).

[Please place table 2.11 about here.]

Three of the four average cross sectional coefficients of lagged *RIvol*s are statistically significant (all positive), confirming our earlier portfolio construction results and excluding the possibility that the positive relationship is due to momentum or return reversals in individual stock returns. The momentum factor has a significantly positive relationship with cross sectional returns, which is consistent with the importance and use of the momentum factor as a standard risk factor in the literature. In contrast to the findings of Chordia *et al.* (2001) who find that both the level and the volatility of trading activity are related to average returns in the U.S. cross-section, we find that the average turnover and its volatility [CV(Turn)] have no statistically significant relationship with average returns for our Canadian sample. Similarly, we find no statistically significant relationship between synchronicity (SYNC) and average returns for our Canadian sample. On the other hand, the half Amihud illiquidity coefficient is positive and highly significant so that returns increase with increasing illiquidity.

2.7.2 Value-weighted Cross-sectional Regression Findings

Fu (2009) argues that the results found in Ang *et al.* (2006) are due to the *RIvols* of small stocks. The standard Fama-MacBeth methodology resembles estimating an equally weighted portfolio since it essentially allocates the same weight to all stocks. To assess the impact of such a weighting, we now use the market weight of each stock in each month to weight the variance covariance matrix used to estimate the monthly coefficient. Since the times series of coefficients are not affected by the weighting scheme, we continue to use the time-series average of the cross-sectional coefficients and t-statistics corrected for autocorrelation to test for statistical significance.

Table 2.11, columns (9-12) report the summary results for the value weighted Fama-Macbeth regressions using control variables for momentum, return reversal, illiquidity and synchronicity. The average weighted cross sectional regressions show that both lagged and contemporaneous *RIvol*s are positive and highly statistically significant even after controlling for return reversals, momentum and illiquidity. These results are consistent with our earlier reported findings that the value-weighted portfolios performed better than the equally weighted portfolios formed based on lagged *RIvol* even after controlling for long- and short-run return reversals.

2.7.3 Risk-adjusted Cross Sectional Regressions

The Fama-MacBeth (1973) methodology uses the coefficient estimates from the time-series regression (1) presented earlier in a second-step cross-section regression where the significance of the coefficients of the variables generated from a series of second steps are tested. Because the betas in equation (2.6) are estimated with error, Brennan *et al.* (1998) recommend the use of risk-adjusted instead of risk-free excess returns as the dependent variable in the second-step cross-sectional regression. The reason is that the use of risk-adjusted excess returns for individual stocks avoids the measurement error problem that occurs when first-step beta estimates are used as independent variables in the second-step cross-sectional regressions in the Fama-MacBeth procedure. The second-step cross-section regressions are as follows:

$$r^*_{i,t} = \gamma_0 + \sum_j \gamma_{j,i,t} X_{j,i,t} + \xi_{i,t} \tag{2.8}$$

where $r_{i,t}^{*} = r_{i,t} - (\hat{\beta} r_{M,t}\delta_t + \hat{s}SMB_t + \hat{h}HML_t + \hat{\gamma}WML_t)$; and $X_{j,i,t}$ is a set of j control variables for stock *i* at time *t*.

Table 2.12 reports the average (equally weighted) of the coefficients from the cross sectional regressions from equation (2.8) using contemporaneous and lagged, adjusted and non-adjusted $RIvol$. Columns (1-4) report the summary results of cross sectional regressions of different $RIvol$ measures in addition to turnover, its coefficient of variation and momentum factors. Columns (5-8) report the summary results of regressions of $RIvol$ measures, momentum factor, negative half Amihud illiquidity measure and synchronicity. Mean contemporaneous and lagged $RIvol$ average coefficients are positive and highly statistically significant regardless of the control variables used in the cross sectional regressions. The average coefficients of the control variables with the exception of synchronicity are consistent in their signs and statistical significance with the results reported earlier in table 11.

[Please place table 2.12 about here.]

The results obtained from the different cross sectional regressions confirm the contemporaneous relationship between $RIvol$ and returns (Duffee 1995; Fu 2009; Huang *et al.* 2010), and finds a positive relationship between $RIvol$ and future returns after controlling for return reversals (Huang *et al.* 2010).

2.7.4 Cross Sectional Regressions of Extreme Positive Values, Idiosyncratic Volatilities and Returns

In this section, we investigate the relationship between the $RIvol$ and future returns in the presence of extreme returns. Bali *et al.* (2011) argue that adding extreme returns to cross sectional regressions changes the sign of the coefficient of $RIvol$ from negative to positive but stays insignificant. Our findings suggest that this relationship is different in the Canadian market where the coefficient of $RIvol$ is positive and statistically significant. As we now show, the positive relationship found earlier persists even after adding extreme returns when using cross sectional regressions.

Table 2.13 reports the average coefficients of the value weighted cross sectional regressions.[9] The first three columns show the results of adding liquidity, momentum, return

[9] Similar results are found using equal weighted Fama MacBeth two step regressions.

reversals and synchronicity, and each of the extreme variables in turn. Only MAX and MIN are weakly related to future returns (positively and negatively, respectively). However, the significance of MAX and MIN disappears and MAXDEV remains insignificant when lagged *RIvol* is added to the regressions. These results are consistent with our earlier findings using univariate and bivariate portfolio analyses.

[Please place table 2.13 about here.]

Table 2.14 reports the results of time series weighted regressions of returns on lagged *RIvol* and other control variables where we isolate the effect of *RIvol* on firms in the highest and lowest deciles of extreme returns. We do so by creating additional variables by multiplying dummy variables taking the value of 1 when the firm is in the highest or lowest decile for MAX, MIN or MAXDEV and 0 otherwise. The average coefficients on these interactive term variables capture the additional effect of *RIvol* on firms in these deciles. The results show that firms in these deciles exhibit a negative relationship with future returns with only three out of six being significant at conventional levels, while *RIvol* continues to be positive and highly significant for stocks in extreme return deciles other than the one under consideration. Consistent with the explanation of Bali *et al.* (2011), we find that there is a behavioral reaction of the market to extreme returns. However, this negative relationship is mitigated by the positive relationship between *RIvol* and future returns in the Canadian market. We confirm this statement by removing RIvol from the regression and running the interactive term consisting of *RIvol* multiplied by the extreme returns deciles dummy. The results show that the average coefficient of the interactive term is negative and statistically significant.

[Please place table 2.14 about here.]

2.8. EGARCH ESTIMATED EXPECTED IDIOSYNCRATIC VOLATILITY (*EIVOL*)

2.8.1 Relationship Including *EIvol* versus *RIvol*

In the spirit of Merton (1987), investors require compensation based on expectations and not on realizations. Hence, Fu (2009) argues for tests of the impact of expected idiosyncratic volatilities (*EIvol*) and not *RIvol*. Both Fu (2009) and Huang *et al.* (2010) find a positive relationship between returns and *EIvol*.

To capture the time varying property of *Ivol*, we use conditional volatility measures to forecast the following month's *Ivol*. While GARCH models are very useful to capture the value of conditional volatility, the choice of the number of lags and the GARCH model that best fits the characteristics of the time series is an issue in many studies. Pagan and Schwert (1990), Engle and Mustafa (1992) and Engle and Ng (1993) test different variations of GARCH and conclude that the simplest lag structures are the most efficient models, and that the EGARCH model of Nelson (1991) that reflects the "leverage effect" is best. When the residuals from equation (2.1) are distributed as $\varepsilon_{i,t} \sim N(0, \sigma_{i,t}^2)$, the variance process is given by:

$$\ln(\sigma_{i,t}^2) = a_i + \sum_{l=1}^{p} b_{i,l} \ln \sigma_{i,t-l}^2 + \sum_{k=1}^{q} c_{i,k} \left\{ \theta \left(\frac{\epsilon_{i,t-k}}{\sigma_{i,t-k}} \right) + \gamma \left[\left| \frac{\epsilon_{i,t-k}}{\sigma_{i,t-k}} \right| - (2/\pi)^{1/2} \right] \right\} \quad (2.9)$$

Guo *et al.* (2014) argue that the *EIvol* estimates reported in Fu (2009) contain a look-ahead bias when SAS is used, since the SAS methodology also includes a contemporaneous observation. In his rebuttal, Fu (2010) argues that the contrary findings of Gao *et al.* (2014) suffer from the use of estimates from poorly converting models and possibly a low number of EGARCH iterations. Fink *et al.* (2012) test these differences by adding one more data point to the estimate while controlling for the number of iterations used. They conclude that the look-ahead bias not only has a considerable impact on the *EIvol* estimate but it induces a bias in the relationship between *EIvol* and expected returns that adversely affects inferences. The *EIvol* estimates reported in table 2 of their paper show that moving from a "biased" *EIvol* to a "bias-free" *EIvol* affects its standard deviation considerably more than its mean.[10] In order to avoid any potential bias that may change the results, we model our EGARCH by specifically using only data points available publically at time *t*-1. We also use two different statistical software packages (Eviews and Matlab) to cross check our results.

Similar to Fu (2009), Huang *et al.* (2010) and Fink *et al.* (2012), we use the Akaike Information Criterion (AIC) to choose the best forecast from nine EGARCH models for various (*p*, *q*) lags of (1,1), (1,2), (1,3), (2,1), (2,2), (2,3),(3,1), (3,2) and (3,3) for each one of the data points. Thus, the same series of *EIvol* estimates includes estimates from the nine different models depending on the value of their AIC for each month. This methodology is purely an econometric procedure with no theoretical merit nor practical merit for most investors. AIC is based on the Kullback and Leibler (1951) divergence between the potential

[10] While the standard deviation increases from 9.12% to 13.94%, the mean only increases from 11.39% to 11.88%.

model and the "true" process generating model based on a minimum discrepancy estimation approach. Since AIC exhibits a potentially high degree of negative bias in small-sample applications (Hurvich and Tsai 1989), various studies use an AIC based on a sample size of 60 months with 30 months being the minimum number of observations for any particular estimation. [11] The mean, median and standard deviation of our $EIvol_{60}$ estimates are 18.96%, 12.46% and 23.7%, respectively, which indicates that they change considerably across estimation periods.

We also propose and use an alternative methodology where the *EIvol* estimate at time *t* is based on all available data points since the start of the sample (i.e. January 1, 1975) to *t*-1, which we refer to henceforth as $EIvol_{\text{All}}$. Using this methodology, we obtain mean, median and standard deviations estimates of $EIvol_{\text{All}}$ of 10.35%, 10.14% and 3.75%, respectively. All of these statistics are small in magnitude compared to those obtained using the fixed 60-month period.

Next we address the question of whether lagged *RIvol* is superior to *EIvol* as a predictor of the future *Ivol* that is contemporaneously related to returns. We use the Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) to assess the forecasting ability of the *EIvol* estimates from the EGARCH models versus a simple lagged *RIvol* when we assume that the current *RIvol* is its "true" estimate. Both criteria give the same rankings of the ability of the variables to forecast *Ivol* based on untabulated results. Lagged *RIvol* ranks first with the lowest RMSE of 0.1037 and lowest MAE of 0.0698, followed by $EIvol_{\text{All}}$ with a RMSE of 0.294 and a MAE of 0.2564. $EIvol_{60}$ has an RMSE of 0.3546 and a MAE of 0.2756.

2.8.2 Relation between *EIvol* and Returns

Using the "best" *EIvol* estimate from the EGARCH models (9) specified earlier, we again form zero investment portfolios with a long and short position in high and low *EIvol* stocks, respectively. For both portfolio weighting schemes (equally and value weighted) and all subsamples (all, big and small), returns increase monotonically with an increasing *EIvol*. Based on untabulated results, the non-risk-adjusted performance of the long/short portfolio based on value-weighting is a highly statistically significant 1.10% for the full sample and 1.03% and 1.41% for the subsamples of large and small stocks but all become insignificant when risk-adjusted. The corresponding performances of the equal-weighted portfolios are

[11] These include Fu (2009), Guo *et al.* (2014), Fink *et al.* (2012) and Huang *et al.* (2010).

positive but statistically insignificant with the exception of the non-risk-adjusted performance of the long/short portfolio of big stocks. When we use the estimate of *EIvol* based on 60 months of returns, the monotonous increase in the portfolio returns based on *EIvol* disappears for all samples regardless of whether they are or are not risk-adjusted.

We obtain consistent untabulated results when we account for the impact of short- and long-term return reversals. The non-risk-adjusted returns are positive for the long/short position in the value- but not equal-weighted portfolios. The risk-adjusted returns for the long/short position are statistically insignificant and tend to be negative when we use equal-weighted portfolios. Hence, the lowest AIC EGARCH model estimate provides a significant positive performance for the long/short position only when the portfolios are value weighted and the differential performance is not risk adjusted. These results are robust to the choice of which EGARCH model is used to generate the *EIvol* estimates. Based on untabulated results, most of the non-risk-adjusted returns on the long/short position based on the *EIvol* estimates from the other nine EGARCH models yield significantly positive returns that either become negative or lose their statistical significance when they are risk adjusted.

To further investigate the relationship between the quality of the *EIvol* forecasts and the performance of the long/short position based on high and low *EIvol*, we calculate the RMSE and MAE for 20 different *EIvol* models (ten models for both periods of 60 months and using all available at time t-1). Based on untabulated results, we find a negative relationship between the performance of a long/short position and the two measures of forecast quality (RMSE and MAE). Thus, as expected, the performance of the position increases as the forecast quality improves. The correlation between portfolio performance and the RMSE and MAE based on $EIvol_{All}$ is -0.56 and -0.53, respectively, and based on $EIvol_{60}$ is -0.32 and -0.22, respectively.

2.9. CONCLUSION

In this essay, we examine the relationship between *Ivol* and future returns in the Canadian market. We argue that the Canadian market is different than the US market including a large concentration of firms in the energy and mining industries, a high level of correlation with commodities, and the lack of evidence for the existence of sharp return reversals in monthly returns. Unlike the anomalous findings of Ang *et al.* (2006, 2009), we find that *RIvol* is positively (and not negatively) related to future returns. We explain that our findings are analogous to the findings of Huang *et al.* (2010) who argue that after controlling for return reversals in the US, that the negative relationship disappears. Our findings are consistent with the theory and are robust to risk loadings, return reversals, skewness and illiquidity.

Bali *et al.* (2011) uncover a negative relationship between extreme within-the-month positive returns and future returns and conjecture that this relationship is what is mistakenly explained by Ang *et al.* (2006) as the *RIvol* effect. Bali *et al*. (2011) argue that investors distort their beliefs and overweight stocks with extreme lagged daily returns. We hypothesize that this relationship might be a manifestation of the return reversal process in the US market. For the Canadian market, we find no sharp reversals in extreme returns. Unlike Bali *et al.* (2011), after controlling for extreme positive returns in the prior month, we find that the relationship between lagged *RIvol* and returns does not disappear after controlling for extreme positive returns in the prior month. Our results are confirmed using Fama-MacBeth equally and value weighted two stage regressions and Brennan *et al.* (1998) two stage risk-adjusted regressions.

CHAPTER THREE

DOES UNCERTAINTY ABOUT A CLOSED-END FUND'S HOLDINGS LEAD TO A DISCOUNT?

3.1. INTRODUCTION

Negative closed-end fund (CEF) premiums are ongoing phenomena that many financial academics find is inconsistent with the market efficiency hypothesis (Cherkes 2012). In their concluding chapter, Brealey *et al.* (2011) continue to list "why closed-end investment companies or any of the other firms sell at a discount on the market values of their assets" as the fourth of ten unsolved problems in finance. Many CEFs have the unique characteristics of having both their own price and the prices of the majority of their underlying assets determined in publicly traded markets (i.e., marked-to-market). The market efficiency hypothesis and the law of one price imply that the price of a share of the CEF and the CEF's Net Asset Value Per Share (NAVPS) should be equal in frictionless markets. Although a negative premium at issue of up to ten percent of the initial NAVPS can be explained by the underwriting fees and start-up costs associated with a CEF IPO, this initial negative price premium persists and fluctuates according to a mean-reverting pattern. At the liquidation of a CEF with a negative premium, the share price rises and the negative premium disappears (Brauer, 1988; Brickley and Schallheim, 1985).

In this essay, we advance the argument by Pontiff (2006) and others that one primary reason for the existence and persistence of a negative price premium for a CEF is that investors face uncertainty about the value created by packaging securities in a CEF. Since a CEF can add benefits and costs to the returns of its NAVPS, their effect on a CEF's premium will depend on whether the present value of future benefits less costs is positive or negative. Any premium will be less positive or more negative if there is more uncertainty associated with primarily the benefits of the CEF as they tend to be more uncertain. For example, if arbitrageurs cannot replicate the fundamental value represented by a CEF's NAVPS because of their uncertainty about the CEF holdings, this uncertainty due to limits to arbitrage will be captured in the CEF's premium, and will depend on the time-varying differences between the return-generating processes of CEF prices and its NAVPS. In this essay, we use the unhedged risk (both systematic and idiosyncratic) associated with an arbitrage position in the CEF and its NAVPS to proxy for this uncertainty.

Pontiff (2006) argues that the costs of arbitrage consist of transaction and holding costs.

Transaction costs are the direct costs that are more easily measurable, such as brokerage fees, commissions and market impacts. Holding costs are the opportunity costs of capital, not receiving full interest on short-sale proceeds, idiosyncratic costs and recall risk costs. Pontiff (2006) claims that CEF mispricing does not disappear even after controlling for transaction costs, opportunity costs, and the expected holding period of arbitrageurs even if they are efficient. Specifically, Pontiff (2006, p. 49) concludes that:

> "The fact that idiosyncratic risk is an arbitrage cost is commonly misunderstood, and because of this, very few studies of market efficiency have examined the impact of idiosyncratic risk on mispricing. The empirical studies that have pursued this course share a common thread—idiosyncratic risk appears to be the single largest impediment to market efficiency."

We argue that the characteristics of the holdings of CEFs affect both the risk of the arbitrage position, and the CEF's future net benefits. We use CEF holdings in cash, bonds, options and lottery-like assets to capture some of these characteristics. If CEFs hold stocks with lottery-like or jackpot features, these assets are expected to earn lower average returns (Kumar *et al.* 2011; Conrad *et al.* 2013). Conrad *et al.* (2013) extract higher distribution moments from options prices and find that the skewnesses of individual stocks are priced. Similar to out-of-the-money options, lottery-like stocks are defined as stocks with low prices, high idiosyncratic volatilities and high idiosyncratic skewness (Barberis and Huang 2008; Kumar 2009) and jackpot stocks are those with small probabilities of very high returns.

This essay makes five contributions to the literature on CEF premiums. Our first contribution is to provide a tradeoff model that incorporates the different CEFs models proposed in the literature. We augment the models of Cherkes *et al.* (2009) and Berk and Stanton (2007) by incorporating the work of Pontiff (2006) that adds an unhedgeable risk component that is faced by arbitrageurs due to incomplete information. We extend the insight of Pontiff (2006) to consider not only the idiosyncratic volatility associated with the CEF's incomplete fundamental value as represented by its NAVPS but also by the idiosyncratic volatility of the CEF's market-determined price. According to Merton (1987), the shadow cost of incomplete information depends upon idiosyncratic risk, firm size and investor recognition as captured by the relative size of the shareholder base. Of the many studies that support Merton's hypothesis, Bodnaruk and Ostberg (2009) report that zero-cost portfolios based on the shadow cost/shareholder base yield positive excess returns that are never positively correlated with the market and only modestly explained by the four-factor model.

Our second contribution is to link the holdings of the CEF to its premium. Since an arbitrage hedge position between the CEF's price and its NAVPS will be incomplete, we hypothesize that an arbitrageur with such a long-short position is exposed to hedging costs and both non-zero systematic and idiosyncratic risks. If the arbitrageur has full knowledge of the composition of the assets holdings, this arbitrage-risk exposure and any related premium for the CEF become smaller, and in the limiting case of a fully replicating index fund become approximately non-existent.

Our third contribution is to link the characteristics of the CEF holdings to the premium since we argue that arbitrage position risk increases as the CEF holds assets with asymmetric returns. While holdings of cash and bonds in an equity fund can provide strategic diversification and capital preservation in the case of a market downturn, they also are expected to provide lower returns than what an equity investor expects. Thus, an increase in these holdings may decrease the value of a CEF. Holding "lottery-like assets" with their low prices and low probabilities of potentially extreme positive returns is expected to increase the unhedgeable risks as captured by the idiosyncratic skewness of an arbitrage position in the CEF and its NAVPS. Increasing the weight of options in a CEF portfolio, especially those that are out-of-the-money, should increase the idiosyncratic skewness of the fund, and hence the premium demanded by arbitrageurs to hedge their positions (Mitton and Vorkink 2007).

Our fourth contribution is to use a more inclusive measure of the liquidity benefits of a CEF. Although previous studies discuss the importance of such a measure but only use the liquidity of the CEF itself (Datar 2001; Benveniste *et al.* 2011; Cherkes *et al.* 2009), we believe that we are the first to use the liquidity differential between the CEF and its actual holdings to measure the liquidity benefits of a CEF. Our measure is based on the amortized spread of the CEF less the weighted amortized spread of the CEF's holdings.

Our fifth contribution is, we believe, to be the first to use the κ test of Kapadia and Pu (2012) to examine if the changes in CEF prices and their NAVPS are integrated or segmented. The results from this test imply that the daily changes in CEF and NAVPS prices, on average, are more integrated than segmented, and that the differences in these two prices series not attributable to the CEF's net value-added would disappear given costless and risk-free arbitrage. This further supports our findings that (a) CEF premiums are less negative or more positive with greater CEF liquidity enhancement, better CEF performance and greater net leverage, and (b) are more negative or less positive with higher management fees, cash and bond holdings, and proxies for more costly and risky arbitrage.

The remainder of this essay is organized in eight sections. Section 3.2 reviews the literature on the different explanations proposed to explain CEF premiums. Section 3.3

provides a rational trade-off model for the CEF premium and develops the hypotheses. Section 3.4 describes the sample, data and the calculation of our idiosyncratic risk (*Ivol*) proxy. Section 3.5 estimates the Pontiff (1996) model using our data set and finds similar results as reported by him. Section 3.6 presents our test methodology. Section 3.7 presents and discusses our empirical findings. Section 3.8 presents and discusses the results of various robustness tests including a test of whether concurrent changes in the prices of a CEF and its NAVPS are integrated or segmented. Section 3.9 concludes the essay.

3.2. EXPLANATIONS PROPOSED FOR CEF PREMIUMS

The literature explaining the CEF premium anomaly can be divided into rational expectations and behavioral explanations. The former explanations are based on possible biases in NAV calculations such in the evaluation of private equity holdings, agency problems, the impact of the expense ratio, differences in tax treatment between holding a CEF and its portfolio of assets (NAV), the dividend yield, and liquidity. In contrast, behavioral explanations refer mainly to the inability to arbitrage differences between the value of the CEF (represented by its NAVPS) and its price caused by unpredictable changes in investor sentiment.

We observe the absence of these effects when a CEF is converted into or merged with an open-end fund. To illustrate, Brauer (1988) finds that a strategy of buying shares of US CEFs planning to "open-end" yields significant abnormal returns. Minio-Paluello (1998) reports similar results for UK CEFs. Bradley *et al.* (2010) find that "activist arbitrage", which consists of taking action or exhibiting an active interest to force convergence of CEF prices to their fundamental values, does lower the levels of CEF premiums.

One possible explanation from the rational expectations family is the agency costs arising from the delegation of fund management (Jensen and Meckling 1976). Investors anticipate an additional cost to the CEF, which leads to a negative premium. However, Malkiel (1977) reports that no correlation exists between the premiums for US CEFs and their management expenses as a proportion of NAV. This implies that a negative CEF premium cannot be explained solely by the management expense ratio and agency problems. Thompson (1978) and Malkiel (1977) find no significant relationship between CEF premiums and their performances. Kumar and Noronha (1992) find that differences in fees explain a small proportion of the cross-sectional variation in CEF premiums.

Agency costs also may exist between small and large shareholders. Barclay, *et al.* (1993)

find that large shareholders secure private benefits from keeping a CEF closed. While opening the CEF would automatically lead to the disappearance of its negative premium, large block shareholders tend to veto opening the CEF to keep their private benefits. Grullon and Wang (2001) argue that the CEF premium and institutional ownership are negatively related, as arbitrageurs prefer CEFs with large negative premiums.

The level of governance is found to reduce negative CEF premiums. Zhao (2007) finds that premiums increase with disclosures of higher ownerships by CEF directors. The size and the efficiency of the board are also important determinants of the level of the premium. Del Guercio *et al.* (2003) report that characteristics identified with effective board independence are associated with lower expense ratios and value-enhancing CEF restructurings.

Deaves and Krinsky (1994) argue that CEF premiums can be explained within a market efficiency framework using managerial costs if the relationship between the two is not always monotone. The effect of management fees on CEF premiums is affected by endogeneity since management fees are lowered in response to high negative CEF premiums (Cherkes 2012, p. 6). Nevertheless, Kumar and Noronha (1992), Gemmil and Thomas (2002, 2006), Cherkes (2001) and Cherkes *et al.* (2010) provide evidence that fees are an important source of negative CEF premiums.

Management fees are also related to CEF performance. Building on the work of Ross (2002), Berk and Stanton (2007) develop a rational expectations model of a fee-based management contract that captures the dynamic relationship between CEF performance and a manager's pay that is able to explain the behavior of the positive premium at the CEF's IPO and its subsequent decrease to a negative value. If the manager's performance is good (bad), the CEF will trade at a positive (negative) premium until the manager's compensation is renegotiated leading to a negative (less negative) premium. In support, Wermers *et al.* (2006) find a dynamic relationship between manager talent and a CEF's premium. Given their similarity to CEFs, Ramadorai (2012) finds a significant relationship between premiums and manager skills and compensation, and fund liquidity for a unique data set of hedge funds.

The tax liability of unrealized capital gains (referred to as tax efficiency) is another possible explanation for CEF premiums. According to Constantindes (1983, 1984), the optimal timing strategy is to realize capital losses immediately and to delay the realization of capital gains until forced liquidation. Unlike the market, a CEF NAV does not account for the potential tax liabilities of fund investors, which increase as the relative sizes of the unrealized capital gains in the CEF increase. Under fairly generous assumptions, Malkiel (1977) finds that tax liabilities cannot account for more than six percent of the CEF premium (Lee *et al.*

1991, p. 80). Day *et al.* (2011) find a short- (not long-term) relationship between unrealized capital gains and the fluctuations in CEF premiums. These findings are consistent with Seyhun and Skinner (1994) who argue that fund investors do not monitor the present value of their tax liabilities or adjust their holdings for tax reasons since a large majority (90 percent) of investors follow a buy and hold fund strategy.

The level of dividends is another possible explanation for CEF premium. Under the signaling theory, an increase in the dividend payout foresees an increase in future cash flows. Wang and Nanda (2006) and Johnson *et al.* (2006) find that the announcement of dividend-plan adoption leads to a less negative CEF premium. However, Nanda and Wang (2011) attribute this result to a decrease in agency costs, and not as a signal of future performance improvement. Kim *et al.* (2012) find similar results to Johnson *et al.* for dividend plans, but find no relationship between share repurchases and CEF premiums.

The level of the dividend yield is also considered as a limitation to arbitrage between the NAVPS and the price of a CEF. Pontiff (1996) argues for the existence of a positive relationship between a CEF's premium and its dividend yield. The higher the dividend yield, the lower the duration of the arbitrage position and the lower the cost of arbitrage for covering the dividend obligations on the short position of the underlying asset. While Pontiff (2006) argues that arbitrageurs avoid shorting low dividend paying stocks because it is expensive to do so, Dechow *et al.* (2001) considers this to be a myth and report that the relationship between dividend yields and the cost of arbitrage is insignificant.

Another potential explanation of the CEF premium is the liquidity theory that argues that premiums decrease with larger differences between the liquidity of the CEF and its underlying assets (Datar 2001) due to the greater cost associated with the less liquid arm of an arbitrage position. Datar (2001) reports that CEF premiums are related to various measures of CEF liquidity. Benveniste *et al.* (2011) find that that such bundling in an exchange-traded REIT increases the valuation of its illiquid assets by 12% to 22%.

Even when informed traders possess information about the systematic factors, the model of Subrahmanyam (1991) predicts lower adverse selection costs when trading a single security embodying multiple securities compared to trading the individual securities, due to the tendency of the directions of different firm value signals to offset each other in a security representing multiple securities. Cherkes (2003) argues for a higher or less negative CEF premium if a clientele effect is associated with holding a fund of illiquid assets. Cherkes *et al.* (2009) propose a liquidity-based model that explains the level of the CEF premium as a trade-off between the compensation of its managers and the liquidity premium that investors are willing to pay to hold the liquid fund instead of its less liquid underlying assets.

Within the behavioral (investor sentiment) family of CEF premium theories, Zweig (1973) argues that premiums reflect the expectations of individual investors. Weiss (1989) finds larger participations in CEFs by individuals versus institutional investors. Since the existence of irrational investors and noise traders make predicting the level of the CEF premium extremely difficult if not impossible for rationale investors, such investors are deterred from being aggressive arbitrageurs. Lee *et al.* (1991) use the CEF premium as a proxy for market sentiment, which limits the scope of arbitrage by driving market prices away from fundamentals (Shleifer and Vishny 1997). Lee *et al.* (1991) argue that CEF premium exhibit high levels of correlation, have a tendency to converge towards a grand mean and are issued "in waves" when CEFs tend to trade at a premium. Hwang (2011) finds that as the level of popularity of a certain country increases, the premiums of ADRs and country CEFs increase.

The investor sentiment explanation is debated extensively in the literature. Severn (1998) provides evidence that investor sentiment increases CEF risk, although he suggests that using large caps as part of the portfolio would diversify away this risk exposure. Flynn (2012) finds support for this explanation for CEF premiums using US data. Chen *et al.* (1993), Elton *et al.* (1998) and Gemmill and Thomas (2002) do not find support for the investor sentiment explanation. Qiu and Welch (2006), Lemmon and Portniaguina (2006), and Ramadorai (2012) find no significant relation between CEF premiums and sentiment indices based on consumer confidence surveys.

3.3. RATIONAL TRADE-OFF MODEL FOR CEF PREMIUMS

3.3.1 The Model

Rational trade-off theories focus on comparisons of the benefits (enhanced liquidity, managerial contribution, and leverage) and costs (managerial fees) associated with a CEF. With regard to liquidity, CEFs unlike open-end funds (OEFs) provide small investors with access to some otherwise unavailable illiquid assets since CEFs can concentrate their investments in illiquid assets due to their protection from liquidity withdrawal shocks (Nanda *et al.* 2000). Chordia (1996) reports that his sample of CEFs holds predominantly illiquid assets, and Deli and Varma (2002) find that CEF premiums are sensitive to CEF liquidity. Cherkes *et al.* (2009) develop a model where CEF premiums depend upon a netting of liquidity benefits against the (managerial) fees paid by CEF investors.

Berk and Stanton (2007) extend the model of Ross (2002) to link CEF premiums to include not only the costs of management fees but also investor perceptions of the benefits of managerial ability. In their model, new managers and investors only learn about the former's abilities with the accumulation of on-the-job performance. Since managers earn guaranteed compensation until contracts are renegotiated, the compensations of new managers with inferior and superior abilities fall short and exceed their contributions, respectively. Thus, newly issued CEF with superior managerial abilities trade at positive premiums prior to managerial compensations being renegotiated upwards, and then trade at negative premiums thereafter. In their model and ignoring issue costs, the interplay between informational asymmetry about managerial abilities, competitive managerial compensations, and managerial renegotiations of contracts explains why the positive premium of a CEF at IPO is almost always followed by a negative premium.

Cherkes *et al.* (2009) report that the premiums of bond CEF are positively associated with fund leverage, and Ramadorai (2012) finds that CEF premiums are negatively impacted by increases in short-term interest rates. Elton *et al.* (2012) conclude that the positive relation between leverage and performance, which is greater for bond CEF versus bond OEF, is the reason for the existence of bond CEFs.

When we combine all of these identified costs and benefits associated with a CEF into one model and assume that they are completely identified, the premium for CEF i in period *t* in a frictionless market for arbitrage becomes:

$$P_{CEF_{i,t}} - NAVPS_{CEF_{i,t}} = PV(Liquidity\ Benfits)_{CEF_{i,t}} PV(Leverage\ Provision)_{CEF_{i,t}} \quad (3.1)$$

$$+PV(Managerial\ Abilities)_{CEF_{i,t}} - PV(Managerial\ Fees)_{CEF_{i,t}} + \varepsilon_{i,t}$$

where the NAVPS plus the first four terms on a per-share basis on the right-hand-side (RHS) of (1) represents the CEF's intrinsic value.

An arbitrageur could earn the CEF premium minus the expected values of each of the first four terms on the RHS side of (3.1) by buying (selling) the CEF and simultaneously selling (buying) the equivalent NAVPS when that difference is negative (positive). In determining if this strategy could provide the arbitrageur's required risk-adjusted return, the arbitrageur needs to use the appropriate discount rate or rates that reflect the unhedged (arbitrage) risk of such a long-short position. Based on our previous discussion, this arbitrage risk is associated with the uncertainties associated with an incomplete hedge and the four terms on the RHS of (3.1). An arbitrageur's uncertainty about CEF liquidity benefits depends on the time-varying liquidity differentials between the CEF and its holdings. For simplicity in model development, Cherkes *et al.* (2009) assume that the CEF is highly liquid but note that their liquidity premium is the liquidity difference between the fund and its holdings so that the CEF premium becomes more positive or less negative with a greater positive liquidity advantage of the CEF over that of its holdings all else held equal. In support, Beneviste *et al.* (2001) provide empirical evidence that exchange traded real estate investment trusts (REIT) increase the values of their illiquid assets held by them by 12 to 22%. In contrast, and as reported in the literature (e.g. Ackert and Tian 2000), passive CEF tracking indexes have little or no positive or negative premiums due to the minimal uncertainty about their liquidity and managerial abilities (Aber *et al.* 2009). Thus, any informational asymmetry associated with CEF liquidity benefits is decreased somewhat by having continuously updated knowledge about CEF holdings.

An arbitrageur's perceived uncertainty about the benefits from the ability of a CEF manager to add value is expected to be lower with a better track record over a longer period of time. An arbitrageur's perceived uncertainty about the leverage benefits from using non-common-equity depends upon whether the CEF not only can obtain such funding on more favorable terms (including favorable tax treatment) than its representative investor but also on whether such funding is used to fund cash holdings or is invested in other assets whose time-varying returns exceed fixed or time-varying funding costs. To illustrate one such possible advantage, Elton *et al.* (2013) explain that favorable tax treatment of preferred dividends reduces funding costs to rates close to those on federal funds for bond CEFs and to lower than the federal funds rate for muni bond CEFs. However, this literature does not assess whether the benefits differ when measured using gross or net leverage where the latter is the difference between the book leverage and the cash-to-assets ratio.

Unlike the risks associated with the benefits, managerial costs are reasonably stable as a proportion of NAV for funds like those examined herein. Thus, as Berk and Stanton (2007) show for various managerial contract types, managerial fees tend to exceed managerial benefits. All else held equal, an increase (decrease) in the level of risk decreases the expected net present value of managerial ability benefits versus managerial costs leading to a less positive or more negative (more positive or less negative) premium. Furthermore, since the perceived uncertainties are likely to be higher for the CEF benefits versus CEF costs, the benefits would be discounted at a higher rate(s).

3.3.2 The Discount Rate for the Risk of the Arbitrage Position

We now provide a rationale for the required rate of return that the arbitrageur should use to determine if some of the gap between a CEF's price and NAVPS should be arbitraged away. We start with replicating the arbitrage position by calculating the net return from holding a long position in the CEF and short position in its NAVPS given by:

$$r_{net_{i,t}} = r_{CEF_{i,t}} - r_{NAV_{i,t}} \tag{3.2}$$

where $r_{CEF_{i,t}}$ is the return of holding CEF stock i in period t and $r_{NAV_{i,t}}$ is the return of the equivalent NAVPS short holding for CEF stock i in period t.

If the arbitrage is classic in that it is cost- and risk-free and no net benefit is provided by the CEF, then the return on the CEF and its underlying assets as captured by the NAVPS would be exactly the same. Uncertainty about the CEF's holdings, its net benefits and the inability to replicate the exact return-generating process of the underlying assets of the CEF leads to potential differences in both the hedgeable and unhedgeable components of an arbitrage strategy. An arbitrageur is very unlikely to be fully hedged due to not having the correct hedge ratio or the ability to continuously adjust the hedge (Kapadia and Pu 2012), particularly if information on CEF holdings is not updated continuously. In such cases, the arbitrageur faces a systematic risk exposure for which the arbitrageur requires compensation. This is supported by various studies that argue for the existence of systematic components in arbitrage positions related to market conditions that prevent the arbitrage from being perfect (e.g., Barberis *et al.* 2005; Greenwood 2008; and De Jong *et al.* 2009).

We model the net position of the arbitrage as a portfolio of two assets faced by a set of systematic risk factors f so that the return-generating process of the arbitrage position in CEF i in period t is:

$$r_{net_{i,t}} = \propto_{net_{i,t}} + \beta_{net_{i,t,f}} \times f_t + \varepsilon_{net_{i,t}} \tag{3.3}$$

where $r_{net_{i,t}}$ is the excess return of the long/short position in the CEF's price and its NAVPS, f is a vector of systematic risk factors, $\beta_{net_{i,t,f}}$ is the factor loading of the systematic risk factor f of the long/short position for the CEF's price and its NAVPS, and $\varepsilon_{net_{i,t}}$ is the component unexplained by the systematic risk factors f. If the systematic risks are hedged perfectly, all $\beta_{net_{i,t,f}}$ would be equal to zero, leaving the idiosyncratic component as the only source of risk for the arbitrageur.[12] This is consistent with the use of idiosyncratic volatility (*Ivol*) as a proxy for the holding cost constraint in Gagnon and Karoyli (2010) when examining arbitrage profits from the simultaneous purchase and sale of equivalent securities in two different markets. According to Deither *et al.* (2009), arbitrageurs who hold stocks for longer (shorter) periods may be more concerned with holding (transaction) costs, where holding costs include idiosyncratic risks and lending fees.

Pontiff (2006) discusses the treatment of idiosyncratic volatility in the finance literature. He argues that while idiosyncratic volatility does not matter in a CAPM framework where investors are well diversified, an arbitrageur cannot costlessly diversify away idiosyncratic risk regardless of the level of portfolio diversification. To illustrate this point, Pontiff (2006) considers a simple market with one risk factor (the market) where an investor is faced with a certain number of mispriced securities. A sophisticated investor could create a hedge portfolio for the mispriced securities, where a hedge portfolio packages a long position in the mispriced security and a short position in the market portfolio proportional to the risk loading of the security. Assuming that the hedge is complete, the "packaged" position still bears idiosyncratic risk. Duan *et al.* (2010) conclude that it is unlikely that lending fees on shorted shares can fully explain the lack of arbitrage, and that arbitrage costs represented by idiosyncratic volatility are a more likely candidate.

Thus, the rate of return required by the arbitrageur holding the long-short position becomes:

$$r_{net_{i,t}} = \propto_{net_{i,t}} + \beta_{net_{i,t,f}} \times f_t + \gamma_i Ivol_{net_{i,t}} + \eta_{net_{i,t}} \tag{3.4}$$

where γ_i is the sensitivity of the return of the arbitrageur to the unhedgeable risk of the long-short position, and all the other terms are as previously defined. Thus, an increase in *Ivol* should increase the required rate of return from the arbitrage position leading to a decrease in the mispricing portion of the CEF premium from the perspective of the arbitrageur, all else held equal. The uncertainty about a CEF's holdings based on publicly available information that is not updated continuously also affects the ability of the arbitrageur to replicate the NAVPS suitably. This limitation in replicating the systematic factors by the arbitrage

[12] This does not depend upon the mixed findings on whether idiosyncratic volatility (*Ivol*) is priced in an asset-pricing context. For example, Fu (2008) finds that idiosyncratic volatility (*Ivol*) has a positive premium for individual stocks in the US while other studies conclude that the relationship between idiosyncratic volatilities and expected returns is negative (Guo and Savickas 2006; Ang *et al.* 2006, 2009).

position, which is captured by $\beta_{net_{i,t,f}}$, also leads to an increase in the rate of return required from the long-short position.

3.3.3 Hypotheses

Our hypotheses follow from the model described above where we argued that the premium is a result of a tradeoff between CEF benefits and costs, the risks associated with the realization of the net benefits and the costs and risks of arbitraging away any remaining mispricing. When the investor has confidence in the manager's ability to provide positive net benefits, the fund should trade at a positive premium based on this benefit. To measure the uncertainty for the arbitrageur about CEF mispricing, we use the systematic and idiosyncratic risk exposures of taking a long/short position in the CEF and its NAVPS.

Hence, our first hypothesis in its alternative form (H_A^1) is that the level of the CEF premium is related to the risks associated with an arbitrage position undertaken to eliminate any CEF mispricing. As noted earlier, an arbitrageur is faced with replicating the systematic risk exposures of the arbitrage portfolio and any remaining idiosyncratic risk exposure, which would be reduced if the arbitrageur knew the exact composition of the CEF's portfolio at all points in time. We expect a negative relationship between this arbitrage risk and the dollar premium.

Our second alternative hypothesis (H_A^2), which relates CEF benefits to the CEF premium, is that the liquidity differential between the CEF and its holdings or its managerial net benefits decreases a negative premium or increases a positive CEF premium. Cherkes *et al.* (2009) and Berk and Stanton (2007) argue that CEFs with distributions of liquidity and net managerial benefits that differ in their means are associated with different CEF premiums.

Our third alternative hypothesis (H_A^3) is that arbitrage uncertainty is related to the characteristics of CEF holdings. We expect that premiums will be more negative or less positive with the greater use of cash, bonds, and lottery-like assets for an equity CEF. We conjecture that greater holdings of cash and bonds decrease the present value of future CEF benefits by increasing the rate of return that other holdings need to earn. Similarly, we conjecture that lottery-like assets increase the asymmetry of the cash flows from the assets held by the CEF. This would increase the overall risk of the long-short position and its required return, leading to a wider deviation between the CEF's share price and its NAVPS.

3.4. SAMPLE, DATA AND ARBITRAGE RISK

3.4.1. Sample and Data

We draw our sample of US equity CEFs listed in the US market from the Morningstar Direct database. After collecting the detailed historical holdings, our initial sample of 153 funds is reduced to 93 funds which represent 85% of all domestic equity CEFs in the US.[13] Although holdings data became available in 1998, most of the fund holdings are only available after 2002. Morningstar collects the data directly from fund managers making the information available before being reported officially in the SEC filings. The holdings (asset names, dollar values and weights) are reported on a monthly or quarterly basis. According to the filters that we set to obtain our sample, most of the weights of the funds are invested in US stocks, but there are investments in other asset categories such as bonds, options, swaps, and currencies. We manually identify each of the asset types based on the name descriptions and other information, and match them to the stocks in the CRSP database. We are able to identify a total of 5,567 unique permno CRSP identifiers. We report the descriptive statistics for the different asset holdings in table 3.1. The average holdings over the time period are 83.00% for equity, 8.05% for debt, 4.81% for cash, and 3.61% for options.

[Please place table 3.1 about here.]

3.4.2 Calculation of Arbitrage Risk Proxies

To estimate the arbitrage risk proxies discussed earlier for CEFs and months with at least 15 daily returns, we use the Carhart (1997) 4-factor model:

$$r_{net_{i,d_t}} = \gamma_0 + \beta_{net_{i,t,mkt}} r_{M,d_t} + \beta_{net_{i,t,SMB}} SMB_{d_t} + \beta_{net_{i,t,HML}} HML_{d_t} + \beta_{net_{i,t,WML}} WML_{d_t} + \varepsilon_{i,d_t} \quad (3.5)$$

Where for each day d of month t, $r_{net_{i,d_t}}$ is the net return of the long/short position in CEF i and its NAVPS, r_{M,d_t} is the excess return of the market portfolio, SMB_{d_t} and HML_{d_t} are the two additional Fama-French factors, WML_{d_t} is the momentum factor,[14] and ε_{i,d_t} is the error term. We calculate the NAVPS returns using the methodology outlined in Wermers *et al.*

[13] The percentage is calculated based on the average yearly number of closed end funds reported by the Investment Company Institute. http://www.ici.org/cef/background/bro_g2_ce

[14] The daily factors are obtained from the Kenneth French website at: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_factors.html

(2006) and Cherckes *et al.* (2009) where the expense ratio is incorporated in the NAVPS returns. As in Goyal and Santa Clara (2003), we add a second term to capture the covariance between lagged returns so that the $Ivol_{net,i,t}$ from equation (3.6) is given by:

$$Ivol_{net,i,t} = \sqrt{\sum_{d_t=1}^{T} \varepsilon_{i,d_t}^{2} + 2\sum_{t=2}^{T} \varepsilon_{i,d_t}\varepsilon_{i,d_{t-1}}} \tag{3.6}$$

where T is the number of days in the month, and all the other terms are defined as earlier.

If the arbitrageur can perfectly hedge the systematic shocks to the net position returns, then the arbitrageur is only exposed to idiosyncratic risk. However, as argued earlier, this may not be the case if the arbitrageur does not adopt the perfect hedge ratio due to the lack of up-to-date information about the holdings of the CEF. Table 3.2 reports the mean and median of these monthly factor sensitivities for the net positions for our full sample which indicates statistically significant average factor sensitivities for three factors (SMB, HML and WML) but not for the market risk factor. These statistically significant average sensitivities show that arbitrageurs using a 1-to-1 hedge ratio are not able to completely eliminate the hedgeable risk for an arbitrage position involving its CEF and NAVPS using the Carhart 4-factor model.

The arbitrageur will always be exposed to idiosyncratic uncertainty. The average monthly R-square of equation (3.6) of 28.64% indicates that 71.36% of the return variation for the net position ($Ivol_{net}$) is not explained by the systematic factors and is unhedgeable using systematic factor arbitrage. Thus, uncertainty about the holdings of the fund, which also creates inaccuracy of the hedge ratio, creates uncertainty about both the hedgeable and unhedgeable components of the net position. The average $Ivol_{net}$ is 6.98% with a median of 4.8%. The mean difference (premium) between the prices of a CEF and its NAVPS of -5.62% is comparable to the values previously reported in the literature (Pontiff 1996; Cherkes *et al.* 2009).

[Please insert table 3.2 about here.]

3.5. REPLICATION OF PONTIFF'S MODEL USING OUR SAMPLE DATA

Pontiff (1996) was the first to consider CEF arbitrage risk, as measured by the idiosyncratic risk of the NAVPS portfolio, as a limitation for exploiting any potential CEF mispricing.[15] We benchmark our empirical analysis by replicating Pontiff's (1996) analysis (as reported in his table I, p. 1143) using our sample data composed of equity-only funds for a different time period. Our findings, which are reported in table 3.3, confirm the negative

[15] The concept of arbitrage risk in CEF arbitrage was further explained in Pontiff (2006).

relationship between the unhedgeable component and the premium level as identified by Pontiff. The median explanatory power of unhedgeable risk, liquidity, transaction costs and hedgeable risk in explaining premium variation is around 25%. However, when the control variables are excluded, the median explanatory power drops to 2.54%. When we add the idiosyncratic skewness of the residuals from the NAVPS returns to the regression as a preliminary test of its importance, the median adjusted R-square increases to 46%, and the premium and idiosyncratic skewness are positively and significantly related. In the next sections, we provide more detailed examinations of the determinants of the variations in CEF premiums.

[Please place table 3.3 about here.]

3.6. METHODOLOGY

We run Fama-MacBeth type cross-sectional regressions for each month over the period 2001:01 to 2010:12. The number of funds with available holding information from Morningstar Direct changes over the period. We test the impact on premium levels due to the cost of CEF arbitrage as captured by the sensitivities of a CEF's net position returns to the systematic risk factors and its idiosyncratic volatility, the characteristics of its holdings and its potential benefits and costs as specified earlier in equation (3.1). We estimate the following regression for $Premium_{i,t}^{m}$ (i.e., the level or change in the CEF premium when *m* = level and *m* = change, respectively) for CEF *i* for month *t*:

$$\begin{aligned}Premium_{i,t}^{m} =\ & \gamma_{0,t} + \gamma_{1,t}\,\hat{\beta}_{net_{mkt,i,t-1}} + \gamma_{2,t}\hat{\beta}_{net_{SMB,i,t-1}} + \gamma_{3,t}\ \hat{\beta}_{net_{HML,i,t-1}} + \\ & \gamma_{4,t}\hat{\beta}_{net_{WML,i,t-1}} + \gamma_{5,t}Ivol_{net,i,t-1} + \gamma_{6,t}Iskew_{i,t-1} + \gamma_{7,t}\%Options_{i,t-1} + \\ & \gamma_{8,t}\%Cash_{i,t-1} + \gamma_{9,t}\%Bonds_{i,t-1} + \gamma_{10,t}Leverage_{i,t-1} + \\ & \gamma_{11,t}\partial AS_{i,t-1} + \gamma_{12,t}Alpha_{i,t-1} + \gamma_{13,t}\log\left(MktVal_{i,t-1}\right) + \\ & \gamma_{14,t}\left(1/P_{i,t-1}\right) + \gamma_{15,t}DY_{i,t-1} + \gamma_{16,t}MgmtFees_{i,t-1} + \gamma_{17,t}Tenure_{i,t-1} + \\ & \nu_{i,t} \qquad (3.7)\end{aligned}$$

The expected mean coefficients are zero for $\hat{\beta}_{net_{i,t-1,mkt}}$,$\hat{\beta}_{net_{i,t-1,SMB}}$, $\hat{\beta}_{net_{i,t-1,HML}}$, and $\hat{\beta}_{net_{i,t-1,WML}}$(i.e., the factor sensitivity estimates from the 4-factor Carhart model of the net returns of a long/short CEF/NAVPS position obtained from equation (3.5)). The expected coefficient is negative for $Ivol_{net,i,t-1}$ (i.e., the idiosyncratic volatility of the net returns).

The expected coefficient for $Iskew_{i,t-1}$ (i.e., the CEF's idiosyncratic skewness) is negative if this variable captures the preferences of under-diversified investors. Boyer *et al.* (2010) develop and report empirical support for an equilibrium model that captures under-diversified investor preferences for idiosyncratic skewness as measured by (also, see Bali *et al.* 2011):

$$Iskew_{i,t-1} = N_{t-1}^{-1} \times \left[\left(\sum_{d_t=1}^{T} \varepsilon_{i,d_{t-1}}^{3}\right) / \left(\sigma\left(\varepsilon_{i,t-1}\right)^{3}\right)\right] \tag{3.8}$$

where all the terms are as defined earlier.

We have no a priori expectation for the coefficient of $\%Options_{i,t-1}$ (i.e., the total weight of a CEF's holdings of options) since it may signal the level of reliance of the CEF manager on "lottery-like" assets (Boyer and Vorkink 2014) or the use of a more cost-effective trading strategy for risk management purposes. The average (maximum) weight of the more than 10,000 different options in our sample of CEF portfolios is 3.61% (7.97%), and the average increases to 27.55% when we exclude CEFs with no option holdings. Thus, the average CEF that uses options places a heavy reliance on options.

The expected coefficient for $\%Cash_{i,t-1}$ (i.e., the weight of cash and cash equivalent assets) is, on balance, negative. The effect on the deviations between CEF market prices and NAVPS depends upon the net effect of the low uncertainty and high liquidity associated with cash holdings versus the decrease in managerial contribution to CEF value if cash is not held for strategic purposes.

The expected coefficient for $\%Bonds_{i,t-1}$ (i.e., the weight of bonds in the CEF) is, on balance, negative for similar reasons as for cash.

The expected coefficient is negative for gross $Leverage_{i,t-1}$ (i.e., the ratio of non-common equity to total assets using CEF financial statements from S&P Capital IQ) and positive for net $Leverage_{i,t-1}$ (i.e., when the cash ratio is removed). Elton *et al.* (2013) argue that CEFs unlike OEFs have the unique ability to finance themselves using instruments in addition to common equity so that a CEF's market price is equal to its NAVPS plus the per-share value of leverage. The value of CEF leverage depends upon its cost. It may contribute positively to CEF value if the non-common-equity instruments can be financed at lower rates than are available to the dominant (individual) investor group in a CEF because their payments are treated as dividends with favorable tax treatment, and they provide the benefit of limited liability.[16] The CEF leverage may contribute negatively to CEF value if used to fund cash for the same reasons given earlier for the weight of cash or positively to CEF value if used to earn the return differential between their cost and equity returns. Deli and Varma (2002) and Cherkes *et al.* (2009) report that CEF premiums are related to their leverage ratios,[17] and Elton *et al.* (2013) find that the systematically greater leverages of CEFs partially explain the coexistence of otherwise identical CEFs and OEFs for their sample of only bond funds where leverage benefits through favorable tax treatment are material. The mean and median non-common equity financing percentages for our CEF sample are 14.03% and 9.8%, respectively, with our mean being smaller than that of Cherkes *et al.* of 16%.

The expected coefficient is negative for $\partial AS_{i,t-1}$ (i.e., the difference in the amortized spreads between the CEF and its asset holdings) leading to a positive premium if large enough (Datar 2001). Given the liquidity characteristics of a CEF and its asset holdings, this variable mimics the same arbitrage strategy of taking a long (short) position in low (high) liquidity stocks that Idzorek *et al.* (2012) find yields a significant abnormal return. The inclusion of this variable allows for a test of the hypothesis of Cherkes *et al.* (2009), among others, that CEFs provide investors with the opportunity to hold a portfolio of illiquid stocks in a liquid instrument. Arbitrage between the fund and its portfolio also becomes less costly with lower liquidity differences between the CEF and its asset holdings. We proxy liquidity for the CEF and its asset holdings by the amortized spread measure of Chalmers and Kadlec (1998) given for CEF *i* and month *t* by:[18]

$$\mathrm{AS}_{\mathrm{i,t}}^{\mathrm{CEF}} = \frac{\sum_{d_t=1}^{\mathrm{T}} |\mathrm{P}_{\mathrm{CEF},d_t} - \mathrm{M}_{\mathrm{CEF},d_t}| \times \mathrm{V}_{\mathrm{CEF},d_t}}{\mathrm{P}_{\mathrm{CEF,t}} \times \mathrm{OS}_{\mathrm{CEF,t}}} \tag{3.9}$$

$$\mathrm{AS}_{\mathrm{i,t}}^{P} = \sum_{w \in f} w \left(\frac{\sum_{d_t=1}^{\mathrm{T}} |\mathrm{P}_{d_t} - \mathrm{M}_{d_t}| \times \mathrm{V}_{\mathrm{t}d_t}}{\mathrm{P}_{\mathrm{t}} \times \mathrm{OS}_{\mathrm{t}}} \right) \tag{3.10}$$

where $|P_{CEF,d_t} - M_{CEF,d_t}|$ and $|P_{d_t} - M_{d_t}|$ are the effective spread for the CEF and its portfolio of assets, respectively; $OS_{CEF,t}$ and OS_t are the number of outstanding shares at month end for the CEF and its underlying assets, respectively; $\mathrm{V}_{\mathrm{CEF},d_t}$ and V_{d_t} are the trading volumes for the CEF and its underlying assets, respectively; and *w* is the weight of each asset in the CEF's holdings.

[16] However, extensive use of leverage increases the riskiness of the arbitrage position because the future claims of non-common equity would be less volatile than the revenues generated by leveraging the fund (i.e. distress costs). The maximum level of leverage in our sample is 36%.

[17] While Cherkes *et al.* (2009) discuss the impact of leverage on illiquidity, they did not formally incorporate leverage into their model.

[18] The daily closing price is taken as a proxy for the execution price, and the closing mid-spread is used in its absence. This measure is only appropriate for assets that trade.

The expected coefficient is positive for $Alpha_{i,t-1}$ (i.e., the contribution of the management team and others such as trader executors and advisors to CEF performance, which is obtained from the Carhart 4-factor model over the five years prior to month t using the monthly returns for ret_{NAV}). In the rational models of Berk and Stanton (2007) referred to earlier, managerial performance enhancement is positive (negative) for superiorly (inferiorly) managed CEFs as their managers are under- (over-) compensated between compensation setting dates when the management fees are adjusted upwards (downwards) to better reflect the manager's performance.

The coefficients are expected to be positive for $\ln(MktVal_{i,t-1})$ and $1/P_{i,t-1}$ (i.e., the market value and the inverse of the price for the CEF). These variables are included to control for the effect of transaction costs on a CEF's premium. Pontiff (1996) argues that transaction costs are higher for smaller-sized CEFs as measured by market values or share prices because smaller CEFs tend to be more illiquid leading to a higher level of persistence in their premiums.

The coefficient is expected to be positive for $DY_{i,t-1}$ (i.e., the dividend yield for the CEF). Early papers considered dividend yield as a transaction cost of arbitrage (e.g., Pontiff 1996) which are expected to be higher for dividend-paying firms because stock prices tend to fall by less than the dividend that the short-seller is required to pay (e.g., from 0.7653 to 0.8626 for taxable and non-taxable cash dividends in Bali and Hite (1998)). Elton *et al.* (2003) find that dividend tax treatment affects CEF prices based on a comparison of the dividend price effects for different taxable (Bond) and non-taxable (Munis) CEFs. These differential tax issues should be minimized in our sample because our sample consists of only domestic equity funds. More recent studies consider CEF dividend yields as signals of value so that CEF premiums are expected to increase (become less negative or more positive as the CEF commits to distribute more of its cash flows. While Wang (2004) and Johnson, Lin and Song (2006) find supportive evidence for this hypothesis, Wang and Nanda (2011) and Cherkes *et al.* (2011) do not.

The coefficients are expected to be negative and positive, respectively, for $MgmtFees_{i,t-1}$ and $Tenure_{i,t-1}$ (i.e., tenure of the CEF manager in years obtained from Morningstar). The positive relation between managerial tenure and CEF premiums depends on the benefits of managerial abilities being positively related to managerial tenure and the benefits being shared between the manager and the CEF.

[Please place table 3.4 about here.]

Table 3.4 reports summary statistics (e.g., median, mean and standard deviation) for all the potential determinants of the CEF premiums used in the subsequent empirical tests. As we discussed earlier, our average premium is in line with the literature (e.g., Pontiff 1996). The standard deviation of the premiums is high reflecting the existence of some deeply discounted funds in our sample. We observe that an arbitrageur is exposed to an average monthly idiosyncratic risk ($Ivol_{net}$) of 6.98% with a standard deviation of 4.3%. To put these numbers into perspective, Fu (2009) reports that the average monthly idiosyncratic volatility for a pooled sample of 2,946,521 firm-month observations is 14.17% with a standard deviation of 13.91%. The average $Iskew$ of -0.014 indicates that the average CEF in our sample has little to offer investors who prefer idiosyncratic skewness.

The average ∂AS of 0.3% indicates that an average CEF has a higher liquidity than its underlying holdings. The mean and median $\ln(MktVal)$ are 5.59 and 5.64 (corresponding to 267 and 281 million dollars respectively), with a standard deviation of 1.25. The mean and median inverse prices (1/P) are 0.06 and 0.08, respectively, with a standard deviation of 0.08. The mean and median DY are 1.59% and 1.26%, respectively, with a standard deviation of 1.14%.

The mean and median $MgmtFees$ is 1.59% and 1.26%, respectively, with a standard deviation of 1.14%. The mean and median average $Tenure$ is 9.52 and 7.75 years, respectively. The mean and median $Alpha$ are -0.44% and -0.42%, respectively, with a standard deviation of 0.82%. Thus, the contribution of an average CEF manager for the studied period is negative, implying that any value added by the manager does not cover fund expenses for the sample of CEFs and time period studied herein.

[Please place table 3.5 about here.]

Table 3.5 reports the average cross-sectional correlation coefficients between each pair of explanatory and control variables and their corresponding p-values. Our explanatory variables have low levels of correlations implying that multicollinearity should not be a concern. As expected, the CEF premium is significantly and negatively correlated at -0.40 with $Ivol_{net}$ and marginally significant and positively correlated at 0.21 with managerial contribution (Alpha). $Tenure$ is the most correlated dependent variable. It is negatively correlated with $Ivol_{net}$, $\log(MktVal)$, $1/P$ and $MgmtFees$ and, as expected, positively correlated with $Alpha$. The second most correlated dependent variable, $MgmtFees$, is positively correlated with $Ivol_{net}$, and ∂AS and negatively correlated with DY. The negative correlation of -0.326 between $Ivol_{net}$ and $Alpha$ is consistent with the premise that the nonhedgeable risk of the arbitrage position increases as the performance of the fund decreases.

3.7. DETERMINANTS OF CEF PREMIUM LEVELS AND THEIR CHANGES

Before proceeding to a presentation and discussion of the empirical results, our estimates of the Fama-MacBeth regression coefficients are adjusted for autocorrelation using a method first used by Pontiff (1996) and subsequently used by Cornett *et al.* (2008), Irvine and Pontiff (2009), amongst others. The adjusted versions of the coefficient estimates and their standard errors are obtained by regressing the time-series of the parameter estimates on an intercept term and modeling the residuals as a sixth-order autoregressive process. The standard error of the intercept is then the corrected standard error for that coefficient. As long as the sixth-order autoregressive process captures all of the serial dependence, these standard errors are not biased by serial or cross-sectional correlation.

Furthermore, in this and subsequent sections of the essay, we not only examine statistical significance but also the elasticities of some of the variables that have statistical significance using two measures. The first measure is obtained by multiplying the estimated coefficient of an independent variable by the ratio of that variable's mean to the mean of the dependent variable. The second measure is obtained by first multiplying the estimated coefficient of the independent variable by its mean value to get the absolute reduction in the mean of the dependent variable from driving the mean value of the independent variable to zero (as in Aggarwal *et al.* 2009). Then the relative reduction is obtained by dividing this absolute reduction by the mean of the dependent variable.

3.7.1 Fama-MacBeth Cross-sectional Regressions for CEF Premiums

[Please place table 3.6 about here.]

The regression results for the monthly Fama-MacBeth cross-sectional regressions of CEF premium levels on various potential determinants for the period 2001-2010 are reported in table 3.6. We find that the average explanatory power of the regressions increases from a mean R^2 of 12.69% [run (2)] when only $Ivol_{net}$ is included to 27.88% [run (3)] when the systematic-risk exposures of the arbitrage portfolio are also included to 67% [run (6)] when all the potential determinants of CEF premiums considered herein are included. The mean coefficient estimate of the sensitivity of the net returns of the long CEF/short NAVPS position on the market, HML and momentum factors are statistically insignificant implying that the average factor loadings of these risks do not significantly affect the changes in the CEF dollar premium. However, the significant (negative) coefficient for the SMB factor implies that the Fama-French size factor contributes to the cross-sectional variation in CEF dollar premiums. This finding of hedging difficulties with the SMB factor is consistent with a behavioral explanation of the CEF premium given that Qui and Welsh (2006) find that proxies for market sentiment are correlated with small stock returns but not with CEF premiums.

Since the mean coefficient estimate for $Ivol_{net}$ is consistently negative and highly significant, CEF premiums become less positive or more negative as idiosyncratic volatilities increase. When we multiply the estimated coefficients of $Ivol_{net}$ in table 3.6 by the ratio of the mean $Ivol_{net}$ to the mean CEF premium from table 3.4, we estimate that a 1% change in $Ivol_{net}$ results in a CEF premium change ranging from 9.74% to 17.64%. We obtain the impact when $Ivol_{net} = 0$ by first multiplying the estimated coefficients of $Ivol_{net}$ from table 3.6 by the mean $Ivol_{net}$ from table 3.4 to get the absolute reductions in the mean CEF premium that range from 68.05% to 123.18%. Then we divide these absolute reductions by the mean CEF premium from table 3.4 to get the relative increases in the mean CEF premium that range from 12.1 to 21.9 times.

The mean coefficient estimates for $Iskew$ are consistently negative as expected but their statistical significances change considerably between runs 4, 5 and 6. However, the importance of $Iskew$ is marginal since a one percentage change in $Iskew$ changes the premium by 0.002%. The mean coefficient estimate of $\%Options$ is positive and highly significant only in run (5) where its importance is marginal since a one percent increase in this variable only increases the premium by 0.06%. The significance for $\%Options$ disappears when control variables for transaction costs and managerial characteristics are included in the regressions. The mean coefficient estimate of holding cash has its expected negative sign but becomes insignificant when all the independent variables are included in regression runs (5) and (6). The mean coefficient of $\%Bonds$ has its expected negative sign even after adding all the other control variables. An increase of 1% in bond holdings leads to a 0.07% decrease in the CEF premium.

The mean coefficient estimate of ∂AS is positive and highly significant. When the ∂AS (i.e., the difference in liquidities between the CEF and its asset holdings) is eliminated (i.e., $\partial AS = 0$), the mean CEF premium is reduced by 0.2% of its mean value. A one percent change in ∂AS would lead to an increase of 1.4% in the CEF premium. This is consistent with our expectation and the findings of Datar (2001) and Deli and Varma (2002). The highly significant mean coefficient estimate of $Alpha$ of 0.51 implies that a one percent increase in the performance of the CEF manager would increase a positive or decrease a negative CEF premium by 0.31%. The mean coefficient estimate for gross *Leverage* is negative and significant as expected but becomes marginally significant when all potential determinants are considered [run (6)]. Thus, all the three potential benefits of the CEF in the conceptual model discussed earlier are statistically significant with their expected signs. Given the same level of risk of the arbitrage position, an increase in either liquidity or managerial contribution increases the CEF premium while an increase in gross leverage decreases the CEF premium.

The mean coefficient estimate of $\ln(MktVal)$ (i.e., natural log of market value as a proxy for arbitrage costs) is negative and highly significant as expected, which implies that the CEF premium decreases as firm size increases. Thus, a 1% increase in this variable would decrease the CEF premium by 0.06%. The mean coefficient estimate of $1/P$ (i.e., inverse of the CEF's price and another proxy for arbitrage costs) is positive and highly significant. Thus, a 1% increase in the inverse of the CEF's price would lead to a 1.04% increase of the CEF premium. The mean coefficient estimate of DY (i.e., CEF dividend yield) is positive but not significant at conventional levels. While Pontiff (1996) did not find any statistical significance for the two size variables [$\ln(MktVal)$ and DY], he argues that the CEF premium would be higher due to the higher cost of an arbitrage trade to take advantage of the CEF premium for small and low priced CEFs.[19]

The mean coefficient estimate of $MgmtFees$ is negative and strongly significant as expected. A 1% increase in $MgmtFees$ would only marginally change the CEF premium by -0.2%. The mean coefficient estimate for $Tenure$ is positive, and statistically and economically significant, since an increase in $Tenure$ by 1% would increase the CEF premium by 9.91%.

3.7.2 Fama-MacBeth Cross-sectional Regressions for CEF premiums with Idiosyncratic Risk Conditioned on Past CEF Performance

[Please place table 3.7 about here.]

[19] Pontiff (1996) reports that the median and mean R-squares increase from 11.77% to 22.73% and 14.75 to 27.16%, respectively, with the addition of these three variables: dividend yield, natural log of market value and inverse of CEF price.

We now explore the relationship between the premium levels and idiosyncratic volatilities when the latter is conditioned on the sign of the change in the CEF price as reported in table 3.7. Similar to our results in tables 3.6, the average explanatory power exceeds 60% for the regression with all potential determinants. When only the arbitrage risk proxies are included and $Ivol_{net}$ is conditioned using the previous month's CEF price, the average explanatory power increases from 23.55% [table 3.6, run (1)] to 30.20% [table 3.7, run (2)]. Similar to our findings in table (3.6), the mean coefficient estimates for the systematic risk factors for the net return position are statistically insignificant except for $\beta_{net_{SMB}}$. The mean estimate of $Ivol_{net}$is negative and statistically significant regardless of the sign of the previous month's CEF price change, although the negatively conditioned $Ivol_{net}$ loses its significance when all CEF premium determinants are included in run (4). The decrease in the premium ranges from 17.95% to 26.70% for a 1% decrease in a positively conditioned $Ivol_{net}$ and from 3.50% to 4.69% for its negatively conditioned equivalent. When $Ivol_{net} = 0$, we find that the premium is positive with maximum absolute value changes of 150% and 30.50% when conditioned on positive and negative previous month's CEF prices, respectively.

The results for all the other variables reported in table (3.7) generally are consistent with our findings reported earlier in table (3.6). The mean coefficient estimate of gross $Leverage$ is still significantly negative. Unlike our results reported in table (3.6), the mean estimate of ∂AS is positive and significant at the 10% level and a 1% change in ∂AS now only leads to a change of 0.01% in the CEF premium. The mean coefficient estimate of $Alpha$ is positive and highly significant so that a 1% increase in $Alpha$ would increase the CEF premium by 0.13%. Similar to table (3.6), coefficients estimates of $\log(MktVal)$ and $MgmtFees$ are negative and statistically significant, while those for $1/P$, DY and $Tenure$ are statistically insignificant at conventional levels.

[Please place table 3.8 about here.]

At this point, we summarize our findings from tables 3.6 and 3.7 with our expectations for each determinant in table 3.8. The principal arbitrage risk determinant represented by $Ivol_{net}$is negative and statistically significant for all the regression runs. Only one of the hedge completeness proxies for systematic risk exposures (namely, $\beta_{net_{SMB}}$) is consistently significantly different from zero. Consistent with the first hypothesis, the three CEF benefits are statistically significant with their expected signs. Specifically, we find that our proxies for relative liquidity (∂AS) and managerial contributions to value ($Alpha_{i,t}$) are associated with an increase in the value of the CEF versus its NAVPS, and that for gross Liquidity is associated with a decrease in the value of the CEF versus its NAVPS. In our second hypothesis, we argued that if the arbitrageur knows exactly what the CEF holdings are, she can more accurately form the arbitrage position. We also argued that the type of the CEF holdings increase the cost of the arbitrage position either because of uncertainty and asymmetry of the NAVPS returns ($\%Options$) or because of their lower expected returns (e.g. cash and bonds) compared to the higher expected rate of return expected on an all-equity CEF. We could not confirm our hypothesis about the weight of options most likely because the mean idiosyncratic skewness is close to zero but do so for cash and bonds where the mean coefficient estimates are consistently significant and negative as expected.

3.7.3 Fama–MacBeth Cross-sectional Regressions for Changes in CEF Premiums

[Please place table 3.9 about here.]

Regression results reported in Table 3.9 for month-by-month changes in CEF premiums provide insights into the determinants of the mechanism that may cause CEF prices to recalibrate to their fundamental values. The average explanatory powers (R^2) increase from 10.73% when conditional $Ivol_{net}$ is the sole independent variable [run (1)] to 68.56% with the inclusion of all potential determinants [run (4)]. The mean coefficient estimate of $Ivol_{net}$ is consistently negative and highly significant (not significant) when conditioned on the lagged positive (negative) monthly changes in the previous month's CEF price. For the full model [run (4) in table 3.9], the magnitude of the $Ivol_{net}$ coefficient estimate is considerably higher than in the other runs but its sign and statistical significance remain. For this full model, a 1% decrease in $Ivol_{net}$ would result in a 4.3% decrease in the average monthly change in CEF premiums. The average monthly change in CEF premiums decreases by 251% (2.5 times) in relative terms if idiosyncratic risk is eliminated ($Ivol_{net} = 0$). We once again observe that only $\beta_{net_{SMB}}$ is significantly different from zero. The mean coefficients of $Iskew$, $\%Options$, $Leverage$, and ∂AS are insignificant at conventional levels.

The mean coefficient estimate for $\%Options$ is positive and highly significant in run (3) but becomes insignificant in run (4) for the full model. The mean coefficient estimates of $\ln(MktVal)$, $MgmtFees$, and DY are all insignificant in run (4). The mean coefficient estimate of $1/P$ is positive and significant at the 10% level in run (4), which indicates that a 1% increase in this variable would lead to a 0.05% decrease in the change of the CEF premium. The mean coefficient estimate for $Tenure$ is negative and statistically significant at conventional levels.

3.8. TESTS OF ROBUSTNESS

3.8.1 Fama-MacBeth Cross-sectional Regressions for CEF Premiums over the Subperiod of 2006-2010

We run cross-sectional regressions over the sub-period 2006-2010 for two reasons. First, it provides a test of the relationship between CEF premiums and its determinants that encapsulates the financial crisis of 2008-2009. Second, it allows us to use our Data Explorer database, whose coverage starts in 2006, to add determinants that further control for the ability of investors to short a CEF. Asset mispricing may disappear if short selling is allowed and loaning securities is available. Flynn (2010) argues that the level of short selling increases with more negative CEF premiums, which should induce a positive relationship between the level of the premium and short-selling activity. Thus, as a test of robustness, we add controls for the number of short positions in the holdings of the CEF, and the utilization rate of shorts for the stocks held by the CEF. Utilization rate is defined as the number of shares being borrowed against the total value of the inventory available for lending. We expect the deviation of the CEF's price from its incomplete fundamental value (i.e., NAVPS) will be lower with higher utilization rates.

[Please place table 3.10 about here.]

Comparing the results that are reported in table 3.10 with those reported earlier in table 3.7, we draw four overriding observations. First, the significant negative relationship between $Ivol_{net}$ and the CEF premium level persists. Second, the explanatory power of our determinants is still high (75.92%). Third, the CEF benefits from manager contribution become insignificant and from relative liquidity remain positive but only marginally significant during this period. Fourth, the two short-selling proxies do not help in explaining the cross-sectional variation in CEF premiums.

Specifically, we find that the mean coefficient estimate for $Ivol_{net}$ ranges from -13.77 to -23.29 and is highly significant, which implies that a 1% decrease of $Ivol_{net}$ would result in a CEF premium increase from 17.10% to 29.68% depending upon the model estimated. The incomplete hedge for the systematic risks also persists as a strong and persistent relationship continues between the SMB exposure of the net arbitrage position and CEF premiums. The mean coefficient estimates for $\%Bonds$ and $\%Cash$ are negative and statistically significant at the 10% level. Other than $\ln(MktVal)$ and ∂AS, all the other control variables are statistically insignificant including the two short-selling proxies. To isolate the effect of the great recession from the addition of our short selling proxies we run the cross sectional regression over the period 2008-2010. The relationship between $Ivol_{net}$ and CEF premium does not change and the short-selling proxies remain statistically insignificant.

3.8.2 Correcting for Sentiment and Macro Variables

As reported earlier, the proponents of the behavioral theory explanation argue that CEF premiums reflect investors' sentiments about the market. To control for sentiment, we use the University of Michigan Household Sentiment Index (UMSI), The Chicago Fed National Activity Index (CFNAI) developed by Stock and Watson (1999) and the policy Uncertainty Index (PUI) of Baker *et al.* (2012). The UMSI is a regular survey of a large number of households regarding their financial situations and economic expectations. This measure is closely related to other survey-based measures of investor sentiment (Fisher and Statman 2003; and Qiu and Welch 2006), and has been shown to be related to investor economic activity (Ludvigson 2004). Most importantly, Lemmon and Portniaguina (2006) find that this measure predicts the returns on small stocks and stocks with low institutional ownership. This is consistent with Fisher and Statman (2003), who find that consumer confidence does not forecast S&P returns, but can predict returns on NASDAQ and small-cap stocks.

The CFNAI of economic activity was developed by Stock and Watson (1999), is maintained by the Federal Reserve Bank of Chicago and is used to control for the business cycle in academic research.[20] The CFNAI is a weighted average of 85 existing monthly indicators of national economic activity constructed to have an average value of zero and a standard deviation of one. Since economic activity tends to move towards the trend growth rate over time, a positive (negative) index value corresponds to growth above (below) the trend. The PUI measures policy-related economic uncertainty based on three types of underlying components: namely, newspaper coverage of policy-related economic uncertainty; the number of federal tax code provisions set to expire in future years; and disagreement among economic forecasters as a proxy for uncertainty.

[20] Available at: http://www.chicagofed.org/webpages/research/data/cfnai/historical_data.cfm

The macro variables that we control for are the corporate spread and the term structure based on data from the Federal Reserve Bank of St Louis (FRED).[21] The corporate spread is the difference between AAA bonds and default-free government bonds, as in Longstaff *et al.* (2005). The term structure variable is the difference between the ten-year constant yield on US treasuries and 3-month yield on T-bills. The last additional variable is the Pastor and Stambaugh (2003) measure of aggregate liquidity obtained from Wharton Research Data Services (WRDS). To isolate the effect of these systematic factors that is not already reflected in the previously used fund-specific determinants in our cross-sectional regressions, we follow a two-step approach. The first step consists of running each fund-specific determinant of CEF i on the sentiment, macro and aggregate liquidity factors. The residuals obtained from these regressions represent the "pure" fund-specific determinants after removing their systematic components. The second step is to estimate equation (3.7) using these "pure" fund-specific determinants.

[Please place table 3.11 about here.]

When we compare these new results reported in table 3.11 with those reported earlier in table 3.6 [runs (5) and (6)], we find that the "pure" fund-specific determinants still explain more than 50% of the average variations of CEF premiums. This finding supports the rational explanation for CEF premiums and is consistent with Chen *et al.* (1993) and Elton *et al.* (1998). The mean negative and statistically significant coefficient estimate of $Ivol_{net}$ persists with a 1% decrease in $Ivol_{net}$ leading to a decrease of 7.4% in CEF premiums for the full model. Like the total effects reported earlier in table 3.6, we find that the coefficient estimate for "pure" managerial contribution is positive and significant and those for "pure" gross leverage, "pure" $\%Bonds$, "pure" $\%Cash$ holdings, and "pure" $\ln(MktVal)$ are negative and significant. Unlike the total effects reported earlier in table 3.6, we find that the coefficient estimate for "pure" liquidity is still positive but insignificant, that for the "pure" $1/P$ is still significant but now negative, and that for the "pure" DY is still positive but now significant. Thus, most of our previous findings are robust to accounting for the effects of market sentiment and economic conditions.

3.8.3 Fama-MacBeth Cross-sectional Regressions for CEF Premiums using a "Bottom-up" Calculation of the Ivol using CEF Holdings

[21] http://research.stlouisfed.org/fred2/

In theory, a portfolio's beta is defined as the weighted-average of the betas of its components. Thus, computing a fund`s betas using the individual security betas from holdings data at a point in time ("bottom-up" approach) or by a time-series regression on fund returns ("top-down" approach) should be the same. However, Elton *et al.* (2011) show that this argument would hold under the assumption that a fund`s composition is held constant between holding disclosure points and that it is more appropriate to calculate a fund's betas as the weighted betas of the holdings. They argue that using this "bottom-up" approach decreases the level of distortion caused by changes in the composition of a portfolio over time.

We estimate that the average change per asset per month in our sample portfolio is 7.52%. To assess if this distortion affected our previously reported findings, we use an alternative measure of arbitrage risk that we develop based on the holdings of the funds. Instead of calculating the idiosyncratic volatility of the net returns of the arbitrage position, we calculate the difference between the idiosyncratic volatilities of the CEF (the "top-down" approach) and the weighted-average of the individual holdings of the CEF (the "bottom-up" approach). For the purpose of this robustness test, we invoke the fairly strong assumption that the relative idiosyncratic risk contribution of the non-equity, non-derivative assets in a CEF's portfolio are similar to that from its equity holdings. More formally, our new proxy is given by:

$$Ivol_{Diff,i,t} = \sqrt{\sum_{d=1}^{T} \boldsymbol{\varepsilon}_{i,t_d}^{2} + 2\sum_{d=2}^{T} \boldsymbol{\varepsilon}_{i,d_t}\boldsymbol{\varepsilon}_{i,t_{d-1}}} - \sqrt{\sum_{j\in f} \boldsymbol{\omega}_j\left(\sum_{d=1}^{T} \boldsymbol{\varepsilon}_{j,t_d}^{2} + 2\sum_{t=2}^{T} \boldsymbol{\varepsilon}_{j,t_d}\boldsymbol{\varepsilon}_{j,t_{d-1}}\right)} \quad (11)$$

where $\boldsymbol{\varepsilon}_{i,t_d}$ ($\boldsymbol{\varepsilon}_{j,t_d}$) is the daily residual of the 4-factor Carhart model for CEF i (CEF i`s holding *j*) in day *d* in month *t*; and T is the number of days during the month.

[Please place table 3.12 about here.]

Table 3.12 reports the results of the mean estimates from cross-sectional regressions using this alternative measure of arbitrage risk in the full model for CEF premiums. Compared to the results previously reported in table 3.6, the mean R-square of these new cross-sectional regressions decrease from 12.69% (table 3.6, run 2) to 8.88% (table 3.11, run 1). The mean coefficient estimates of both measures of $Ivol_{Diff}$ are negative and highly significant. A 1% change in $\partial Ivol$ now results in a 7.54% change in the average CEF premium, and the absolute increase in the mean CEF premium now is 12.89% when $Ivol_{Diff} = 0$.

Our hypothesis that the CEF premium includes the present value of the additional benefits provided by a CEF is supported by the findings for this alternative measure. The positive and significant mean estimate of $Alpha$ shows that the CEF premium increases with a manager's ability to add value to the CEF. We also find that increasing leverage increases the opportunity cost for the CEF and consequently decreases a positive or increases a negative CEF premium. This explanation is confirmed by the negative and significant mean coefficient estimate for $\%Bonds$ and $\%Cash$. An increase in these holdings affects the returns of the CEF and leads to lower positive or more negative premiums. The significant positive then negative sign on the coefficient estimate of $\%Options$ indicates that this may be due to our treatment of options when estimating the idiosyncratic volatility of the arbitrage position. Thus, the use of an alternative method to calculate the idiosyncratic volatility of the arbitrage position does not change the results for this variable. Furthermore, we find that the CEF premium is still positively related to managerial contribution and negatively correlated to an increase of the holding with returns less than what the investor requires.

3.8.4 Panel Regression for the Determinants of the CEF Premium

We now explore the robustness of our results to the use of unbalanced panel data regressions. We use panel regressions because they use all cross-sectional and times-series data in a single step in order to avoid problems with measurement errors that may be caused by the use of the two-step Fama-MacBeth methodology, and various authors (e.g., Skoulakis 2006) encourage the use of both methods to test the reliability of their results.

Thus, we begin by testing whether or not our data are poolable. Testing poolability examines if the coefficients of the regressors are the same for the 93 CEFs in our sample. The null hypothesis is: $\beta_{CEF_1} = \beta_{CEF_2} = \cdots = \beta_{CEF_{93}}$ where the β_{CEF_i} are the vector of coefficients for fund i for all regressors. If the individual error variance components do not follow a normal distribution given by $N(0, s^2 I_{N,T})$, where s^2 is the sample standard deviation of residuals and N and T are the number of cross sections and periods respectively, then simple OLS may not be used to conduct the Chow test (Baltagi 2001, p. 53). To determine if this assumption behind the Chow test is satisfied, we estimate each of the models for the CEF premiums using OLS and test for the equality of the residual variances. F-, Siegel-Tukey and Levene tests all reject the null hypothesis that the residual variances of the cross sections are equal. When such is the case, Kennedy (2008) recommends the use of SURE (Seemingly Unrelated Regressions Estimation) to estimate the cross-sectional SSE (error sum of squares) when conducting the Chow test of poolability. Our model contains two variables, number of shorts and utilization rate, which are available only over the sub-period of 2006-2010. Given the specification of the SUR estimation that requires at least as many time periods as cross sections and their insignificance in a previous test of robustness, we drop these two variables when estimating the SUR model with the remaining variables. Using the value of the SSE from the SURE and the SSEs of each cross section, we are unable to reject the null hypothesis that the coefficients are constant given that the F-value for the Chow test is 0.48.

The next step is to identify the possible source of the unobserved heterogeneity to choose the optimal effects model to use (random, fixed). The choice of model should have no effect on the coefficient estimates of the regressors, as it merely implies the existence of unobserved variables whose effects are either constant (fixed effects), random (random effects) or none (OLS). We start with the random effects model, which assumes that the unobserved effect is random and should be part of the error term of each cross section. We test for this model by using the Breusch and Pagan (1979) Lagrange multiplier test and the augmented version of the test by Pesaran (2004). We reject the null hypothesis for each test of the null that the variances of the unobserved heterogeneity are zero.

We next test using a cross-sectional F-test (or the likelihood ratio test) of whether the intercept estimates are constant across the funds. While OLS assumes that they are constant, fixed-effects estimation does not. The null hypothesis is that all the intercept dummies for the cross sections are equal to zero. A F-value of 30.15 leads to a rejection of the null hypothesis. Hence, OLS is rejected against both the random- and fixed-effects models. The last test that we perform is the Hausman test, which examines the random and period effects. If the null hypothesis that an individual effect is uncorrelated with the regressors is rejected, fixed-effects estimation should be used. If this null is not rejected, then the use of random-effects estimation captures the unobservable components. The Hausman test rejects the null hypothesis supporting the use of a fixed-effects estimation model for our data set.

Before we proceed with the modeling of our panel premium regressions, it is important to test the level of autocorrelation in the CEF premium series. We perform a correlogram and find that the coefficient of autocorrelation is highly significant with a value of 0.814. This finding implies the need to use a lagged premium variable in our estimation to capture this effect, thus making our panel regression dynamic. However, the use of a lagged dependent variable as an explanatory variable renders the use of least squares no longer consistent as this issue is referred to in the literature as the LSDV bias (Hsiao 2003). Hsiao (2003) shows that even Maximum Least Square (MLE) are not consistent when modeling a fixed effects panel with a lagged dependent variable, and only Instrumental Variable GMM would yield consistent estimates. We use the Arellano and Bond (1991) difference GMM estimator. We form our instrument variables from lagged levels of the endogenous regressors in a two-step least square estimation of the GMM criterion.

[Please place table 3.13 about here.]

We report in table 3.13 the results of the GMM dynamic regression of the CEF premium on the previously mentioned determinants. The R-square values increase monotonically from 65.43% in run (1) to 71.59% in run (3). The coefficient estimate of the lagged premium variable is close to the autocorrelation level found in the correlogram, which proves the importance of modeling the panel as a dynamic one. In runs (1) to (3), the coefficient estimate for $Ivol_{net}$ is negative and statistically significant implying that an increase in the arbitrage cost of the position decreases the CEF premium. A one percent increase in $Ivol_{net}$ would lead to a small decrease of 0.01% in the premium, and the premium closes by 0.5% when $Ivol_{net}$ is forced to zero. The addition of CEF holdings of options, cash and bonds increases the explanatory power of the model but only the coefficient on $\%Bonds$ is statistically significant supporting our earlier finding that a high level of bonds in the portfolio decreases the level of the premium. The benefits of CEFs in our model show their appropriate signs. Our liquidity differential measure and leverage are positive and negative respectively; and both are statistically significant. The coefficient estimates are both negative and statistically significant for $\ln(MktVal)$ and $1/P$. An increase in market value and a decrease in the price of the CEF increase the level of a CEF's premiums.

3.8.5 Gross versus Net Leverage

Elton *et al.* (2012) show that gross leverage is an important distinction between CEF and OEF. They find that bonds CEF are outperforming their comparable bonds OEF only because they have the ability to raise cheaper funds. However, our findings suggest that equity CEF premiums are negatively related to the gross leverage ratio. We explained this result by the possible use of leverage as a source of cash.

Like some studies in corporate finance that treat cash as negative debt (e.g., Bates *et al.* 2009; Acharya *et al.* 2011),[22] we use an alternative measure of leverage, called net leverage,

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[22] Bates *et al.* (2009) note that when "we consider the average net leverage ratio, which subtracts cash from debt, we obtain a dramatically different perspective regarding the time trend in leverage for U.S. firms". Acharya *et al.* (2011, p. 27) state that the net leverage measure is obviously important "if firms react to anticipated distress costs by managing cash reserves rather than (or in addition to) altering the choice of direct leverage".

that is given by the difference between the ratio of non-equity to total assets (gross leverage) minus the ratio of cash holdings to total assets. Running the Fama and MacBeth cross sectional regression equation (3.7) with net instead of gross leverage, we find that the coefficient of net leverage is positive (unlike the previous negative value for gross leverage) and significant at the 10% level. This result supports our explanation that leverage adds value when its relatively cheaper money is invested in higher returning assets.

3.8.6 Level of Market Integration between a CEF's Price and its NAVPS

Kapadia and Pu (2012) propose a simple non-parametric measure that tests the variation in the prices of two assets over a certain time horizon. If two assets are integrated, increases (decreases) in both should be simultaneous. Using this logic, we test the level of integration between the intrinsic value of the CEF's portfolio of assets (as represented by its NAVPS) and its price (CEF), which should have a high level of integration in a frictionless market. If on a given date we have k = 1, . . . , M observations of CEF prices and NAVPS, then:

$$\hat{\kappa}_i = \sum_{\tau-1}^{M-1} \sum_{k=1}^{M-\tau} \mathbb{I}_{[\Delta NAVPS_{i,k}^{\tau} \Delta CEF_{i,k}^{\tau} > 0]} \qquad (3.12)$$

where M is the number of periods, and $\Delta NAVPS$ and ΔCEF are respectively changes in NAVPS and CEF prices over the non-overlapping interval τ.This parametric test simply calculates the number of times that both changes in the price of CEF and NAVPS are in the same direction. We calculate the cross-sectional mean and median percentage changes in the price of the CEF and its respective NAVPS that have the same sign across all intervals τ for all possible $0.5M(M-1)$pairs. We find that the percentage of instances where both the CEF and NAVPS move in the same (opposite) direction is 67.45% (32.52%) across all intervals τ.[23]

Kapadia and Pu (2012) use the Kendall correlation to allow for the testing of the hypothesis of market integration using standard statistical theory. The Kendall correlation consists of calculating the difference between the number of concordant and discordant pairs divided by the number of pairs in the whole sample. Kapadia and Pu (2012) argue that a measure of concordance can serve as a measure of market integration without any parametric assumptions. Unlike alternative measures such as the coefficient of determination, this measure is directly linked to pricing discrepancies with no ambiguity in its interpretation. We follow the same methodology to obtain Kapadia and Pu's (2012) equation (2):

[23] Tabulated results are available from the authors.

$$\kappa = \frac{C-D}{C+D} = \frac{C-(C+D-C)}{C+D} = \frac{2C}{C+D} - 1 = \frac{4\hat{\kappa}}{M(M-1)} - 1 \quad (3.13)$$

where C and D refer to the number of concordant and discordant pairs, respectively, in our sample. Since the value of κ corresponds to the Kendal tau, it is bounded by -1 and +1. If the value of κ is positive (negative), it implies that there are more (less) concordant pairs than discordant ones. Thus, κ values of -1 (+1) indicate that the two series are fully segmented (integrated) while a value of zero indicates that the two series are not closer to either being fully integrated or fully segmented.

We test the value of κ using a one tail test for the null hypothesis that the two series are fully segmented (H_0: κ = -1) and fully integrated (H_0: κ = 1). Kendall and Gibbons (1990) argue that a normal distribution approximation can be used for the Kendall tau statistic when the number of pairs is large. We calculate κ for different time intervals in days $\tau = \{1,2,5, 10,25\}$ and test the statistical significance of each κ using a z test where the standard error is calculated as $S_\kappa = (1/3)\sqrt{(2M+5)/(C+D)}$. As expected, we find that the level of integration (κ) increases with the time interval used in the calculation. The number of concordant pairs increases from 56% to 67% and κ increases from 0.19 to 0.28 when we move from a 1- to a 25-day interval. Thus, we are able to reject the null hypothesis that these two price-change series are fully segmented (κ = -1) 98% of the time for the 1-day time interval and 100% of the time for the other four time intervals. Similarly, we are able to reject the null hypothesis that these two price-change series are fully integrated (κ =1) 82% of the time for all time intervals. These results imply that the CEF and NAVPS prices, on average, are more integrated than segmented, and that the differences in these two prices series not attributable to the CEF's net benefits (over managerial fees) should disappear given costless and frictionless arbitrage. Thus, even if the net present value of the net benefits (over managerial fees) provided by a CEF is zero, costly and risky arbitrage would still lead to a CEF premium.

We run cross-sectional regressions of the CEF premium when κ is included in the full model represented by equation (3.7). This was done using a lagged rolling-window kappa estimate with(out) the four benefit/cost variables from our model and the arbitrage proxies for tau intervals of one, two and five days. We find no significant relationship between the CEF premium and κ in any of these estimations most likely because κ only captures the concurrence of the directional movements of the two series and not the magnitude of their differences.[24]

3.9. CONCLUSION

This essay provides further evidence to help unravel the well-documented closed-end fund (CEF) negative premium anomaly. By investigating this phenomenon from an arbitrageur's perspective, we provide additional evidence that at least a significant portion of the gap of a CEF's price from its fundamental value is due to limits to arbitrage. It reflects the compensation that an arbitrageur would require for the hedgeable and non-hedgeable risks arising from the fund's portfolio composition and its uncertainty. This is consistent with the findings of Ackert and Tian (2000) for exchange traded funds that the premiums disappears when the portfolio compositions and weights are known, and the total risk of the portfolio is easily hedgeable.

Our tradeoff model relates to the benefits from holding the fund which the literature identifies as enhanced liquidity, managerial abilities and leverage, and costs such as management fees. The difference between the liquidities of the CEF and its holdings capture the liquidity benefit, Jensen's alpha captures managerial ability benefits and the ratio of non-common equity to assets (less the cash-to-asset ratio) captures the gross (net) leverage benefit. Our findings support the hypotheses that state that CEF premiums are positively related to these benefits (net but not gross leverage) and negatively related to management fees.

We hypothesize that the premium not captured by our model is related to the unhedged systematic and idiosyncratic risk exposures associated with the net position from risk arbitrage between the CEF and its equivalent NAVPS. We identify systematic replication risk exposure for the small-minus-big factor as a significant determinant of CEF premiums. We attribute this non-zero exposure of the arbitrage position to this systematic risk factor as being due to uncertainty about the fund's holdings which leads to inexact hedge ratios. Using the idiosyncratic volatility (*Ivol*) of the net position return obtained from a long/short position in the CEF price and its NAVPS, we identify a significant relationship between CEF premiums and *Ivol* differences only when the fund has positive returns in the previous period.

[24] Tabulated results are available from the authors.

For the other proxies for the uncertainty of holdings, we find that CEF premiums are related negatively to idiosyncratic skewness but not related to options holdings.

CHAPTER FOUR
M&A RUMOR CREDIBILITY AND INFORMATION CONTAINED IN IDIOSYNCRATIC VOLATILITY

4.1. INTRODUCTION

Analysts and market participants generally consider publicly available information regardless of its source. Whether the arrival of information included in a rumor changes the price of the stock depends on its perceived credibility (reliability or veracity) and its anticipated impact on the future cash flows or the discount rate of the firm. Unlike earnings announcements, merger and acquisition (M&A) announcements are less frequent and more unpredictable events with a considerable impact on stock prices, especially for the acquired firms. Thus, being able to assess the credibility of rumors about potential M&A could be profitable.

In this essay we argue that buying rumored target firms does not always lead to a negative performance, as previously documented (Gao and Oler, 2012; Zivney *et al.* 1997). Target firm performance after a M&A rumor depends on its credibility. We use a proprietary database hand-collected from different sources and with different characteristics to test the level of the credibility of types of M&A rumors. We find that good (bad) quality rumors lead to a positive (negative) performance. We also find that daily changes in idiosyncratic volatilities around initial credible rumor dates are positively related to the performance of the target firm after the rumor release date.

Trading rumored target stocks before a potential announcement exposes traders to considerable risk given the high level of uncertainty about whether a subsequent M&A announcement will actually occur. Gao and Oler (2012) conclude that the increase in trading activities in the pre-announcement periods for rumored target stocks is not due to noise nor liquidity trading but is due to trading by rational investors who only trade if they are compensated for the risk of doing so. Thus, buyers of rumored target firms expect that the rumors are reliable and will lead to increased prices at some unspecified future announcement dates. In contrast, sellers believe that any price run-ups in the uncertain pre-announcement periods will dissipate due to the lack of credibility of the rumors or because the prices represent over-valuations of the benefits of the M&A.

Under a rational expectations model with normally distributed returns, the absolute expected return conditional on the sign of the return increases with return volatility. All else equal, a (positive) negative relationship is expected between return volatilities and expected returns conditional on (good) bad news (Diamond and Verrecchia 1987). Around M&A rumor dates, buyers (sellers) of the potential targets over-weight (under-weight) the probabilities of subsequent M&A announcements and/or their values.

If the M&A rumors are from more credible sources (henceforth more credible rumors), then the increased trading for the target firms leads to increased idiosyncratic volatilities. If the rumors increase expectations that actual M&A announcements will subsequently follow, this should lead to increased prices for the targets. If the rumors lack credibility (henceforth less credible rumors), market participants may diverge in their expectations about future M&A announcements, leading to increased idiosyncratic volatilities and possibly decreased target prices.

There is considerable evidence of a positive target price run-up pre-M&A announcement whose beginning date varies, on average, from 7 days (Keown and Pinkerton 1981) to 9 days (Gao and Oler 2008) to 15 days (Jarrell and Poulsen 1989) to 30 days (Borges and Gairifo, 2013) to 42 days (Schwert 1996) to 60 days (Clements *et al.* 2007). While some authors argue that price run-ups prior to M&A announcements are due to insider trading (e.g., Agarwal and Singh 2006), others argue that the run-ups reflect legitimate market anticipations by investors resulting from public information that increases the probabilities of subsequent takeovers (e.g., Pound and Zeckhauser 1990; Schwert 1996; and King and Padalko 2005). If this latter view prevails, then the run-up returns during the periods between the initial rumor dates and actual M&A (non-)announcements capture the market's expectation about a possible M&A.

We investigate the relationship between M&A probabilities and daily idiosyncratic volatilities by calculating market-implied probabilities before M&A announcements. Betton *et al.* (2014) argue against the existence of a positive feedback loop in the market prices of M&A targets. Hence, the price run-ups for targets are adjustments in the probabilities that subsequent M&A announcements will happen. We conjecture that changes in idiosyncratic volatilities are an indicator of the market's expectations about the values of the targets. Consistent with our predictions, we find that the changes in idiosyncratic volatilities around the M&A rumor release dates are only (and positively) related to the market implied probabilities when conditioned on more credible M&A rumors.

Thus, the focus of this essay differs considerably from that of most of the M&A literature. Our focus is mainly on the information content around the initial rumor dates, the impacts of the rumor reliabilities, and the market expectations during the run-up periods defined as the periods between the initial rumors and the actual M&A announcement dates. In contrast, most of the literature on M&A focuses on market behaviors on and after actual M&A announcements, which may be due to some extent to the need to hand collect data on M&A rumors.

Our contribution to the literature is three-fold. First, we find that market participants receive highly uncertain signals about the probabilities of M&A that depend on the credibility of the sources of M&A rumors. We are able to examine the market reactions to rumors depending on their credibilities since we rely on a large hand-collected database of rumors drawn from the print and electronic media beyond the Wall Street Journal (as in Gao and Oler, 2012; Zivney *et al.* 1997).[25] While Zivney *et al.* (1996) find that the market-adjusted cumulative abnormal return (CAR) of a portfolio of rumored stocks has a mean of -4.32%, and -1.8% for the 70 trading days and one year after the M&A rumors, respectively, for the 1984-1988 time period, Gao and Oler (2012) find increased active selling offsets increased active buying in target stocks before M&A announcements. Unlike Gao and Oler (2012), we find that a strategy consisting of shorting rumored M&A targets leads to a positive return only for low-credible M&A rumors. Since more credible rumors lead to positive performances, we conjecture that market participants are able to differentiate between valuable signals and white noise. We find that more credible rumors always have statistically significant probabilities of leading to subsequent M&A announcements, and hence to potential premiums for the target-firm stockholders. We also find that the price movements around the rumor announcement days exhibit a different behavior for target firms with less versus more credible M&A rumors.

Our second contribution relates M&A with idiosyncratic-volatility pricing, and enriches the debate on the relationship between idiosyncratic volatilities and expected returns. We find that idiosyncratic volatilities have a positive relationship with the future returns of targets. This adds to the literature during the last two decades, which has witnessed an increase in the importance of idiosyncratic volatility in asset pricing and in forecasting future expected

[25] The rumor samples for the few existing papers on M&A rumors use the section "Heard on The Street (HOT)" or "Abreast of the Market (ATM)" from the Wall Street Journal. Zivney *et al.* (1996) argue that ATM discloses the rumor about a M&A earlier than the HOT used by Pound and Zeckhauser (1990).

returns. Various theoretical models predict that an increase in idiosyncratic volatilities lead to positive expected returns (e.g., Levy 1978; Kryzanowski and To 1982; and Merton 1987), which is supported by empirical findings (e.g., Goyal and Santa-Clara 2003; Fu 2009). Some studies conclude that the relationship between idiosyncratic volatilities and expected returns is negative (Guo and Savickas, 2006; Ang *et al.* 2006, 2009), while others conclude that idiosyncratic volatility is just noise with no pricing implications (Bali and Cakici, 2008).

Our third contribution is to provide a rationale for the positive relationship between idiosyncratic volatilities and future returns. We show that the change in idiosyncratic volatilities is a manifestation of the market anticipation about a rumor outcome, provided that the rumor signal is credible. We link idiosyncratic volatilities to a market-implied probability of an M&A and the change in the level of idiosyncratic volatilities around the initial rumor date. We calculate the implied probability as the ratio of the market value of the M&A at the announcement and the market value of the M&A rumor signal, assuming no positive feedback loop as shown in Betton *et al.* (2014). We find a statistically significant relation between idiosyncratic volatilities and the market-implied probabilities of the M&A, which persists even after controlling for information flow, ex-ante market expectations about the values of the targets, firm characteristics, and firm specific and sector misvaluation.

The remainder of this essay is organized as follows. Section 4.2 details the steps used to collect data about the rumors and the matching process for the rumor database. Section 4.3 discusses the cumulative abnormal returns (CAR) of rumored firms and returns of strategies consisting of buying rumored firms and selling the market portfolio. Section 4.4 outlines the methodology followed to calculate the intraday realized volatilities and discusses the changes in idiosyncratic volatilities around the initial rumor dates. Section 4.5 outlines the relation between idiosyncratic volatilities and the CAR of rumored firms. Section 4.6 discusses the methodology used to calculate implied market probabilities and outlines the cross-sectional model to show the relation between idiosyncratic volatilities and the probabilities of M&A. Section 4.7 discusses the empirical results of cross-sectional regressions of implied market probabilities and idiosyncratic volatilities for a subsample of our database. Section 4.8 discusses the relation between target misvaluations and implied probabilities. Section 4.9 concludes the essay.

4.2. SAMPLE SELECTION AND DATA MANIPULATION

4.2.1 Construction of the Rumors Database

Unlike the existing literature discussed earlier, we use our access to a unique hand-collected database of rumors whose construction is now described.[26] Since a rumor is not an announcement, its wording can be ambiguous and unclear. Thus, a list of identifiers (keywords) compiled from a selection of M&A rumors reported in S&P Takeover Talk was used to search Factiva, Pro-quest (only for publications/newswires not covered by Factiva), S&P Takeover Talk, Capital IQ, Zephyr, SDC and a variety of newswires. Once a M&A rumor identifier was found in an article, the article was stored and catalogued. Since rumors have a tendency to ricochet throughout other news outlets, a search to identify the first time the rumor was published in the 90 days prior was done. Only reports for the same M&A rumor with the earliest date were retained. To ensure that the retained rumor date was indeed the initial rumor, a continuous search using an additional 90-day window was undertaken.

[Please place table 4.1 about here]

Our initial sample contains 2,250 rumor events that have no publicly reported rumors in the preceding ninety days. The decomposition of this sample by rumor type and the number of rumors that materialize in actual announcements using SDC Thomson Reuters for different time frames are reported in table 4.1. For this sample of M&A rumors, we find that 1,762 targets have actual subsequent M&A announcements and that only 361 of these announcements occur within one year after the rumor started about a possible M&A. We also report the number of acquisitions during the 70 days following the rumor to be consistent with Gao and Oler (2012) who categorize a rumor with no announcement after 70 trading days as misinformation. Although our sample is 14 times larger than theirs, we have approximately the same percentage (12%) of rumored firms announcing a M&A during this 70-day window.

The rumor types obtained from the manual search through the news releases about the rumors provide the existence or not of a source of the rumor. We hypothesize that the credibility of the rumor depends on the source that issued it. We categorize our rumors into more and less credible rumors according to the probability of an M&A announcement happening within 70 days or one year after the rumor date. More-credible rumors are those emanating from reliable sources, including: (i) firms that indicate their interest in looking for

[26] We would like to thank Fred Davis, Thomas Walker for providing us with access to this database.

a potential acquirer; (ii) firms that confirm the existence of talks about a possible takeover; (iii) rumors disclosed by insiders of the target; (iv) target firms hire financial advisors that generally indicate their interests in pursuing "strategic alternatives"; and (v) rumors attributable to analysts following the stock. Less-credible rumors are not attributable to actual sources, but inferred from stock price movements, changes in options trading, or chatter about possible synergies.

4.2.2 Measuring the Credibility of a Rumor

We verify our conjecture about the relationship between the source and its credibility by calculating the likelihood that the rumor leads to an M&A announcement. We calculate the probability of a M&A announcement within 70 days for the total sample, more- and less-credible rumors and their subcategories. We test the following null hypothesis: H_0: *Pr*(Announcement| More credible)= *Pr*(Announcement| Less credible). Our test statistic is: $TS = (\hat{p}_S - \hat{p}_I)/\sqrt{\hat{p}(1-\hat{p})(\frac{1}{n_S} + \frac{1}{n_I})}$ where $\hat{p}_S$ is the probability of a actual M&A being completed or just an announcement for the more-credible rumored sample, $\hat{p}_I$ is the probability of a M&A or an announcement for the less-credible rumored sample, $\hat{p}$ is the estimate of the common proportion under the null hypothesis calculated as $\hat{p} = (\#\, MA_S + \#\, MA_I)/(n_S + n_I)$ and n_S and n_I are the number of rumors in the more- and less-credible rumor samples respectively. We calculate the probabilities and their significance for M&A announcements that occur within 70 days and one year after the initial rumors. Since M&A announcements do not always result in actual M&As, we also calculate the probabilities of actual M&A within a time frame of 18 months.

[Please place table 4.2 about here]

Table 4.2 reports the probabilities of an announcement or M&A for all, more credible and less credible subcategories. The likelihood of a M&A for a more-credible rumor (15.04%) is approximately double that for a less-credible rumor (8.8%) within 70 days of the initial rumor release date (same period as in Gao and Older, 2012). The corresponding probabilities are 19.97%and 11.74% for one-year post-rumor. These differences are statistically significant at 1%. We obtain statistically significant differences for the various subcategories of the more-credible rumors and their likelihoods. For announcements within 70 days of the rumor date, the announcement likelihoods with the greatest to least likelihoods are for rumors confirmed by targets (24.56%), rumors indicating a financial advisor is hired by the target (19.85%), rumors attributed to an insider (19.09%), rumors initiated by the target itself (16.79%), and finally rumors initiated by an analyst (12.13%). All of these probabilities are statistically different at the 1% level, and statistically different than those associated with less-credible rumors within 70 days at 1%, except for the last most-credible rumor category (analyst is the rumor source), which is significant at the 5% level.

We also find consistent results using a one-year window as in Pound and Zeckhauser (1990) to calculate the probability of a subsequent M&A announcement. The probability of an M&A announcement for more- versus less-credible rumors is approximately double (19.97% vs. 11.74%). Although all the respective percentages are higher, the ranking of the credibility of the various categories of more-credible rumors does not change with this longer window. The announcement likelihoods with the greatest to least likelihoods are for more-credible rumors confirmed by targets (28.07%), rumors indicating a financial advisor is hired by the target (26.59%), rumors attributed to an insider (22.51%), rumors initiated by the target itself (16.79%), and finally rumors initiated by an analyst (21.88%). These probabilities are statistically larger at the 1% level than that for the less-credible rumors within the one year.

4.3. RETURNS OF TRADING STRATEGIES PREDICATED ON RUMORS

We begin this section by calculating the returns of trading strategies based on rumors. The first methodology is a conventional event study by calculating the CARs using a Carhart (1997) model for different event windows. We use an estimation window of [-125; -5] to avoid contaminating the factor loadings with possible non-media whispers about the rumor earlier than our release date. We obtain the time series of the Fama-French factors and the momentum factor from the website of Kenneth French. The second methodology consists of calculating the buy-and-hold abnormal returns (BHAR) from buying the rumored firms and shorting the S&P 500 portfolio. Gao and Oler (2012) propose a similar strategy consisting of shorting the rumored firms and investing in the market portfolio, which they argue is more realistic than CAR. Our strategy differs from that of Gao and Oler (2012) because our objective is to estimate the values of the rumors and not to bet against the benchmark-adjusted performance of the rumored firms.

We report the CAR and BHAR for four different event windows: three around the rumor date: [-1; +1], [-1; +5], [-5; +5] and a longer time span similar to Gao and Oler (2012): [+1; +70]. Table 4.3 reports the Carhart model CARs, and the BHAR performance of the long-short strategy. Both strategies yield statistically significant positive returns for all samples for the three short-term windows. The CAR for the total sample is 4.16%, 3.83% and 3.54% with highly significant t-values for event windows [-1; +1], [-1; +5] and [-5; +5] respectively. The long-short strategy yields slightly higher and highly significant returns of 4.34%, 4.42% and 4.31% for the same three event windows. The performance of less-credible rumor firms is always significantly higher for these three windows than that for the more-credible rumored firms. Their CAR differences for windows of [-1; +1], [-1; +5] and [-5; +5] are 1.04%, 1.11% and 1.12% with t-values of 2.52, 2.16 and 2.24, respectively. We observe similar results for the BHAR where the differences are 1.10%, 1.54% and 1.90% with t-values of 2.75, 3.11 and 3.54, respectively. Thus, less-credible rumored firms yield higher CARs around the rumor ADs due to their greater risk given their lower credibility. This result could be explained by the anticipation of the rumor before it becomes public.

[Please place table 4.3 about here]

We observe mixed results when we examine the abnormal returns over the longer event window of [1, +70] used by Gao and Oler (2012) and Zivney *et al.* (1996). We find that the marginally significant (t-value of -1.89) and negative CAR of -1.73% for the total sample is due to the significantly negative CAR of -3.45% (t-value of -2.48) for the sample of more-credible rumor firms and an insignificant positive BHAR of 0.06% for the sample of less-credible rumored firms. However, these results are not robust. We now find that the marginally significant (t-value of 1.95) and positive BHAR of 0.47% is due to the now significantly positive BHAR of 1.97% (t-value of 2.38) for the sample of more-credible rumored firms and an insignificant positive BHAR of 0.31% for the sample of less-credible rumored firms. Since the CARs are benchmark-adjusted unlike the BHAR, these results suggest that the risk induced by the rumor itself has increased over the longer window.

4.4. REALIZED BETAS AND VOLATILITIES

We hypothesize that the change in the ratios of idiosyncratic to total volatilities provides information about the market expectations about the values of the rumors. To obtain conditional measures of volatilities and betas, we use intraday data with the same sampling frequency. Patton and Verardo (2012) estimate the change in betas around earnings announcements by calculating realized betas ($R\beta$).

4.4.1 Calculation of Realized Betas using Intraday Data

The choice of sampling frequency is important when using intraday data to calculate daily betas. Market microstructure effects can adversely affect the behavior of realized variances and realized betas as the sampling frequency increases. The sources of such market microstructure effects include price discreteness (e.g., Harris, 1990, 1991), and other trading mechanism designs (Black, 1976; Amihud and Mendelson, 1989). As advocated by Andersen *et al.* (2000, 2001, 2003), one possible solution to microstructure-induced biases is sparse sampling where returns are computed at arbitrarily selected lower frequencies, such as every 5 or 15 minutes, instead of at every tick. However, Aït-Sahalia *et al.* (2005) show that this is not an adequate solution to the problem. If a stock trades infrequently relative to the market portfolio, it leads to a bias towards zero, known as the "Epps effect" (Epps, 1979; Hayashi and Yoshida, 2005). Patton and Verardo (2012) use a 25-minute sampling frequency for intra-day returns to balance possible measurement errors with the need to avoid the microstructure biases that arise at the highest frequencies. Patton and Verardo (2012) argue that although there is a possible loss of accuracy of the estimator because of the lower number of observations per day, this frequency allows microstructure effects to be minimized leading to better daily beta estimates.

We use the methodology outlined in Patton and Verardo (2012) to calculate daily realized betas using intraday returns.[27] Modeling the return-generating process as a multivariate stochastic process for asset i yields a daily beta that is robust to jumps in intraday data given by:

$$R\beta_{i,t}^{S} \equiv \left(RCov_{i,m,t}^{S}\right)/\left(RV_{m,t}^{S}\right) = \left(\sum_{k=1}^{S} r_{i,t,k} r_{m,t,k}\right)/\left(\sum_{k=1}^{S} r_{m,t,k}^{2}\right) \tag{4.1}$$

where $r_{\bullet,t,k} = logP_{\bullet,t,k} - logP_{\bullet,t,k-1}$ when the return of asset ● is either security i or market m during intraday interval k on day t, and S is the number of intraday periods.

Patton and Verardo (2012) argue that the quantity of interest when calculating daily betas using high frequency data is the integrated covariance matrix of daily returns, which is the stochastic integral of the instantaneous covariance over the period t-1 to t. This matrix can be estimated consistently by the N-by-N "realized covariance" matrix as the number of intraday returns diverges to infinity. Barndorf–Nielson and Shephard (2004) provide a central limit theorem for the realized covariance, and show that the asymptotic distribution of realized betas for stock i on day t is:

[27] Their work uses the econometric contributions of Anderson *et al.* (2003) and Barndorff-Nielsen and Shephard (2004) on estimating volatilities and covariances for high frequency data.

$$\sqrt{S}\left(R\beta_{i,t}^{S} - \beta_{i,t}\right) \xrightarrow{D} N\left(0, W_{i,t}\right), \text{ as } S \to \infty \tag{4.2}$$

which implies that $R\beta_{i,t}^{S} = \beta_{i,t} + \varepsilon_{i,t}$, where $\varepsilon_{i,t} \sim N(0, W_{it}/S)$.

We obtain 16 intra-day returns for stocks in the TAQ database by using quotes every 25 minutes between 9:45am and 4:00pm and overnight from 4:00 pm on the previous day to 9:45am on the current day in order to capture information arrival overnight. We use the exchange-traded fund tracking the S&P 500 index (SPDR, traded on Amex with ticker SPY, and available on the TAQ database) to measure the market return, as in Bandi and Russell (2006) and Todorov and Bollerslev (2010). Trading in this fund is very active. Since it can be redeemed for the underlying portfolio of S&P 500 stocks, arbitrage opportunities guarantee that the fund's price has minimal deviation from the fundamental value of the underlying index.

The realized variance (RV) of the market index and each individual stock is calculated as the squared sum of the 25-minute log returns:

$$RV_{i,t} = \sum_{k=1}^{S} r_{i,t,k}^{2} \tag{4.3}$$

where all the terms are as previously defined.

4.4.2 Changes in Realized Idiosyncratic Volatilities around the Rumor Dates

Roll (1988) attributes the low explanatory power of asset pricing models to arbitrage trading activities based on private information. Based on findings that support this conjecture, Durnev *et al.* (2003) argue that the ratios of firm specific to total volatilities contain information about future earnings. If the rumor represents a release of (mis)information that is based on private information, then it could lead to an increase in the proportion of idiosyncratic to total volatility (Roll 1988). This ratio is calculated for firm *i* and day *t* as follows:

$$IV\_Ratio_{i,t} = 1 - \frac{\beta_{i,t}^{2} RV_{M,t}}{RV_{i,t}} \tag{4.4}$$

where $\beta_{i,t}^{2}$ is the intraday beta; and $RV_{M,t}$ and $RV_{i,t}$ are the intraday realized volatilities of the market index and firm *i,* respectively.

4.4.3 Changes in Volatilities around the M&A Rumors

To examine the behavior of volatilities around the M&A rumor dates we use the changes in total, systematic, and idiosyncratic volatilities. To this end, we regress each volatility measure on event-day dummies. We illustrate the specification for idiosyncratic volatilities as follows:

$$\Delta IV\_Ratio_{i,t} = \sum_{d=-5}^{+5} \delta_d I_{\tau+d} + \overline{IV\_Ratio_i} D + \varepsilon_{i,t} \tag{4.5}$$

where τ is the rumor day, D is a dummy variable that takes the value of 1 over the estimation period and zero otherwise, and $I_{\tau+d}$ is a dummy variable that takes the value of 1 for each of the 11 days in the event window centered on the date of the rumor (i.e., when d=0 in τ+d). $\overline{IV\_Ratio_i}$ is the estimated average of the idiosyncratic to total volatility ratio over the estimation period from 125 days before to 25 days after the rumor dates. The regression estimate of δ_d represents the change in the IV ratio in excess of the average $\overline{IV\_Ratio_i}$ for day d.

Table 4.4 reports the average daily changes in the ratios of idiosyncratic to total volatilities over the event window of [-5, +5]. The increase in the idiosyncratic volatility ratios start two days before the publication of the rumors and peak on the rumor dates. This implies the possibility of informed trading before the rumors are circulated in the media. The changes in the idiosyncratic volatility ratios persist until the fifth day after the rumors first becomes public. The overall sample shows a mean increase of 5.28% (t-value of 13.07) for rumor AD. Furthermore, 95% of the rumored firms have an increase of at least 4.49%.

[Please place table 4.4 about here]

The more-credible rumored firms experience a relatively smaller abnormal IV ratio than the less-credible rumored firms for all the days in the event window. The mean abnormal IV ratios are 4.36% and 6.36% for the more- and less-credible rumored firms, respectively, for the rumor AD. The difference between the change in the IV ratios for the more- and less-credible rumored firms are statistically significant. These results lend support to our hypothesis that less-credible rumored firms experience greater informational asymmetries than more-credible rumored firms. In the next section, we further analyze the relation between the level of information asymmetry and the information content of the rumor itself.

4.5. CROSS-SECTIONAL REGRESSIONS OF THE PERFORMANCE OF RUMORED FIRMS

Earlier, we reported that more-credible rumored firms experience lower benchmark-adjusted abnormal returns and lower levels of idiosyncratic to total volatility ratios than less-credible rumored firms. We argued that the increase in the IV ratios is a risk that investors are expecting to be compensated for. To further examine the relation between IV and the performances of rumored firms, we run cross-sectional regressions of CARs and BHARs on the ratios of idiosyncratic to total volatilities and additional control variables; namely: Book to market ratio B/M and the log of the market value of the firm ln(size). We use COMPUSTAT to calculate the book to markets ratios using the book value as of the fiscal year ending in calendar year t-1 divided by the market value (stock price time shares outstanding) in December t-1. Following Fama and French (1993), book value is the book value of stockholder's equity plus deferred taxes and investment credit, if available, minus the book value of preferred stocks depending on availability using redemption, liquidation or par-value in this order. We run the CARs and BHARs for the individual rumored firms over the different event windows on the changes in their IV ratios. The first regression shows the relation between the performances of the rumored firms and their IV ratios only. The second regression examines the same relation but with the addition of the two control variables (B/M and ln(size)).

[Please place table 4.5 about here]

Table 4.5 reports the results of the regressions for each of the CAR and BHAR for more-credible rumored firms. The coefficient estimates for the IV ratio represent the impact of the change in abnormal returns as a function of the change in the level of the IV ratio on the day rumors were released. The coefficient estimates for the IV ratio are 0.06 with a t-stat of 1.97, 0.084 with a t-stat of 1.82, and 0.108 with a t-stat of 1.68 for the CARs over event windows of [-1; +1], [-1; +5] and [-5; +5], respectively. Adding the control variables B/M and ln(size) to the regressions does not qualitatively change the relationship between the IV ratios and CAR for event windows [-1; +1] and [-1; +5]. The coefficients of B/M and ln(size) are negative implying that value stocks (high B/M) and large firms tend to have lower CAR. The results of the regressions for BHAR and the IV ratios (including the control variables) are similar. The estimated coefficients of the IV ratios are positive and statistically significant at the 10% level and the estimated coefficients of both control variables are negative. To calculate the standard errors of the coefficients, we use White heteroscedasticity-consistent estimator (HAC), which accounts for both heteroscedasticity and autocorrelation.

[Please place table 4.6 about here]

The regression results reported in table 4.6 for the CARs and BHARs for the less-credible rumored firms show a different (negative) relation with their IV ratios for event windows [-1; +1] and [-1; +5] that is significant at the 0.10 level. As the level of information asymmetry increases, the abnormal returns around the rumor dates become more negative. The estimated coefficient for the IV ratios become insignificant in all regressions for the [-5; +5] and [1; +70] event windows.

4.6. IMPLICIT MARKET PROBABILITY OF M&A AND THE IV RATIO

4.6.1 Market-implicit Probability of a M&A

The change in the market value of the target firm after the first rumor about a possible M&A is released is subject to the credibility of the signal about the value of the synergies created by the M&A and the probability that the M&A will materialize. Betton *et al.* (2014) argue against the existence of a costly feedback loop where the bid price is positively related to the increase in the target market value before the bid announcement. They assume that the signal released in the market does not change the market expectation about the value of the synergy before the bid announcement, and thus that a rumor signals a change in the probability of a M&A materializing.

Investors keep updating their posterior probability distribution that the deal will materialize. If market participants were able to extract reliable signals before the announcement of a M&A, the price run-up would be larger leading to a decrease in the surprise effect of the announcement itself. The substitution hypothesis, developed by Schwert (1996), advocates that there is a one-to-one linear relationship between the increase in the value of the run-up and a decrease in the value of the markup. Betton *et al.* do not find a one-to-one substitution between the run-up and markup. A major finding of Betton *et al.* is that the rejection of the existence of a costly feedback loop causes the premium to increase with the value of the run-up. This implies that the market expectation of the value of any synergies depends on the expected fair value of the synergy.

All available signals gathered by investors help them form the probability that the bidder's gain from the M&A is positive where π=*Prob* (Synergy value>Cost of acquisition). Prior to a M&A announcement, investors form expectations about the value of a possible bid based on information gleaned from the market. Even on the day of the announcement, the increase in the value of the target is an expectation that the value of the bid will materialize or even be exceeded.

Under a rational expectation hypothesis with no feedback loop for M&A deals, the relationship between the markup and run-up would be defined as follows:

$$\frac{V_P - V_R}{V_R} = \frac{1-\pi}{\pi} \tag{4.6}$$

where V_P and V_R are the estimates of the premium and the run-up respectively; and π is the probability that the bid will be announced.

For our purposes, we measure the value of the premium as the expected market value of the M&A deal when it is announced. Schwert (1996) argues that the market expectation of the deal should include the change in price as a result of the anticipation of the deal and the change in the price after the announcement. We calculate the markup $(V_{P,i} - V_{R,i})$ directly by calculating the CAR around the takeover announcement date [-1; +1], where the run-up is calculated as the CAR over the period between the rumor date and two days before the announcement date. Calculating the implicit probability of an announcement requires knowing the market's expected value of the synergies created by the M&A, V_P, and the run-up amount V_R. Hence, we calculate the implied probability for a limited subsample that has an announcement within one year of the rumor date and also has a minimum of 21 days between the rumor and the announcement dates. These two conditions are satisfied by 233 firms.

4.6.2 Cross-sectional Regressions of Market-implied Probabilities

We run the following regression of the market-implied probabilities of M&A on the changes in the IV ratios for target firm *i*:

$$imp_{prob_i} = \gamma_1 + \gamma_2 IV_{Ratio_i} + \gamma_3 \#days_i + \gamma_4 \#\mathrm{rumors}_i + \gamma_5 B/M_i$$

$$+\gamma_6 \ln(Size_i) + \gamma_7 \#Analysts_i + \gamma_8 Disp_i + \gamma_9 LT\_Growth_i + \epsilon_i$$

(4.7)

where imp_prob is the market-implied probability of a takeover of firm i calculated using equation (4.6), where $V_{P,i} - V_{R,i}$ is calculated as the CAR around the M&A announcement day given by CAR [-1; 1], and $V_{R,i}$is the run-up return calculated as the CAR during the period from the rumor date +1 to two days prior to the M&A announcement. With regard to the other independent variables in (4.7), $\#days$ is the number of days between the rumor date and the M&A announcement date for target firm i, $\#\text{rumors}$ is the number of rumors appearing between the initial rumor and the M&A announcement date for target firm i, B/M is the book to market ratio for target firm i calculated as of the last available book value and last end of year market value before rumor date for target firm i. $\ln(Size_i)$ is the natural logarithm of market value of the target firm i 41 days before its initial rumor date, $\#Analysts$ is the number of analysts following target firm i, $Disp$ is the coefficient of variation of the last I/B/E/S summary estimates for target firm i, LT_Growth is the last I/B/E/S consensus estimate for long term growth reported before the rumor is made public for target firm i.

We use three different categories of control variables; namely, the information flow during the post rumor pre-announcement period, market expectations before the rumor announcement period, and firm characteristics. There are two measures of information flow during the post-rumor pre-announcement period of the M&A: $\#days$ and $\#\text{rumors}$. The proxies for period length are for the arrival of information and the time available to disseminate the information. If markets are efficient, information is quickly impounded into the price of an asset. If no new information enters the market after the initial rumor, then the length of the period should be irrelevant. Hence, our use of the number of days is a measure of information flow about a potential M&A during a potential pre-announcement period. The $\#\text{rumors}$ variable refers to the number of identified rumors in the hand-collected database used herein about a possible M&A during the period between an initial rumor and the M&A announcement date. If the information conveyed by a subsequent rumor is important in evaluating the success (failure) of the M&A, then its relation with the implicit probability would be positive (negative).

The second set of control variables are market expectations about the target firm. We use the consensus estimates of analysts from I/B/E/S as a proxy for market expectations about the target firm. The expected growth potential of the target as well as the level of consensus about that growth provides information about the likelihood of the success of the M&A. We collect the last available I/B/E/S consensus estimates about long-term growth of the target before the initial rumor date. LT_Growth represents the arithmetic mean of the available long-term growth estimates. We expect that firms with long-term potential growth are more likely to be potential targets with an increased probability of actually being acquired. $Disp$ is the coefficient of variation calculated as the ratio of the standard deviation to the mean long-term I/B/E/S consensus estimates. The higher the level of dispersion the more uncertainty there is about the future earnings of the target firm. We expect that firms with high levels of earnings uncertainty will have higher levels of uncertainty about the M&A success. The variable $\#Analysts$ controls for the firm's level of visibility. The higher the number of analysts following the target firm, the better the market expectations should be about the value creation associated with the M&A. Hence, we expect a positive relationship between the number of analysts and the probability that the M&A succeeds.

The last set of control variables are the characteristics of the target firm, which are widely used in the asset-pricing literature to capture the size and growth potential of firms. Small firms are expected to have good growth potential and easy targets for acquisition given their size. Our expectation is that the higher the market to book ratio, the higher the perceived growth of the firm. Since acquirers are more likely to be interested in firms with high growth potentials, we expect implied probabilities to be negatively related to size, and to the *B/M* ratios.

[Please place table 4.7 about here]

Based on Table 4.7, most of the correlations between the variables are small and not statistically significant. The correlations between the IV ratio and the other control variables are only statistically significant for the number of rumors (#rumors). Since the IV ratio precedes the release of subsequent rumors after the initial rumor, this suggests a leading relationship between the IV ratios and the number of rumors during the run-up period. The positive relationship between ln(size) and the number of rumors is consistent with the belief that large firms tend to attract more media attention.

The information flow variables are not correlated with a non-significant 0.05 correlation. This reinforces our earlier claim that an increase in the length of the run-up period does not increase the flow of information about the rumor. With regard to significant correlations between the earnings expectations variables, the dispersion in the earnings forecasts of analysts is positively correlated with the number of analysts (0.392; p-value of 0.000) and long-term growth is positively correlated with the dispersion in the earnings forecasts of analysts (0.15; p-value of 0.038). Both of these positive correlations are consistent with expectations. The correlation between *B/M* and ln(size) (-0.25; p-value of 0.008) is consistent with the previous literature that reports a positive relation between firm growth and firm size (Fama and French, 1992, 1993). In untabulated results, we estimate the correlation matrices for more- and less-credible rumored firms separately. The results differ only in the relationship between the implied probabilities and IV ratio. For the more-credible rumored firms, the correlation is positive and significant at 10%, where it is insignificant for the less-credible rumored firms..

4.7. CROSS SECTIONAL REGRESSION RESULTS

Summary results from regressing the measure of the implicit probability of an M&A on the change in the IV ratio and the other control variables are reported in Table 4.8. In the first regression, the estimated coefficient for the non-conditioned IV ratio is positive (9.73) and statistically significant (t-value of 2.01), remains significant (t-value of 2.215) and increases in magnitude to 12.31 for the more-credible rumors, and remains positive but becomes insignificant for the less-credible rumors.

[Please place table 4.8 about here]

When the variables to control for information flow during the pre-M&A announcement period (#rumors and #days) are added to regression run (2), the coefficient of the IV ratio remains positive and significant (t-value of 1.980), and the estimated coefficient of -0.006 for the number of rumors is not significant (t-value of -0.014). When the other control variables are also added in regression runs (3) and (4), the magnitude of the estimated coefficient for the IV ratio becomes significant at the 0.01 level instead of the 0.05 level. Except for the natural log of target size, which is significant in regression (3) but not regression (4), all the other estimated coefficients for the control variables are not significant.

While the estimated coefficients for the IV ratios are positive for both types of rumors, they are only significant for more-credible rumors when we separate the IV ratios based on whether the M&A rumor is more- or less-credible. Furthermore, none of the estimated coefficients for the control variables are significant at conventional levels.

4.8. MISVALUATIONS AND M&A PROBABILITIES

4.8.1. Estimation of Misvaluations

A growing body of literature argues that mispricing is an M&A motivation. Rhodes-kropf and Viswanathan (2005), RKV henceforth, provide a test of two alternative competing explanations about M&A waves and their motives. They find that the neoclassical explanation that M&A lead to a reorganization of the assets in a certain industry is not the only reason for M&S waves. They find that acquiring firms are overvalued significantly by approximately 20% more than targets according to their (M/B) ratios, and misvaluations explain about 15% of sector merger activity. They also find that firm-specific overvaluations are more important than sector overpricing. RKV find that sectors with high levels of common misvaluation components tend to experience higher levels of M&A activities.

We hypothesize that the level of mispricing has an effect on the probabilities of M&A announcements after the release of M&A rumors. We expect that the probabilities of firms being taken over is higher with higher levels of target underpricing. Although RKV suggest that the markets make mistakes in estimating either cash flows or discount rates or both, and that such mispricing could be firm-, industry-, or market-specific, we use a firm-specific misvaluation variable developed by RKV.

RKV develop a model based on a decomposition of the market to book ratio to capture possible mispricings. Assume that the "true" value of a firm is a linear function of firm i in sector j using accounting data at time t: $\vartheta_{i,t} = \varphi(\alpha_{j,t}, \theta_{i,t})$. Since mispricing could be sector- or market-wide, firm relative mispricing is zero. RKV argue for the existence of a mispricing wave that changes over time. The sector-wide long-term valuation captures the movement of this wave and allows for a decomposition of the mispricing into firm- and sector-specific mispricings. The sector-wide fundamental value is also the time series average value of the firms in that sector, since an average value of the coefficients for the accounting variables is used to calculate the overall sector "true" value. The last component is what RKV called long-term value to book value, where the value is calculated based on long-term estimates of the sector and firm accounting variables.

The overall decomposition is as follows:

$$\log\left(\frac{M}{B}\right) = m_{i,t} - b_{i,t} = \underbrace{\left(\mathrm{m}_{i,t} - \vartheta\left(\alpha_{j,t}, \theta_{i,t}\right)\right)}_{Firm}$$

$$+ \underbrace{\left(\vartheta\left(\alpha_{j,t}, \theta_{i,t}\right) - \vartheta\left(\alpha_{j}, \theta_{i,t}\right)\right)}_{Sector} + \underbrace{\left(\vartheta\left(\alpha_{j}, \theta_{i,t}\right) - b_{i,t}\right)}_{Long-term}$$

(4.8)

where $m_{i,t}$and $b_{i,t}$ are the natural logarithms of market and book values of firm i at time t; φ is the linear function for "true" value; and α is the sensitivity of the value ϑ to the accounting variable θ.

The empirical implementation of this decomposition requires few assumptions about the determinants of the value of the firm. RKV propose that the value of a firm is the value of the actual assets (i.e., book value) plus the discounted added value created by those assets in the future obtained by multiplying the book value by the difference between the return on equity and cost of capital, or: $M_t = B_t + E\sum_{\tau=t+1}^{+\infty}\frac{(ROE_\tau - r_\tau)B_\tau}{(1+r_\tau)^\tau}$. RKV propose three models for the valuation of the firm. The first model assumes that the book value is the only independent variable, the second model is the first one with the addition of net income, and the third adds leverage to the second model. Similarly to Hertzel and Li (2010), we use the third model to estimate the true value of the firm as:

$$m_{i,t} = \alpha_{0,j,t} + \alpha_{1,j,t} b_{i,t} + \alpha_{2,j,t} ln(|NI|)_{it} I_{(>0)} + \alpha_{3,j,t} ln(|NI|)_{ijt}\left(1 - I_{(>0)}\right)$$

$$+\alpha_{4,j,t}\mathrm{Lev}_{i,t} + \varepsilon_{i,t} \qquad (4.9)$$

where $b_{i,t}$is the natural log of the book value of firm i at time t, $ln(|NI|)_{it}$ is the natural log of the absolute value of net income, $I_{(>0)}$ is a dummy variable that take the value of 1 when net income is positive and zero otherwise, and $\mathrm{LEV}_{i,t}$ is the leverage ratio. $\alpha_{1\ldots4,j,t}$ are the sensitivities of the values of firms to different accounting variables in industry j in year t. RKV identify firm-specific mispricing with respect to the industry average as the difference between the actual value of the firm and the fitted value from equation (4.9) using the firm's accounting data in year t and industry-specific estimates of $\hat{\alpha}_{0\ldots4,j,t}$. The second type of mispricing is industry mispricing explained as a short-term deviation of the industry from its long-term average. This deviation is also referred to in RKV as the time series sector error. Calculating this latter value requires the use of the average sensitivities for the industry over the sample period. Hence, we calculate the period average of industry sensitivities $\bar{\alpha}_{0\ldots4,j,t} =$

$\sum_t \frac{1}{t} \hat{\alpha}_{0\ldots4,j,t}$, and we use the average sensitivities to forecast the value of the firm using the industry averages. The time series sector error is the difference between the firm value calculated using time-varying sensitivities and the firm value using the period average sensitivities.

4.8.2 Empirical Implementation

The implementation of the model requires the use of all firms in the COMPUSTAT/CRSP universe to calculate the industry and market-relative pricing of different accounting variables. We download all the firms in COMPUSTAT and categorize them into the 12 Fama-French industries obtained from the Kenneth French website. We match the COMPUSTAT sample of firms to CRSP in order to obtain the closing prices and the outstanding number of shares required to calculate the market values of these firms (as previously defined). Net incomes and book values are taken directly from COMPUSTAT and Leverage is calculated as: 1-(book equity/book value). The resulting sample after matching all firms between CRSP and COMPUSTAT is 155,420 firm-years spanning over the period 1990 to 2011.

[**Please place table 4.9 about here**]

Table 4.9 reports the summary statistics for the average sensitivities $\bar{\alpha}_{0\ldots4,j,t}$ for each industry j when equation (4.9) is estimated cross-sectionally for each year for a 10-year period prior to the date of the rumour announcement. Our findings are in line with the RKV findings about the relationship between firm values and book value and net income but differ with respect to leverage. $E(\alpha_0), E(\alpha_1), E(\alpha_2)$ and $E(\alpha_3)$ are all positive and highly significant, where the leverage average coefficient oscillates between significantly negative for industries 1, 6, 10, and 12 to not significant for industries 4, 7, and 9 to significantly positive for the rest of the industries. These differences could be explained by the behavior of firms during the Global Financial Crisis (GFC) where interest rates were at a historical low. Obreja (2013) argues that during countercyclical periods firms tend to create value by stock repurchases of depressed equities using lower cost debt, which leads to a positive relationship between debt and firm values.

Using these fitted values, we calculate two different measures of misvaluation: firm specific and time-series sector errors. Firm-specific errors are calculated as the component of the market-to-book ratio that is due to the deviation of the firm from its industry average. Hence, we use contemporaneous accounting variables and cross-sectional estimates of the coefficients to estimate the following implied value of the firm: $\mathrm{m}_{i,t} - \vartheta\left(\widehat{\alpha}_{0\ldots4,j,t}, \mathrm{b}_{i,t}, ln(|NI|)_{it}I_{(>0)}, ln(|NI|)_{ijt}\left(1 - I_{(>0)}\right), \mathrm{Lev}_{i,t}\right)$, where all the variables are as defined earlier. The time-series sector error is the component of the market-to-book ratio that captures the relative misvaluation of the sector. It is calculated as the difference between the implied firm value using contemporaneous accounting variables and cross-sectional sensitivities and a times-series average implied valuation

$$TS_{error} = \vartheta\left(\widehat{\alpha}_{0\ldots4,j,t}, \mathrm{b}_{i,t}, ln(|NI|)_{it}I_{(>0)}, ln(|NI|)_{ijt}\left(1 - I_{(>0)}\right), \mathrm{Lev}_{i,t}\right)$$
$$-\vartheta\left(\overline{\alpha}_{0\ldots4,j}, \mathrm{b}_{i,t}, ln(|NI|)_{it}I_{(>0)}, ln(|NI|)_{ijt}(1 - I_{(>0)}), \mathrm{Lev}_{i,t}\right). \quad (4.10)$$

RKV report that firms in overvalued sectors tend to engage in more M&A activities, where relatively overvalued firms acquire less overvalued ones. Since the firm-specific error should be lower for target firms relative to its industry, the probability of a takeover should increase as the level of overvaluation increase. RKV argue that firm errors are different between acquirers and targets, and that a high level of firm-specific error implies a high probability that a firm will be involved in a M&A or that it will be an acquirer. Since our simple is limited to target firms only, we initially test our hypothesis by comparing the average difference between the firm-specific error for every firm with its corresponding average industry firm-specific error, which would show the relative misvaluation of our targets versus its sector. We find statistically insignificant differences between the firm error component of rumored firms and their corresponding industries, which suggest that rumored firms are not particularly undervalued within their industries.

[Please place table 4.10 about here]

We further test the importance of misvaluations in explaining the implied probabilities of announcements of takeover rumor of firms. Table 4.10 reports the results of regressing the implied probabilities on the misvaluation estimates and the relation between implied probabilities, idiosyncratic volatilities and misvaluation estimates. The positive relationship between Betton *et al.* implied probabilities and changes in idiosyncratic volatilities around the rumor release dates is still positive and statistically significant at the

10% level even after adding firm error and time-series industry error components of the market-to-book ratio. Other coefficients on size, number of rumors, number of days, number of analysts, and IBES estimates remain statistically insignificant.

4.9. CONCLUSION

In this essay we tested the hypothesis that the uncertainty associated with M&A rumors affects stock prices (and idiosyncratic volatilities) around the release dates of the initial rumors. We categorize the hand-collected rumor database based on the credibility of the rumors where the more-credible group of rumors comes from identifiable sources. We calculate the probabilities of subsequent M&A announcements and find that more-credible rumors have significantly higher probabilities of leading to such announcements within the 70 days after the initial rumors are made public. Furthermore, we find that the credibility level is positively related to the performances of target firms over the period of 70 days after the initial rumors are made public.

Any change in stock prices and its direction depends upon the aggregate effect of the heterogeneous beliefs about the ultimate fate of the rumored target M&A. We find that idiosyncratic volatilities are positively (negatively) related to the performances of the target firms for more- (less-) credible M&A rumors. This relationship is further supported by the finding that the ratio of idiosyncratic volatility is positively related to the market-implied probability of an M&A using the run-up to markup price ratio as discussed in Betton *et al.* (2014). This relationship is robust to various firm-specific controls (such as size, book to market, long-term growth expectations), and firm- and sector-specific misvaluations.

CHAPTER FIVE

CONCLUSION

Financial theory has generally under-played the role of idiosyncratic volatility (*Ivol*) in financial markets and assumed that *Ivol* has no effect on the pricing of assets and no effect on the risk preferences of investors since they are mean-variance rational optimizers. However, more recent developments in financial economics find that realized *Ivol* (*RIvol*) is important and should be considered. In the first essay, we examined the relationship between *Ivol* and future returns in the Canadian market. We argued that the Canadian market is different than the US market due to a large concentration of firms in the energy and mining industries, a high level of correlation with commodities, and with little evidence for the existence of sharp return reversals in monthly returns. Unlike the anomalous findings of Ang *et al.* (2006, 2009), we found that *RIvol* was positively (and not negatively) related to future returns. We explained that our findings are analogous to the findings of Huang *et al.* (2010) who argued that the negative relationship disappears after controlling for return reversals in the US. Our findings are consistent with the theory for the relation between *Ivol* and returns, and are robust to risk loadings, return reversals, skewness and illiquidity.

Bali *et al.* (2011) uncover a negative relationship between extreme within-the-month positive returns and future returns and conjecture that this relationship is what is mistakenly explained by Ang *et al.* (2006) as the *RIvol* effect. Bali *et al.* (2011) argue that investors distort their beliefs and overweight stocks with extreme lagged daily returns. We hypothesized that this relationship might be a manifestation of the return reversal process in the US market which we found is not the case in the Canadian market. Unlike Bali *et al.* (2011), we found that the relationship between lagged *RIvol* and returns does not disappear after controlling for extreme positive returns in the prior month. Our results are confirmed using Fama-MacBeth equally and value weighted two stage regressions and Brennan *et al.* (1998) two stage risk-adjusted regressions.

In the second essay, we provided evidence that *Ivol*, which is used to proxy for uncertainty about CEF holdings, partially explains the well documented negative CEF premium. We investigated this phenomenon from an arbitrageur's perspective, and provided additional evidence that at least a significant portion of the gap of a CEF's price from its fundamental value is due to limits to arbitrage. This gap reflects the compensation that an arbitrageur would require for the hedgeable and non-hedgeable risks arising from the fund's portfolio composition and its uncertainty. This is consistent with the findings of Ackert and Tian (2000) for exchange traded funds that the premiums disappear when the portfolio compositions and weights are known, and the total risk of the portfolio is easily hedgeable.

Our tradeoff model included benefits from holding the CEF, which the literature identifies as enhanced liquidity, managerial abilities and leverage, and costs such as management fees. The difference between the liquidities of the CEF and its holdings capture the liquidity benefits, Jensen's alpha captures managerial ability benefits, and the ratio of non-common equity to assets (less the cash-to-asset ratio) captures the gross (net) leverage benefit. Our findings support the hypotheses that state that CEF premiums are positively related to these benefits (net but not gross leverage) and are negatively related to management fees.

We hypothesized that the premiums not captured by our model are related to the unhedged systematic and idiosyncratic risk exposures associated with the net position from risk arbitrage between the CEF and its equivalent NAVPS. We identified the systematic replication risk exposure for the small-minus-big factor as a significant determinant of CEF premiums. We attributed this non-zero exposure of the arbitrage position to this systematic risk factor as being due to uncertainty about a fund's holdings which leads to inexact hedge ratios. Using the idiosyncratic volatility (*Ivol*) of the net position return obtained from a long/short position in the CEF price and its NAVPS, we identified a significant relationship between CEF premiums and *Ivol* differences only when the fund has positive returns in the previous period. For the other proxies for the uncertainty of holdings, we find that CEF premiums are related negatively to idiosyncratic skewness but not related to options holdings.

In the third essay, we tested the hypothesis that the uncertainty associated with M&A rumors affects stock prices (and *Ivol*) around the release dates of the initial rumors. We categorized the hand-collected rumor database based on the credibility of the rumors where the more-credible group of rumors was from identifiable sources. We calculated the probabilities of subsequent M&A announcements and found that more-credible rumors have significantly higher probabilities of leading to such announcements within the 70 days after the initial rumors are made public. Furthermore, the credibility level of a rumor is positively related to the performances of target firms over the 70 days after the initial rumor is made public.

Any change in stock prices and its direction depends upon the aggregate effect of the heterogeneous beliefs about the ultimate fate of the rumored target M&A. We found that *Ivols* are positively (negatively) related to the performances of the target firms for more- (less-) credible M&A rumors. This relationship is further supported by the finding that the ratio of *Ivol* is positively related to the market-implied probability of an M&A using the run-up to markup price ratio as discussed in Betton *et al.* (2014). This relationship is robust to various firm-specific controls (such as size, book to market, long-term growth expectations), and firm- and sector-specific misvaluations.

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Tinic, S. M., & West, R. R. (1986). Risk, return, and equilibrium: A revisit. *Journal of Political Economy, 94*(1), 126-147.

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Table 2.1. Performance of a short-run contrarian strategy in the Canadian market

This table reports the value and equally-weighted returns for ten deciles for Canadian stocks sorted by their lagged monthly returns and then by size where big refers to stocks with market capitalizations higher than the 50th percentile in any given month and small to the remaining stocks in that month. Quintiles 1 and 10 are composed of the stocks with the lowest and highest lagged monthly returns, respectively. The p-values of the differences between the highest and lowest decile portfolios are reported in the parentheses. "**a**", "**b**" and "**c**" indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Lagged Return Decile	Value Weighted			Equally Weighted		
	All	Big	Small	All	Big	Small
1 (Lowest)	3.10%	2.46%	6.17%	2.69%	1.30%	5.63%
2	1.81%	1.91%	2.25%	0.90%	1.20%	1.20%
3	1.83%	1.80%	2.19%	1.09%	1.28%	1.13%
4	1.77%	1.62%	1.99%	1.06%	1.13%	0.92%
5	1.57%	1.56%	1.10%	1.07%	1.31%	0.30%
6	1.67%	1.62%	1.32%	1.20%	1.21%	0.48%
7	1.64%	1.60%	1.48%	1.35%	1.35%	0.62%
8	1.65%	1.61%	2.05%	1.38%	1.25%	0.89%
9	1.71%	1.68%	1.93%	1.39%	1.45%	0.37%
10 (Highest)	3.07%	2.57%	1.95%	1.22%	1.78%	-1.01%
10-1	-0.03%	0.10%	-4.18%	-1.47%	0.48%	-6.61%
	(0.9442)	(0.7580)	(0.0000)[a]	(0.0000)[a]	(0.1061)	(0.0000)[a]
α CAPM	-0.52%	-0.41%	-4.69%	-1.98%	-0.01%	-7.09%
	(0.1955)	(0.2211)	(0.0000)[a]	(0.0000)[a]	(0.9613)	(0.0000)[a]
α 4-Factor	-0.63%	-0.48%	-4.84%	-2.07%	-0.10%	-7.18%
	(0.1154)	(0.1515)	(0.0000)[a]	(0.0000)[a]	(0.7290)	(0.0000)[a]

Table 2.2. Time series properties of realized idiosyncratic volatilities (*RIvols*)

This table summarizes the time-series properties of individual stock realized idiosyncratic volatilities (*RIvols*). The sample consists of all stocks reported in the CFMRC for the period January 1975 to December 2012. The non-adjusted *RIvol* is estimated as the square root of the residuals of the regression of daily excess returns for every month from $r_{i,d_t} = \alpha + \beta r_{M,d_t} + sSMB_{d_t} + hHML_{d_t} + \gamma WML_{d_t} + \varepsilon_{i,d_t}$ multiplied by the square root of the number of days in the month. The Adjusted *RIvol* is calculated using the same residuals, and applying the following formula: $RIvol_{i,t}^{adj} = \sqrt{\sum_{t=1}^{T} \varepsilon_{i,d_t}^2 + 2\sum_{t=2}^{T} \varepsilon_{i,d_t}\varepsilon_{i,d_{t-1}}}$. "**a**", "**b**" and "**c**" indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	N	Mean	Median	Skew	Autocorrelation lags											
					1	2	3	4	5	6	7	8	9	10	11	12
$RIvol_t$	325,648	14.59%	11.14%	1.61	0.244 (55.485)[a]	0.185 (48.793)[a]	0.151 (43.793)[a]	0.114 (35.307)[a]	0.097 (32.072)[a]	0.080 (27.850)[a]	0.065 (23.795)[a]	0.057 (21.564)[a]	0.049 (19.063)[a]	0.038 (15.359)[a]	0.024 (9.948)[a]	0.021 (8.784)[a]
$RIvol_t^{Adj}$	325,648	16.94%	11.97%	1.56	0.098 (26.931)[a]	0.069 (23.554)[a]	0.053 (20.055)[a]	0.035 (14.518)[a]	0.028 (13.03)[a]	0.017 (8.087)[a]	0.010 (5.440)[a]	0.013 (6.988)[a]	0.009 (5.33)[a]	0.005 (2.734)[b]	-0.002 (-1.35)	-0.001 (-0.477)
$\ln\left(\frac{RIvol_t}{RIvol_{t-1}}\right)$	296,693	-0.024	-0.024	-0.04	-0.366 (-149.873)[a]	-0.040 (-14.480)[a]	-0.004 (-1.622)	-0.018 (-7.631)[a]	-0.005 (-2.338)[b]	-0.005 (-3.151)[a]	-0.006 (-2.951)[b]	-0.004 (-1.853)[c]	0.001 (0.710)	-0.004 (-1.891)[c]	-0.009 (-4.411)[a]	0.008 (4.203)[a]
$\ln\left(\frac{RIvol_t^{Adj}}{RIvol_{t-1}^{Adj}}\right)$	296,693	-0.057	0.061	-0.03	-0.398 (-163.064)[a]	-0.030 (-10.701)[a]	-0.002 (-1.043)	-0.017 (-7.120)[a]	0.001 (0.204)	-0.006 (-2.837)[b]	-0.006 (-3.080)[a]	-0.003 (-1.439)	0.001 (0.045)	-0.002 (-1.258)	-0.006 (-3.289)[a]	0.006 (3.266)[a]

Table 2.3.Returns of portfolios formed based on lagged realized idiosyncratic volatilities

This table reports the value-weighted returns for ten deciles for Canadian stocks sorted by their realized idiosyncratic volatilities (*RIvol*) derived from the Carhart model and then each of them is sorted into ten size deciles. In the table, big refers to stocks with a market capitalizations higher than the 90th percentile in any given month and small refers to stocks with a market capitalizations lower than the 10th percentile in any given month for each of the lagged *RIvol* deciles. The adjusted lagged *RIvol* is the adjusted realized idiosyncratic volatility. $RIvol_{i,t}^{adj} = \left(\sum_{t=1}^{T} \varepsilon_{i,d_t}^2 + 2\sum_{t=2}^{T} \varepsilon_{i,d_t}\varepsilon_{i,d_{t-1}}\right)^{0.5}$ where ε_{i,d_t} are the residuals from the regressions using daily returns in the Carhart 4 factor model: $r_{i,d_t} = \alpha + \beta r_{M,d_t} + sSMB_{d_t} + hHML_{d_t} + \gamma WML_{d_t} + \varepsilon_{i,d_t}$. Deciles 1 and 10 are composed of the stocks with the lowest and highest lagged *RIvol*, respectively. The p-values of the differences between the highest and lowest portfolios are reported in the parentheses. "**a**", "**b**" and "**c**" indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Lagged *RIvol* Decile	$RIvol^{Adj}$						$RIvol$					
	VW			EW			VW			EW		
	All	Big	Small	All	Big	Small	All	Big	Small	All	Big	Small
1 (Lowest)	1.55%	1.53%	0.79%	1.08%	1.21%	-0.07%	1.29%	1.31%	0.81%	1.04%	1.07%	0.23%
2	1.42%	1.50%	1.31%	1.10%	1.15%	0.58%	1.56%	1.50%	0.94%	1.11%	1.20%	0.23%
3	1.50%	1.39%	1.07%	1.23%	1.26%	0.16%	1.73%	1.55%	1.16%	1.24%	1.18%	0.18%
4	1.85%	1.68%	1.70%	1.34%	1.49%	0.60%	2.00%	1.87%	0.56%	1.27%	1.40%	-0.40%
5	1.87%	1.85%	1.39%	1.29%	1.42%	0.16%	2.16%	1.99%	1.32%	1.34%	1.43%	-0.05%
6	1.93%	1.92%	1.47%	1.16%	1.37%	0.17%	2.37%	2.10%	1.73%	1.16%	1.33%	0.16%
7	2.39%	1.95%	1.71%	1.14%	1.29%	0.23%	2.58%	2.23%	1.73%	1.13%	1.43%	-0.14%
8	2.67%	2.30%	1.58%	0.83%	1.30%	-0.56%	2.14%	2.32%	1.88%	0.79%	1.31%	-0.21%
9	2.83%	2.59%	2.04%	0.88%	1.09%	-0.13%	3.47%	2.58%	2.77%	0.63%	1.25%	0.21%
10 (Highest)	3.89%	3.05%	2.62%	0.55%	1.22%	-0.30%	4.16%	3.09%	3.55%	0.86%	1.19%	0.39%
10-1	2.34%	1.52%	1.89%	-0.53%	0.00%	-0.18%	2.87%	1.78%	2.88%	-0.18%	0.12%	0.30%
	(0.0000)[a]	(0.0001)[a]	(0.0044)[a]	(0.1664)	(0.9944)	(0.7641)	(0.0000)[a]	(0.0000)[a]	(0.0001)[a]	(0.7012)	(0.7137)	(0.6491)
α CAPM	1.40%	0.65%	1.01%	-1.39%	-0.84%	-1.00%	1.98%	0.88%	1.99%	-1.07%	-0.75%	-0.57%
	(0.0044)[a]	(0.0642)[c]	(0.1145)	(0.0001)[a]	(0.0020)[a]	(0.0859)[c]	(0.0003)[a]	(0.0192)[b]	(0.0061)[a]	(0.0118)[b]	(0.0085)[a]	(0.3675)
α 4-Factor	1.18%	0.49%	0.82%	-1.67%	-1.02%	-1.19%	1.66%	0.73%	1.70%	-1.43%	-0.95%	-0.88%
	(0.0087)[a]	(0.1226)	(0.1849)	(0.0000)[a]	(0.0000)[a]	(0.0361)[b]	(0.0007)[a]	(0.0332)[b]	(0.0147)[b]	(0.0000)[a]	(0.0001)[a]	(0.1428)

Table 2.4.Returns of value-weighted doubled sorted portfolios of lagged adjusted realized idiosyncratic volatilities and other control variables

This table reports the value-weighted returns for ten deciles for Canadian stocks sorted first by their realized idiosyncratic volatilities (*RIvol*) derived from the Carhart model and then separately in deciles by risk loadings, lagged monthly returns, the returns from 11 months prior ending 2 months prior to month t, skewness of daily returns over the previous month, and the Amihud illiquidity measure. High refers to stocks with values higher than the 90th percentile in any given month and low refers to stocks with values lower than the 10th percentile in any given month. The adjusted lagged $RIvol$ is calculated as $RIV_{i,t}^{adj} = \left(\sum_{t=1}^{T}\varepsilon_{i,d_t}^2 + 2\sum_{t=2}^{T}\varepsilon_{i,d_t}\varepsilon_{i,d_{t-1}}\right)^{0.5}$ where ε_{i,d_t} are the residuals from regressions using daily returns in the Carhart 4 factor model: $r_{i,d_t} = \alpha + \beta r_{M,d_t} + sSMB_{d_t} + hHML_{d_t} + \gamma WML_{d_t} + \varepsilon_{i,d_t}$. Deciles 1 and 10 are composed of the stocks with the lowest and highest lagged *RIvol*, respectively. The p-values of the differences between the highest and lowest portfolios are reported in the parentheses. “**a**”, “**b**” and “**c**” indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Lagged $RIvol$ Deciles	Beta		SMB		HML		Reversal		Momentum		Skewness		Illiquidity	
	High	Low	High	Low	High	Low	High	Low	High	Low	High	Low	High	Low
1 (Lowest)	1.60%	2.27%	1.58%	0.90%	1.58%	0.23%	1.57%	1.50%	1.30%	1.29%	1.90%	1.28%	1.47%	1.54%
2	1.43%	1.49%	1.44%	1.38%	1.41%	1.45%	1.43%	1.40%	1.48%	1.49%	1.94%	1.17%	1.34%	1.42%
3	1.53%	1.68%	1.51%	0.41%	1.50%	3.24%	1.47%	1.44%	1.76%	1.59%	2.00%	1.18%	1.61%	1.48%
4	1.89%	1.45%	1.90%	2.23%	1.92%	1.83%	1.88%	1.73%	1.95%	1.77%	2.52%	1.38%	1.68%	1.91%
5	1.90%	1.91%	1.86%	1.60%	1.88%	1.77%	1.80%	1.65%	2.13%	1.94%	2.52%	1.42%	1.77%	1.82%
6	1.96%	2.17%	2.00%	1.47%	1.93%	2.08%	1.95%	1.72%	2.26%	2.08%	2.53%	1.44%	1.94%	2.01%
7	2.44%	1.78%	2.37%	2.10%	2.32%	2.70%	2.03%	1.93%	2.57%	1.93%	3.62%	1.36%	2.35%	2.19%
8	2.80%	2.77%	2.82%	2.64%	2.84%	3.00%	2.86%	2.15%	2.47%	2.12%	3.41%	2.01%	2.33%	2.79%
9	2.85%	2.49%	2.66%	3.90%	2.43%	4.87%	2.72%	1.97%	2.91%	2.58%	3.92%	1.54%	2.69%	2.58%
10 (Highest)	3.71%	4.67%	3.87%	4.45%	3.27%	6.24%	3.77%	3.16%	4.02%	3.23%	5.49%	2.27%	3.52%	3.89%
10-1	2.11%	2.70%	2.29%	3.57%	1.69%	5.95%	0.23%	0.15%	0.83%	0.65%	3.59%	1.00%	2.05%	2.35%
	(0.0000)[a]	(0.0256)[b]	(0.0000)[a]	(0.0014)[a]	(0.0006)[a]	(0.0161)[b]	(0.0164)[b]	(0.0325)[b]	(0.0000)[a]	(0.0001)[a]	(0.0000)[a]	(0.0502)[c]	(0.0001)[a]	(0.0000)[a]
α CAPM	1.16%	2.13%	1.35%	2.85%	0.76%	5.35%	1.26%	0.80%	1.81%	1.10%	2.63%	0.06%	1.14%	1.40%
	(0.0130)[b]	(0.0758)[c]	(0.0047)[a]	(0.0082)[a]	(0.0921)	(0.0308)[b]	(0.0051)[a]	(0.1051)	(0.0006)[a]	(0.0970)[c]	(0.0000)[a]	(0.8982)	(0.0231)[b]	(0.0027)[a]
α 4-Factor	0.94%	1.84%	1.16%	2.67%	0.58%	4.81%	1.03%	0.60%	1.49%	0.80%	2.37%	-0.15%	0.88%	1.20%
	(0.0262)[b]	(0.1200)	(0.0088)[a]	(0.0117)[b]	(0.1534)	(0.0450)[b]	(0.0115)[b]	(0.2919)	(0.0017)[a]	(0.2482)	(0.0000)[a]	(0.7261)	(0.0563)[c]	(0.0048)[a]

Table 2.5. Returns of equal-weighted doubled sorted portfolios of lagged realized idiosyncratic volatilities and other control variables

This table reports the equal-weighted returns for ten deciles for Canadian stocks sorted first by their realized idiosyncratic volatilities (*RIvol*) derived from the Carhart model and then separately by risk loadings over the last month, lagged monthly returns, returns for the 11 months prior through the 2 months prior to month t, skewness of daily returns over the previous month, and Amihud illiquidity measure. High refers to stocks with values higher than the 90th percentile in any given month and low refers to stocks with values lower than the 10th percentile in any given month. The adjusted lagged $RIvol$ is calculated as $RIvol_{i,t}^{adj} = \left(\sum_{t=1}^{T} \varepsilon_{i,d_t}^2 + 2\sum_{t=2}^{T} \varepsilon_{i,d_t}\varepsilon_{i,d_{t-1}}\right)^{0.5}$ where ε_{i,d_t} are the residuals from regressions using daily returns and the Carhart 4 factor model: $r_{i,d_t} = \alpha + \beta r_{M,d_t} + sSMB_{d_t} + hHML_{d_t} + \gamma WML_{d_t} + \varepsilon_{i,d_t}$. Deciles 1 and 10 are composed of the stocks with the lowest and highest lagged *RIvol*, respectively. The p-values of the differences between the highest and lowest portfolios are reported in the parentheses. "**a**", "**b**" and "**c**" indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Lagged $RIvol$ Decile	Beta		SMB		HML		Reversal		Momentum		Skewness		Illiquidity	
	High	Low	High	Low	High	Low	High	Low	High	Low	High	Low	High	Low
1 (Lowest)	1.25%	2.02%	1.23%	0.33%	1.17%	-0.28%	1.12%	1.00%	1.04%	1.02%	1.74%	0.68%	1.05%	1.12%
2	1.21%	0.67%	1.21%	0.86%	1.19%	1.04%	1.11%	1.05%	1.13%	1.08%	1.80%	0.84%	1.00%	1.12%
3	1.36%	1.00%	1.33%	-0.05%	1.32%	2.38%	1.24%	1.15%	1.31%	1.16%	1.95%	0.84%	1.23%	1.26%
4	1.45%	0.54%	1.46%	0.97%	1.39%	1.41%	1.38%	1.14%	1.26%	1.10%	2.26%	0.83%	1.34%	1.37%
5	1.44%	0.79%	1.42%	0.46%	1.40%	0.60%	1.41%	1.26%	1.47%	1.27%	2.10%	0.74%	1.23%	1.33%
6	1.32%	1.01%	1.37%	0.35%	1.29%	1.08%	1.27%	1.08%	1.29%	0.97%	2.03%	0.59%	0.98%	1.27%
7	1.38%	0.40%	1.30%	1.48%	1.29%	1.08%	1.20%	0.89%	1.16%	0.79%	2.29%	0.38%	0.99%	1.22%
8	1.01%	2.58%	1.00%	0.49%	1.02%	1.61%	1.06%	0.73%	1.22%	0.76%	1.94%	0.01%	0.95%	1.03%
9	1.03%	0.32%	0.87%	1.24%	0.74%	2.60%	1.18%	0.52%	0.94%	0.29%	1.95%	-0.33%	0.66%	0.95%
10 (Highest)	0.93%	1.58%	0.83%	0.70%	0.65%	1.86%	0.90%	0.22%	1.04%	0.62%	2.39%	-1.02%	0.40%	0.70%
10-1	-0.31%	-0.23%	-0.40%	0.29%	-0.52%	1.56%	0.29%	0.27%	0.43%	0.25%	0.65%	-1.69%	-0.65%	-0.42%
	(0.4385)	(0.8299)	(0.2991)	(0.7651)	(0.1640)	(0.3798)	(0.0201)[b]	(0.0303)[b]	(0.0030)[a]	(0.1005)	(0.1357)	(0.0000)[a]	(0.0883)	(0.2677)
α CAPM	-1.17%	-0.83%	-1.25%	-0.26%	-1.37%	0.98%	-1.07%	-1.60%	-0.90%	-1.26%	-0.22%	-2.52%	-1.48%	-1.29%
	(0.0017)[a]	(0.4241)	(0.0004)[a]	(0.7874)	(0.0001)[a]	(0.5794)	(0.0015)[a]	(0.0000)[a]	(0.0266)[b]	(0.0033)[a]	(0.5837)	(0.0000)[a]	(0.0000)[a]	(0.0002)[a]
α 4-Factor	-1.45%	-1.13%	-1.52%	-0.47%	-1.62%	0.66%	-1.36%	-1.86%	-1.25%	-1.59%	-0.54%	-2.78%	-1.77%	-1.57%
	(0.0000)[a]	(0.2576)	(0.0000)[a]	(0.6207)	(0.0000)[a]	(0.7065)	(0.0000)[a]	(0.0000)[a]	(0.0001)[a]	(0.0000)[a]	(0.1019)	(0.0000)[a]	(0.0000)[a]	(0.0000)[a]

Table 2.6. Transition matrix for extreme returns

This table reports the probabilities of stocks moving across deciles. MAX (MIN) refers to the highest (lowest) daily returns in the month prior, and MAXDEV is the difference between the highest and lowest daily returns in a given prior month. The shaded area represents the probability that a stock in a specific decile in month t remains in the same decile in month t+1.

	1 (Lowest)	2	3	4	5	6	7	8	9	10 (Highest)
MAX										
1 (Lowest)	41.33%	20.80%	13.08%	8.78%	5.83%	3.70%	2.44%	1.54%	0.90%	0.54%
2	21.27%	22.49%	17.61%	12.93%	9.34%	6.39%	4.25%	2.68%	1.65%	1.00%
3	13.89%	17.63%	17.88%	14.69%	11.70%	8.68%	6.38%	4.26%	2.75%	1.47%
4	8.78%	13.99%	15.32%	15.44%	13.32%	10.84%	8.62%	6.35%	4.46%	2.50%
5	5.73%	9.66%	11.97%	14.28%	14.14%	13.17%	11.23%	8.78%	6.51%	4.00%
6	3.76%	6.86%	9.51%	11.45%	13.41%	14.41%	13.19%	11.77%	9.25%	6.06%
7	2.52%	4.55%	6.73%	9.39%	12.12%	14.04%	14.91%	14.48%	12.72%	8.94%
8	1.52%	2.78%	4.66%	6.89%	9.97%	12.73%	15.13%	16.84%	16.50%	13.21%
9	1.05%	1.81%	2.92%	4.58%	6.77%	9.94%	13.94%	17.59%	21.04%	20.75%
10 (Highest)	1.49%	1.12%	1.71%	2.56%	4.15%	6.60%	10.12%	15.14%	23.53%	36.28%
MIN										
1 (Lowest)	41.28%	23.17%	13.71%	8.49%	5.33%	3.22%	1.98%	1.26%	0.85%	0.54%
2	21.32%	23.07%	18.79%	13.48%	9.24%	6.20%	3.71%	2.40%	1.42%	0.79%
3	12.76%	17.86%	18.08%	16.11%	12.56%	9.26%	6.24%	4.04%	2.40%	1.26%
4	7.51%	12.59%	15.68%	15.81%	14.83%	12.34%	8.98%	6.17%	4.14%	2.14%
5	4.96%	8.73%	11.85%	14.03%	14.94%	14.08%	11.82%	9.55%	6.34%	3.56%
6	3.15%	5.46%	8.33%	11.43%	13.73%	15.12%	14.49%	12.54%	9.90%	5.98%
7	1.92%	3.53%	5.63%	8.49%	11.56%	13.71%	16.45%	16.11%	13.59%	9.14%
8	1.16%	2.35%	3.77%	6.30%	8.63%	11.74%	15.25%	18.12%	18.39%	13.87%
9	0.97%	1.41%	2.34%	3.83%	6.17%	9.12%	13.40%	17.89%	23.15%	21.83%
10 (Highest)	0.58%	0.76%	1.42%	2.05%	3.31%	5.52%	8.59%	13.42%	21.66%	41.96%
MAXDEV										
1 (Lowest)	49.00%	22.50%	12.28%	6.76%	3.76%	2.10%	1.24%	0.67%	0.39%	0.34%
2	22.48%	25.83%	19.50%	12.92%	8.41%	4.86%	2.66%	1.52%	0.82%	0.47%
3	12.19%	20.02%	20.46%	16.80%	12.10%	7.98%	4.91%	2.77%	1.54%	0.86%
4	6.88%	13.55%	17.03%	17.93%	15.16%	11.77%	7.84%	5.14%	2.79%	1.50%
5	4.01%	8.36%	12.71%	16.14%	16.56%	14.64%	11.63%	8.40%	4.92%	2.55%
6	2.15%	5.07%	8.17%	12.28%	15.54%	16.67%	15.27%	12.19%	8.33%	4.31%
7	1.19%	2.75%	5.25%	8.38%	12.48%	16.12%	17.70%	16.21%	12.94%	7.13%
8	0.81%	1.50%	2.93%	5.35%	8.82%	13.02%	17.20%	19.47%	18.62%	12.49%
9	0.57%	0.82%	1.62%	3.04%	5.23%	9.01%	14.08%	19.65%	24.67%	21.77%
10 (Highest)	1.02%	0.55%	0.83%	1.35%	2.41%	4.57%	8.41%	14.38%	25.14%	43.19%

Table 2.7.Returns of portfolios formed based on lagged daily extreme returns

This table reports the equal- and value-weighted returns for ten deciles for Canadian stocks sorted by their extreme returns (*MAX*, *MIN* and *MAXDEV*), and then by size. Big refers to stocks with market capitalizations higher than the 90th percentile in any given month and small refers to stocks with market capitalizations lower than the 10th percentile in any given month, respectively. *MAX* (*MIN*) refers to the highest (lowest) daily returns in the prior month, and *MAXDEV* is the difference between the highest and lowest daily returns in a given prior month. The p-values of the differences between the highest and lowest portfolios are reported in the parentheses. "**a**", "**b**" and "**c**" indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Lagged Extreme returns Decile	MAX						MIN						MAXDEV					
	Value Weighted			Equal Weighted			Value Weighted			Equal Weighted			Value Weighted			Equal Weighted		
	All	Big	Small	All	Big	Small	All	Big	Small	All	Big	Small	All	Big	Small	All	Big	Small
1 (Lowest)	1.43%	1.43%	1.05%	1.09%	1.21%	0.28%	1.35%	1.31%	0.62%	1.03%	1.04%	-0.01%	1.32%	1.27%	0.89%	1.07%	1.10%	0.24%
2	1.60%	1.49%	0.98%	1.22%	1.22%	0.18%	1.60%	1.53%	0.79%	1.18%	1.26%	0.001%	1.54%	1.52%	1.22%	1.20%	1.21%	0.36%
3	1.55%	1.61%	1.22%	1.21%	1.30%	0.37%	1.65%	1.66%	1.26%	1.19%	1.22%	0.18%	1.75%	1.68%	1.14%	1.22%	1.34%	0.22%
4	1.81%	1.73%	1.15%	1.25%	1.40%	-0.06%	2.14%	1.69%	0.77%	1.44%	1.30%	-0.52%	1.91%	1.70%	0.59%	1.28%	1.31%	-0.47%
5	2.00%	1.77%	1.36%	1.17%	1.26%	-0.06%	2.35%	2.01%	0.88%	1.39%	1.48%	-0.52%	2.10%	1.88%	1.22%	1.35%	1.34%	-0.35%
6	1.95%	1.96%	1.42%	1.11%	1.28%	0.07%	1.95%	2.22%	1.70%	1.14%	1.61%	0.06%	2.22%	2.03%	2.24%	0.99%	1.34%	0.48%
7	2.36%	1.89%	2.01%	1.07%	1.28%	0.23%	2.32%	1.97%	2.33%	0.91%	1.30%	0.33%	2.67%	2.08%	1.46%	1.23%	1.40%	-0.09%
8	2.43%	2.27%	1.09%	1.02%	1.27%	-0.70%	2.31%	2.23%	2.03%	0.82%	1.45%	-0.53%	2.36%	2.41%	2.05%	0.88%	1.39%	-0.23%
9	3.05%	2.31%	1.31%	0.81%	1.25%	-1.02%	2.89%	2.26%	2.64%	0.65%	1.16%	-0.17%	2.92%	2.48%	2.53%	0.68%	1.19%	0.01%
10 (Highest)	3.75%	3.05%	2.87%	0.64%	1.27%	0.08%	3.06%	2.50%	3.74%	0.88%	1.00%	1.37%	3.69%	2.78%	3.27%	0.69%	1.17%	0.01%
10-1	2.32%	1.61%	2.09%	-0.45%	0.06%	0.05%	1.71%	1.19%	3.22%	-0.15%	-0.03%	1.49%	2.38%	1.51%	2.57%	-0.38%	0.08%	0.30%
	(0.0000)[a]	(0.0000)[a]	(0.0013)[a]	(0.3010)	(0.8561)	(0.9289)	(0.0007)[a]	(0.0012)[a]	(0.0000)[a]	(0.7212)	(0.9155)	(0.0245)[b]	(0.0000)[a]	(0.0002)[a]	(0.0005)[a]	(0.4004)	(0.8225)	(0.6474)
α CAPM	1.41%	0.72%	1.26%	-1.34%	-0.81%	-0.75%	-1.87%	1.39%	3.43%	0.06%	0.20%	1.70%	1.41%	0.58%	1.72%	-1.30%	-0.82%	-0.57%
	(0.0040)[a]	(0.0345)[b]	(0.0455)[b]	(0.0007)[a]	(0.0033)[a]	(0.1969)	(0.0000)[a]	(0.0000)[a]	(0.0000)[a]	(0.8766)	(0.4395)	(0.0079)[a]	(0.0043)[a]	(0.1021)	(0.0170)[b]	(0.0015)[a]	(0.0039)[a]	(0.3702)
α 4-Factor	1.16%	0.60%	0.97%	-1.68%	-0.99%	-1.04%	1.67%	1.29%	3.19%	-0.22%	0.08%	1.42%	1.16%	0.44%	1.36%	-1.63%	-1.00%	-0.90%
	(0.008 2)[a]	(0.0561)[c]	(0.1072)	(0.0000)[a]	(0.0000)[a]	(0.0620)	(0.0001)[a]	(0.0000)[a]	(0.0000)[a]	(0.4866)	(0.7400)	(0.0190)[b]	(0.0086)[a]	(0.1776)	(0.0455)[b]	(0.0000)[a]	(0.0000)[a]	(0.1329)

Table 2.8.Returns of value-weighted doubled sorted portfolios of lagged extreme returns and high/low monthly returns

This table reports the equal and value weighted returns for ten deciles of Canadian stocks first sorted by their lagged monthly returns, and then by their extreme return measures, where *MAX* (*MIN*) refers to the highest (lowest) daily returns in the prior month, and *MAXDEV* is the difference between the highest and lowest daily returns in the prior month. High (low) refers to stocks with returns in the highest (lowest) decile for the prior month. The p-values of the differences between the highest and lowest portfolios are reported in the parentheses. "**a**", "**b**" and "**c**" indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Lagged Extreme returns Deciles	MAX				MIN				MAXDEV			
	Value Weighted		Equal Weighted		Value Weighted		Equal Weighted		Value Weighted		Equal Weighted	
	High (Ret_{t-1})	Low (Ret_{t-1})	High (Ret_{t-1})	Low (Ret_{t-1})	High (Ret_{t-1})	Low (Ret_{t-1})	High (Ret_{t-1})	Low (Ret_{t-1})	High (Ret_{t-1})	Low (Ret_{t-1})	High (Ret_{t-1})	Low (Ret_{t-1})
1 (Lowest)	1.58%	1.01%	1.35%	0.60%	1.52%	0.91%	1.30%	0.57%	1.44%	0.97%	1.28%	0.70%
2	1.85%	0.89%	1.69%	0.37%	1.79%	0.90%	1.62%	0.40%	1.79%	0.96%	1.58%	0.51%
3	1.91%	0.78%	1.85%	0.02%	2.11%	0.80%	1.89%	0.10%	2.05%	0.80%	1.78%	0.14%
4	2.23%	0.64%	2.13%	-0.35%	2.41%	0.74%	2.24%	-0.20%	2.38%	0.66%	2.13%	-0.15%
5	2.68%	0.51%	2.54%	-0.75%	3.03%	0.46%	2.74%	-0.76%	2.74%	0.34%	2.46%	-0.71%
6	2.81%	0.01%	2.82%	-1.54%	2.87%	-0.20%	2.90%	-1.50%	3.08%	-0.03%	2.93%	-1.38%
7	3.77%	-0.21%	3.45%	-2.13%	3.48%	-0.32%	3.32%	-2.26%	4.01%	-0.56%	3.45%	-2.24%
8	4.21%	-1.17%	3.91%	-3.23%	3.97%	-1.18%	4.00%	-3.33%	4.39%	-1.25%	4.03%	-3.37%
9	5.18%	-1.74%	5.08%	-4.46%	5.01%	-1.65%	4.97%	-4.63%	5.37%	-2.46%	5.09%	-4.79%
10 (Highest)	7.60%	-3.64%	7.84%	-6.87%	7.30%	-3.19%	7.62%	-6.87%	8.36%	-4.05%	8.10%	-7.23%
10-1	6.01%	-4.65%	6.48%	-7.47%	5.78%	-4.10%	6.32%	-7.44%	6.91%	-5.01%	6.82%	-7.93%
	(0.0000)[a]	(0.0000)[a]	(0.0000)[a]	(0.0000)[a]	(0.0000)[a]	(0.0000)[a]	(0.0000)[a]	(0.0000)[a]	(0.0000)[a]	(0.0000)[a]	(0.0000)[a]	(0.0000)[a]
α CAPM	5.13%	-5.42%	5.56%	-8.22%	5.98%	-3.80%	6.53%	-7.10%	5.95%	-5.81%	5.88%	-8.70%
	(0.0000)[a]	(0.0000)[a]	(0.0000)[a]	(0.0000)[a]	(0.0000)[a]	(0.0000)[a]	(0.0000)[a]	(0.0000)[a]	(0.0000)[a]	(0.0000)[a]	(0.0000)[a]	(0.0000)[a]
α 4-Factor	4.83%	-5.51%	5.22%	-8.38%	5.72%	-3.87%	6.23%	-7.23%	5.64%	-5.91%	5.52%	-8.86%
	(0.0000)[a]	(0.0000)[a]	(0.0000)[a]	(0.0000)[a]	(0.0000)[a]	(0.0000)[a]	(0.0000)[a]	(0.0000)[a]	(0.0000)[a]	(0.0000)[a]	(0.0000)[a]	(0.0000)[a]

Table 2.9.Returns of value-weighted doubled sorted portfolios of lagged extreme returns and high/low *RIvol*

This table reports the equal and value weighted returns for ten deciles of Canadian stocks first sorted by their *RIvol*, and then by their extreme return measures. *MAX* (*MIN*) refers to the highest (lowest) daily returns in the prior month, and *MAXDEV* is the difference between the highest and lowest daily return in the prior month. High (low) refers to stocks with *RIvol* in the highest (lowest) decile for the prior month. The p-values of the differences between the highest and lowest decile portfolios are reported in the parentheses. "**a**", "**b**" and "**c**" indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Lagged Extreme returns Deciles	MAX				MIN				MAXDEV			
	Value Weighted		Equal Weighted		Value Weighted		Equal Weighted		Value Weighted		Equal Weighted	
	High (*RIvol*)	Low (*RIvol*)	High (*RIvol*)	Low (*RIvol*)	High (*RIvol*)	Low (*RIvol*)	High (*RIvol*)	Low (*RIvol*)	High (*RIvol*)	Low (*RIvol*)	High (*RIvol*)	Low (*RIvol*)
1 (Lowest)	1.59%	1.44%	1.40%	1.15%	1.58%	1.33%	1.34%	1.06%	1.49%	1.31%	1.32%	1.12%
2	1.71%	1.55%	1.43%	1.22%	1.76%	1.46%	1.43%	1.21%	1.79%	1.55%	1.47%	1.25%
3	1.89%	1.53%	1.48%	1.24%	1.84%	1.71%	1.46%	1.23%	1.82%	1.60%	1.42%	1.17%
4	2.04%	1.65%	1.45%	1.12%	2.48%	1.79%	1.91%	1.29%	2.21%	1.75%	1.54%	1.27%
5	2.04%	2.00%	1.35%	1.16%	2.25%	2.17%	1.51%	1.33%	2.17%	1.86%	1.57%	1.18%
6	2.45%	1.67%	1.49%	0.81%	2.18%	1.77%	1.38%	1.00%	2.53%	1.90%	1.34%	1.05%
7	2.48%	2.05%	1.50%	0.82%	2.66%	1.99%	1.28%	0.58%	2.93%	1.99%	1.60%	0.69%
8	2.85%	1.70%	1.49%	0.37%	2.51%	2.01%	1.21%	0.30%	2.61%	2.16%	1.31%	0.43%
9	3.56%	2.00%	1.55%	-0.14%	3.16%	1.52%	1.22%	-0.26%	3.34%	1.62%	1.37%	-0.30%
10 (Highest)	4.38%	1.75%	1.65%	-0.98%	3.51%	1.27%	2.01%	-1.07%	4.50%	1.31%	1.75%	-1.43%
10-1	2.78%	0.32%	0.25%	-2.13%	1.93%	-0.05%	0.67%	-2.13%	3.01%	0.00%	0.43%	-2.54%
	(0.0000)[a]	(0.3749)	(0.5958)	(0.0000)[a]	(0.0003)[a]	(0.8730)	(0.1586)	(0.0000)[a]	(0.0000)[a]	(0.9933)	(0.3870)	(0.0000)[a]
α CAPM	1.85%	-0.49%	-0.62%	-2.91%	2.14%	0.21%	0.92%	-1.83%	2.05%	-0.88%	-0.47%	-3.36%
	(0.0006)[a]	(0.1378)	(0.1612)	(0.0000)[a]	(0.0000)[a]	(0.4916)	(0.0406)[b]	(0.0000)[a]	(0.0003)[a]	(0.0119)[b]	(0.3064)	(0.0000)[a]
α 4-Factor	1.57%	-0.62%	-0.98%	-3.07%	1.93%	0.13%	0.62%	-1.95%	1.74%	-1.05%	-0.83%	-3.52%
	(0.0013)[a]	(0.0404)[b]	(0.0052)[a]	(0.0000)[a]	(0.0000)[a]	(0.6631)	(0.0965)[c]	(0.0000)[a]	(0.0007)[a]	(0.0010)[a]	(0.0233)[b]	(0.0000)[a]

Table 2.10. Returns of value-weighted doubled sorted portfolios of lagged *RIvol* and high/low extreme returns

This table reports the equal and value-weighted returns for ten deciles for Canadian stocks first sorted by their realized idiosyncratic volatilities (*RIvol*) derived from the Carhart model and then separately by *MAX*, *MIN* and *MAXDEV*. High refers to stocks with values higher than the 90th percentile in any given month and low refers to stocks with values lower than the 10th percentile in any given month. The adjusted lagged *RIvol* is is calculated from: $RIvol_{i,t}^{adj} = \left(\sum_{t=1}^{T}\varepsilon_{i,d_t}^2 + 2\sum_{t=2}^{T}\varepsilon_{i,d_t}\varepsilon_{i,d_{t-1}}\right)^{0.5}$ where ε_{i,d_t} are the residuals from regressions using daily returns and the Carhart 4 factor model: $r_{i,d_t} = \alpha + \beta r_{M,d_t} + sSMB_{d_t} + hHML_{d_t} + \gamma WML_{d_t} + \varepsilon_{i,d_t}$. *MAX* (*MIN*) refers to the highest (lowest) daily returns in the prior month, and *MAXDEV* is the difference between the highest and lowest daily return in a given month. Quintiles 1 and 10 are composed of the stocks with the lowest and highest lagged *RIvol*, respectively. The p-values of the differences between the highest and lowest portfolios are reported in the parentheses. "**a**", "**b**" and "**c**" indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Lagged *RIvol* Deciles	MAX				MIN				MAXDEV			
	Value Weighted		Equal Weighted		Value Weighted		Equal Weighted		Value Weighted		Equal Weighted	
	MAX (High)	MAX (Low)	MAX (High)	MAX (Low)	MIN (High)	MIN (Low)	MIN (High)	MIN (Low)	MAXDEV (High)	MAXDEV (LOW)	MAXDEV (High)	MAXDEV (Low)
1 (Lowest)	2.57%	1.45%	1.85%	0.83%	1.07%	1.64%	0.94%	1.42%	1.92%	1.52%	1.45%	1.05%
2	2.36%	1.40%	1.95%	1.06%	0.93%	1.53%	0.78%	1.32%	1.72%	1.44%	1.38%	1.13%
3	2.52%	1.41%	1.97%	1.12%	1.33%	1.50%	1.11%	1.49%	2.10%	1.46%	1.60%	1.28%
4	2.37%	1.70%	1.91%	1.13%	1.42%	1.94%	1.20%	1.69%	1.95%	1.80%	1.58%	1.34%
5	2.50%	1.63%	1.79%	0.98%	1.61%	1.94%	1.18%	1.74%	2.13%	1.76%	1.51%	1.30%
6	2.38%	1.78%	1.54%	0.88%	1.64%	2.20%	1.10%	1.77%	2.02%	1.98%	1.33%	1.26%
7	2.99%	1.66%	1.41%	0.53%	2.51%	2.25%	1.13%	1.81%	2.81%	1.88%	1.26%	1.02%
8	2.89%	2.05%	1.33%	0.13%	2.56%	3.11%	1.13%	1.94%	2.73%	2.57%	1.22%	0.83%
9	3.15%	1.61%	1.07%	-0.53%	2.91%	3.19%	0.91%	1.91%	3.00%	2.25%	0.96%	0.41%
10 (Highest)	4.36%	1.16%	1.28%	-2.22%	4.18%	4.30%	1.20%	2.18%	4.21%	2.20%	1.23%	-0.70%
10-1	1.79%	-0.29%	-0.57%	-3.05%	3.11%	2.66%	0.25%	0.75%	2.28%	0.68%	-0.21%	-1.75%
	(0.0011)[a]	(0.4428)	(0.1634)	(0.0000)[a]	(0.000)[a]	(0.0000)[a]	(0.5316)	(0.0143)[b]	(0.0000)[a]	(0.0767)[c]	(0.5961)	(0.0000)[a]
α CAPM	0.95%	-1.15%	-1.34%	-3.82%	2.27%	1.78%	-0.53%	-0.08%	1.46%	-0.17%	-0.98%	-2.52%
	(0.0707)[c]	(0.0007)[a]	(0.0006)[a]	(0.0000)[a]	(0.0000)[a]	(0.0000)[a]	(0.1728)	(0.7741)	(0.0063)[a]	(0.6381)	(0.0124)[b]	(0.0000)[a]
α 4-Factor	0.71%	-1.30%	-1.63%	-3.97%	2.03%	1.59%	-0.82%	-0.28%	1.23%	-0.31%	-1.27%	-2.67%
	(0.1414)	(0.0000)[a]	(0.0000)[a]	(0.0000)[a]	(0.0001)[a]	(0.0000)[a]	(0.0149)[b]	(0.2117)	(0.0127)[b]	(0.3321)	(0.0002)[a]	(0.0000)[a]

Table 2.11. Time-series averages of the cross-sectional equal and value weighted Fama-MacBeth regressions of returns on the idiosyncratic volatility measures and control variables

Time-series averages of the parameter estimates for the series of cross-sectional regressions using turnover and its coefficient of variation as control variables similar to Fu (2009) are reported in this table. BETA, ME and BE/ME are estimated as in Fama and French (1992). The not adjusted *RIvol* is estimated as the square root of the residuals of the regression using daily excess returns for every month in $r_{i,d_t} = \alpha + \beta r_{M,d_t} + sSMB_{d_t} + hHML_{d_t} + \gamma WML_{d_t} + \varepsilon_{i,d_t}$ multiplied by the square root of the number of days in the month. The adjusted RIV is calculated as $RIvol_{i,t}^{adj} = \left(\sum_{t=1}^{T} \varepsilon_{i,d_t}^2 + 2\sum_{t=2}^{T} \varepsilon_{i,d_t}\varepsilon_{i,d_{t-1}}\right)^{0.5}$. RET (-2,-11) is a momentum variable calculated as the cumulative return of each stock from month t-11 to t-2. The liquidity control measures are TURNOVER and CV(TURN) as in Easley, Hvidkjaer and O'Hara (2002). They are respectively the log of a stock's average turnover and its coefficient of variation over the 36 months previous to month t . Half Amihud (-) is the modified illiquidity measure of Amihud (2002) as in Brennan *et al.* (2013). Synchronicity *SYNC* is the logistic transformation of the R-square from the Carhart 4-factor model. The average R^2 values are reported in the table. t-values are reported in the parentheses. The coefficients are the means of the cross-sectional regression coefficients. The standard errors used in the t-tests are adjusted for autocorrelation as in Pontiff (1996). "a", "b" and "c" indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Model	Equal Weighted								Value Weighted			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Intercept	-0.029	-0.025	-0.003	-0.001	-0.155	-0.085	-0.069	-0.042	-0.092	-0.066	-0.075	-0.055
	(-2.986)[a]	(-2.290)[b]	(-0.467)	(-0.085)	(-15.333)[a]	(-12.684)[a]	(-9.768)[a]	(-7.860)[a]	(-9.929)[a]	(-7.361)[a]	(-6.356)[a]	(-5.270)[a]
Beta	-0.005	-0.005	-0.005	-0.004	-0.009	-0.007	-0.005	-0.003	-0.005	-0.001	-0.002	0.000
	(-2.183)[b]	(-1.959)[b]	(-1.347)	(-1.094)	(-5.758)[a]	(-4.563)[a]	(-3.416)[a]	(-2.515)[a]	(-2.082)[b]	(-0.521)	(-0.850)	(0.119)
Log(ME)	0.001	0.002	0.145	0.121	0.001	0.000	0.401	0.372	0.000	0.000	0.001	0.000
	(1.973)[b]	(2.460)[a]	(0.511)	(0.408)	(1.897)[c]	(1.683)	(2.274)[b]	(2.208)[b]	(0.653)	(0.624)	(1.096)	(0.452)
Log(BE/ME)	-0.005	0.000	-0.002	0.000	0.002	0.002	0.002	0.002	-0.001	-0.001	-0.001	-0.002
	(-0.897)	(-0.083)	(-0.339)	(0.067)	(0.816)	(1.017)	(0.859)	(1.354)	(-0.126)	(-0.214)	(-0.208)	(-0.386)
$RIvol_t$	0.113				0.324				0.362			
	(4.298)[a]				(12.877)[a]				(9.179)[a]			
$RIvol_{i,t}^{adj}$		0.394				0.840				1.862		
		(3.021)[a]				(8.457)[a]				(6.914)[a]		
$RIvol_{t-1}$			0.029				0.082				0.180	
			(1.870)[c]				(5.405)[a]				(4.352)[a]	
$RIvol_{i,t-1}^{adj}$				-0.072				0.031				0.676
				(-0.437)				(4.972)[a]				(2.879)[a]
Ret (-2,-11)	0.177	0.169	0.175	0.171	0.171	0.169	0.177	0.178	0.191	0.197	0.205	0.210
	(13.136)[a]	(12.568)[a]	(11.374)[a]	(10.903)[a]	(24.770)[a]	(26.955)[a]	(32.000)[a]	(33.097)[a]	(26.773)[a]	(27.316)[a]	(26.801)[a]	(27.903)[a]
RET_{t-1}	-0.228	-0.222	-0.206	-0.212	-0.203	-0.204	-0.208	-0.201	-0.212	-0.212	-0.227	-0.225
	(-8.190)[a]	(-8.187)[a]	(-9.885)[a]	(-8.973)[a]	(-22.557)[a]	(-21.909)[a]	(-20.065)[a]	(-20.257)[a]	(-13.648)[a]	(-13.352)[a]	(-12.923)[a]	(-13.072)[a]
Turnover	0.007	0.005	0.001	0.001								
	(1.148)	(0.874)	(0.071)	(0.034)								
CV(Turn)	0.000	-0.001	0.003	0.003								
	(0.203)	(-0.228)	(0.569)	(0.545)								
Half Amihud (-)					0.008	0.005	0.004	0.003	0.004	0.003	0.003	0.003
					(12.173)[a]	(9.840)[a]	(10.656)[a]	(8.578)[a]	(10.992)[a]	(8.678)[a]	(6.522)[a]	(5.741)[a]
SYNC					0.003	0.001	-0.005	-0.004	-0.002	-0.004	-0.007	-0.005
					(1.407)	(-0.154)	(-2.154)[b]	(-1.778)[c]	(-0.585)	(-1.261)	(-2.233)[b]	(-1.706)[c]

Adj. R^2	32.86%	33.87%	29.67%	30.55%	32.10%	32.49%	27.69%	27.90%	62.95%	62.29%	61.42%	60.89%

Table 2.12. Time-series averages of the cross-sectional regressions for risk-adjusted excess returns and *RIvol* and control variables

Time-series averages of the parameter estimates for the series of cross-sectional regressions of risk-adjusted returns on idiosyncratic volatilities and various control variables are reported in this table. The non-adjusted *RIvol* is estimated as the square root of the residuals of the regression using daily excess returns for every month in: $r_{i,d_t} = \alpha + \beta r_{M,d_t} + sSMB_{d_t} + hHML_{d_t} + \gamma WML_{d_t} + \varepsilon_{i,d_t}$ multiplied by the square root of the number of days in the month. Adjusted *RIvol* is calculated as $RIvol_{i,t}^{adj} = \left(\sum_{t=1}^{T} \varepsilon_{i,d_t}^2 + 2\sum_{t=2}^{T} \varepsilon_{i,d_t}\varepsilon_{i,d_{t-1}}\right)^{0.5}$. The liquidity control measures are TURNOVER and CV(TURN) as in Easley, Hvidkjaer and O'Hara (2002). They are respectively given by the log of a stock's average turnover and its coefficient of variation over the 36 months previous to month *t*. RET (-2,-11) is a momentum control variable calculated as the cumulative return of each stock for month t-11 to t-2. The coefficients are the means of the cross-sectional regression coefficients. Half Amihud (-) is the modified illiquidity measure of Amihud (2002) as in Brennan *et al.* (2013). Synchronicity *SYNC* is the logistic transformation of the R-square from the Carhart 4-factor model. The average R^2 values are reported in the table. t-values are reported in the parentheses. The standard errors used in the t-tests are adjusted for autocorrelation as in Pontiff (1996). "a", "b" and "c" indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	-0.025	-0.006	-0.005	0.001	-0.159	-0.088	-0.100	-0.072
	(-8.056)[a]	(-3.539)[a]	(-1.907)	(0.301)	(-9.834)[a]	(-10.413)[a]	(-13.620)[a]	(-13.632)[a]
$RIvol_t$	0.377				0.551			
	(9.425)[a]				(13.470)[a]			
$RIvol_{i,t}^{adj}$		1.933				2.120		
		(9.281[a])				(10.217)[a]		
$RIvol_{t-1}$			0.089				0.182	
			(3.516)[a]				(9.848)[a]	
$RIvol_{i,t-1}^{adj}$				0.334				0.413
				(2.458)[a]				(5.206)[a]
RET_{t-1}	-0.203	-0.204	-0.208	-0.201	-0.212	-0.212	-0.227	-0.225
	(-22.557)[a]	(-21.909)[a]	(-20.065)[a]	(-20.257)[a]	(-13.648)[a]	(-13.352)[a]	(-12.923)[a]	(-13.072)[a]
RET (-2,-11)	0.016	0.012	0.018	0.019	0.008	0.008	0.012	0.013
	(3.496)[a]	(2.882)[a]	(4.063)[a]	(4.234)[a]	(2.649)[a]	(3.075)[a]	(4.611)[a]	(4.661)[a]
Turn	0.001	0.001	0.001	0.001				
	(1.704)[c]	(1.567)	(1.529)	(1.587)				
CV turn	0.001	0.004	0.006	0.006				
	(0.268)	(1.060)	(1.203)	(1.373)				
Half					0.007	0.005	0.006	0.005
Amihud (-)					(8.146)[a]	(9.510)[a]	(11.675)[a]	(12.117)[a]
SYNC					0.002	-0.001	-0.004	-0.004
					(2.075)[b]	(-1.393)	(-4.554)[a]	(-5.037)[a]
Adj. R^2	10.61%	13.39%	5.10%	6.09%	11.21%	12.85%	4.98%	4.87%

Table 2.13. Time-series averages of the cross-sectional equal and value weighted Fama-MacBeth regressions of returns on lagged idiosyncratic volatility measures, extreme returns, and control variables

Time-series averages of the parameter estimates for the series of cross-sectional regressions using turnover and its coefficient of variation as control variables similar to Fu (2009) are reported in this table. BETA, ME and BE/ME are estimated as in Fama and French (1992). The adjusted lagged realized idiosyncratic volatility is calculated as $RIvol_{i,t}^{adj} = \left(\sum_{t=1}^{T} \varepsilon_{i,d_t}^2 + 2\sum_{t=2}^{T} \varepsilon_{i,d_t}\varepsilon_{i,d_{t-1}}\right)^{0.5}$ whereε_{i,d_t} are the residuals from regressions using daily returns in the Carhart 4 factor model: $r_{i,d_t} = \alpha + \beta r_{M,d_t} + sSMB_{d_t} + hHML_{d_t} + \gamma WML_{d_t} + \varepsilon_{i,d_t}$. MAX (MIN) refers to the highest (lowest) daily returns in the prior month, and MAXDEV is the difference between the highest and lowest daily returns in a the prior month. RET (-2,-11) is a momentum control variable calculated as the cumulative return of each stock for month t-11 to t-2. Half Amihud (-) is the modified illiquidity measure of Amihud (2002) as in Brennan *et al.* (2013). Synchronicity *SYNC* is the logistic transformation of the R-square from the Carhart 4-factor model. The average R^2 values are reported in the table. t-values are reported in the parentheses. The coefficients are the means of the cross-sectional regression coefficients. The standard errors used in the t-tests are adjusted for autocorrelation as in Pontiff (1996). "a", "b" and "c" indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Model	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	-0.051	-0.021	-0.049	-0.056	-0.034	-0.054
	(-3.545)[a]	(-1.422)	(-3.256)[a]	(-3.791)[a]	(-2.058)	(-3.335)[a]
Beta	-0.002	-0.001	-0.002	0.000	0.001	0.000
	(-0.626)	(-0.146)	(-0.671)	(-0.070)	(0.367)	(0.114)
Log(ME)	0.000	-0.001	0.000	0.000	-0.001	0.000
	(0.397)	(-1.126)	(0.363)	(-0.216)	(-1.211)	(-0.134)
Log(BE/ME)	-0.001	-0.001	-0.001	-0.005	-0.006	-0.006
	(-0.166)	(-0.205)	(-0.167)	(-0.914)	(-1.116)	(-1.034)
$RIvol_{t-1}$				0.407	0.443	0.383
				(1.735)[c]	(2.188)[b]	(1.819)[c]
MAX	0.039			0.029		
	(1.694)[c]			(1.161)		
MIN		-0.057			-0.016	
		(-1.698)[c]			(-0.454)	
			0.011			0.016
MAXDEV			(0.700)			(1.014)
RET (-2,-11)	0.200	0.202	0.200	0.202	0.205	0.203
	(26.968)[a]	(28.669)[a]	(27.298)[a]	(26.485)[a]	(27.232)[a]	(26.565)[a]
RET_{t-1}	-0.236	-0.244	-0.238	-0.241	-0.238	-0.243
	(-13.984)[a]	(-13.814)[a]	(-14.261)[a]	(-12.299)[a]	(-11.411)[a]	(-12.534)[a]
Half	0.003	0.002	0.003	0.003	0.003	0.003
Amihud (-)	(4.541)[a]	(3.885)[a]	(4.921)[a]	(5.602)[a]	(5.638)[a]	(5.775)[a]
SYNC	-0.001	-0.002	-0.001	-0.003	-0.007	-0.004
	(-0.300)	(-0.529)	(-0.301)	(-0.835)	(-2.063)	(-1.184)
Adj. R^2	62.85%	63.34%	63.03%	65.62%	65.91%	65.74%

Table 2.14. Time-series averages of the cross-sectional equal and value weighted Fama-MacBeth regressions of returns on control variables and idiosyncratic volatility measures conditioned on extreme returns

Time-series averages of the parameter estimates for the series of cross-sectional regressions using turnover and its coefficient of variation as control variables similar to Fu (2009) are reported in this table. BETA, ME and BE/ME are estimated as in Fama and French (1992). The adjusted lagged realized idiosyncratic volatility is calculated as $RIvol_{i,t}^{adj} = \left(\sum_{t=1}^{T} \varepsilon_{i,d_t}^2 + 2\sum_{t=2}^{T} \varepsilon_{i,d_t}\varepsilon_{i,d_{t-1}}\right)^{0.5}$ where ε_{i,d_t} are the residuals from the regression using daily returns in the Carhart 4 factor model: $r_{i,d_t} = \alpha + \beta r_{M,d_t} + sSMB_{d_t} + hHML_{d_t} + \gamma WML_{d_t} + \varepsilon_{i,d_t}$. MAX1 (MAX10) are dummy variables that take the value of 1 when the highest daily return of stock i in month t is in the lowest (highest) decile and zero otherwise. MIN1 (MIN10) are dummy variables that take the value of 1 when the lowest daily return of stock i in month t is in the lowest (highest) decile and zero otherwise. MAXDEV1 (MAXDEV10) are dummy variables that take the value of 1 when the difference between the highest and lowest daily returns of stock i in month t is in the lowest (highest) decile and zero otherwise. RET (-2,-11) is a momentum control variable calculated as the cumulative return of each stock for month t-11 to t-2. Half Amihud (-) is the modified illiquidity measure of Amihud (2002) as in Brennan *et al.* (2013). Synchronicity *SYNC* is the logistic transformation of the R-square from the Carhart 4-factor model. The average R^2 values are reported in the table. t-values are reported in the parentheses. The coefficients are the means of the cross-sectional regression coefficients. The standard errors used in the t-tests are adjusted for autocorrelation as in Pontiff (1996). "a", "b" and "c" indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Model	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	-0.047	-0.063	-0.057	-0.056	-0.055	-0.059
	(-4.231)[a]	(-5.458)[a]	(-5.414)[a]	(-5.346)[a]	(-5.348)[a]	(-5.113)[a]
Beta	0.000	0.001	0.000	-0.001	0.000	0.000
	(0.010)	(0.261)	(-0.083)	(-0.168)	(-0.014)	(-0.061)
Log(ME)	0.000	0.000	0.000	0.000	0.000	0.000
	(-0.426)	(0.860)	(0.144)	(0.238)	(0.199)	(0.785)
Log(BE/ME)	0.000	-0.005	-0.005	-0.001	-0.001	-0.004
	(0.037)	(-0.890)	(-0.868)	(-0.156)	(-0.160)	(-0.795)
RIvol $_{t-1}$	0.543	0.620	0.662	0.656	0.625	0.652
	(2.413)[a]	(2.597)[a]	(2.835)[a]	(2.832)[a]	(2.423)[a]	(2.621)[a]
*RIvol t-1*MAX1*	-5.310					
	(-0.493)					
*RIvol t-1*MAX10*		-0.768				
		(-0.165)				
*RIvol t-1*MIN10*			-0.309			
			(-0.156)			
*RIvol t-1*MIN1*				-10.570		
				(-7.941)[a]		
*RIvol t-1*MAXMIN1*					-9.529	
					(-3.759)[a]	
*RIvol t-1*MAXMIN10*						-2.333
						(-2.482)[a]
RET (-2,-11)	0.212	0.206	0.205	0.210	0.213	0.208
	(23.698)[a]	(30.006)[a]	(30.107)[a]	(25.350)[a]	(24.685)[a]	(30.865)[a]
RET_{t-1}	-0.230	-0.218	-0.207	-0.224	-0.230	-0.214
	(-11.475)[a]	(-12.597)[a]	(-13.011)[a]	(-12.312)[a]	(-11.003)[a]	(-11.728)[a]
Half Amihud (-)	0.003	0.003	0.003	0.003	0.003	0.003
	(5.421)[a]	(6.688)[a]	(6.543)[a]	(5.818)[a]	(5.903)[a]	(6.204)[a]
SYNC	-0.005	-0.006	-0.007	-0.007	-0.007	-0.006
	(-1.907)[a]	(-2.566)[a]	(-3.412)[a]	(-2.289)[a]	(-2.550)[a]	(-2.684)[a]
Adj. R^2	61.72%	59.95%	60.43%	61.74%	61.72%	60.20%

Table 3.1: Summary statistics for the asset holdings of closed-end funds

This table reports the mean, median, maximum and minimum holdings of all closed-end equity funds (CEF) in our sample over the period 2001:01 to 2010:12.

	US equity	Cash	Foreign equity	Options	Swaps	Currencies	Debt	Unidentified
Mean	77.56%	4.81%	4.78%	3.61%	-1.62%	0.26%	8.35%	2.26%
Median	77.84%	5.78%	5.47%	2.57%	0.00%	0.02%	8.09%	2.31%
Maximum	102.32%	13.37%	9.38%	7.97%	5.62%	1.82%	18.87%	4.42%
Minimum	68.23%	-4.41%	0.15%	-0.06%	-32.19%	-0.71%	3.30%	0.00%

Table 3.2: Summary statistics for various measures of the idiosyncratic volatilities of equity CEF

This table presents the summary statistics for arbitrage risk proxies calculated from daily net returns of the simultaneous long position in CEF i and short position in its equivalent NAVPS i for each day of month $t\left(r_{net_{i,d_t}}\right)$. We use these returns in the following Carhart (1997) 4-factor model for each CEF i with at least 15 daily returns in month t: $r_{net_{i,d_t}} = \gamma_0 + \beta_{net_{i,t,mkt}} r_{M,d_t} + \beta_{net_{i,t,SMB}} SMB_{d_t} + \beta_{net_{i,t,HML}} HML_{d_t} + \beta_{net_{i,t,WML}} WML_{d_t} + \varepsilon_{i,d_t}$ where r_{M,d_t} is the excess return of the market portfolio, SMB_{d_t} and HML_{d_t} are two additional Fama-French factors, WML_{d_t} is the momentum factor, and ε_{i,d_t} is the error term. Based on Goyal and Santa Clara (2003), we add a second term to capture the covariance between lagged returns so that $Ivol_{net,i,t}$ becomes: $Ivol_{net,i,t} = \sqrt{\sum_{t=1}^{T} \varepsilon_{i,d_t}^2 + 2\sum_{t=2}^{T} \varepsilon_{i,d_t}\varepsilon_{i,d_{t-1}}}$. Significance of the means and medians are tested using t-tests and Wilcoxon Rank tests, respectively. The superscripts [a] and [b] represent significance at the 1% and 5% levels, respectively. N refers to the sample size.

Variables		N	Mean	Median	St. Deviation
$\beta_{net_{mkt}}$		7940	-0.14	-0.046	6.028
$\beta_{net_{SMB}}$		7940	-0.771[a]	-0.035[a]	16.553
$\beta_{net_{HML}}$		7940	-0.708[a]	-0.006[a]	16.45
$\beta_{net_{WML}}$		7940	-0.598[a]	-0.023[a]	13.068
$Ivol_{net}$		7940	6.98%[a]	4.80%[a]	13.78%
Premium	Level	8419	-5.62%[a]	-6.74%[a]	18.18%
	Difference	8322	-0.12%[a]	0.14%[a]	0.32%

Table 3.3: Absolute premium regressions as in Pontiff (1996)

This table reports the average coefficients of the cross-sectional regressions of the absolute level of CEF discounts and arbitrage costs as in Pontiff (1996). The estimated regression is:

$$Discount_{i,t} = \varphi_{0,t} + \varphi_{1,t}(1/P_{i,t-1}) + \varphi_{2,t}ln(\sigma_{i,t-1}^{Nav}) + \varphi_{3,t}ln(\sigma_{i,t-1}^{NavRes}) + \varphi_{4,t}Iskew_{i,t-1}^{Nav} + \omega_{i,t}$$

$1/P_{i,t-1}$ is the inverse of the price of CEF i in month t-1; $\sigma_{i,t-1}^{Nav}$ is the standard deviation of CEF i's NAVPS at time *t-1* based on the previous three months; $ln(\sigma_{i,t-1}^{NavRes})$, $ln(\hat{\sigma}_{i,t-1}^{Nav})$ and $Iskew_{i,t-1}^{Nav}$ are the natural logs of the standard deviations of the residuals, the explained portion and the skewness of the residuals, respectively, of the regression of the NAVPS returns on the CRSP equally-weighted index. $Iskew$, which is included in regressions (1) and (4), is not part of Pontiff's (1996) table I. The t-values using adjusted standard errors are reported in the parentheses. [a], [b] and [c] represent significance at the 1%, 5% and 10% levels, respectively. Median R-square values are reported in the table.

Variable	Regression			
	(1)	(2)	(3)	(4)
φ_0	0.141 (8.93)[a]	0.153 (8.40)[a]	0.149 (2.09)[b]	0.078 (1.21)
$1/P_{i,t-1}$			1.906 (1.64)	2.245 (1.17)
$\sigma_{i,t-1}^{Nav}$			0.002 (1.86)[c]	0.002 (2.27)[b]
$ln(\sigma_{i,t-1}^{NavRes})$	0.002 (0.60)	0.010 (1.57)	0.053 (1.72)[c]	0.024 (2.25)[b]
$ln(\hat{\sigma}_{i,t-1}^{Nav})$			0.0195 (1.35)	0.0278 (1.64)
$Iskew_{i,t-1}^{Nav}$	0.008 (3.71)[a]			0.010 (1.92)[b]
R-square (%)	10.64	2.54	26.05	44.86

Table 3.4: Descriptive statistics for the variables

This table reports the mean, median and standard deviation of each of the various variables used in subsequent cross-sectional and panel regressions. $Premium$ is the premium for CEF i in month *t* measured as the ln of the ratio of the CEF price to its NAVPS; $Premium_t = (P_t - NAV/NAV_t)$; $\hat{\beta}_{net_{mkt}}$,$\hat{\beta}_{net_{SMB}}$, $\hat{\beta}_{net_{HML}}$, and $\hat{\beta}_{net_{WML}}$are estimated factor loadings of the 4-factor Carhart model of the net returns of a long CEF and short NAVPS position for CEF i based on the daily return in month t; $Ivol_{net}$ is the auto-correlation-adjusted idiosyncratic volatilities of the daily returns of the net returns on an arbitrage position for CEF i in month t; $Iskew$ is the idiosyncratic skewness of the daily residuals from the Carhart (1997) four-factor model regression for CEF i in month *t*; $\%Options$ is the weight of options in CEF i's portfolio in month *t*; $\%Cash$ is the weight of cash and cash equivalent assets in the portfolio of CEF i in month *t*; $\%Bonds$ is the weight of bonds in the portfolio of CEF i in month t; ∂AS is the difference in the amortized spreads between CEF i and its asset holdings in month t, where the amortized spread of the CEF is defined as $\mathrm{LIQ}^{\mathrm{AS}}_{\mathrm{CEF,t}} = \left[\sum_{\mathrm{d}_t=1}^{\mathrm{T}} \left|\mathrm{P}_{\mathrm{CEF,d}_t} - \mathrm{M}_{\mathrm{CEF,d}_t}\right| \times \mathrm{V}_{\mathrm{CEF,d}_t}\right] / \left[\mathrm{P}_{\mathrm{CEF,t}} \times \mathrm{OS}_{\mathrm{CEF,t}}\right]$ where $\mathrm{M}_{\mathrm{CEF,t}}$ is the mid-spread, $\mathrm{V}_{\mathrm{CEF,t}}$ is the traded volume of the CEF, and $\mathrm{OS}_{\mathrm{CEF,T}}$ is the number of outstanding shares; $Leverage$ is the ratio of non-common equity to total assets; $Alpha$ is the conditional alpha for CEF *i* in month *t* based on the returns for the 60 months including month t; $\ln(MktVal)$ is the natural log of the market value of CEF i in month *t*; $1/P$ is the inverse of the price of CEF i in month *t*; DY is the dividend yield of CEF i in month *t*; $MgmtFees$ is the management fees of CEF i in month *t*; $Tenure$ is the tenure of the manager of CEF i in month *t*; $Urate$ is the value of a stock being utilized for securities lending against total value of inventory available for lending in month *t*; and $\#short$ is the number of stocks shorted by CEF i in month *t*. In the subsequent regressions the variables other than *Premium* are lagged one month.

	Median	Mean	Standard Deviation
$Premium$	-5.62%	-6.74%	18.18%
$\hat{\beta}_{net_{mkt}}$	-0.14	-0.046	6.028
$\hat{\beta}_{net_{SMB}}$	-0.771	-0.035	16.553
$\hat{\beta}_{net_{HML}}$	-0.708	-0.006	16.45
$\hat{\beta}_{net_{WML}}$	-0.598[a]	-0.023	13.068
$Ivol_{net}$	6.98%	4.80%	13.78%
$Iskew$	-0.003	-0.014	2.77
$\%Options$	3.61%	2.57%	3.1%
$\%Cash$	4.81%	5.78%	4.06%
$\%Bonds$	8.35%	8.09%	13.30%
∂AS	0.08%	0.30%	7.05%
$Leverage$	14.03%	9.8%	8.98%
$Alpha$	-0.42%	-0.44%	0.82%
$Ln(MktVal)$	5.64	5.59	1.25
$1/P$	0.06	0.08	0.08
DY	1.34%	3.42%	5.19%
$MgmtFees$	1.26%	1.59%	1.14%
$Tenure$	7.75	9.52	6.65
$Urate$	6.59%	19.51%	25.72%
$\#short$	22	21.98	18.54

Table 3.5: Correlation matrix of the various variables

This table reports the correlation coefficients between the various variables used in subsequent cross-sectional and panel regressions. $Premium$ is the premium for CEF i in month t measured as the ln of the ratio of the CEF price to its NAVPS; $Premium_t = (P_t - NAV/NAV_t)$; $\hat{\beta}_{net_{mkt}}$,$\hat{\beta}_{net_{SMB}}$, $\hat{\beta}_{net_{HML}}$, and $\hat{\beta}_{net_{WML}}$are estimated factor loadings of the 4-factor Carhart model of the net returns of a long CEF and short NAVPS position for CEF i based on the daily return in month t-1; $Ivol^{+}_{net}$ and $Ivol^{-}_{net}$ are the auto-correlation-adjusted idiosyncratic volatilities of the returns of a long CEF and short NAVPS position for CEF i in month t-1 when the dummy variable D takes the value of 1 for positive price changes in month t-1 and the value 0 for negative price changes in month t-1 for CEF i, respectively; $Iskew$ is the idiosyncratic skewness of the daily residuals from the Carhart (1997) four-factor model regression for CEF i in month t-1; $\%Options$ is the weight of options in CEF i's portfolio in month t-1; $\%Cash$ is the weight of cash and cash equivalent assets in the portfolio of CEF i in month t-1; $Leverage$ is the ratio of total assets minus total common equity to total assets in CEF i in month t-1; ∂AS is the difference in the amortized spreads between CEF i and its asset holdings in month t-1, where the amortized spread is defined as $\mathrm{LIQ}^{\mathrm{AS}}_{\mathrm{CEF,T}} = \left[\sum_{t=1}^{T} \left|\mathrm{P}_{\mathrm{CEF,t}} - \mathrm{M}_{\mathrm{CEF,t}}\right| \times \mathrm{V}_{\mathrm{CEF,t}}\right] / \left[\mathrm{P}_{\mathrm{CEF,T}} \times \mathrm{OS}_{\mathrm{CEF,T}}\right]$ where $\mathrm{M}_{\mathrm{CEF,t}}$ is the mid spread, $\mathrm{V}_{\mathrm{CEF,t}}$ is the trading volume, and $\mathrm{OS}_{\mathrm{CEF,T}}$ is the number of outstanding shares; $Alpha$ is the conditional alpha for CEF i in month t-1 based on the returns for the 60 months including month t-1; $\log(MktVal)$ is the log of the market value of CEF i in month t-1; $1/P$ is the inverse of the price of CEF i in month t-1; DY is the dividend yield of CEF i in month t-1; $MgmtFees$ is the management fees of CEF i in month t-1; $Tenure$ is the tenure of the manager of CEF i in month t-1. The p-values for tests of statistical significance are reported in the parentheses. [a], [b] and [c] represent significance at the 1%, 5% and 10% levels, respectively.

	$Premium$	$\hat{\beta}_{net_{mkt}}$	$\hat{\beta}_{net_{SMB}}$	$\hat{\beta}_{net_{HML}}$	$\hat{\beta}_{net_{WML}}$	$Ivol_{net}$	$Iskew$	$\%Options$	$\%Cash$	$Leverage$	∂AS	$Alpha$	$\ln(MktVal)$	$1/P$	DY	$MgmtFees$
$\hat{\beta}_{net_{mkt}}$	-0.028 (0.81)															
$\hat{\beta}_{net_{SMB}}$	0.054 (0.64)	-0.111 (0.337)														
$\hat{\beta}_{net_{HML}}$	-0.039 (0.733)	-0.003 (0.982)	0.189 (0.098)[c]													
$\hat{\beta}_{net_{WML}}$	0.025 (0.829)	-0.135 (0.24)	0.053 (0.649)	0.097 (0.402)												
$Ivol_{net}$	-0.403 (0.000)[a]	-0.128 (0.266)	-0.051 (0.658)	0.023 (0.845)	0.016 (0.892)											
$Iskew$	-0.002 (0.986)	-0.029 (0.801)	0.025 (0.827)	0.013 (0.912)	0.023 (0.842)	0.066 (0.565)										
$\%Options$	0.033 (0.773)	0.070 (0.546)	-0.041 (0.723)	-0.025 (0.832)	0.001 (0.992)	0.051 (0.658)	-0.042 (0.716)									
$\%Cash$	-0.120 (0.296)	-0.074 (0.52)	0.003 (0.978)	0.033 (0.777)	0.053 (0.65)	0.153 (0.184)	-0.021 (0.856)	-0.026 (0.822)								
$Leverage$	-0.137 (0.233)	-0.013 (0.913)	-0.020 (0.862)	0.011 (0.922)	-0.030 (0.795)	0.055 (0.634)	0.044 (0.706)	0.020 (0.862)	0.031 (0.789)							
∂AS	-0.050 (0.663)	-0.023 (0.844)	-0.063 (0.588)	0.003 (0.979)	-0.031 (0.786)	0.059 (0.608)	0.079 (0.494)	-0.035 (0.763)	-0.138 (0.231)	-0.021 (0.857)						
$Alpha$	0.215 (0.06)[b]	0.107 (0.355)	-0.013 (0.909)	-0.025 (0.829)	-0.084 (0.465)	-0.326 (0.004)[a]	-0.052 (0.651)	0.023 (0.842)	-0.078 (0.498)	0.162 (0.159)	0.007 (0.952)					
$\ln(MktVal)$	-0.038 (0.741)	0.021 (0.854)	0.014 (0.906)	0.007 (0.952)	-0.015 (0.900)	-0.045 (0.700)	0.048 (0.679)	-0.148 (0.197)	0.049 (0.672)	0.154 (0.182)	0.125 (0.278)	0.013 (0.909)				
$1/P$	0.197 (0.086)[c]	0.007 (0.954)	0.051 (0.66)	0.000 (0.900)	0.061 (0.600)	-0.013 (0.912)	0.043 (0.711)	-0.034 (0.770)	-0.049 (0.671)	-0.159 (0.165)	-0.080 (0.489)	-0.283 (0.012)[b]	-0.170 (0.138)			
DY	0.041 (0.724)	0.004 (0.97)	0.020 (0.863)	-0.047 (0.685)	-0.001 (0.994)	-0.067 (0.561)	-0.020 (0.866)	-0.064 (0.582)	0.097 (0.400)	-0.242 (0.033)[b]	-0.082 (0.477)	-0.127 (0.271)	0.039 (0.734)	-0.004 (0.973)		
$MgmtFees$	-0.087 (0.452)	-0.019 (0.87)	-0.035 (0.762)	0.049 (0.671)	0.03 (0.782)	0.201 (0.079)[c]	0.082 (0.477)	0.045 (0.695)	0.050 (0.667)	-0.001 (0.996)	0.203 (0.076)[c]	0.059 (0.609)	0.123 (0.285)	0.166 (0.148)	-0.216 (0.058)	

$Tenure$	0.034 (0.772)	0.065 (0.572)	-0.024 (0.835)	-0.044 (0.701)	-0.090 (0.436)	-0.278 (0.014)[a]	-0.051 (0.658)	0.038 (0.745)	-0.050 (0.665)	0.178 (0.120)	-0.074 (0.524)	0.286 (0.011)[b]	-0.243 (0.033)[b]	-0.222 (0.052)[c]	-0.023 (0.843)	-0.349 (0.002)[a]

Table 3.6:. Determinants of closed-end fund (CEF) premiums based on monthly Fama-MacBeth cross-sectional regressions using lagged $Ivol_{net}$

This table reports the mean coefficients of Fama-MacBeth cross-sectional regressions for the discount for CEF i in month t given by:

$$\begin{aligned} Prem_t = {} & \gamma_{0,t} + \gamma_{1,t}\,\hat{\beta}_{net_{mkt,i,t-1}} + \gamma_{2,t}\hat{\beta}_{net_{SMB,i,t-1}} + \gamma_{3,t}\,\hat{\beta}_{net_{HML,i,t-1}} + \gamma_{4,t}\hat{\beta}_{net_{WML,i,t-1}} + \gamma_{5,t}Ivol_{net,i,t-1} \\ & + \gamma_{6,t}Iskew_{i,t-1} + \gamma_{7,t}\%Options_{i,t-1} + \gamma_{8,t}\%Cash_{i,t-1} + \gamma_{9,t}\%Bonds_{i,t-1} \\ & + \gamma_{10,t}Leverage_{i,t-1} + \gamma_{11,t}\partial AS_{i,t-1} + \gamma_{12,t}Alpha_{i,t-1} + \gamma_{13,t}\ln\left(MktVal_{i,t-1}\right) \\ & + \gamma_{14,t}\left(1/P_{i,t-1}\right) + \gamma_{15,t}DY_{i,t-1} + \gamma_{16,t}MgmtFees_{i,t-1} + \gamma_{17,t}Tenure_{i,t-1} + \nu_{i,t} \end{aligned}$$

$\hat{\beta}_{net_{mkt}}$,$\hat{\beta}_{net_{SMB}}$, $\hat{\beta}_{net_{HML}}$, and $\hat{\beta}_{net_{WML}}$are estimated factor loadings of the 4-factor Carhart model of the net returns of a long CEF and short NAVPS position for CEF i based on the daily return in month *t-1*; $Ivol_{net}$ is the auto-correlation-adjusted idiosyncratic volatilities of the daily returns of the net returns on an arbitrage position for CEF i in month *t-1*; $Iskew$ is the idiosyncratic skewness of the daily residuals from the Carhart (1997) four-factor model regression for CEF i in month *t-1*; $\%Options$ is the weight of options in CEF i's portfolio in month *t-1*; $\%Cash$ is the weight of cash and cash equivalent assets in the portfolio of CEF i in month *t-1*; $\%Bonds$ is the weight of bonds in the portfolio of CEF i in month *t-1*; $Leverage_{i,t}$is the ratio of total assets minus total common equity to total assets in CEF i in month *t-1*; ∂AS is the difference in the amortized spreads between CEF i and its asset holdings in month *t-1*; $Alpha$ is the conditional alpha for CEF i in month *t-1* based on the returns for the 60 months including month *t-1*; $\ln(MktVal)$ is the natural log of the market value of CEF i in month *t-1*; $1/P$ is the inverse of the price of CEF i in month *t-1*; DY is the dividend yield of CEF i in month *t-1*; $MgmtFees$ is the management fees of CEF i in month *t-1*; and $Tenure$ is the tenure of the manager of CEF i in month *t-1*. The reported coefficients are the means of the cross-sectional regression coefficients. The standard errors used in the t-tests are adjusted for autocorrelation as in Pontiff (1996). The t-values are reported in the parentheses. [a], [b] and [c] represent significance at the 1%, 5% and 10% levels, respectively.

	Regressions					
	(1)	(2)	(3)	(4)	(5)	(6)
γ_0	-0.039 (-4.320)[a]	-0.037 (-3.461)[a]	-0.042 (-3.726)[a]	-0.021 (-1.089)	-0.054 (-2.441)[a]	0.017 (0.741)
$\hat{\beta}_{net_{mkt}}$	0.002 (0.363)		0.000 (0.050)	0.002 (0.207)	0.011 (1.499)	0.01 (1.036)
$\hat{\beta}_{net_{SMB}}$	-0.008 (-1.959)[b]		-0.008 (-1.985)[b]	-0.01 (-1.927)[c]	-0.014 (-3.327)[a]	-0.015 (-3.426)[a]
$\hat{\beta}_{net_{HML}}$	-0.006 (-1.754)[c]		-0.003 (-0.681)	-0.004 (-0.847)	0.007 (1.592)	0.006 (0.839)
$\hat{\beta}_{net_{WML}}$	0.001 (0.157)		0.005 (0.843)	-0.001 (-0.382)	0.012 (1.079)	0.009 (0.926)
$Ivol_{net}$		-7.852 (-2.707)[a]	-9.195 (-1.786)[c]	-8.879 (-1.853)[c]	-14.213 (-2.242)[a]	-11.17 (-1.723)[c]
$Iskew$				-0.001 (-0.737)	-0.002 (-2.059)[b]	-0.002 (-1.613)
$\%Options$				-0.004 (-0.972)	0.002 (2.792)[a]	0.001 (0.898)
$\%Cash$				-0.005 (-2.010)[b]	-0.001 (-0.132)	-0.001 (-1.349)
$\%Bonds$				-0.002 (-3.685)[a]	0 .001 (3.304)[a]	-0.001 (-2.846)[a]
$Leverage$					-0.115 (-2.709)[a]	-0.056 (-1.802)[c]
∂AS					0.017 (6.271)[a]	0.008 (2.006)[b]
$Alpha$					0.036 (2.953)[a]	0.051 (4.032)[a]
$\ln(MktVal)$						-0.011 (-3.391)[a]
$1/P$						0.429 (2.509)[a]
DY						0.026 (0.132)
$MgmtFees$						-0.002 (-5.106)[a]
$Tenure$						0.667 (16.141)[a]
Mean R^2	23.55%	12.69%	27.88%	36.00%	53.00%	67.00%
Median R^2	14.99%	1.54%	18.30%	27.00%	50.00%	66.00%

Table 3.7:. Relationship between closed-end fund (CEF) premiums and lagged $Ivol_{net}$ conditioned on sign of lagged price change

This table reports the mean coefficients of Fama-MacBeth cross-sectional regressions for CEF *i*'s premium for month *t* given by:

$$
\begin{aligned}
Prem_t = \gamma_{0,t} &+ \gamma_{1,t}\,\hat{\beta}_{net_{mkt,i,t-1}} + \gamma_{2,t}\hat{\beta}_{net_{SMB,i,t-1}} + \gamma_{3,t}\,\hat{\beta}_{net_{HML,i,t-1}} \\
&+ \gamma_{4,t}\hat{\beta}_{net_{WML,i,t-1}} + \gamma_{5,t}Ivol^{+}_{net,i,t-1}D_{i,t-1} + \gamma_{6,t}Ivol^{-}_{net,i,t-1}(1-D_{i,t-1}) + \gamma_{7,t}Iskew_{i,t-1} \\
&+ \gamma_{8,t}\%Options_{i,t-1} + \gamma_{9,t}\%Cash_{i,t-1} + \gamma_{10,t}\%Bonds_{i,t-1} + \gamma_{11,t}Leverage_{i,t-1} \\
&+ \gamma_{12,t}\partial AS_{i,t-1} + \gamma_{13,t}Alpha_{i,t-1} + \gamma_{14,t}\log(MktVal_{i,t-1}) + \gamma_{15,t}(1/P_{i,t-1}) + \gamma_{16,t}DY_{i,t-1} \\
&+ \gamma_{17,t}MgmtFees_{i,t-1} + \gamma_{18,t}Tenure_{i,t-1} + \nu_{i,t}
\end{aligned}
$$

$\hat{\beta}_{net_{mkt}}$,$\hat{\beta}_{net_{SMB}}$, $\hat{\beta}_{net_{HML}}$, and $\hat{\beta}_{net_{WML}}$are estimated factor loadings of the 4-factor Carhart model of the net returns of a long CEF and short NAVPS position for CEF *i* based on the daily return in month *t-1*; $Ivol^{+}_{net}$ and $Ivol^{-}_{net}$ are the auto-correlation-adjusted idiosyncratic volatilities of the returns of a long CEF and short NAVPS position for CEF *i* in month *t-1* when the dummy variable *D* takes the value of 1 for positive price changes in month *t-1* and the value 0 for negative price changes in month *t-1* for CEF *i*, respectively; $Iskew$ is the idiosyncratic skewness of the daily residuals from the Carhart (1997) four-factor model regression for CEF *i* in month *t-1*; $\%Options$ is the weight of options in CEF *i*'s portfolio in month *t-2*; $\%Cash$ is the weight of cash and cash equivalent assets in the portfolio of CEF *i* in month *t-1*; $\%Bonds$ is the weight of bonds in the portfolio of CEF *i* in month *t-1*; $Leverage_{t-1}$is the ratio of total assets minus total common equity to total assets in CEF *i* in month *t-1*; ∂AS is the difference in the amortized spreads between CEF *i* and its asset holdings in month *t-1*; $Alpha$ is the conditional alpha for CEF *i* in month *t-1* based on the returns for the 60 months including month *t-1*; $\ln(MktVal)$ is the natural log of the market value of CEF *i* in month *t-1*; $1/P$ is the inverse of the price of CEF *i* in month *t-1*; DY is the dividend yield of CEF *i* in month *t-1*; $MgmtFees$ is the management fees of CEF *i* in month *t-1*; and $Tenure$ is the tenure of the manager of CEF *i* in month *t-1*. The reported coefficients are the means of the cross-sectional regression coefficients. The standard errors used in the t-tests are adjusted for autocorrelation as in Pontiff (1996). The t-values are reported in the parentheses. [a], [b] and [c] represent significance at the 1%, 5% and 10% levels, respectively.

	Regressions			
	(1)	(2)	(3)	(4)
γ_0	-0.05 (-3.912)	-0.053 (-4.557) [a]	-0.04 (-2.857) [a]	0.007 (0.245)
$\hat{\beta}_{net_{mkt}}$		-0.005 (-0.734)	-0.006 (-0.926)	0.01 (0.951)
$\hat{\beta}_{net_{SMB}}$		0.001 (0.317)	-0.002 (-0.507)	-0.011 (-2.643) [a]
$\hat{\beta}_{net_{HML}}$		-0.003 (-1.135)	-0.002 (-0.632)	0.009 (1.33)
$\hat{\beta}_{net_{WML}}$		0.005 (0.942)	0.002 (0.435)	-0.002 (-0.234)
$Ivol^{+}_{net}$	-14.467 (-4.882)[a]	-16.418 (-4.671) [a]	-17.006 (-4.584) [a]	-21.503 (-3.665) [a]
$Ivol^{-}_{net}$	-2.844 (-2.797) [a]	-4.376 (2.629) [a]	-3.782 (2.257)[b]	-3.463 (-0.406)
$Iskew$			-0.001 (-0.686)	-0.002 (-1.9) [c]
$\%Options$			-0.004 (-2.304) [a]	0.001 (1.581)
$\%Cash$			-0.004 (-3.239) [a]	0.001 (-0.927)
$\%Bonds$			-0.001 (-2.36) [a]	-0.001 (-2.194)
$Leverage$				-0.078 (-2.295)
∂AS				0.009 (1.903) [c]
$Alpha$				0.037 (3.275) [a]
$\ln(MktVal)$				-0.008 (-1.865) [c]
$1/P$				0.224 (1.647)
DY				-0.013 (-0.047)
$MgmtFees$				-0.002 (-5.699) [a]
$Tenure$				-0.006 (-0.674)
Mean R^2	30.00%	43.31%	50.00%	72.31%
Median R^2	22.00%	40.29%	46.00%	72.53%

Table 3.8: Recap of the relationships between CEF premiums and their determinants

This table reports a recap of all expected relationships and our findings between premiums and their determinants. $\hat{\beta}_{net_{mkt}}$,$\hat{\beta}_{net_{SMB}}$, $\hat{\beta}_{net_{HML}}$, and $\hat{\beta}_{net_{WML}}$are estimated factor loadings of the 4-factor Carhart model of the net returns of a long CEF and short NAVPS position for CEF i based on the daily return in month t-1; $Ivol_{net}^{+}$ and $Ivol_{net}^{-}$ are the auto-correlation-adjusted idiosyncratic volatilities of the returns of a long CEF and short NAVPS position for CEF i in month t-1 when the dummy variable *D* takes the value of 1 for positive price changes in month *t-1* and the value 0 for negative price changes in month t-1 for CEF *i*, respectively; $Iskew$ is the idiosyncratic skewness of the daily residuals from the Carhart (1997) four-factor model regression for CEF i in month t-1; $\%Options$ is the weight of options in CEF i's portfolio in month t-1; $\%Cash$ is the weight of cash and cash equivalent assets in the portfolio of CEF i in month *t-1*; $\%Bonds$ is the weight of bonds in the portfolio of CEF *i* in month *t-1*; $Leverage$is the ratio of total assets minus total common equity to total assets in CEF *i* in month t-1; ∂AS is the difference in the amortized spreads between CEF i and its asset holdings in month t-1; $Alpha$ is the conditional alpha for CEF *i* in month t-1 based on the returns for the 60 months including month t-1: $\ln(MktVal)$ is the natural log of the market value of CEF i in month *t-1*; $1/P$ is the inverse of the price of CEF *i* in month *t-1*; DY is the dividend yield of CEF i in month *t-1*; $MgmtFees$ is the management fees of CEF i in month *t-1*; and $Tenure$ is the tenure of the manager of CEF *i* in month *t-1*.

	Premium		
	Expected Sign	Reasoning	Findings
$\hat{\beta}_{net_{mkt}}$	-/+	Arbitrage risk	Insignificant
$\hat{\beta}_{net_{SMB}}$	-/+		-
$\hat{\beta}_{net_{HML}}$	-/+		Insignificant
$\hat{\beta}_{net_{WML}}$	-/+		Insignificant
$Ivol_{net}$	-		-
$Ivol_{net}^{+}$	-		-
$Ivol_{net}^{-}$	-		+/ Insignificant
$Iskew$	-	Uncertainty	-
$\%Options$	-/+	Uncertainty/cost	Insignificant
$\%Cash$	-	Cost to the arbitrage position	-
$\%Bonds$	-		-
$Leverage$	-		-
∂AS	+	Liquidity benefit	+
$Alpha$	+	Managerial benefit	+
$\ln(MktVal)$	-	Transaction cost	-
$1/P$	+		+
DY	+	Transaction cost/Signaling	Insignificant
$MgmtFees$	-	Managerial cost	-
$Tenure$	+	Uncertainty about managerial benefits	+

Table 3.9:. Determinants of changes in closed-end fund (CEF) premiums based on monthly Fama-MacBeth cross-sectional regressions using *Ivol* *net*

This table reports the mean coefficients of Fama-MacBeth cross-sectional regressions for the premium for CEF i in month t given by:

$$\begin{aligned}\partial Prem_t = \gamma_{0,t} &+ \gamma_{1,t}\,\hat{\beta}_{net_{mkt,i,t-1}} + \gamma_{2,t}\hat{\beta}_{net_{SMB,i,t-1}} + \gamma_{3,t}\,\hat{\beta}_{net_{HML,i,t-1}} \\ &+ \gamma_{4,t}\hat{\beta}_{net_{WML,i,t-1}} + \gamma_{5,t} Ivol^{+}_{net,i,t-1} D_{i,t-1} + \gamma_{6,t} Ivol^{-}_{net,i,t-1}(1 - D_{i,t-1}) + \gamma_{7,t} Iskew_{i,t-1} \\ &+ \gamma_{8,t}\%Options_{i,t-1} + \gamma_{9,t}\%Cash_{i,t-1} + \gamma_{10,t}\%Bonds_{i,t-1} + \gamma_{11,t} Leverage_{i,t-1} \\ &+ \gamma_{12,t}\partial AS_{i,t-1} + \gamma_{13,t} Alpha_{i,t-1} + \gamma_{14,t}\log(MktVal_{i,t-1}) + \gamma_{15,t}(1/P_{i,t-1}) + \gamma_{16,t} DY_{i,t-1} \\ &+ \gamma_{17,t} MgmtFees_{i,t-1} + \gamma_{18,t} Tenure_{i,t-1} + \nu_{i,t}\end{aligned}$$

$\hat{\beta}_{net_{mkt}}$, $\hat{\beta}_{net_{SMB}}$, $\hat{\beta}_{net_{HML}}$, and $\hat{\beta}_{net_{WML}}$ are estimated factor loadings of the 4-factor Carhart model of the net returns of a long CEF and short NAVPS position for CEF i based on the daily return in month *t-1*; $Ivol^{+}_{net}$ and $Ivol^{-}_{net}$ are the auto-correlation-adjusted idiosyncratic volatilities of the returns of a long CEF and short NAVPS position for CEF i in month *t-1* when the dummy variable *D* takes the value of 1 for positive price changes in month *t-1* and the value 0 for negative price changes in month *t-1* for CEF *i*, respectively; $Iskew$ is the idiosyncratic skewness of the daily residuals from the Carhart (1997) four-factor model regression for CEF *i* in month *t-1*; $\%Options$ is the weight of options in CEF *i*'s portfolio in month *t-1*; $\%Cash$ is the weight of cash and cash equivalent assets in the portfolio of CEF *i* in month *t-1*; $\%Bonds$ is the weight of bonds in the portfolio of CEF *i* in month *t-1*; $Leverage$is the ratio of total assets minus total common equity to total assets in CEF *i* in month *t-1*; ∂AS is the difference in the amortized spreads between CEF i and its asset holdings in month *t-1*; $Alpha$ is the conditional alpha for CEF *i* in month *t-1* based on the returns for the 60 months including month *t-1*; $\ln(MktVal)$ is the natural log of the market value of CEF *i* in month *t-1*; $1/P$ is the inverse of the price of CEF *i* in month *t-1*; DY is the dividend yield of CEF *i* in month *t-1*; $MgmtFees$ is the management fees of CEF *i* in month *t-1*; and $Tenure$ is the tenure of the manager of CEF *i* in month *t-1*. The reported coefficients are the means of the cross-sectional regression coefficients. The standard errors used in the t-tests are adjusted for autocorrelation as in Pontiff (1996). The t-values are reported in the parentheses. [a], [b] and [c] represent significance at the 1%, 5% and 10% levels, respectively.

	Regressions			
	(1)	(2)	(3)	(4)
γ_0	0.002 (0.643)	0.001 (0.635)	-0.004 (-0.941)	-0.016 (-1.844)[c]
$\hat{\beta}_{net_{mkt}}$		-0.003 (-1.091)	0.004 (2.328)[a]	-0.002 (-0.82)
$\hat{\beta}_{net_{SMB}}$		0.002 (0.486)	-0.009 (-3.617)[a]	-0.011 (-1.803)[c]
$\hat{\beta}_{net_{HML}}$		-0.001 (-0.409)	0.004 (2.189)[b]	0.003 (1.612)
$\hat{\beta}_{net_{WML}}$		0 .001 (0.054)	0.011 (5.465)[a]	0.002 (0.502)
$Ivol^{+}_{net}$	-1.106 (-3.796)[a]	-1.126 (-2.756)[a]	-24.008 (-14.912)[a]	-7.409 (-6.62)[a]
$Ivol^{-}_{net}$	0.270 (0.984)	0.405 (1.085)	0.269 (1.549)	0.919 (1.415)
$Iskew$			-0.002 (-4.331)[a]	-0.001 (-0.796)
$\%Options$			0.009 (85.851)[a]	0.001 (1.041)
$\%Cash$			0.001 (-4.232)[a]	-0.001 (-2.82)[a]
$\%Bonds$			0.001 (0.995)	0.001 (-0.055)
$Leverage$			0.023 (3.327)[a]	0.019 (1.534)
∂AS			0.006 (3.156)[a]	0.003 (1.403)
$Alpha$			0.001 (0.014)	0.006 (1.334)
$\ln(MktVal)$				0.002 (1.295)
$1/P$				0.101 (1.792)[c]
DY				-0.014 (-0.384)
$MgmtFees$				0.001 (1.038)
$Tenure$				-0.004 (-2.059)[b]
Mean R^2	10.73%	30.20%	54.95%	68.56%
Median R^2	5.89%	25.70%	53.89%	68.06%

Table 3.10: Determinants of CEF premiums based on monthly Fama-MacBeth cross-sectional regressions using lagged arbitrage risk measures over the sub-period 2006-2010

This table reports the mean coefficients of Fama-MacBeth cross-sectional regressions for the discount for CEF i in month t given by:

$$\begin{aligned} Prem_t = {} & \gamma_{0,t} + \gamma_{1,t}\,\hat{\beta}_{net_{mkt,i,t-1}} + \gamma_{2,t}\hat{\beta}_{net_{SMB,i,t-1}} + \gamma_{3,t}\,\hat{\beta}_{net_{HML,i,t-1}} \\ & + \gamma_{4,t}\hat{\beta}_{net_{WML,i,t}} + \gamma_{5,t} Ivol^{+}_{net,i,t} D_{i,t-1} + \gamma_{6,t} Ivol^{-}_{net,i,t}(1 - D_{i,t-1}) + \gamma_{7,t} Iskew_{i,t} \\ & + \gamma_{8,t}\%Options_{i,t-1} + \gamma_{9,t}\%Cash_{i,t-1} + \gamma_{10,t}\%Bonds_{i,t-1} + \gamma_{11,t}Leverage_{i,t-1} \\ & + \gamma_{12,t}\partial AS_{i,t-1} + \gamma_{13,t}Alpha_{i,t-1} + \gamma_{14,t}\log(MktVal_{i,t-1}) + \gamma_{15,t}(1/P_{i,t-1}) + \gamma_{16,t}DY_{i,t-1} \\ & + \gamma_{17,t}MgmtFees_{i,t-1} + \gamma_{18,t}Tenure_{i,t-1} + \gamma_{19,t}Urate_{i,t-1} + \gamma_{20,t}\#short_{i,t-1} + \nu_{i,t} \end{aligned}$$

$\hat{\beta}_{net_{mkt}}$, $\hat{\beta}_{net_{SMB}}$, $\hat{\beta}_{net_{HML}}$, and $\hat{\beta}_{net_{WML}}$ are estimated factor loadings of the 4-factor Carhart model of the net returns of a long CEF and short NAVPS position for CEF i based on the daily return in month *t-1*; $Ivol^{+}_{net}$ and $Ivol^{-}_{net}$ are the auto-correlation-adjusted idiosyncratic volatilities of the returns of a long CEF and short NAVPS position for CEF i in month *t-1* when the dummy variable *D* takes the value of 1 for positive price changes in month *t-1* and the value 0 for negative price changes in month *t-1* for CEF i, respectively; $Iskew$ is the idiosyncratic skewness of the daily residuals from the Carhart (1997) four-factor model regression for CEF i in month t-*1*; $\%Options$ is the weight of options in CEF i's portfolio in month *t-1*; $\%Cash$ is the weight of cash and cash equivalent assets in the portfolio of CEF *i* in month *t-1*; $\%Bonds$ is the weight of bonds in the portfolio of CEF i in month *t-1*; $Leverage$ is the ratio of total assets minus total common equity to total assets in CEF *i* in month *t-1*; ∂AS is the difference in the amortized spreads between CEF i and its asset holdings in month *t-1*; $Alpha$ is the conditional alpha for CEF *i* in month *t-1* based on the returns for the 60 months including month t-*1*; $\log(MktVal)$ is the log of the market value of CEF *i* in month *t-1*; $1/P$ is the inverse of the price of CEF *i* in month *t-1*; DY is the dividend yield of CEF *i* in month *t-1*; $MgmtFees$ is the management fees of CEF *i* in month *t-1*; $Tenure$ is the tenure of the manager of CEF *i* in month *t-1*; $Urate$ is the value of a stock being utilized for securities lending against total value of inventory available for lending in month *t-1*; and $\#short$ is number of stocks shorted by CEF *i* in month *t-1*. The reported coefficients are the means of the cross-sectional regression coefficients. The standard errors used in the t-tests are adjusted for autocorrelation as in Pontiff (1996). The t-values are reported in the parentheses. [a], [b] and [c] represent significance at the 1%, 5% and 10% levels, respectively.

	Regressions			
	(1)	(2)	(3)	(4)
γ_0	-0.060 (-2.825)[a]	-0.091 (-2.541)[a]	-0.093 (-2.254)[b]	-0.020 (-0.519)
$\hat{\beta}_{net_{mkt}}$	-0.012 (-2.498)[a]		-0.016 (-2.613)[a]	-0.002 (-0.084)
$\hat{\beta}_{net_{SMB}}$	-0.007 (-1.96)[b]		-0.006 (-1.724)	-0.006 (-1.763)[c]
$\hat{\beta}_{net_{HML}}$	0.001 (-0.004)		-0.001 (-0.262)	0.005 (0.343)
$\hat{\beta}_{net_{WML}}$	0.003 (1.148)		0.002 (0.627)	0.009 (1.195)
$Ivol^{+}_{net}$	-13.770 (-4.841)[a]	-13.136 (-3.772)[a]	-13.625 (-4.070)[a]	-23.296 (-2.682)[a]
$Ivol^{-}_{net}$	1.087 (3.378)[a]	0.506 (2.684)[a]	0.567 (2.115)	3.318 (1.788)[c]
$Iskew$				-0.001 (-0.389)
$\%Options$				0.001 (0.406)
$\%Cash$				-0.001 (-1.678)[c]
$\%Bonds$				-0.001 (-1.827)[c]
$Leverage$				-0.062 (-0.716)
∂AS				0.009 (1.695)[c]
$Alpha$				0.028 (0.901)
$\ln(MktVal)$				-0.008 (-2.597)[a]
$1/P$				0.277 (0.732)
DY				0.095 (0.507)
$MgmtFees$				-0.002 (-0.389)
$Tenure$				-0.006 (-0.659)
$Urate$		0.000 (-0.782)	0.000 (-0.456)	0.001 (0.389)
$\#short$		0.001 (1.223)	0.001 (1.293)	0.001 (0.389)
Mean R^2	28.77%	25.75%	34.73%	75.92%
Median R^2	26.26%	21.32%	34.40%	76.37%

Table 3.11: Sentiment-adjusted determinants of closed-end fund (CEF) discounts based on monthly Fama-MacBeth cross-sectional regressions using lagged $Ivol_{net}$

This table reports the mean coefficients of Fama-MacBeth cross-sectional regressions for the discount for CEF i in month t given by:

$$Prem_t = \gamma_{0,t} + \gamma_{1,t}\,\hat{\beta}^{\varepsilon}_{net_{mkt,i,t-1}} + \gamma_{2,t}\hat{\beta}^{\varepsilon}_{net_{SMB,i,t-1}} + \gamma_{3,t}\hat{\beta}^{\varepsilon}_{net_{HML,i,t-1}} + \gamma_{4,t}\hat{\beta}^{\varepsilon}_{net_{WML,i,t-1}} + Ivol^{\varepsilon}_{net,i,t-1}$$
$$+\gamma_{6,t}Iskew^{\varepsilon}_{i,t-1} + \gamma_{7,t}\%Options^{\varepsilon}_{i,t-1} + \gamma_{8,t}\%Cash^{\varepsilon}_{i,t-1} + \gamma_{9,t}\%Bonds^{\varepsilon}_{i,t-1} + \gamma_{10,t}Leverage^{\varepsilon}_{i,t-1}$$
$$+\gamma_{11,t}\partial AS^{\varepsilon}_{i,t-1} + \gamma_{12,t}Alpha^{\varepsilon}_{i,t-1} + \gamma_{13,t}\ln\left(MktVal^{\varepsilon}_{i,t-1}\right) + \gamma_{14,t}\left(1/P^{\varepsilon}_{i,t-1}\right) + \gamma_{15,t}DY^{\varepsilon}_{i,t-1} + \gamma_{16,t}MgmtFees^{\varepsilon}_{i,t-1}$$
$$+ \gamma_{17,t}Tenure^{\varepsilon}_{i,t-1} + v_{i,t}$$

The superscript ε refers to the residuals obtained from running the determinant series on three sentiment indicators [University of Michigan Household Sentiment Index (UMSI), The Chicago Fed National Activity Index (CFNAI) and the policy Uncertainty Index (PUI)], two macroeconomic indicators [corporate spread is the difference between AAA bonds and default-free government bonds, and the term structure is the difference between the ten year constant yield on US treasuries and 3-month yield on T-bills], and the Pastor and Stambaugh (2003) measure of aggregate liquidity.
$\hat{\beta}_{net_{mkt}}$,$\hat{\beta}_{net_{SMB}}$, $\hat{\beta}_{net_{HML}}$, and $\hat{\beta}_{net_{WML}}$are estimated factor loadings of the 4-factor Carhart model of the net returns of a long CEF and short NAVPS position for CEF i based on the daily return in month t-1; $Ivol_{net}$ is the auto-correlation-adjusted idiosyncratic volatilities of the daily returns of the net returns on an arbitrage position for CEF i in month t-1; $Iskew$ is the idiosyncratic skewness of the daily residuals from the Carhart (1997) four-factor model regression for CEF i in month t-1; $\%Options$ is the weight of options in CEF i's portfolio in month t-1; $\%Cash$ is the weight of cash and cash equivalent assets in the portfolio of CEF i in month t-1; $\%Bonds$ is the weight of bonds in the portfolio of CEF i in month t-1; $Leverage$ is the ratio of total assets minus total common equity to total assets in CEF i in month t-1; ∂AS is the difference in the amortized spreads between CEF i and its asset holdings in month t-1; $Alpha$ is the conditional alpha for CEF i in month t-1 based on the returns for the 60 months including month t-1; $\ln(MktVal)$ is the natural log of the market value of CEF i in month t-1; $1/P$ is the inverse of the price of CEF i in month t-1; DY is the dividend yield of CEF i in month t-1; $MgmtFees$ is the management fees of CEF i in month t-1; and $Tenure$ is the tenure of the manager of CEF i in month t-1. The reported coefficients are the means of the cross-sectional regression coefficients. The standard errors used in the t-tests are adjusted for autocorrelation as in Pontiff (1996). The t-values are reported in the parentheses. [a], [b] and [c] represent significance at the 1%, 5% and 10% levels, respectively.

	Regressions	
	(1)	(2)
γ_0	-0.009 (-0.427)	0.501 (13.914) [a]
$\beta_{net_{mkt}}$	0.018 (3.284)[a]	0.016 (0.931)
$\beta_{net_{SMB}}$	-0.019 (-4.777) [a]	0.017 (1.578)
$\beta_{net_{HML}}$	0.011 (3.682) [a]	-0.01 (-2.296)[b]
$\beta_{net_{WML}}$	0.038 (5.887) [a]	0.003 (0.156)
$Ivol_{net}$	-7.510 (-4.854) [a]	-6.033 (-8.874) [a]
$Iskew$	0 (-0.019)	-0.006 (-3.243)[a]
$\%Options$	0.007 (5.592) [a]	0.138 (26.461) [a]
$\%Cash$	-0.002 (-5.26)[a]	-0.001 (-2.656) [a]
$\%Bonds$	-0.001 (-1.436)	-0.001 (-1.827) [b]
$Leverage$	-0.164 (-3.571) [a]	-0.091 (-2.265)[b]
∂AS	0.072 (7.006)[a]	0.001 (0.426)
$Alpha$	0.003 (0.316)	0.104 (10.063) [a]
$\ln(MktVal)$		-0.071 (-13.537) [a]
$1/P$		-0.677 (-5.227) [a]
DY		1.268 (7.168)[a]
$MgmtFees$		0.001 (-0.477)
$Tenure$		-0.100 (-11.941)[a]
Mean R^2	39.00%	56.00%
Median R^2	31.00%	49.00%

Table 3.12: Relationship between closed-end fund (CEF) premiums and an alternative measure of arbitrage risk

This table reports the mean coefficients of Fama-MacBeth cross-sectional regressions for the premium of CEF i in month t given by:

$$Prem_t = \gamma_{0,t} + \gamma_{1,t} Ivol_{Diff,i,t-1} + \gamma_{2,t} Iskew_{i,t-1} + \gamma_{3,t} \%Options_{i,t-1} + \gamma_{4,t} \%Cash_{i,t-1} + \gamma_{5,t} \%Bonds_{i,t-1} + \gamma_{6,t} Leverage_{i,t-1} + \gamma_{7,t} \partial AS_{i,t-1} + \gamma_{8,t} Alpha_{i,t-1} + \gamma_{9,t} \log(MktVal_{i,t-1}) + \gamma_{10,t}(1/P_{i,t-1}) + \gamma_{11,t} DY_{i,t-1} + \gamma_{12,t} MgmtFees_{i,t-1} + \gamma_{13,t} Tenure_{i,t-1} + v_{i,t}$$

$Ivol_{Diff}$ is the difference between the weighted-average, auto-correlation-adjusted idiosyncratic volatilities of the daily returns on the stocks held by CEF i in month t-1 and CEF i's auto-correlation-adjusted idiosyncratic return volatility in month t-1; $Iskew$ is the idiosyncratic skewness of the daily residuals from the Carhart (1997) four-factor model regression for CEF i in month t-1; $\%Options$ is the weight of options in CEF i's portfolio in month t-1; $\%Cash$ is the weight of cash and cash equivalent assets in the portfolio of CEF i in month t-1; $\%Bonds$ is the weight of bonds in the portfolio of CEF i in month t-1; $Leverage$ is the ratio of total assets minus total common equity to total assets in CEF i in month t-1; ∂AS is the difference in the amortized spreads between CEF i and its asset holdings in month t-1; $Alpha$ is the conditional alpha for CEF i in month t-1 based on the returns for the 60 months including month t-1; $\ln(MktVal)$ is the natural log of the market value of CEF i in month t-1; $1/P$ is the inverse of the price of CEF i in month t-1; DY is the dividend yield of CEF i in month t-1; $MgmtFees$ is the management fees of CEF i in month t-1; and $Tenure$ is the tenure of the manager of CEF i in month t-1. The reported coefficients are the means of the cross-sectional regression coefficients. The standard errors used in the t-tests are adjusted for autocorrelation as in Pontiff (1996). The t-values are reported in the parentheses. [a], [b] and [c] represent significance at the 1%, 5% and 10% levels, respectively.

Variable	Regression (1)	(2)	(3)
γ_0	-0.015 (-1.09)	-0.021 (-1.62)	0.193 (4.70)
$\partial Ivol$	-7.546 (-6.67)[a]	-6.184 (-5.71)[a]	-5.085 (-5.68)[a]
$Iskew$		-0.003 (-3.04)[a]	-0.002(-1.31)
$\%Options$		0.026 (0.68)	-0.029(-9.48)[a]
$\%Cash$		-0.003 (-1.72)[c]	-0.002(-2.01)
$\%Bonds$		-0.001 (-1.436)	-0.001 (-1.827)[b]
$Leverage$			-0.103 (-2.69)[a]
∂AS			0.255 (1.35)
$Alpha$			0.047 (1.98)[b]
$\ln(MktVal)$			0.153 (0.52)
$1/P$			-0.036 (-2.79)[a]
DY			0.069 (0.45)
$MgmtFees$			0.008 (0.63)
$Tenure$			-0.002 (-3.76)[a]
Mean R^2	8.88%	14.75%	54.25%
Median R^2	4.24%	11.77%	55.49%

Table 3.13:. Dynamic GMM panel regression of CEF premium

This table reports the coefficients of Dynamic GMM panel regression for the premium CEF i in month t given by:

$$Prem_t = \gamma_{0,t} + \gamma_{1,t}\, Prem_{t-1} + \gamma_{2,t}\, \beta_{net_{mkt,i,t-1}} + \gamma_{3,t}\beta_{net_{SMB,i,t-1}} + \gamma_{4,t}\ \beta_{net_{HML,i,t-1}} + \gamma_{5,t}\beta_{net_{WML,i,t-1}}$$
$$+\gamma_{6,t}Ivol_{net,i,t-1} + \gamma_{7,t}Iskew_{i,t-1} + \gamma_{8,t}\%Options_{i,t-1} + \gamma_{9,t}\%Cash_{i,t-1} + \gamma_{10,t}\%Bonds_{i,t-1}$$
$$+\gamma_{11,t}Leverage_{i,t-1} + \gamma_{12,t}\partial AS_{i,t-1} + \gamma_{13,t}Alpha_{i,t-1} + \gamma_{14,t}\ln(MktVal_{i,t-1}) + \gamma_{15,t}(1/P_{i,t-1})$$
$$+ \gamma_{16,t}DY_{i,t-1} + \gamma_{17,t}MgmtFees_{i,t-1} + \gamma_{18,t}Tenure_{i,t-1} + v_{i,t}$$

$\hat{\beta}_{net_{mkt}}$, $\hat{\beta}_{net_{SMB}}$, $\hat{\beta}_{net_{HML}}$, and $\hat{\beta}_{net_{WML}}$ are estimated factor loadings of the 4-factor Carhart model of the net returns of a long CEF and short NAVPS position for CEF i based on the daily return in month *t-1*; $Ivol_{net}$ is the auto-correlation-adjusted idiosyncratic volatilities of the daily returns of the net returns on an arbitrage position for CEF i in month *t-1*; $Iskew$ is the idiosyncratic skewness of the daily residuals from the Carhart (1997) four-factor model regression for CEF i in month *t-1*; $\%Options$ is the weight of options in CEF i's portfolio in month *t-1*; $\%Cash$ is the weight of cash and cash equivalent assets in the portfolio of CEF i in month *t-1*; $\%Bonds$ is the weight of bonds in the portfolio of CEF i in month *t-1*; $Leverage$ is the ratio of total assets minus total common equity to total assets in CEF i in month *t-1*; ∂AS is the difference in the amortized spreads between CEF i and its asset holdings in month *t-1*; $Alpha$ is the conditional alpha for CEF i in month *t-1* based on the returns for the 60 months prior to month t; $\ln(MktVal)$ is the natural log of the market value of CEF i in month *t-1*; $1/P$ is the inverse of the price of CEF i in month *t-1*; DY is the dividend yield of CEF i in month *t-1*; $MgmtFees$ is the management fees of CEF i in month *t-1*; and $Tenure$ is the tenure of the manager of CEF i in month *t-1*. The standard errors used in the t-tests are adjusted for autocorrelation and herterosckedasticity (HAC). The t-values are reported in the parentheses. [a], [b] and [c] represent significance at the 1%, 5% and 10% levels, respectively.

	Regressions		
	(1)	(2)	(3)
$Premium_{t-1}$	0.896 (40.431)[a]	0.859 (24.589)[a]	0.796 (14.27)[a]
$\beta_{net_{mkt}}$	0.001 (1.178)	0.001 (0.96)	0.003 (1.349)
$\beta_{net_{SMB}}$	0.001 (-0.823)	0.001 (-0.465)	-0.001 (-1.717)[c]
$\beta_{net_{HML}}$	0.001 (1.625)	0.001 (2.097)[b]	0.001 (0.347)
$\beta_{net_{WML}}$	0.001 (1.656)	0.001 (0.827)	0.001 (1.020)
$Ivol_{net}$	-0.374 (-3.94)[a]	-0.254 (-1.903)	-1.045 (-3.613)[a]
$Iskew$		0.011 (0.414)	0.01 (1.011)
$\%Options$		0.001 (-1.023)	0.001 (-0.432)
$\%Cash$		0.001 (-0.618)	0.001 (1.020)
$\%Bonds$		-0.001 (-2.915)[a]	-0.001 (-2.772)
$Leverage$			-0.058 (-2.370)[b]
∂AS			0.003 (3.739)[a]
$Alpha$			0.001 (0.191)
$\ln(MktVal)$			-0.008 (-2.297)[b]
$1/P$			-0.338 (-2.901)[a]
DY			-0.122 (-1.593)
$MgmtFees$			-0.005 (-1.950)[c]
$Tenure$			0.001 (0.043)
Mean R^2	65.43%	68.04%	71.59%
N	5393	4882	4444

Table 4.1: Descriptive statistics for the rumor database

This table reports the number of rumored target firms over the sample period (2004-2011) categorized by year, initial rumor to announcement day (AD), and type of rumors.

	2004	2005	2006	2007	2008	2009	2010	2011	Total
Number of firms	158	164	220	236	258	409	369	436	2250
Firms with announcements	87	89	108	114	125	184	176	172	1055
Firms with an effective date of a M&A	67	59	63	65	64	63	64	46	491
M&A AD within 70 days of the rumor	29	30	33	30	37	34	47	32	272
M&A AD within 1 year of the rumor	39	37	49	40	47	48	59	42	361
More-credible rumors:									
Insider cited	64	64	44	30	49	48	18	34	351
Confirmed by target	27	18	17	11	10	2	17	12	114
Analyst is source	82	47	90	112	72	79	52	76	610
Target has a financial advisor	27	30	32	24	46	37	23	48	267
Initiated by target	38	45	33	41	65	66	35	70	393
Less-credible rumors	26	33	60	71	90	246	272	275	1073

Table 4.2: Summary statistics for the M&A rumored target firms

This table reports the summary statistics of the M&A rumored sample of target firms categorized by type of rumor and the percentages of M&A announcements within 70 days and one year of the initial M&A rumor. % of announcement is the probability of an announcement within 70 days and one year of the date of the rumor release date. % M&A completed is the probability that the M&A will be completed. The numbers in parentheses are the t-statistics testing the null hypothesis: Pr(M&A Announcement |More-credible)=Pr(M&A Announcement| Less-credible). The t-statistic is calculated as $TS = (\hat{p}_S - \hat{p}_I)/\sqrt{\hat{p}(1-\hat{p})(\frac{1}{n_S}+\frac{1}{n_I})}$ where $\hat{p}_S$ is the probability of a actual M&A being completed or just an announcement for the more-credible rumored sample, $\hat{p}_I$ is the probability of a M&A or an announcement for the less-credible rumored sample, $\hat{p}$ is the estimate of the common proportion under the null hypothesis calculated as $\hat{p} = (\#\ MA_S + \#\ MA_I)/(n_S + n_I)$ and n_S and n_I are the number of rumors in the more- and less-credible samples respectively. [a], [b] and [c] represent significance at the 1%, 5% and 10% levels, respectively.

Rumor Type	Total Rumors	# of Announcements within		# of completed M&A	% of Announcements within		% of completed M&A
		70 days	One year		70 days	One year	
All	2250	272	361	491	12.09% (2.674)[a]	16.04% (2.132)[b]	21.82% (2.582)[a]
Less-credible rumors	1073	95	126	172	8.85%	11.74%	16.03%
More-credible rumors	1177	177	235	319	15.04% (4.495)[a]	19.97% (2.029)[b]	27.10% (2.834)[a]
Insider cited	351	67	79	104	19.09% (5.106)[a]	22.51% (2.044)[b]	29.63% (2.651)[a]
Confirmed by target	393	66	86	106	16.79% (4.131)[a]	21.88% (1.975)[b]	26.97% (2.145)[b]
Analyst is source	114	28	32	39	24.56% (4.891)[a]	28.07% (2.247)a	34.21% (2.482)[a]
Target has a financial advisor	610	74	108	162	12.13% (1.983)[b]	17.70% (1.239)	26.56% (2.328)[a]
Initiated by target	267	53	71	93	19.85% (4.932)[a]	26.59% (2.726)[a]	34.83% (3.537)[a]

Table 4.3: Cumulative abnormal returns (CARs) and Long stock-short market strategy around rumor announcement dates

This table reports the cumulative abnormal returns (CARs) and the abnormal returns for the long-short strategy for rumored target firms over different event windows. CAR is calculated using the Carhart 4-factor model, and the long-short strategy consists of buying the rumored firm and selling the market portfolio. Difference is obtained by subtracting the CAR or BHAR for the less-credible rumors minus it corresponding value for the more-credible rumors. The event windows are [-1; +1], [-1; +5], [-5; +5] and [+1; +70]. The coefficients of the Carhart model are estimated over an estimation window of [-125; -5]. T-values, which are shown in the parentheses, are computed from (HAC) standard errors. [a], [b] and [c] represent significance at the 1%, 5% and 10% levels, respectively.

	Window	All		More-credible		Less-credible		Difference	
CAR	[-1; +1]	4.16%	(13.825)[a]	3.63%	(8.284)[a]	4.67%	(11.301)[a]	1.04%	(2.52)
	[-1; +5]	3.83%	(10.460)[a]	3.26%	(6.277)[a]	4.38%	(8.483)[a]	1.11%	(2.16)
	[-5; +5]	3.54%	(8.820)[a]	2.92%	(4.930)[a]	4.14%	(7.604)[a]	1.12%	(2.24)
	[+1; +70]	-1.73%	(-1.891)	0.06%	(0.053)	-3.45%	(-2.477)[a]	-3.51%	(1.899)
N		2250		1177		1073			
BHAR	[-1; +1]	4.34%	(14.437)[a]	3.78%	(8.414)[a]	4.88%	(12.152)[a]	1.10%	(2.75)
	[-1; +5]	4.42%	(12.489)[a]	3.63%	(7.201)[a]	5.17%	(10.435)[a]	1.54%	(3.11)
	[-5; +5]	4.31%	(10.954)[a]	3.34%	(5.794)[a]	5.24%	(9.777)[a]	1.90%	(3.54)
	[+1; +70]	0.47%	(1.952)[b]	1.97%	(2.382)[b]	0.31%	(0.908)	-1.66%	(2.307)
N		2250		1177		1073			

Table 4.4: The change in the ratio of idiosyncratic to total volatility around the rumor announcement date

This table reports the changes in the ratios of idiosyncratic to total volatilities where the ratio is calculated as: $IV_{Ratio\,i,t} = 1 - (\beta_{i,t}^2 RV_{M,t}/RV_{i,t})$. $\beta_{i,t}$is the intraday beta calculated as the covariance between stock i and the market index using returns based on 25 minute intraday intervals. $RV_{i,t}$ and $RV_{M,t}$ are the realized daily intraday volatilities for stock i and the market, respectively. The change in the ratio of idiosyncratic to total volatility is obtained from a regression of the daily ratios on a dummy variable for each of the eleven days centered on the rumor announcement date and an intercept representing the pre- and post-rumor period averages. The average estimation period is 120 days before and 20 days after the rumor announcement date. Event day 0 is the rumor announcement date. T-values, which are shown in the parentheses, are computed from (HAC) standard errors. The columns labeled 5% and 95% represent the 5% and 95% percentiles of the change in the IV ratio for every event date. [a], [b] and [c] represent significance at the 1%, 5% and 10% levels, respectively.

	All Rumors				More-credible Rumors				Less-credible Rumors				Differences	
	Mean	t-value	5%	95%	Mean	t-value	5%	95%	Mean	t-value	5%	95%	Mean	t-stat
-5	0.18%	(0.425)	-0.63%	0.98%	0.52%	(1.117)	-0.39%	1.44%	0.28%	(0.613)	-0.61%	1.16%	-0.24%	(-3.850)[a]
-4	0.22%	(0.557)	-0.55%	0.99%	1.43%	(3.274)[a]	0.57%	2.28%	0.08%	(0.168)	-0.80%	0.95%	-1.35%	(-41.043)[a]
-3	0.81%	(1.931)[c]	-0.01%	1.63%	0.85%	(1.827)[c]	-0.06%	1.76%	1.21%	(2.633)[a]	0.31%	2.11%	0.36%	(35.960)[a]
-2	1.35%	(3.331)[a]	0.55%	2.14%	1.17%	(2.574)[a]	0.28%	2.07%	1.46%	(3.298)[a]	0.59%	2.34%	0.29%	(37.559)[a]
-1	1.79%	(4.391)[a]	0.99%	2.59%	1.93%	(4.170)[a]	1.02%	2.85%	2.44%	(5.509)[a]	1.57%	3.31%	0.51%	(18.147)[a]
0	5.28%	(13.07)[a]	4.49%	6.07%	4.36%	(9.607)[a]	3.47%	5.25%	6.36%	(14.291)[a]	5.48%	7.23%	2.00%	(24.973)[a]
1	3.13%	(7.587)[a]	2.32%	3.94%	2.88%	(6.193)[a]	1.97%	3.79%	3.00%	(6.622)[a]	2.11%	3.89%	0.12%	(0.436)
2	2.04%	(4.882)[a]	1.22%	2.85%	1.71%	(3.614)[a]	0.78%	2.64%	2.01%	(4.43)[a]	1.12%	2.89%	0.30%	(2.373)[a]
3	1.79%	(4.502)[a]	1.01%	2.57%	1.99%	(4.343)	1.09%	2.89%	1.27%	(2.876)[a]	0.40%	2.14%	-0.72%	(-12.449)[a]
4	1.50%	(3.765)[a]	0.72%	2.28%	0.80%	(1.731)[c]	-0.11%	1.72%	1.94%	(4.468)[a]	1.09%	2.79%	1.14%	(25.505)[a]
5	1.70%	(4.233)[a]	0.91%	2.49%	1.23%	(2.791)[a]	0.37%	2.10%	1.09%	(2.392)[a]	0.20%	1.98%	-0.14%	(-4.537)[a]
N	2250				1177				1073					

Table 4.5: Cross-sectional regressions of CAR on the IV ratios and control variables for more-credible rumored firms

This table reports the results of regressions on the cumulative abnormal returns (CAR) using the Carhart (1997) model and BHAR using a buy and hold strategy consisting of buying the rumored firm and selling the S&P500 index. The dependent variables are the IV ratio, BE/ME and LOGSIZE. IV ratio is calculated as ${IV_{Ratio}}_{i,t} = 1 - (\beta_{i,t}^2 RV_{M,t}/RV_{i,t})$. $\beta_{i,t}$is the intraday beta calculated as the covariance between stock i and the market index using returns for 25 minutes intraday intervals. $RV_{i,t}$ and $RV_{M,t}$ are the realized daily intraday volatilities for stock i and the market respectively. The change in the ratio of idiosyncratic to total volatility is obtained from a regression of daily ratios on a dummy variable for each of the eleven days around the rumor date and an intercept representing the pre- and post-rumor period average. The average estimation period is 120 days before and 20 days after the rumor. The BE/ME ratio is calculated as the book value as of the fiscal year ending in calendar year t-1 divided by the market value in December t-1. The market value is the price of the stock multiplied by the number of outstanding shares. LOGSIZE is the log of the market value of the firm. t -statistics, which are shown in the parentheses, are computed from (HAC) standard errors. [a], [b] and [c] represent significance at the 1%, 5% and 10% levels, respectively.

Windows	[-1; +1]		[-1; +5]		[-5; +5]		[1; +70]	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Cumulative Abnormal return (CAR)								
Intercept	0.021	-0.007	0.023	0.009	0.021	-0.009	-0.003	0.042
	(3.314)[a]	(-0.395)	(2.544)[b]	(0.377)	(2.025)[b]	(-0.312)	(-0.146)	(0.594)
IV ratio	0.060	0.053	0.084	0.075	0.108	0.105	0.050	0.048
	(1.977)[b]	(1.940)[c]	(1.821)[c]	(1.919)[c]	(1.684)[c]	(1.578)	(0.280)	(0.274)
BM		-0.019		-0.019		-0.012		0.006
		(-2.584)[b]		(-2.096)[b]		(-1.057)		(0.245)
Log(Size)		-0.009		-0.005		-0.009		0.012
		(-2.155)[b]		(-0.904)		(-1.252)		(0.684)
Adj. R^2	0.96%	3.38%	0.96%	1.67%	1.27%	1.98%	0.05%	0.24%
N	1177							
Buy and Hold Abnormal Return (BHAR)								
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Intercept	0.024	-0.006	0.026	0.015	0.026	0.002	0.008	0.013
	(3.694)[a]	(-0.343)	(2.744)[a]	(0.596)	(2.468)[b]	(0.049)	(0.489)	(0.260)
IV ratio	0.059	0.051	0.071	0.060	0.089	0.081	0.143	0.132
	(1.915)[c]	(1.902)[c]	(1.892)[c]	(1.984)[b]	(1.240)	(1.107)	(1.406)	(1.264)
BM		-0.020		-0.023		-0.019		-0.021
		(-2.515)[b]		(-2.368)[b]		(-1.567)		(-1.082)
Log(Size)		-0.010		-0.005		-0.008		0.000
		(-2.209)[b]		(-0.851)		(-1.073)		(-0.026)
Adj. R^2	0.90%	3.54%	0.64%	1.52%	0.83%	1.64%	0.81%	0.98%
N	1177							

Table 4.6: Cross-sectional regression of CAR on IV ratio and control variables for less-credible rumored firms

This table reports the results of regressions on the cumulative abnormal returns (CAR) using Carhart (1997) model and the buy and hold abnormal returns (BHAR) on a strategy consisting of buying the rumored firm and selling the S&P500 index. The independent variables are the IV ratio, BE/ME and LOGSIZE. IV ratio is calculated as ${IV_{Ratio}}_{i,t} = 1 - (\beta_{i,t}^2 RV_{M,t} / RV_{i,t})$. $\beta_{i,t}$is the intraday beta calculated as the covariance between stock i and market index using returns for 25 minute intraday intervals. $RV_{i,t}$ and $RV_{M,t}$ are the realized daily intraday volatilities for stock i and market respectively. The change in the ratio of idiosyncratic to total volatility is obtained from a regression of the daily ratios on dummy variables for each of the eleven days around the rumor date and an intercept representing the pre- and post-rumor period average. The average estimation period is 120 days before and 20 days after the rumor. The BE/ME ratio is calculated as the book value as of the fiscal year ending in calendar year t-1 divided by the market value in December t-1. The market value is the price of the stock multiplied by the number of outstanding shares. Ln(size) is the log of the market value of the firm. t - statistics, which are shown in the parentheses, are computed from (HAC) standard errors. [a], [b] and [c] represent significance at the 1%, 5% and 10% levels, respectively.

Interval	[-1; +1]		[-1; +5]		[-5; +5]		[1; +70]	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Cumulative Abnormal Return (CAR)								
Intercept	0.035	0.013	0.034	0.025	0.030	-0.006	-0.036	0.072
	(4.873)[a]	(1.041)	(3.685)[a]	(1.439)	(2.612)[a]	(-0.223)	(-1.066)	(1.082)
IV ratio	-0.053	-0.055	-0.078	-0.081	-0.070	-0.068	0.178	0.154
	(-1.706)[c]	(-1.737)[c]	(-1.837)[c]	(-1.891)[c]	(-1.272)	(-1.209)	(1.189)	(0.983)
BM		-0.011		-0.010		-0.010		-0.008
		(-3.255)[a]		(-1.972)[b]		(-1.481)		(-0.483)
Ln(Size)		-0.006		-0.003		-0.010		0.027
		(-1.970)[c]		(-0.670)		(-1.564)		(1.873)
Adj. R^2	0.95%	3.12%	0.99%	1.43%	0.46%	1.54%	0.38%	1.28%
N	1073							
Buy and Hold Abnormal Return (BHAR)								
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Intercept	0.041	0.022	0.042	0.038	0.043	0.004	0.002	0.126
	(5.448)[a]	(1.619)	(4.614)[a]	(2.142)[b]	(3.605)[a]	(0.146)	(0.082)	(2.249)
IV ratio	-0.070	-0.073	-0.099	-0.107	-0.094	-0.096	0.144	0.095
	(-2.139)[b]	(-2.227)[b]	(-2.379)[b]	(-2.524)[b]	(-1.631)	(-1.638)	(1.256)	(0.800)
BM		-0.014		-0.017		-0.020		-0.051
		(-3.393)[a]		(-2.953)[a]		(-2.489)[a]		(-3.727)[a]
Ln(Size)		-0.006		-0.003		-0.011		0.027
		(-1.788)[c]		(-0.584)		(-1.722)[c]		(2.057)[b]
Adj. R^2	1.54%	3.85%	1.64%	2.66%	0.74%	2.48%	0.38%	2.79%
N	1073							

Table 4.7: Correlation matrix

This table reports the correlation matrix of implied market probabilities, IV ratios and other control variables. Market implied probability of a M&A is calculated as $(V_P - V_R)/V_R$ where $V_P - V_R$ is the markup around the M&A announcement day, and $V_R$is the run-up calculated as the CAR over the period between the initial rumor date and the M&A announcement day. The IV ratio is calculated as $IV_{Ratio_{i,t}} = 1 - (\beta_{i,t}^2 RV_{M,t}/RV_{i,t})$. $\beta_{i,t}$is the intraday beta calculated as the covariance between stock i and the market index using returns measured over 25 minute intraday intervals. $RV_{i,t}$ and $RV_{M,t}$ are the realized daily intraday volatilities for stock i and the market respectively. The change in the ratio of idiosyncratic to total volatility is obtained from a regression of the daily ratios on a dummy variable for each of the eleven days around the rumor date and an intercept representing the pre- and post-rumor period average. The average estimation period is 120 days before and 20 days after the rumor. $\#days$ is the number of days between the rumor date and the M&A announcement date, #rumors is the number of rumors appearing between the initial rumor and M&A announcement dates, B/M is the book to market ratio calculated as of the last available book value and last end of year market value, $\ln(Size_i)$ is the natural logarithm of the market value of the target firm 41 days before the initial rumor date, $\#Analysts$ is the number of analysts following the target firm, $Disp$ is the coefficient of variation of the last I/B/E/S summary estimates, LT_Growth is the last I/B/E/S consensus estimate for long-term growth reported before the rumor is public. Firm-specific error (Firm Misval.) is the component of m/b ratio that capture the firm relative mispricing versus its industry peers calculated as $m_{i,t} - \vartheta(\alpha_{j,t}, \theta_{i,t})$, where $m_{i,t}$ is the natural log of the firm value (market-to-book ratio or M/B) and $\vartheta(\alpha_{j,t}, \theta_{i,t})$ is the value of the firm estimated using accounting data $\theta_{i,t}$ and sensitivities $\alpha_{j,t}$ estimated using industry j data in year *t*. Time-series industry error (Ind. Misval.) is the component of M/B that captures the level of mispricing of an industry versus its historical average. It is calculated as $\vartheta(\alpha_{j,t}, \theta_{i,t}) - \vartheta(\alpha_j, \theta_{i,t})$, where $\vartheta(\alpha_j, \theta_{i,t})$ is the long-term value of the firm according to its sector average over the 10 year period preceding year *t*. The number reported in each parentheses is the p-value of the pairwise correlation. [a], [b] and [c] represent significance at the 1%, 5% and 10% levels, respectively.

	Implied								Misval.	
	Prob.	IV_{Ratio}	#rumors	$\#days$	$\ln(Size)$	B/M	$\#Analysts$	$Disp$	Firm	Ind.
IV_{Ratio}	0.230									
	(0.083)[c]									
#rumors	-0.023	-0.137								
	(0.861)	(0.078)[c]								
$\#days$	-0.016	0.009	0.048							
	(0.906)	(0.907)	(0.479)							
$\ln(Size)$	0.005	-0.029	0.251	0.067						
	(0.969)	(0.709)	(0.000)[a]	(0.328)						
B/M	-0.051	0.040	0.044	-0.018	-0.259					
	(0.705)	(0.724)	(0.662)	(0.854)	(0.008)[a]					
$\#Analysts$	0.117	-0.071	-0.051	0.091	-0.006	-0.074				
	(0.380)	(0.392)	(0.479)	(0.208)	(0.936)	(0.482)				
$Disp$	0.135	0.044	-0.087	-0.116	0.020	0.036	0.393			
	(0.314)	(0.594)	(0.232)	(0.111)	(0.787)	(0.738)	(0.000)[a]			
LT_Growth	-0.054	0.006	-0.092	-0.066	0.010	-0.049	0.007	0.150		
	(0.687)	(0.939)	(0.204)	(0.364)	(0.893)	(0.641)	(0.921)	(0.039)[b]		
Firm misval.	0.015	0.043	0.066	0.150	-0.247	-0.005	-0.089	-0.029	-0.214	
	(0.909)	(0.751)	(0.623)	(0.260)	(0.061)[b]	(0.968)	(0.508)	(0.831)	(0.107)	
Ind misval.	0.018	-0.037	0.138	0.084	0.146	-0.037	-0.056	-0.013	-0.088	-0.627
	(0.895)	(0.783)	(0.302)	(0.531)	(0.274)	(0.782)	(0.675)	(0.924)	(0.513)	(0.000)[a]

Table 4.8: Summary results for cross-sectional regressions of market-implied probabilities on IV ratios and control variables

This table reports the summary results of cross-sectional regressions of the implied market probabilities calculated as $(V_P - V_R)/V_R$ where $V_P - V_R$ is the markup around the M&A announcement day, and $V_R$is the run-up calculated as the CAR over the period between the initial rumor date and the M&A announcement day. IV ratio is calculated as $IV_{Ratio\,i,t} = 1 - (\beta^2_{i,t} RV_{M,t}/RV_{i,t})$. $\beta_{i,t}$is the intraday beta calculated as the covariance between stock i and the market index based on returns for 25 minute intraday intervals. $RV_{i,t}$ and $RV_{M,t}$ are the realized daily intraday volatilities for stock i and the market respectively. The change in the ratio of idiosyncratic to total volatility is obtained from a regression of the daily ratios on a dummy variable for each of the eleven days around the rumor date and an intercept representing the pre- and post-rumor period average. The average estimation period is 120 days before and 20 days after the M&A rumor. $\#days$ is the number of days between the M&A rumor date and the M&A announcement date, #rumors is the number of rumors appearing between the initial M&A rumor and the M&A announcement date, B/M is the book to market calculated as of the last available book value and last end of year market value, $\ln(Size_i)$ is the natural logarithm of the market value of the target firm 41 days before the initial M&A rumor date, $\#Analysts$ is the number of analysts following the target firm, $Disp$ is the coefficient of variation of the last I/B/E/S summary estimates, and LT_Growth is the last I/B/E/S consensus estimate for long-term growth reported before the M&A rumor is made public. t-values, which are reported in the parentheses, are computed from (HAC) standard errors. [a], [b] and [c] represent significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
C	-0.852	0.110	-0.193	-3.059	-0.988	-0.070	-0.268	-3.141
	(-0.514)	(0.046)	(-0.010)	(-0.143)	(-0.593)	(-0.029)	(-0.014)	(-0.145)
IV_{Ratio}	9.738	9.791	17.429	20.730				
	(2.016)[b]	(1.980)[b]	(1.782)[c]	(1.724)[c]				
IV_{Ratio}					12.319	12.221	18.053	21.897
$\times$ *more* *Credible*					(2.215)[b]	(2.164)[b]	(1.786)[c]	(1.753)[c]
IV_{Ratio}					7.168	7.279	16.845	19.533
$\times$ *Less* *Credible*					(1.290)	(1.278)	(1.521)	(1.441)
$\#days$		-0.006	-0.007	-0.013		-0.006	-0.007	-0.013
		(-0.653)	(-0.396)	(-0.599)		(-0.587)	(-0.393)	(-0.604)
#rumors		-0.006	0.277	0.468		-0.023	0.264	0.440
		(-0.014)	(0.334)	(0.439)		(-0.057)	(0.314)	(0.405)
$\ln(Size_i)$			-0.101	-0.302			-0.094	-0.292
			(-0.083)	(-0.217)			(-0.077)	(-0.208)
B/M			-1.036	-1.387			-1.081	-1.479
			(-0.469)	(-0.559)			(-0.479)	(-0.581)
LT_Growth				-0.240				-0.249
				(-0.878)				(-0.891)
$Disp$				5.486				5.621
				(0.835)				(0.844)
$\#Analysts$				0.431				0.426
				(0.835)				(0.817)
Adj. R^2 (%)	2.57	2.85	4.88	9.24	3.13	3.36	4.90	9.31
N	233	233	175	157	233	233	175	157

Table 4.9. Summary results for within industry cross-sectional regressions of market firm value on accounting variables for all firms in CRSP and COMPUSTAT

This table reports summary results for cross-sectional estimations of : $m_{i,t} = \alpha_{0,j,t} + \alpha_{1,j,t}b_{i,t} + \alpha_{2,j,t}ln(|NI|)_{it}I_{(>0)} + \alpha_{3,j,t}ln(|NI|)_{ijt}(1 - I_{(>0)}) + \alpha_{4,j,t}\text{Lev}_{i,t} + \varepsilon_{i,t}$ for firm *i* and time *t*, where $b_{i,t}$is the natural log of book value, $ln(|NI|)_{it}$ is the natural log of the absolute value of net income, $I_{(>0)}$ is a dummy variable that takes the value of 1 when net income is positive and zero otherwise, and LEV$_{i,t}$ is the leverage ratio. $\alpha_{0\ldots4,j,t}$ are the sensitivities of firm values to the accounting variables in industry *j* in year *t*. The choice of industries follows the Fama-French 12 industries as detailed on the website of Kenneth French. The reported estimated coefficients are industry specific averages of yearly cross-sectional estimates over the period 1990-2011. The numbers reported in the parentheses are t-statistics calculated using Fama-MacBeth (1973) standard errors. $\overline{R^2}$ is an average adjusted R-square for every industry, $\overline{N}$ is the average number of companies used in the cross-sectional regressions. [a], [b] and [c] represent significance at the 1%, 5% and 10% levels, respectively.

	Fama-French 12 Industries											
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
$E(\alpha_0)$	2.114	1.842	1.803	1.980	2.055	2.501	2.621	1.514	2.044	2.428	1.520	2.466
	(27.945)[a]	(16.144)[a]	(21.254)[a]	(15.643)[a]	(25.643)[a]	(25.563)[a]	(21.240)[a]	(4.604)[a]	(26.847)[a]	(38.853)[a]	(12.983)[a]	(33.416)[a]
$E(\alpha_1)$	0.590	0.624	0.631	0.681	0.557	0.650	0.513	0.714	0.618	0.584	0.606	0.573
	(37.362)[a]	(23.909)[a]	(52.353)[a]	(38.207)[a]	(25.804)[a]	(60.885)[a]	(30.214)[a]	(17.716)[a]	(43.332)[a]	(70.765)[a]	(44.289)[a]	(36.615)[a]
$E(\alpha_2)$	0.415	0.362	0.355	0.254	0.441	0.332	0.358	0.243	0.363	0.389	0.345	0.396
	(26.389)[a]	(15.384)[a]	(38.941)[a]	(15.831)[a]	(23.041)[a]	(33.874)[a]	(23.577)[a]	(6.716)[a]	(25.421)[a]	(55.349)[a]	(28.299)[a]	(27.342)[a]
$E(\alpha_3)$	0.345	0.360	0.344	0.262	0.375	0.252	0.384	0.302	0.291	0.286	0.227	0.243
	(23.621)[a]	(17.274)[a]	(31.986)[a]	(18.413)[a]	(17.284)[a]	(19.890)[a]	(29.800)[a]	(7.669)[a]	(23.266)[a]	(27.069)[a]	(17.946)[a]	(11.536)[a]
$E(\alpha_4)$	-0.040	0.045	0.043	0.019	0.042	-0.187	0.028	0.152	0.023	-0.062	0.347	-0.059
	(-2.477)[a]	(2.069)[b]	(2.821)[a]	(1.197)	(2.014)[b]	(-7.612)[a]	(0.734)	(2.209)[b]	(1.378)	(-3.206)[a]	(19.761)[a]	(-3.250)[a]
$\overline{R^2}$	88.26%	89.47%	87.36%	89.28%	89.43%	85.41%	83.28%	92.33%	87.54%	81.79%	82.81%	82.93%
$\overline{N}$	275	137	549	219	127	1012	171	143	507	785	1515	143

Table 4.10: Summary results for cross-sectional regressions of market-implied probabilities on IV ratios and control variables

This table reports the summary results of cross-sectional regressions of the implied-market probabilities calculated as $(V_P - V_R)/V_R$ where $V_P - V_R$ is the markup around the M&A announcement day, and $V_R$is the run-up calculated as the CAR over the period between the initial rumor date and the M&A announcement day. IV ratio is calculated as $IV_{Ratio\,i,t} = 1 - (\beta_{i,t}^2 RV_{M,t}/RV_{i,t})$. $\beta_{i,t}$is the intraday beta calculated as the covariance between stock i and the market index based on returns for 25 minute intraday intervals. $RV_{i,t}$ and $RV_{M,t}$ are the realized daily intraday volatilities for stock i and the market respectively. The change in the ratio of idiosyncratic to total volatility is obtained from a regression of the daily ratios on a dummy variable for each of the eleven days around the initial rumor date and an intercept representing the pre- and post-rumor period average. The average estimation period is 120 days before and 20 days after the M&A rumor. Firm-specific error is the component of m/b ratio that capture the firm relative mispricing versus its industry peers calculated as $m_{i,t} - \vartheta(\alpha_{j,t}, \theta_{i,t})$, where $m_{i,t}$ is the natural log of the firm value (market-to-book ratio or MB) and $\vartheta(\alpha_{j,t}, \theta_{i,t})$ is the value of the firm estimated using accounting data $\theta_{i,t}$ and sensitivities $\alpha_{j,t}$ estimated using industry j date in year t. Time-series industry error is the component of M/B that captures the level of mispricing of an industry versus its historical average. It is calculated as $\vartheta(\alpha_{j,t}, \theta_{i,t}) - \vartheta(\alpha_j, \theta_{i,t})$, where $\vartheta(\alpha_j, \theta_{i,t})$ is the long-term value of the firm according to its sector average over the 10 years preceding year t. $\#days$ is the number of days between the M&A rumor date and the M&A announcement date, #rumors is the number of rumors appearing between the initial M&A rumor and the M&A announcement date, $\ln(Size_i)$ is the natural logarithm of the market value of the target firm 41 days before the initial M&A rumor date, $\#Analysts$ is the number of analysts following the target firm for the last IBES estimate, $Disp$ is the coefficient of variation of the last I/B/E/S summary estimates, and LT_Growth is the last I/B/E/S consensus estimate for long-term growth reported before the initial M&A rumor announcement. t-values, which are reported in the parentheses, are computed from (HAC) standard errors. [a], [b] and [c] represent significance at the 1%, 5% and 10% levels, respectively

	(1)	(2)	(3)	(4)
C	-1.046	-1.114	0.970	-8.237
	(-0.355)	(-0.375)	(0.226)	(-0.464)
IV_{Ratio}	12.621		12.685	16.787
	(1.913) [c]		(1.877) [c]	(1.929)[c]
$IV_{Ratio} \times More - credible$		14.113		
		(1.850) [c]		
$IV_{Ratio} \times Less - credible$		11.234		
		(1.175)		
Firm misvaluation	0.201	0.217	0.219	0.794
	(0.274)	(0.294)	(0.296)	(0.703)
Industry sector misvaluation	0.194	0.240	0.264	1.042
	(0.175)	(0.213)	(0.234)	(0.600)
$\#days$			-0.011	-0.017
			(-0.670)	(-0.871)
#rumors			-0.072	-0.163
			(-0.099)	(-0.176)
$\log(Size_i)$				0.377
				(0.309)
LT_Growth				-0.026
				(-0.101)
$Disp$				2.057
				(0.398)
$\#Analysts$				0.427

				(0.863)
Adj. R^2 (%)	2.83%	2.93%	3.39%	6.98%
N	233	233	157	157