Derivative-Market Leverage and Risk Premia Implications

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Abstract

We use the futures commission merchants (FCMs) reports released by CFTC to construct a frequent (monthly) and timely (one-month delay) market-level leverage measure, based on the aggregate margin of market participants. The derivative-market leverage negatively (positively) predicts returns of risky (safe) assets, as a market indicator of the investors' risk tolerance. This effect is robust across both futures and spot markets, persistent up to one year, and stronger during the deleveraging periods. The derivative-market leverage is responding to market uncertainty, co-moves with economic activities, but preceding capital demands. These results are consistent with a stylized model of the futures and spot markets.

Keywords: Derivative-Market Leverage, Risk Premia, Return Predictability, Risk Aversion

JEL Classification: G12, G13, G14

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1 Introduction

Leverage embedded in financial derivatives provides a way of magnifying profits or losses for derivatives investors who actively hedge and speculate through margin trading. Normally, risk-taking investors intend to increase leverage to enlarge their risk exposure, therefore, aggregating the leverage of individual investors at the market level can provide a trading-aggressiveness profile for the entire market. Theoretical evidence suggests that the equilibrium leverage is endogenously determined by investors' risk tolerance and affects asset prices (see, e.g., Kupiec and Sharpe, 1991; Geanakoplos, 2010; Santos and Veronesi, 2022).

Our paper is the first to provide a monthly-updated leverage measure, using real-time trading data at the aggregate market level, and the first to find empirical evidence of the market leverage's predictability of risk premia. The novel derivative-market leverage (DML) measure in our paper, constructed as the ratio of the aggregated dollar open interest for major futures contracts over the total margin amount of investors,[1] is a powerful predictor of asset returns in all mainstream financial markets both for derivatives (e.g., futures) and spot assets over monthly-to-annual horizons.

With the overall dollar trading position in the numerator and the total amount of pledge in the denominator, our DML measure is a natural proxy for time-varying investor risk preferences; i.e., when investors become more risk-seeking, they would take a larger position with a relatively smaller amount of capital, or higher leverage. Indeed, DML's negative correlation with the risk aversion measure constructed by Bekaert, Engstrom, and Xu (2021) is prominent in periods both with (-0.53) and without recessions (-0.28) at the 1% significance level, with the latter being a model-based measure and marginally predicting returns.

Moreover, our DML measure is negatively correlated with the volatility index (VIX), a proxy for market fear, significant at the 1% level both in periods with (-0.63) and without (-0.38) recessions. As for other risk appetite measures in literature, we find that DML is positively correlated (0.39) with the proxy for broker-dealer risk tolerance proposed by Adrian, Etula, and Muir (2014), positively correlated (0.29) with the intermediary risk tolerance proxy developed by He, Kelly, and Manela (2017), and negatively correlated (-0.23) with the proxy for household risk aversion initiated by Lettau and Ludvigson (2001).

The classical intertemporal capital asset pricing theory (ICAPM, see, e.g., Merton, 1973) suggests a positive link between the risk premia of risky assets and risk aversion of a representative investor. Thus, high risk premia correspond to periods of low market leverage when investors become more risk averse. This is confirmed by our empirical evidence of such a negative relationship in both the futures and spot markets for a comprehensive set of risky asset

[1] Note that options on futures are treated as the delta amount of their underlying.

classes. In futures markets, a one-unit increase in our detrended DML measure ($DDML$)[2] predicts a next-month 39 basis point (bp) decrease (t-statistic = -3.95) for commodities, a 65 bp decrease (t-statistic = -4.89) for stock indices, and a 20 bp decrease (t-statistic = -3.97) for currencies. In spot markets, this predictability also persists for stocks (-79 bps, t-statistic = -9.26), foreign exchange (-15 bps, t-statistic = -3.78), emerging-market sovereign bonds (-17 bps, t-statistic = -1.27), corporate bonds (-11 bps, t-statistic = -2.53), and credit default swaps (CDSs) (-17 bps, t-statistic = -7.61). The predictability is persistent up to one year across the abovementioned markets.

Conversely, the "flight to safety" drives up Treasury prices, a phenomenon well documented in the literature (see, e.g., Longstaff, 2004; Krishnamurthy and Vissing-Jorgensen, 2012), and thus lowers their risk premia when the market is highly risk averse, accompanied by a lower willingness to take leverage. On average, a one-unit increase in $DDML$ leads to a 7.64 bp (t-statistic = 2.52) and 4.36 bp (t-statistic = 3.89) increase in the next-month returns for futures and spot fixed-income securities, respectively.[3]

Furthermore, the DML-risk premia relationship is highly nonlinear—it is magnified during deleveraging periods when assets are exposed to greater downside risks. For risky assets, investors demand a substantially higher risk premium in low-leverage periods than in high-leverage periods. For example, in low-leverage periods, a one-unit increase in $DDML$ predicts a 78 bp extra drop (t-statistic = -4.04) in next-month returns on stock indices futures or a 137 bp additional decline (t-statistic = -11.05) in next-month returns on stock portfolios relative to those in high-leverage periods. Similarly, for Treasuries, a one-unit increase in $DDML$ predicts a 12 bp higher monthly return (t-statistic = 2.14) on fixed-income futures or a 13 bp higher monthly return (t-statistic = 6.89) on government bonds in low-leverage periods than that in high-leverage periods.

To illustrate these empirical findings, we build a theoretical model where hedgers, speculators, and consumers interact in the futures and spot markets. Hedgers take a short position in the futures market to hedge away price risks, originating from customers' demand variation in the spot market. Speculators, as counterparties to hedgers, trade with a margin pledged such that leverage is endogenously generated. In this setting, we identify an inverse relation between leverage and risk aversion, i.e., deleveraging happens when investors are relatively more risk averse. The model further indicates a negative relationship between leverage and risk premia in both futures and spot markets of risky assets and a positive relationship between risk aversion and the demand for safe assets that leads to a positive

[2]We detrend DML by subtracting its moving average of the past 12-month levels.

[3]These empirical results correspond to the negative stock-bond relationship documented by Campbell, Pflueger, and Viceira (2020) and Li, Zha, Zhang, and Zhou (2022).

linkage between leverage and risk premia of safe assets.

There are two potential underlying drivers for leverage changes: funding conditions and market risks. A dynamic impulse-response analysis further confirms our conjecture that DML is primarily risk-driven, not funding liquidity-driven. We also find that DML is procyclical, responding to changes in economic and financial uncertainty but leading to changes in borrowing and credit conditions.

Literature

Our paper relates and contributes to the literature in several important ways. First, leverage is more pervasive in the derivatives market, where investors in the futures market deposit on average only one of every twenty dollars of a contract, than in the spot market, where investors pay for a larger portion of the assets out of their own pockets, due to tighter margin requirements by regulators. Garleanu and Pedersen (2011) deduce a margin premium for assets with higher margin requirements that discourage excessive speculation. In particular, derivatives' embedded leverage alleviates investors' funding constraints and lowers required returns (Frazzini and Pedersen, 2021).

Existing studies mostly regard margins as a risk management tool for clearinghouses[4] and are thus viewed as exogenous to investors' trading processes. For example, Hedegaard (2014) empirically test that margin requirements are determined by futures price risks and margin increases reduce speculators' position more than hedgers'. Daskalaki and Skiadopoulos (2016) investigate the effects of the 2010 Dodd-Frank Act,[5] which imposed significant margin changes to restore the price stability of the commodity futures market. They document that changes in margin requirements have a negative relationship with commodity futures returns. Capponi and Cheng (2018) build a theoretical model of a profit-maximizing clearinghouse's margin decision. Although the initial margin on the derivatives market is mechanically set by the clearinghouse, investors still have the discretion to choose excess equity as a buffer against unexpected losses from margin calls. This is empirically documented by Subrahmanyam, Tang, Wang, and Yang (2023) using account-level futures trading data.

In addition to the derivatives market, there is extensive research on the effects of margin changes in the stock market. For example, Kupiec and Sharpe (1991) illustrate that, in an overlapping generations (OLG) model with heterogeneous preferences, fluctuations in the average investor's risk-bearing propensity impact the relationship between margin and

[4]To minimize the counterparty credit risk between clearinghouses and traders, each futures contract entails an initial margin requirement (or the minimum paid-in capital) and variation margin adjustments (also called mark-to-market payments).

[5]This regulation was designed to set a higher margin to curb excessive speculation and to prevent market failures, following the forensic evidence confirming that oil speculators were driving up prices.

price volatility. Rytchkov (2014) further endogenizes the margin requirement and finds that margin has no standalone impact on the volatility of returns but that its interactions with other market imperfections are more important. Empirically, Kahraman and Tookes (2017) use unique data from India on the daily total outstanding margin position for each stock and find that the eligibility to margin financing relieves capital constraints but is negatively related to stock returns. Jylhä (2018) focuses on the episodes when margin requirements changed during the 1990s and attributes the failure of the capital asset pricing model (CAPM) to the margin constraint, which significantly affects the price of risk. Using detailed account-level data in China, Bian, Da, He, Lou, Shue, and Zhou (2023) find that margin traders actively adjust their leverage level by liquidating stocks when approaching margin calls. However, in our setting, market leverage turns out to be less related to capital constraints but more related to investors' risk preferences.

Also, our paper relates to the literature on intermediary asset pricing. For example, Fleckenstein and Longstaff (2020) propose a price measure to quantify the shadow cost of renting intermediary balance sheet space—the basis differential between derivatives and cash funding on the Treasury futures market. Santos and Veronesi (2022) endogenize the intermediary leverage driven by heterogeneous time-varying risk aversion. Adrian, Etula, and Muir (2014) construct a leverage ratio of brokers and dealers using Federal Reserve Flow of Funds quarterly data. He, Kelly, and Manela (2017) aggregate public financial information of primary dealers' holding companies to derive their intermediary capital ratio. Deuskar, Kumar, and Poland (2020) compute intermediaries' margin capacity based on the margin statistics of primary securities dealers. The last three papers provide empirical measures of intermediary leverage, but are all at a quarterly frequency and largely rely on much-delayed balance sheet information.

Our market leverage ratio is distinguished from these book leverage ratios in two important aspects. First, we start from derivative traders' funding status rather than intermediaries' capital constraints. Notably, for intermediaries, as counterparties to investors, their leverage appears to be naturally countercyclical; whereas DML, representing the risk exposure of investors, appears to be naturally procyclical. Second, these book-based intermediary leverage ratios are much-delayed due to reporting lag, prone to measurement errors due to accounting practices, and less-frequently updated—quarterly at best. In contrast, our DML measure relies on more timely updated futures trading data at a monthly frequency. Nearly all trades go through futures commission merchants (FCMs), who report the aggregate equity of all trading accounts to the Commodity Futures Trading Commission (CFTC) every month. These monthly reports, along with market data available to the public, enable us to precisely measure the aggregate leverage in the derivatives market in a more timely manner.

One important strand of literature focuses on the relationship between funding liquidity and risk premia. The classical model of a liquidity spiral by Brunnermeier and Pedersen (2009) illustrates the destabilizing effect of margins on asset prices. Empirically, specifically for the stock market, Lee (2013) constructs a proxy for funding liquidity based on the differential margin requirement of large and small stocks and shows that his funding liquidity measure significantly forecasts aggregate stock market excess returns and future GDP growth. In addition, Adrian, Etula, and Muir (2014) approximate funding liquidity with intermediary leverage, and identify a positive price of risk such that assets correlated with their intermediary leverage earn higher risk premia. However, He, Kelly, and Manela (2017) find a negative price of leverage risk, since the intermediary leverage is countercyclical in their framework. Kargaer (2021) reconciles the seemingly contradictory patterns of these two intermediary leverage measures through the framework of the heterogeneity nature of intermediaries—such that broker-dealers are more aggressive than bank-holding companies.

Derivative-market leverage, DML, reflects the extent to which investors lever up their own capital to increase not only funding liquidity but also asset purchases. Our evidence shows that, specifically, leverage and illiquidity are only negatively correlated during recession periods but are not substantially correlated during expansion periods. Empirically, various capital and liquidity proxies have no predictive power for leverage, yet leverage changes precede funding condition changes. Moreover, the return predictability of leverage holds in the median term up to one year, unlike the extreme short-term impact of funding liquidity—in days or weeks.

Lastly, our market-level leverage also relates to the derivative pricing literature. The fundamental determinants of risk premia in commodity futures markets have been attributed to the level of inventories and convenience yield (see, e.g., Fama and French, 1987; Gorton, Hayashi, and Rouwenhorst, 2013; Szymanowska, de Roon, Nijman, and van den Goorbergh, 2014). The most relevant market-level measure is the open-interest growth variable proposed by Hong and Yogo (2012), which has macroeconomic implications and predicts returns. We have included the aggregate open interest as the denominator of our measure. However, our market leverage measure, combining futures dealers' margin positions with the aggregate trading positions, contains much richer information on investors' risk-taking capacity month-by-month. Thus, after controlling for the fundamental determinants, market leverage still has significant risk premium implications.

The remainder of this paper is organized as follows. Section 2 describes how to construct the DML and other main variables with summary statistics. Section 3 documents the predictive power of the $DDML$ on asset returns across various markets. Section 4 links market leverage to economic and financial conditions. Section 5 analyzes the components of derivative-market leverage. Section 6 presents a simplified model to interpret our empirical findings. Section 7 concludes the paper.

2 Summary Statistics

In this section, we describe how to construct our market leverage measure and provide summary statistics for key variables. We use publicly available data on aggregate margin holdings of all investors from the U.S. CFTC official releases and all futures' dollar open interest to construct our leverage measure in the derivatives market. Futures price data are from Commodity Research Bureau.

2.1 Variable Construction

Derivative-Market Leverage: The derivative-market leverage (DML) is constructed as the ratio of the total dollar amount traded in the U.S. futures and options on futures markets divided by the total equity in the corresponding margin accounts:

$$Leverage_t = \frac{\sum_i OpenInterest_{i,t} * Price_{i,t}}{\sum_j Margin_{j,t}} \tag{1}$$

where $OpenInterest_{i,t}$ and $Price_{i,t}$ are the open interest and the futures price of asset i at month t. $Margin_{j,t}$ is the overall margin of customers separately managed by the FCM j at month t.[6]

Since 2002, the CFTC has required FCMs and retail foreign exchange dealers (RFEDs) to file a monthly report (FCM report) within 17 business days after the end of each month. Each FCM must report the total amount of funds that are segregated on behalf of customers who are trading on futures and options markets under the regulatory oversight of the CFTC. We sum up the funds segregated for the customers across all FCMs, which can be regarded as the overall margin for U.S. derivatives investors.

The numerator is the total dollar amount of open interest for all futures and options on futures (accounted as Black-Scholes deltas of futures) traded in the U.S. market. The CFTC publishes the total open interest (futures and options combined) in the Commitments of Traders (COT) reports for each asset every Tuesday. Based on the open interest of various contracts, we select 45 actively traded futures on U.S. exchanges since 2002, covering 97.36% of dollar total open interest at the end of 2002. To ensure the representativeness

[6] Following the convention in the futures market, e.g., Kang, Rouwenhorst, and Tang (2020), we use the nearby futures prices because they are the most liquid prices and closely move with prices of other maturities.

of our sample, we cover a broad range of assets, including 26 commodities,[7] 8 currencies of developed economies, 6 fixed incomes with varying maturities, and 5 equity indices of four exchanges.[8] The details of the futures are shown in the Appendix (Table A1).

In Figure 1, we plot the time series of the DML level for the full sample period—March 2002 to December 2021—in the top left, along with the denominator (total margin) and numerator (dollar open interest) in the top right. Both components present an upward trend over two decades. The open interest tends to decline sharply during recessions due to weakened trading demand. However, the total margin increases abruptly, corresponding to higher margin requirements of clearinghouses during periods of turmoil. These two opposing forces reinforce the deleveraging outcomes during the 2008 financial crisis and the 2020 COVID-19 pandemic shock. Graphically, DML appears to track economic booms and busts reasonably well. Presumably, the variation in leverage and economic growth, presenting similar cyclicality, should be interconnected through the price effect of financial assets (Geanakoplos, 2010), which motivates us to further investigate its risk premia implications.

[Figure 1 about here]

To ensure stationarity and better exploit the economic meaning of the variation in the leverage ratio, we construct the detrended derivative-market leverage, $DDML$, by subtracting the moving average of past 12-month leverage levels (bottom left of Figure 1). Statistically, this alleviates the spurious regression problem since a highly persistent regressor magnifies bias and weakens the power of inference. As a comparison, we also detrend the denominator ($DTMargin$) and the numerator ($DTOpInt$) of the derivative-market leverage by subtracting their past 12-month average (bottom right of Figure 1).

It seems that investors are continuously taking more leverage during economic expansions and deleverage aggressively once entering an economic contraction. As shown in the right panels of Figure 1, the (detrended) open interest exhibits substantial variation and plummets during recessions. However, the total (detrended) margin rises more abruptly once entering a recession. Therefore, the sharp decline in leverage during a financial crisis is driven by both shrinking market trading activities, gauged by the open interest, and higher margins in trading accounts as safe buffers.

For spot markets, following Haddad and Muir (2021), we collect a wide range of assets, including stocks, government bonds, currencies, emerging-market sovereign bonds, corporate

[7]The same set of commodities selected by Kang, Rouwenhorst, and Tang (2020).

[8]For euro dollar and federal fund futures contracts, since the market price quote is presented as 100 minus the interest rates, we thus use 100-minus-the-market-price as the real price quote.

bonds, and CDS. For stocks, we have 25 size and value sorted portfolios developed by Fama and French (1993). For government bonds, we have 10 maturity-sorted government bond portfolios from CRSP's "Fama Bond Portfolios" file with maturities with six-month intervals up to five years. For foreign exchange, we have 10 portfolios, 5 sorted based on interest differentials following Lettau, Maggiori, and Weber (2014) and 5 based on one-month momentum following Menkhoff, Sarno, Schmeling, and Schrimpf (2012). For emerging-market sovereign bonds, we have 6 portfolios from Borri and Verdelhan (2011) sorted 41 emerging market bond indices, which are risky assets for U.S. investors, by the bond's covariance with stock market return and that with credit rating. For corporate bonds, we have 10 portfolios sorted on yield spreads from Nozawa (2017). For CDS, we have 20 portfolios sorted by spreads constructed by He, Kelly, and Manela (2017).

2.2 Summary Statistics

As shown in Table 1, we have 238 observations for the DML level, spanning from March 2002 to December 2021, with a mean of 16.72 during the sample period. The denominator, the total margin, on average, is 0.14 trillion dollars with a standard deviation (SD) of 0.05 trillion. The numerator, the aggregate open interest, is worth 2.41 trillion dollars on average, with an SD of 1.07 trillion.

[Table I about here]

As an initial step to explore the relationship between DML and financial market conditions, we plot the time series with the volatility index (VIX), the default spread (DEF), the funding liquidity proxy (TED spread), and the market liquidity proxy ($Noise$) in Figure 2. Graphically, when entering recessions (gray areas in the graphs), leverage declines in tandem with the surge in volatility risk, credit risk, and liquidity costs. Leverage is negatively correlated with market risks not only during recessions but also during normal periods. However, as shown in Panel B of Table 2, when excluding recession periods, leverage is not significantly correlated with either the funding or market illiquidity proxies.[9]

[Figure 2 about here]

[Table II about here]

[9]Note that the $DDML$ is negatively correlated with illiquidity and risk (aversion) for the full sample period.

Furthermore, we examine the relationship between DML and risk aversion by first plotting the time-series of risk aversion coefficients (RA_{BEX}) deduced by Bekaert, Engstrom, and Xu (2021), the implied risk aversion from volatility risk measures (variance risk premium, or VRP) created by Zhou (2018), and the risk-bearing capacity of intermediaries (intermediary capital ratio, or ICR) developed by He, Kelly, and Manela (2017). As shown in Figure 3, when risk aversion rises or risk-bearing capacity declines, DML declines sharply to a low level, mostly during recessions. This is also consistent with Santos and Veronesi (2022), where the authors theoretically demonstrate that households will borrow less when their risk-bearing capacity diminishes as economic conditions deteriorate. In addition, $DDML$ is significantly negatively correlated with the risk aversion level both in and out of recessions, although with a lower magnitude during normal times (Table 2). This supports our main hypothesis that the impact of risk premia from derivative-market leverage mainly goes through the investors' risk attitude channels.[10]

[Figure 3 about here]

Table A1 provides standard summary statistics of excess returns on futures used in our sample. The mean excess return of all futures is positive for 39 of 45 markets, averaging 0.36% per month across all futures, with an average SD of 6.05%. This corresponds to an average annualized excess return of 4.32% and an annualized SD of 20.96%. For commodity markets, the average annualized excess return is 4.66%, with an average annualized SD of 29.35%. For financial futures, the average annualized excess return is slightly lower, 3.92%, but with a substantially lower SD of 9.44%. Specifically, the average annualized excess return for 8 currency futures is 1.08%, with an average SD of 9.90%. The average annualized excess return for 6 fixed income futures is 1.82%, with an average SD of 3.51%. The average annualized excess return for 5 stock index futures is 10.99%, with an average SD of 15.83%.

For spot markets, Table A2 presents summary statistics of portfolio returns. Stock portfolios have a higher average excess return in the spot market, annualized at 12.48% with an average SD of 19.81%. The average annualized excess return for 10 government bond portfolios is 1.2%, with an average SD of 2.22%. Currencies have negative returns (-0.12%) in the spot markets with a substantial SD (8.49%), because we add currencies for developing countries, whereas only currencies for developed countries are included for futures markets.

[10] The variance risk premium (VRP) and the intermediary capital risk factor ($ICRF$ as a stationary version of ICR) are positively correlated during normal times but have no significant relation during recessions, indicating that these two measures capture different aspects of economic risks, specifically, variance risk and capital risk.

Among the other three non-Treasury bonds, emerging-market sovereign bonds have the highest average return (7.44%) and SD (11.60%).

We further decompose the total open interest by each asset class. As shown in Figure 4, fixed income futures constitute the most significant proportion, approximately 25% to 50% of the aggregate dollar open interest. Commodities futures and stock index futures have comparable open interest values, although the former is declining and the latter is considerably more stable in our sample period. Futures on currencies present the lowest weights, with nearly 5% of total interest.

[Figure 4 about here]

We also calculate the dollar-based net trading positions of noncommercial traders and commercial traders by asset class[11], shown in Figure IA1. The net positions of fixed income futures negatively correlate with stock indices and commodities for both commercials and noncommercials.[12] These opposite trading positions would lead to diverging risk premia between fixed income and risky asset classes, as well as their responses to leverage changes, which we examine in later sections.

3 Return Predictability of Derivative-Market Leverage

In this section, we focus on assessing the predictive power of detrended derivative-market leverage ($DDML$) for returns of different asset classes in both futures and spot markets.

3.1 Predictability in Futures Markets

We run a baseline panel regression of one- and two-month ahead futures returns on $DDML$ as well as other control variables for various asset classes including equity indices, fixed income, currencies and commodities:[13]

[11]Note that the net trading position for each futures contract is the nearest price multiplied by the difference between the number of long contracts and the number of short contracts. We aggregate the net positions of all futures in that asset class.

[12]For commercial traders, the net position for fixed income has a -0.22 correlation coefficient with commodities and a -0.38 correlation with stock indices. For noncommercial traders, the net position for fixed income has a -0.24 correlation with commodities and a -0.43 correlation with stock indices. All these correlations are significant at the 1% level.

[13]Typically we regard one month ahead as the short-term return horizon. However, since the margin data are released with at most a one-month delay, hence the market leverage measure, we also use two months ahead as the "real-time available" short-term return horizon.

$$R_{i,t+j} = b_0 + b_1 DDML_t + b_2 R_{i,t} + b_3 M_{i,t} + b_4 B_{i,t} + b_5 TED_t + FE_{futures_i} + FE_{year_T} + \epsilon_{i,t+j} \quad (2)$$

where $R_{i,t+j}$ is the excess return of futures i in month $t+j$, $j = 1, 2$, $R_{i,t}$ is the excess return of futures i in month t, $B_{i,t}$ is the log basis of futures i at the end of month t, $M_{i,t}$ is the momentum return of futures i for month t, TED_t is the TED spread in month t, $FE_{futures_i}$ is the fixed effect for futures i, and FE_{year_T} is year T's fixed effect. In all of the predictive regressions, we make a Newey-West correction (Newey and West, 1987) to the t-statistics for serial correlation and heteroskedasticity of the residuals.

Note that we construct two futures characteristics that are widely adopted to forecast futures returns, basis and momentum, as control variables.[14] The (log) basis is motivated by the concept of carry (Koijen, Moskowitz, Pedersen, and Vrugt, 2018), which is the return on a futures position when the price remains constant over the holding period. It also has prominent predictive power for returns across all asset classes. We define $Basis_{i,t}$ as $\frac{ln(F_i(t,T_2))-ln(F_i(t,T_1))}{T_2-T_1}$, where $F_i(t,T_1)$ and $F_i(t,T_2)$ are the prices of the closest- and next-closest-to-maturity contracts for futures i in month t. For momentum ($M_{i,t}$), following Asness, Moskowitz, and Pedersen (2013), the price momentum measure is calculated as the futures' past twelve-month cumulative returns, omitting the most recent month. In addition, we adopt the lagged return variable to capture the short-term impact of past prices. Last, referring to Frazzini and Pedersen (2014), we include the TED spread as the proxy for funding liquidity conditions.

Table 3 reports the coefficients, Newey-West adjusted t-statistics, and adjusted R^2 for the $DDML$ and controls for the sample period from March 2003 to December 2021. For the one-month ahead return prediction, an additional unit of $DDML$ is associated with a 39 bp (t-statistic = -3.95) decrease in excess returns for commodities, a 65 bp (t-statistic = -4.89) decrease for futures on stock indices, and a 20 bp (t-statistic = -3.97) decrease for futures on currencies. Conversely, changes in $DDML$ have a significantly positive influence on returns of fixed-income futures. A one-unit increase in $DDML$ leads to an 8 bp (t-statistic = 2.52) higher excess return for fixed income.[15] In addition, we provide results for two-month ahead return prediction in Panel B. The results are consistent with the one-month forecast but with

[14]For commodities, Bakshi, Gao, and Rossi (2017) find that the three-factor model—an average commodity factor, a carry factor, and a momentum factor—can explain the cross-sectional variations of returns. Moreover, carry and momentum are also effective in a broad set of asset classes, as documented by Koijen, Moskowitz, Pedersen, and Vrugt (2018), and Asness, Moskowitz, and Pedersen (2013).

[15]Equivalently, a one-standard-deviation decrease in leverage is associated with a 0.97% increase in commodities returns, a 1.61% increase in stock-index returns, a 0.50% increase in currency returns, and a 0.20% decrease in fixed-income returns.

slightly lower magnitude and significance. Given that market leverage information would typically be available with a one-month lag, the two-month predictability offers investors sufficient time to react and adjust portfolios based on the movements of $DDML$.

[Table III about here]

As shown in Section 2, investors deleverage when they become more risk averse and thus demanding a higher risk premium on risky assets and leading to a flight-to-safety effect. This explains our empirical results that $DDML$ negatively predicts returns on risky assets, e.g., futures on stock indices, commodities, and currencies, but positively predicts returns on safe assets, i.e., futures on Treasuries.

3.2 Predictability in Spot Markets

Similar to Haddad and Muir (2021), we deduce $DDML$'s risk premia implications across asset classes by regressing the one- and two-month ahead portfolio excess returns on the $DDML$ for each asset class:

$$R_{m,t+j} = b_0 + b_1 DDML_t + b_2 TED_t + b_3 R_{m,t} + FE_{port_m} + FE_{year_T} + \epsilon_{m,t+j}, \tag{3}$$

where $R_{m,t+j}$ is spot portfolio m's excess return in month $t+j$, $j = 1, 2$. We add two controls to the regressions, i.e., the TED spread controlling for the market liquidity and the one-month lagged returns controlling for short-term momentum or reversal.

As shown in Panel A of Table 4, for the one-month ahead return prediction, the signs of the coefficients of $DDML$ are significantly negative for risky assets and positive for government bonds (the safe-heaven asset), consistent with the results in the futures market. Particularly, a one-unit increase in $DDML$ predicts a 79 bp (t-statistic = -9.26) drop in stock returns, a 15 bp (t-statistic = -3.78) drop in currency returns, a 17 bp (t-statistic = -1.27) drop in emerging-market sovereign bond returns, an 11 bp (t-statistic = -2.53) drop in corporate bond returns, and a 17 bp (t-statistic = -7.61) drop in CDS returns. Moreover, $DDML$ positively predicts the return on government bonds, 4 bps (t-statistic = 3.89) higher corresponding to a one-unit increase in $DDML$. For two-month ahead return prediction (Panel B of Table 4), $DDML$ also negatively predicts returns on risky assets such as stocks, currencies, emerging-market sovereign bonds and CDSs but positively forecasts the returns of safe-haven assets. Overall, these findings are consistent with the results of the one-month prediction.

[Table IV about here]

Moreover, in contrast to the finding in Haddad and Muir (2021) that more intermediated asset classes are more predictable by the intermediary leverage (e.g., CDS and currencies), we find that our $DDML$ has similar, if not stronger, predictive power for even less intermediated asset classes (e.g., stocks and corporate bonds). An illustrative comparison between the market leverage ratio and intermediary leverage ratio can be found in Appendix A.

Overall, the results in above two subsections suggest that the $DDML$ decreases with the risk premia of various asset classes but rises with the safety premium of Treasuries.[16] The predictive power holds for both one- and two-month ahead returns (thus tradable) in both futures and spot markets across various asset classes.

3.3 Long-Term Predictability

To evaluate the long-term predictive power of $DDML$ in the futures market, we estimate the same panel regression as in Equation (3) with longer horizons:

$$R_{i,t+1\to t+j} = b_0 + b_1 DDML_t + \sum_n b_n Controls_{n,i,t} + FE_{futures_i} + FE_{year_T} + \epsilon_{i,t+1\to t+j} \quad (4)$$

where $R_{i,t+1\to t+j}$ is the cumulative return of futures i from month $t+1$ to month $t+j$, $j = 1, 2, 3, ...$, and the $Controls_{n,i,t}$ include lag return $R_{i,t}$, momentum $M_{i,t}$, and basis $B_{i,t}$.

Panel A of Table 5 reports the coefficient estimates of the $DDML$ over longer time horizons in the futures market. The magnitudes of the estimates monotonically increase over the coming quarter. The magnitude of coefficients begins to decline after approximately one year for commodities, stock indices, and currencies; whereas the significance for fixed income lasts for approximately one quarter, while the estimates remain positive up to a one-year horizon.

Panel B of Table 5 reports the long-term estimates of the $DDML$ in spot markets. For risky assets, $DDML$ significantly negatively predicts stock returns, foreign exchanges returns, emerging-market sovereign bonds returns, corporate bonds returns, and CDS returns at an annual horizon. For government bonds, $DDML$ positively predicts returns with a shorter significant horizon (approximately one quarter) but still with a positive sign for up to one year.

Overall, the return predictability persists for approximately one year for risky assets in both futures and spot markets; it holds for approximately one quarter for safe assets, i.e.,

[16] As elaborated by Krishnamurthy and Vissing-Jorgensen (2012), the safety attribute of Treasuries drives investors' high valuation of Treasuries and generates the safety premium.

Treasuries. The long-term return predictability supports $DDML$'s strong relevance to risk aversion, which has a more long-lasting impact on risk premia, rather than to alternative short-term factors such as market or funding liquidity.

[Table V about here]

3.4 Nonlinear Predictability

As shown in the time-series plots, extreme deleveraging happens during market downturns, when the market would demand a disproportionately higher risk premium. To investigate the potential nonlinear effect of our market leverage measure on risk premia, we include an interaction term of the dummy variable $P50$ and the leverage $DDML$ in the regression. To avoid potential look-ahead bias, we set $P50$ to one when $DDML$ in month t is lower than the median level of those in the past 36 months and zero otherwise. For futures markets, Panel A of Table 6 shows that the coefficients of the interaction term for commodities, stock indices, and currencies are all negative. During below-median periods, a one-unit increase in $DDML$ is associated with an on average 78 bp (t-statistic = -4.04) lower next-month returns in stock indices, 25 bps (t-statistic = -2.63) lower in currencies, and 30 bps (t-statistic = -1.51) lower in commodities, compared with those in above-median periods. On the other hand, during below-median periods, a one-unit increase in $DDML$ is associated with 12 bps (t-statistic = 2.14) higher next-month returns on fixed income futures than during above-median periods. In addition, as shown in Panel A of Table A3, the nonlinear predictability does not only hold in one month but also in the long-term—more than one year for futures on commodities, stock indices and fixed income and approximately half a year for currencies futures.

[Table VI about here]

In spot markets, as shown in Panel B of Table 6, $DDML$ has a much stronger effect during low-leverage periods relative to high-leverage periods across all asset classes. Specifically, during below-median periods, a one-unit increase in $DDML$ is associated with an on average 137 bp (t-statistic = -11.05) lower return on stocks, 29 bps (t-statistic = -4.34) lower next-month returns on currencies, 52 bps (t-statistic = -2.63) lower returns on emerging-market sovereign bonds, 19 bps (t-statistic = -2.55) lower returns on corporate bonds, and 26 bps (t-statistic = -7.80) lower returns on CDSs, compared with those in above-median periods. Government bonds, on the other hand, increase 13 bps (t-statistic = 6.89) more in the next month in low-leverage periods than in high-leverage periods when $DDML$ increases by one unit. Similarly, the nonlinear predictability also holds for assets in the spot market in the long-term, for more than a year (Panel B of Table A3).

Such a nonlinearity in both futures and spot markets can originate from risky assets' asymmetric exposure to risk. They covary more strongly with the market when the market declines than that when the market improves, i.e., they have higher downside betas than upside betas (see, e.g., Ang, Chen, and Xing, 2006; Lettau, Maggiori, and Weber, 2014). During deleveraging periods, risky assets, with declining prices, are exposed to greater risks (larger betas), hence associated with considerably higher risk premia. On the contrary, Treasuries as safe assets, with higher prices due to the "flight-to-safety" effect during deleveraging periods, are associated with a considerably lower risk premium (see, e.g., Longstaff, 2004; Krishnamurthy and Vissing-Jorgensen, 2012). The long-term nonlinear return predictability supports the risk-based explanation such that the downside risk, more prominent in the low-leverage state, persistently reinforces the impact of $DDML$ on risk premia.

3.5 Horse Race with Leading Competitors

To verify the unique contribution of $DDML$, we first compare its predictive power with two leading competitors: VRP, the difference between implied variance and realized variance, capturing the priced variance risk (Zhou, 2018), and $ICRF$, a risk factor based on the intermediary capital level that determines intermediaries' risk-bearing capacity (He, Kelly, and Manela, 2017). Table 7 presents the results.

[Table VII about here]

For risky assets, the first row of Panel A and Panel B of Table 7 shows that the univariate forecasting power of the $DDML$ alone is already strong enough to explain a substantial fraction of the variation in the next month's return in both futures and spot markets.[17] Adding controls mildly enhances the predictive power of $DDML$, in terms of magnitude and significance, as shown in the 3rd row. Regarding the leading competing predictors, VRP has significant predictive power for non-Treasuries futures, as shown in the 4th and 5th rows; whereas $ICRF$ has significant predictive power for all assets, though with non-differentiable negative coefficients. However, $DDML$ substantially increases the $Adj.R^2$ in both panels and remains quite significant, as illustrated from the 4th to the 5th and from the 6th to the 7th rows, suggesting that $DDML$ contains different risk premia implications from VRP and $ICRF$.

[17] The magnitudes of $Adj.R^2$ in the 1st row are considerably higher than those in the 2nd row (the regression with only controls).

For safe assets, as shown in the bottom panels of Table 7, $DDML$ has persistently positive return predictions for government bonds in both futures and spot markets with or without additional predictors. Similarly, $DDML$ substantially increases the $Adj.R^2$ in both panels for Treasuries and maintains its statistical significance, as illustrated from the 12th to the 13th and from the 14th to the 15th rows, suggesting $DDML$'s unique contribution to explaining the safety premium.

Ultimately, the last row of each panel in Table 7 shows that $DDML$'s forecasting power survives the horse-race tests, with its significance and economic magnitude almost unchanged, if not slightly enhanced. $DDML$, variance risk, and intermediary leverage, although positively correlated as shown in Table 2, all have different risk premium implications.

3.6 Robustness Checks

First, we directly use the derivative-market leverage level (DML) instead of $DDML$ in the baseline regression. As shown in Table 8, the leverage level still significantly predicts returns but mostly with lower magnitudes and significance of the coefficients than those using detrended leverage $DDML$ in both futures and spot markets. The trend component of the leverage level might impair its predictive power due to obvious nonstationarity.

[Table VIII about here]

For robustness, we apply an alternative detrending methodology, using the change in leverage relative to its level with a one-year lag ($yoyDML_t = DML_t - DML_{t-12}$). Note that the change on a year-over-year basis removes any potential seasonality effect. The results are presented in the middle panel of Table 8. The magnitudes of the coefficients are slightly lower than those of the $DDML$ and modestly higher than those of the leverage level.

Finally, we calculate the dollar open interest using a one-month lagged price rather than the contemporaneous price to downplay the potential lead-lag effect caused by asset prices. As shown in Figure IA2, the market leverage (blue line) and the lagged version of leverage (red dashed line) comove closely. Using the new $DDML$, our results also hold significantly, i.e., leverage negatively (positively) predicts the returns of risky (safe) assets (the last panel of Table 8) in both futures and spot markets.

In summary, the significant relationship between market leverage and risk premia holds for three alternative leverage measures, which confirms the robustness of our results.

4 Determinants of Derivative-Market Leverage

In this section, we provide a heuristic analysis of the potential determinants of the derivative-market leverage, DML, which is more of a risk-based than a liquidity-based outcome. Moreover, DML is procyclical—it rises during economic expansions and decreases during economic contractions.[18]

4.1 Market and Economic Risks

The time-series plot of DML and VIX in Figure 2 (top-left) provides a graphical indication that market leverage has a close link with market risks. Following Deuskar, Kumar, and Poland (2020), we investigate this linkage using a bivariate vector autoregressive (VAR) model to test the Granger causality between $DDML$ and various proxies for market risks, which includes the VIX index, and the realized volatility, RV, which is the model-free realized variance measure based on high-frequency intraday S&P 500 index pricing data obtained from Zhou's personal website.[19] Table 9 displays the results. We find that these volatility measures strongly predict the declines in $DDML$ in the next period, which is significant at the 1% level, but the prediction does not hold in the opposite direction.

[Table IX about here]

Moreover, we test the relationship between $DDML$ and economic risks or uncertainties, including macroeconomic uncertainty ($MACRO_U$) (Jurado, Ludvigson, and Ng, 2015) and financial uncertainty ($FINANCIAL_U$) (Ludvigson, Ma, and Ng, 2021). The Chicago Fed also releases a comprehensive measure of macroeconomic risk, $NFCI_{Risk}$, the risk subindex of the National Financial Conditions Index (NCFI). [20] We find that $DDML$ responds to macroeconomic risks but does not lead to them. Among these risk (uncertainty) measures, macroeconomic uncertainty has the largest impact on market leverage such that a SD increase in $MACRO_U$ would lead to a 0.20-SD decline in $DDML$. For financial uncertainty ($FINANCIAL_U$, $NFCI_{RISK}$), the predictability is bidirectional, both from risk to $DDML$ and from $DDML$ to risk. However, a one-SD increase in $FINANCIAL_U/NFCI_{RISK}$ is associated with a substantially larger $DDML$ decrease (-0.16/-0.08) than the impact in the opposite direction (0.03/0.05).

[18] A detailed analysis is presented in Appendix B.

[19] The annually updated series of implied variance, realized variance, and the variance risk premium can be downloaded from http://sites.google.com/site/haozhouspersonalhomepage/.

[20] It is a weighted average of 34 indicators capturing volatility and funding risk in the financial sector.

Next, we employ the local projection method proposed by Jordà (2005) to characterize the dynamic relationship between $DDML$ and risks. We construct a composite risk index by estimating the first principal component (PC) of the five risk measures.[21] After standardizing both $DDML$ and the composite index to have zero means and unit standard deviations, we estimate two-way impulse responses between leverage and the composite risk for 12 months.[22] As shown in the top panels of Figure 5, a one-SD increase in the risk index would lead to an approximately 0.5-SD contemporaneous decrease in leverage and a nearly 0.8-SD decline at the quarterly horizon. This depressive effect persists for approximately one year. However, innovations in DML have no significant impact on risks, suggesting a one-way transmission channel from risk to leverage, not vice versa.[23]

[Figure 5 about here]

Overall, we find that the market deleverage responds to the observed increase in market risks. This mechanism aligns with our theoretical model's implication such that investors, on aggregate, take less leverage when market volatility is higher.

4.2 Funding Conditions

In this section, we perform a bivariate VAR analysis on $DDML$ and funding conditions, which includes three measures of the cost of capital and two measures of borrowing, i.e., the U.S. Federal funds rate ($FFunds$), the bank prime lending rate ($Bank_{Prime}$), and the Treasury bill rate (TBL) used by Welch and Goyal (2008), the monthly percentage change in bank credit for all commercial banks ($Credit_{CHG}$) following Gandhi (2016), and the percentage change in borrowing for all commercial banks ($Borrow_{CHG}$).

As shown in Table 10, a higher willingness to borrow, proxied by higher interest rates and greater amount of credits/borrowing, has no significant predictive power for $DDML$. Conversely, higher $DDML$ predicts higher capital demand. A one-SD increase in $DDML$ would lead to a 0.03-SD rise in the Federal funds rate and the bank prime rate, a 0.02-SD rise in the T-bill rate, a 0.17-SD rise in borrowing growth, and a 0.10-SD increase in credit growth. Therefore, higher leverage is a signal for a higher demand for capital, driving up the cost of capital and total capital growth.

[21] The first PC explains 72.31% of the total variation in risk proxies. The eigenvalues of each variable in the first PC are all positive: 0.49 for VIX, 0.42 for RV, 0.42 for $MACRO_U$, 0.47 for $FINANCIAL_U$, and 0.43 for $NFCI_{risk}$.

[22] Based on the Akaike information criterion (AIC) and Schwarz Bayesian information criterion (SBIC), we choose three-period lags of the response variable and four-period lags of the variable with the shock.

[23] $DDML$ only has limited alleviating effects on risks, with marginal statistical significance in the first month.

[Table X about here]

We also conduct the same impulse-response analysis by first forming a composite capital index based on the first PC of five funding proxies.[24] As shown in the bottom panels of Figure 5, shocks to capital conditions have no significant effect on leverage, but higher leverage indicates significantly higher capital demand up to the following year. The high level of DML indicates that investors are more risk seeking, and thus willing to bear higher interest rates to borrow more money. Moreover, the impulse-response analysis shows that the impact of $DDML$ is persistent, which can predict capital demand for as long as a year.

5 Components of Derivative-Market Leverage

In this section, we explore the characteristics and predictive power of the numerator (the total open interest) and the denominator (the aggregate margin) of derivative-market leverage and further compare their predictive power for returns to that of $DDML$.

5.1 Variation in Margin

Due to margin requirement regulation, one may wonder if the variation in market leverage mainly originates from that of open interest and not substantially from orthogonal margin adjustments. Based on the summary statistics in Table 1, the coefficient of variation of the aggregate margin (0.34) is significant, although less than that of open interest (0.44), but still higher than that of the leverage ratio (0.27). In the following, we also show that the aggregate margin far exceeds the required margin.

The customers' funds segregated by FCMs can be decomposed into the initial margin as a requirement to enter futures contracts and the additional margin as a buffer against price risks. The former is predetermined by clearinghouse rules and futures trading size, while the latter is entirely at the discretion of futures traders. We quantitatively compared the total amount of customer funds held for futures trading and the aggregated customers' futures initial margin using the cleared margin reports published by CFTC since December 2013.[25] The average ratio of excess margin (the aggregate margin deducted by the initial margin) to the aggregated initial margin is 0.64 for all contracts (refer to Figure 6). Therefore, the

[24] The first PC explains 64.05% of the total variation in capital condition proxies. The eigenvalues of each variable in the first PC are all positive: 0.55 for $FFunds$, 0.54 for $Bank_{Prime}$, 0.54 for TBL, 0.25 for $Credit_{CHG}$, and 0.22 for $Borrow_{CHG}$.

[25] Since the summary information of the initial margin includes non-U.S. exchanges, we calculated the total amount of funds including customers who trade on commodity exchanges located both inside and outside of the U.S., using the FCMs' financial reports.

aggregate margin exceeds the initial margin to a large extent and is hardly bound by the required *maintenance* margin, which is substantially lower than the initial margin.[26] This is consistent with Subrahmanyam, Tang, Wang, and Yang (2023), which shows that leverage in the futures market is overall harmful to investors mainly due to the forced liquidation of margin calls. Therefore, to avoid the negative impact of forced liquidations, investors tend to preemptively deposit additional margin as a cushion.

[Figure 6 about here]

Furthermore, we also find that both the aggregate margin (denominator) and open interest (numerator) contribute comparably to the variation in DML. The orthogonalized $DTOpInt$ explains 50% of the variation in $DDML$, while the orthogonalized $DTMargin$ accounts for 45%. Therefore, both components are indispensable for explaining the market leverage variation.

5.2 Predictive Power of the Components

For futures markets, we present the return predictability estimates for the denominator $DTMargin$ and the numerator $DTOpInt$ of DML in Table A4 (Panel A to Panel D). For comparison, we report the baseline result in the first column of each panel. As expected, $DTMargin$ positively predicts risk premiums since a higher margin indicates a larger buffer against risks. $DTOpInt$, representing trading activeness, negatively predicts risk premiums but has no significant power in predicting government bond returns. Overall, the same predictive regression using $DDML$ has higher significance and explanatory power (adjusted R^2) than predicting using its denominator ($DTMargin$) or numerator ($DTOpInt$) in a univariate regression with the same set of controls.

In the bivariate regression with the combination of $DDML$ and $DTMargin$ (Column (4)) or $DTOpInt$ (Column (5)), the coefficients for $DDML$ always have a higher significance than its components. Combining $DTMargin$ and $DTOpInt$ (Column (6)), the explanatory power is mostly comparable to the regression using $DDML$ alone. If we include all three detrended series in the predictive regression (Column (7)), the explanatory power does not increase, but the significance level declines substantially, due to the multicollinearity issue. These additional tests all confirm that the leverage ratio encompasses the information in its denominator and numerator. The leverage ratio alone already possesses strong predictive power for returns.

[26] For example, as listed by the CME group, the latest maintenance margin requirement for crude oil is \$7000, which is approximately 8.9% of the contract price as of December 2022, while the initial margin required to enter the contract is \$7700, which is approximately 10%.

We also present the return predictability estimates of DML's denominator $DTMargin$ and numerator $DTOpInt$ in Table A4 for each asset class in spot markets (Panel E to Panel J). $DTMargin$ has insignificant predictive power for returns on sovereign bonds, corporate bonds, and CDSs, while $DTOpInt$ insignificantly predicts returns of currencies and sovereign bonds. These results, overall, show that $DTMargin$ (denominator) and $DTOpInt$ (numerator) in the derivative market, separately, have limited implications for asset returns in the spot market. In the bivariate regression with $DDML$, the estimates of $DDML$ always have a higher magnitude of t-statistic, suggesting $DDML$'s superior predictive power for returns compared to its components.[27]

5.3 Determinants of Components

Moreover, we conduct the same bivariate VAR test on $DTMargin$ and $DTOpInt$ separately as in Section 4, examining whether the components of DML have similar economic implications.

As shown in Table IA1, $DTMargin$ has an insignificant relationship with economic activities;[28] it does not have significant responses to risk measures either. For funding conditions, a higher margin precedes changes in interest rates but not credit amount changes.

From Table IA2, we can see that $DTOpInt$ is nearly unrelated to economic activities.[29] Moreover, it only mildly increases capital demand with substantially lower magnitudes than those using leverage.

Overall, the two components of DML, margins and open interest, have unclear relationships with both risk and funding proxies. The leverage ratio, scaling the total open interest by the aggregate margin, as a substantially purer risk-tolerance indicator, has a better economic interpretation and better relevance to risk premia than its two components.

6 Model-Based Interpretation

In this section, we build a two-period model to rationalize our new findings on the predictive power for returns of the derivative-market leverage DML. The model implication is consistent with our empirical results.

[27]Similarly as shown in futures markets, when we include all three predictors in the regression, the explanatory power is comparable to the bivariate regression due to multicollinearity.

[28]It only significantly responds to unemployment.

[29]It only has a positive response to the $CFNAI$ index at the 10% significance level

6.1 Model Setup

Our model is based on three assumptions. First, there is a positive relationship between the risk premium and the coefficient of risk aversion for a representative investor under the ICAPM (See, e.g., Merton, 1973) framework. Second, as documented empirically by Campbell, Pflueger, and Viceira (2020) and justified theoretically by Li, Zha, Zhang, and Zhou (2022), we assume that the risk premia of risky assets and those of safe assets are negatively correlated. Finally, for brevity, we assume zero inventory costs for all asset classes.[30]

Following the literature, we assume that there are three players: a hedger (h), a speculator (s), and a consumer.[31] The hedger is endowed with two assets ($i = 1, 2$) in each period: a risky asset such as a stock and a safe-heaven asset such as a Treasury bill. The risky asset, by nature, has substantially higher price risks than the safe asset. There are two markets, the spot and futures markets, in the economy, and the two periods are indexed by t and T.

The hedger participates in both the spot market to trade against the consumer, who has an exogenous demand for spot assets, and the futures market to trade against the speculator. In our setting, the price risks are captured by the variances of asset spot prices, which are determined by the variation in the consumer's demand in the spot market: $S_i(T) = \omega D_i(T), D_i(T) \sim N(\mu_i, \sigma_i^2)$, where $S_i(T)$ is the spot price of asset i at time T, $D_i(T)$ is the consumer's demand for asset i at time T, which has a mean μ_i and variance σ_i^2, and ω is a positive constant. Therefore, the expected spot price $E[S_i(T)] = \omega\mu_i$, and the price variance $\sigma^2_{S_i(T)} = \omega^2\sigma_i^2$. Both the hedger and speculator are mean-variance investors.

6.2 Hedger's Problem

In period t, the hedger decides how to allocate her endowment $N_i(t)$ by selling x_i units of endowment to generate a profit of $\sum_i x_i S_i(t)$ and carrying the rest as inventory ($I_i = N_i(t) - x_i$) to the second period T. She also determines the amount to hedge by shorting y_i^h units of futures contracts, to be delivered in period T. At time T, the hedger sells the inventory (I_i) from the previous period and the new endowment ($N_i(T)$), honors the return from futures contracts, and realizes a total profit of $\sum_i (N_i(T) + I_i)S_i(T) + y_i^h(F_i(t,T) - S_i(T)),\ i = 1, 2$, where $F_i(t,T)$ is the price of a futures contract that is initiated in period t and will mature in period T for asset i.

[30] Note that financial assets do have zero inventory costs, while commodity futures do not. Our results do not change when adding inventory costs.

[31] See, e.g., Hirshleifer (1988); Hong and Yogo (2012); Acharya, Lochstoer, and Ramadorai (2013). Although there could be an infinite number of investors in the economy, we normalize the mass to be one, as applied to other market players in this simplified model.

Therefore, the hedger's objective function is:

$$
\begin{aligned}
\max_{I_i, y_i^h} \sum_i x_i S_i(t) \quad &+ \quad E_t[\sum_i (N_i(T) + I_i) S_i(T) + y_i^h (F_i(t,T) - S_i(T))] \\
&- \quad \frac{\gamma^h}{2} Var[\sum_i (N_i(T) + I_i) S_i(T) + y_i^h (F_i(t,T) - S_i(T))] \qquad (5)
\end{aligned}
$$

where the hedger's risk-aversion coefficient γ^h magnifies the hedging demand against price risks.

6.3 Speculator's Problem

The speculator takes the long positions offsetting the hedger's net short positions to allow market-clearing. She can naturally take leverage by depositing W^s endowment in the margin account.[32] Note that for simplicity, we restrict leverage-taking behavior only to the speculator; nonetheless, in the real world, hedgers indeed have considerably less intention to take leverage than speculators.[33]

The objective function for the speculator can be written as:

$$
\max_{y_i^s} E_t[\sum_i y_i^s (S_i(T) - F_i(t,T))] - \frac{\gamma^s}{2} Var[\sum_i y_i^s (S_i(T) - F_i(t,T))] \qquad (6)
$$

where γ^s is the risk-aversion coefficient of the speculator. Additionally, her leverage is $L^s = \frac{\sum_i y_i^s F_i(t,T)}{W^s}$.

6.4 Model Equilibrium

Both futures and spot markets clear, and we have $y_i^h = y_i^s \equiv y_i^*,\ i = 1, 2$, where y_i^* is the equilibrium solution of the hedging amount. Then, the futures risk premium can be shown as in Appendix C:

$$
E_t[S_i(T)] - F_i(t,T) = \gamma^s \{ y_i^* \sigma^2_{S_i(T)} + y_{-i}^* Cov[S_i(T), S_{-i}(T)] \} \qquad (7)
$$

[32] We assume that W^s is a fixed endowment for the speculator, which also satisfies the maintenance margin requirement.

[33] Note that the model would have similar results as long as hedgers take lower leverage than speculators, not necessarily zero leverage. Hedgers enter the futures market to hedge price risks and therefore are more reluctant to enter into large leverage, which imposes a stronger price risk for them. Kang, Rouwenhorst, and Tang (2020) finds that hedgers (commercials) indeed have a substantially lower propensity to trade than speculators (noncommercials). On the other hand, as shown by Daskalaki and Skiadopoulos (2016), speculators are more sensitive to margin changes than hedgers. Overall, speculators trade more aggressively and are more sensitive to funding than hedgers and hence are more willing to take leverage than hedgers.

where $-i$ denotes the type of asset other than i. Based on the leverage definition above, we have $L^s W^s = \sum_i y_i^* F_i(t,T)$, and from Appendix C, we have:

$$L^s W^s = E_t[\sum_i y_i^* S_i(T)] - \gamma^s Var[\sum_i y_i^* S_i(T)] \tag{8}$$

This expression for leverage resembles a mean-variance utility function—either higher portfolio volatility or a higher risk aversion depresses leverage-taking behavior, which is consistent with our empirical findings in Section 4. In Appendix C, we also impose a leverage constraint corresponding to the initial margin requirement in the futures market. The results are qualitatively similar, although with a smaller magnitude, scaled by the shadow cost of capital if under constraint (Lagrangian multiplier).[34]

6.5 Model Implications

Based on the analytical expressions regarding the futures risk premium and market leverage, we can infer certain key comparative statics with respect to the observed leverage from the derivatives market.

Proposition 1: Leverage is negatively correlated with the risk-aversion coefficient of the speculator: i.e., $\frac{\partial L^s}{\partial \gamma^s} < 0$.

Holding the price variation constant, if the speculator has a higher risk-taking capacity, we will observe a higher leverage level in the derivatives market. The first proposition is consistent with our finding (and the common sense) that when investors are more risk averse, they respond by deleveraging to reduce risk exposure.

Next, we can investigate the relationship between leverage and risk premia via the channel of risk aversion. Specifically, when risk aversion (γ^s) rises, investors are willing to pay a lower spot price for the risky asset at time t, i.e., $Cov[S_1(t), \gamma^s] < 0$; whereas they have a higher demand for the safe asset, i.e., $Cov[S_2(t), \gamma^s] > 0$, termed the "flight-to-safety" effect. Therefore, holding all else constant, when risk aversion rises from time t to T, we would expect a higher (lower) risk premium for the risky (safe) asset in the spot market.

Proposition 2: Leverage negatively (positively) predicts spot market risk (safety) premia: i.e., $\frac{\partial [E_t[S_1(T)] - S_1(t)]}{\partial L^s} < 0$ if $Cov[S_1(t), \gamma^s] < 0$, whereas $\frac{\partial [E_t[S_2(T)] - S_2(t)]}{\partial L^s} > 0$ if $Cov[S_2(t), \gamma^s] > 0$.

[34] One possible empirical proxy for such a shadow cost of capital constraint could be the price of renting intermediary balance sheet space—the basis differential between derivatives and cash funding on the Treasury futures market (Fleckenstein and Longstaff, 2020).

For the futures market, the relationship also holds since the futures price equals the spot price at time t. Additionally, the variance of the risky asset is substantially larger than its covariance with the safe asset ($\sigma^2_{S_1(T)} >> |Cov[S_1(T), S_2(T)]|$).[35] Therefore, the sign of the bracketed term in Equation (7) is positive for risky assets, indicating a positive relationship between risk aversion and the excess return of futures on risky assets. However, the sign of the bracketed term in Equation (7) is negative for safe assets ($\sigma^2_{S_2(T)} << |Cov[S_1(T), S_2(T)]|$), indicating a negative relationship between risk aversion and the excess return of futures on the safe asset.

Proposition 3: Leverage negatively (positively) predicts futures risk (safety) premia in the futures market: i.e., $\frac{\partial[E_t[S_1(T)]-F_1(t,T)]}{\partial L^s} < 0$ if $\sigma^2_{S_1(T)} >> |Cov[S_1(T), S_2(T)]|$, whereas $\frac{\partial[E_t[S_2(T)]-F_2(t,T)]}{\partial L^s} > 0$ if $\sigma^2_{S_2(T)} << |Cov[S_1(T), S_2(T)]|$.

Through this model, we show that derivative-market leverage is inversely related to aggregate risk aversion, and it also has predictive power for risky and safe assets in both futures and spot markets. These model implications are consistent with our empirical findings in Section 3.

7 Conclusion

In this paper, we introduce a new leverage measure, derivative-market leverage, based on the positions of futures commission merchants, information that is updated more frequently (monthly) and timely (one-month delay) than those proposed in the literature. Our empirical results suggest that the detrended derivative-market leverage ($DDML$) has significant explanatory power for the risk premia of both futures and spot markets across various asset classes and is persistent up to one year.

Specifically, $DDML$ negatively predicts returns on risky assets, such as commodities, stocks, and currencies, while it positively predicts returns on safe assets, such as Treasuries. We argue that our leverage measure represents a market-implied risk perception, such that deleveraging happens when investors become more risk averse and demand a higher risk premium. This is consistent with the fact that our leverage measure has a prominent correlation with various risk tolerance measures. Meanwhile, the "flight-to-safety" effect, in terms of higher Treasury prices, emerges when investors are highly risk averse and have a lower willingness to take leverage.

[35] As documented in Campbell, Pflueger, and Viceira (2020), the volatility of stock returns is 20.00% in the first decade of the 2000s, the volatility of Treasury returns is 5.98%, and the correlation between bonds and stock returns is -0.64 for this period.

We also discover a nonlinear asymmetric effect of leverage—it has a stronger predictive power for asset returns during deleveraging periods, in terms of higher significance and larger magnitude. This nonlinear predictability also holds in the long run. We further show that leverage has a strong response to risk proxies but is a precursor to capital demand.

Moreover, we rationalize our empirical findings in an illustrative model. In the model, speculator's risk-taking capacity impacts her trading volume, which, in turn, influences her market exposure per unit of capital input (or leverage) in the derivative market. The model, therefore, presents an inverse relationship between leverage and risk aversion. It also shows that the market leverage is negatively (positively) correlated with the risk (safety) premia in spot and futures markets, consistent with our empirical findings.

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Appendix A: Leverage Comparison

This section is devoted to investigating the relationship between our measure of market leverage and widely-used leverage measurements in the literature. We first adjust the market leverage to a quarterly frequency and examine the contemporaneous correlation (Panel A of Table A5). AEM from Adrian, Etula, and Muir (2014), the innovation term of the broker-dealer leverage level, has a positive correlation (0.39) with the detrended $DML(DDML)$. The intermediary capital risk factor ($ICRF$), obtained from the intermediary capital ratio, is also positively correlated with the $DDML$ (0.29).

DML is, by construction, approximately the total assets over the capital of investors in the derivatives market, whereas the measure of the intermediary capital ratio is the aggregate capital over the total assets of primary dealers. These two by construction should be the inverse of each other, assuming that most investors in derivatives markets are institutional investors. Indeed, excluding the observations during recession periods, $DDML$ and $ICRF$ are negatively correlated (Panel B of Table A5). However, the comovement of $DDML$ and $ICRF$ is quite positive during recessions, when both decline sharply in tandem (Figure A1), remaining at a low level until the economy recovers. Certainly, the intermediary leverage is depressed by shrunken equity value during economic contractions. By contrast, in the derivatives market, aggressive deleveraging during a recession is due to both less trading demand and a higher margin as a safe buffer when facing high uncertainty. Therefore, the two factors comove in recessions but for different reasons.

Moreover, Haddad and Muir (2021) average the leverage factor from Adrian, Etula, and Muir (2014) and the intermediary capital risk factor from He, Kelly, and Manela (2017) as a proxy for the intermediary risk aversion that might be proportional to risk premia. In addition, they borrow CAY from Lettau and Ludvigson (2001), which is a combination of aggregate consumption, labor income, and asset wealth, as a proxy for household risk-bearing capacity. Our market leverage is negatively correlated with CAY, indicating that market deleveraging also occurs in periods of high risk aversion in the household sector, instead of constraining to intermediaries.

For dynamic analysis, as shown in Table IA3, $ICRF$ comoves with economic activities, thus the intermediary leverage is countercyclical. Moreover, $ICRF$ negatively responds to funding conditions and slightly decreases market uncertainties. Overall, given the small correlation among the three leverage-related factors as well as diverging economic meanings, our $DDML$ factor is distinguished from existing intermediary leverage measures.

As shown in the last row of Table A5, the GDP growth is significantly positively correlated with $DDML$ and AEM, while insignificantly positively correlated with $ICRF$. These reflect the procyclicality of derivative-market leverage and broker-dealer leverage, while the countercyclicality of intermediary leverage (or the procyclicality of the intermediary capital) proposed by He, Kelly, and Manela (2017). These results accord with the findings in the original papers.

Also, most primary dealers are banks, as documented by He, Kelly, and Manela (2017). However, non-bank financial institutions are taking a more prominent role after more stringent regulation on banks after global financial crisis in 2008 (Aramonte, Schrimpf and Shin, 2021). The speculators in the derivative markets are mostly these non-bank financial intermediaries such as money managers and hedge funds. Therefore, the derivative-market leverage depicts a more up-to-date risk capacity portrait of dominant intermediaries in the financial market.

Appendix B: Derivative-Market Leverage and Real Economic Activities

Since risk and uncertainty shocks often precede changes in macroeconomic conditions, we expect that DML is also likely related to real economic activities more contemporaneously. As expected, $DDML$ has a significant and positive contemporaneous correlation with the monthly growth rates of real GDP (0.25).[36] The trend deviation of DML is highly procyclical, as graphically illustrated in Figure 1 (bottom left), which shows that $DDML$ tends to rise during expansions and decline abruptly once entering a recession.

We formally run a bivariate VAR as in Section 4, testing the Granger causality between $DDML$ and six proxies for real economic activity ($EAct$). First, $\Delta Uemp$ is the average change in the unemployment level for the next 12 months (Deuskar, Kumar, and Poland, 2020). The unemployment data are from the Bureau of Labor and Statistics website. In addition, we obtained the CFNAI and its subindices from Chicago Fed's website. The positive value of each of these indices indicates an optimistic economic outlook, whereas negative values imply less potential for economic growth. These four subindices of CFNAI encompass different aspects of economic growth: production and income (CFNAI-PI); employment, unemployment, and hours (CFNAI-EUH); personal income (CFNAI-PCH); and sales, orders, and inventories (CFNAI-SOI). We take the moving average for each of these five indices over the next 12 months.

Table A6 presents the VAR results for standardized $DDML$ and $EAct$. A higher $DDML$ significantly predicts higher unemployment and lower economic activity in all aspects except for "personal income" and "sales, orders, and inventories." Economically, a one-SD increase in $DDML$ implies a 0.14-SD rise in unemployment and a 0.04-SD decrease in general economic activity (CFNAI). Moreover, we find that economic activities can predict $DDML$ with higher magnitude and significance than vice versa, except for "personal income." For instance, a one-SD increase in CFNAI implies a 0.09-SD increase in $DDML$.

Therefore, margin investors actively adjust their capital and trading accounts in response to current economic conditions. DML is indeed procyclical.

[36]We use the Brave-Butters-Kelley Index (BBKI) from the Federal Reserve Bank of Chicago as a proxy for the monthly GDP level. It is constructed from a collapsed dynamic factor analysis of a panel of 500 monthly measures of real economic activity and quarterly real GDP growth.

Appendix C: The Proof of the Illustrative Model

In the following, we show how we solve the illustrative model in Section 6.

Hedger's Problem: Solving the objective function (Equation (5)) by taking the first-order condition with respect to the inventory (I_i) and the quantity hedged for each asset (y_i^h), we obtain:

$$\begin{aligned} I_i^* = & \frac{E_t[S_i(T)] - S_i(t)}{\gamma^h \sigma^2_{S_i(T)}} + y_i^{h*} - N_i(T) \\ & - \frac{(N_{-i}(T) + I^*_{-i} - y^h_{-i})Cov[S_i(T), S_{-i}(T)]}{\sigma^2_{S_i(T)}} \end{aligned} \tag{C.1}$$

$$\begin{aligned} y_i^{h*} = & -\frac{E_t[S_i(T)] - F_i(t,T)}{\gamma^h \sigma^2_{S_i(T)}} + I_i^* + N_i(T) \\ & + \frac{(N_{-i}(T) + I^*_{-i} - y^{h*}_{-i})Cov[S_i(T), S_{-i}(T)]}{\sigma^2_{S_i(T)}} \end{aligned} \tag{C.2}$$

where $\sigma^2_{S_i(T)}$ is the variance of the spot price of asset i at time T.

Speculator's Problem: Solving the objective function (Equation (6)) by taking the first-order condition with respect to the quantity speculated for each asset (y_i^s), we obtain:

$$y_i^s = \frac{E_t[S_i(T)] - F_i(t,T)}{\gamma^s \sigma^2_{S_i(T)}} - \frac{y^s_{-i}Cov[S_i(T), S_{-i}(T)]}{\sigma^2_{S_i(T)}} \tag{C.3}$$

Model Equilibrium: By equating y_i^h to y_i^s, we can solve for the futures risk premia:

$$\begin{aligned} E_t[S_i(T)] - F_i(t,T) &= \frac{\gamma^h \gamma^s}{\gamma^h + \gamma^s} \sigma^2_{S_i(T)} Q_i(T) \\ Q_i(T) &= I_i^* + N_i(T) + \frac{(N_{-i}(T) + I^*_{-i})Cov[S_i(T), S_{-i}(T)]}{\sigma^2_{S_i(T)}} \end{aligned} \tag{C.4}$$

Plugging in the expression for I_i^* (Equation (C.1)) and substituting $S_i(t)$ with $F_i(t,T)$, we obtain Equation (7).

Furthermore, from Equations (7) and (8), we can explicitly obtain the expression for the risk premia in terms of leverage:

$$E_t[S_i(T)] - F_i(t,T) = \frac{E_t[\sum_i y_i^* S_i(T)] - L^s W^s}{Var[\sum_i y_i^* S_i(T)]} \{y_i^* \sigma^2_{S_i(T)} + y^*_{-i} Cov[S_i(T), S_{-i}(T)]\} \tag{C.5}$$

Model Equilibrium under Leverage Constraint: Since there is an initial margin requirement in the futures market, leverage-taking is constrained to a certain level either set by CFTC[37] or the clearing house.[38] We add a maximum leverage constraint (L^*) to the speculator's problem:

$$\sum_i y_i^s F_i(t,T) \leq L^* W^s \tag{C.6}$$

Following the same procedure, we obtain the equilibrium:

$$E_t[S_i(T)] - (1+\phi)F_i(t,T) = \gamma^s\{y_i^* \sigma^2_{S_i(T)} + y^*_{-i} Cov[S_i(T), S_{-i}(T)]\} \tag{C.7}$$

where ϕ is the shadow cost of capital, zero if not binding. Additionally, leverage can be expressed as:

$$L^* W^s = \{E_t[\sum_i y_i^* S_i(T)] - \gamma^s Var[\sum_i y_i^* S_i(T)]\}/(1+\phi) \tag{C.8}$$

Note that the leverage constraints do not alter the three properties in the main text of the paper.

[37]For example, Heimer and Imas (2021) use CFTC's restriction on brokerages' provision of leverage to traders in 2010 as a natural experiment and find that the leverage constraint enables higher returns due to more cautious trading.

[38]Etula (2013) reports that broker-dealers adjust the leverage in commodity derivatives based on their risk-bearing capacity, which is an important determinant of risk premia.

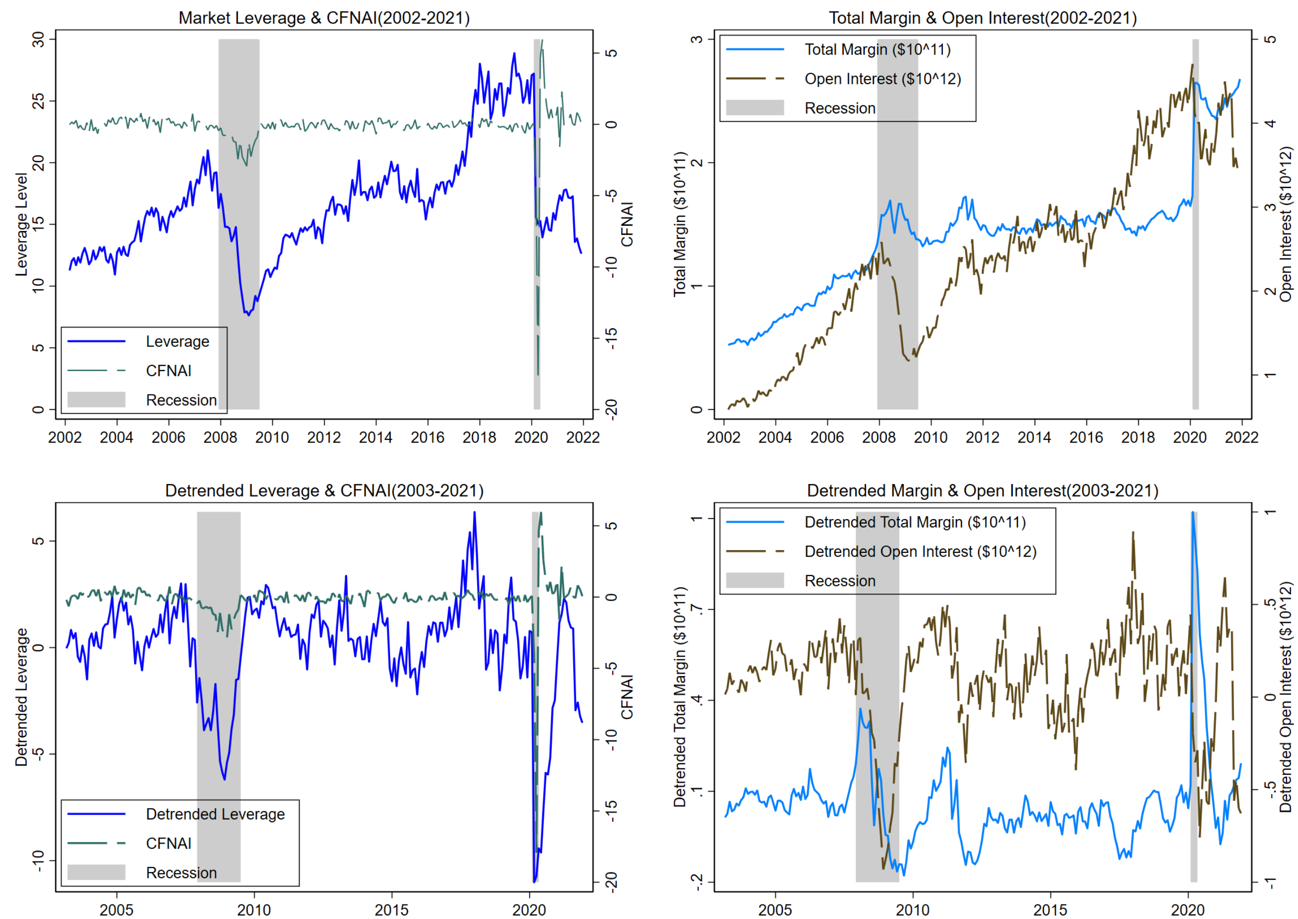


Figure 1: **Derivative-Market Leverage and Components**

The top-left figure plots the time series of the derivative-market leverage level (DML) on the left axis and the Chicago Fed National Activity Index (CFNAI) on the right axis (2002m3-2021m12). The top-right figure plots the time series of the total margin reported by FCMs on the left axis and the aggregate dollar open interest of 45 futures on the right axis (2002m3-2021m12). The bottom-left figure plots the time series of the detrended DML level ($DDML$) on the left axis and the CFNAI on the right axis (2003m3-2021m12). The bottom-right figure plots the time series of the detrended margin ($DTMargin$) on the left axis and the detrended ($DTOpInt$) on the right axis (2003m3-2021m12). The shaded vertical regions show NBER recessions.

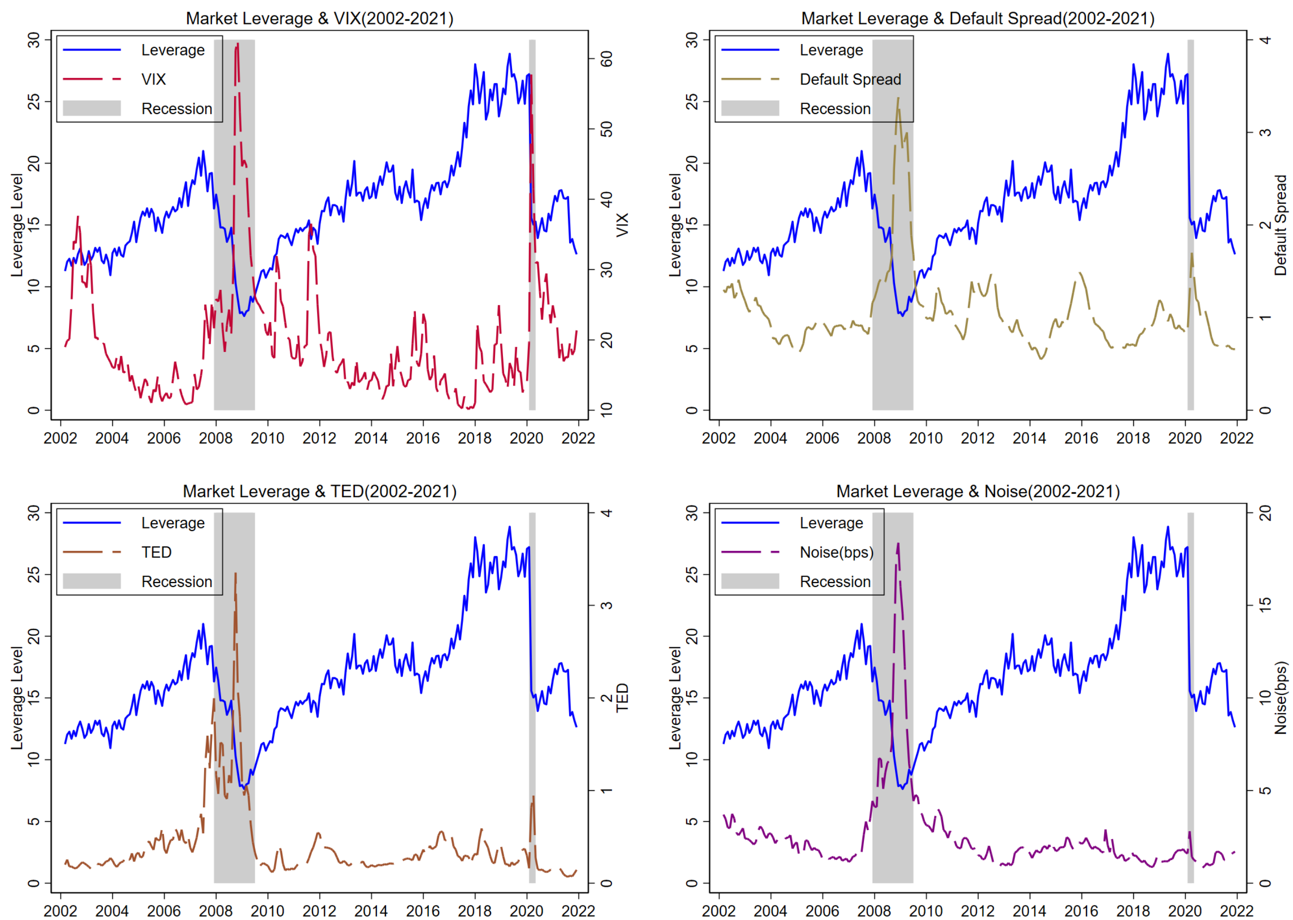


Figure 2: **Derivative-Market Leverage and Risk/Liquidity**

The top-left figure plots the time series of leverage and the volatility index (VIX) from CBOE, representing the market's expectations for the volatility of the U.S. stock market over the coming 30 days, or an indicator of the market's fear. The top-right figure plots the time series of market leverage and the default spread, which is the Baa-Aaa Corporate Bond Spread. The bottom-left figure plots the time series of leverage and the TED spread, capturing the funding cost of capital. The bottom-right figure plots the time series of leverage and the *noise* measure of Hu, Pan, and Wang (2013), a proxy for market illiquidity. The shaded vertical regions show NBER recessions. The sample spans from 2002m3 to 2021m12, at a monthly frequency.

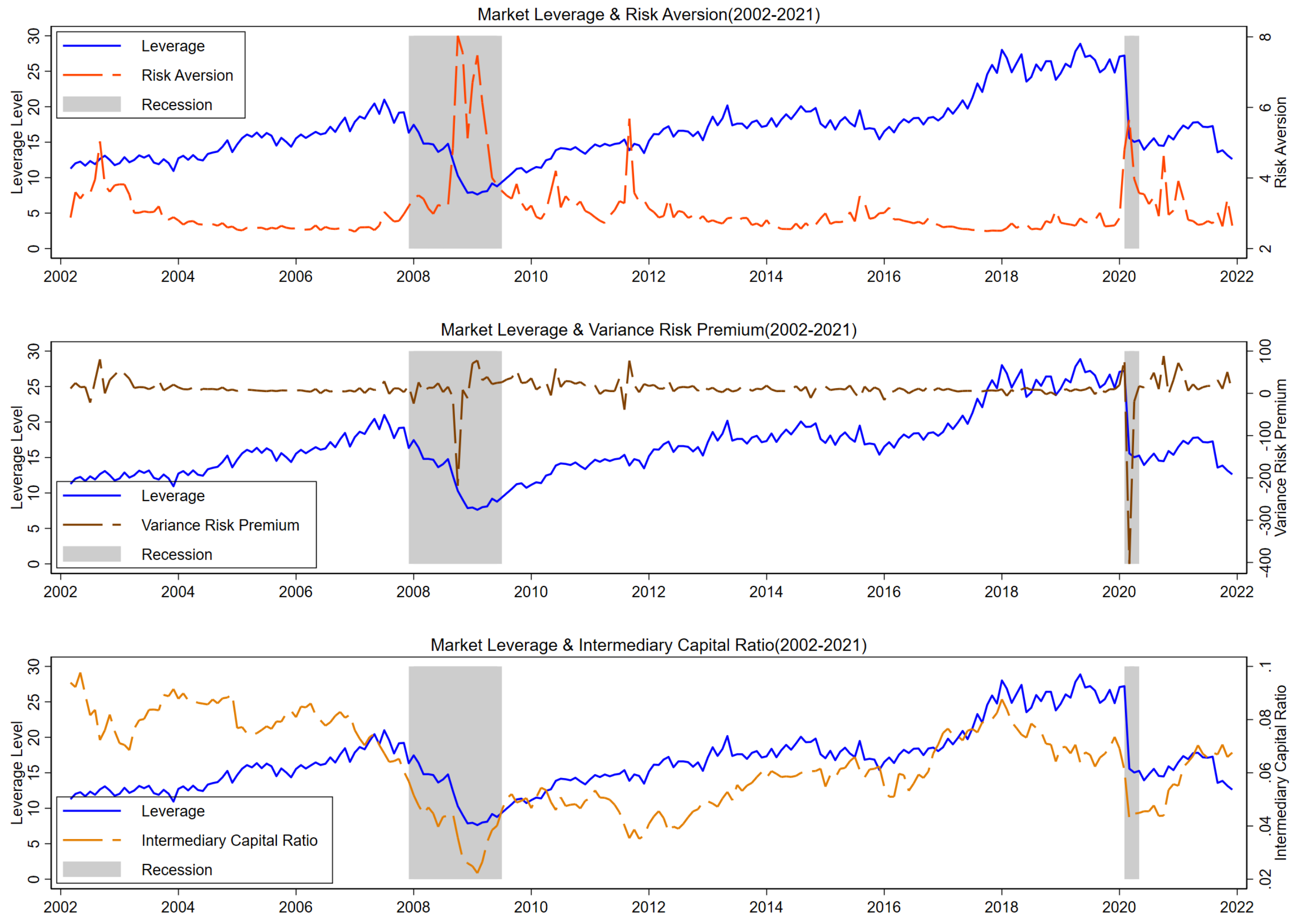


Figure 3: **Derivative-Market Leverage and Risk Aversion**

The top figure plots the time series of DML and time-varying risk aversion measure (RA_{BEX}), constructed by Bekaert, Engstrom, and Xu (2021). The middle figure plots the time series of DML and the variance risk premium (VRP), constructed by Zhou (2018). The bottom figure plots the time series of DML and intermediary capital ratio, constructed by He, Kelly, and Manela (2017). The shaded vertical regions show NBER recessions. The sample spans from 2002m3 to 2021m12, at a monthly frequency.

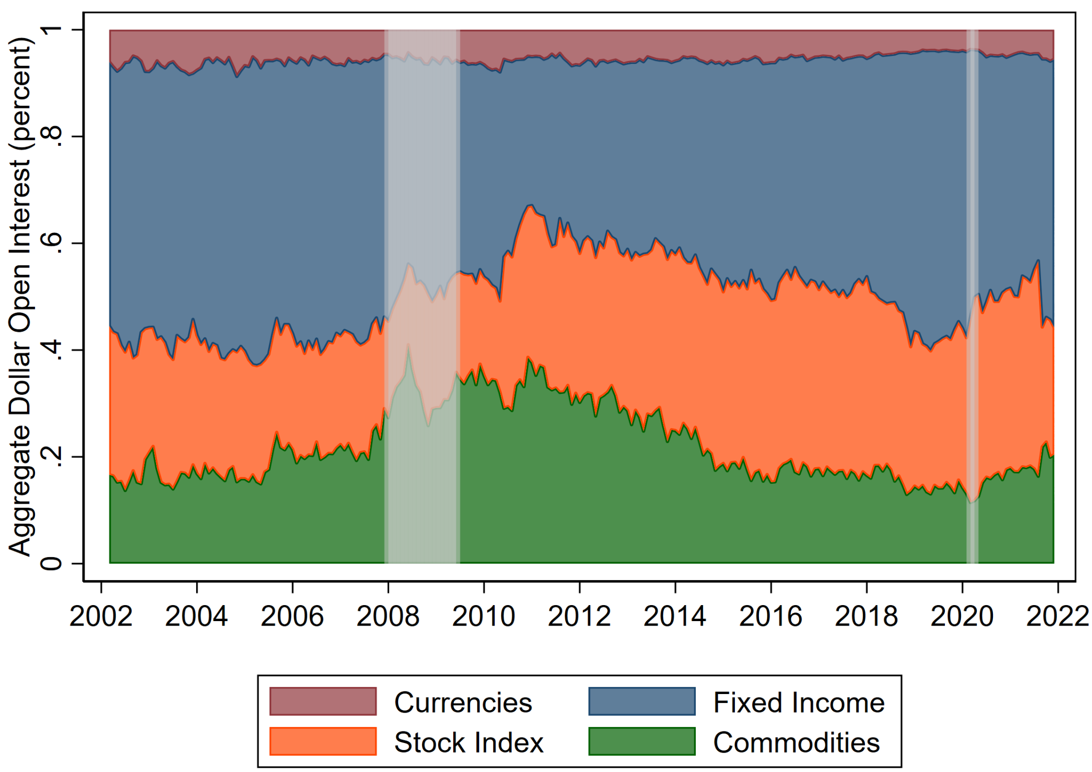


Figure 4: **Open Interest Decomposition**

The figure plots the decomposition of dollar open interest by sector. The share of dollar open interest in commodity futures, stock index futures, fixed income futures, and currency futures that each sector represents is shown. The shaded vertical regions show NBER recessions. The sample spans from 2002m3 to 2021m12, at a monthly frequency.

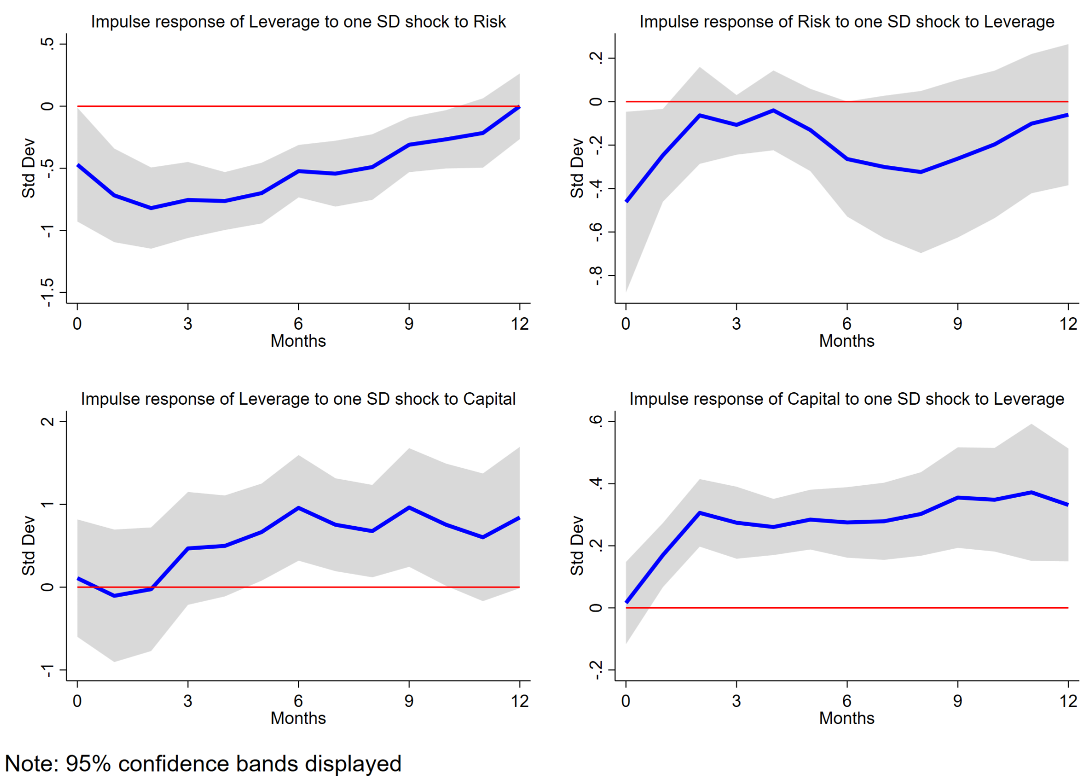


Figure 5: **Impulse Response of Leverage and Risk/Capital Proxies**

This figure plots the impulse responses calculated using the local projection method designed by Jordà (2005). The top-left figure is the impulse response of $DDML$ to a one-standard-deviation shock to the risk proxy, and the top right is the opposite. The bottom-left figure is the impulse response of $DDML$ to a one-standard-deviation shock to the capital proxy, and the bottom right is the opposite. The sample spans from 2003m3 to 2021m12.

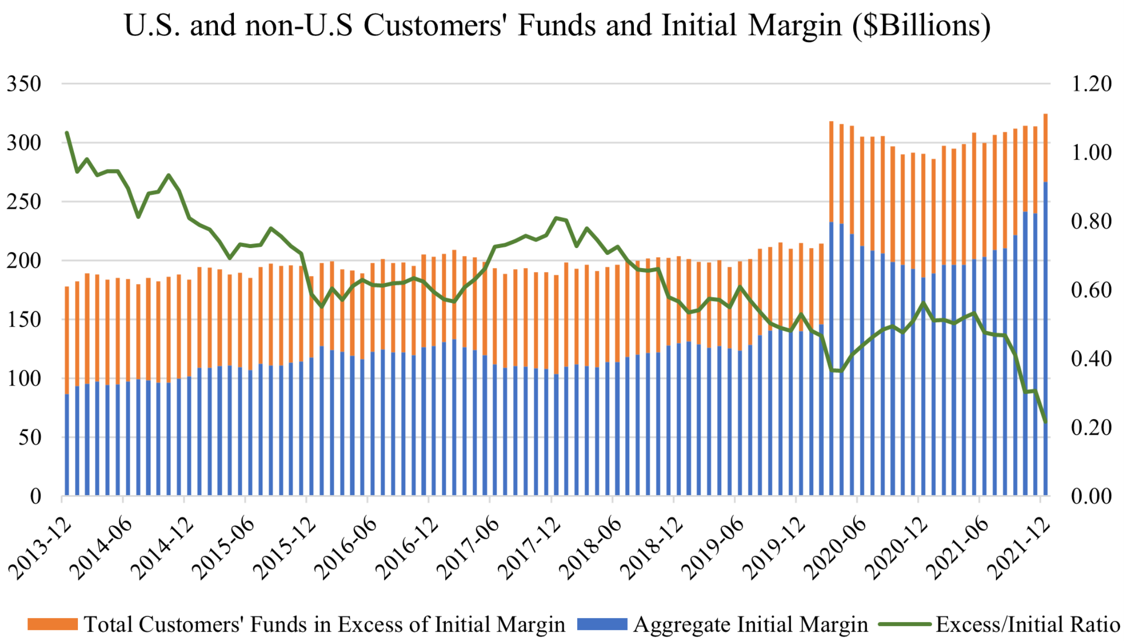


Figure 6: **Total Margin Decomposition**

The figure plots the aggregate initial margin (blue bars) documented by the cleared margin reports published by CFTC, the total customers' funds in futures accounts held by FCMs in the U.S. in excess of the initial margin (orange bars), and the ratio of excess margin over initial margin (green line on right axis). The total margin refers to funds that customers used to trade on commodity exchanges located both inside and outside of the U.S. The sample spans from 2013m12 to 2021m12.

Table 1: **Summary Statistics**

	N	Mean	Median	SD	Min	Max	Skewness	Kurtosis
DML	238	16.72	16.35	4.46	7.63	28.87	0.73	3.36
$LevTrend$	226	16.88	16.56	4.19	8.90	26.60	0.63	3.12
$DDML$	226	0.08	0.58	2.48	-11.02	6.37	-1.68	7.63
$Margin(*10^{11})$	238	1.41	1.47	0.48	0.52	2.68	0.46	3.72
$MarginTrend(*10^{11})$	226	1.40	1.48	0.42	0.55	2.49	0.21	3.81
$DTMargin(*10^{11})$	226	0.06	0.04	0.15	-0.18	1.02	3.19	18.65
$OpenInterest(*10^{12})$	238	2.41	2.40	1.07	0.59	4.71	0.19	2.18
$OpIntTrend(*10^{12})$	226	2.41	2.33	1.01	0.67	4.33	0.21	2.18
$DTOpInt(*10^{12})$	226	0.09	0.14	0.29	-0.93	0.90	-1.10	4.81

This table displays the summary statistics for key variables. DML is the market leverage ratio constructed using the public data from CFTC (2002m3-2021m12). $LevTrend$ is the average of the past 12-month leverage level. $DDML$ is the detrended leverage by subtracting the trend from the raw leverage level. $Margin$ is the total equity of traders in the derivative market. $MarginTrend$ is the average of the past 12-month margin level. $DTMargin$ is the increase in total margin relative to the average of the past 12-month margin level. $OpenInterest$ is the total dollar open interest in the derivative market. $OpIntTrend$ is the average of past 12-month open interest. $DTOpInt$ is the net increase in the aggregate open interest relative to the average of past 12-month interest level.

Table 2: **Pairwise Correlation between Leverage and Liquidity/Risk Aversion**

Panel A: Full Sample								
	$DDML$	TED	$Noise$	VIX	DEF	RA_{BEX}	VRP	$ICRF$
$DDML$	1.00							
TED	-0.38***	1.00						
$Noise$	-0.41***	0.68***	1.00					
VIX	-0.63***	0.54***	0.72***	1.00				
DEF	-0.51***	0.57***	0.84***	0.77***	1.00			
RA_{BEX}	-0.53***	0.55***	0.79***	0.89***	0.80***	1.00		
VRP	0.23***	-0.31***	-0.04	-0.27***	-0.04	-0.13**	1.00	
$ICRF$	0.16**	-0.26***	-0.19***	-0.33***	-0.07	-0.32***	0.32***	1.00
Panel B: Excluding Recession								
	$DDML$	TED	$Noise$	VIX	DEF	RA_{BEX}	VRP	$ICRF$
$DDML$	1.00							
TED	0.04	1.00						
$Noise$	0.10	0.23***	1.00					
VIX	-0.38***	0.01	0.36***	1.00				
DEF	-0.27***	0.08	0.27***	0.52***	1.00			
RA_{BEX}	-0.28***	-0.10	0.31***	0.77***	0.48***	1.00		
VRP	-0.17**	-0.17**	0.18**	0.34***	0.15**	0.74***	1.00	
$ICRF$	-0.03	-0.11	-0.02	-0.20***	0.03	-0.23***	-0.04	1.00

This table reports the pairwise correlation between detrended leverage, and several liquidity/risk aversion proxies. Liquidity proxies include TED spread, and noise measure by Hu, Pan, and Wang (2013). Risk appetite proxies includes Volatility index (VIX) from CBOE, Baa-Aaa Corporate Bond Spread (DEF), time-varying risk aversion measure (RA_{BEX}) by Bekaert, Engstrom, and Xu (2021), variance risk premium (VRP) from Zhou (2018), and intermediary capital risk factor (ICRF) from He, Kelly, and Manela (2017). Panel A includes the full sample from 2003m3 to 2021m12. Panel B excludes recession periods, that is 2008m1 to 2009m6, and 2020m3 to 2020m4. *, ** and *** indicate significance at the 10%, 5%, and 1% levels.

Table 3: **Futures Return Prediction**

Panel A: Dependent Variable = $R_{i,t+1}$				
	Commodities	Stock Indices	Fixed Income	Currencies
$DDML_t$	-0.39***	-0.65***	0.08**	-0.20***
	(-3.95)	(-4.89)	(2.52)	(-3.97)
$R_{i,t}$	-1.71	-6.28**	-0.89	-7.73***
	(-0.90)	(-2.10)	(-0.21)	(-2.60)
$B_{i,t}$	0.08	1.12	0.86	4.40
	(0.12)	(0.07)	(0.32)	(0.61)
$M_{i,t}$	-0.90*	-4.07***	-6.17***	-2.20**
	(-1.76)	(-4.85)	(-3.48)	(-2.10)
TED_t	-0.58	-2.98***	1.10***	-0.60*
	(-1.06)	(-6.30)	(3.03)	(-1.78)
Constant	2.19***	3.99***	0.00	1.87***
	(3.48)	(12.27)	(0.00)	(3.22)
No. Futures	26	5	6	8
Futures FE	yes	yes	yes	yes
Year FE	yes	yes	yes	yes
Adj.R^2 (%)	2.90	14.51	6.30	4.49
Panel B: Dependent Variable = $R_{i,t+2}$				
	Commodities	Stock Indices	Fixed Income	Currencies
$DDML_t$	-0.27**	-0.18**	0.07**	-0.01
	(-2.57)	(-2.55)	(2.51)	(-0.30)
$R_{i,t}$	0.26	-18.66***	-23.97***	-1.01
	(0.15)	(-5.59)	(-3.05)	(-0.39)
$B_{i,t}$	1.40*	8.00	4.19**	0.57
	(1.75)	(0.60)	(2.18)	(0.08)
$M_{i,t}$	-1.40**	-4.94***	-5.32***	-2.45**
	(-2.45)	(-5.18)	(-3.81)	(-2.46)
TED_t	2.31***	-1.66*	1.12***	1.05*
	(3.34)	(-1.89)	(3.98)	(1.90)
Constant	2.14***	3.65***	-0.08	1.49**
	(3.36)	(9.37)	(-0.59)	(2.56)
No. Futures	26	5	6	8
Futures FE	yes	yes	yes	yes
Year FE	yes	yes	yes	yes
Adj.R^2 (%)	5.13	15.53	10.51	4.73

This table mainly reports the estimates for predicting one-month ahead returns ($R_{i,t+1}$) or two-month ahead returns ($R_{i,t+2}$) of different future contracts using the detrended leverage ($DDML$) and other controls. The returns are calculated based on individual futures pricing each month. There are 26 commodities contracts, and 19 financial contracts, including 5 stock indices, 6 fixed income, and 8 currencies. The regression all have included controls, including return in month $t(R_{i,t})$, log basis for futures i in month $t(B_{i,t})$, momentum for futures i in month $t(M_{i,t})$, Ted spread (TED_t), contract fixed effect, and year fixed effect. Reported Newey-West t-statistics, in parentheses below the coefficients (multiplied by 100), have been adjusted for heteroscedasticity and autocorrelated up to 12 lags. *, ** and *** indicate significance at the 10%, 5%, and 1% levels.

Table 4: **Predictive Regression by Asset Class in Spot Markets**

Panel A: Dependent Variable = $R_{i,t+1}$

	Stocks	Gov't Bonds	Currencies	EM Sov. Bonds	Corp. Bonds	CDS
$DDML_t$	-0.79***	0.04***	-0.15***	-0.17	-0.11**	-0.17***
	(-9.26)	(3.89)	(-3.78)	(-1.27)	(-2.53)	(-7.61)
$R_{m,t}$	-1.52	0.21	-0.06**	20.71***	25.74***	13.86***
	(-1.14)	(0.07)	(-2.39)	(4.11)	(4.74)	(3.88)
TED_t	-3.15***	0.52***	0.79**	1.29**	0.43*	-0.57***
	(-9.51)	(6.08)	(2.40)	(2.27)	(1.72)	(-6.89)
Constant	5.25***	-0.09**	0.55***	0.35	0.46***	0.31***
	(11.18)	(-2.19)	(2.74)	(1.04)	(2.99)	(4.25)
No. Portfolios	25	10	10	6	10	20
Portfolio FE	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes
$Adj.R^2(\%)$	13.23	8.58	11.63	12.68	19.42	21.41

Panel B: Dependent Variable = $R_{i,t+2}$

	Stocks	Gov't Bonds	Currencies	EM Sov. Bonds	Corp. Bonds	CDS
$DDML_t$	-0.29***	0.04***	-0.23***	-0.24*	-0.03	-0.14***
	(-5.71)	(4.13)	(-5.58)	(-1.70)	(-0.40)	(-5.85)
$R_{m,t}$	-9.76***	-10.34***	-0.10***	-3.70	-12.89**	-9.63***
	(-5.54)	(-2.91)	(-4.77)	(-0.40)	(-2.22)	(-3.08)
TED_t	-1.23***	0.54***	-0.22	2.22***	1.33***	-0.26***
	(-2.96)	(5.39)	(-0.86)	(4.11)	(3.83)	(-2.80)
Constant	4.43***	-0.05	0.92***	-0.02	0.37**	0.20**
	(9.96)	(-0.92)	(4.21)	(-0.06)	(2.07)	(2.46)
No. Portfolios	25	10	10	6	10	20
Portfolio FE	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes
$Adj.R^2(\%)$	12.94	8.12	9.36	17.57	22.98	14.88

This table reports one-month ahead (Panel A) and two-month ahead (Panel B) predictive regression by asset classes. For equities, we have Fama and French (1993) 25 size and value sorted portfolios (Stocks: 2003m3-2021m12). For government bonds, we have 10 maturity-sorted government bond portfolios from CRSP's "Fama Bond Portfolios" file with maturities with six months' intervals up to five years (Gov't Bonds: 2003m3-2021m12). For foreign exchange, we have sorted currency excess returns of 20 countries into 5 portfolios based on interest differentials following Lettau, Maggiori, and Weber (2014) and 5 portfolios based on one-month momentum following Menkhoff, Sarno, Schmeling, and Schrimpf (2012)(Currencies: 2003m3-2021m12). For emerging-market sovereign bonds, we have 6 portfolios from Borri and Verdelhan (2011) sorted by the bond's covariance with stock market return and that with credit rating (EM Sov. Bonds: 2003m3-2011m4). For corporate bonds, we have 10 portfolios sorted on yield spreads from Nozawa (2017) (Corp. Bonds: 2003m3-2011m12). For CDS, we have 20 portfolios sorted by spreads constructed by He, Kelly, and Manela (2017) (CDS: 2003m3-2012m12). The predictors are the detrended leverage ratio ($DDML$) along with the TED spread (TED) and the contemporaneous portfolio return ($R_{m,t}$). Reported Newey-West t-statistics, in parentheses below the coefficients (multiplied by 100), have been adjusted for heteroscedasticity and autocorrelated up to 12 lags. *, ** and *** indicate significance at the 10%, 5%, and 1% levels.

Table 5: **Long-Term Cumulative Return Prediction**

	Panel A: Futures Markets				Panel B: Spot Markets					
Months	Commodities	Stock Indices	Fixed Income	Currencies	Stocks	Gov't Bonds	Currencies	EM Sov. Bonds	Corp. Bonds	CDS
1	-0.39***	-0.65***	0.08**	-0.20***	-0.79***	0.04***	-0.15***	-0.17	-0.11**	-0.17***
	(-3.95)	(-4.89)	(2.52)	(-3.97)	(-9.26)	(3.89)	(-3.78)	(-1.27)	(-2.53)	(-7.61)
2	-0.64***	-0.85***	0.15***	-0.21***	-1.13***	0.08***	-0.39***	-0.40	-0.14	-0.31***
	(-3.56)	(-4.61)	(2.59)	(-2.66)	(-8.84)	(4.21)	(-7.78)	(-1.53)	(-1.29)	(-7.14)
3	-0.70***	-0.70***	0.15**	-0.37***	-1.04***	0.07***	-0.53***	-0.44	-0.15	-0.39***
	(-3.33)	(-4.17)	(2.28)	(-3.84)	(-8.19)	(3.11)	(-7.44)	(-1.17)	(-0.94)	(-6.37)
4	-0.68***	-0.69***	0.12*	-0.44***	-1.04***	0.05**	-0.52***	-0.30	-0.20	-0.42***
	(-2.84)	(-3.75)	(1.81)	(-3.85)	(-7.14)	(2.05)	(-5.89)	(-0.62)	(-0.92)	(-5.88)
5	-0.56**	-0.57***	0.07	-0.38***	-1.09***	0.03	-0.59***	-0.52	-0.43	-0.43***
	(-2.18)	(-2.80)	(0.95)	(-3.18)	(-7.01)	(0.88)	(-5.76)	(-0.85)	(-1.59)	(-5.20)
6	-0.36	-0.40*	0.02	-0.40***	-1.13***	0.00	-0.62***	-0.95	-0.67**	-0.49***
	(-1.41)	(-1.87)	(0.29)	(-2.99)	(-6.64)	(0.05)	(-6.05)	(-1.29)	(-2.24)	(-5.43)
9	-1.12**	-1.03***	0.08	-0.49***	-2.39***	0.02	-0.63***	-1.62*	-0.83**	-0.54***
	(-2.28)	(-4.15)	(0.73)	(-3.20)	(-9.49)	(0.48)	(-5.57)	(-1.72)	(-2.18)	(-5.17)
12	-1.26**	-1.39***	0.14	-0.34**	-2.78***	0.04	-0.58***	-2.15**	-1.12***	-0.60***
	(-2.22)	(-5.98)	(1.33)	(-2.29)	(-12.53)	(1.28)	(-5.17)	(-2.03)	(-2.66)	(-5.22)
15	0.02	-1.26***	0.08	-0.30*	-2.57***	0.07*	-0.50***	-3.27***	-1.63***	-0.76***
	(0.04)	(-4.34)	(0.96)	(-1.82)	(-11.79)	(1.92)	(-4.20)	(-2.72)	(-3.68)	(-6.81)
18	-0.64	-0.65*	0.09	-0.28	-1.66***	0.05	-0.36***	-3.09**	-1.52***	-0.55***
	(-1.28)	(-1.89)	(0.90)	(-1.53)	(-6.99)	(1.21)	(-3.15)	(-2.55)	(-3.64)	(-5.10)

This table reports estimates of the detrended leverage ($DDML$) along with all other controls (as shown in the one-month ahead return predictive regression) predicting cumulative returns of different future contracts (Panel A) or different assets in the spot market (Panel B) at longer horizons. *, ** and *** indicate significance at the 10%, 5%, and 1% levels.

Table 6: **Nonlinear Prediction**

Panel A: Futures Markets						
	Stock Indices	Fixed Income	Currencies	Commodities		
$P50_t * DDML_t$	-0.78***	0.12**	-0.25***	-0.30		
	(-4.04)	(2.14)	(-2.63)	(-1.51)		
$DDML_t$	-0.22**	-0.01	0.08	-0.03		
	(-2.17)	(-0.25)	(1.23)	(-0.27)		
$P50_t$	-0.08	-0.14	1.07***	1.46***		
	(-0.22)	(-1.28)	(4.86)	(3.96)		
TED_t	-3.22***	1.15***	-0.74**	-0.76		
	(-6.98)	(3.13)	(-2.14)	(-1.36)		
$R_{i,t}$	-5.83*	-0.92	-8.06***	-1.87		
	(-1.93)	(-0.22)	(-2.70)	(-0.99)		
$B_{i,t}$	2.41	0.88	3.92	0.07		
	(0.17)	(0.33)	(0.54)	(0.11)		
$M_{i,t}$	-3.56***	-5.91***	-2.12**	-0.84		
	(-4.20)	(-3.28)	(-2.04)	(-1.63)		
Constant	4.04***	-0.03	1.93***	2.24***		
	(12.61)	(-0.17)	(3.33)	(3.56)		
No. Futures	5	6	8	26		
Futures & Year FE	yes	yes	yes	yes		
$Adj.R^2$ (%)	15.83	6.42	5.38	3.07		
Panel B: Spot Markets						
	Stocks	Gov't Bonds	Currencies	EM Sov. Bonds	Corp. Bonds	CDS
$P50_t * DDML_t$	-1.37***	0.13***	-0.29***	-0.52***	-0.19**	-0.26***
	(-11.05)	(6.89)	(-4.34)	(-2.63)	(-2.55)	(-7.80)
$DDML_t$	0.06	-0.03**	0.02	0.06	-0.04	-0.00
	(1.05)	(-2.24)	(0.33)	(0.49)	(-1.01)	(-0.24)
$P50_t$	0.53**	-0.04	-0.06	-0.31	-0.13	0.35***
	(2.51)	(-0.97)	(-0.31)	(-0.77)	(-1.04)	(7.30)
$R_{m,t}$	-0.62	-0.88	-0.06**	20.83***	25.97***	13.49***
	(-0.46)	(-0.30)	(2.44)	(4.10)	(4.72)	(3.90)
TED_t	-3.67***	0.58***	0.67**	1.13*	0.38	-0.75***
	(-11.37)	(6.60)	(2.10)	(1.81)	(1.39)	(-8.19)
Constant	5.39***	-0.11***	0.59***	0.40	0.48***	0.36***
	(11.98)	(-2.62)	(2.89)	(1.14)	(3.03)	(5.06)
No. Portfolios	25	10	10	6	10	20
Portfolio & Year FE	yes	yes	yes	yes	yes	yes
$Adj.R^2$(%)	15.57	10.20	12.40	19.76	13.09	24.00

This table reports the panel regression estimates same as in Table 3 (Panel A) or Table 4 (Panel B) with a dummy variable $P50_t$, where, $P50_t$, which is one if $DDML_t$ is below the median of past 36 months' values, else 0; and the interactions between the dummy and $DDML_t$. The panel regression has controlled for contract-level (Panel A) / portfolio-level (Panel B) and year fixed effects. Reported Newey-West t-statistics, in parentheses below the coefficients (multiplied by 100), have been adjusted for heteroscedasticity and autocorrelated up to 12 lags. *, ** and *** indicate significance at the 10%, 5%, and 1% levels.

Table 7: **Horse-Race Forecast Tests**

	Panel A: Futures Markets								Panel B: Spot Markets					
#	$DDML_t$ (t-stat)	$R_{i,t}$ (t-stat)	$B_{i,t}$ (t-stat)	$M_{i,t}$ (t-stat)	TED_t (t-stat)	VRP_t (t-stat)	$ICRF_t$ (t-stat)	$a.R^2$ (%)	$DDML_t$ (t-stat)	$R_{m,t}$ (t-stat)	TED_t (t-stat)	VRP_t (t-stat)	$ICRF_t$ (t-stat)	$a.R^2$ (%)
	All Futures Except Fixed Income								All Except Government Bonds					
1	-0.36***							2.95	-0.40***					8.81
	(-5.62)								(-7.95)					
2		-1.31	0.01	-0.91**	0.31			2.46		3.00**	0.03			6.87
		(-0.74)	(0.01)	(-2.01)	(0.86)					(2.27)	(0.15)			
3	-0.39***	-1.42	-0.00	-0.77*	-0.78**			3.03	-0.52***	2.46*	-1.38***			9.49
	(-5.63)	(-0.81)	(-0.00)	(-1.67)	(-2.04)				(-9.26)	(1.86)	(-6.63)			
4		-1.49	-0.01	-0.89**	0.67*	0.01**		2.54		4.05***	-0.32*	-0.01**		7.17
		(-0.85)	(-0.02)	(-1.96)	(1.74)	(2.04)				(2.77)	(-1.73)	(-2.39)		
5	-0.41***	-1.65	-0.02	-0.73	-0.39	0.01***		3.16	-0.52***	3.52**	-1.73***	-0.01***		9.80
	(-5.83)	(-0.95)	(-0.04)	(-1.60)	(-0.92)	(2.58)			(-9.81)	(2.50)	(-6.44)	(-2.77)		
6		-0.86	-0.02	-0.91**	0.23		-2.94**	2.51		4.63***	-0.01		-2.32***	6.95
		(-0.49)	(-0.02)	(-2.01)	(0.62)		(-2.06)			(3.00)	(-0.08)		(-3.62)	
7	-0.39***	-1.04	-0.02	-0.76*	-0.84**		-2.49*	3.06	-0.52***	3.72**	-1.40***		-1.78***	9.53
	(-5.51)	(-0.60)	(-0.03)	(-1.67)	(-2.20)		(-1.72)		(-9.23)	(2.47)	(-6.75)		(-3.00)	
8	-0.40***	-1.12	-0.06	-0.72	-0.39	0.01***	-3.73***	3.23	-0.52***	4.43***	-1.74***	-0.01***	-1.34**	9.82
	(-5.69)	(-0.65)	(-0.09)	(-1.58)	(-0.94)	(3.04)	(-2.61)		(-9.73)	(2.83)	(-6.47)	(-2.67)	(-2.24)	
	Futures on Fixed Income								Government Bonds					
9	0.01							1.73	0.01					5.49
	(0.43)								(1.08)					
10		-0.64	0.89	-6.13***	0.88***			5.73		0.96	0.40***			7.63
		(-0.15)	(0.34)	(-3.43)	(2.79)					(0.32)	(5.28)			
11	0.08**	-0.89	0.86	-6.17***	1.10***			6.30	0.04***	0.21	0.52***			8.58
	(2.52)	(-0.21)	(0.32)	(-3.48)	(3.03)				(3.89)	(0.07)	(6.08)			
12		-0.85	0.83	-6.05***	0.78***	-0.00		5.82		0.97	0.40***	0.00		7.59
		(-0.20)	(0.32)	(-3.46)	(2.99)	(-1.11)				(0.32)	(5.78)	(0.05)		
13	0.08**	-1.14	0.79	-6.07***	1.00***	-0.00		6.45	0.04***	0.11	0.52***	-0.00		8.54
	(2.53)	(-0.28)	(0.30)	(-3.51)	(3.17)	(-1.43)			(3.91)	(0.04)	(6.31)	(-0.42)		
14		-3.56	0.91	-5.91***	0.80***		-2.53**	6.81		-2.02	0.37***		-1.08***	8.60
		(-0.77)	(0.35)	(-3.37)	(2.81)		(-2.50)			(-0.65)	(5.03)		(-5.11)	
15	0.08***	-3.96	0.87	-5.94***	1.03***		-2.64**	7.47	0.05***	-3.03	0.51***		-1.16***	9.69
	(2.62)	(-0.87)	(0.33)	(-3.42)	(3.09)		(-2.56)		(4.13)	(-1.00)	(5.98)		(-5.45)	
16	0.08***	-3.94	0.84	-5.90***	0.98***	-0.00	-2.52**	7.45	0.05***	-2.93	0.52***	0.00	-1.19***	9.67
	(2.63)	(-0.87)	(0.32)	(-3.45)	(3.22)	(-0.74)	(-2.56)		(4.15)	(-0.97)	(6.33)	(0.77)	(-5.58)	

This table reports estimates from panel regression of one-month ahead futures returns (Panel A) and asset returns in the spot market (Panel B) on lagged variables named at the head of a column. Same future contract returns and regression model as shown in Table 3 for Panel A. Same asset returns and regression model as shown in Table 4 for Panel B. The competing predictors are the detrended leverage ($DDML$), the variance risk premium (VRP), and the intermediary capital risk factor ($ICRF$). VRP is downloaded from http://sites.google.com/site/haozhoupersonalhomepage/. $ICRF$ is obtained from https://voices.uchicago.edu/zhiguohe/data-and-empirical-patterns/intermediary-capital-ratio-and-risk-factor/. Reported Newey-West t-statistics, in parentheses below the coefficients (multiplied by 100), have been adjusted for heteroscedasticity and autocorrelated up to 12 lags. *, ** and *** indicate significance at the 10%, 5%, and 1% levels.

Table 8: **Predictive Regression Using Alternative Leverage Measures**

	Panel A: Futures Markets				Panel B: Spot Markets					
	Commodities	Stock Indices	Fixed Income	Currencies	Stocks	Gov't Bonds	Currencies	EM Sov. Bonds	Corp. Bonds	CDS
DML_t	-0.34***	-0.49***	0.06*	-0.12**	-0.81***	0.04***	-0.05	-0.29**	-0.18***	-0.09***
	(-3.15)	(-3.57)	(1.83)	(-2.50)	(-9.08)	(3.33)	(-0.89)	(-2.32)	(-4.87)	(-4.57)
Constant	5.88***	2.44	-0.07	3.00***	15.32***	-0.56***	1.06	4.00**	2.75***	1.36***
	(3.98)	(1.36)	(-0.14)	(3.78)	(12.30)	(-3.69)	(1.51)	(2.44)	(5.57)	(5.34)
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
$Adj.R^2$ (%)	2.53	13.16	6.94	4.25	14.03	8.47	9.78	13.37	20.32	18.72
	Commodities	Stock Indices	Fixed Income	Currencies	Stocks	Gov't Bonds	Currencies	EM Sov. Bonds	Corp. Bonds	CDS
$yoyDML_t$	-0.27***	-0.33***	0.05**	-0.11***	-0.59***	0.03***	-0.11***	-0.14**	-0.07***	-0.07***
	(-3.66)	(-3.45)	(2.21)	(-2.94)	(-10.35)	(3.53)	(-3.55)	(-2.00)	(-3.81)	(-6.08)
Constant	0.02	1.69***	-0.40**	1.11***	1.82***	-0.36***	1.07***	-0.04	0.06	0.21***
	(0.03)	(5.03)	(-2.35)	(2.84)	(4.41)	(-5.57)	(4.87)	(-0.11)	(0.44)	(3.72)
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
$Adj.R^2$ (%)	2.92	11.67	6.72	4.08	12.49	10.09	11.03	12.76	19.64	17.80
	Commodities	Stock Indices	Fixed Income	Currencies	Stocks	Gov't Bonds	Currencies	EM Sov. Bonds	Corp. Bonds	CDS
$DDML_t^{lag}$	-0.36***	-0.59***	0.09***	-0.18***	-0.72***	0.05***	-0.14***	-0.17	-0.09**	-0.15***
	(-3.64)	(-4.48)	(2.76)	(-3.51)	(-8.51)	(4.37)	(-3.90)	(-1.20)	(-2.10)	(-7.11)
Constant	2.16***	4.04***	-0.00	1.87***	5.33***	-0.10**	0.52***	0.34	0.45***	0.30***
	(3.44)	(12.15)	(-0.01)	(3.20)	(11.14)	(-2.21)	(2.64)	(1.04)	(2.96)	(4.09)
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
$Adj.R^2$ (%)	2.87	13.96	6.57	4.38	12.72	8.98	10.44	12.71	19.28	21.16

This table reports the estimates for predicting one-month ahead returns ($R_{i,t+1}$) of different future contracts (Panel A) or different assets in the spot market (Panel B) using the leverage (DML), the change of leverage relative to the leverage one year ago, ($yoyDML_t = DML_t - DML_{t-12}$), and the detrended leverage calculated with one-month lag price ($DDML_t^{lag}$). The regressions have included controls, for futures, including return in month $t(R_{i,t})$, log basis for futures i in month $t(B_{i,t})$, momentum for futures i in month $t(M_{i,t})$, Ted spread (TED_t), contract fixed effect, and year fixed effect; while for spot markets, including Ted spread (TED_t) and portfolio's contemporaneous return ($R_{m,t}$), portfolio fixed effect, and year fixed effect. Reported Newey-West t-statistics, in parentheses below the coefficients (multiplied by 100), have been adjusted for heteroscedasticity and autocorrelated up to 12 lags. *, ** and *** indicate significance at the 10%, 5%, and 1% levels.

Table 9: **Market Leverage and Risk Proxies**

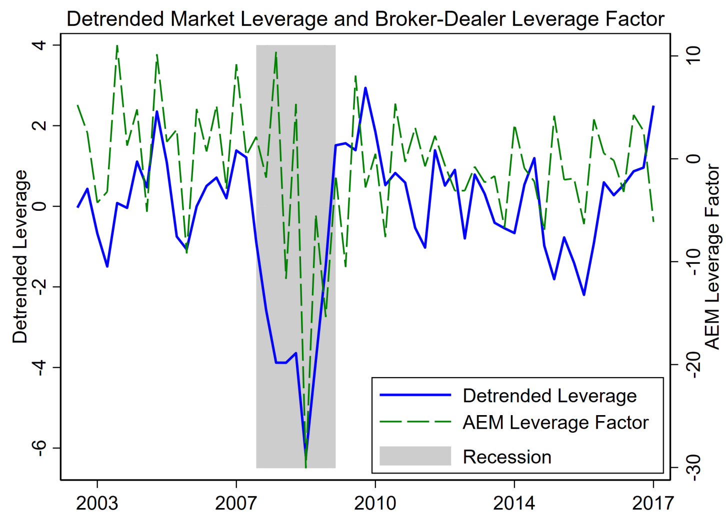
	$\rightarrow DDML_{t+1}$		$DDML_{t-1} \rightarrow$	
	β	P-val	β	P-val
VIX	-0.11	0.01	0.02	0.74
RV	-0.12	0.00	-0.06	0.37
$MACRO_U$	-0.20	0.00	0.01	0.50
$FINANCIAL_U$	-0.16	0.00	0.03	0.06
$NFCI_{RISK}$	-0.08	0.04	0.05	0.01

This table reports Granger causality results based on bivariate VAR for the detrended market leverage ratio ($DDML$) and various proxies of risk and uncertainty. VIX is the Chicago Board Options Exchange volatility index (2003m3 - 2021m12). RV is the model-free realized variance measure based on high-frequency intraday S&P 500 index pricing data (2003m3 - 2021m12). $MACRO_U$ and $FINANCIAL_U$ are the measures of macroeconomic and financial uncertainty as constructed in Jurado, Ludvigson, and Ng (2015) and Ludvigson, Ma, and Ng (2021) taken from Ludvigson's website (2003m3 - 2021m12). $NFCI_{RISK}$ is the risk subindex of the Chicago Fed's National Financial Conditions Index (2003m3 - 2021m12). $DDML$ and all variables have been scaled to have a unit standard deviation. $\rightarrow DDML_{t+1}$ columns present the coefficients and p-values for the null hypothesis that the potential determinant does not predict $DDML$. $DDML_{t-1} \rightarrow$ columns present the coefficient and p-values for the null hypothesis that $DDML$ does not predict the corresponding determinant.

Table 10: **Market Leverage and Funding Conditions**

	$\rightarrow DDML_{t+1}$		$DDML_{t-1} \rightarrow$	
	β	P-val	β	P-val
$FFunds$	-0.02	0.66	0.03	0.00
$Bank_{Prime}$	-0.02	0.59	0.03	0.00
TBL	-0.01	0.81	0.02	0.04
$Credit_{CHG}$	-0.06	0.11	0.10	0.05
$Borrow_{CHG}$	-0.03	0.33	0.17	0.01

This table reports Granger causality results based on bivariate VAR for the detrended market leverage ratio ($DDML$) and various liquidity proxies. $FFunds$ is the federal funds rate and $Bank_{Prime}$ is the bank prime lending rate (2003m3 - 2021m12). TBL is the treasury-bill rate (2003m3 - 2021m12). $Credit_{CHG}$ is the monthly percent change of bank credit for all commercial banks (2003m3 - 2021m12). $Borrow_{CHG}$ is the percentage change of borrowings for all commercial banks at an annual rate (2003m3 - 2021m12). The indicators are all obtained from http://fred.stlousfed.org. $DDML$ and all variables have been scaled to have a unit standard deviation. $\rightarrow DDML_{t+1}$ columns present the coefficients and p-values for the null hypothesis that the potential determinant does not predict $DDML$. $DDML_{t-1} \rightarrow$ columns present the coefficient and p-values for the null hypothesis that $DDML$ does not predict the corresponding determinant.



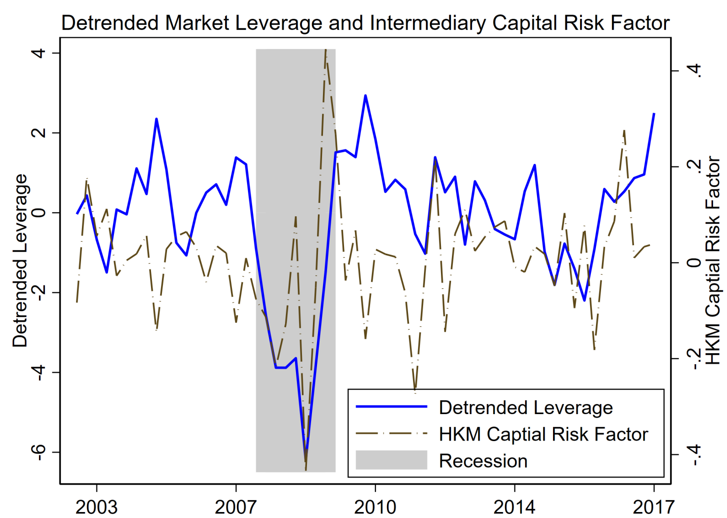


Figure A1: **Leverage Factor Comparison**

The top figure plots the time series of $DDML$ and the leverage factor developed by Adrian, Etula, and Muir (2014). The bottom figure plots the time series of $DDML$ and the intermediary capital risk factor ($ICRF$) created by He, Kelly, and Manela (2017). All values are at a quarterly frequency and span from 2003Q1 to 2017Q3. The shaded vertical regions show NBER recessions.

Table A1: **Summary Statistics of Futures Excess Return**

		Monthly Excess Return (in %)		Categories
Code	Contract Name	Mean	Std.	Type
BO	Soybean Oil	0.49	7.60	Commodities - Agriculture
C	Corn	0.16	8.49	Commodities - Agriculture
CC	Cocoa	0.57	8.72	Commodities - Agriculture
CT	Cotton	0.38	8.08	Commodities - Agriculture
JO	Orange Juice	0.30	9.19	Commodities - Agriculture
KC	Coffee	0.28	9.06	Commodities - Agriculture
KW	Wheat(Kansas)	0.08	8.71	Commodities - Agriculture
LB	Lumber	0.68	12.27	Commodities - Agriculture
MW	Wheat/Spring 14% Protein	0.69	8.80	Commodities - Agriculture
O	Oats/No.2 White Heavy	0.93	9.77	Commodities - Agriculture
RR	Rough Rice #2	0.07	7.23	Commodities - Agriculture
S	Soybean	0.96	7.54	Commodities - Agriculture
SB	Sugar	0.14	8.79	Commodities - Agriculture
SM	Soybean Meal	1.40	8.98	Commodities - Agriculture
W	Wheat	-0.24	8.97	Commodities - Agriculture
CL	Crude Oil	0.23	10.79	Commodities - Energy
HO	Heating Oil	0.38	8.89	Commodities - Energy
NG	Natural Gas	-1.99	12.35	Commodities - Energy
FC	Feeder Cattle	0.29	4.77	Commodities - Livestock
LC	Live Cattle	0.16	4.54	Commodities - Livestock
LH	Lean Hogs	-0.16	8.70	Commodities - Livestock
GC	Gold	0.69	4.90	Commodities - Metals
HG	Copper	1.10	7.74	Commodities - Metals
PA	Palladium	1.23	9.47	Commodities - Metals
PL	Platinum	0.31	6.67	Commodities - Metals
SI	Silver	0.97	9.30	Commodities - Metals
ES	S&P 500 Index, E-mini	0.88	4.14	Stock Indices
NK	NIKKEI 225 Index	0.70	5.51	Stock Indices
NN	NASDAQ 100 Index, E-mini	1.30	5.03	Stock Indices
SP	S&P 500 Index	0.87	4.13	Stock Indices
ZM	Dow Jones Industrial Mini-Sized	0.83	4.04	Stock Indices
FF	Federal Funds / 30-day	0.02	0.14	Fixed Income
ED	Eurodollar, 3-month	0.02	0.17	Fixed Income
FV	Treasury Note, U.S., 5-year	0.17	1.02	Fixed Income
TU	Treasury Note, U.S., 2-year	0.06	0.36	Fixed Income
TY	Treasury Note, U.S., 10-year	0.26	1.59	Fixed Income
US	Treasury Bonds,U.S., 30-year	0.38	2.80	Fixed Income
AD	Australian Dollar/U.S. Dollar	0.31	3.56	Currencies
BP	British Pound/U.S. Dollar	-0.01	2.54	Currencies
CD	Canadian Dollar /U.S. Dollar	0.11	2.65	Currencies
DX	U.S. Dollar Index	-0.03	2.25	Currencies
EC	Euro FX	0.00	2.71	Currencies
JY	Japanese Yen/U.S. Dollar	-0.09	2.53	Currencies
NE	New Zealand Dollar/ U.S. Dollar	0.35	3.74	Currencies
SF	Swiss Franc/U.S. Dollar	0.08	2.88	Currencies

This table provides summary statistics of futures excess returns. The excess returns are calculated using the futures price data obtained from CFTC reports between 2003m3 and 2021m12. The excess return in month t is defined as $R_{i,t} = (F_i(t,T) - F_i(t-1,T))/F_i(t-1,T)$, where T denotes the maturity of the front-month futures contract for futures i. The first 26 items are commodity futures, and the last 19 items are financial futures.

Table A2: **Summary Statistics of Excess Return in Spot Markets**

Asset Class	Mean (%)	Std (%)	Portfolios	Sample Period	N
Stocks	1.04	5.72	25	2003m3-2021m12	5650
Gov't Bonds	0.10	0.64	10	2003m3-2021m12	2260
Currencies	-0.01	2.45	10	2003m3-2021m12	2260
EM Sov. Bonds	0.62	3.35	6	2003m3-2011m4	588
Corp. Bonds	0.46	1.68	10	2003m3-2011m12	1060
CDS	0.09	0.82	20	2003m3-2012m12	2360

This table provides summary statistics of monthly excess returns of different assets in the spot market. For stocks, we have Fama and French (1993) 25 size and value sorted portfolios. For government bonds (Gov't Bonds), we have 10 maturity-sorted government bond portfolios from CRSP's "Fama Bond Portfolios" file with maturities with six months' intervals up to five years. For currencies, we have sorted currency excess returns of 20 countries into 5 portfolios based on interest differentials following Lettau, Maggiori, and Weber (2014) and 5 portfolios based on one-month momentum following Menkhoff, Sarno, Schmeling, and Schrimpf (2012). For emerging-market sovereign bonds (EM Sov. Bonds), we have 6 portfolios from Borri and Verdelhan (2011) sorted by the bond's covariance with stock market return and that with credit rating. For corporate bonds (Corp. Bonds), we have 10 portfolios sorted on yield spreads from Nozawa (2017). For CDS, we have 20 portfolios sorted by spreads constructed by He, Kelly, and Manela (2017).

Table A3: **Long-Term Nonlinear Return Prediction**

	Panel A: Futures Markets				Panel B: Spot Markets					
Months	Commodities	Stock Indices	Fixed Income	Currencies	Stocks	Gov't Bonds	Currencies	EM Sov. Bonds	Corp. Bonds	CDS
1	-0.30	-0.78***	0.12**	-0.25***	-1.37***	0.13***	-0.29***	-0.52***	-0.19**	-0.26***
	(-1.51)	(-4.04)	(2.14)	(-2.63)	(-11.05)	(6.89)	(-4.34)	(-2.63)	(-2.55)	(-7.80)
2	-0.92***	-1.41***	0.28**	-0.39***	-2.11***	0.25***	-0.27***	-1.19***	-0.33**	-0.47***
	(-2.61)	(-5.55)	(2.40)	(-2.67)	(-11.44)	(7.22)	(-2.87)	(-2.59)	(-2.09)	(-6.71)
3	-1.19***	-1.48***	0.32**	-0.49***	-2.45***	0.31***	-0.19	-1.87***	-0.64***	-0.79***
	(-2.66)	(-4.97)	(2.19)	(-2.83)	(-12.17)	(6.48)	(-1.42)	(-3.00)	(-2.67)	(-7.47)
4	-1.17**	-1.55***	0.30*	-0.52**	-3.09***	0.31***	-0.31*	-2.46***	-0.84**	-0.96***
	(-2.17)	(-4.31)	(1.95)	(-2.40)	(-12.74)	(6.02)	(-1.67)	(-2.94)	(-2.37)	(-7.41)
5	-1.36**	-1.95***	0.39**	-0.57**	-3.85***	0.36***	-0.15	-3.40***	-1.28***	-1.08***
	(-2.32)	(-4.83)	(2.26)	(-2.21)	(-14.68)	(6.55)	(-0.70)	(-3.15)	(-2.85)	(-6.97)
6	-1.68***	-2.03***	0.44**	-0.50	-4.44***	0.37***	-0.02	-4.26***	-1.80***	-1.17***
	(-2.76)	(-4.32)	(2.29)	(-1.64)	(-15.56)	(6.04)	(-0.11)	(-3.30)	(-3.46)	(-6.59)
9	-4.41***	-2.80***	0.73***	-0.64	-6.68***	0.37***	-0.19	-5.77***	-2.60***	-1.32***
	(-4.51)	(-5.10)	(3.21)	(-1.59)	(-17.68)	(5.44)	(-0.60)	(-3.50)	(-3.85)	(-6.54)
12	-4.67***	-2.55***	0.88***	-0.45	-5.64***	0.44***	-0.37	-6.16***	-2.81***	-1.76***
	(-4.12)	(-3.22)	(3.89)	(-0.99)	(-12.59)	(5.92)	(-1.09)	(-3.20)	(-3.43)	(-7.42)
15	-2.59**	-1.53**	0.57***	-0.20	-3.96***	0.32***	-0.20	-5.89***	-2.60***	-1.44***
	(-2.23)	(-2.12)	(2.75)	(-0.47)	(-9.03)	(4.02)	(-0.65)	(-2.75)	(-3.10)	(-5.84)
18	-2.32**	-0.85	0.19	-0.24	-3.58***	0.19**	-0.36	-5.63**	-2.31***	-0.85***
	(-2.26)	(-1.26)	(0.86)	(-0.54)	(-8.37)	(2.25)	(-1.21)	(-2.56)	(-3.14)	(-3.60)

This table reports estimates of the interaction term between the below-medium indicator, $P50$, and detrended leverage ($P50 * DDML$) along with all other controls (as shown in the nonlinear return predictive regression) predicting cumulative returns of different future contracts (Panel A) or different assets in the spot market (Panel B) at longer horizons. *, ** and *** indicate significance at the 10%, 5%, and 1% levels.

Table A4: **Predictive Regression - Margin & Open Interest**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Futures on Commodities							
$DDML_t$	-0.39***			-0.38***	-0.42***		-0.52
	(-3.95)			(-3.56)	(-2.77)		(-1.57)
$DTMargin_t(*10^{-11})$		3.43**		0.17		3.71**	-1.09
		(2.11)		(0.09)		(2.26)	(-0.30)
$DTOpInt_t(*10^{-12})$			-1.98***		0.27	-2.09***	0.84
			(-2.75)		(0.25)	(-2.91)	(0.38)
Controls	yes	yes	yes	yes	yes	yes	yes
$Adj.R^2(\%)$	2.90	2.62	2.69	2.88	2.89	2.84	2.87
Panel B: Futures on Stock Indices							
$DDML_t$	-0.65***			-0.46***	-0.84***		0.09
	(-4.89)			(-4.10)	(-4.57)		(0.25)
$DTMargin_t(*10^{-11})$		8.72***		4.83**		9.25***	10.05**
		(4.16)		(2.37)		(4.75)	(2.31)
$DTOpInt_t(*10^{-12})$			-2.62***		1.87*	-3.03***	-3.52
			(-3.16)		(1.70)	(-3.94)	(-1.48)
Controls	yes	yes	yes	yes	yes	yes	yes
$Adj.R^2(\%)$	14.51	13.80	11.63	15.14	14.72	15.35	15.27
Panel C: Futures on Fixed Income							
$DDML_t$	0.08**			0.06	0.11***		0.10
	(2.52)			(1.56)	(3.09)		(0.82)
$DTMargin_t(*10^{-11})$		-0.95***		-0.45		-1.00***	-0.06
		(-2.80)		(-1.01)		(-2.98)	(-0.05)
$DTOpInt_t(*10^{-12})$			0.28		-0.29	0.31	-0.26
			(1.44)		(-1.43)	(1.61)	(-0.42)
Controls	yes	yes	yes	yes	yes	yes	yes
$Adj.R^2(\%)$	6.30	6.10	5.82	6.29	6.30	6.23	6.23
Panel D: Futures on Currencies							
$DDML_t$	-0.20***			-0.19***	-0.22**		-0.25
	(-3.97)			(-3.62)	(-2.54)		(-1.64)
$DTMargin_t(*10^{-11})$		1.82**		0.24		1.98**	-0.35
		(2.11)		(0.26)		(2.29)	(-0.23)
$DTOpInt_t(*10^{-12})$			-0.95***		0.21	-1.02***	0.39
			(-2.97)		(0.37)	(-3.24)	(0.43)
Controls	yes	yes	yes	yes	yes	yes	yes
$Adj.R^2(\%)$	4.49	3.91	3.97	4.44	4.45	4.35	4.40
Panel E: Stocks							
$DDML_t$	-0.79***			-0.73***	-0.76***		0.13
	(-9.26)			(-9.92)	(-5.77)		(0.58)
$DTMargin_t(*10^{-11})$		7.78***		1.64		8.54***	9.79***
		(4.96)		(1.15)		(5.79)	(3.20)
$DTOpInt_t(*10^{-12})$			-4.35***		-0.31	-4.67***	-5.43***
			(-8.74)		(-0.43)	(-9.49)	(-3.43)
Controls	yes	yes	yes	yes	yes	yes	yes
$Adj.R^2$ (%)	13.23	10.93	11.58	13.27	13.22	13.61	13.61

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	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel F: Government Bonds							
$DDML_t$	0.04***			0.03**	0.06***		-0.06*
	(3.89)			(2.16)	(4.10)		(-1.73)
$DTMargin_t(*10^{-11})$		-0.69***		-0.48***		-0.73***	-1.33***
		(-5.79)		(-3.75)		(-6.14)	(-3.84)
$DTOpInt_t(*10^{-12})$			0.17***		-0.13*	0.20***	0.57***
			(2.70)		(-1.79)	(3.18)	(2.81)
Controls	yes	yes	yes	yes	yes	yes	yes
Adj.R^2 (%)	8.58	8.70	7.90	8.90	8.61	9.07	9.17
Panel G: Currencies							
$DDML_t$	-0.15***			0.01	-0.40***		-0.15
	(-3.78)			(0.22)	(-7.15)		(-1.53)
$DTMargin_t(*10^{-11})$		4.18***		4.26***		4.14***	2.77**
		(6.29)		(5.05)		(6.39)	(2.36)
$DTOpInt_t(*10^{-12})$			0.35		2.44***	0.16	1.00*
			(1.16)		(5.55)	(0.58)	(1.84)
Controls	yes	yes	yes	yes	yes	yes	yes
Adj.R^2 (%)	10.43	12.39	9.78	12.36	12.24	12.37	12.38
Panel H: Emerging-Market Sovereign Bonds							
$DDML_t$	-0.17			-0.15	-0.11		0.60
	(-1.27)			(-1.18)	(-0.52)		(1.57)
$DTMargin_t(*10^{-11})$		1.58		0.95		3.50	10.70
		(0.50)		(0.30)		(0.98)	(1.50)
$DTOpInt_t(*10^{-12})$			-0.99		-0.46	-1.57*	-5.49**
			(-1.23)		(-0.34)	(-1.81)	(-2.18)
Controls	yes	yes	yes	yes	yes	yes	yes
Adj.R^2 (%)	12.68	12.49	12.64	12.55	12.54	12.79	12.94
Panel I: Corporate Bonds							
$DDML_t$	-0.11**			-0.11**	-0.07		0.23
	(-2.53)			(-2.52)	(-1.04)		(1.59)
$DTMargin_t(*10^{-11})$		0.22		-0.05		1.59	4.18*
		(0.24)		(-0.06)		(1.56)	(1.84)
$DTOpInt_t(*10^{-12})$			-0.67***		-0.37	-1.02***	-2.53***
			(-2.60)		(-0.95)	(-3.25)	(-2.64)
Controls	yes	yes	yes	yes	yes	yes	yes
Adj.R^2 (%)	19.42	18.97	19.40	19.35	19.42	19.62	19.72
Panel J: CDS							
$DDML_t$	-0.17***			-0.17***	-0.12***		0.02
	(-7.61)			(-7.68)	(-4.85)		(0.57)
$DTMargin_t(*10^{-11})$		-0.08		-0.45*		1.67***	1.90***
		(-0.32)		(-1.93)		(5.51)	(3.82)
$DTOpInt_t(*10^{-12})$			-0.90***		-0.42***	-1.30***	-1.44***
			(-7.11)		(-3.03)	(-8.26)	(-4.87)
Controls	yes	yes	yes	yes	yes	yes	yes
Adj.R^2 (%)	21.41	17.44	20.73	21.52	21.75	22.07	22.04

This table mainly reports the estimates for predicting one-month ahead returns ($R_{i,t+1}$) of different future contracts using the combinations of detrended leverage ($DDML_t$), detrended total margin($DTMargin_t$) and detrended open interest ($DTOpInt_t$) for futures (Panel A to Panel D) and assets in spot markets (Panel E to Panel J). Reported Newey-West t-statistics, in parentheses below the coefficients (multiplied by 100), have been adjusted for heteroscedasticity and autocorrelated up to 12 lags. *, ** and *** indicate significance at the 10%, 5%, and 1% levels.

Table A5: **Quarterly Measures Pairwise Correlations**

Panel A: Full Sample						
	$DDML$	AEM	$ICRF$	CAY	TED	ΔGDP
$DDML$	1.00					
AEM	0.39***	1.00				
$ICRF$	0.29**	-0.02	1.00			
CAY	-0.23*	0.11	-0.22*	1.00		
TED	-0.73***	-0.46***	-0.36***	0.17	1.00	
ΔGDP	0.60***	0.36***	0.20	0.06	-0.64***	1.00
Panel B: Excluding Recession						
	$DDML$	AEM	$ICRF$	CAY	TED	ΔGDP
$DDML$	1.00					
AEM	0.18	1.00				
$ICRF$	-0.01	-0.30**	1.00			
CAY	0.03	0.20	-0.08	1.00		
TED	-0.02	-0.07	-0.06	-0.13	1.00	
ΔGDP	0.23*	0.00	0.04	0.33**	-0.17	1.00

This table displays Pearson pairwise correlation coefficients for the detrended leverage ($DDML$), the leverage factor (AEM) from Adrian, Etula, and Muir (2014), which is the innovation term to the broker-dealer leverage level; intermediary capital risk factor ($ICRF$) from He, Kelly, and Manela (2017), who look at the primary dealer capital ratio and its residual term standardized by the lagged capital ratio; CAY from Lettau and Ludvigson (2001), using a combination of aggregate consumption, labor income, and asset wealth, the TED spread, and the ΔGDP is the percent change of GDP from the preceding period. All in quarterly frequency and span from 2003Q1 to 2017Q3. *, ** and *** indicate significance at the 10%, 5%, and 1% levels.

Table A6: **Market Leverage and Economic Activities**

	$\to DDML_{t+1}$		$DDML_{t-1} \to$	
	β	P-val	β	P-val
$\Delta Unemp$	-0.12	0.00	0.14	0.00
$CFNAI$	0.09	0.01	-0.04	0.09
$CFNAI_{PI}$	0.09	0.01	-0.05	0.03
$CFNAI_{EUH}$	0.10	0.01	-0.05	0.08
$CFNAI_{PCH}$	0.01	0.77	0.01	0.61
$CFNAI_{SOI}$	0.08	0.03	-0.03	0.26

This table reports Granger causality results based on bivariate VAR for the detrended market leverage ratio ($DDML$) and various indicators of economic activities. $\Delta Unemp$ is the change in the unemployment level (2003m3-2021m12). $CFNAI$ is the Chicago Fed National Activity Index measuring the growth of the U.S. national economy. $CFNAI_{PI}$ (production and income), $CFNAI_{EUH}$ (employment, unemployment, and hours), $CFNAI_{PCH}$ (personal consumption and housing), and $CFNAI_{SOI}$ (sales, orders, and inventories) are four subfields of $CFNAI$, all spanning from 2003m3 to 2021m12. $DDML$ and all variables have been scaled to have a unit standard deviation. $\to DDML_{t+1}$ columns present the coefficients and p-values for the null hypothesis that the potential determinant does not predict $DDML$. $DDML_{t-1} \to$ columns present the coefficient and p-values for the null hypothesis that $DDML$ does not predict the corresponding determinant.

Internet Appendix

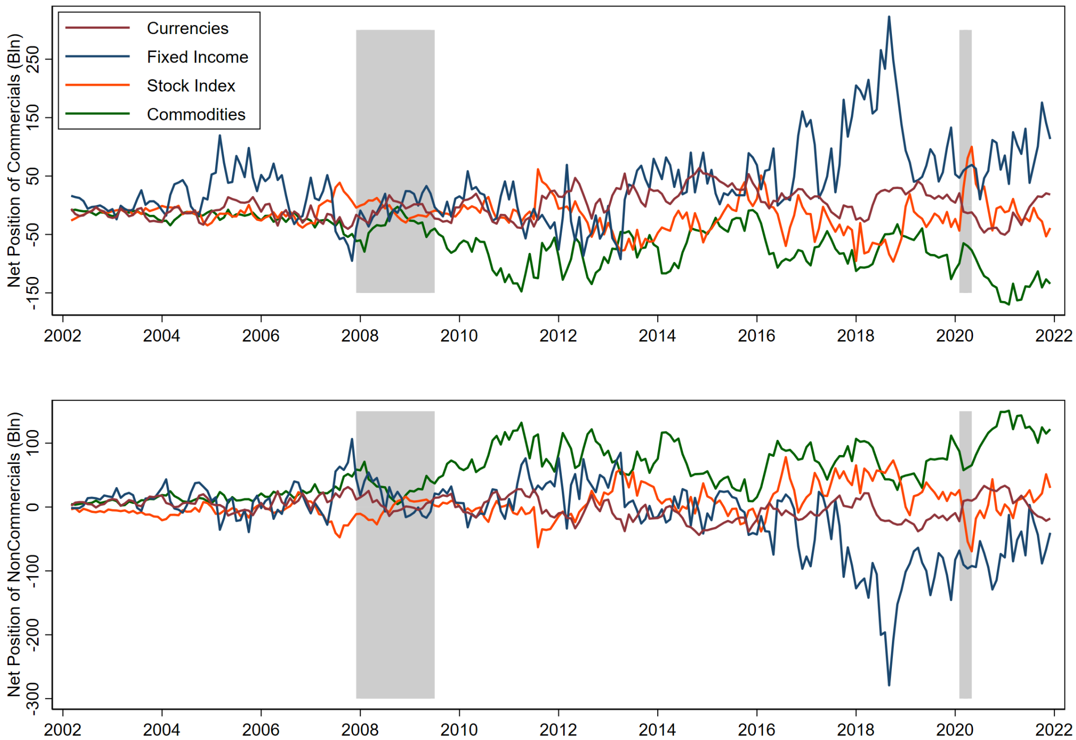
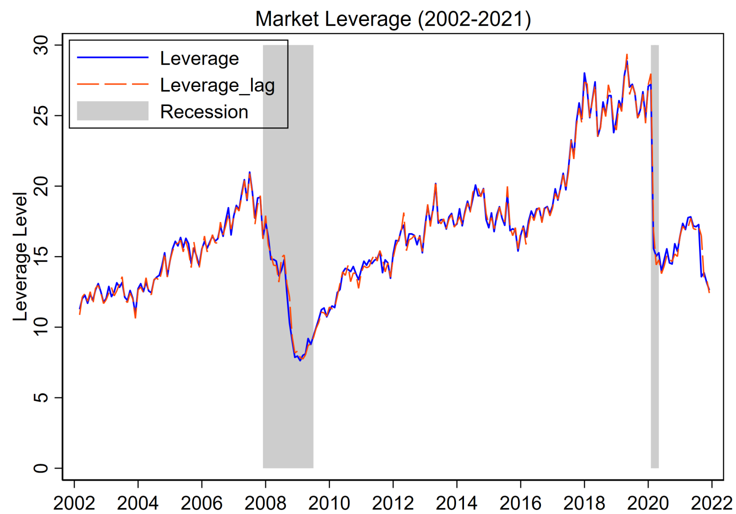


Figure IA1: **Net Position Decomposition**

The figure plots the net trading position, which is the difference between the long and short of commercial traders (top) and non-commercial traders (bottom) for four asset classes. Units have been standardized to billions of dollars. The sample spans from 2002m3 to 2021m12, at a monthly frequency.



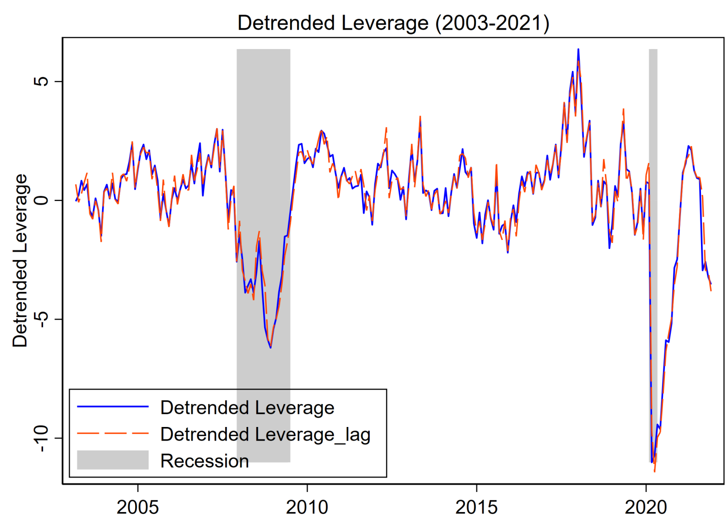


Figure IA2: **Derivative-Market Leverage – Alternative**

The top figure plots the time series of DML level and a lagged version using a one-month lagged price to calculate the numerator. The bottom figure plots the time series of detrended DML by subtracting its trend. The shaded vertical regions show NBER recessions. The sample spans from 2002m3 to 2021m12, at a monthly frequency.

Table IA1: **Determinants of Total Margin**

Panel A: Economic Activities				
	$\rightarrow DTMargin_{t+1}$		$DTMargin_{t-1} \rightarrow$	
	β	P-val	β	P-val
$\Delta Unemp$	0.15	0.00	-0.21	0.00
$CFNAI$	-0.05	0.14	0.04	0.16
$CFNAI_{PI}$	-0.06	0.08	0.03	0.23
$CFNAI_{EUH}$	-0.07	0.05	0.06	0.03
$CFNAI_{PCH}$	0.02	0.56	-0.01	0.64
$CFNAI_{SOI}$	-0.04	0.31	-0.01	0.83
Panel B: Risk Proxies				
	$\rightarrow DTMargin_{t+1}$		$DTMargin_{t-1} \rightarrow$	
	β	P-val	β	P-val
VIX	-0.06	0.10	-0.02	0.68
RV	-0.01	0.82	-0.05	0.48
$MACRO_U$	0.01	0.71	0.03	0.05
$FINANCIAL_U$	0.02	0.55	-0.01	0.55
$NFCI_{RISK}$	-0.03	0.32	-0.01	0.71
Panel C: Funding Conditions				
	$\rightarrow DTMargin_{t+1}$		$DTMargin_{t-1} \rightarrow$	
	β	P-val	β	P-val
$FFunds$	0.05	0.10	-0.03	0.00
$Bank_{Prime}$	0.05	0.10	-0.03	0.00
TBL	0.05	0.15	-0.01	0.05
$Credit_{CHG}$	0.07	0.07	-0.05	0.36
$Borrow_{CHG}$	0.03	0.34	-0.14	0.03

This table reports Granger causality results based on bivariate VAR for the detrended margin ($DTMargin$) and various determinants. $DTMargin$ as well all proxies have been scaled to have a unit standard deviation. $\rightarrow DTMargin_{t+1}$ columns present the coefficient and p-values for the null hypothesis that the economic activity proxy does not predict $DTMargin$. $DTMargin_{t-1} \rightarrow$ columns present the coefficient and p-values for the null hypothesis that $DTMargin$ does not predict the corresponding determinants.

Table IA2: **Determinants of Aggregate Open Interests**

Panel A: Economic Activities				
	$\rightarrow DTOpInt_{t+1}$		$DTOpInt_{t-1} \rightarrow$	
	β	P-val	β	P-val
$\Delta Unemp$	-0.04	0.35	0.04	0.30
$CFNAI$	0.07	0.10	-0.03	0.22
$CFNAI_{PI}$	0.06	0.13	-0.05	0.05
$CFNAI_{EUH}$	0.07	0.07	-0.02	0.45
$CFNAI_{PCH}$	0.03	0.52	0.01	0.50
$CFNAI_{SOI}$	0.06	0.14	-0.04	0.12
Panel B: Risk Proxies				
	$\rightarrow DTOpInt_{t+1}$		$DTOpInt_{t-1} \rightarrow$	
	β	P-val	β	P-val
VIX	-0.25	0.00	0.03	0.55
RV	-0.18	0.00	-0.07	0.33
$MACRO_U$	-0.23	0.00	0.06	0.00
$FINANCIAL_U$	-0.20	0.00	0.04	0.01
$NFCI_{RISK}$	-0.18	0.00	0.07	0.00
Panel C: Funding Conditions				
	$\rightarrow DTOpInt_{t+1}$		$DTOpInt_{t-1} \rightarrow$	
	β	P-val	β	P-val
$FFunds$	0.05	0.25	0.01	0.07
$Bank_{Prime}$	0.04	0.30	0.02	0.02
TBL	0.05	0.21	0.00	0.67
$Credit_{CHG}$	-0.05	0.30	0.09	0.06
$Borrow_{CHG}$	-0.02	0.67	0.14	0.03

This table reports Granger causality results based on bivariate VAR for the detrended open interests ($DTOptInt$) and various determinants. $DTOptInt$ as well all proxies have been scaled to have a unit standard deviation. $\rightarrow DTOptInt_{t+1}$ columns present the coefficient and p-values for the null hypothesis that the proxy does not predict $DTOptInt$. $DTOptInt_{t-1} \rightarrow$ columns present the coefficient and p-values for the null hypothesis that $DTOptInt$ does not predict the corresponding determinants.

Table IA3: **Determinants of Intermediary Capital Risk Factors**

Panel A: Economic Activities				
	$\rightarrow ICRF_{t+1}$		$ICRF_{t-1} \rightarrow$	
	β	P-val	β	P-val
$\Delta Unemp$	-0.17	0.01	0.13	0.00
$CFNAI$	0.21	0.00	-0.06	0.01
$CFNAI_{PI}$	0.22	0.00	-0.06	0.01
$CFNAI_{EUH}$	0.19	0.00	-0.06	0.03
$CFNAI_{PCH}$	0.08	0.25	-0.03	0.01
$CFNAI_{SOI}$	0.22	0.00	-0.05	0.03
Panel B: Risk Proxies				
	$\rightarrow ICRF_{t+1}$		$ICRF_{t-1} \rightarrow$	
	β	P-val	β	P-val
VIX	0.03	0.68	-0.06	0.10
RV	-0.08	0.24	-0.10	0.13
$MACRO_U$	-0.03	0.59	-0.03	0.01
$FINANCIAL_U$	-0.08	0.22	-0.03	0.01
$NFCI_{RISK}$	-0.08	0.24	-0.03	0.07
Panel C: Funding Conditions				
	$\rightarrow ICRF_{t+1}$		$ICRF_{t-1} \rightarrow$	
	β	P-val	β	P-val
$FFunds$	-0.10	0.09	-0.00	0.74
$Bank_{Prime}$	-0.10	0.08	-0.00	0.53
TBL	-0.09	0.10	0.00	0.59
$Credit_{CHG}$	-0.06	0.33	-0.06	0.22
$Borrow_{CHG}$	-0.09	0.12	-0.03	0.68

This table reports Granger causality results based on bivariate VAR for the intermediary capital risk factor ($ICRF$) and various determinants. $ICRF$ as well all proxies have been scaled to have a unit standard deviation. $\rightarrow ICRF_{t+1}$ columns present the coefficient and p-values for the null hypothesis that the proxy does not predict $ICRF$. $ICRF_{t-1} \rightarrow$ columns present the coefficient and p-values for the null hypothesis that $ICRF$ does not predict the corresponding determinants.