# Spillover Effects of U.S. Investor Sentiment on Global Indices

Arham Malik (1007009620)

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**Abstract**

As the largest economy in the world, consumer confidence in the United States' financial markets can impact financial markets and investment decisions around the globe. In this paper, we study the impact of individual and institutional sentiments on four different indices in three different continents. The research is driven by concepts such as efficient market hypothesis and global financial system dynamics to investigate interconnectedness of financial markets. Using a vector autoregressive (VAR) model and a variance decomposition approach, we find statistically insignificant spillover effects in the mean returns of futures prices. Using pre-COVID-19 pandemic data, the contribution of the U.S. institutional and individual sentiment index to the forecast error variance is 2.55% and 6.42% respectively. Our results suggest that spillovers from the largest financial market do exist, sentiment in the U.S. does not have predictive power in other markets around the world.

**Keywords**: Sentiment Analysis, International Finance, Volatility Spillover

# 1 Introduction

## 1.1 Research Question

Understanding and predicting the behavior of the stock market has been a popular research topic within the broader fields of mathematics and statistics. Contributors such as Eugene Fama, who discussed the Efficient Market Hypothesis (EMH), Kenneth French, who expanded market returns beyond the Capital Asset Pricing Model (CAPM), and Andrew Lo, who delved into investor behavior and market bubbles, have laid the groundwork for estimating and predicting market returns. Motivated by the dynamics of the global financial system and the intricate interconnectedness of modern financial markets, along with a keen interest in how investor sentiment can act as a barometer for market movements, this paper seeks to explore new dimensions of market analysis. We aim to delve deeper into the econometric aspect of forecasting, employing empirical analysis and time series to scrutinize the role of anomalies, particularly investor sentiment, and their impact on world index prices.

The purpose of our research is driven by two key concepts: 'Global Financial System Dynamics' and 'Investor Sentiment'. Initially, we aim to explore how sentiments in the world's largest economy, the United States, could influence global financial markets and to what extent there is an interconnectedness within modern financial systems. Subsequently, we plan to delve into the growing field of behavioral economics and finance by quantifying how a variable such as investor sentiment can serve as a leading indicator for market movements. This analysis will help us understand an alternative model for assessing market returns and could provide new insights to build upon existing studies in these popular areas.

## 1.2 Literature Review

Research in the field of international monetary economics and dynamic spillovers is plentiful. Among these, Sarwar & Khan (2017) offered pivotal insights into the interconnectedness of financial markets. They detailed the influence of US macroeconomic activities—such as changes in interest rates, growth rates, and economic uncertainty—on stock markets in Latin America. Their analysis, which utilized the Chicago Board Options Exchange (CBOE) Volatility Index (VIX) as a metric, demonstrated that increases in the VIX, triggered by various macroeconomic indicators, lead to significant immediate and subsequent declines in the returns of emerging markets. Alqahtani et al. (2020) uses Sarwar & Khan (2017) analysis to assess long-run impacts of equity market volatility on index returns in over 7 countries globally. They employ the Economic Market Volatility (EMV) index to measure US stock market uncertainty. They find that rising US market volatility has significant negative impacts on all their observed stock market except China and Hong Kong. They conclude that US-Asia has lower market integration than European and Latin American indexes, which shows lower impacts. On a global level, Marfatia (2020) explains the significance of Investors' risk perceptions in the US and global stock market integration. The author uses the time-varying impact of the VIX index on the dynamic correlation across international stock markets

Various measures of investor sentiment and consumer confidence have been used in behavioral economics, financial econometrics, and monetary economics. Wurgler & Baker (2006) discusses the role of investor sentiment on the future returns of various stocks within the United States. Shiller (2020) advanced the discussion on investor psychology, focusing on how overconfidence and herd behavior could lead to stock market volatility and crashes. Daniel et al. (1998) determines the role of psychological biases causing investors to over or under-react to market news, which could potentially disrupt an investor's fundamental values. Both Shiller (2020) and Daniel et al. (1998) contribute significantly to the growth of behavioral economics to evaluate how investor perception could cause changes in stock markets. Bing (2008) provides insights into how sentiments drive variations in index risk levels His analysis uses proxies such as survey newsletters to assess investor intelligence and trading activity in the S&P500 to assess how different investors react to market news that could change their investing habits. Their research provides evidence that investor sentiment helps explain the shape of the S&P500 option volatility smile and the risk of the index return. Kamath et al. (2024) developed a paper on the effect of Indian sentiment on Nifty 500. Their paper uses seven proxy sentiment indicators and finds a significant positive sentiment effect on market movements.

Cakici et al. (2024) recently published a paper on whether market anomalies can predict stock market returns. Their paper discusses potential ways we can predict market outcomes using unexpected patterns. Their thorough analysis concluded that they failed to reject the null hypothesis as anomalies failed to predict market return in foreign markets. Zhang et al. (2021) adopts a similar VaR approach to discuss spillover in the Chinese market to understand the interconnectedness of financial systems. They find a small negative relation between sentiment and returns and how there only exists short-term effects of sentiment on foreign markets. Lastly, Liu & Pan (1997) uses the GARCH model and identifies strong but insignificant spillovers of U.S market on returns in various Asian emerging markets.

### 1.3 Summary of Empirical Strategy

The primary independent variables are the U.S. institutional and individual investor sentiment indices calculated by the Investor Behavior Project at Yale University. The stock market confidence indices are expressed as percentages of the population anticipating an increase in the Dow Jones Industrial Average. The primary outcome variable is the futures prices of four major world stock indices: Toronto Stock Exchange, London Stock Exchange (FTSE 100), Shanghai and Shenzhen Stock Exchange (FTSE China A50), and Indian National Stock Exchange (Nifty 50). The choice of futures prices over actual index values is due to their greater dependence on future market expectations, potentially indicating U.S. market spillovers. Additional controls include long-term government bond yields, consumer price index, and exchange rates, which help account for economic variations between countries.

We employ a Vector Autoregression (VAR) approach, specifically utilizing the generalized framework proposed by Diebold & Yilmaz (2012). This framework calculates volatility spillover measures from forecast error variance decompositions, allowing for the examination of how shocks in U.S. investor sentiment impact other stock markets without the bias introduced by variable ordering. The methodology utilizes moving average representations and variance decompositions to analyze the dynamics and the distribution of shocks in the system, thereby providing a deep insight into the interdependencies between markets. We quantify total and directional spillovers of sentiment across the examined indices. The total spillover index measures the contribution of inter-market sentiment shocks to the overall forecast error variance, providing a quantifiable measure of market interconnectivity. Directional spillovers, calculated using normalized elements of the generalized variance decomposition matrix, elucidate the specific pathways of volatility transmission between markets. This aspect of the model highlights how sentiment in one market can influence others, either as a recipient or as a source of volatility spillovers, thereby enhancing the understanding of global financial interrelations facilitated by investor sentiment. This VAR-based methodology effectively captures the nuances of cross-market dynamics, making it a robust tool for studying international financial markets.

### 1.4 Data

To test our hypothesis, we acquire data from numerous sources. For most of our covariates, we gather monthly futures closing prices/values from January 2010 to December 2023. Our main indices are S&P 500, TSX, NIFTY 50, China A50, and FTSE 100, as we hope to cover a set of culturally and economically different countries. We use closing prices to account for the efficient market hypothesis. If true, monthly U.S. sentiment might be taken into the closing price of the futures index. Our 2 main variables are institutional and individual sentiment, extracted from the Yale School of Management Confidence Index. We also gather multiple economic indicators as controls to eliminate any bias and see the true effect of sentiment on index returns. These economic indicators include interest rate, reported in percentage; average exchange rate, reported in local currency; and Consumer Price Index, reported in percentage. For better interpretation, we differentiate and log our index values, changing them from prices to rate of return.

### 1.5 Main Findings

The study investigates the potential effects of U.S. investor sentiment on global stock indices using various econometric tools and provides several key findings. The vector autoregressive results demonstrates that the U.S. investor sentiment does not have a statistically significant effect on the TSX, China A50 and Nifty 50 indices, with both institutional and individual sentiments showing minimal and non-robust relationships. A previous period's increase in U.S. institutional sentiment shows a small but statistically significant inverse relationship with the FTSE 100 index. However, none of these results is robust enough to assert strong predictive power confidently. The impulse response analysis indicates no statistically significant responses to shocks in U.S. sentiment for the UK and TSX futures. For emerging markets like China A50 and Nifty 50, there is an observable initial negative response. This suggests that while U.S. investor sentiment does not significantly influence these markets in the long term, there may be short-term reactions, particularly in emerging markets. The mixed findings from Granger causality tests reveal that while U.S. institutional sentiment has a slight predictive power for the FTSE 100, it does not for the TSX. U.S. individual sentiment shows predictive power for emerging markets, such as the China A50 and Nifty 50 indices. These results imply that sentiment might play a more significant role in emerging markets than developed ones. The variance decomposition shows that most of the forecast error variance for the sentiment indices is explained by their own shocks rather than spillovers. However, the largest directional spillover is observed from the U.S. institutional sentiment to the China A50 index, suggesting a greater sensitivity of this emerging market to U.S. institutional investor sentiment. Except for the TSX, other indices are more influenced by institutional rather than individual sentiment, possibly reflecting institutional investors' higher stakes in global markets. Using pre-COVID-19 pandemic data, the contribution of the U.S. institutional and individual sentiment index to the forecast error variance is 2.55% and 6.42% respectively.

### 1.6 Limitations

Our study faces a standard limitation in financial econometrics, where the relationships between variables are not statistically robust. This indicates a need for caution when interpreting the results and suggests that other factors may have more explanatory power over the index returns. While IRFs provide insights into dynamic reactions to shocks, they do not imply causality. This means that the observed responses cannot be taken as evidence that changes in U.S. sentiment directly cause changes in the futures markets. The results may capture only the short-term effects and not the long-term relationships, which are crucial for understanding the economic significance of U.S. sentiment on global indices. The spillover analysis does not account for differences in market structure or inter-country economic sensitivities, which could significantly affect how investor sentiment is transmitted across borders.

Furthermore, eliminating omitted variable bias in this situation can be difficult as numerous drivers could affect index returns. Hence, adding more economic indicators in our model, such as GDP growth rate, unemployment rate, etc., as controls could help showcase the true effect of sentiment on index returns. However, as we look at a very diverse set of countries and indices globally, it can be challenging to acquire all that information for each of our models.

## 2 Econometric Model

### 2.1 Variables

We are investigating the effects of U.S. investor sentiment about the U.S. stock market on other indices around the world so our primary independent variables are the U.S. institutional investor sentiment and the U.S. individual investor sentiment indices. The variables are percentages indicating the percentage of the population expecting an increase in the Dow Jones Industrial Average (DJI) in the coming year.

The primary outcome variable of interest is the futures prices of four major world stock market indices: Toronto Stock Exchange (TSX), London Stock Exchange (FTSE 100), Shanghai and Shenzhen Stock Exchange (FTSE China A50), and Indian National Stock Exchange (Nifty 50). We are interested in the futures' exchanges of these indices because derivatives contracts are highly dependent on the outlook of the index in the future, much more than the actual price of the underlying exchange. Therefore, futures prices may indicate more of a spillover from the U.S. markets. We conduct robustness checks to see if our results also hold for the underlying index prices. Our unit of observation is the monthly closing prices of the futures' prices of these indices.

We also include controls for each country: long-term 10-year government bond yields, consumer price index, exchange rate between the USD, and the country's national currency. These covariates, among others, are widely used in literature to control for variation in the economic strength and stability between countries.

### 2.2 Model Building

We follow the methodology proposed by Diebold & Yilmaz (2012). The Diebold and Yilmaz (DY) framework introduces a volatility spillover measure based on forecast error variance decompositions from vector autoregressions (VARs). They also proposed spillover indices across asset markets under a more generalized VAR framework in which variance decompositions are invariant to variable ordering. We can utilize such spillover indices to analyze the contributions and directions of shocks from the U.S. investor market to other markets based on the decomposition of forecast error variance.

We utilize futures index returns to estimate a generalized vector autoregressive framework using a covariance stationary N-variable VAR(p) model:

$$r_t = \sum_{i=1}^{p} \phi_i r_{t-i} + \epsilon_t$$

where $\phi_i$ denotes an $N \times N$ parameter matrix and $\epsilon_t \sim (0, \sum)$ represents independent and identically distributed disturbances. The moving average representation is $r_t = \sum_{i=0}^{\infty} A_i \epsilon_{t-i}$ where the $N \times N$ coefficient matrices $A_i$ obey the recursion $A_i = \phi_1 A_{i-1} + \phi_2 A_{i-2} + \cdots + \phi_p A_{i-p}$ with $A_0$ is an $N \times N$ identity matrix. With technical reference to Lütkepohl (2005), the generalized vector autoregressive framework for each futures index with the sentiment indices is:

$$r_{jt} = \sum_{i=1}^{p} \phi_{ji} r_{jt-i} + \sum_{i=1}^{p} \beta_{1i} InstSent_{t-i} + \sum_{i=1}^{p} \beta_{2i} IndivSent_{t-i} + \epsilon_{jt}$$

where $j \in \{TSX, FTSE, CA50, NIFTY\}$ and $p$ represents the order of the vector autoregressive model.

We will use variance decomposition to assess the fraction of the H-step-ahead error variance in forecasting $r_i$. Identification based on Cholesky factorization achieves orthogonality, but the variance decompositions still depend on the ordering of the variables. To deal with the issue of ordering in the VAR, the Koop et al. (1996) method, hereafter referred to as KPPS, constructs orthogonalized innovations that are not sensitive to the ordering. The generalized approach allows correlated shocks but accounts for them appropriately using the historically observed distribution of the errors. Diebold & Yilmaz (2012) proposed the KPPS H-step-ahead forecast error variance for $H = 1, 2, \ldots$ as:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Sigma e_j)}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_j)}$$

where $\Sigma$ is the variance matrix of $\epsilon_h$, $\sigma_i j$ is the standard deviation of the $j$-th error term of the equation, and $e_i$ denotes the column vector with element $i$ being 1 and the remaining elements being 0. $\theta_{ij}^{g}(B)$ denotes the element of the $i$-th row and $j$-th column of the coefficient matrix. Since the shocks to each variable are not orthogonalized, $\sum_{j=1}^{N} \theta_{ij}^{g} \neq 1$, we normalize each entry of the variance decomposition matrix by the row sum as:

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)}$$

### 2.2 Total Spillover Index

$$S^{g}(H) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} \cdot 100 = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} \cdot 100$$

The total spillover index measures the contribution of spillovers of sentiment shocks across all four indices to the total forecast error variance.

### 2.2 Directional Spillovers

We follow Diebold & Yilmaz (2012) to use the generalized VAR approach to learn about the direction of sentiment spillovers across the four indices. Generalized impulse responses and the KPPS variance decompositions are invariant to the ordering of variables so we calculate directional spillovers using the normalized elements of the generalized variance decomposition matrix. Following Diebold & Yilmaz (2012), we measure directional volatility spillovers received by market $i$ from all other markets $j$ as:

$$S^g_{\bullet\leftarrow i}(H) = \frac{\sum_{\substack{j=1\\ j\neq i}}^{N} \tilde{\theta}^g_{ij}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}^g_{ij}(H)} \cdot 100 = \frac{\sum_{\substack{j=1\\ j\neq i}}^{N} \tilde{\theta}^g_{ij}(H)}{N} \cdot 100$$

Similarly, the directional volatility spillovers from market $i$ to all other markets $j$ as:

$$S^g_{i\leftarrow \bullet}(H) = \frac{\sum_{\substack{j=1\\ j\neq i}}^{N} \tilde{\theta}^g_{ji}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}^g_{ji}(H)} \cdot 100 = \frac{\sum_{\substack{j=1\\ j\neq i}}^{N} \tilde{\theta}^g_{ji}(H)}{N} \cdot 100$$

To summarize the contributions between variable $i$ to variable $j$, the net return spillover is expressed as follows:

$$S^g_i(H) = S^g_{i\leftarrow \bullet}(H) - S^g_{\bullet\leftarrow i}(H)$$

## 3 Data

To formulate our model, we use data from various sources to analyze the correlation between our covariates. Our coverage period includes monthly data from January 2010 to December 2023, unless otherwise specified in the sources listed below.

### 3.1 Sources

To assess our main covariate: Investor Sentiment, we adopted the Yale School of Management, U.S. One-Year Confidence Index dataset. The index is more recent and is the only available data set that divides sentiment into individual and institutional sentiment. The individual sentiment is a random monthly sample of high-income Americans on how they believe DOW will do one year from now. The institutional sentiment is sampled in surveys from the investment section of large pension plans and investment banks predicting how financial institutes believe DOW will behave in one year. The One-Year Confidence Index measures the percentage of respondents who predict that the DOW will rise next year. Participants respond with any number greater than zero to the question, "in 1 year." It is important to note that the wording of the question allows for the possibility of predicting a decrease, which may result in more negative responses compared to other surveys that use more optimistic phrasing. Despite this, question-wording consistency over time is crucial as it helps track changes in responses longitudinally. The data reported is in percentage, which means that a 55% on the individual sentiment would mean "of the surveyed investors, 55% believe DOW will go up in value in a year". To simply our results and interpretation, we differentiate and log our index values, changing them from prices to rate of return. We were looking to use the more popular Michigan Consumer Sentiment Index (MCSI) which is widely used in many papers; however, the index does not segment public and institutional sentiments separately which made us divert to the Yale Confidence Index.

[Insert Figure 3 here]

Figure 3 shows the institutional and individual sentiment trends across our period. An interesting observation we notice is the negative trend of the sentiment over time. The average sentiment score for institutional and institutes decreased from high 70 percent to mid 60 percent and has been highly volatile.

To gather data on our various indices, S&P500, TSX, NIFTY 50, China A50, and FTSE100, we use Yahoo Finance Inc. to consolidate the monthly closing price of futures. We use monthly data from a 13-year period to analyze the sentiment effect on their returns. Data for China A50 is from August 2010, while the rest are from January 2010. Discuss the time series.

[Insert Figure 2 here]

Using figure 2 we notice that our index values have a positive trend over time as expected.

In our concentrated period, TSX, S&P500, and FTSE100 indices have been much less volatile than ChinaA50 and Nifty.

We use January 1st, 2020, as our dividing date for our pre and post-COVID segmentation. All months from January 2010 up to this date are considered pre-COVID, while all dates from January 2020 to December 2023 are categorized as post-COVID.

To gather macroeconomic data for each country, we mainly use Federal Reserve Economic Data (FRED):

- Interest Rate: We use each country's seasonally adjusted monthly interest rate. Coverage for most countries spans from January 2010 to December 2023. However, interest rate data is available only from December 2011 onwards for India. The unit for the interest rate is expressed as a percentage.

- Exchange Rate: We use the monthly currency to U.S. Dollar Spot Exchange Rate for each of our indices. We collect the average exchange rate for the month as an estimate. The unit is the country's currency needed to exchange for 1 US Dollar.

- Consumer Price Index (CPI): We collect each country's monthly average CPI growth rate, taking 2015 as the index year, set to 100. The unit of CPI is expressed as a percentage.

### 3.2 Summary Statistics

Our basic summary statistics from our consolidated dataset give us a good overview of various financial indices and economic variables.

[Insert Table 1 here]

Using Table 1, we observe a diverse range of mean values indicating the average state of each measure, along with measures on volatility and the Augmented Dickey-Fuller test statistics (ADF t-stat) suggest varying degrees of stationary within the time series data.

A few noticeable observations are that our main variables, Institutional and Individual sentiment, have an average index score of 74 and 70.07 percent, respectively. The volatility for both was around 6 percent. This means that both sentiments were usually more optimistic when predicting the future value of DOW. Their minimum score of 61.54 and 58.16 percent suggest that over our 13-year period, over 50% of surveyed individuals and institutes would predict DOW to increase in value every time. Other elements that are important to look at are our index's future prices. We notice that over the period the price of our indices have varied greatly. An example is the S&P500, which has a mean value of around \$2500 but has a volatility of \$1075. Such high fluctuations can exist as our data incorporates COVID-19 pandemic years where markets went to all-time lows. The Index with the least amount of fluctuation is the United Kingdom's FTSE100 which had an average value of \$6638 with \$735 deviation. This indicates that their index has been considerably more stable.

Regarding our Augmented Dickey-Fuller (ADF) test statistics, our institutional and individual sentiment t-stat values are high, -3.61 and -3.34, respectively. For institutional sentiment, this would typically be considered strong evidence against the null hypothesis of a unit root, suggesting that the time series is stationary at a 1% significance level. For individuals, this would generally be considered evidence against the null hypothesis of a unit root at the 5% level, suggesting that the time series could also likely be stationary at this level. For most of our other variables, especially future index values, the ADF is generally very low, which suggests a lack of evidence to conclude that these time series are stationary, leading us to fail to reject our null hypothesis.

With the lack of stationarity, we further dive deeper into our indices to see how they perform from period to period.

[Insert Table 2 here]

Table 2 gives us an overview of differentiated and logged returns for each index. The means here indicate a slight upward movement of index returns on average from one month to the next during the period studied. In our results, ChinaA50 had the lowest average increase of 0.14% while Nifty50 had the highest of 0.87%. All the indices also experience a very low standard deviation indicating that the monthly returns do not deviate wildly from the average, however, there still exists slight volatility. Another interesting observation comes from skewness, where every index but ChinaA50 had a negative value. This means that for all other indices, there were more instances of significant negative monthly returns than there were of significant positive returns.

We also observe that the differenced and logged returns exhibit a strongly negative ADF and Phillips-Perron (PP) test statistic, which is -5.9797 and -175.1695, respectively, for the TSX Futures. For ADF, this value is sufficiently negative to allow us to reject the null hypothesis of a unit root at conventional significance levels, indicating stationarity in the time series. While specific critical values would be necessary to confirm this, a statistic as negative as -5.9797 typically implies significance at the 1% level. This suggests that the time series does not exhibit time-dependent trends or seasonality, contributing to a consistent mean and variance over time. Consequently, this enhances the predictability of the time series in terms of its statistical properties, although it does not necessarily allow for precise predictions of future values. The absence of a unit root implies that movements in the index from one month to the next are not systematically linked to its past values, which implies that the impact of any shocks is likely to be temporary. Therefore, we can shift our focus to exploring other factors that may influence the movements of the TSX Futures index from period to period. For the PP test statistic, a large negative value indicates that after accounting for potential heteroskedasticity and autocorrelation, the time series appears to be stationary. The same can be said for the other 3 indices in our table, which follow a similar negative score for both ADF and PP, indicating stationarity in our time series.

# 4 Results

## 4.1 Vector Autoregressive Results

With our basic statistics laid out, we adopted the Vector Autoregression (VAR) model to run our regression and address whether US sentiments could potentially affect indices across the globe. All specifications in Table 4 have controls for the exchange rate between the host country and the U.S. dollar, the 10-year government bond yield, and the consumer price index. In this subsection, we focus on specifications 3, 6, 9, and 12 of Table 4.

[Insert Table 4 here]

Table 3 shows the results of our regression using the four indices of interest. The future returns are logged while all other variables are in their original state, as mentioned in section 3.1. In specification 3, the index coefficient is -0.1511 indicating that a 1% increase in the return of the TSX in the previous period is associated with a 0.15% decrease in the return of the TSX, this finding is economically and statistically significant at a 10% significance level. A similar negative relationship between the TSX index's value two periods ago and its current value exists; however, this lacks significance. None of the sentiment coefficients in specification 3 are statistically significant, so we fail to reject the null hypothesis that there is no relationship between US institutional sentiment and the return in the TSX index.

For the FTSE 100 futures index, with regards to specification 6, the index coefficient one year prior is -0.1670 and is statistically significant at a 10% significance level. This suggests a negative relationship between the return on FTSE 100 futures in the previous and current period. This means that a 1% increase in the return of FTSE 100 futures in the previous period is associated with a 0.167% decrease in returns in the current period. The relationship fades after the first lag. Interestingly, the mean return spillover from U.S. institutional sentiment is statistically significant coefficient of -0.0023. A ten percentage point increase in the U.S. investor sentiment index in the previous month is associated, on average, with a decrease in the returns of the FTSE 100 by 0.023%. This is a small decrease and fairly economically insignificant. The effect fades after the first lag. Furthermore, individual sentiment are positive in relation however they are too small and not significant.

In specification 9, we estimate the spillover effects in the China A50 futures index. There is a similar trend with the TSX, as seen by the negative relationships between indices in both lags and institutional sentiment in the prior period. Intriguingly, a small positive effect on the China A50 is observed two periods after an increase in the US institutional sentiment index. A ten percentage point increase in the U.S. institutional investor sentiment index is associated, on average, with a 0.046% increase in the return of China A50 futures. This indicates that financial institutes becoming more optimistic about the DOW is associated with the China A50 futures returns increasing two months after. All remaining variables are economically and statistically insignificant.

Lastly, for Nifty 50, in specification 12, we see a similar trend of economically significant negative relationships as before, however, no variable is statistically significant to have a major effect on index returns.

The R-squared values on all our indices are small, varying from approximately 6% for FTSE 100 in specification 6, to 9.3% for Nifty 50 in specification 12. The small values indicate that only a small variation in the indices of interest can be explained by the current model. This shows that other factors not included in the model might explain the majority of the movements in our indices.

### 4.2 Vector Autoregressive Results - Pre v.s. Post COVID

We dive deeper into the potential effects of the pandemic on investor sentiment and market returns to see whether our results changed pre and post-COVID period. Table 4 defines the period from 2010 to 2019 as "Pre-2020" and unaffected by the COVID-19 pandemic. We define the subsample from 2020 to 2023 as "Post-2019" and during the COVID-19 pandemic. Accounting for the pandemic environment, a few key observations arise. In specifications 2, 8, and 11, the estimate for the mean spillover of the index's previous month's return becomes more negative. This may indicate that during the pandemic, the reliance on the performance of a country's own futures index was more important. However, apart from the Nifty 50, none of the lagged mean spillover returns are statistically significant. The effects of U.S. institutional sentiment are more varied. For almost all markets, an increase in the U.S. institutional sentiment index is associated with a decrease in the futures returns in the following month. These coefficients are statistically and economically significant as a ten percentage point increase in the U.S. institutional sentiment was associated with a 0.05% decrease in futures returns in the

TSX and the FTSE 100. Given that the mean return in these markets was 0.38 percent return, this is a fairly large mean return spillover.

Strikingly, for the emerging markets (China and India), the mean spillover return is more significant in lag 2 becomes more positive in the pandemic period. For the Nifty 50 futures, in specification 10, the mean spillover return due to U.S. individual sentiment during the pre-COVID period is more negative than in specification 12 with the full sample.

Furthermore, assessing all four indices pre-2020 and post-2019, the direction of the U.S. sentiment spillover on mean return–both institutional and individual–changes from negative to positive for the TSX and FTSE 100, and changes from positive to negative for the emerging markets China A50 and Nifty 50. However, very few of the estimates are statistically significant so we fail to reject the null hypothesis that our coefficients are equal to zero. The $R^2$ in all post-COVID periods is much higher, varying from 0.21 to 0.33, which shows that our model better explains the variability of the response data around its mean during that period.

### 4.3 Impulse Response Functions

We use impulse response functions (IRF) to analyze dynamic economic systems, particularly within the context of vector autoregressions (VAR). This technique provides a way to visualize and quantify how a shock to one variable within a system reverberates through other variables over time, which is invaluable in understanding complex interactions between U.S. sentiment and other stock indices. The impulse response function traces the effects of a one-time shock to one of the variables in a VAR model while holding all other shocks at zero. We standardize the shock to one standard deviation of the error term associated with U.S. sentiment. The response of the system is then plotted over several time periods, providing a temporal illustration of the dynamic adjustment process following the shock.

The impulse response functions (IRFs) depicted in Figures 4-11 illustrate the reaction of UK, TSX, and China A50 Futures to shocks in U.S. institutional and individual investor sentiment. For all IRFs, the confidence intervals include zero, meaning that there are no statistically significant responses to a one standard deviation increase in U.S. sentiment. However, the responses to future returns differ based on the sentiment index. For the UK futures and TSX futures indices, there is a tight band around zero for both sentiment indices, suggesting no significant response. For the emerging markets–China A50 and Nifty 50–a notable initial negative response gradually stabilizes around the zero line. The wider confidence intervals, particularly in the initial steps, indicate greater uncertainty about the response magnitude but suggest a more noticeable reaction compared to UK and TSX futures.

Overall, these IRFs suggest that none of the futures markets exhibit a strong or consistent response to U.S. investor sentiment shocks over the observed time steps. The relatively stable responses within narrow confidence intervals suggest that the markets in question may not be highly sensitive to U.S. investor sentiment in the short term. However, the initial negative responses in the TSX, China A50 and Nifty 50 futures to institutional sentiment shocks might indicate a short-term adjustment or market participants' risk-averse reaction to unexpected changes in institutional U.S. sentiment. It is more plausible that changes in institutional sentiment may result in changes in their global portfolios and, subsequently, price fluctuations in global markets. It is also important to note that while IRFs provide insights into the dynamic reactions to shocks, they do not imply causality, and the actual economic significance would need to be assessed in the broader context of market behavior and economic conditions.

### 4.4 Granger Causality

We employ Granger causality tests to examine whether past values of U.S. institutional and individual investor sentiment can predict future movements in these international futures indices. The null hypothesis is that U.S. sentiment exhibits no predictive power over international index futures returns. The alternative hypothesis is that U.S. sentiment does indeed have predictive power over these markets, suggesting sentiment spillover effects. The Chi-square statistics from these tests provide evidence on the direction and strength of these relationships.

[Insert Table 3 here]

We find a mixed landscape of sentiment spillovers. Institutional sentiment appears to Granger-cause the FTSE 100 Futures, as indicated by a Chi-square value of 5.5, which is slightly statistically significant. Changes in institutional sentiment in the U.S. can be considered as precursors to movements in the FTSE 100 futures returns, hinting a transantlantic spillover effect. Individual sentiment appears to Granger cause futures returns in emerging markets such as China and India. For China A50 Futures, the Chi-square value is 6.19, which is statistically significant at the 5% level. Similarly, for Nifty 50 Futures, the individual sentiment yields a Chi-square value of 7.35, which is also statistically significant. These results suggest a stronger behavioral contagion where individual sentiment, potentially a proxy for retail investor behavior, exerts a more substantial influence on emerging markets.

Intriguingly, neither institutional nor individual U.S. investor sentiment Granger-causes the TSX futures returns, suggesting that the Canadian market might be more insulated to U.S. sentiment. However, given the interdependices between the U.S. and Canada, it is more likely that our sentiment data is not capturing the dynamics at play. More measures of U.S. sentiment that are localized to North America may be helpful in decreasing the noise and bias of the estimates.

### 4.5 Spillovers

The generalized VAR (KPPS) of Order 2 and a generalized variance decomposition of 5-month-ahead return forecast errors are used to estimate the full-sample return spillover, including the directional and total spillover indices for all 4 markets and the sentiment indices. We also note that in the table below, each variance decomposition is measured with controls for each country's exchange rate with the U.S. dollar, 10-year government bond yield, and CPI.

[Insert Table 5 here]

The diagonal elements represent the percentage of forecast error variance for each market attributable to their own shocks. The institutional and individual sentiment indices have notably high own variance share of 78.27% and 96.44%, respectively, indicating that the majority of its forecast error variance is explained by their own innovations rather than by spillovers from the sentiment indices and other markets. In the other indices, we see that approximately 50% of the forecast error variance is explained by its own innovations. Each $ij$th entry is the estimated contribution to the forecast error variance of market $i$ (row variable) coming from innovations to market $j$ (column variable). Focusing on the first two columns, we note that the range of forecast error variance from the institutional sentiment index to the four market indices is between 0.69% and 3.33%, and between 0.53% and 2.25% for the individual sentiment index. In our sample, the largest directional spillover occurs from the U.S. institutional sentiment index to the China A50 Futures index. The China A50 index receives 3.33% of its forecast error variance from US institutional investor sentiment and 2.25% from US individual investor sentiment. This indicates strong ties between the U.S. and China, such as the volume of U.S. investment in Chinese companies. Interestingly, for all of the indices except the TSX index, the contribution of the institutional investor sentiment to the forecast error variance is larger than the individual investor sentiment. This may indicate that indices outside the U.S. are more sensitive to the sentiment and confidence of large institutions than individual investors.

These estimates are economically significant. Although the countries in our sample have distinct macroeconomic environments, varying market structures, and diverse sets of publicly traded companies, the directional spillover effects suggest that investor sentiment in the U.S. can transcend these differences. This can be partially explained by the role of the U.S. as a global financial hub. International investors closely watch the U.S. financial market, and shifts in sentiment can have ripple effects worldwide, affecting capital flows, foreign exchange rates, and investment decisions.

### 4.5 Spillovers before COVID-19 Pandemic

Table 6 presents a volatility spillover table showing the percentage of forecast error variance attributed to shocks from different sources before January 2020. The cross-market spillovers from U.S. institutional sentiment ranged from 1.07% to 3.7% prior to the COVID-19 pandemic. Compared to Table 5, generally, we see that the forecast error variance contributions to the market indices in our sample from the U.S investor sentiment indices are larger. Furthermore, the "Directional TO others" spillover estimate for U.S. institutional sentiment is 68.8% larger and 101.25% larger for U.S. individual sentiment than what was estimated in the full sample. This suggests that U.S. sentiment may have had a more pronounced impact on global markets before the onset of the COVID-19 pandemic. Strikingly, our results show that retail investor sentiment can also significantly affect global markets, possibly due to the cumulative effect of individual actions and a potentially more stable environment. The larger spillover from both investor types before the pandemic could reflect a period where global financial markets were more integrated and responsive to U.S. economic signals. Also, the COVID-19 pandemic impact and response differs greatly by country so relationships between the U.S. and other markets may have been disrupted. Interestingly, the total spillover index remained stable at around 5.4%, which suggests that general spillover among the U.S., Canadian, British, Indian, and Chinese stock markets is not affected by including COVID-19 futures data, indicating that the financial markets are still vastly distinct and unique.

## 5 Discussions

In this section, we corroborate our findings with empirical work by Liu & Pan (1997), Zhang et al. (2021), and Cakici et al. (2024). We also discuss the economic significance of our research and how it can explain market dynamics, international sentiment transmission mechanisms, and the role the U.S. plays as a financial hub.

The paper by Zhang et al. (2021) explores the spillover effect of sentiment between China and the United States, utilizing a VaR approach similar to ours to examine the interconnectedness of modern financial systems. They identify a negative correlation between U.S. investor sentiment and stock market returns in China, suggesting that high investor sentiment correlates with an increase in noise traders. This finding aligns closely with our observations of spillover effects impacting indices and stocks on the Chinese stock exchange, as detailed in section 4.5 of our analysis. Moreover, our results echo their findings regarding impulse response functions, where sentiment initially triggers a negative shock that gradually stabilizes over time. Although our model indicates a lesser impact compared to theirs, this discrepancy may be from variations in the sentiment indices employed in construction. Despite these differences, the overall result underscores a consistent theme: the minimal influence and predicted power of US sentiments on Chinese markets. This theme is further supported by the findings in Cakici et al. (2024), who also investigated market anomalies as predictors of market returns. Their research, which fails to reject the null hypothesis, suggests that market anomalies are ineffective predictive tools on international markets due to numerous other variables that strongly influence prediction. Similarly, our analysis indicates that while investor sentiment does impact market outcomes, it is not the sole determinant of returns.

An important characteristic of our results is that the U.S. investor sentiment does not exhibit any predictive power on the indices we studied. This is similar to the findings by Liu & Pan (1997), who found strong but insignificant spillovers from the U.S. market on the returns in four emerging markets in Asia. They utilized a GARCH model to identify spillover effects and found that these effects are magnified post the October 1987 stock market crash, illustrating a dynamic interaction among these international markets influenced by significant market events. Additionally, they implemented volatility spillover measures to examine the volatility transmission in the U.S. financial markets to emerging markets in Asia, finding that the volatility spillover from the U.S. to returns in Hong Kong was 4.6%

## 6 Conclusion

This article explores the influence of U.S. investor sentiment on global financial markets. The U.S., as the largest economy, plays a pivotal role in global financial dynamics, making the study of its investor sentiment critical for understanding global market behaviors. This research is driven by concepts such as the efficient market hypothesis, which suggests that investors should consider all relevant information, including internationally generated information. Increased economic integration, diverse trade relationships, and global diversification of investment portfolios may affect the nature of cross-market relationships.

We utilize the Yale University U.S. institutional and individual investor confidence indices as measures of U.S. market outlook. We chose four global market futures indices of varying size, macroeconomic state, and volume: TSX (Canada), FTSE 100 (UK), China A50 (China), and Nifty 50 (India). Literature on direct spillovers between the returns of various markets is plentiful, but few have utilized futures prices as indicators of spillovers. We believe that futures prices are more likely to be influenced by fluctuations in U.S. sentiment and market outlook since they are inherently forward-looking and are heavily influenced by speculation. Additionally, when U.S. investors are optimistic or pessimistic, their sentiment can lead to large flows of capital into or out of futures markets worldwide, impacting prices.

To estimate the mean return and volatility spillover effects, we employed a generalized vector autoregressive (VAR) model as proposed by Diebold & Yilmaz (2012). The model is able to capture the transmission of shocks to the U.S. sentiment indices on the forecast variance of our markets of interest. We find that U.S. sentiment indices have a negative relationship with returns in future indices around the globe; however, given the lack of statistical significance and adequate controls, there is potentially omitted variable bias. A statistically significant mean return spillover was observed in the FTSE 100 futures return where a 10 percentage point increase in U.S. institutional sentiment was associated with a 0.023% decrease in returns of the FTSE 100 futures in the following period. Accounting for differences in pandemic responses, we split our sample into "pre-2020" and "post-2019" sub-samples. Generally, the direction of the U.S. sentiment–institutional and individual spillover on mean return changed from positive to negative for emerging markets and negative to positive for the Canadian and British futures markets. Additionally, we observe larger negative and statistically significant spillovers from institutional sentiment in the TSX, FTSE 100, and Nifty 50. Finally, given the high statistical significance, U.S. individual sentiment appears to Granger cause futures returns in China A50 and Nifty 50.

We then proceed with variance decomposition. By using forecast error variance, forecasting 5 months ahead, approximately 50% of the forecast error variance in each of the returns in the four indices of interest is explained by innovations in their own returns. Institutional sentiment contributes around 0.69% to 3.33% across the four indices, and individual sentiment contributes between 0.53% and 2.25%. The total spillover index was 5.2%, indicating that while some spillovers do exist, the markets are very different and cannot be adequately forecasted with the returns of other markets. Analyzing spillovers excluding data past 2019, we find that the "Directional TO others" spillover estimate for U.S. institutional sentiment is 68.8% larger and 101.25% larger for U.S. individual sentiment than what was estimated in the full sample.

Our results are similar to what has already been contributed by other researchers in this field. Zhang et al. (2021) also identify a negative correlation between U.S. investor sentiment and stock market returns in China in relation to the direction of the mean return spillover effects we estimate. Liu & Pan (1997) estimated a volatility spillover from the U.S. to returns in the Hong Kong markets that were similar in direction and magnitude as our estimate.

In summary, our research underscores the need to comprehend how U.S. investor sentiment potentially influences market dynamics worldwide. Investors, both retail and institutional, can leverage insights from our research to refine their global investment strategies, better anticipate market movements, and manage risks. Policymakers and regulatory bodies can further extend this to maintain global financial stability by recognizing areas of financial dependence between various markets. Lastly, our research contributes to a growing body of literature on market efficiency, international monetary economics, and finance.

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# Appendix

Table 1: Descriptive Statistics

| Variables | Mean | Std. Dev | Min | Max | ADF t-stat |
|---|---|---|---|---|---|
| USInstitutionalIndexValue | 74.00 | 5.69 | 61.54 | 90.32 | -3.61 |
| USIndividualIndexValue | 70.09 | 6.00 | 58.16 | 81.25 | -3.34 |
| SP_TSXCanada | 15491.94 | 2802.13 | 11094.31 | 21890.16 | -0.80 |
| NASDAQ | 21748.39 | 8055.34 | 9774.02 | 37689.54 | -0.11 |
| FTSE_100UK | 6663.32 | 731.62 | 4916.87 | 7876.28 | -2.06 |
| Nikkei225Japan | 19127.66 | 6926.20 | 8434.61 | 33486.89 | -0.12 |
| Nifty50India | 10100.89 | 4445.77 | 4624.30 | 21731.40 | 1.20 |
| ChinaA50 | 11203.10 | 2946.47 | 6565.00 | 18204.00 | -1.69 |
| SP500 | 2542.14 | 1075.98 | 1030.71 | 4769.83 | 0.26 |
| TSXFutures | 911.95 | 181.07 | 646.80 | 1317.10 | -0.54 |
| NASDAQFutures | 6822.44 | 4416.98 | 1738.00 | 17232.00 | 0.90 |
| FTSE100Futures | 6638.14 | 735.04 | 4880.50 | 7875.50 | -2.00 |
| Nikkei225Futures | 19071.22 | 6908.88 | 8420.00 | 33475.00 | -0.12 |
| Nifty50Futures | 10127.32 | 4463.45 | 4634.40 | 21885.95 | 1.18 |
| ChinaA50Futures | 11203.10 | 2946.47 | 6565.00 | 18204.00 | -1.69 |
| SP500Futures | 2541.21 | 1080.43 | 1026.50 | 4871.50 | 0.36 |
| USMonthlyNominalGDPIndex | 19878.82 | 3644.20 | 14707.27 | 28189.24 | 1.04 |
| USMonthlyRealGDPIndex | 19403.23 | 1764.46 | 16526.08 | 22863.38 | -0.60 |
| UMCSENT | 81.32 | 13.06 | 50.00 | 101.40 | -2.06 |
| China_Interest_Rate | 3.01 | 0.17 | 2.79 | 3.25 | -1.87 |
| UKCPI | 104.52 | 9.99 | 88.80 | 130.20 | 3.00 |
| UK_Interest_rate | 2.01 | 1.12 | 0.21 | 4.57 | -1.84 |
| ChinaCPI | 249.28 | 20.49 | 207.70 | 280.60 | -1.68 |
| CanadaCPI | 2.30 | 1.64 | -0.37 | 8.13 | -1.89 |
| Canada_Interest | 2.07 | 0.80 | 0.52 | 4.06 | -2.22 |
| Canada_Exchange | 1.21 | 0.14 | 0.96 | 1.42 | -1.29 |
| IndiaCPI | 6.82 | 2.80 | 1.08 | 16.22 | -3.39 |
| India_Interest | 7.37 | 0.78 | 5.81 | 8.99 | -1.84 |
| India_Exchange | 64.97 | 10.92 | 44.30 | 83.27 | -0.77 |

Table 2: Descriptive Statistics for Differenced and Logged

| | TSX Futures | FTSE 100 Futures | Nifty 50 Futures | China A50 Futures |
|---|---|---|---|---|
| Mean | 0.0038 | 0.0025 | 0.0087 | 0.0014 |
| Std. Dev. | 0.0349 | 0.0358 | 0.0503 | 0.0676 |
| Min | -0.1763 | -0.1471 | -0.2572 | -0.1735 |
| Max | 0.0993 | 0.1231 | 0.1343 | 0.3176 |
| Skewness | -0.9910 | -0.5055 | -0.7981 | 0.4833 |
| Kurtosis | 6.9959 | 4.8467 | 6.9041 | 5.5874 |
| | | | | |
| ADF Test | -5.9797 | -5.3763 | -5.5825 | -4.9582 |
| PP Test | -175.1695 | -173.8038 | -155.6386 | -150.5054 |

Table 3: Granger Causality table

| Market | U.S. Sentiment | Granger Causality ($\chi^2$) |
|---|---|---|
| TSX Futures | Investor | 2.3128 |
| | Individual | 0.4595 |
| FTSE 100 Futures | Investor | 5.5496* |
| | Individual | 0.1348 |
| China A50 Futures | Investor | 4.511 |
| | Individual | 6.1923** |
| Nifty 50 Futures | Investor | 6.1335 |
| | Individual | 7.353* |

Table 4: Vector Autoregressive Regression across 4 Indices

| Dependent Variables: | TSX | | | FTSE 100 | | | China A50 | | | Nifty 50 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Sample: | Pre-2020 | Post-2019 | Full | Pre-2020 | Post-2019 | Full | Pre-2020 | Post-2019 | Full | Pre-2020 | Post-2019 | Full |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| Index (1 lag) | -0.0771 | -0.3178 | $-0.1511^{*}$ | $-0.2782^{***}$ | -0.2456 | $-0.1670^{**}$ | -0.0953 | -0.1773 | -0.0666 | -0.1823 | $-0.3064^{*}$ | -0.0570 |
| | (0.0997) | (0.2027) | (0.0887) | (0.0977) | (0.1824) | (0.0818) | (0.0952) | (0.1861) | (0.0832) | (0.1177) | (0.1625) | (0.0944) |
| Index (2 lags) | 0.1067 | -0.2402 | -0.0319 | -0.0396 | -0.2456 | -0.0525 | -0.1216 | -0.134 | -0.0839 | $-0.3324^{***}$ | -0.2128 | -0.0865 |
| | (0.0957) | (0.1951) | (0.0869) | (0.0969) | (0.1824) | (0.0822) | (0.0940) | (0.1753) | (0.0832) | (0.1065) | (0.1876) | (0.0918) |
| US Inst. Index (1 lag) | -0.0002 | $-0.0055^{**}$ | -0.0014 | 0.0002 | $-0.0057^{**}$ | $-0.0023^{**}$ | 0.0001 | -0.0026 | -0.0032 | 0.0016 | $-0.0054^{*}$ | -0.0001 |
| | (0.0012) | (0.0025) | (0.0011) | (0.0014) | (0.0023) | (0.0012) | (0.0027) | (0.0032) | (0.0021) | (0.0017) | (0.0030) | (0.0015) |
| US Inst. Index (2 lags) | -0.0002 | 0.0027 | 0.0008 | 0.0005 | 0.0017 | 0.0018 | $0.0060^{**}$ | -0.0004 | $0.0046^{**}$ | 0.0010 | $-0.0055^{*}$ | 0.0025 |
| | (0.0012) | (0.0026) | (0.0011) | (0.0014) | (0.0024) | (0.0015) | (0.0029) | (0.0032) | (0.0021) | (0.0017) | (0.0029) | (0.0015) |
| US Indiv. Index (1 lag) | -0.0012 | 0.0011 | -0.0003 | 0.0010 | 0.0013 | 0.0002 | 0.0001 | -0.0012 | 0.0002 | $-0.0038^{**}$ | -0.0043 | -0.0019 |
| | (0.0011) | (0.0029) | (0.0011) | (0.0013) | (0.0025) | (0.0016) | (0.0027) | (0.0034) | (0.0021) | (0.0016) | (0.0031) | (0.0015) |
| US Indiv. Index (2 lags) | -0.0001 | 0.0035 | 0.0007 | 0.0007 | 0.0024 | 0.0000 | $-0.0071^{**}$ | 0.0012 | -0.0031 | 0.0010 | $0.0069^{**}$ | $0.0029^{*}$ |
| | (0.0011) | (0.0031) | (0.0011) | (0.0013) | (0.0029) | (0.0001) | (0.0028) | (0.0036) | (0.0021) | (0.0017) | (0.0032) | (0.0015) |
| Multiple $R^2$ | 0.1185 | 0.3309 | 0.0665 | 0.148 | 0.2639 | 0.0598 | 0.2033 | 0.209 | 0.0842 | 0.2421 | 0.4462 | 0.093 |
| Observations | 117 | 45 | 164 | 117 | 45 | 164 | 109 | 45 | 156 | 95 | 45 | 142 |

$***\ p < 0.01$, $**\ p < 0.05$, $*\ p < 0.1$; All futures are log transformed and differenced. Most specifications include controls for the 10-year government bond yield, exchange rate with USD, and CPI. Specification 8 does not include a control for bond yield since there was no change to the 10-year interest rate.

Table 5: Volatility spillover table - Full Sample

| | US Inst. | US Indiv. | TSX | FTSE 100 | Nifty 50 | China A50 | Directional FROM others |
|---|---|---|---|---|---|---|---|
| US Inst. | 78.27 | 14.25 | 0.85 | 0.06 | 4.31 | 2.26 | 3.62 |
| US Indiv. | 2.27 | 96.44 | 0.63 | 0.21 | 0.13 | 0.33 | 0.59 |
| TSX | 0.69 | 1.22 | 50.65 | 27.40 | 16.20 | 3.84 | 8.23 |
| FTSE 100 | 1.52 | 0.53 | 27.38 | 51.22 | 15.18 | 4.17 | 8.13 |
| Nifty 50 | 1.22 | 0.88 | 18.64 | 17.52 | 59.47 | 2.28 | 6.76 |
| China A50 | 3.33 | 2.25 | 5.64 | 6.89 | 3.39 | 78.50 | 3.58 |
| Directional TO others | 1.51 | 3.19 | 8.86 | 8.68 | 6.54 | 2.15 | 30.91 |
| Directional including own | 87.3 | 115.57 | 112.65 | 103.3 | 98.68 | 91.38 | Total spillover index (30.91/600): 5.2% |

Table 6: Volatility spillover table - Pre COVID-19 Pandemic

| | US Inst. | US Indiv. | TSX | FTSE 100 | Nifty 50 | China A50 | Directional FROM others |
|---|---|---|---|---|---|---|---|
| US Inst. | 59.72 | 25.02 | 5.49 | 5.35 | 3.63 | 0.79 | 6.71 |
| US Indiv. | 4.34 | 87.67 | 2.42 | 3.06 | 2.33 | 0.18 | 2.05 |
| TSX | 3.29 | 1.92 | 57.94 | 26.34 | 5.18 | 5.34 | 7.01 |
| FTSE 100 | 1.07 | 1.51 | 26.79 | 57.84 | 7.79 | 5.00 | 7.03 |
| Nifty 50 | 3.70 | 5.22 | 10.23 | 11.93 | 67.47 | 1.45 | 5.42 |
| China A50 | 2.88 | 4.84 | 7.20 | 7.31 | 3.82 | 73.94 | 4.34 |
| Directional TO others | 2.55 | 6.42 | 8.69 | 9.00 | 3.79 | 2.13 | 32.57 |
| Directional including own | 75 | 126.18 | 110.07 | 111.83 | 94.01 | 88.83 | Total spillover index (32.56/600): 5.4% |

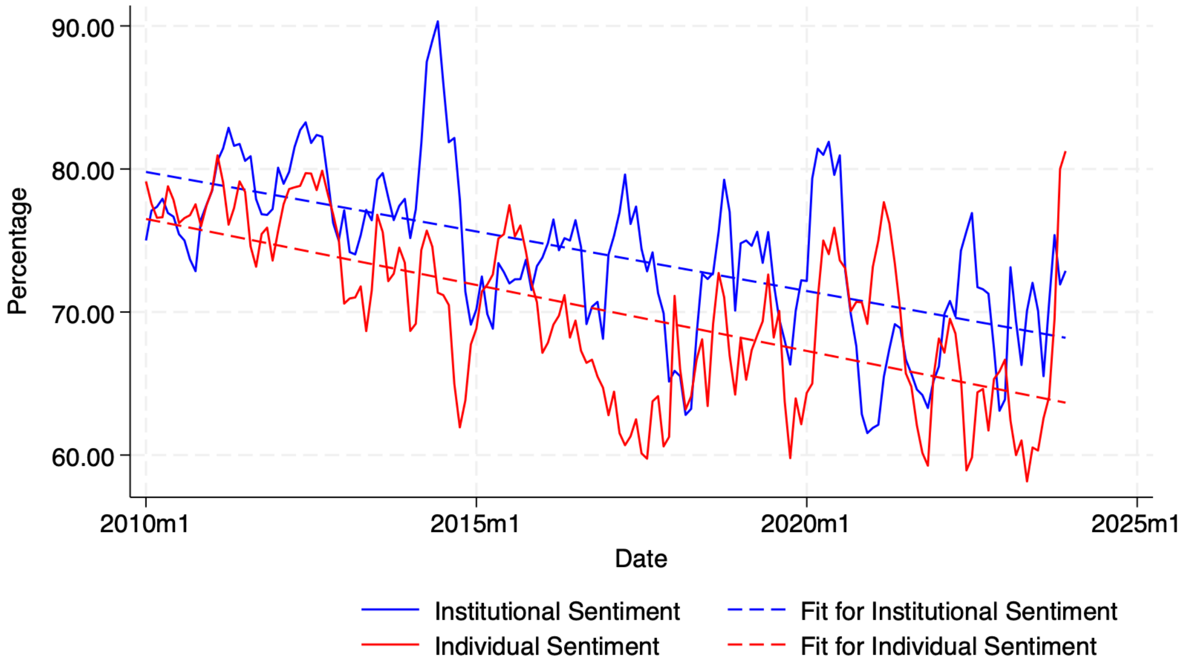


Figure 1: Institutional and Individual Sentiment from January 2010 to December 2023

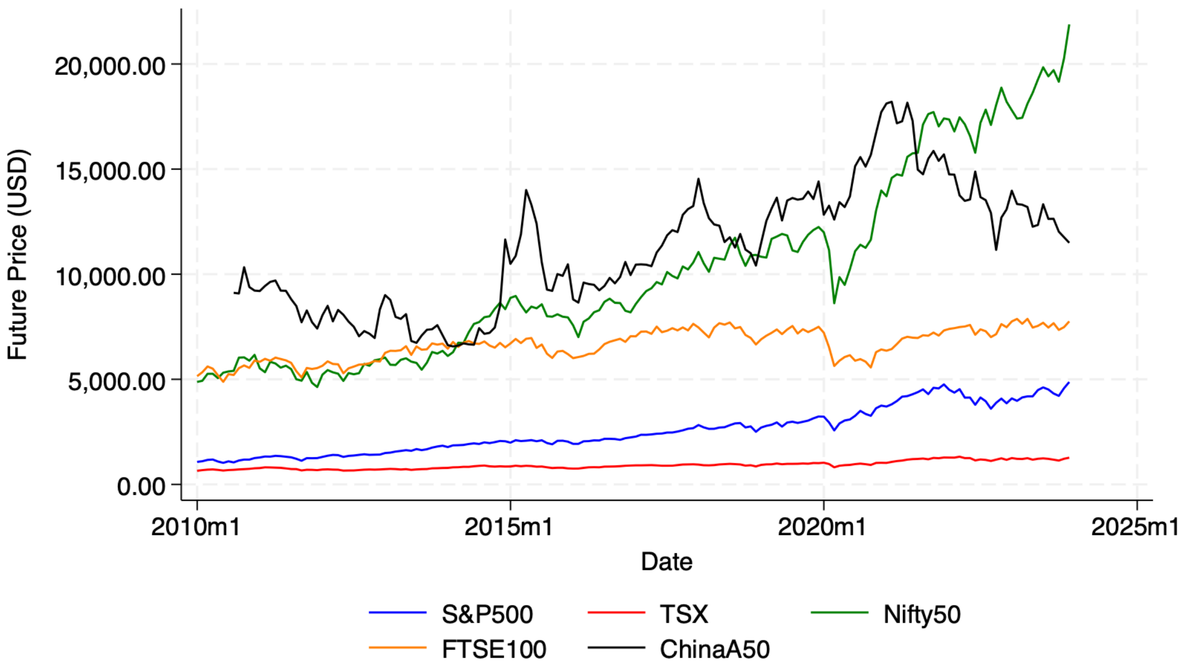


Figure 2: Indices Future prices from January 2010 to December 2023

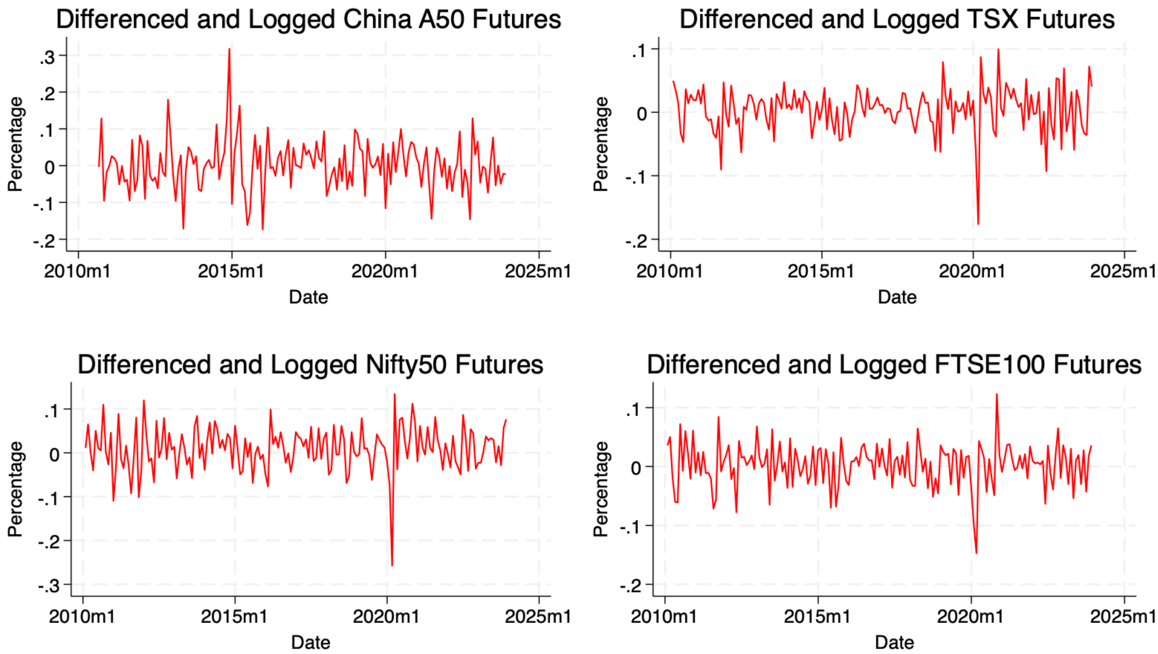


Figure 3: Differenced and Logged Returns

UK Futures Impulse Response Functions

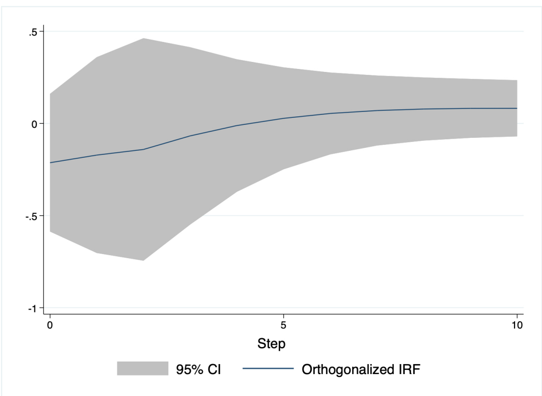


Figure 4: Institutional Sentiment

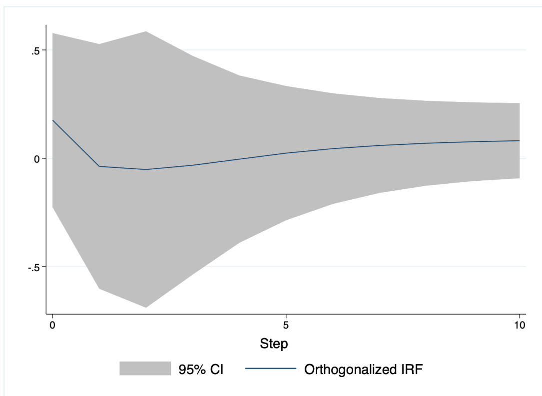


Figure 5: Individual Sentiment

TSX Futures Impulse Response Functions

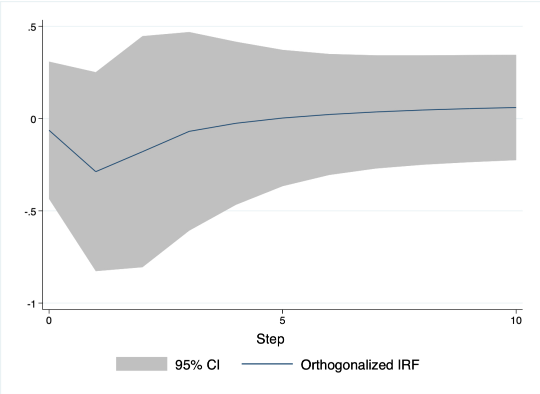


Figure 6: Institutional Sentiment

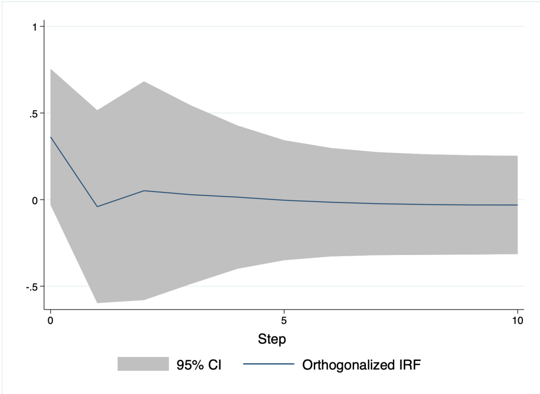


Figure 7: Individual Sentiment

China A50 Futures Impulse Response Functions

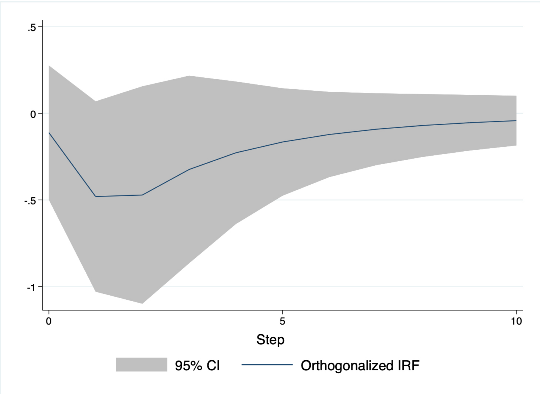


Figure 8: Institutional Sentiment

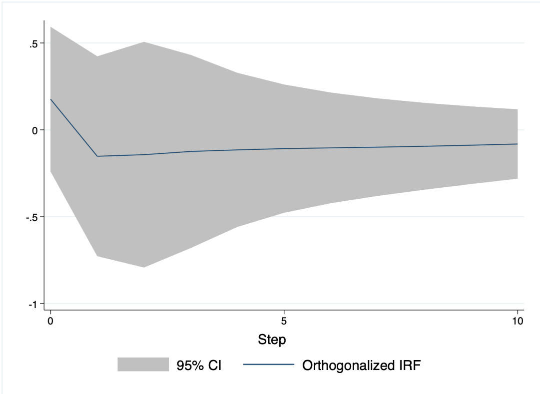


Figure 9: Individual Sentiment

Nifty 50 Futures Impulse Response Functions

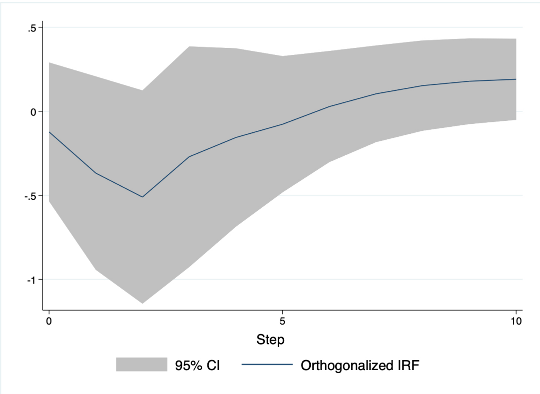


Figure 10: Institutional Sentiment

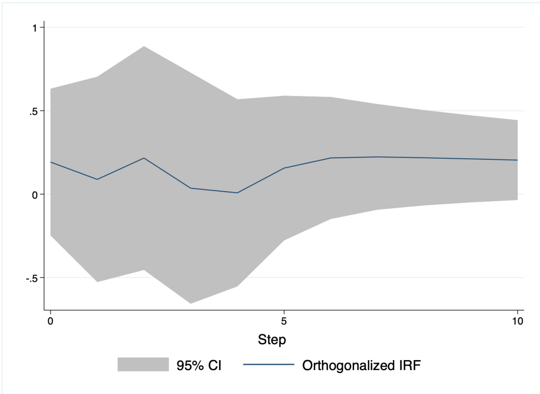


Figure 11: Individual Sentiment