ECO475: Applied Econometrics II

Does Leverage Lead to Mean Reversion? Evidence from Mutual Funds

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Abstract

This paper examines whether leverage causes mean reversion in mutual fund returns. It uses a panel from the Fundata database of Canadian mutual funds from 2005 to 2020. It employs two empirical approaches to measure mean reversion: the Augmented Dickey-Fuller (ADF) test and the Variance Ratio (VR) statistic, with the latter preferred for its robustness in short panels. Leverage was derived from the CAPM framework as the ratio of the standard deviation of fund returns to that of the market. The regression models incorporate macroeconomic controls, and endogeneity is addressed by using short-term bond yields as an instrument for leverage. We find that leverage has a significant causal effect on mean reversion and that this effect is stronger for larger funds. These findings contribute to the literature by empirically finding a causal link between leverage and financial return mean-reversion.

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I. Introduction

The 2008 crisis exposed a dangerous fragility in financial markets. In the lead-up, financial institutions leveraged themselves excessively. Optimism ran high, credit was cheap, and investors rode a wave of euphoria. But as concerns grew over inflated asset prices, credit conditions tightened. Prices didn't just fall—they snapped back. This correction of past overshoots is an instance of mean reversion. This dynamic is captured in Fostel and Geanakoplos' (2008) theory of the leverage cycle. In boom times, loose lending standards and high leverage push prices upward; in downturns, tighter margins force rapid deleveraging, accelerating price declines. The cycle is self-reinforcing: as leverage amplifies gains on the way up, it also magnifies losses on the way down. While Fostel and Geanakoplos provide a formal and equilibrium-based model of these dynamics, the core intuition traces back to Minsky's Financial Instability Hypothesis, developed in *Stabilizing an Unstable Economy* (1986). Minsky offers a broader conceptual framework for understanding how financial systems drift toward fragility—even in the absence of external shocks.

According to Minsky financial markets are inherently prone to cycles of boom and bust. Following a crisis, or during a prolonged calm, markets enter what Minsky calls the hedge phase where borrowers are cautious, and revenues cover both interest and principal. As volatility falls and asset prices rise, investors begin to extrapolate past returns assuming recent gains will continue. This optimism fuels risk-taking, weakens lending standards, and drives up leverage. The system then shifts into the speculative phase where borrowers can pay interest but must refinance principal, and eventually into the Ponzi phase where even interest payments depend on rising asset prices. In this progression, stability breed fragility; the absence of crisis invites behaviours that make crisis inevitable.

Minsky emphasized that this progression is endogenous: the financial system, left to its own devices, evolves toward instability. What interests us most for our paper is the correction that follows the build-up of financial excess. When reality intervenes—whether through falling earnings, policy changes, or shifts in investor sentiment—prices adjust sharply. In this view, mean reversion is not random fluctuation, but the system's natural response to prior overextension. If Minsky is right, we should observe negative autocorrelation in the returns of highly leveraged assets—and this is the hypothesis that we set out to test.

Adrian and Shin (2010) is another work that has explored the role of leverage in financial cycles. They show that leverage at broker-dealers rises in good times and falls in bad times, adjusting mainly through repos. They find that when financial intermediaries expand their balance sheets, it signals rising risk appetite and predicts future changes in how markets price risk and volatility. Adrian and Shin (2010) use time-series regressions to show that growth in dealer balance sheets predicts future changes in market volatility and the price of risk. In contrast, we use fund-level data and an instrumental variable approach to test whether leverage causally drives mean reversion in asset returns.

Other studies provide additional motivation for examining the relationship between leverage and price dynamics. Brunnermeier and Pedersen (2009) show how rising volatility tightens margin requirements, forcing leveraged investors to unwind positions. This feedback loop can amplify price declines and generate sharp corrections, providing a mechanism through which leverage can contribute to mean reversion. Davis and Taylor (2022) find that credit booms tend to be followed by lower asset returns across countries, consistent with a pattern of return reversals.

These studies collectively motivate our investigation into whether leverage plays a causal role in driving return corrections. We test whether the dynamics implied by the leverage cycle—

price increases followed by reversals—can be observed in mutual fund data. Furthermore, we seek to answer whether we observe a stronger causal effect of leverage on mean reversion among larger funds. These answers have implications not only for the theoretical interpretations of booms and busts, but also for understanding investor behaviour, market dynamics, and the appropriate design of macroeconomic policy and the regulation of financial intermediaries.

In section II of the paper, we discuss our different data sources for fund level data and macroeconomic variables. We also then explain how we derived our main independent variable, leverage, grounding our discussion in the capital asset pricing model (CAPM). In section III, we go over our methodology where we outline our two approaches to measure mean reversion using an augmented Dickey-Fuller (ADF) test and variance ratios. Next, given the endogeneity of leverage we specify our instrumental variable approach, and we demonstrate that short-term bond yields satisfy the exclusion and relevance criteria. In Section IV, we present and discuss our results in detail. We find that, in our preferred specification, leverage causally increases the degree of mean reversion in mutual fund returns, consistent with the theoretical predictions of the leverage cycle. Furthermore, this effect is stronger among larger funds, suggesting that size may amplify the impact of leverage on return dynamics. In Section V, we conclude and further discuss the implications of our findings for financial market efficiency and regulation. Our results suggest that leverage introduces inefficiencies by driving return reversals, supporting the case for macroprudential policies that limit leverage—particularly among large financial institutions.

II. Data and Variable Construction

a. Mutual Fund Data

Two datasets were merged for the purpose of our research. First, a comprehensive panel dataset of global mutual funds was obtained from University of Toronto's CHASS *Fundata* portal. The database's longest possible date range spanned 2005 to 2020. FUNDATA is a database which includes 7,500 Canadian active funds from almost 440 sponsor companies. Initially comprising of over 3 million observations, our sample was filtered to focus exclusively on Canadian mutual funds with domestic-only investments, resulting in approximately 20 thousand observations with more than 20 thousand individual funds.[1] Upon some preliminary cleaning, a mutual fund dataset was compiled with fund-month pairs as units of observation. This dataset included fund-level characteristics such as Total Net Assets (TNA), Net Asset Value Per Share (NAVPS), the Value of Investment, and Expense Ratios.

Figure 1: Summary Statistics for Mutual Fund Data

	Mean	S.D.	Min	Max
Total Net Assets (Millions)	5.0	2143.1	0.0	982222.0
NAV per Share (Millions)	12.8	5.6	5.6	293.4
Value of Investment (Millions)	14.2	12.5	1.0	358.0
Expense Ratio	2.1	1.2	0.0	7.9

Observations: 210,120 (fund-month pairs)

Figure 1 provides summary statistics related to all Canadian mutual funds with domestic investment present in FUNDATA[2]. Evidently, the average total net assets are approximately CAD 5 million, although this distribution is substantially skewed with a considerable variance of CAD ~2 billion. NAV per share and investment values show more moderate volatility, obeying typical

[1] Note: number seems large, but it is a reflection of the fact that FUNDATA counts different asset types as separate funds (e.g. BMO equities is separate from BMO commodities, etc).
[2] For the purpose of our econometric model, not all of these funds were kept. More in *III. Methodology*.

financial intermediary characteristics. Expense ratios average 2.1%, with less pronounced dispersion (an S.D. of 1.2%). These statistics help contextualize the distribution of funds in the raw dataset before further preparations to the data were performed.

b. Macroeconomic Controls

A second, macroeconomic dataset was compiled[3] to control for macroeconomic factors potentially affecting mutual fund returns and leverage dynamics. Macroeconomic data was sourced from the Federal Reserve Economic Database (FRED), Bank of Canada (BOC), Statistics Canada, and Yahoo Finance. These data included indicators capturing economic activity (GDP growth rate, unemployment rate, and BOC's business confidence survey), price levels and stability (Consumer Price Index), financial conditions (the overnight rate, bond yields, and stock market volatility), and fiscal health (total government debt). To address non-stationarity in variables such as CPI which exhibits a clear deterministic trend, we applied log-differencing transformations to stabilize the variance and eliminate trend components. This allowed us to isolate the rates of change in variables rather than their absolute levels, making the resulting variable stationary and more suitable for regression analysis. Combining macro variables into one dataset, it was merged with FUNDATA.

c. Leverage via CAPM

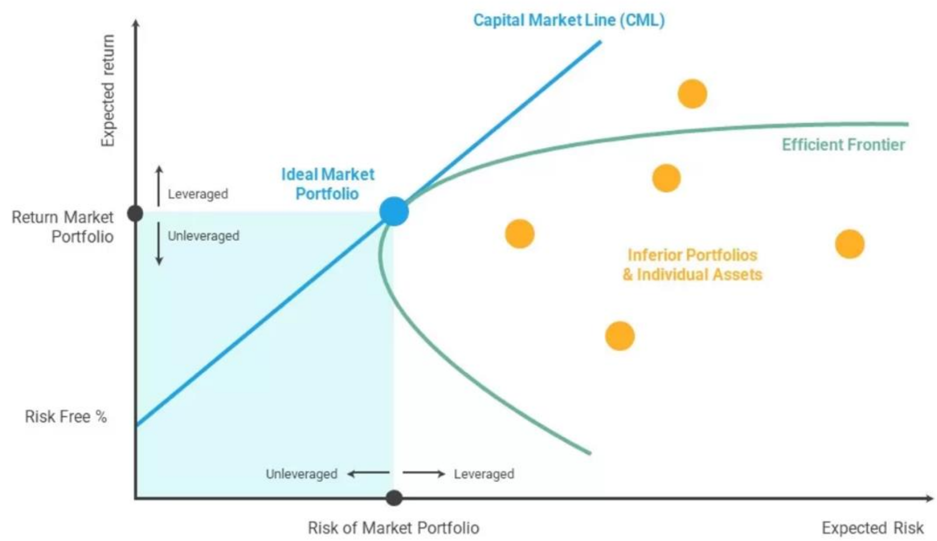
Our dependent variable of leverage was not in the FUNDATA database. For our purpose, leverage is defined as the fund's investment value divided by its equity. Such a deficiency in the dataset posed a challenge to identifying the causal link between leverage and mean-reversion in mutual fund returns. To address this deficiency, we calculated the implied leverage of each fund

[3] For an overview of the merging of both datasets, check *CODE – Data Compiling (Python)*

as the standard deviation of its returns divided by the standard deviation of the S&P/TSX returns over the same time period.

Such an implied leverage is justified by the Capital Asset Pricing Model. According to CAPM, funds should either lend or leverage along the capital market line described in Figure 2.

Figure 2: The CAPM Framework with a Leverage Distinction



Source: SlideBazaar

This means that the optimal investment for a mutual fund is a linear combination of the risk-free asset and the market portfolio (i.e., the S&P/TSX). To illustrate this definition of implied return, if the fund's leverage is exactly 1 (i.e., it is neither lending nor borrowing), then it would be investing its entire portfolio into the market portfolio and no weight into the risk-free asset and hence the standard deviation of its returns would equal that of the market's. Meanwhile, if the fund's leverage is 2 (i.e., investing twice as much as its equity, and hence half of its portfolio is financed by debt), then the fund's moves to the right-hand side of Figure 2, with a weight on the risk-free asset of −1 and the weight on the market portfolio of 2, and hence the standard deviation of its returns would be twice as much of the market. Conversely, if the fund's leverage is 0.5, then it is placing half of its portfolio into the risk-free asset and the other half into the market, therefore the standard deviation of its returns is half of the market's.

III. Methodology

a. Measures of Mean-Reversion

Two complementary methodologies with regard to defining mean reversion were undertaken. The first approach involves an Augmented Dickey Fuller (ADF) test following Lo and MacKinlay (1988). The ADF test helps determine whether fund returns exhibit stationarity, in which case they deviate from a random walk and imply mean reversion. The test thus identifies funds whose returns systematically correct towards their historical means, enabling the creation of a binary indicator for fund mean reversion—this served as the dependent variable in the ADF regression specifications. Importantly, in order to validly compute the ADF indicator, several observations per fund (investments, in our case), were required. For this reason, we decreased the sample size by filtering-out funds with fewer than twenty observations throughout the entire time period. This decreases the sample size from ~210 thousand to ~100 thousand rows, decreasing the number of funds from 20 thousand to 2 thousand. The ADF test was then run on the remaining sample using a significance level of 5%.

The second approach to mean reversion draws from Summers and Poterba (1988), who employed the variance ratio statistic to quantify mean reversion through return volatility over various investment horizons. The variance ratio approach stems from the logic that, in a random-walk, return variance scales linearly with time. But if long-term returns do not follow a linear trend and are less volatile than expected, we encounter mean reversion—a correction back toward fundamental value. In the VR ratio statistic, we can see the numerator accounts for long-term variance and the denominator accounts for short-term variance. A number greater than 1 implies momentum, a number lower than 1 implies mean reversion.

$$\mathrm{VR}(q) = \frac{\mathrm{Var}(r_t + r_{t-1} + \cdots + r_{t-q+1})}{q \cdot \mathrm{Var}(r_t)}$$

A critical finding from Summers and Poterba was contrary to the efficient market hypothesis, that there exists long-term mean reversion in asset returns. This gave us an empirical precedent for our own consideration of mean reversion in leveraged mutual funds. For our purposes, we chose the number of periods of two (q = 2). As Lo and MacKinlay describe, this is sufficient to test whether or not financial returns are a random walk or mean-reverting. In addition, a number of periods of 2 also has a convenient economic interpretation, because the first-order of autocorrelation is asymptotically equal the variance ratio minus 1.

In order to match the ADF test sample and rule out funds with single or few investments, the sample on which the variance ratio was run also included the removal of funds with fewer than 20 investments between 2005 and 2020. Combining the two approaches to mean reversion allowed our analysis to capture different dimensions of mean reversion; discrete episodes were identified via the ADF approach, while continuous volatility patterns were highlighted by the variance ratio test statistic. This feature of our methodology thus makes our econometric approach more robust and capable of generating nuanced insight.

b. Summary plot of mean-reversion and leverage over time

As part of an exploratory analysis, we calculated the average variance ratio—as a measure of mean-reversion—and the average leverage of all funds per year. Figure 3 shows the demeaned time series of both the average variance ratio and average leverage over time.

Figure 3: Demeaned Plot of Average Leverage versus Average Variance Ratio Over Time

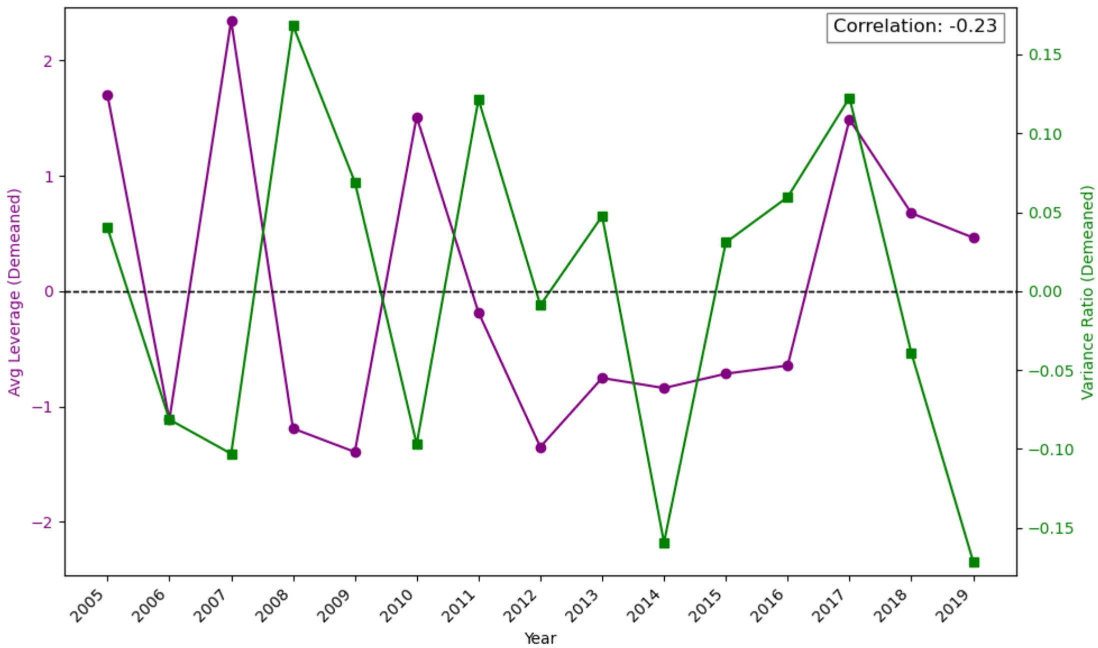


Figure 3 shows that these two variables often have opposite signs. That is to say, when the average variance ratio is above its mean, then the average leverage tends to be below its mean, and vice-versa. For example, in 2007, average leverage was above its mean while average variance ratio was below its mean. And subsequently in 2008, the series flipped such that average leverage was below its mean and average variance ratio was above its mean. Additionally, the correlation between the two is negative at -0.23. The fact that both of these variables are negatively correlated provides some evidence that leverage causes mean reversion in mutual funds. However, to conclude causal inference requires a regression analysis to eliminate any potential endogeneity.

c. The Instrumental Variable Approach

As outlined before, we expected endogeneity concerns with leverage. For instance, managers might choose leverage levels based on expectations about future returns. Additionally, the regressions are potentially endogenous by construction. Our dependent variable, the measure of mean reversion of either the ADF test result or the variance ratio statistic, is a function of mutual fund returns. And our independent variable, leverage as defined as the standard deviation of fund returns divided by that of the market returns, is also a function of the mutual fund returns. Hence there is potential endogeneity which can be corrected by instrumental variables.

We thus implemented an instrumental variable (IV) approach, using short-term (1-3 year) bond yields as an instrument for leverage. Support for this solution comes from existing literature surrounding asset returns. Axelson et. al. (2013) find that, among private equity funds, higher leverage is associated with higher transaction prices and ultimately lower buyout fund returns. However, in order to address the endogeneity in leverage they decide to use credit spreads as an instrument. This provided an important methodological precedent for our own analysis, demonstrating that an interest rate-related instrument can be used to address the endogeneity problem in leverage, and for our purpose, estimate the true causal effect on mean reversion.

Furthermore, though Axelson et. al (2013) focus on private equity firms, we can infer that bond yields are strongly correlated with mutual funds' leverage choices because lower borrowing costs broadly reduce the cost of capital across management contexts, which in turn incentivizes managers to take on more aggressive positions. In terms of the exclusion restriction for bond yields as an instrument, we satisfy this because the impact of bond yields on fund returns is indirect – it occurs through their effect on leverage decisions rather than a direct influence on fund performance. This IV strategy will thus enable us to isolate a causal relationship between leverage and mean reversion. A rigorous overview of the validity of our instrument is provided in section IV below.

d. Specifications

Specifically, there are 6 regression specifications we run. Specification (1) is a simple OLS in which the independent variable is the dummy variable is_mean_reverting, which is produced from the ADF test, and the independent variable is the average leverage of the mutual fund over its life. The unit of observation in Specification (1) is a fund and hence it is cross-sectional. Specification (2) is an instrumental variables regression in which the independent variable is still is_mean_reverting and the dependent variable is average leverage, with the instrument for leverage being the 1-3-year bond yields. However, the unit of observation is a fund-quarter and hence it is a panel regression.

Specification (3) then adds to Specification (2) by adding year fixed-effects and the macroeconomic control variables of the Bank of Canada future sales indicator, the percent debt-to-GDP, and the unemployment rate. We added these macroeconomic controls and year fixed-effects to control for potential endogeneity. For example, an increase in business confidence or other time-varying shocks could increase both leverage and mean-reversion in returns, hence adding the Bank of Canada future sales survey and year fixed-effects controls for that endogeneity. Additionally, adding such controls also supports the instrument exogeneity of using the 1–3-year yield as an instrument for leverage.

Specifications (4), (5), and (6) are identical to (1), (2), and (3) respectively except that they replace the dependent variable with the variance ratio test statistic as a measure of mean-reversion.

Mathematically, the regression specifications are described as follows.

$$\text{Specification (1):} \quad \text{Is\_Mean\_Reverting}_i = \alpha + \gamma \log(\text{Leverage})_i + \varepsilon_i \quad \text{(OLS)}$$

$$\text{Specification (2):} \quad \text{Is\_Mean\_Reverting}_{it} = \alpha + \gamma \log(\text{Leverage})_{it} + \varepsilon_{it} \quad \text{(IV)}$$

$$\text{Specification (3):} \quad \text{Is\_Mean\_Reverting}_{it} = \alpha + \gamma \log(\text{Leverage})_{it} + \delta \log(X)_{it} + \eta_t + \varepsilon_{it} \quad \text{(IV)}$$

$$\text{Specification (4):} \quad \text{Variance Ratio}_i = \alpha + \gamma \log(\text{Leverage})_i + \varepsilon_i \quad \text{(OLS)}$$

$$\text{Specification (5):} \quad \text{Variance Ratio}_{it} = \alpha + \gamma \log(\text{Leverage})_{it} + \varepsilon_{it} \quad \text{(IV)}$$

$$\text{Specification (6):} \quad \text{Variance Ratio}_{it} = \alpha + \gamma \log(\text{Leverage})_{it} + \delta \log(X)_{it} + \eta_t + \varepsilon_{it} \quad \text{(IV)}$$

Where i is the fund and t is the quarter. X is the vector of macroeconomic controls and η are the year fixed-effects. The term ε represents the unobserved disturbances.

e. Sub-samples by Total Net Assets

Finally, to examine whether the causal effect of leverage on mean-reversion in mutual fund returns is stronger for larger funds, we partitioned the entire sample by quartiles based on the fund's total net assets. Then, we ran Specifications (4), (5), and (6) on each subsample to obtain the parameter estimate on leverage.

To further analyze the interaction between total net assets of the mutual fund and the causal effect of leverage on mean-reversion, we added an interaction term between the log of leverage and the log of total net assets to Specification (6) for the full sample. Mathematically, regression specification with the interaction term is as follows.

$$\begin{aligned}\text{Variance Ratio}_{it} = \alpha + \gamma \log(\text{Leverage})_{it} + \lambda \log(\text{Leverage})_{it} \times \log(TNA_{it}) \\ + \delta \log(X)_{it} + \eta_t + \varepsilon_{it} \qquad \text{(IV)}\end{aligned}$$

The combination of the results from each sub-sample, and adding the interaction term to the full sample, supports the conclusion that the size of the fund amplifies the extent that leverage causes mean-reversion.

IV. Results and Discussion

a. Analysis of All Funds

The results of running all 6 model specifications are presented in Figure 4. At first glance, we get an unclear picture of whether leverage causes mean-reversion in mutual fund returns. However, an analysis of the specifications suggests that the evidence points towards our alternative hypothesis being true: that there is a positive causal relationship of leverage and such mean-reversion.

Figure 4: Regression Results

	Mean Reverting Measure					
	Using ADF Test			Using Variance Ratio		
	(1) Simple	(2) Multiple	(3) Multiple	(4) Simple	(5) Multiple	(6) Multiple
Leverage Coefficient	-.0362*** (.0006)	-.3730*** (.0123)	-.0538 (.2015)	-.0096*** (.0017)	.5617*** (.0674)	-.6621*** (0.0578)
Unit	Fund	Fund-Year	Fund-Year	Fund	Fund-Year	Fund-Year
Fixed Effects	No	No	Yes	No	No	Yes
Controls	No	No	Yes	No	No	Yes
Instrument	None	1–3 Yield	1–3 Yield	None	1–3 Yield	1–3 Yield
First-Stage Coefficient	N/A	-.0469*** (.0110)	-.0899 (.0645)	N/A	-.1366*** (.0086)	-.8792*** (.0453)

*Notes: *p < 0.1; **p < 0.05; ***p < 0.01.*

Before we analyze the regression results, it is noteworthy that the coefficients of interest in the first-stage regressions for Specification (2), (3), (5), and (6) are negative, at –0.05, –0.09, –0.14, and –0.88 respectively. This suggests that an increase in the short-term yield by 1 percent decreases the average leverage by 5, 9, 20, or 88 percent respectively, and all but the coefficient for (3) is statistically significant. Hence these first-stage regressions provide support for the relevance of using short-term yields as an instrument for leverage.

Although the coefficients of interest—the estimated parameter on average leverage—is statistically significantly negative for Specifications (1) and (2), being -0.047 and -0.37 respectively, which points towards our alternative hypothesis being false, this can be attributed to the fact that the dummy variable is_mean_reverting is a negatively biased estimator of whether the fund displays mean-reverting returns. Being a linear probability model, Specifications (1) and (2) suggest that for every 10% increase in average leverage, the probability the fund's returns are mean-reverting decreases by 0.47 or 3.7 percentage points respectively. The dummy variable is_mean_reverting is defined as 1 if the Augmented Dickey–Fuller test applied on the fund (or fund-quarter) favours stationarity and 0 otherwise. However, although this estimator, is_mean_reverting, is consistent, it is negatively biased in the sense that having fewer observations makes it more likely to make a Type II error—estimating that there is no mean reversion present in situations when in actuality there is. Such a negative bias may bias Specifications (1), (2), and (3), which rely on the ADF test. This is why we prefer the results from Specifications (4), (5), and (6), which use the variance ratio test statistic as the measure of mean-reversion.

It is noteworthy that when adding macroeconomic controls and year fixed-effects to the ADF regressions—along with using the short-term yield as an instrument for average leverage—the coefficient of interest in Specification (3) is statistically insignificant. This suggests that our alternative hypothesis, if it is true, emerges after controlling for confounders.

Moving on to the specifications which use the variance ratio test statistic as a dependent variable to measure mean-reversion—Specifications (4), (5), and (6)—these specifications favour our alternative hypothesis. The coefficient of interest in Specification (4) is statistically significantly negative at –0.010. This means that a simple OLS suggests that for every 1 percent increase in leverage, there is a –0.010 decrease in the variance ratio. Although Specification (5) has a statistically significantly positive coefficient of interest at 0.34—contrary to our alternative hypothesis—when adding macroeconomic controls and year fixed-effects in addition to the instrumental variable of short-term yields, Specification (6) has a statistically significantly negative coefficient of –0.66. Specification (6) is our most robust specification. It implies that every 1 percent increase in leverage results in a –0.66 decrease in the variance ratio. Because, at our chosen number of periods (q = 2), the first-order autocorrelation is asymptotically equal to variance ratio minus 1, this result is also economically significant since it implies that an increase in fund leverage causes an increase in negative autocorrelation of fund returns and hence mean-reversion.

b. Analysis of Sub-Samples

The results from running Specifications (4), (5), (6) on each quartile of the fund's total net assets are shown in Figure 5. These results support the conclusion that the degree to which leverage causes mean reversion in mutual fund returns is amplified by the size of the mutual fund's portfolio.

Figure 5: Subsample Regression Results

Coefficient: Leverage			
	Variance Ratio Specification		
	(4)	(5)	(6)
TNA Quartile	Simple	Multiple	Multiple
0–25%	0.0001	0.5702***	-0.5826***
25–50%	-0.0035	0.4386**	-0.7823***
50–75%	-0.0031	0.8763***	-0.7448***
75–100%	-0.0166***	0.6247**	-0.3436***

*Notes: *p < 0.1; **p < 0.05; ***p < 0.01. Standard errors omitted for clarity.*

Starting with Specification (4)—the simple OLS of the variance ratio statistic on leverage—note that the coefficient on leverage is statistically insignificant for the first 3 quartiles, but then for the largest funds in the 4th quartile it is statistically significantly negative. Admittedly, our most robust Specification (6) paints an unclear picture, with the leverage coefficient decreasing significantly from the first quartile to the second quartile (from –0.58 to –0.78) but then that mean-reversion attenuates from the third quartile to the fourth quartile (from –0.74 to –0.34).

To verify the fact that total net assets amplifies the mean reversion caused by leverage, we added an interaction term between the log of leverage and the log of total net assets to Specification (6). When running Specification (6) with this interaction term, the coefficient on leverage is still statistically significantly negative at –0.59. Most importantly, the coefficient on the interaction term is statistically significantly negative at –0.0042. Hence we can conclude that this causal link between mean reversion and leverage is stronger for larger funds.

V. Conclusion

Our paper aimed to empirically and econometrically verify the role of leverage in fueling financial crises. Namely, the evidence should show that financial institutions which are more leveraged, such as mutual funds, should display mean-reverting returns. Although there is evidence for mean-reversion in stock market returns more broadly, our paper contributes to the literature by empirically demonstrating a causal link between leverage and mean-reverting returns; the evidence suggests that an increase in mutual fund leverage causes an increase in the degree of mean-reversion of their returns.

Such a connection between leverage and mean-reverting returns has implications for the structure of financial markets and regulation. As Lo and MacKinlay describe, since the efficient-markets hypothesis implies that stock prices follow a random walk, deviations from a random walk is evidence of inefficiencies. Hence the fact that leverage causes mean-reversion implies that leverage causes inefficiencies in the financial markets. If Minsky and Fostel & Geanakoplos are correct, this inefficiency is due to investor sentiment driven by leverage cycles causing asset prices to inflate from their fundamental values, ultimately causing financial busts.

In terms of regulation, our paper provides support for another avenue in which macroprudential policies which limit the amount of leverage financial intermediaries can use can promote financial stability. In addition to the traditional justification of mitigating credit risk and preventing bank runs, our paper suggests that leverage limits prevent the speculative bubbles which drive financial instability. Additionally, as a result of our sub-sample analysis on the total net assets of the mutual funds, we showed that the degree to which leverage causes mean reversion is stronger for larger funds. Therefore, there is evidence that larger financial institutions can contribute to financial instability through this leverage cycle mechanism, and hence our paper provides support for regulations promoting competition within the financial sector.

There are some limitations with our paper. Because the FUNDATA dataset contains no data on leverage, we calculated leverage as the standard deviation of the fund's returns divided by the standard deviation of the S&P/TSX returns. Although this calculation makes sense if we assume CAPM is correct, to the extent that reality deviates from CAPM, this calculation weakens our results. Further research can strengthen our results by combining the FUNDATA database with another which provides direct information on leverage such as outstanding debt. Additionally, because of our instrumental variables approach, we only analyze within-year variation in mutual fund returns. If, because of macroeconomic conditions, every mutual fund becomes more leveraged and hence more mean-reverting, that would not be captured because of the year fixed-effects. Additionally, there may be other types of investors—such as hedge funds—which display either more or less of such mean-reverting behaviour.

Our paper opens up many further avenues for research. First, further research can empirically and econometrically verify other aspects of Minsky (1986) and Fostel & Geanakoplos' (2008) theory of financial crises. For example, by examining whether leverage is correlated with investor sentiment. Or by examining whether the mechanism of forced deleveraging or changes in leverage is what causes the financial instability. Additionally, further research can analyze whether certain macroeconomic policies mitigate or exacerbate the causal link between leverage and mean reversion. For example, Minsky posits that times of low interest rates and easy access to credit would worsen such financial instability. Lastly, further research can use these results to run simulations such as stress-testing or forecasting to predict how changes in leverage affect the likelihood and magnitude of financial instability by contributing to the negative autocorrelation of financial returns.

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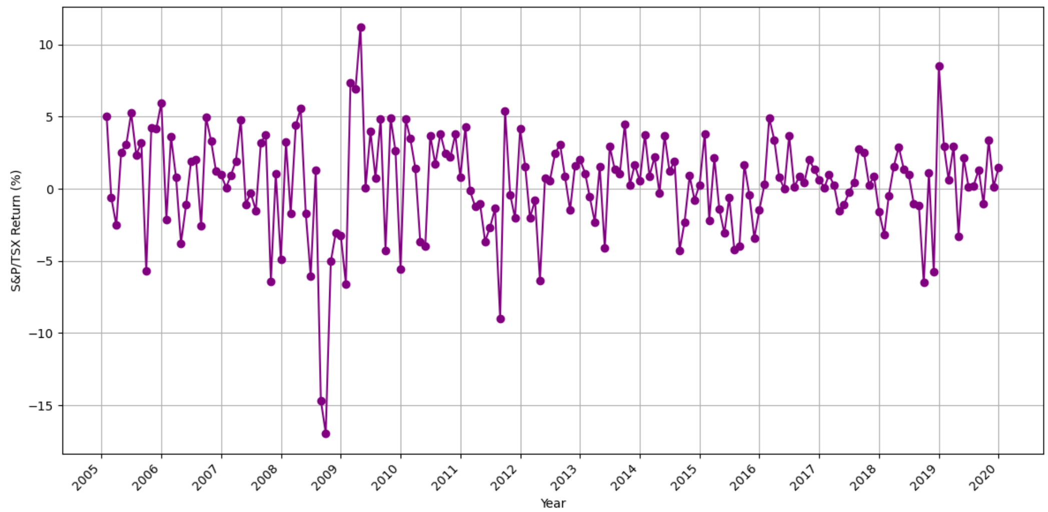
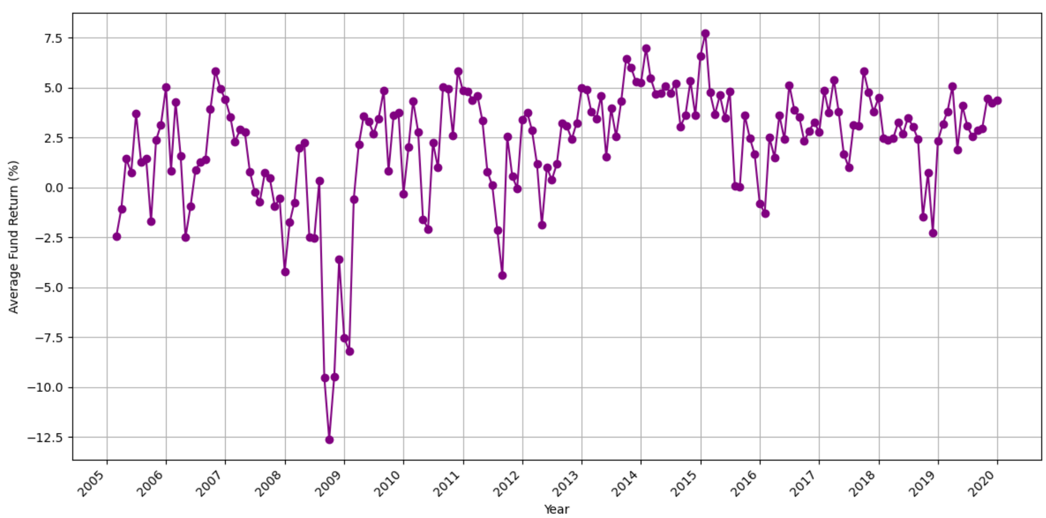
VIII. Appendices

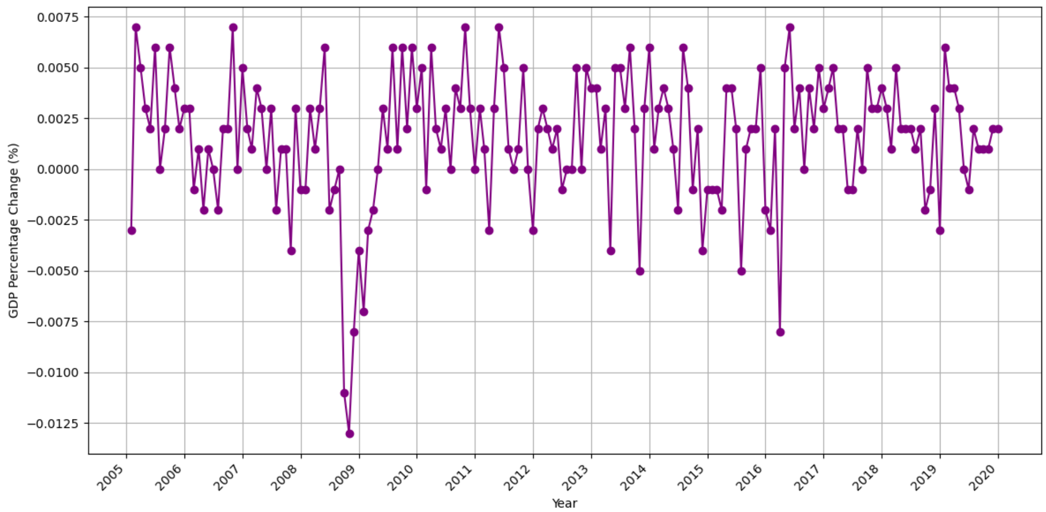
Appendix 1: Average S&P/TSX Return (Monthly)



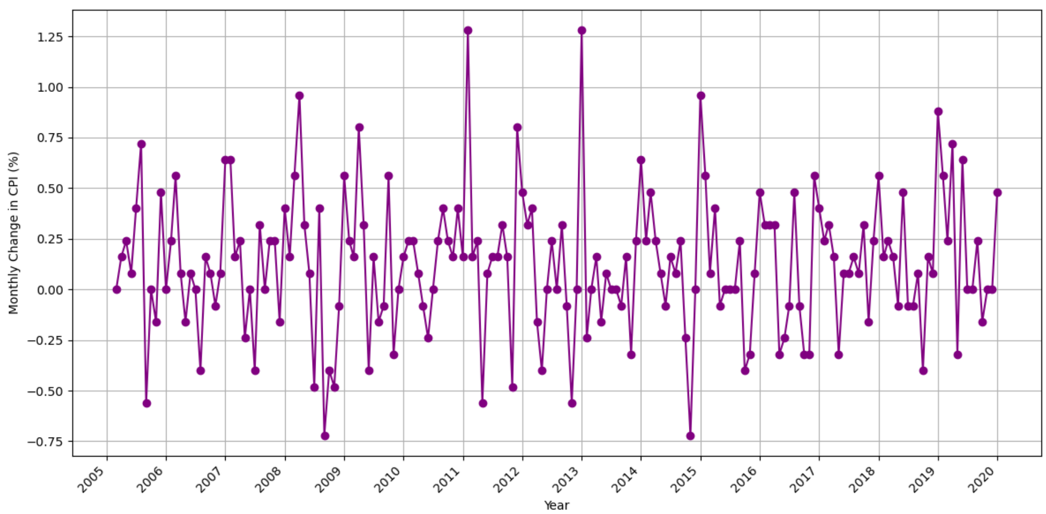
Appendix 3: Average Mutual Fund Return (Monthly)



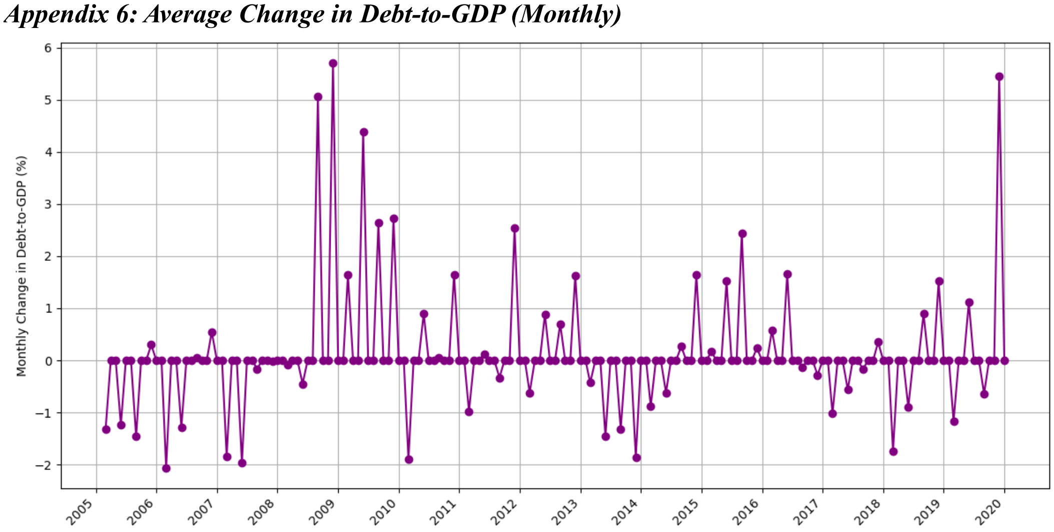
Appendix 4: Average Percentage Change in GDP (Monthly)



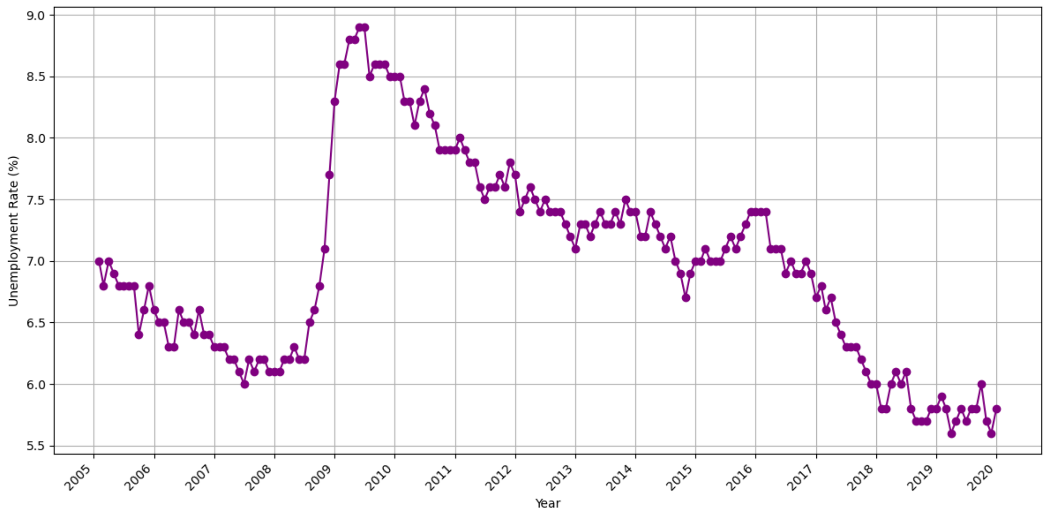
Appendix 5: Average Change in the CPI (Monthly)



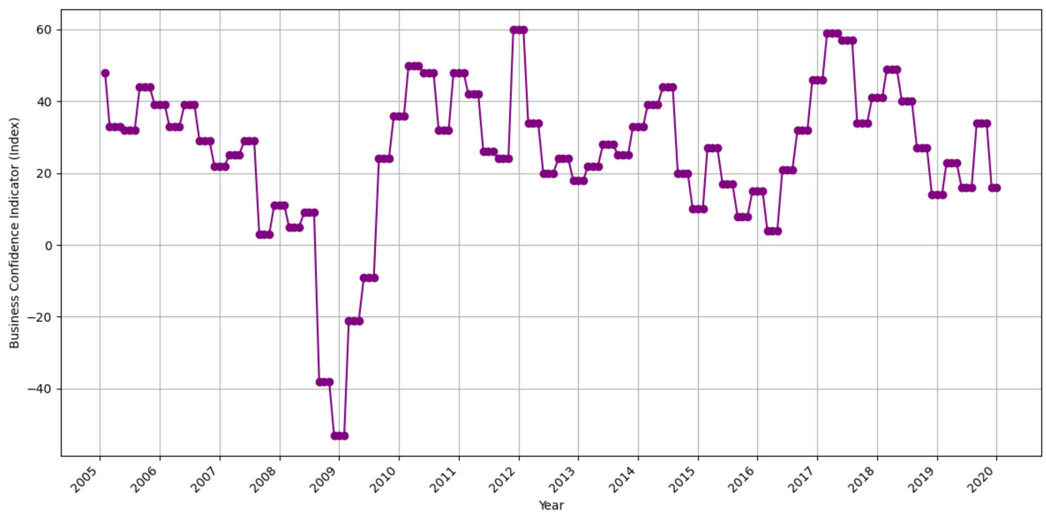
Appendix 6: Average Change in Debt-to-GDP (Monthly)



Appendix 7: Average Unemployment Rate (Monthly)



Appendix 8: Average Change in the Business Confidence Indicator (Monthly)



Appendix 9: Average Bond Yield (1-to-3 year; Monthly)

Appendix 10: Average Bond Yield (5-to-10 year; Monthly)