Textual Analysis in Empirical Asset Pricing

by

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Declarations

This thesis is submitted to The University of Warwick in support of the requirements for the degree of Doctor of Philosophy. I confirm that I have not submitted the thesis or any work therein for a degree at another university.

I declare that the second chapter is co-authored with Dr. Ilias Filippou, Dr. Arie Gozluklu, and Prof. Mark Taylor. The third chapter is co-authored with Dr. Ilias Filippou, Dr. Arie Gozluklu, and Dr. Ganesh Viswanath-Natraj. The fourth chapter is my sole work.

My Tra Nguyen

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Abstract

This thesis consists of three chapters, in which I discuss how textual analysis can contribute to the area of empirical asset pricing. In Chapter 2, I implement textual analysis based on newspapers articles and develop a novel measure of U.S. populist rhetoric. Aggregate Populist Rhetoric (APR) Index spikes around populist events. I decompose the APR Index into sub-indices. I show that APR Index and International Relations sub-index are negatively priced in the cross-section of currency excess returns. Currencies that perform well (badly) when U.S. populist rhetoric is high yield low (high) expected excess returns. Investors require high risk premium for holding currencies which underperform in times of rising U.S. populist rhetoric, especially in the post-crisis period. A long-short strategy that buys (sells) currencies with high (low) exposure to U.S. populism offers diversification benefits.

In Chapter 3, I use textual analysis to identify the set of Trump tweets that contain information on macroeconomic policy, trade or exchange rate content. I then analyse the effects of Trump tweets on the intraday trading activity of foreign exchange markets, such as trading volume, volatility and FX spot returns. I find that Trump tweets reduce speculative trading, with a corresponding decline in trading volume and volatility, and induce a bias reflecting Trump's (optimistic) views on the U.S. economy. I rationalise these results within a model of Trump tweets revealing economic content as a public signal that reduces disagreement among speculators.

In Chapter 4, I apply textual analysis to construct the Fiscal News Index based on a large sample of U.S. Presidential Speeches between February 1929 and December 2020. The Fiscal News Index is a priced risk factor in the cross-section of stock returns. Investors demand higher expected returns for holding stocks with high exposure to Fiscal News Index. A long short trading strategy based on this risk factor generates an average excess returns of 8.2% annually with a Sharpe ratio of 0.86.

Chapter 1

Introduction

This thesis consists of three chapters, in which I discuss how textual analysis can contribute to the area of empirical asset pricing. Two chapters focus on the foreign exchange market and the other chapter focuses on the stock market. Across three chapters, I examine different types of textual documents, including historical documents (i.e., Presidential speeches), traditional media (i.e., newspapers), and social media (i.e., Twitter).

In **Chapter 2**, I construct a novel index of populism by assessing the overall populist rhetoric reported by U.S. leading newspapers. Although "populism" has become the catchword in current global affairs, it is not easy to define (Mudde (2004)), and it can be found in all ideological cleavages, including left or right-wing politics. In more recent work, Müller (2017) highlights a prominent feature of populism, which is "anti, such as anti-pluralist, anti-establishment, anti-globalization, and anti-immigration. I follow the methodology in Baker et al. (2016) to construct my Aggregate Populist Rhetoric (APR) Index. In particular, I rely on the dictionary containing populist terms constructed by Bonikowski and Gidron (2015) to identify populist articles, which contain terms in this dictionary from five leading U.S. newspapers. I then scale this raw count of populist articles by a total number of articles belonging to each newspaper's U.S. politics section. The APR Index is constructed as the average of five individual newspapers, weighted by their circulation figures. My APR Index spikes around key events featuring populism in the U.S. politics, such as Seattle WTO protests, the Tea Party movement, and the 2016 U.S. presidential election. I then implement the LDA Algorithm developed by Blei et al. (2003) to discover topics conveyed in populist articles. This step allows me to decompose the APR Index into six sub-indices, each corresponding to one of the topics identified by the LDA Algorithm. Of those sub-indices, I am particularly interested in the International Relations (IR) component in the context of the foreign exchange market.

My paper is the first major empirical work to investigate the link between populism and the foreign exchange market to the best of my knowledge. My empirical analysis is guided by the theory put forward by Pastor and Veronesi (2020). According to the model, an expectation of a populist regime results in higher stock and bond valuations in the U.S. through a risk channel. However, in its original form, the model does not have any predictions about the foreign exchange market. I extend the idea of these valuation effects to the currency market through a fundamental international parity condition, namely uncovered interest parity (UIP). Currencies with negative U.S. populist rhetoric beta yield low excess returns in times of rising U.S. populist rhetoric. Hence they are considered relatively risky assets by U.S. investors. By contrast, currencies with positive exposure to U.S. populist rhetoric beta yield high excess returns when U.S. populist rhetoric is high, so they are considered a hedge against U.S. populist rhetoric. Therefore U.S. investors demand higher expected returns for holding currencies with low U.S. populist rhetoric beta and are willing to pay higher prices and accept lower returns from currencies with high U.S. populist rhetoric beta. I demonstrate the economic value of such exposure via a trading strategy that buys (sells) currencies with low (high) exposure to U.S. populism. This strategy offers high Sharpe ratios (0.82) and strong diversification benefits on top of the conventional trading strategies such as carry and momentum. The pricing results are stronger in the post-crisis period and around gubernatorial elections in swing states.

In **Chapter 3**, I study the effects of Trump Tweets on the currency market. To guide my empirical analysis, I start with a model of heterogeneous private information and Trump tweets as a public signal in the FX market. The market is populated by a set of speculators, each with their own private signal on the valuation of the future spot rate. Investors then update their private signal based on the Trump tweet, which I assume is known to all traders. There are two distinct types of speculators in the model: (rational) Bayesian investors who update their prior based on the information content of the Trump tweet, and (irrational) Trump followers who fully adopt the Trump tweet. My analysis generates three predictions. First, as investors trade on a common signal, there is a decline in the dispersion of investor beliefs on valuations of the future spot rate. I show that a rise in the share of Trump followers leads to a decline in investor disagreement, and in turn a decline in the volume of trading in the currency market. Second, the Trump tweet leads to a decline in exchange rate volatility if the tweet is more informative than the private signal. If speculators rely on the public information via informative Trump tweets over their private signals, the corresponding reduction in asymmetric information leads to a reduction in bid-ask spreads. Finally, I show that Trump tweets induce a bias in spot returns reflecting differences between the (optimistic) views of Trump and the speculators on the future valuation of macroeconomic fundamentals.

Turning to the data, I first conduct a textual analysis on Trump tweets to identify the information content related to the macroeconomic outlook, trade and international developments that are impounded in exchange rates. My sample period is from 16th June 2015, the starting date of Trump's presidential campaign, to 20th August 2019. I implement two methods to identify Macro and Trade tweets. The first approach follows keywords by topics outlined in Baker et al. (2019). Second, I use the topic modelling approach developed by Yan et al. (2013) to filter out tweets about macroeconomics outlook, trade policy, and exchange rate topics. I proceed to link Trump tweets to outcomes in the FX market, and construct my measures of FX market activity. My main empirical results test a panel specification with the outcome variables of FX volume, volatility, bid-ask spreads and spot returns. I find statistical evidence that Tweet hours are associated with a decrease in FX trading volume. Second, I find declines in my measure of intraday FX spot volatility and bid-ask spreads around Trump tweet hours, indicative of a reduction in investor disagreement during tweet hours. Third, I identify systematic effects of Trump tweets on FX spot returns. The dollar tends on average to appreciate with respect to major bilateral pairs during Trump tweet hours. This appreciation is consistent with the nature of Trump tweets, that reflect typically his positive views on the U.S. economy (relative to other countries), and trigger a protectionist stance on trade policies. I test this mechanism by constructing a proxy for FX disagreement from options data. I hypothesize that during Trump tweet hours, the common signal reduces the dispersion in the future valuation of exchange rate fundamentals, and therefore reduces the measure of disagreement based on the options pricing. In line with my hypothesis, I find a statistically significant reduction in my measured proxy for investor disagreement during Trump tweet hours.

In **Chapter 4**, I construct the Fiscal News Index based on a collection of U.S. Presidents' speeches and examine their impacts on the stock returns. In particular, I first collect a large sample of speeches (i.e., news conferences, interviews, state of union speeches, remarks, radio speeches, oral addresses) of U.S. Presidents from February 1929 to December 2020. LDA Algorithm developed by Blei et al. (2003) is employed to discover the information content that U.S. Presidents convey to the public. The fiscal policy can be clearly identified based on the keywords provided by LDA Algorithm. I then construct the monthly Fiscal News Index as the average of fiscal topic delivered during the month. This index can be considered as a dimension of political risks. Compared with existing political risks in the literature, the advantage of Fiscal News Index is that it is a historical time-series index going back as far as 1929. In addition, it is also not based on subjective assessments of experts. Fiscal News Index spikes during recessions, as the president is more likely to announce changes in fiscal policy to support the economy when the economic conditions are unfavourable.

I then find pricing implications of Fiscal News Index for the cross-section of stock returns. My empirical findings from Fama-Macbeth cross-sectional regressions suggest that Fiscal News is positively priced in the cross-section of stock returns. Investors demand higher expected returns for stocks with high exposure to Fiscal News. Decomposing the expected return into Cash flow news return and Discount rate return, I find that the pricing implications of Fiscal News for cross-sectional stock returns is mainly through the Discount rate news channel. This is consistent with the theoretical model in Pástor and Veronesi (2013), which suggests that political uncertainty increases the discount rates as investors demand a risk premium. I also show the economic value of the exposure to this risk factor though a trading strategy that goes long stocks with high exposure to Fiscal News and short stocks with low exposure to Fiscal News. An equal-weighted portfolio following this strategy generates an average excess returns of 8.2% annually with a Sharpe ratio of 0.86. This outperforms an alternative strategy of investing in the S&P500 Index. During the same time, investing in the S&P500 Index yields an average excess return of 4.5% annually with a Sharpe ratio of 0.25. In addition, the excess return of this portfolio cannot be explained by conventional risk factors.

Chapter 2

U.S. Populist Rhetoric and Currency Returns

[1]

[1]This paper is co-authored with Ilias Filippou, Arie Gozluklu, and Mark Taylor.

"There is a historic battle going on across the west, in Europe, America, and elsewhere. It is globalism against populism. And you may loathe populism, but I'll tell you a funny thing. It is becoming very popular! And it has great benefits." Nigel Farage (2020)

2.1 Introduction

'Populism' was the Word of the year in 2017 based on the word-searches in Cambridge University Press. This confirms the enormous public attention surrounding this topic following a range of recent unexpected political events worldwide, such as the election of Donald Trump as the 45$^{\text{th}}$ president of the U.S. or the U.K.'s vote to exit from the European Union. There has been a rapidly growing number of papers investigating populism and its consequences, mostly in political science and economics literature (see, for example, Guriev and Papaioannou (2020)). However, its effect on financial markets remains unexplored.[2] One of the key challenges to conduct empirical work remains to be quantifying this somewhat elusive concept.

In the foreign exchange market, currencies issued on behalf of sovereign entities are intertwined with politics (e.g., the effect of Brexit on the British Pound).[3] The high trading volume and globally integrated characteristics make the foreign exchange market particularly sensitive to global events. The political climate in the U.S. should be of particular relevance for this market due to the size and importance of the U.S. economy and the intensive use of USD as a vehicle currency (Maggiori et al. (2019)). The victory of Donald Trump in the recent 2016 U.S. presidential election gives us a perfect example showing the extent to which U.S. politics in general, and U.S. populism, in particular, can impact the foreign exchange market. Following the election outcome, the Mexican Peso hit its lowest performance against the USD in 20 years. However, some currencies, such as British Pound, showed resilience against the USD, reaching its best fortnight performance in eight years at some point during that period. This motivates me to investigate the question as to how U.S. populism, which is a growing political tendency, is linked to the cross-section of currency excess returns.

The main contribution of my paper to the literature is twofold. First, I construct a novel index of U.S. populism by assessing the overall populist rhetoric reported by U.S. leading newspapers. Some ongoing large-scale projects are trying to quantify populism by measuring populist characteristics of specific political leaders based on campaign speeches (TeamPopulism 2019 Project), or the demand for populism based on vote shares for populist leaders or parties (Bayerlein et al. (2019)). I differentiate

[2]One exception is the theory proposed by Pastor and Veronesi (2020) which I discuss in detail to motivate my empirical analysis.

[3]The foreign exchange market is the biggest asset market in the world in terms of the trading volume. More than 6.6 trillion USD are traded on average every day based on the BIS (2019) survey.

my work from those projects as I aim to assess the populist rhetoric in U.S. politics using leading newspapers, not populist characteristics of any particular political leader or party. Although "populism" has become the catchword in current global affairs, it is not easy to define (Mudde (2004)), and it can be found in all ideological cleavages, including left or right-wing politics. In more recent work, Müller (2017) highlights a prominent feature of populism, which is "anti, such as anti-pluralist, anti-establishment, anti-globalization, and anti-immigration. Several papers propose some limitations of defining populism as an ideology (Gidron and Bonikowski 2013, Aslanidis 2016). Populist characteristic of political actors or parties is likely to vary over time, whereas their ideologies are much more stable. Therefore, considering populism as an ideology limits the ability to capture the time variation of this concept. Hence, I consider populism as a political style or rhetoric (Jagers and Walgrave (2007), Bonikowski and Gidron (2015)). Rhetoric is the communication strategy used to persuade the audience. Rhetoric therefore differs from sentiment, which mostly focuses on the positivity (and negativity) or uncertainty of the language.

I follow the methodology in Baker et al. (2016) to construct my Aggregate Populist Rhetoric (APR) Index. In particular, I rely on the dictionary containing populist terms constructed by Bonikowski and Gidron (2015) to identify populist articles, which contain terms in this dictionary from five leading U.S. newspapers. I then scale this raw count of populist articles by a total number of articles belonging to each newspaper's U.S. politics section. The APR Index is constructed as the average of five individual newspapers, weighted by their circulation figures. My APR Index spikes around key events featuring populism in the U.S. politics, such as Seattle WTO protests, the Tea Party movement, and the 2016 U.S. presidential election. I then implement the LDA Algorithm to discover topics conveyed in populist articles. This step allows me to decompose the APR Index into six sub-indices, each corresponding to one of the topics identified by the LDA Algorithm. Of those sub-indices, I am particularly interested in the International Relations (IR) component in the context of the foreign exchange market.

Second, my paper is the first major empirical work to investigate the link between populism and the foreign exchange market to the best of my knowledge. My empirical analysis is guided by the theory put forward by Pastor and Veronesi (2020). According to the model, an expectation of a populist regime results in higher stock and bond valuations in the U.S. through a risk channel. However, in its original form, the model does not have any predictions about the foreign exchange market. I extend the idea of these valuation effects to the currency market through a fundamental international parity condition, namely uncovered interest parity (UIP).

While a large literature documents deviations from the UIP (e.g., Fama, 1984; Bussiere et al., 2019)) and provides risk-based explanations for such deviations (see, for example, Lustig et al. (2011)), I first show in the context of standard Fama regressions in a panel setting that the UIP relation does hold once I explicitly account for main risk factors suggested in the literature, especially for developed (G10) countries. More importantly, populist rhetoric is one of such factors that cannot be explained by existing risk channels. In fact, I show that U.S. populist rhetoric is priced in the cross-section of currency excess returns due to heterogeneous sensitivity to USD valuation in times of rising populist rhetoric. I explain this heterogeneity via U.S. assets held by developed economies and USD denominated debt issued by developing countries (a.k.a. original sin, (e.g., Eichengreen et al., 2005)).

Currencies with negative U.S. populist rhetoric beta yield low excess returns in times of rising U.S. populist rhetoric. Hence they are considered relatively risky assets by U.S. investors. By contrast, currencies with positive exposure to U.S. populist rhetoric beta yield high excess returns when U.S. populist rhetoric is high, so they are considered a hedge against U.S. populist rhetoric. Therefore U.S. investors demand higher expected returns for holding currencies with low U.S. populist rhetoric beta and are willing to pay higher prices and accept lower returns from currencies with high U.S. populist rhetoric beta. I demonstrate the economic value of such exposure via a trading strategy that buys (sells) currencies with low (high) exposure to U.S. populism. This strategy offers high Sharpe ratios (0.82) and strong diversification benefits on top of the conventional trading strategies such as carry and momentum. The pricing results are stronger in the post-crisis period and around gubernatorial elections in swing states.

I also examine the robustness of my results after controlling for other determinants of currency premia and find similar results. In particular, portfolio sorts are nonparametric as I do not impose a functional form in the relation between the U.S. populist rhetoric beta and future currency excess returns. On the other hand, portfolio analysis does not take into consideration a large part of the information in the cross-section because of aggregation, and it is more challenging to control for other factors that simultaneously drive the cross-section of currency returns (e.g., Bali et al., 2017). To this end, I also investigate the cross-sectional predictive ability of the U.S. populist rhetoric beta for expected currency returns at the currency level by applying Fama and MacBeth (1973) regressions. I control for FX volatility and FX illiquidity. Consistent with my previous findings, I find that the U.S. populist rhetoric beta is a strong negative predictor of the cross-section of currency returns.

In the Pastor and Veronesi (2020) model, a shift to a populist regime is captured by a move to autarky from globalization. To validate my measure of populist rhetoric, I also test its sensitivity through a firm's exposure to globalization. I measure exposure to globalization using equity data following Barrot et al. (2016) and then sort stock returns of U.S. manufacturing firms into quintiles based on shipping costs. Firms in the low (high) shipping cost portfolio are more (less) exposed to globalization. I show that there is a positive correlation between the low shipping cost portfolio returns and

APR Index. This is consistent with the rationale that an increase in APR Index signals a switch from integrated markets to the autarky in the U.S. so that firms with high exposure to globalization should offer a higher return as compensation for the risk of a U.S. populist regime. Importantly, I find an almost monotonically decreasing pattern as I go from most integrated to least integrated firms. In other words, holding a portfolio of firms with low exposure to globalization offers a hedge in times of rising U.S. populist rhetoric.

I also perform additional robustness tests, and my results still hold. In particular, I control for additional factors that drive the cross-section of currency returns, such as a dollar factor and a carry trade factor, and find similar results. I consider alternative proxies for U.S. populist rhetoric. I also construct a factor mimicking portfolio and find that is priced in the cross-section of currency returns. I also report results for different newspapers.

The rest of the paper is structured as follows. Section 2 summarizes related literature. Section 3 outlines theoretical framework for my empirical work in detail. Section 4 describes the methodology implemented to construct the APR Index and associated sub-indices. Section 5 describes the data and portfolio construction. Section 6 discusses the empirical findings. Section 7 discussed the relation between globalization and U.S. populist rhetoric. Section 8 offers robustness checks. Section 9 concludes.

2.2 Literature Review

My paper is related to several strands of literature. First, it is closely related to political science literature investigating different methodologies to measure populism. The traditional approach is to apply the populist label without any systematic empirical justifications (Hawkins 2009). Alternatively, one can assess populism on a scale basis rather than classifying political parties or actors as *populist*. Textual analysis has been a popular method to measure populism because the input is usually spoken or written statements by political actors. The majority of papers rely on classical manual textual analysis (Jagers and Walgrave 2007, Rooduijn and Pauwels 2011, Balcere 2014, Bos and Brants 2014) to measure populism. The labor-intensive nature of human coding significantly limits the sample size and raises reliability issues. Therefore a growing number of papers have shifted their approach to computer-based textual analysis, which is also widely used in economics. For example, Baker et al. (2016) construct economic policy uncertainty indices by counting the number of uncertainty related words in newspapers articles. Caldara and Iacoviello (2018) also follow a similar methodology, but their interest is in a different type of risk, which is geopolitical risk. Gentzkow and Shapiro (2010) use the similar methodology to construct an index of media slant that measures the similarity of news outlet's language to that of a congressional Republican or Democrat. None of these papers focus on the rising political tendency in the form of populist rhetoric.

Rhodes and Johnson (2017) use a dictionary to identify statements mentioning the wealthy from Democratic presidential campaigns speeches, then create an index of frequency of these statements over time, and analyze the tone of these statements. Its limitation is the narrow focus on left-wing populism. Rooduijn and Pauwels (2011) develop a dictionary containing anti-elitism words, and count the frequency of these words as an index of populism. Bonikowski and Gidron (2015), on the other hand, develop a dictionary of populist terms based on more than 2,400 U.S. presidential campaign speeches between 1952 and 1996. By employing a sophisticated algorithm to construct this dictionary, the authors capture general and U.S. specific context words and validate their dictionary by manually reading 40.1% of their total dataset and hand-coding excerpts from 890 speeches. These merits of their populist dictionary make it an ideal choice for my purpose of searching for newspaper articles with populist rhetoric. My index of populism, however, deviates from previous works using the dictionary-based method in several ways as I do not aim to measure the populism of any particular party or leader but the overall populist rhetoric used in U.S. politics. I choose newspaper articles in order to get a time-varying index of populism at a higher frequency and continuously track the time-variation in populist rhetoric in a relatively long time series, which cannot be attained by focusing on social media content such as Facebook posts and Tweets (Ernst et al. (2017), Filippou et al. (2020b)). The populist rhetoric reported by newspapers captures the populist rhetoric of not only the president in power but also other political agents such as potential presidential candidates.

My paper is also related to papers studying populism in the economics literature investigating the reasons for the rise of populism (Guriev and Papaioannou (2020)). For example, Rodrik (2018) suggests that globalization's shock is one of the reasons leading to the political backlash by increasing domestic inequality. Globalization creates gaps in society, e.g., between skilled and unskilled workers, globally mobile professionals and local producers, elites and ordinary people. This explanation has been supported by empirical evidence (Guiso et al. 2017, Colantone and Stanig 2018). Another strand of literature studies the effects of populism on the macroeconomy, e.g., growth and income distribution (Sachs 1989, Dornbusch and Edwards 2007). In a recent paper, Pastor and Veronesi (2020) establish the link between populism and asset prices in a model that contains elements from both strands of economic literature in terms of inequality and macroeconomic implications of populism. I discuss the details of the model in the next section as part of the motivation for my empirical study.

My paper is also related to broad research investigating the effects of politics on asset prices. Sattler (2013) suggests that stocks decrease considerably after the election of a left party and increase after the election of a right party in countries where political constraints are low. Santa-Clara and Valkanov (2003), examine the stock market's performance during Democratic and Republican presidencies between 1927 and 1998. They find the presidential puzzle, which shows that the excess return of stocks is higher when the Democratic president is in power. Booth and Booth (2003) also confirm this pattern for small stock portfolio, but it is not the case for a large stock portfolio. Other studies also find that this presidential puzzle exists in other countries outside the U.S., such as Germany (Döpke and Pierdzioch 2006), New Zealand (Cahan et al. 2005), Australia (Worthington 2009). I differ from these existing papers since my focus is the effect of populist rhetoric in media on currency markets rather than the bipartisan effect on stock returns.

Last but not least, a vast literature has examined the foreign exchange predictability in the cross-section of currency excess returns. The predictability has been shown using investment strategies, such as carry (Lustig et al. 2011), and momentum (Menkhoff et al. 2012b). Although these papers document the predictability of currency excess returns, the fundamental forces behind them are still unclear. Della Corte et al. (2016) suggest that global imbalance is a risk factor that can be used to explain returns to carry trade. However, Barroso et al. (2018) argue that the evidence is sensitive to the choice of test assets, and it is also not robust once controlling for financial variables. This highlights the challenge of determining the market valuation of currency returns. Also, taking a macroeconomic perspective, Riddiough and Sarno (2016) suggest output gap as the risk factor. Some papers suggest risk factors based on properties of FX returns, such as correlation risk (Mueller et al. 2017), and global FX volatility risk (Menkhoff et al. 2012a). From a political perspective, Filippou et al. (2018) suggest that global political risk explains returns to momentum strategy. In this paper, I do not aim to use U.S. populist rhetoric as a risk factor to explain conventional trading strategies. Instead, I highlight that U.S. populist rhetoric is priced in the cross-section of individual currency excess returns.

2.3 Theoretical Motivation

My empirical work is largely motivated by the theoretical framework established in Pastor and Veronesi (2020). In their model, agents in two countries, the U.S. and the rest of the world (RoW), dislike inequality within their country. U.S. agents are less risk-averse than RoW agents. Under globalization, agents in two countries trade freely, which increases not only aggregate consumption/output in the U.S. but also its domestic inequality. The reverse is the case under financial autarky, in which U.S. aggregate consumption/output decreases, but the gap between the rich and the poor is narrower. A presidential candidate is populist if he or she promises to end globalization as soon as elected. The model suggests that when U.S. output is large enough, more than half of U.S. agents will vote for a populist candidate due to their inequality aversion, which shifts the U.S. to financial autarky. Two important predictions from the model regarding populism and stock prices and bond yields are of particular importance to my paper.

Regarding stock price, the model suggests that as the probability of populist victory increases, the U.S. market price of risk goes down. As a result, U.S. stock market valuation increases. The intuition is as follows: Under autarky, the risk associated with U.S. output is borne by U.S. agents only, which is not the case under globalization, in which this risk is borne by both U.S. and rest of the world (RoW) agents. As U.S. agents are assumed to be less risk-averse, they demand a lower compensation for risk. The model predicts that U.S. bond yields are low, possibly negative, as anticipation for populist victory escalates. The intuition underlying this prediction is that as moving to autarky decreases U.S. agent's consumption, marginal utility to U.S. agents is high in this case. Therefore U.S. bonds are more valuable under the expectation of a populist regime, as they provide future consumption when its marginal utility of consumption to U.S. agents is high.

These theoretical predictions indicate that U.S. populism is a potential state variable that affects asset prices through the risk channel. Pastor and Veronesi (2020) model U.S. populism as a shift from globalization to financial autarky. Market expectation of this outcome, therefore, plays an important role for asset prices.

The high trading volume and globally integrated characteristics make the foreign exchange market particularly sensitive to the political climate in the U.S. Therefore the foreign exchange is the relevant asset class to conduct the empirical test.

In order to see the effect on exchange rate returns, I can write the fundamental equation of asset pricing in the context of currency returns (Kremens and Martin, 2019):

$$\mathbb{E}_t[\frac{S_{t+1}}{S_t}] = \frac{i_t}{i_t^*} - i_t cov_t(M_{t+1}, \frac{S_{t+1}}{S_t}) \tag{2.1}$$

where left-hand-side describes the expectation of gross exchange rate returns under the physical measure, S_t is the spot exchange rate (USD is the pricing currency), $i_t (i_t^*)$ is the U.S. (foreign) short term interest rate and M_{t+1} is the stochastic discount factor (SDF) that prices assets (in USD) in the economy.

Under rational and risk neutral expectations, the last term in equation 2.1 disappears and implies the well-known Uncovered Interest Parity (UIP) condition suggesting that countries with relatively high interest rates are expected to have a depreciating currency. However, an extant empirical literature relying on Fama regressions and portfolio sorts (e.g., Fama (1984), Lustig et al. (2011)) document the importance of risk compensation as a justification for the deviations from the UIP relation.[4]

One of the most common empirical tests of UIP is based on Fama regressions controlling for risk proxies (e.g., Fama (1984), Bussiere et al. (2019)):

$$\Delta s_{t+1} = \alpha + \beta(i_t - i_t^*) + \gamma\Gamma_t + \epsilon_{t+1} \tag{2.2}$$

where Δs_{t+1} is the realized log foreign exchange return and Γ_t is a vector containing empirical proxies of theoretical risk factors represented in the SDF (M_{t+1}).

Based on the prediction of Pastor and Veronesi (2020) model, I argue that the U.S. populist rhetoric index (APR), especially the International Relations (IR) sub-index, is a good observable proxy for the underlying risk facing currency investors beyond other risk proxies. Given that media coverage, and in particular, newspapers, is an important source of information for investors, when there is a rise in populist rhetoric –as reported by leading newspapers especially related to international relations– U.S. investors are likely to consider it as a signal that the U.S. economy is moving from an integrated world to autarky.

I would also expect the U.S. populist tone, captured by my APR Index and IR sub-index, to affect the cross-section of currency excess returns. It is based on the key intuition that U.S. populism leads to lower U.S. consumption/output, increasing marginal utility consumption to U.S. agents. Investors value currencies that provide U.S. investors with high excess returns in times of rising populist rhetoric. Thus, they are willing to pay higher prices and accept lower returns from these currencies. By contrast, they demand higher excess returns as compensation for holding currencies that underperform during rising populist rhetoric. Therefore I expect U.S. populist media tone to be negatively priced in the cross-section of currency excess returns.

[4]Some important risk factors investigated in the literature are currency crash risk (Brunnermeier et al. (2008)), FX liquidity (Mancini et al. (2013)), FX volatility (Menkhoff et al. (2012a)), sovereign risk (Della Corte et al. (2018)), global imbalances (Della Corte et al. (2016)), bond liquidity (Lee and Jung (2020)), credit risk (Della Corte et al. (2020)), global equity market and financial cycle (Panayotov (2020), Rey (2015)).

I further conjecture that the channel through which countries are exposed to U.S. populist rhetoric differs across developed (G10) and emerging economies. While the former benefit from the positive valuation effects under U.S. autarky through their Dollar-denominated assets (Maggiori et al. (2019)), the latter suffer from Dollar-denominated liabilities such as sovereign debt issued in USD (Eichengreen et al. (2005)) and Dollar-denominated credit (BIS (2019)).

2.4 U.S. Populist Rhetoric Index

This section describes the methodology I use to construct my Aggregate Populist Rhetoric Index from leading newspapers and introduces the latent Dirichlet Allocation (LDA) algorithm to obtain its sub-indices.

2.4.1 Newspapers

I rely on digital archives of five leading U.S. newspapers, including The New York Daily News, The New York Post, USA Today, The Washington Post, and The New York Times. Statistics from World Atlas in 2017 suggest that these five newspapers account for around 70% of total circulation from 10 U.S. leading newspapers.[5] Therefore, newspapers captured by my index should reach a majority of U.S. readers. The same political news may be reported differently by different newspapers due to their political bias. To ensure diversity in terms of newspapers' political bias, I draw on both left-leaning and right-leaning newspapers. In particular, two right-leaning newspapers in my sample are The New York Daily News and The New York Post, whereas two left-leaning newspapers are The New York Times and The Washington Post. USA Today is considered politically neutral. The classification of political leanings is obtained from the Boston University Libraries website.[6] My index begins from January 1998, when data for all five newspapers are available in Nexis database, up until October 2018.

[5] https://www.worldatlas.com/articles/the-10-most-popular-daily-newspapers-in-the-united-states.html

[6] https://library.bu.edu/news/bias

2.4.2 U.S. Aggregate Populist Rhetoric Index

My objective is to search for articles containing populist rhetoric published in these five newspapers. I define an article as populist if it falls under the U.S. politics category and contains at least one term in the populist dictionary constructed by Bonikowski and Gidron (2015) either in its title or main content. To minimize the risk of finding articles incorrectly classified as populist by the algorithm (false positives), I rely on the short version of their dictionary. The authors have eliminated all underperforming terms. This final dictionary I use contains 26 terms ranging from uni-grams to four-grams+. There might be potential concerns that there are populist articles not detected for not containing any terms in the populist dictionary (false negatives). However, as Bonikowski and Gidron (2015) emphasize in their paper, this number is expected to be low due to their extensive search for relevant populist terms. I search for populist articles from five newspapers on the Nexis database by entering 26 populist terms in the search box and applying two index terms to filter out non-U.S. politics articles. The first index term is Public and Government Administration as a subject, and the second one is the United States as geography. The list of my populist terms can be found in Table 2.1. This allows me to obtain the count of populist articles from newspapers over my sample period.

Previous studies following similar methodology such as Baker et al. (2016) have pointed out a problem related to the focus on the raw counts of articles, as the volume of articles tends to vary over time and across newspapers. Therefore, I am interested in the ratio of the raw counts of populist articles divided by the total number of U.S political articles published monthly. The latter can be obtained by removing all the populist terms in the search box while still keeping two index terms. Having constructed five individual time series corresponding to each newspaper, I standardize each time-series by demeaning and dividing it by its standard deviation.

My Aggregate Populist Rhetoric (APR) Index is constructed as the average of all time-series, weighted by their circulation figures based on five individual standardized time-series. USA Today is the newspaper with the highest circulation. In contrast, the New York Post is the least circulated among the newspapers[7]. Figure 2.2 shows my APR Index plot, and I provide its summary statistics in Table 2.2. I report summary statistics of both APR Index and its change (i.e., ΔAPR). The interaction between the index and ruling party in the U.S. is shown in Figure A.4. The index is on average higher when the president in power is from Democratic party.

I evaluate my APR Index by uncovering events underlying their patterns. The plot of my APR Index displays several spikes over this sample period. The first spike is

[7] Circulation figures used to construct the index can be found at https://www.worldatlas.com/articles/the-10-most-popular-daily-newspapers-in-the-united-states.html

recorded during the year 2000, reflecting two notable political events featuring populism surrounding this time frame. The first event is the Seattle WTO protests on 30 November 1999. The second event is the run-up to the 2000 presidential election, with several candidates emphasizing economic inequality in their campaigns, such as Al Gore and John McCain. My indices exhibit some significant jumps again between 2010 and 2012. This corresponds to the emergence of the Tea Party movement opposing big government intervention in the economy and the burst of Occupy Wall Street protests against financial greed and corruption. Finally, my indices' spike during the recent period is associated with the remarkable 2016 presidential campaigns, which observed two candidates from both left-wing (Bernie Sanders) and right-wing (Donald Trump) claiming to represent the interests of the American people. The ultimate victory of Donald Trump, together with his populist rhetoric, explain the rise in the index even after the election in November 2016.

In *Panel A* of Table 2.3, I report the correlation between my index and some related uncertainty and political risk indices in the literature. My APR Index seems to have a mild positive correlation with VIX Index, Economic Uncertainty Indices constructed by Jurado et al. (2015), and the Political Risk Index from International Country Risk Guide (ICRG). However, the correlation is not very high. Besides, my APR Index seems to be unrelated to Economic Uncertainty Index constructed by Baker et al. (2016), and it is negatively correlated with the Geopolitical Risk Index constructed by Caldara and Iacoviello (2018). The reason behind this negative correlation is likely to be due to the fundamental differences in index construction. Geopolitical Risk Index captures events associated with wars, terrorist acts, and some events that do not feature U.S. involvement. Overall, correlation results suggest that my APR Index captures a different dimension than the existing economic and political uncertainty indices.

Based on the theoretical framework in Pastor and Veronesi (2020), an increase in populism will result in a decrease in U.S. aggregate consumption or output, therefore we expect a negative link between APR Index and GDP growth. The effects of an increase in APR on the GDP growth in the next 4 quarters are shown in Figure A.1. As can be seen from this graph, an increase in APR is associated with a statistically significant decrease in GDP growth in 2 quarters ahead. The effect fades away after 2 quarters.

2.4.3 Topic Distribution of Populist Rhetoric Articles

This section decomposes the APR Index into sub-indices by discovering the topics reported in populist rhetoric articles.

2.4.3.1 The Latent Dirichlet Allocation (LDA) Algorithm

I choose the LDA topic modeling algorithm, one of the prominent latent topic models, to analyze my data. The LDA algorithm is developed by Blei et al. (2003), and it has been applied in various contexts, including finance (Jegadeesh and Wu 2017, Hansen et al. 2017). This method employs hierarchical Bayesian analysis to discover the semantic structure of textual documents. This method's intuition is that each document is represented as combinations of latent topics, and each latent topic is characterized by a distribution over words. Latent topic models infer these two hidden distributional properties based on the corpus. LDA assumes that these two distributions follow the Dirichlet distribution. My analysis's base unit is a newspaper article, which means that I have a collection of T newspaper articles. Each article is a mixture of a list of words. I denote by V the number of unique words across all T newspaper articles.

Two inputs required when fitting the LDA model are the corpus of documents and the number of topics N. In order to minimize the researcher's subjectivity when choosing the number of topics for the LDA model, a topic coherence score matrix is computed for a number of topics being in the range between 5 and 20. A topic coherence score matrix indicates how well the LDA model fits the data with that particular number of topics. The coherence score suggests that the optimal number of topics given our data is when $N = 6$.

I briefly describe the methodology implemented by LDA. Each document t is constituted by a mixture of N topics. $\theta_d = [\theta_{d,1},...,\theta_{d,N}]$', in which $\theta_{d,n}$ is the proportion of topic n in article t. This mixture of topic proportions is assumed to follow an order -N Dirichlet distribution over the N topics. Each topic n is a mixture of v words, and it is also assumed to follow an order-V Dirichlet distribution over the V words. The probability of each words contributing to document t can be expressed as follows:

$$\prod_{n=1}^{N} \sum_{zn} = Pr[z_n|\theta]Pr[w_n|\beta_{zn}]$$

The probability of each document t is therefore:

$$\int \cdots \int \prod_{k=1}^{K} Pr[\beta_k|\eta]Pr[\theta|\alpha](\prod_{n=1}^{N} Pr[z_n|\theta]Pr[w_n|\beta_{z,n}])t\beta_1 \ldots t\beta_K$$

I focus on two important sets of results of the output from the LDA algorithm. The first one is the top keywords and their distribution for each topic. The second is the proportion of each topic in each article. I implement the LDA algorithm with the corpus being all articles containing populist rhetoric identified in the previous section. This amounts to 19,784 articles in total. I first follow standard text cleaning procedures. In particular, I only extract the text from the articles. Other information such as the journal's name, article title, length, and language from raw Nexis downloaded files are all removed. All words are converted to lowercase, then all website links, email addresses are removed. I also remove English stop words [8], words with length less than two characters, 300 most common words, and 1000 least common words in my sample. After being tokenized into unigrams, the words are stemmed using Porter stemmer (Porter 1980), which is implemented through Python's Natural Language Toolkit.

2.4.3.2 Results from LDA Algorithm

The first set of results obtained from LDA algorithm is the top keywords and their distributions in each topic. For each topic n, there is a set of vectors $\hat{\beta}_n = [\hat{\beta}_{n,1},..., \hat{\beta}_{n,J}]'$, in which $\hat{\beta}_{n,j}$ is the probability that the word j defines topic n.

The full list of the top 15 keywords for all 6 topics can be found in Table A.1. Based on those keywords, I can identify the content of each topic. For example, topic 2 contains words such as insur, price, medicar, reduc, debt..., which suggests that this topic is about Fiscal Matters. Based on keywords of topic 5 such as china, terrorist, iraqi, japan..., I can identify this topic as International Relations. Similarly, the other 4 topics can be clearly identified. In particular, topic 0 covers lawsuits, topic 1 covers judiciary system, topic 3 covers election time, and topic 4 covers campaign contribution.

The second set of output is the proportion of topics for each article. In particular, for each article t there is a set of vectors $\hat{\theta}_t = [\hat{\theta}_{t,0}, \hat{\theta}_{t,1}, \hat{\theta}_{t,2}, \hat{\theta}_{t,3}, \hat{\theta}_{t,4}, \hat{\theta}_{t,5}]'$, in which $\hat{\theta}_{t,n}$ is the proportion of article t that is made up of topic n. Some samples of populist rhetoric articles and their corresponding classification results from LDA can be found in Appendix C.

I am particularly interested in the sub-index corresponding to the International Relations topic for my analysis in the next section. Figure 2.1 displays the set of words that appear more often in this topic. These words are associated with U.S. exposure to the international environment. I also report the average proportion of this topic in Figure A.3. Average proportion of other topics can be found in Figure A.9 to Figure A.12 in the Internet Appendix.

[8] Full list of stop words removed is available upon request

Based on these two sets of output from LDA, I am able to decompose my APR Index into sub-indices, with each of them corresponding to one of the 6 topics identified:

$$subindex_{n,m} = \overline{\hat{\theta}_{n,m}} \times APR_m,$$

where $subindex_{n,m}$ is the sub-index for topic n with $n = 0, 1, 2, 3, 4, 5$ at month m, $\overline{\hat{\theta}_{n,m}}$ is the average of topic n proportion across all populist rhetoric articles in month m, and APR_m is the Aggregate Populist Rhetoric in month m constructed in the previous subsection. I show the plot for International Relations sub-index in Figure A1, and report its summary statistics in Table 2.2.

2.5 Currency Data and Portfolio Construction

This section discusses the exchange rate data and the construction of populism portfolios.

2.5.1 Currency Data

My data focuses on two samples. The first sample covers a rich set of developed and developing economies. A potential concern associated with this broad sample is that market frictions may impede investors from trading particular currencies, affecting the validity of my findings. To address this problem, I follow Della Corte et al. (2018) and apply two filters. In particular, I start with a large sample of 60 countries and eliminate month/country observations of countries that implement fixed or quasi-fixed exchange rate regimes and those imposing restrictions to their capital account (e.g., a negative Chin Ito index). My final sample after these filters include 24 currencies. These currencies include Australia, Brazil, Canada, Chile, Europe, Hungary, Iceland, Indonesia, Israel, Japan, Latvia, Mexico, New Zealand, Norway, Philippines, Poland, Russia, Singapore, South Korea, Sweden, Switzerland, Taiwan, Turkey, and United Kingdom.[9] I refer to this set of the sample as "*All countries*". To guard against hard-to-trade and illiquid currencies, I also use the second set of the sample containing G10 currencies, including Australia, Canada, Euro Area, Japan, New Zealand, Norway, Sweden, Switzerland, and the United Kingdom. These currencies constitute around 85% of the average daily turnover in FX markets based on the BIS (2019) and correspond to a set of countries with significant trade ties with the US economy. My monthly data covers the period between January 1998 to October 2018. I report results of all regressions for both "*All countries*" and "*G10*" samples.

[9] I also eliminate observations of currencies that exhibit significant deviations from CIP.

2.5.2 Currency Excess Returns

My exchange rate data are collected from Barclays and Reuters *via* Thompson Reuters Datastream (Eikon). I denote by S_t (F_t) the level of the spot exchange rate and 1-month forward rate at time t, which are expressed in units of foreign currency per U.S. dollar, meaning that an increase in S_t implies an appreciation of U.S. Dollar. The realised currency excess return at time t+1 (rx_{t+1}) is computed as follows:

$$rx_{t+1} = f_t - s_{t+1}, \tag{2.3}$$

in which s_{t+1} is the log spot exchange rate at time $t+1$ and f_t the log 1-month forward rate at time t. In other words, the currency excess return can be decomposed into the rate of depreciation of the foreign currency subtracted from the forward discount at time t (e.g., $rx_{t+1} = f_t - s_t - (s_{t+1} - s_t)$). Assuming that the Covered Interest Rate Parity (CIP) holds, the above equation can be expressed as $rx_{i,t+1} \simeq i_t^* - i_t - (s_{t+1} - s_t)$, where i_t^* and i_t are the foreign and domestic risk-free interest rates, respectively.[10]

2.5.3 Portfolios sorted on APR and IR betas

One way to test the role of U.S. populist rhetoric as a pricing factor for the cross-section of currency excess returns is to sort currencies into portfolios based on their exposure to U.S. populist rhetoric. If U.S. populist rhetoric is a pricing factor for the cross-section of currencies, there should be a significant dispersion in excess returns between low-beta and high-beta portfolios. Thus, the corresponding spread portfolio (LMH) should generate statistically significant excess returns.

Rolling Betas. My proxies for U.S. populist rhetoric are the APR Index and the IR sub-index. To measure the exposure of each currency to these two proxies of U.S. populist rhetoric, I regress individual currency excess returns at time t on a constant and the APR Index (or IR sub-index). The estimation is based on a 36-month rolling window (with a minimum of 20 observations), which ends in period $t-1$. The time-varying slope coefficient obtained from this regression is $\beta_{i,t}^{APR}$ or $\beta_{i,t}^{IR}$. Intuitively, currencies with negative betas exhibit higher exposure to U.S. populism as an increase of populism is associated with negative currency excess returns.

Populism Portfolios. At time t, I sort currencies into portfolios based on their past (i.e. $t-1$) betas with APR Index (or IR sub-index). To have a reasonable number of currencies in each portfolio, I limit the number of portfolios to three. I rebalance my

[10] I start to include the Euro in our sample following its launch in January 1999.

portfolios monthly. The first portfolio (P_1) includes currencies with the lowest betas, while the third portfolio (P_3) covers currencies with the highest betas. I then construct a zero-cost portfolio (LMH), which goes long the first portfolio (P_1) and short the high beta portfolio (P_3).

2.6 Empirical Results

In this section, I first test the UIP relation in a panel setting controlling for risk proxies relevant for foreign exchange markets, including to assess the importance of U.S. populist rhetoric for currency returns. I then empirically investigate the link between U.S. populist rhetoric and the cross-section of currency excess returns. I explore potential channels through which U.S. populist rhetoric can affect currency markets in developed and emerging markets. I finally show the results of the country-level asset pricing test.

2.6.1 Panel Regressions

Based on the prediction of Pastor and Veronesi (2020) model, I argue that the U.S. populist rhetoric index (APR), especially the International Relations (IR) sub-index, represents an underlying risk factor facing currency investors beyond other risk proxies such as dollar factor Lustig et al. (2011), global equity risk measured by VIX (Panayotov (2020), Rey (2015)), global FX liquidity (Mancini et al. (2013)), FX volatility (Menkhoff et al. (2012a)) and U.S. economic policy uncertainty Baker et al. (2016). Therefore, it should be included in the empirical test of UIP relation with controls for risk factors. In particular, when I run the so-called Fama regressions (see equation 2.2), I expect $\beta = 1$ if risk factors are properly accounted for. I test this relation in a panel setting (Lustig et al. (2014), Kremens and Martin (2019)).[11]

In Table 2.4 I report the results for all the countries in our sample (*Panel A*) and for G10 sub-sample (*Panel B*). The first specification is the UIP relation under risk-neutral expectations without any risk controls. I notice that while β is positive (in contrast with country-specific regressions in the literature that documents forward premium puzzle), it is still significantly smaller than 1 as UIP theory would predict. I gradually add other risk proxies and see that the coefficient increases approaching the theoretical prediction. I see that in the broad set of countries that includes emerging countries as well as developed G10 countries, the coefficient is biased (around 0.82) downwards even in the last specification, suggesting that some important risk factors relevant for emerging economies are omitted in the regression. Importantly, though, both APR and IR index are significant in these regressions. *Panel B* reveals that in the more homogeneous

[11] Filippou et al. (2020c) highlight the benefits of panel regressions for foreign exchange models.

subset of G10 countries, the contribution of populist rhetoric indices is stronger, and β is sufficiently close to the theoretical prediction once I control for the relevant risk factors.

2.6.2 Populism-sorted Portfolios

I next attempt to understand the role of U.S. populism in the foreign exchange market, I allocate currencies into portfolios based on their exposure to populism, as it was analyzed in the previous section. Table 2.5 reports summary statistics of portfolios sorted on APR Index betas (*Panel A*) and IR sub-index betas (*Panel B*).

Panel A shows that there is a significant dispersion in terms of average betas when moving from P_1 to P_3. It increases from -1.07% to 0.31% between these two extreme portfolios. Investing in currencies with the lowest (highest) APR Index beta yields average positive (negative) excess returns. Average portfolio returns are monotonically decreasing in the APR beta. Average excess returns of the first portfolio (P_1) are positive and statistically significant with a Newey and West (1987) t-statistic of 2.25. Of particular interest is the average excess returns to LMH portfolio, which is positive and statistically significant with a Newey and West (1987) t-statistic of 2.67. The populism portfolio yields an annualized average excess returns of 4.95% with a Sharpe ratio of 0.76. Another outstanding feature that can be observed is that a large part of the excess returns is generated from the interest rate differential component rather than the spot exchange rate changes component. The average interest rate differentials of portfolios are not monotonically decreasing. In particular, P_1 contains currencies with the highest interest rate differentials with the U.S., and P_3 contains currencies with higher interest rate differentials than P_2 on average. This suggests that sorting currencies based on U.S. populist rhetoric is different from sorting currencies based on interest rate differentials.

These results can be interpreted as follows. Currencies in P_1 have negative APR betas, which mean that their returns decrease when APR Index increases. An increase in U.S. populist rhetoric, which is proxied by APR index, is a bad state variable in terms of aggregate consumption for U.S. investors (Pastor and Veronesi, 2020). Therefore currencies generating low excess returns in times of rising APR are considered risky by investors. Hence, they require a higher expected return to holding currencies with negative APR betas. By contrast, currencies in P_3 have positive APR betas. As a result, they yield high excess returns in rising APR times and are considered relatively safe assets by investors. As a result, investors are willing to pay a higher price and accept lower expected returns from these currencies.

Panel B also suggests a negative link between average portfolio excess returns and IR sub-index betas. Average excess returns are monotonically decreasing from P_1 to P_3. The LMH portfolio now generates even better performance than in *Panel A* with

APR Index. This portfolio yields 5.27% excess returns annually on average (with a Newey and West (1987) t-statistic of 3.28) and a Sharpe ratio of 0.82.

I repeat the analysis for G10 sample in Table 2.6. I observe a similar pattern compared to a broader cross-section of countries. Investing in the LMH portfolios based on APR Index and IR sub-index still generates statistically significant excess returns for investors on average. Regarding APR Index, it is 2.81% annually with a Sharpe ratio of 0.40. In the IR sub-index case, the annualized average excess returns is 4.10% with a Sharpe ratio of 0.60. As I would like to explore further which currencies drive the profit of the populism portfolio strategy found in Table 2.5, I plot each currency's frequency at the two extreme portfolios in Figure A.6 of the Internet Appendix.

Panel A and *Panel C* of Figure A.6 suggest that the top 4 currencies that are frequently entering the low beta portfolios based on both APR Index betas and IR sub-index betas are Australia, Euro, Mexico, and New Zealand. As these currencies typically have negative betas, they tend to generate low excess returns when U.S. populist rhetoric is high. By contrast, *Panel B* and *Panel D* of the same figure reveal the top 4 currencies in high beta portfolios based on both APR Index betas and IR sub-index betas. These currencies include Canada, Japan, Norway, and Taiwan. Due to their positive betas on average, they generally yield high excess returns when there is an increase in U.S. populist rhetoric.

I also report the performance of trading strategies based on APR Index and IR Sub-index betas (reported in Table 2.5) compared with some prominent currency trading strategies in Table 2.7 (All countries), and in Table 2.8 (G10 countries).

For both tables, I report the results for full sample period (*Panel A*), pre-crisis (*Panel B*), and post-crisis (*Panel C*). The crisis period is based on the NBER business cycle. I denote LMH_{APR} a zero-cost portfolio based on APR Index betas. Similarly, LMH_{IR} is the corresponding strategy based on IR Sub-index betas. *CAR* is the carry trade strategy. I construct this strategy by first sorting currencies into terciles based on their forward discounts. The bottom tercile contains currencies with the lowest forward discounts, and the top tercile contains currencies with the highest forward discounts. Portfolios are rebalanced monthly, and the return to this strategy is the high-minus-low portfolio. MOM is the momentum strategy where I sort currencies into terciles based on their lagged excess return in the previous month. The bottom tercile contains currencies with the lowest lagged excess returns, and the top tercile contains currencies with the highest lagged excess returns. The return to momentum strategy is the high-minus-low portfolio. DOL is the dollar strategy, which involves taking a short position in U.S. Dollar and a long position in all foreign currencies. Regarding the All countries sample, for the full sample and pre-crisis period, APR and IR strategies underperform compared with almost all other strategies in terms of mean excess returns and Sharpe ratio. However, it is worth noticing an interesting feature in the post-crisis period. Although the APR and IR strategies do not generate sizable excess returns than the pre-crisis period, these two strategies show better performance than all other strategies examined. In terms of G10 sample, IR strategy outperforms all other strategies for the full period, and the APR strategy is only slightly outperformed by CAR. Similar to the All countries sample, APR and IR strategies dominate all other strategies examined in the post-crisis period.

Table A.2 in the Internet Appendix reports a range of correlation coefficients between the returns to APR and IR strategies (e.g., LMH_{APR} and LMH_{IR}) and the returns to *CAR*, MOM, and DOL. I split the sample into two periods: pre-crisis (January 1998 to November 2007) and post-crisis (June 2009 to October 2018). In general, APR and IR strategies seem to have the highest correlations with the *CAR* strategy. However, this correlation decreases significantly after the crisis. This result, together with the relatively good performance of APR and IR strategies in the post-crisis period discussed in the last paragraph, motivates me to examine potential diversification benefits of APR and IR strategies for investors. I first report the diversification benefits from adding LMH_{APR} and LMH_{IR} to conventional currency strategies for All Countries sample in Table 2.9.

In *Panel A* of Table 2.9, I report the performance of three individual conventional currency strategies previously discussed. In the last row, the performance of an equally weighted portfolio combining all three strategies is shown. In *Panel B*, I combine these conventional currency strategies with APR strategy and examine the value it adds to portfolio performance. A noteworthy feature is that the APR strategy's inclusion increases the Sharpe ratio in all cases (except for the equally weighted strategy combining all strategies, in which the improvement is not significant). I repeat these exercises with IR strategy in *Panel C* and observe even better performance in terms of Sharpe ratio of all portfolios. I report similar results for G10 sample in Table 2.10.

The G10 sample results further confirm the findings that adding APR and IR strategies to conventional currency strategies brings diversification benefits for currency investors.

2.6.3 Channels of currency exposures to U.S. Populist Rhetoric

To explore the channels through which U.S. populist rhetoric affects currency returns, I uncover the link between countries' currency exposure to U.S. populist rhetoric and its characteristics. Given that my sample consists of currencies from both developed and developing economies, it is natural to investigate the question as to whether U.S. populist rhetoric affects the currency returns of these two groups of economies through different channels.

In its latest quarterly report, BIS (2019) records that the amount of U.S. Dollar-denominated credit to non-bank borrowers in emerging and developing economies reaches $3.6 trillion at the end of 2018. This significantly high amount of U.S. Dollar-denominated debt is concerning emerging and developing economies as it makes them particularly dependent on the strength of the U.S. Dollar. In the case of a stronger U.S. Dollar, it will be harder for these emerging and developing economies with high U.S Dollar-denominated debt to repay their debt. Therefore it would be interesting to examine the link between a country's vulnerability to U.S. Dollar-denominated debt and its exposure to U.S. populist rhetoric. My proxy for a country's vulnerability to U.S. Dollar-denominated debt is constructed by multiplying the ratio of U.S. Dollar-denominated debt to total debt and the ratio of external debt to GDP. This ratio reflects the vulnerability of a country to repay its U.S. Dollar-denominated debt. The higher this ratio, the more a country is vulnerable to U.S. Dollar-denominated debt. A scatter plot between average APR betas and vulnerability to U.S. Dollar-denominated debt for developing countries can be found in *Panel A* of Figure 2.3. The negative slope coefficient suggests that countries with higher vulnerability to U.S. Dollar-denominated debt are more exposed to U.S. populist rhetoric.

Given that U.S. Dollar-denominated debt is not a concern for developed countries due to their relatively low U.S. Dollar-denominated debt, it is likely for U.S. populist rhetoric to affect currencies of developed countries through different channels. Instead of vulnerability to U.S. Dollar-denominated debt, I examine foreign holding of U.S. assets and average APR betas. This scatter plot can be found in panel B of Figure 2.3. Countries with less holding of U.S. assets appear to be more sensitive to U.S. populist rhetoric. By contrast, the effect of U.S. populist rhetoric on countries with higher holdings of U.S. assets is less significant. This result is consistent with the higher valuation of U.S. assets in times of rising populism established in Pastor and Veronesi (2020).

2.6.4 Country-level asset pricing tests

After documenting the significant excess returns of LMH portfolios sorted on U.S. populist rhetoric, I now investigate the risk price of this factor.

Test assets. My test assets are individual currencies rather than portfolios. Ang et al. (2018) suggest that grouping stocks into portfolios make the cross-sectional dispersion of the betas shrink, which leads to a less efficient estimate of factor risk premia. Bali et al. (2017) estimate the risk price of economic uncertainty using individual stocks. In the context of currencies, Barroso et al. (2018) test the risk price of global imbalances using individual currencies.

U.S. Populist Rhetoric Betas. In order to estimate the exposure of each currency to U.S. populist rhetoric proxy $\beta_{i,t}^{PS}$, I run the following time-series regressions based on a 36-month rolling window with a minimum number of 20 observations in each regression:

$$rx_{i,t} = \alpha_{i,t} + \beta_{i,t}^{PR} PR_{t-1} + \epsilon_{i,t+1} \tag{2.4}$$

where $rx_{i,t}$ is the realised excess return on currency i in month t, and PR_{t-1} is the proxy for populist rhetoric in month *t-1*.

Cross-sectional Regressions. Having estimated $\hat{\beta}_{PR,i}$, I investigate the cross-sectional relation between U.S. populist rhetoric betas and expected currency excess returns at the country level (Bali et al., 2017). In particular, I run monthly cross-sectional regressions at each time t:

$$rx_{i,t+1} = \lambda_{0,t} + \lambda_{1,t}\hat{\beta}_{i,t}^{PR} + \lambda_{2,t}X_{i,t} + \epsilon_{i,t+1} \tag{2.5}$$

where $X_{i,t}$ are currency-specific control variables at time t for currency i (volatility, illiquidity). These two variables are constructed as in Menkhoff et al. (2012a). I then take the time-series average of slope coefficients $\lambda_{1,t}$ and report its Newey and West (1987) t-statistic and average adjusted R^2.

Table 2.11 summarises results regarding estimation of risk prices of APR Index and IR sub-index from regressions (2) and (3).

In this table, I report results for All countries sample in *Panel A*. APR Index is the proxy for U.S. populist rhetoric in the first four columns, and IR sub-index is the proxy for U.S. populist rhetoric in the last four columns. The univariate regression results shown in the first column suggest a negatively significant link between the APR beta and the cross-section of future currency excess returns. The market price of risk λ associated with APR factor is -0.43, with a t-statistic of -3.04. This negative coefficient for APR implies that taking a long position in currencies with lower APR betas predicts positive returns in the following period. To examine the economic significance of this result, I compute the difference in average β^{APR} between P_1 and P_3 from Table 2.5, which is 1.38% [=0.31% - 1.07%]. If a currency were to move from P_1 to P_3, its expected return would decrease by 0.59% [=1.38% × -0.43] per month. Therefore, the risk price of the APR Index is not only statistically significant but also economically significant.

In the second column, when I control for the volatility of individual currencies, the risk price of APR beta remains negative and statistically significant with a Newey and West (1987) t-statistic of -3.08, and the risk price of volatility factor is negative but statistically insignificant. The third column controls for the illiquidity of individual currencies, and it still gives me a negative and statistically significant risk price of APR beta. The risk price of the illiquidity factor, on the other hand, is statistically insignificant. In the fourth column, when controlling for both illiquidity and volatility of individual currencies simultaneously, I still get a strongly significant risk price of APR with a Newey and West (1987) t-statistic of -3.74.

In the next four columns, the IR sub-index is chosen as a proxy for U.S. populist rhetoric. In the univariate regression with IR sub-index beta as in the fifth column, this factor's risk price is also negative, suggesting a negative relation between IR sub-index beta and the cross-section of future currency excess returns. This coefficient is -0.07 with a Newey and West (1987) t-statistic of -3.10. Following the same calculation methodology, as in the APR Index case, gives me the economic significance of this risk factor. In particular, if a currency were to move from P_1 to P_3 based on β^{IR} as in Table 2.5, its expected return would decrease by 0.81% [=11.63% × -0.07] per month. Therefore, the economic significance of the IR sub-index as a risk factor is even stronger than that of the APR Index.

In the last three columns, I add control variables. Similar to the risk price of APR beta, the risk price of the IR sub-index remains negative and statistically significant after controlling for these two variables, both separately and simultaneously.

In the same table, I report results for the G10 sample in *Panel B*. Similarly, APR Index is the proxy for U.S. populist rhetoric in the first four columns. The APR beta coefficient is also negative and strongly significant in the univariate regression in the first column. This result holds when adding volatility and illiquidity, both separately and simultaneously, even though its statistical significance is weaker. The IR Index is the proxy for U.S. populist rhetoric in the last four columns. The coefficients of the IR beta remain negative and strongly significant in all specifications.

2.6.4.1 U.S. Populist Rhetoric and Gubernatorial Elections in Swing States

An important question is whether the risk price of U.S. populist rhetoric changes in specific periods, e.g., around elections, and in certain important locations such as swing states. To address this question, I test whether gubernatorial elections in swing states play a role in pricing U.S. populist sentiment in the cross-section of currency excess returns. In particular, I add two more variables in regressions (2) and (3). The first one if Election Dummy, which is equal to 1 if there is a gubernatorial election in at least one swing state in that year, and 0 otherwise[12]. The second variable added is the interaction variable between Election Dummy and U.S. populist rhetoric. The coefficient of this interaction variable is of particular interest, because it implies the risk price of U.S. populist rhetoric during election time in swing states. Results are reported in Table 2.12.

Results for All countries' sample are shown in the first two columns. APR Index and IR sub-index are used as a proxy for U.S. populist rhetoric in the first and second columns, respectively. The interaction variables between U.S. populist rhetoric and Election Dummy are negative and statistically significant in both regressions, even though it is stronger for APR Index. I then replicate these regressions for the G10 sample in the next two columns. The statistical significance of interaction variables in both cases is weaker compared to the other sample. Nevertheless, these two variables still maintain their negative sign. Overall, these results indicate that U.S. populist rhetoric's pricing power is stronger during gubernatorial elections in swing states.

[12] Gubernatorial election data are obtained from the Correlates of State Policy Project (CSPP).

2.7 Globalization and U.S. Populist Rhetoric

In the Pastor and Veronesi (2020) model, a shift to a populist regime is captured by a move to autarky from globalization. Therefore, if my measure of populist rhetoric is well identified, it should be sensitive to exposure to globalization. I measure exposure to globalization using equity data following Barrot et al. (2016), and then sort stock returns of U.S. manufacturing firms into quintiles based on their exposure to globalization, the proxy being shipping cost. Shipping cost is computed as a percentage of the price paid by importers. Firms in the low shipping cost portfolio are more exposed to globalization, whereas firms in the high shipping cost portfolio are more local. I then examine the correlation between these portfolios and our APR Index and show results in Table 2.13.

In *Panel A*, I report the pairwise correlations between the returns of 5 portfolios and the LMH portfolio and APR Index. There is a positive correlation between the low shipping cost portfolio and APR Index for equally weighted portfolios. This is consistent with the rationale that an increase in APR Index signals a switch from integrated to the autarkic regime for the U.S., so firms with low shipping cost (i.e, those with high exposure to globalization) should be positively correlated with my index. I also find an almost monotonically decreasing pattern in terms of this correlation as I go from P_1 to P_5. The negative correlation between P_5 with my index suggests that this portfolio of firms with low exposure to globalization can be a hedge in times of rising U.S. populist rhetoric. This result is consistent for value-weighted portfolios, and also when I control for Fama-French 3 factors in *Panel B* and Fama-French 5 factors in *Panel C*.

2.8 Robustness

Alternative pricing factors. To test for the robustness of my findings, I also control for two prominent factors used in FX literature, which are DOL and CAR. DOL is the average excess return from a strategy that goes long in all foreign currencies and short in the domestic currency. CAR is the excess return to carry trade strategy as in Lustig et al. (2011). With these two factors, my regressions (2) and (3) become:

$$rx_{i,t} = \alpha_{i,t} + \beta_{i,t}^{PR} PR_{t-1} + \beta_{i,t}^{DOL} DOL_t + \beta_{i,t}^{CAR} CAR_t + \epsilon_{i,t} \tag{2.6}$$

$$rx_{i,t+1} = \lambda_{0,t} + \lambda_{1,t}\hat{\beta}_{i,t}^{PR} + \lambda_{2,t}\hat{\beta}_{i,t}^{DOL} + \lambda_{3,t}\hat{\beta}_{i,t}^{CAR} + \epsilon_{i,t+1} \tag{2.7}$$

The first proxy for U.S. populist rhetoric is my APR Index, and the second one is our IR sub-index. I report my regressions results for both APR Index and IR sub-index in Table 2.14.

The results for All countries sample are reported in *Panel A*. In the first three columns, APR Index is the proxy for U.S. populist rhetoric. The first column's result with univariate regression suggests a negative and statistically significant link between APR beta and future currency excess returns. Risk price of APR beta is -0.32 with a Newey and West (1987) *t*-statistic of -2.45. In the second column, when I control for the DOL factor, the risk price of APR beta remains negative and even more statistically significant with a Newey and West (1987) *t*-statistic of -2.52. DOL factor is statistically insignificant, which is consistent with the literature. In the third column, DOL and CAR factors are controlled simultaneously. The coefficient of APR beta is negative and maintains its statistical significance with a *t*-statistic of -2.09. CAR factor is positive and significant with a *t*-statistic of 2.43, which is consistent with the literature. This highlights an important finding. APR beta has predictive power for future currency excess returns beyond DOL and CAR factors. I repeat the same regressions when the IR sub-index is used as a proxy for U.S. populist rhetoric in the next three columns. The risk price of IR beta is negative and statistically significant with a *t*-statistic of -2.31 in the univariate regression shown in the sixth column. This pricing power of IR beta maintains in all specifications. Overall, these empirical findings suggest that U.S. populist rhetoric, proxied by APR Index and IR sub-index carries additional information for future currency excess returns beyond CAR and DOL factors.

I report results for the G10 sample in *Panel B*. When both CAR and DOL factors are controlled for, the coefficients of both APR beta and IR beta remain negative and statistically significant. Overall, findings in this section suggest the important role of U.S. populist rhetoric in predicting the cross-sectional variation in individual currency excess returns beyond prominent predictors.

U.S. Fiscal News pricing factor. I also control for the U.S. Fiscal News Index constructed in Nguyen (2021). With this factor, my regressions (2) and (3) become:

$$rx_{i,t} = \alpha_{i,t} + \beta_{i,t}^{PR} PR_{t-1} + \beta_{i,t}^{FN} FN_t + \epsilon_{i,t} \tag{2.8}$$

$$rx_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} \hat{\beta}_{i,t}^{PR} + \lambda_{2,t} \hat{\beta}_{i,t}^{FN} + \epsilon_{i,t+1} \tag{2.9}$$

The results for All countries sample are reported in Panel A and G10 sample in Panel B in Table A.3. Overall, the coefficients of both APR beta and IR beta remain negative and statistically significant in all regressions. Although the Fiscal News factor is negative and statistically significant in All countries sample, this result does not hold in the G10 sample.

Alternative proxies for U.S. populist rhetoric. I also replicate my regressions in Table 2.11 using different proxies for U.S. populist rhetoric. Firstly, I use other sub-indices identified by LDA Algorithm other than the IR sub-index. Regression results can be found in Table A.4 in the Internet Appendix. Overall, coefficients of other sub-indices are all negative but most of them show weaker results in terms of statistical significance compared to APR Index and IR sub-index. This supports my choice of these two variables as proxy when examining the effects of U.S. populist rhetoric on cross-section currency excess returns. Secondly, I also provide regression results with populist rhetoric index constructed from individual newspapers in Table A.5 in the Internet Appendix. The results are slightly weaker, but the coefficients of populist rhetoric beta are negative in most cases.

Mimicking Portfolio. My previous results demonstrate that my strategy based on a signal from populist rhetoric offers strong diversification benefits for carry trade strategies. To address potential concerns regarding the tradability of such a strategy and reveal hedging opportunities offered by this measure, I build a factor mimicking portfolio based on APR Index (or IR sub-index) by projecting my factor on the returns of carry trade portfolios and implement asset pricing tests. In particular, I run Fama and MacBeth (1973) cross-sectional regressions where in the first step I project currency excess returns of portfolios sorted on forward discounts on a dollar factor (DOL) and my populism mimicking portfolio. In the second step, I regress average currency excess returns of carry trade portfolios on factor betas. I report Newey and West (1987) t-statistics that are corrected for autocorrelation and heteroskedasticity. I also report t-statistics with Shanken (1985) standard errors to guard against the error in variables problem. Results can be found in Table A.6 in the Internet Appendix. Overall, my mimicking portfolio return factor (FPR) is also priced in the cross-section of carry trade portfolios.

2.9 Conclusions

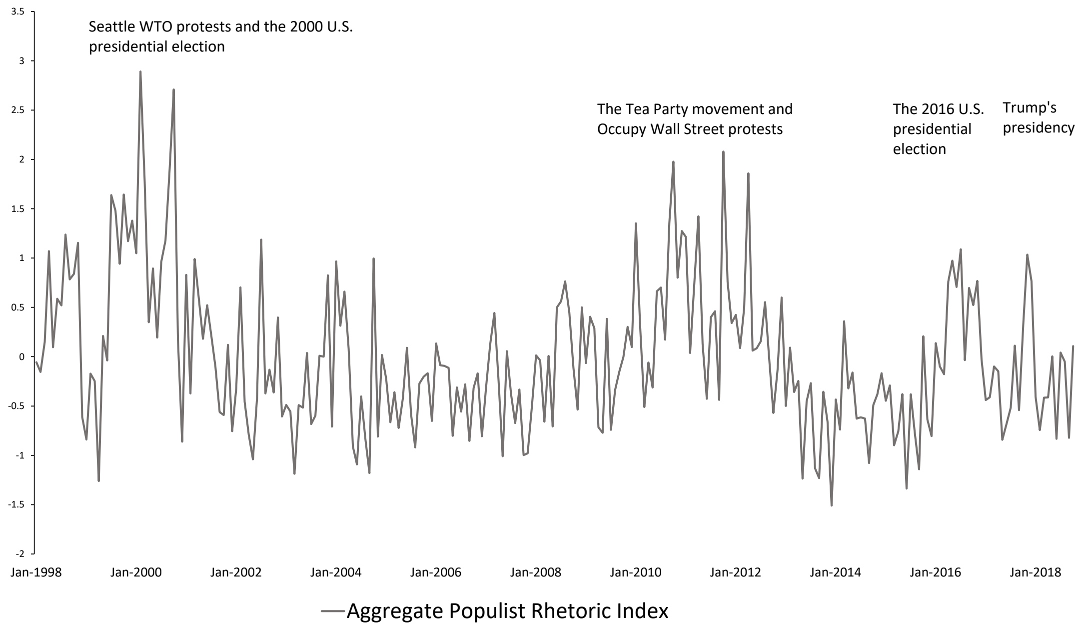
In this paper, I have constructed a novel index of U.S. populism that captures the overall populist rhetoric reported by five leading newspapers. My Aggregate Populist Rhetoric (APR) Index spikes around a range of well-known populist events in the U.S. I then sort currencies into portfolios based on their exposure to U.S. populist rhetoric, proxied by our APR Index and IR sub-index, and find a positive and significant spread between low and high beta portfolios. This trading strategy can generate highly statistically significant average excess returns. I then find strong empirical evidence that U.S. populist rhetoric, proxied by APR Index and IR sub-index, is negatively priced in the cross-section of currency excess returns. Currencies that generate high (low) excess returns in times of rising U.S. populist rhetoric generate lower (higher) expected excess returns.

This empirical evidence is consistent with theoretical work, suggesting that rising populism leads to lower aggregate consumption for U.S. investors, increasing their marginal utility. Assets that generate high excess returns during this state of the world, therefore, are valued by U.S. investors and are willing to accept lower expected returns for holding them. By contrast, assets that generate low returns in times of rising populism are considered risky, which means that investors demand higher expected returns for holding them. My results can be extended to construct a similar index in different countries, which are of particular relevance in the current political climate of rising populism in many parts of the world.

Figure 2.1: International Relations

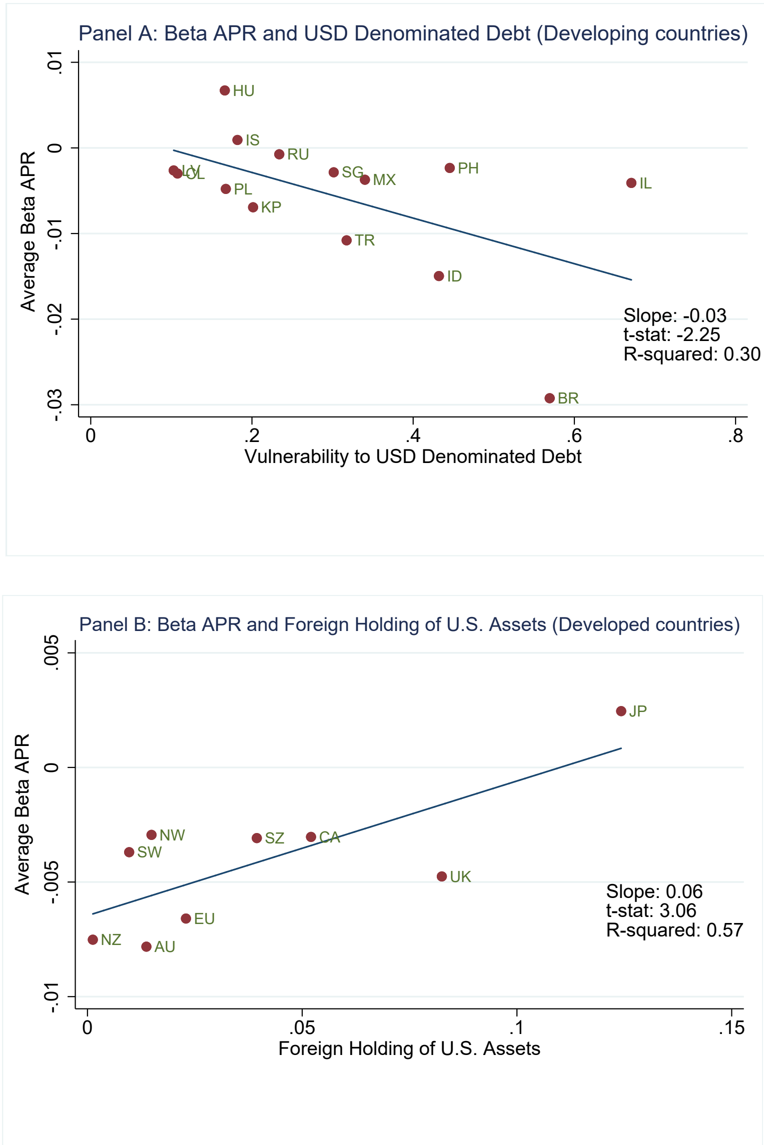
The figure reports the most important words in the International Relations Sub-index. This sub-index is constructed by multiplying the average proportion of International Relations topic across all populist rhetoric newspapers articles from 5 newspaper with the Aggregate Populist Rhetoric Index. The monthly data are between January 1998 and October 2018.

Figure 2.2: U.S. Aggregate Populist Rhetoric (APR) Index



The figure reports my U.S. Aggregate Populist Rhetoric (APR) Index. The index is based on scaled monthly counts of articles containing populist rhetoric reported by The New York Daily News, The New York Post, USA Today, The Washington Post, and The New York Times between January 1998 and October 2018.

Figure 2.3: Average Beta APR and USD Exposure



The figure shows average beta APR and USD exposure. In *Panel A*, I plot the average beta APR and the vulnerability to U.S. Dollar denominated debt for a sample of developing countries. In *Panel B*, I plot the average beta APR and foreign holding of U.S. assets ratio for a sample of developed countries. Data for U.S. Dollar denominated debt are obtained from BIS website, data for foreign holding of U.S. assets are obtained from U.S. Department of the Treasury website. The data are between January 1998 and October 2018.

Table 2.1: Bonikowski and Gidron (2015)'s Populist Dictionary

This table reports the populist terms identified in the dictionary by Bonikowski and Gidron (2015). I use this dictionary to identify newspapers articles containing populist rhetoric.

Populist Dictionary	
N-grams	Words
Unigrams	bureaucrat OR millionaire OR baron OR venal OR crooked OR unresponsive OR arrogant
Bigrams	special interests OR Wall Street OR Main Street OR big corporations OR ordinary taxpayer OR wealthy few OR professional politician OR big interest OR big money OR Washington elite OR rich friend OR power monger OR power grabbing OR easy street OR privileged few OR forgotten Americans OR long nose
Trigrams	top 1 percent OR average American taxpayer
Four-grams+	government is too big OR government that forgets the people

Table 2.2: Summary Statistics of APR Index and IR Sub-Index

This table reports summary statistics of Aggregate Populist Rhetoric Index (APR) and International Relations (IR) sub-index. I report mean, standard deviation, minimum and maximum values, skewness, kurtosis, and first order autocorrelations of APR, IR, changes in APR (i.e.ΔAPR), and changes in IR (i.e.ΔIR). Figures in parentheses are p-values. Monthly data are from January 1998 and October 2018.

	Populism Indices			
	APR Index	ΔAPR Index	IR sub-index	ΔIR sub-index
Mean	-0.00	0.00	-0.01	0.00
Std	0.75	0.65	0.10	0.11
Min	-1.51	-2.07	-0.55	-0.38
Max	2.89	1.79	0.53	0.47
Skewness	0.86	3.19	-0.14	0.13
Kurtosis	3.92	3.43	9.89	6.12
AC (1)	0.49	-0.41	0.40	-0.40
	(0.00)	(0.00)	(0.00)	(0.00)

Table 2.3: Correlations with Economic Uncertainty and Political Risk Indices

This table reports correlations between APR Index, IR sub-index and some indices for economic uncertainty and political risks. EPU is the Economic Policy Uncertainty from Baker et al. (2016); UNC^m, UNC^q, UNC^y are 1-month-ahead, 3-month-ahead, and 12-month-ahead macroeconomic uncertainty indices respectively from Jurado et al. (2015), GPR is the geopolitical risk index from Caldara and Iacoviello (2018), ICRG PR is the Political Risk index from International Country Risk Guide (ICRG), VIX is the CBOE Volatility Index. Figures in parentheses are p-values. I report results for both index level (*Panel A*) and its percentage change (*Panel B*). Monthly data are between January 1998 and October 2018 (except for ICRG PR data which is up until January 2014).

Panel A: Index Level							
	EPU	UNC^m	UNC^q	UNC^y	GPR	ICRG PR	VIX
APR Index	0.02	0.33	0.33	0.35	-0.31	0.39	0.18
	(0.73)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
IR sub-index	-0.02	0.26	0.26	0.26	-0.44	0.34	0.15
	(0.70)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)
Panel B: Index Change							
	ΔEPU	ΔUNC^m	ΔUNC^q	ΔUNC^y	ΔGPR	ΔICRG PR	ΔVIX
ΔAPR Index	0.01	-0.11	-0.11	-0.11	0.00	0.01	0.01
	(0.88)	(0.10)	(0.09)	(0.09)	(0.96)	(0.87)	(0.86)
ΔIR sub-index	0.03	-0.11	-0.12	-0.12	0.04	0.02	0.03
	(0.65)	(0.07)	(0.07)	(0.06)	(0.49)	(0.71)	(0.62)

Table 2.4: Fama UIP regressions

This table reports augmented UIP panel regression results with country fixed effects showing the role of APR index and IR sub-index in explaining UIP deviations. Specifically, I regress in a panel setting spot exchange rate changes on interest rate differentials and a number of controls including the populism measures. The control variables are CBOE VIX Index, volatility and illiquidity as in Menkhoff et al. (2012a), U.S. Economic Policy Uncertainty from Baker et al. (2016), and dollar factor as in Lustig et al. (2011). *Panel A* (*Panel B*) reports results for All Countries (G10 Countries). Newey and West (1987) t-statistics are reported in squared brackets, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. The data are monthly between January 1998 and October 2018.

Panel A: All Countries

			APR Index			IR Sub-index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Interest rate differential	0.36	0.72***	0.73***	0.77***	0.82***	0.73***	0.77***	0.82***
	[1.48]	[2.80]	[2.83]	[3.01]	[3.26]	[2.83]	[3.0]	[3.25]
VIX		-0.28***	-0.29***	-0.31***	-0.31	-0.29***	-030***	-031***
		[-5.14]	[-5.30]	[-5.45]	[-5.57]	[-5.30]	[-5.42]	[-5.54]
PR			0.01**	0.01**	0.01**	0.08***	0.08***	0.08***
			[1.97]	[2.28]	[2.32]	[3.18]	[3.25]	[3.27]
Dollar				-0.37***	-0.38***		-0.35***	-0.36***
				[-6.02]	[-6.51]		[-5.65]	[-6.08]
FX Illiquidity				-0.06	-0.07		-0.06	-0.07
				[-0.52]	[-0.66]		[-0.49]	[-0.62]
FX Volatility				-0.01	-0.01		-0.01	-0.02
				[-0.91]	[-1.54]		[-0.96]	[-1.60]
U.S. EPU					0.01***			0.01***
					[3.79]			[3.70]
Constant	0.00	0.05***	0.05***	0.06***	0.06***	0.07***	0.06***	0.06***
	[0.59]	[4.59]	[4.75]	[5.0]	[4.84]	[3.18]	[5.05]	[5.04]
Obs	4,443	4,354	4,354	4,354	4,341	4,354	4,354	4,341
R^2	0.04	0.07	0.08	0.08	0.08	0.07	0.08	0.08

Panel A: G10

			APR Index			IR Sub-index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Interest rate differential	0.26	0.65	0.75*	1.01***	1.02***	0.77*	1.03**	1.05***
	[1.48]	[1.49]	[1.84]	[2.45]	[2.45]	[1.91]	[2.47]	[2.47]
VIX		-0.27***	-0.29***	-0.34***	-0.30***	-0.29***	-0.34***	-0.34***
		[-3.53]	[-3.65]	[-3.34]	[-3.37]	[-3.68]	[-3.33]	[-3.35]
PR			0.01***	0.01***	0.01***	0.13***	0.11***	0.11***
			[3.62]	[3.27]	[3.30]	[4.46]	[4.37]	[4.68]
Dollar				-0.43***	-0.42***		-0.4***	-0.39***
				[-5.29]	[-5.21]		[-5.0]	[-4.92]
FX Illiquidity				1.76**	1.73**		1.74**	1.72**
				[2.32]	[2.25]		[2.36]	[2.29]
FX Volatility				-0.03***	-0.03***		-0.03***	-0.03***
				[-2.87]	[-3.09]		[-3.22]	[-3.46]
U.S. EPU					0.01***			0.01***
					[3.83]			[3.76]
Constant	0.00	0.05***	0.06***	0.07***	0.07***	0.06***	0.08***	0.08***
	[0.65]	[3.56]	[3.74]	[3.43]	[3.45]	[3.75]	[3.45]	[3.46]
Obs	2,018	1,977	1,977	1,977	1,969	1,977	1,977	1,969
R^2	0.00	0.03	0.04	0.05	0.05	0.04	0.05	0.05

Table 2.5: Portfolios sorted on APR and IR Betas - All Countries Sample

This table reports summary statistics for the excess returns of three currency portfolios sorted on exposure to APR Index (*Panel A*), IR sub-index (*Panel B*). Portfolio 1 (P_1) contains currencies with the lowest APR Index (IR sub-index) betas, and Portfolio 3 (P_3) contains currencies with the highest APR Index (IR sub-index) betas. LMH represents the portfolios that has a short position in the high beta portfolio (P_3) and a long position in the low beta portfolio (P_1). For each portfolio, I report annualized mean and its t-statistics (reported in squared brackets), standard deviation (Std) and Sharpe ratios (SR), average betas of individual currencies(β), all in percentage points. I also report skewness and kurtosis, exchange rate change component of excess returns. Interest rate differential is the forward premium component of excess returns. The data are monthly from January 1998 and October 2018.

Panel A: APR Index

	P_1	P_2	P_3	LMH_{APR}
Mean	4.86	1.55	-0.08	4.95
	[2.25]	[0.91]	[-0.05]	[2.67]
Std	9.45	7.48	7.74	6.49
Skewness	-0.60	-0.52	-0.41	0.29
Kurtosis	5.33	4.74	4.00	3.99
Exchange rate changes	0.79	-0.38	1.56	-0.70
	[0.34]	[-0.22]	[0.89]	[-0.56]
Interest rate differential	5.52	1.16	1.48	4.04
	[6.48]	[7.95]	[3.51]	[3.97]
SR	0.52	0.21	-0.01	0.76
β^{APR}	-1.07	-0.35	0.31	

Panel B: IR sub-index

	P_1	P_2	P_3	LMH_{IR}
Mean	5.28	0.72	0.01	5.27
	[2.02]	[0.40]	[0.00]	[3.28]
Std	9.58	7.27	7.16	6.53
Skewness	-0.64	-0.43	-0.38	0.22
Kurtosis	5.77	4.35	3.96	3.50
Exchange rate changes	2.39	0.27	1.75	-1.51
	[0.10]	[0.15]	[1.02]	[-1.00]
Interest rate differential	5.33	1.03	1.76	3.57
	[4.41]	[4.47]	[3.96]	[3.34]
SR	0.58	0.09	0.00	0.82
β^{IR}	-9.06	-3.00	2.57	

Table 2.6: Portfolios sorted on APR and IR Betas - G10 Sample

This table reports summary statistics for the excess returns of three currency portfolios sorted on exposure to APR Index (*Panel A*), IR sub-index (*Panel B*). Portfolio 1 (P_1) contains currencies with the lowest APR Index (IR sub-index) betas, and Portfolio 3 (P_3) contains currencies with the highest APR Index (IR sub-index) betas. LMH represents the portfolios that has a short position in the high beta portfolio (P_3) and a long position in the low beta portfolio (P_1). For each portfolio, I report annualized mean and its t-statistics (reported in squared brackets), standard deviation (Std) and Sharpe ratios (SR), average betas of individual currencies(β), all in percentage points. I also report skewness and kurtosis, exchange rate change component of excess returns. Interest rate differential is the forward premium component of excess returns. The data are monthly from January 1998 and October 2018.

Panel A: APR Index				
	P_1	P_2	P_3	LMH_{APR}
Mean	2.19	0.38	-0.63	2.81
	[0.95]	[0.18]	[0.33]	[1.75]
Std	10.03	8.74	8.38	6.99
Skewness	-0.52	-0.29	0.16	0.83
Kurtosis	5.85	3.99	3.03	7.19
Exchange rate changes	-0.94	-0.07	0.34	-1.28
	[-0.41]	[-0.03]	[0.18]	[-0.78]
Interest rate differential	1.25	0.31	-0.29	1.54
	[7.40]	[2.22]	[-1.59]	[8.71]
SR	0.22	0.043	-0.07	0.40
β^{APR}	-0.98	-0.42	0.20	

Panel B: IR sub-index				
	P_1	P_2	P_3	LMH_{IR}
Mean	3.08	0.3	-1.02	4.10
	[1.21]	[0.01]	[-0.54]	[2.50]
Std	10.06	8.61	8.21	6.82
Skewness	-0.48	-0.12	0.08	0.22
Kurtosis	6.00	3.10	3.12	4.38
Exchange rate changes	-1.70	0.24	0.63	-2.33
	[-0.67]	[0.12]	[0.34]	[-1.41]
Interest rate differential	1.38	0.27	-0.39	1.77
	[8.31]	[1.51]	[-1.80]	[9.80]
SR	0.31	0.00	-0.12	0.60
β^{IR}	-8.92	-3.44	1.65	

Table 2.7: Comparisons with other currency trading strategies - All Countries Sample

This table reports summary statistics for the excess returns of different currencies strategies. LMH_{APR} is the strategy that goes long the lowest tercile portfolio sorted by APR Index beta and sells the top tercile portfolio. LMH_{IR} is the strategy that buys the lowest tercile portfolio sorted by IR Sub-index beta, and goes short the top tercile portfolio sorted by IR Sub-index beta. *CAR* is the carry trade strategy. MOM is the momentum strategy. DOL is the dollar strategy. For each portfolio, I report annualized mean and its t-statistics (reported in squared brackets), standard deviation (Std) and Sharpe ratios (SR), all in percentage points. I also report skewness and kurtosis. I report three sample periods: January 1998 to October 2018 (*Panel A*), January 1998 to November 2007 (*Panel B*), July 209 to October 2018 (*Panel C*).

Panel A: Full Sample					
	LMH_{APR}	LMH_{IR}	*CAR*	MOM	DOL
Mean	4.95	5.27	8.82	6.11	2.41
Std	6.49	6.41	7.77	6.76	7.58
Skewness	-0.29	-0.22	-0.50	0.08	-0.63
Kurtosis	3.99	3.50	3.88	5.08	5.20
SR	0.76	0.82	1.14	0.91	0.31

Panel B: Pre-Crisis					
	LMH_{APR}	LMH_{IR}	*CAR*	MOM	DOL
Mean	8.69	10.4	18.97	11.44	7.08
Std	7.07	6.49	6.87	6.91	5.97
Skewness	-0.31	-0.19	-0.21	-0.49	0.11
Kurtosis	3.47	3.34	3.00	3.95	2.71
SR	1.23	1.61	2.76	1.66	1.19

Panel C: Post-Crisis					
	LMH_{APR}	LMH_{IR}	*CAR*	MOM	DOL
Mean	3.09	2.24	0.52	0.56	-0.54
Std	4.99	5.41	7.24	5.38	7.45
Skewness	-0.40	-0.32	-0.38	-0.31	-0.41
Kurtosis	3.91	3.71	3.74	3.48	4.35
SR	0.62	0.41	0.07	0.10	-0.07

Table 2.8: Comparisons with other currency trading strategies - G10 Sample

This table reports summary statistics for the excess returns of different currencies strategies. APR is the strategy that shorts the lowest quintile portfolio sorted by APR Index beta, and buys the top quintile portfolio sorted by APR Index beta. IR is the strategy that shorts the lowest quintile portfolio sorted by IR Sub-index beta, and buys the top quintile portfolio sorted by IR Sub-index beta. CAR is the carry trade strategy. MOM is the momentum strategy. DOL is the dollar strategy. For each portfolio, I report annualized mean and its t-statistics (reported in squared brackets), standard deviation (Std) and Sharpe ratios (SR), all in percentage points. I also report skewness and kurtosis. I report three sub samples: January 1998 to November 2007 (*Panel A*), December 2007 to June 2009 (*Panel B*), July 2009 to October 2018 (*Panel C*).

Panel A: Full Sample

	LMH_{APR}	LMH_{IR}	CAR	MOM	DOL
Mean	2.81	4.10	3.24	1.14	0.65
Std	6.99	6.82	7.67	7.40	8.28
Skewness	-0.83	-0.22	-0.84	0.26	-0.16
Kurtosis	7.17	4.38	5.58	5.67	3.85
SR	0.40	0.60	0.42	0.15	0.07

Panel B: Pre-Crisis

	LMH_{APR}	LMH_{IR}	CAR	MOM	DOL
Mean	2.76	5.93	7.15	0.21	3.44
Std	6.51	5.41	6.22	6.68	7.38
Skewness	-0.74	-0.74	-0.67	-0.00	0.23
Kurtosis	3.89	3.89	3.18	3.74	2.62
SR	0.43	1.04	1.15	0.03	0.47

Panel C: Post-Crisis

	LMH_{APR}	LMH_{IR}	CAR	MOM	DOL
Mean	4.23	4.23	2.11	1.39	-0.88
Std	5.69	5.69	7.13	6.14	7.87
Skewness	-0.40	-0.40	-0.30	-0.00	-0.12
Kurtosis	3.32	3.32	3.00	2.88	3.41
SR	0.74	0.74	0.30	0.23	-0.11

Table 2.9: Diversification Benefits of APR and IR Strategies - All Countries Sample

This table reports the benefits of adding APR and IR strategies to conventional currency strategies. LMH_{IR} is the strategy that goes buys the lowest quintile portfolio sorted by APR Index beta while short selling the top quintile portfolio sorted by APR Index beta. LMH_{IR} is the strategy that shorts the lowest quintile portfolio sorted by IR Sub-index beta, and buys the top quintile portfolio sorted by IR Sub-index beta. CAR is the carry trade strategy. MOM is the momentum strategy. DOL is the dollar strategy. For each portfolio, we report annualized mean, standard deviation (Std) and Sharpe ratios (SR), all in percentage points. I also report skewness and kurtosis. I report portfolio performance of individual trading strategies (*Panel A*), portfolio performance including APR to each individual strategy and the the equally weighted (EW) portfolio (*Panel B*), portfolio performance including IR strategy to each individual strategy and the equally weighted (EW) portfolio (*Panel C*). The data are monthly between January 1998 and October 2018.

Panel A: Excluding APR and IR Strategies				
	CAR	MOM	DOL	EW
Mean	8.82	6.11	2.41	5.78
Std	7.77	6.76	7.58	4.69
Skewness	-0.50	0.08	-0.63	-0.17
Kurtosis	3.88	5.08	5.20	3.35
SR	1.14	0.90	0.32	1.23

Panel B: Including the APR Strategy				
	$CAR + LMH_{APR}$	$MOM + LMH_{APR}$	$DOL + LMH_{APR}$	$EW + LMH_{APR}$
Mean	6.89	5.53	3.68	5.57
Std	5.95	5.06	5.73	4.52
Skewness	-0.39	-0.06	-0.58	-0.21
Kurtosis	3.78	3.86	5.23	3.79
SR	1.16	1.09	0.64	1.23
$w_{LMH_{APR}}$	0.50	0.50	0.50	0.25

Panel C: Including the IR Strategy				
	$CAR + LMH_{IR}$	$MOM + LMH_{IR}$	$DOL + LMH_{IR}$	$EW + LMH_{IR}$
Mean	7.05	5.69	3.84	5.66
Std	5.95	4.84	5.60	4.42
Skewness	-0.50	-0.04	-0.69	-0.32
Kurtosis	3.65	4.31	5.20	3.93
SR	1.18	1.18	0.69	1.28
$w_{LMH_{IR}}$	0.50	0.50	0.50	0.25

Table 2.10: Diversification Benefits of APR and IR Strategies - G10 Sample

This table reports the benefits of adding APR and IR strategies to conventional currency strategies. APR is the strategy that shorts the lowest quintile portfolio sorted by APR Index beta, and buys the top quintile portfolio sorted by APR Index beta. IR is the strategy that shorts the lowest quintile portfolio sorted by IR Sub-index beta, and buys the top quintile portfolio sorted by IR Sub-index beta. CAR is the carry trade strategy. MOM is the momentum strategy. DOL is the dollar strategy. For each portfolio, I report annualized mean, standard deviation (Std) and Sharpe ratios (SR), all in percentage points. I also report skewness and kurtosis. I report portfolio performance of individual trading strategies (*Panel A*), portfolio performance including APR to each individual strategy and the the equally weighted (EW) portfolio (*Panel B*), portfolio performance including IR strategy to each individual strategy and the equally weighted (EW) portfolio (*Panel C*). The data are monthly between January 1998 and October 2018.

Panel A: Excluding APR and IR Strategies				
	CAR	MOM	DOL	EW
Mean	3.24	1.14	0.65	1.69
Std	7.67	7.40	8.28	4.86
Skewness	-0.93	0.26	-0.16	-0.18
Kurtosis	6.62	5.67	3.85	4.91
SR	0.42	0.15	0.08	0.35

Panel B: Including APR Strategy				
	$CAR + LMH_{APR}$	$MOM + LMH_{APR}$	$DOL + LMH_{APR}$	$EW + LMH_{APR}$
Mean	3.03	1.98	1.73	1.96
Std	6.32	5.07	6.07	4.63
Skewness	-1.09	-0.35	-0.93	-0.43
Kurtosis	9.15	7.00	8.25	6.83
SR	0.48	0.39	0.29	0.42
w_{APR}	0.50	0.50	0.50	0.25

Panel C: Including IR Strategy				
	$CAR + LMH_{IR}$	$MOM + LMH_{IR}$	$DOL + LMH_{IR}$	$EW + LMH_{IR}$
Mean	3.67	2.62	2.37	2.28
Std	6.39	5.12	6.04	4.68
Skewness	-0.66	-0.12	-0.52	-0.25
Kurtosis	6.79	5.66	6.14	5.80
SR	0.57	0.51	0.39	0.49
w_{IR}	0.50	0.50	0.50	0.25

Table 2.11: Cross-section FX Asset Pricing with U.S. Populist Rhetoric

This table reports regressions results for the estimation of the market price of APR index and IR sub-index (λ_{PR}). The control variables are volatility ($\lambda_{Volatility}$) and illiquidity ($\lambda_{Illiquidity}$) as in Menkhoff et al. (2012a). *Panel A* (*Panel B*) reports results for All Countries (G10 Countries). Newey and West (1987) t-statistics are reported in squared brackets, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. The data are monthly between January 1998 and October 2018.

Panel A: All Countries								
	APR Index				IR Sub-index			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
λ_{PR}	-0.43***	-0.44***	-0.49***	-0.49***	-0.07***	-0.08***	-0.07***	-0.08***
	[-3.04]	[-3.08]	[-3.63]	[-3.74]	[-3.10]	[-3.46]	[-3.57]	[-3.89]
$\lambda_{Volatility}$		-0.01		-0.01		-0.01		-0.01
		[-1.23]		[-0.95]		[-1.07]		[-0.76]
$\lambda_{Illiquidity}$			0.05	0.01			0.06	0.03
			[1.16]	[0.35]			[1.50]	[0.82]
Constant	-0.00	-0.00	-0.00	-0.00	0.00	-0.00	0.00	-0.00
	[-0.39]	[-0.79]	[-0.13]	[-0.58]	[0.18]	[-0.01]	[0.25]	[-0.03]
Obs	3,649	3,649	3,648	3,648	3,649	3,649	3,648	3,648
Adj R^2	0.17	0.27	0.26	0.35	0.16	0.27	0.25	0.35
Panel B: G10								
	APR Index				IR Sub-index			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
λ_{PR}	-0.29***	-0.23**	-0.29**	-0.21*	-0.04***	-0.04***	-0.04***	-0.03**
	[-2.92]	[-2.17]	[-2.43]	[-1.85]	[-2.97]	[-2.71]	[-2.67]	[-2.40]
$\lambda_{Volatility}$		0. 00		0.00		-0.00		-0.01
		[0.06]		[0.10]		[-0.11]		[-0.70]
$\lambda_{Iliquidity}$			-0.27**	-0.32**			-0.24*	-0.33**
			[-2.17]	[-2.42]			[-1.83]	[-2.53]
Constant	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00
	[-0.40]	[-0.20]	[-0.72]	[-1.05]	[-0.31]	[-0.08]	[-0.60]	[-0.71]
Obs	2,049	2,049	2,048	2,048	2,049	2,049	2,048	2,048
Adj R^2	0.20	0.36	0.36	0.49	0.19	0.35	0.34	0.48

Table 2.12: U.S. Populist Rhetoric and Gubernatorial Elections in Swing States

This table reports regressions results for the estimation of the market price of APR index and IR sub-index (λ_{PR}), interaction variable between PR and Gubernatorial Election in swing states ($\lambda_{ElectionDummy*PR}$), and Gubernatorial Election in swing states dummy ($\lambda_{ElectionDummy}$). Election Dummy is equal to 1 if there is a gubernatorial election in at least one swing state in that year, and 0 otherwise. The control variables are volatility ($\lambda_{Volatility}$) and illiquidity ($\lambda_{Illiquidity}$) as in Menkhoff et al. (2012a). I report results for All Countries and G10 Countries. Newey and West (1987) t-statistics are reported in squared brackets, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. The data are monthly between January 1998 and October 2018.

	All Countries		G10	
	APR Index	IR Sub-index	APR Index	IR Sub-index
λ_{PR}	-0.53***	-0.07***	-0.52***	-0.05**
	[-3.81]	[-3.95]	[-2.76]	[-2.40]
$\lambda_{ElectionDummy}$	-0.10	-0.07	-0.02	0.03
	[-1.31]	[-0.90]	[-0.13]	[0.26]
$\lambda_{ElectionDummy*PR}$	-0.27***	-0.06*	-0.38*	-0.02
	[-2.77]	[-1.83]	[-1.96]	[-1.12]
$\lambda_{Volatility}$	-0.00	-0.00	0.02	0.01
	[-0.68]	[-0.38]	[1.33]	[0.87]
$\lambda_{Illiquidity}$	0.03	0.04	-0.26	-0.21
	[0.75]	[1.02]	[-1.33]	[-1.48]
Constant	-0.00	-0.00	-0.00*	-0.00
	[-0.71]	[-0.35]	[-1.89]	[-1.48]
Obs	3,648	3,648	2,048	2,048
Adj R^2	0.50	0.51	0.73	0.72

Table 2.13: Portfolios of stocks sorted by shipping cost and APR Index

This table reports correlations between portfolios of stock returns sorted by shipping cost and APR Index. Portfolio 1 (P_1) contains stocks with the lowest shipping cost, and Portfolio 5 (P_5) contains stocks with the highest shipping cost. LMH represents the portfolios that has a long position in the low shipping cost portfolio (P_1) and a short position in the high shipping cost portfolio (P_5). I report p-values in parenthesis. The data are monthly between January 1998 and December 2017.

Panel A: Pairwise correlations

	Equally-weighted portfolios						Value-weighted portfolios					
	P_1	P_2	P_3	P_4	P_5	LMH	P_1	P_2	P_3	P_4	P_5	LMH
APR Index	0.07	0.03	0.01	-0.04	-0.04	0.14	0.10	0.04	0.07	0.00	-0.02	0.15
						(0.03)						(0.02)

Panel B: Pairwise correlations controlling for Fama-French 3 factors

	Equally-weighted portfolios						Value-weighted portfolios					
	P_1	P_2	P_3	P_4	P_5	LMH	P_1	P_2	P_3	P_4	P_5	LMH
APR Index	0.07	0.00	-0.03	-0.14	-0.13	0.14	0.14	0.03	0.10	-0.02	-0.06	0.15
						(0.03)						(0.03)

Panel C: Pairwise correlations controlling for Fama-French 5 factors

	Equally-weighted portfolios						Value-weighted portfolios					
	P_1	P_2	P_3	P_4	P_5	LMH	P_1	P_2	P_3	P_4	P_5	LMH
APR Index	0.05	-0.02	-0.07	-0.17	-0.14	0.14	0.14	0.03	0.09	-0.06	-0.08	0.16
						(0.04)						(0.01)

Table 2.14: Cross-section FX Asset Pricing with U.S. Populist Rhetoric with DOL and CAR

This table reports regressions results for the estimation of the market price of APR index and IR sub-index (λ_{PR}). The control variables are Dollar factor (λ_{DOL}), Carry factor (λ_{CAR}) as in Lustig et al. (2011). Panel A (Panel B) reports results for All Countries (G10 Countries). Newey and West (1987) t-statistics are reported in squared brackets, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. The data are monthly between January 1998 and October 2018.

Panel A: All Countries						
	APR Index			IR Sub-index		
	(1)	(2)	(3)	(4)	(5)	(6)
λ_{PR}	-0.32**	-0.31**	-0.25**	-0.07**	-0.08***	-0.05**
	[-2.45]	[-2.52]	[-2.09]	[-2.31]	[-2.76]	[-2.35]
λ_{DOL}		0.00	0.00		0.00*	0.00
		[1.63]	[1.45]		[1.70]	[1.38]
λ_{CAR}			0.01***			0.08***
			[2.76]			[2.67]
Constant	-0.00	-0.00	-0.00	0.00	0.00	-0.00
	[-2.04]	[-1.15]	[-0.63]	[0.96]	[-1.42]	[-0.65]
Obs	3,649	3,649	3,649	3,649	3,648	3,649
Adj R^2	0.10	0.25	0.44	0.51	0.57	0.10

Panel B: G10						
	APR Index			IR Sub-index		
	(1)	(2)	(3)	(4)	(5)	(6)
λ_{PR}	-0.19	-0.27*	-0.25**	-0.03*	-0.05**	-0.05**
	[-1.62]	[-1.93]	[-2.03]	[-1.88]	[-2.36]	[-2.48]
λ_{DOL}		0.00	0.00		0.00	0.00
		[1.15]	[0.98]		[1.03]	[0.70]
λ_{CAR}			0.00			0.00
			[1.17]			[1.28]
Constant	0.00	-0.00	-0.00	0.00	-0.00	-0.00
	[0.33]	[-1.15]	[-0.88]	[0.32]	[-0.93]	[-0.53]
Obs	2,049	3,649	3,649	3,649	3,648	3,649
Adj R^2	0.16	0.33	0.55	0.15	0.32	0.56

Chapter 3

The Information Content of Trump Tweets and the Currency Market

[1]

[1] This paper is co-authored with Ilias Filippou, Arie Gozluklu, and Ganesh Viswanath-Natraj.

3.1 Introduction

Since Donald J. Trump started his U.S. presidential campaign in June 2015, he has extensively used Twitter as a means of communication to the public. Although he is not the first U.S. president to be active on social media, his personal Twitter account attracts enormous attention at an unprecedented level due to various aspects, such as the frequency, content, and language of his tweets.[2] The figure of more than 77.5 million followers (as of April 2020) has shown how much attention the public is paying to the views shared by the U.S. 45^{th} President. Although the information content of these tweets is a matter of dispute, a growing area of research is identifying the effects of his tweets on financial markets.[3] For example, research by Bank of America suggests that days with more than 35 Trump tweets see negative returns of the Dow Index. The JPMorgan 'Volfefe' index, on the other hand, tracks how Trump tweets move the bond markets. In contrast, this paper focuses on the information content of Trump tweets related to the macroeconomic outlook and trade on the foreign exchange (FX) market, which is the most traded financial market worldwide (BIS, 2019).[4]

Trump tweets provide a novel experiment to study the effects of an unexpected public signal on trading, volatility and returns in the currency market. Exchange rates in principle aggregate macroeconomic information on future fundamentals of a country, yet the link between economic fundamentals and foreign exchange markets is difficult to connect in a high-frequency environment. To shed light on the effects of Trump tweets on exchange rates, I use textual analysis to filter the set of Trump tweets that contain information on future macroeconomic fundamentals relevant for FX market participants. This includes tweets on trade, such as tariffs with China or Mexico, tweets on U.S. employment figures, or tweets influencing the financial market perceptions of interest rates (e.g., Bianchi et al., 2019). In a market with heterogeneous private information in spot rate expectations, a common public signal can reduce investor disagreement in the FX market (e.g., Ranaldo and Santucci de Magistris, 2019; Kruger, 2020). I hypothesize Trump tweets cause a reduction in investor disagreement, and in turn, a decline in FX volume, volatility and bid-ask spreads. Spot returns during Trump tweet hours reflect an (optimistic) bias regarding the future macroeconomic fundamentals of the U.S. and foreign economies.

To guide my empirical analysis, I start with a model of heterogeneous private information and Trump tweets as a public signal in the FX market. The market is populated by a set of speculators, each with their own private signal on the valuation of the future spot rate. Investors then update their private signal based on the Trump tweet,

[2] His Twitter account has been permanently suspended in January 2021 because of his tweets after the U.S. Capitol attack.

[3] https://www.washingtonpost.com/technology/2020/05/26/trump-twitter-label-fact-check/

[4] https://www.bis.org/statistics/rpfx19_fx.pdf

which I assume is known to all traders. There are two distinct types of speculators in the model: (rational) Bayesian investors who update their prior based on the information content of the Trump tweet, and (irrational) Trump followers who fully adopt the Trump tweet. My analysis generates three predictions. First, as investors trade on a common signal, there is a decline in the dispersion of investor beliefs on valuations of the future spot rate. I show that a rise in the share of Trump followers leads to a decline in investor disagreement, and in turn a decline in the volume of trading in the currency market. Second, the Trump tweet leads to a decline in exchange rate volatility if the tweet is more informative than the private signal. If speculators rely on the public information via informative Trump tweets over their private signals, the corresponding reduction in asymmetric information leads to a reduction in bid-ask spreads. Finally, I show that Trump tweets induce a bias in spot returns reflecting differences between the (optimistic) views of Trump and the speculators on the future valuation of macroeconomic fundamentals.

Turning to the data, I first conduct a textual analysis on Trump tweets to identify the information content related to the macroeconomic outlook, trade and international developments that are impounded in exchange rates. My sample period is from 16th June 2015, the starting date of Trump's presidential campaign, to 20th August 2019. I implement two methods to identify Macro and Trade tweets. The first approach follows keywords by topics outlined in Baker et al. (2019). Second, I use the topic modelling approach developed by Yan et al. (2013) to filter out tweets about macroeconomics outlook, trade policy, and exchange rate topics. This approach is suitable for an analysis of short texts and hence ideal for the analysis of tweets. To my knowledge, my paper is the first paper to use this approach in the finance literature.

I proceed to link Trump tweets to outcomes in the FX market, and construct our measures of FX market activity. For FX volume, I use CLS, a real time gross settlement system which is the largest available dataset on trading volume across a wide range of market participants, e.g., banks, funds and corporations, for up to 16 bilateral pairs at an hourly frequency (e.g., Hasbrouck and Levich, 2019). I combine our hourly volume data with currency spot rates from Thomson Reuters Tick History. In addition, I have data on bid-ask quotes for a series of banks, and construct intraday measures of volatility based on high frequency changes in the spot rate.

My main empirical results test a panel specification with the outcome variables of FX volume, volatility, bid-ask spreads and spot returns. Explanatory variables include an hourly dummy for a macro or trade tweet, and controls for hour-of-day, day-of-week, scheduled monetary announcements, fundamentals in financial markets such as the VIX index. I find statistical evidence that Tweet hours are associated with a decrease in FX trading volume. This result holds for all groups in my sample, with the biggest decline observed for banks, non-bank financial institutions and funds. Second, I find declines in my measure of intraday FX spot volatility and bid-ask spreads around Trump tweet hours, indicative of a reduction in investor disagreement during tweet hours. Third, I identify systematic effects of Trump tweets on FX spot returns. The dollar tends on average to appreciate with respect to major bilateral pairs during Trump tweet hours. I find significant cumulative returns in the hour following the tweet for an equal weighted average return of all 16 bilateral pairs, as well as a USD ETF index. This appreciation is consistent with the nature of Trump tweets, that reflect typically his positive views on the U.S. economy (relative to other countries), and trigger a protectionist stance on trade policies.

In robustness exercises, I show that the results hold when controlling for a set of macroeconomic releases that occur on the day of the tweet. This rules out an alternative view that the effects of Trump tweets are due to the reaction of news that occurred earlier in the day. I also provide a placebo test to show that Trump tweets in the set of non-macro/trade topics do not have significant effects on FX markets. Finally, I test the proposed mechanism through which Trump tweets cause a decline in trading volume and volatility. In a FX market populated by speculators with heterogeneous information, Trump tweets result in a reduction in investor disagreement. I test this mechanism by constructing a proxy for FX disagreement from options data. I hypothesize that during Trump tweet hours, the common signal reduces the dispersion in the future valuation of exchange rate fundamentals, and therefore reduces the measure of disagreement based on the options pricing.[5] In line with my hypothesis, I find a statistically significant reduction in my measured proxy for investor disagreement during Trump tweet hours.

The rest of the paper is structured as follows. Section 3.2 summarizes related literature. Section 3.3 introduces a model with my theoretical predictions on the effects of Trump tweets on FX volume, volatility and returns. Section 3.4 outlines the data. Section 3.5 discusses my empirical findings. Section 3.6 concludes.

[5]The measure of options disagreement I use is the absolute value of the moneyness ratio based on Salomé (2020). The metric is intuitively measuring the difference between the strike and current spot price after controlling for volatility and time to expiry.

3.2 Related Literature

The paper contributes to a growing literature on studying the effects of Twitter content on financial markets. Focusing on the stock market, studies examine the relationship between Twitter sentiment and the stock market returns and volatility of stock indices (Bollen et al., 2011; Mittal and Goel, 2012; Behrendt and Schmidt, 2018), the effects of company-specific tweets (e.g., Sprenger et al. 2014, Bartov et al. 2018), and the impact of twitter sentiment around FOMC announcements on stock returns (Azar and Lo, 2016). Focusing on the currency market, Gholampour and Van Wincoop (2017) examine investor tweets regarding the Euro/dollar exchange rate and classify them into positive, negative, and neutral opinions. They create a trading strategy based on this sentiment and find that the Sharpe ratio of this strategy outperforms that of carry trade.[6]

Turning to Trump tweets, there are a number of recent papers on studying the effects of Trump tweets on the stock market, interest rate futures and the currency market. The effects of Trump tweets on publicly traded firm stock returns and volatility (e.g., Ge et al., 2018; Born et al., 2017; Ajjoub et al., 2019; Juma'h and Alnsour, 2018; Colonescu et al., 2018; Abdi et al., 2021), tweets on threatening central bank independence signalling a lower future path of the Federal Funds rate (Bianchi et al., 2019), and tweets with a negative stance on Mexico-U.S. trade on the Peso/Dollar exchange rate (Benton and Philips, 2018), tweets on the China-US trade dispute (Ferrari et al., 2021), and the role of tweets on macroeconomic policies to divert attention from media articles on the Mueller report (Lewandowsky et al., 2020). Abdi et al. (2021) conduct a textual analysis of Trump tweets and investigate whether Trump tweets contain information relevant for stock prices. The authors find evidence that Trump tweets are responding to information earlier in the day, and information effects for a subset of Trump tweets on the NAFTA trade agreement and the US China trade war, which is consistent with my hypothesis that Trump tweets with macroeconomic and trade content are more informative. Benton and Philips (2018) and Ferrari et al. (2021) find that Trump tweets on Mexico-U.S. trade relations and China-US Trade tensions cause an appreciation of the U.S. dollar. My results extend their analysis by conducting a textual analysis to identify the macroeconomic and trade content of Trump tweets. This will include tweets on how the Federal Reserve should set interest rates, trade tensions with Korea, the Middle East and Mexico. Second, I examine the effects of informative trading on a number of metrics measuring returns and liquidity for a larger wide basket of currencies. Third, through a model, I illustrate how Trump tweets can affect spot

[6] In related work, Filippou et al. (2020a) construct a measure of U.S. populist rhetoric –using a broad set of newspapers– and find that currencies which perform well (badly) when U.S. populist rhetoric is high offer low (high) currency excess returns. In addition, Filippou et al. (2020d) show that FX news sentiment is a strong negative predictor of the cross-section of currency returns.

returns due to differences in expectations of future exchange rate fundamentals between Trump and investors.

The second major literature my paper relates to is on the microstructure of currency markets. Information asymmetry in currency markets have typically been studied by signing trades in inter-dealer and dealer-customer markets through order flow (e.g., Evans and Lyons, 2002; Ranaldo and Somogyi, 2019). More recently, a number of papers have examined the information content of FX trading volume using CLS data (e.g., Fischer and Ranaldo, 2011; Hasbrouck and Levich, 2019; Cespa et al., 2020). On the theory side, my paper speaks to microstructural models of the FX spot market that connect trading and volatility through a set of informed and "noise" traders, with heterogeneous information on the fundamentals of the exchange rate (e.g., Jeanne and Rose, 2002; Bacchetta and Van Wincoop, 2006; Gholampour and Van Wincoop, 2017). I adapt the model framework to include a discussion of the introduction of a public signal, the Trump tweet, on spot volume and volatility. Traders are differentiated in how they update their signal based on the Trump tweet, with two sets of agents, rational Bayesian agents, and irrational Trump followers, that have differing weights on private and public information.

Finally, I make a connection between FX market microstructure and the literature on investor disagreement in financial markets. The theory of investor disagreement assumes that investors have heterogeneous priors on the payoff of the asset (Hong and Stein, 2007). Differences in investor information sets translate to disagreement on the future payoff, and can induce trading and increase volatility, a finding consistent with studies in both stock and currency markets (e.g., Ranaldo and Santucci de Magistris, 2019; Kruger, 2020). On this front, my paper is closely related to Ranaldo and Santucci de Magistris (2019), which also has a model of FX trading and heterogeneous information, and use an unexpected monetary policy event of the Swiss National Bank in 2015 to show how increased investor disagreement translated to increases in volume and volatility. I find complementary evidence in my paper through an alternative event: using the information content of Trump tweets. I hypothesize that Trump tweets cause a reduction in investor disagreement, which in turn leads to less trading, lower volatility, and reduced asymmetric information through lower bid ask spreads.

3.3 Model

I derive a simple model of trading in the FX market with public information. Each investor has a prior of the exchange rate in one period from now. These traders follow a similar functional form to informed traders in information models of the exchange (Jeanne and Rose, 2002; Bacchetta and Van Wincoop, 2006; Gholampour and Van Wincoop, 2017). A public signal, the Trump tweet, is a common signal interpreted by all speculative traders. A rational Bayesian agent combines their prior with the public signal. The posterior distribution of the Bayesian agent's signal is a weighted average of the public and private information, with the weights a function of the relative precision of each signal. In addition to Bayesian agents, a fraction of traders are characterized as Trump followers, and update their prior to put a weight of one on the public signal. Using this setting, I examine the impact of the public signal on the volume of trading, volatility and spot returns. My key mechanism is that the public signal induces a decline in investor disagreement, a channel that can lead to a decline in trading volume and volatility, consistent with models of investor disagreement in FX and stock markets (Ranaldo and Santucci de Magistris, 2019; Kruger, 2020).

Exchange rates

Consider a market of N agents with heterogeneous priors on the future payoff of the exchange rate s_t dollars per unit of foreign currency.[7] The expectations of the future exchange rate s^j_{t+1} for agent j is defined in equation 3.1. The expectation conditional on the private signal is θ^j. The precision of the private signal is governed by the variance σ^2_j.

$$s^j_{t+1} = \theta^j + \epsilon^j_{t+1}, \epsilon^j \sim N(0, \sigma^2_j) \tag{3.1}$$

Trump tweets

I characterize the Trump tweet in equation 3.2 as a public signal known to all investors. The arrival of the public signal is unexpected. For example, tweets can occur at any time of the day, unlike scheduled monetary announcements of the central bank. The public tweet has expectation θ^T, with precision of the public signal governed by σ^2_T. For my analysis, I assume the public and private signal are uncorrelated, $cov(\epsilon^T, \epsilon^j) = 0$.

[7] Under this notation, an increase in s_t implies a depreciation of the dollar.

$$s_{t+1}^{T} = \theta^{T} + \epsilon_{t+1}^{T}, \epsilon^{T} \sim N(0, \sigma_{T}^{2}) \tag{3.2}$$

An important assumption I make is that the Trump tweet aggregates private information, and is equal to the average of the investor priors, $\theta^{T} = \frac{1}{N}\sum_{j=1}^{N}\theta^{j}$. Critically, the information aggregation of Trump is not known in advance by Bayesian agents.[8]

Bayesian agents

A rational agent will update their prior based on the public signal. Their expectation, conditional on the public and private information, is a weighted average of the public and private signal. Let me denote the weights on the public and private signal for a Bayesian agent as ω_{j}^{B} and $1-\omega_{j}^{B}$ respectively, in equation B.1.

$$\mathbb{E}[s_{t+1}^{j}|I_{j}, I_{T}] = \omega_{j}^{B}\theta^{T} + (1-\omega_{j}^{B})\theta^{j} \tag{3.3}$$

A Bayesian agent will update their prior based on the relative precision of the public and private signal. Formally, I define the weight on the public signal, $\omega_{j}^{B} = \frac{\sigma_{j}^{2}}{\sigma_{T}^{2}+\sigma_{j}^{2}}$, in equation 3.4.

$$\mathbb{E}[s_{t+1}^{j}|I_{j}, I_{T}] = \frac{\sigma_{j}^{2}}{\sigma_{T}^{2}+\sigma_{j}^{2}}\theta^{T} + \frac{\sigma_{T}^{2}}{\sigma_{T}^{2}+\sigma_{j}^{2}}\theta^{j} \tag{3.4}$$

If the relative precision of the public signal is $\frac{\sigma_{T}^{2}}{\sigma_{j}^{2}} \to 0$, the Trump tweet is more precise, and the investor's weight on the public signal approaches one. Conversely, if the public signal is noisy relative to the private signal, the investor puts a weight of zero on the public signal.

Trump Followers

As well as Bayesian agents, a subset of agents are characterized as Trump followers. These traders adopt the Trump tweet as their complete signal. This is defined formally in equation 3.5.

[8] If I model multiple periods traders will learn that the Trump signal is aggregating private information, causing Bayesian agents to put a weight of 1 on the Trump signal. Therefore all agents would be Trump followers in a multi-period setting. I avoid this problem by assuming a 2 period model, that is, the Bayesian agents only form an expectation today (time t) of the payoff in period $t+1$.

$$\mathbb{E}[s^j_{t+1}|I_j, I_T] = \theta^T \tag{3.5}$$

In the context of our model, an increase in the number of Trump followers reduces investor disagreement in the FX market about the future spot rate. We can see this visually in Figure 3.1, which plots the distribution of investor priors, and the posterior distribution of each agent type. Under the assumption that the Trump tweet is centered at the distribution, if a fraction of agents are Trump followers, the distribution of posteriors is now more compact around θ_T. The reduction in investor disagreement reduces the dispersion in investor expectations of the future spot rate, with implications for the amount of trading and volatility of the spot rate, consistent with related literature on the link between investor disagreement and volume and volatility in FX and stock markets (Ranaldo and Santucci de Magistris, 2019; Kruger, 2020).[9]

Investor optimization

The investor maximizes exponential utility over their next period wealth, $U_t = -e^{-\gamma W_{t+1}}$, and invests entire wealth in foreign currency bonds $W_{t+1} = \rho^j_t b^j_t$. The excess return made on the foreign currency bond for a Bayesian agent is defined in equation 3.6. Similarly, the excess return on the domestic bond for a Trump follower is given by equation 3.7.

$$\rho^{j,B}_t = \omega^B_j s^T_{t_1} + (1-\omega^B_j)s^j_{t+1} - s_t + i^*_t - i_t \tag{3.6}$$

$$\rho^{j,T}_t = s^T_{t+1} - s_t + i^*_t - i_t \tag{3.7}$$

The optimization problem of the investor is to maximize utility subject to all wealth invested in domestic bonds. This is given by a mean-variance problem, maximizing equation 3.8 subject to the constraint on next period wealth in equation 3.9.

$$\max_{b^j_t} \qquad L = \mathbb{E}[W^j_{t+1}] - \frac{1}{2}\gamma Var(W^j_{t+1}) \tag{3.8}$$

[9] Ranaldo and Somogyi (2019) has similar predictions to my model, and show that an increase in the dispersion of trader expectations of the future payoff lead to an increase in trading and volatility in the currency market. I depart from their framework in showing the channels through which a public signal can generate a decline in information disagreement.

subject to:

$$W_t^j = \rho_t^j b_t^j \tag{3.9}$$

Solving for the optimal level of bond demand by Bayesian agents in equation 3.10, and optimal bond demand by Trump followers in equation 3.11.

$$b_t^j = \frac{\omega_j^B \theta^T + (1-\omega_j^B)\theta^j - s_t + i_t^* - i_t}{\gamma({\omega_j^B}^2 \sigma_T^2 + (1-\omega_j^B)^2 \sigma_j^2)} \tag{3.10}$$

$$b_t^j = \frac{\theta^T - s_t + i_t^* - i_t}{\gamma \sigma_T^2} \tag{3.11}$$

Market clearing

Given a total of N agents, let me define N_B as the number of Bayesian agents and N_T denote the number of Trump followers. In equilibrium, market clearing requires the net bond supply to be equal to zero, giving rise to equation 3.12.[10]

$$\sum_{j \in N_B} b_t^j + \sum_{j \in N_T} b_t^j = 0 \tag{3.12}$$

Substituting the formulae for optimal bond holdings by Bayesian agents and Trump followers into the market clearing condition yields equation 3.13.

$$\sum_{j \in N_B} \frac{\omega_j^B \theta^T + (1-\omega_j^B)\theta^j - s_t + i_t^* - i_t}{{\omega_j^B}^2 \sigma_T^2 + (1-\omega_j^B)^2 \sigma_j^2} + \sum_{j \in N_T} \frac{\theta^T - s_t + i_t^* - i_t}{\sigma_T^2} = 0 \tag{3.13}$$

Under the simplifying assumption that the Trump tweet is equal to the average of investor priors, $\theta^T = \frac{1}{N}\sum_{j=1}^N \theta_j$, the equilibrium spot exchange rate is given by equation 3.14.

[10]This is similar to the market clearing condition in Bacchetta and Van Wincoop (2006) and Gholampour and Van Wincoop (2017), in which the net bond demands of informed and liquidity (noise) traders are equal to zero. The deviation in my model is the distinction between informed traders and Trump followers.

$$s_t = \theta^T + i_t^* - i_t \tag{3.14}$$

Asset pricing view of the exchange rate

I now determine the equilibrium exchange rate based on equilibrium in money markets, following Jeanne and Rose (2002). First I use simple money demand functions for home and foreign in equations 3.15 and 3.16.

$$m_t - p_t = -\alpha i_t + \eta y_t \tag{3.15}$$

$$m_t^* - p_t^* = -\alpha i_t^* + \eta y_t^* \tag{3.16}$$

Imposing purchasing power parity in equation 3.17, I derive an expression for s_t as a function of the difference in money supplies and income differences between the domestic and foreign currencies in equation 3.18.

$$s_t = p_t - p_t^* \tag{3.17}$$

$$s_t = m_t - m_t^* + \alpha(i_t - i_t^*) - \eta(y_t - y_t^*) \tag{3.18}$$

Let me denote future fundamentals f_t in equation 3.19.

$$f_t = \frac{m_t - m_t^*}{1+\alpha} - \frac{\eta(y_t - y_t^*)}{1+\alpha} \tag{3.19}$$

I now obtain an expression for s_t in terms of fundamentals m_t and y_t, and the expected future spot rate, which is a weighted average of the Trump tweet and the public signal.

$$s_t = f_t + \frac{\alpha}{1+\alpha}\mathbb{E}_t[s_{t+1}] \tag{3.20}$$

Iterating forward, I obtain equation 3.21, which states that the spot rate is a function of expected future fundamentals (Engel and West, 2005; Froot and Ramadorai, 2005).

$$s_t = f_t + \sum_{s=1}^{\infty}\left(\frac{\alpha}{1+\alpha}\right)^s \mathbb{E}_t[f_{t+s}] \tag{3.21}$$

I now present three predictions on the introduction of the Trump tweet on the volume of trading, the conditional volatility of the spot exchange rate, and the bias of spot returns.

Prediction 1: Trading volume decreases as the share of Trump followers increases.

Define aggregate bilateral FX volume as $V_{FX} = \frac{1}{2}\sum_{j=1}^{N}|b_t^j|$*. The effect on FX volume is given by equation 3.22. All else equal, a higher fraction of Trump followers will lower trading volume.*

$$\frac{V_{FX}|I_j, I_T}{V_{FX}|I_j} = \frac{\sum_{j\in N_B}|\frac{\theta^j-\theta^T}{\sigma_j^2}|}{\sum_{j\in N_B}|\frac{\theta^j-\theta^T}{\sigma_j^2}| + \sum_{j\in N_T}|\frac{\theta^j-\theta^T}{\sigma_j^2}|} < 1 \tag{3.22}$$

Proof: see appendix.

The ratio of trading volume is then proportional to the fraction of Bayesian agents. The intuition is that an increase in the fraction of Trump followers leads to a reduction in investor disagreement about the future spot rate. The reduction in disagreement, in turn, causes a decline in net trading as a larger fraction of investors have exchange rate expectations that yield zero excess returns, and zero trading in the currency market.

Mathematically, I can show the reduction in investor disagreement by examining the bond holdings of Trump followers and Bayesian agents. Assuming the Trump tweet is equal to the average of investor priors, Trump followers earn a zero expected excess return. Therefore, their optimal bond holdings in equilibrium are zero, and they do not trade in the market. In contrast, the bond holdings of Bayesian agents in the equilibrium with public information is equal to their bond holdings without the public signal.

Prediction 2: Conditional variance of the future spot rate is lower if the Trump tweet is informative.

The volatility of the spot exchange rate conditional on private and public information is reduced if the share of Bayesian agents is less than the upper bound given by equation 3.24. This depends on the relative precision of the Trump signal $R = \frac{\sigma_T^2}{\sigma_j^2}$ and the relative share of Bayesian agents $\frac{N_B}{N}$.

$$\frac{var(s_{t+1|I_j,I_T})}{var(s_{t+1|I_j})} = R\left(1 - \frac{N_B}{N}\frac{R}{1+R}\right) \tag{3.23}$$

$$\frac{var(s_{t+1|I_j,I_T})}{var(s_{t+1|I_j})} < 1 \quad \text{if} \quad \frac{N_B}{N} > \frac{R^2-1}{R^2} \tag{3.24}$$

Proof: see Appendix

The effect of the Trump tweet on the conditional variance of the spot rate depends on the information content of the signal. If the Trump signal is more precise than the private signal, the variance of the future spot rate for Bayesian agents and Trump followers are always lower in the equilibrium with public information. Mathematically, the threshold $\frac{N_B}{N} > 0 > \frac{R^2-1}{R^2}$ is satisfied for any fraction of Bayesian agents when the public signal is relatively more precise, $R < 1$.

If the Trump tweet does not have information content, and the public signal is imprecise, the effect of spot rate volatility conditional on the public and private signal is ambiguous. While there is still a decline in conditional variance for Bayesian agents, Trump followers now experience an increase in spot rate volatility conditional on the public signal. Mathematically, there is a decline in conditional volatility of the spot rate if and only if the share of Bayesian agents is sufficiently high, given by the threshold in equation 3.24.

If Trump tweets are informative, more Bayesian agents will rely on public information over their private signals, which in turn should lead to a reduction in information asymmetry in the currency market. I conjecture that the decline in information asymmetry leads to dealers quoting smaller bid-ask spreads, as they are more willing to take the other side of trades based on public information. Therefore, an informative public signal via Trump tweets should reduce not only the dispersion of investor beliefs on the future spot rate, but also bid-ask spreads in the FX market.[11]

[11] While I do not model bid-ask spreads explicitly, based on the theory in Glosten and Milgrom (1985), the bid-ask spread is a positive function of the share of informed traders in the market. Therefore, a decline

Prediction 3: An informative Trump tweet affects FX spot returns due to a bias between the Trump tweet and speculators' expectations.

Define the exchange rate fundamental $f_t = \frac{m_t - m_t^*}{1+\alpha} - \frac{\eta(y_t - y_t^*)}{1+\alpha}$. *The spot rate with the introduction of the Trump tweet is defined in equation 3.25. The dollar can appreciate due to a bias between Trump expectations of future fundamentals and expectations of the average speculator.*

$$s_{t|I_T,I_j} - s_{t|I_j} = \underbrace{\frac{w_j^B N_B + N_T}{N}}_{\text{public signal adoption}} \sum_{s=1}^{\infty}\left(\frac{\alpha}{1+\alpha}\right)^s \underbrace{\left(\mathbb{E}_t[f_{t+s}^T] - \frac{1}{N}\sum_{j\in N} E[f_{t+s}^j]\right)}_{\text{bias}} \tag{3.25}$$

Proof: see Appendix

The change in the spot rate conditional on public information is a weighted average of the bias in Trump's expectations of future fundamentals. This is equal to the difference between the average of investor priors and the Trump signal for Trump followers. The bias is weighted by the share of agents that adopt the public signal, and is given by the $\frac{w_j^B N_B + N_T}{N}$. This is increasing in the weight given by Bayesian agents to the public signal. I illustrate the bias in fundamentals in Figure 3.1. The average of investor priors is given by $\bar{f_{t+s}}$, and Trump's prior of the future fundamental is given by f_{t+s}^T. The posterior distribution of Trump followers and Bayesian agents shifts toward Trump expectations, and this causes a change in the spot exchange rate based on equation 3.21.[12]

The bias between Trump's exchange rate fundamentals and the fundamentals of speculators causes a change in the spot exchange rate. I can further decompose the direction of the bias into differences between expectations of future fundamentals, output growth and the money supply. For example, if growth expectations at home (U.S.) are systematically higher for the Trump tweet, $\mathbb{E}_t[y_{t+s}^T] > E_t[y_{t+s}^j] \forall s = 0, 1, 2,$. This implies the bias will be negative, causing an appreciation of the U.S. dollar. Similarly, tweets that imply an increase in trade barriers and protectionism imply higher tariffs, a relative contraction in foreign output growth, and an appreciation of the dollar spot exchange rate. I test this empirically by examining spot returns during Trump tweets, with respect to tweets with macroeconomic and trade content.

in the share of informed traders, due to adoption of the public signal by Trump followers, reduces the effective share of informed (private) traders, and in turn leads dealers to quote smaller bid-ask spreads.

[12]Note that I am assuming a bias in investor priors on the future macroeconomic fundamentals. This relaxes the assumption on the prior of the Trump signal being equal to the average of investor priors, $\theta^T = \frac{1}{N}\sum_{j=1}^{N}\theta_j$.

3.4 Data

3.4.1 Donald Trump's Tweets

I obtain Donald Trump's tweets from http://www.trumptwitterarchive.com, which collects all tweets from account @realDonaldTrump. I am interested in the period starting from June 16 2015, as it is the day when Donald Trump announced his presidential campaign. Donald Trump extensively used Twitter to express his views on important issues, both global and domestic since he started his campaign. Given that he is a well connected businessman, he is likely to have access to information. My sample ends in August 20 2019. During this period, there are 17,865 tweets posted from his account in total. As expected, there are various topics covered in these tweets. [13]

I have two approaches to identify the information content of Trump tweets, and to filter tweets that have macroeconomic, trade or exchange rate content. The first approach uses a dictionary approach, and the second uses a textual analysis based on a bi-term topic modelling approach.[14] I combine the relevant Tweets identified by these two methods for my empirical analysis.

3.4.1.1 Dictionary approach

Baker et al. (2019) provides a dictionary of policy related terms about the macroeconomics outlook, trade policy, and exchange rate topics that are most relevant for the foreign exchange market. Other topics such as healthcare and energy are clearly much less connected with currencies. Therefore, my focus is on Tweets containing terms falling into macroeconomics outlook, trade policy, and exchange rate categories. Term sets in this dictionary are constructed by careful audit and validation with a large sample of newspapers articles, so it should generate a good level of accuracy. A comprehensive list of these terms associated with three categories (macroeconomics outlook, trade policy, and exchange rates) can be found in Table 3.6.

After filtering tweets containing at least one term in any of these three specific categories, I do a manual reading of those tweets to remove all tweets not expressing the topic intended (false positives). I am left with a sample of 458 tweets.[15] In particular, there are 218 tweets about trade, 247 tweets about macroeconomics outlook, and

[13] The website from which I obtain the data also provides a list of some topics frequently tweeted by the 45th President of the U.S., such as personal superlatives (e.g., 'My I.Q. is one of the highest - and you all know it!"), global warming (e.g., " Global warming is a HOAX"), and media disdain (e.g., "CNN Politics just plain dumb").

[14] Conventional textual analysis algorithms like LDA or LSA are difficult to use in this setting as their algorithms are not well suited to defining topics with short messages.

[15] Retweets are excluded from the sample

6 tweets about exchange rates. A sample of tweets can be found in Table B in the Appendix.

3.4.1.2 Bi-term topic modelling (BTM) approach

BTM is a topic modelling approach developed by Yan et al. (2013) to address shortcomings associated with conventional topic modelling approaches such as LDA and LSI when it comes to discovering content of short texts. To the best of my knowledge, I am the first to employ this method of textual analysis in the finance literature.

Two sets of input are required from BTM approach. The first is the collection of words, which is the corpus. I apply BTM approach on my full sample of tweets after these tweets are properly cleaned with standard text-cleaning procedures, such as lower capitalization, removing numbers and English stop words. The second input required is the number of topics, which I set as 9.[16]

Two sets of output are generated from BTM algorithm. The first set of output includes the list of top keywords in each topic and the respective probabilities of observing each word in the topic. For each topic n, there is a set of vectors $\hat{\beta}_n = [\hat{\beta}_{n,1},...,$ $\hat{\beta}_{n,J}]$', in which $\hat{\beta}_{n,j}$ is the probability that the word j belongs to topic n. A full list of top keywords for all 9 topics can be found in Figure B.1 in the Appendix. I summarise the keywords for the two topics I identify as having relevant information content in Figure 3.2a and 3.2b. I classify the keywords in Figure 3.2a as the trade topic, with keywords such as trade, tariff, china, dollar, deal. Similarly, the keywords in Figure 3.2b refer to the macroeconomic topic. This contains keywords such as job, tax, number, economy, market. These are the 2 out of 9 topics of my interest as they are directly relevant for the FX markets.

Now that I have identified the keywords in each topic, I use a second set of output that measures the proportion of topics for each tweet. Formally, I define a set of vectors for each tweet $\hat{\gamma}_t = [\hat{\gamma}_{t,1}, \hat{\gamma}_{t,2}, \hat{\gamma}_{t,3},..., \hat{\gamma}_{t,n}]$', in which $\hat{\gamma}_{t,n}$ measures the proportion of tweet t that is made up of topic n. My condition for a tweet with macroeconomic or trade content is a probability associated with Trade or Macroeconomics topics being at least 30%.[17] I then also check all these Tweets to manually to remove false positives, leaving me with a filtered set of 181 Trade and 242 Macroeconomics tweets.

[16]The choice of the optimal number of topics depends on key tradeoffs between interpretation and goodness of fit (Chang et al., 2009; Hansen et al., 2018). For example, in applying probabilistic topic modelling, a lower number of topics increases the interpretation of the topics, whereas a larger number of topics leads to better goodness-of-fit of the model. My choice of 9 topics is the maximum number of topics which still offers an intuitive interpretation of trade and macroeconomic content.

[17]Reducing the threshold to 20% results in many false positives.

3.4.1.3 Combined Tweets identified by dictionary approach and BTM approach

I combine all tweets identified by dictionary approach and BTM approach as carrying relevant information for the FX markets. There are occasions when multiple relevant tweets are posted at the same hour. This leaves me with 506 hours with relevant tweets in total. I merge the tweets data at an hourly frequency with FX order flow and indicative quotes data. I summarise the distribution of these tweets across day of the week, and hour of the day based on London time is shown in Panel A and Panel B of Figure 3.3. In Panel C and Panel D of the same figure, I report these patterns for all tweets posted during the sample period.

It can be seen that tweets are distributed relatively equally across all days of the week. It means that a number of tweets are posted during the weekend when the FX market is relatively illiquid and the availability of trading data is also limited. I follow the literature to handle tweets during the weekend by treating all these tweets as if they are posted during the first hour of the next trading week (10pm on Sunday London Time).[18] In terms of hour of the day, most tweets are posted at late afternoon and early morning London Time, which corresponds with morning and evening time based on EST time.

3.4.2 FX Trading Volume Data

I use the CLS FX volume dataset provided by Quandl. CLS Group handles over 50% of global FX transaction volume (spot, swap, and forward), for up to 16 bilateral currency pairs. [19] The advantage of CLS data is spot FX volume aggregated and delivered at a hourly frequency, in contrast to the BIS Survey. The data records volume of transactions for four groups of market participants, banks, funds, non-bank financial institutions, and corporations. Market makers are typically banks, and price takers in the market are divided into three categories, including funds, non-bank financials, and corporates. This gives me four groupings for measuring trading volume: transactions between the bank and funds, bank and non-bank financials, bank and corporates, and bank-bank transactions. Transactions between two market makers (inter-dealer transactions) or two price takers are excluded from this dataset.

As my time period of interest is from when Donald Trump started his presidential campaign on 16th June 2015, this dataset provides me with hourly data of over 4 years. Data is recorded for 5 days a week, with each trading week beginning from 9pm

[18] I also implement the second approach by removing all tweets during the weekend from the sample. Results are mostly similar and are available upon request.

[19] The currencies included covers bilateral exchange rates of the U.S. with respect to Australia, Canada, Euro Area, Japan, New Zealand, Norway, Sweden, Switzerland, United Kingdom, Hong Kong, Hungary, South Africa, Iceland, Singapore, Mexico and Korea. Denmark's currency is excluded from my sample as it is pegged to the Euro

on Sunday and ending at 9pm on Friday (London Time). It therefore covers market transactions between the time when Sydney market opens on Monday morning and New York market closes on Friday evening. The pattern of average hourly spot FX trading volume based on London time is shown in Figure 3.4.

In early morning London time, when only Asian markets are open, trading volume is relatively low. It starts to go up at around 7am as European markets begin their trading day. Trading volume slightly decreases around lunchtime, but it quickly bounces back and reaches its peak of the day at around 1pm. This is when both European and the U.S. markets are active. The trading volume declines gradually after 5pm and reaches its lowest level around 10pm, when only Australian market is open.

FX trading volume for the different groups of market participants are catergorized by different groups is plotted in Figure 3.5. Most of the trading in the spot FX market included in this dataset (around 85%) occurs in inter-bank transactions between a market maker and price taker bank. In contrast, trading between bank and corporates makes up only around 1% of the total volume.

I follow the literature (e.g., Krohn and Sushko 2017) to remove data on some holidays when the FX trading volume is relatively thin. Those holidays include Christmas (24th - 26th December), New Years (31st December - 2nd January), July 4th, Good Friday, Easter Monday, Memorial Day, Labour Day, and Thanksgiving and the day after.

3.4.3 Intraday FX Volatility and Bid Ask Spread

I obtain tick-by-tick high frequency data for spot indicative quotes from Thomson Reuters Tick History. My sample is from 16th June 2015 to 20th August 2019. This dataset contains indicative quotes sampled at milli-second frequency.

Hourly Volatility: I follow Mueller et al. (2017) to construct intraday realised volatility. Specifically, I compute spot exchange rate changes sampled at five-minute intervals based on mid price of the quote. Hourly realised variance is the sum of squared changes, and hourly volatility is the square root of realised hourly variance.

Hourly Bid Ask Spread: I first obtain the last quote of each hour and then construct the bid-ask spread indicator as the difference between the ask and the bid prices divided by the midpoint.

Hourly Returns: All currencies are quoted against the USD, meaning an increase in s implies an appreciation of the USD. I calculate the exchange rate return as the log difference in the exchange rate over an hour:

$$\Delta s_{t+1} = s_{t+1} - s_t \tag{3.26}$$

where s_t is the log midpoint of the last quote at hour t.

3.5 Empirical analysis

In this section, I discover the effects of tweets on several characteristics of FX market, including trading volume, volatility, bid ask spreads, and returns.

3.5.1 Panel regressions

I pool all observations from 16 currency pairs and run fixed-effects panel regressions with hourly data. My fixed-effects panel regression specification is in equation 3.27.

$$x_{i,t} = \alpha_i + \beta_1 Tweet_t + \beta_2 X_t + \mu_d + \sigma_h + \epsilon_{i,t} \tag{3.27}$$

The outcome variable $x_{i,t}$ is either the trading volume, realised volatility, bid ask spreads, or returns for currency pair i at time t. $Tweet_t$ is the dummy variable equal 1 if there is a tweet about macroeconomics outlook, trade, or FX posted by Donald Trump at that hour and 0 otherwise, X_t is a set of control variables (i.e., Presidency dummy, FOMC dummy, VIX, TED spread, and EPU). Specifically, Presidency dummy is a variable equal 1 if date is after 8th November 2016, which is the day when Donald Trump won the election and got elected as the U.S. President. FOMC dummy is equal 1 if during that hour FOMC announcements are announced, and 0 otherwise. VIX is the CBOE Volatility Index, and TED spread is the spread between 3-month LIBOR and 3-month T-Bill. EPU is the Economic Policy Uncertainty from Baker et al. (2016) μ_d and σ_h are time fixed effects that control for the day of week and hour-of-day respectively. Standard errors are clustered at the level of the currency pair.

3.5.2 Trump tweets and FX Trading Volume

I start by testing the first prediction of the model which suggests a link between FX trading volume and Trump tweets with relevant content. To control for persistence in FX volume, I follow Cespa et al. (2020) in constructing a measure of abnormal FX trading volume. I construct my abnormal volume measure for currency pair i at time t is the log deviation from the moving average of FX trading volume at the same hour over the last 21 trading days. Regression results for the panel specification with FX spot trading volume are reported in Table 3.2.

The regression results shown in the first column suggest a negatively significant link between the presence of a Tweet and spot FX trading volume during that hour. The coefficient of Tweet hour dummy is -0.647, with a t-statistic of -4.12. This negative coefficient for Tweet hour dummy implies that during an hour when there is a Trump Tweet relevant for the foreign exchange market, there is a decrease in abnormal spot FX trading volume of approximately 0.64 per cent. To capture a time trend since Trump's presidency, the second column controls for presidency dummy and it still gives me a negatively significant Tweet hour dummy's coefficient. The presidency dummy in this regression is significant, meaning that since Donald Trump won his presidency on 8th November 2016, spot FX trading volume increases. In the third column, I add FOMC dummy into the regression, and Tweets hour dummy remains strongly significant. The FOMC dummy is positive and significant with a t-statistic of 2.62. This implies that the release of FOMC announcement is associated with an increase in abnormal spot FX trading volume during that hour. This result is consistent with evidence that FX volume increases following FOMC announcements (Fischer and Ranaldo, 2011). In the fourth column, I add VIX as an additional control, and the coefficient of Tweets hour dummy becomes even stronger, with a t-statistic of -4.16. The coefficient of VIX in this regression is positively significant, with a t-statistic of 3.65. This finding implies that during a time of higher uncertainty, spot FX trading volume spikes up. In the fifth column, I incorporate TED spread into the specification. In the last column, I add the Economic Policy Uncertainty (EPU) from Baker et al. (2016). When all control variables are included in the regression simultaneously, the coefficient of my variable of interest, which is Tweet hour dummy, remains its negative sign and strongly significant with a t-statistic of -4.26. Overall, results from this table suggest that during hour when there is a Trump Tweet containing relevant information for the foreign exchange market, spot FX trading volume decreases.

I now examine if there is variation in the effects on FX volume across the four groups of market participants of banks, funds, non-financial and corporate firms. Regression results for FX volume of each group are reported in Table 3.3.

In Panel A of the table, I examine the impact of tweets on trading activity between of inter-bank transactions, where one bank is a market maker and the other is a price taker. The coefficient of the Tweet dummy is negative and strongly significant in all specifications. Similar patterns are also observed in the next two panels, where I show the results for trading volume between banks and funds and banks and non-bank financial firms, where the bank acts as the market maker (Panel C). In both panels, when the full set of control variables enters the regression, the coefficient of Twitter dummy remains negative and significant at a 1% level of significance. In panel D, I look at the trading activity between market maker bank and the corporate sector (e.g., multinational firms). The coefficient of Tweet dummy is positive and slightly significant at the first column. However, in the next four columns, this coefficient loses its statistical significance. Therefore I do not find empirical evidence showing clear effects of Tweets on trading volume between the bank and corporate sector. Overall, empirical results from Table 3.2 and Table 3.3 suggest that Donald Trump's Tweets decrease overall trading volume in the spot FX market in line with the first prediction of the model. When I break down the trading volume by different market participants, this result holds for three groups of informed market participants. In contrast, I do not find evidence for this effect for uninformed group of market participants, i.e., corporate sector.[20]

3.5.3 Trump Tweets and FX Volatility

I now test the second prediction of the model, which states that volatility declines for informative Trump tweets.[21] I address the persistence of volatility by using innovations to realised intra-day volatility as the relevant outcome variable. The regression results are reported in Table 3.4. In the first column, when day of the week and hour of the day dummies are the only control variables in the regression, the coefficient of Tweet dummy is negative and strongly significant with a *t*-statistic of -5.07. It implies that Tweets reduce FX realised volatility. When more variables are controlled for in the next columns, the magnitude of Tweet dummy's coefficient slightly decreases, however, it remains its statistical significance. In the last column, when the full set of control variables is included in the regression, the coefficient of our interest is negative with a a

[20]The corporate sector is typically characterized as liquidity traders, using the spot market for hedging purposes rather than speculative activity (Ranaldo and Somogyi, 2019).

[21]In the context of the model, I classify an informative Trump tweet as having a higher precision than private information.

t-statistic of -2.94. These empirical findings provide strong evidence suggesting that tweets reduce the realised volatility in the FX market.

3.5.3.1 Trump Tweets and FX Bid-Ask Spreads

The reduction in volatility is consistent with a reduction in asymmetric information, and this should also have an impact on market makers ability to quote smaller bid-ask spreads. [22] To investigate the effects of tweets on bid-ask spreads, following Krohn and Sushko (2017), I measure bid-ask spreads using price quotes by big banks based on the 2016 G-SIB Classification as these banks provide quotes across most pairs of currency in my sample. Results showing the link between Tweets and bid-ask spreads are reported in Table 3.5. In the first column, the coefficient of Tweet dummy is negative with a *t*-statistic of -3.11, and the relationship is robust to adding controls. The reduction in bid-ask spreads during Trump Tweet hours, suggesting a reduction in information asymmetry due to trading on the common public signal.[23]

3.5.4 Trump Tweets and FX Spot Returns

Testing the third prediction of the model, I examine the impact of Trump tweets on FX spot returns. Theoretically, spot returns arise due to a bias between the expectations of public and private information. If Trump tweets are more optimistic about the U.S. economy, or more protectionist about trade relations than speculators, there is a bias in the expectation of future macroeconomic fundamentals. Regression results are reported in Table 3.6.

The positive coefficient of Tweet dummy in the first column suggests Trump tweets lead to an appreciation of the U.S. dollar. My estimates suggest that the USD appreciates by an average of 0.5 percent during Trump tweet hours against a basket of currencies.[24] The results are robust to adding additional controls, such as the Presidency, FOMC meetings, and the VIX. These results support the model prediction that FX returns reflect Trump's optimistic view on the U.S. economy. Although the presidency dummy variable is not significant in this table, results from the interaction variable between presidency dummy and tweet hour dummy in Table 3.10 imply that the effects of tweets on spot returns are stronger post presidency.

[22]While I do not explicitly model bid-ask spreads, adoption of the public signal by speculators reduces the information advantage of informed trading. A market maker needs to be compensated less for taking the other side of informed trades, leading to lower bid-ask spreads.

[23]While bid-ask spreads can also reflect changes in liquidity, I attribute the decline in bid-ask spreads due to a decline in information asymmetry due to the decline in trading during these periods. If bid-ask spreads declined due to increased liquidity, I may expect an increase in trading volume during Tweet hours.

[24]I am using a notation of units of foreign currency per USD. Therefore a positive coefficient indicates an appreciation of the USD with respect to the foreign currency.

3.5.4.1 Macro versus Trade Tweets

I now test if the appreciation of the USD is specific to tweets about trade or macroeconomic content. Effects of presidential tweets on spot returns have been found in Benton and Philips (2018), which shows that trade relations between Mexico and the U.S. lead to an appreciation of the USD/Peso. I report results for the subset of trade and macro tweets in Table 3.7. In another study that uses textual analysis of Presidential tweets on the China-US trade dispute, Ferrari et al. (2021) find that trade tensions between China and the U.S lead to an appreciation of emerging markets.

In Panels A and B, I show results for regressions with trade and macro tweets respectively. In all specifications, the coefficient of the trade tweet is positive, implying that hours with trade tweets are linked with appreciation of the USD. However, this effect is rather weak as the statistical power is just 10%. In Panel B, I replace trade tweets with macro tweets in the regressions. The coefficient of Macro tweet is positive and strongly significant in all specifications. With the full set of control variables in the last column, the coefficient of Macro tweet is 0.005 (0.5 per cent) with a *t*-statistic of 4.08. This is similar to the unconditional effect of Trump tweets on spot returns, suggesting that the appreciation of the USD against the panel of currencies is driven more by tweets with macro content. This confirms the model prediction that spot returns are related to the bias in Trump's expectation of future macroeconomic fundamentals.

3.5.4.2 Sentiment analysis of Trump tweets

I can also consider measuring the direction of tweets based on a sentiment analysis. For example, the bias between Trump tweets and private information are conditional on whether Trump's tweets are optimistic or pessimistic regarding the future growth of the U.S. economy. To measure the direction of sentiment, I classify tweets into positive and negative tone based on the dictionary developed by Liu and Hu (2004). Regressions showing the link between positive and negative tweets and currency returns are reported in Table 3.8.

In Panel A, I run regressions with independent variable of interest being positive tweet. The coefficient of positive tweet is positive and strongly significant in all regressions. In the last column with the full set of control variable, the coefficient of positive tweet is 0.005 with a *t*-statistic of 5.18. This result implies that relevant Trump tweets with positive sentiment are associated with USD's appreciation. In Panel B, I examine tweets with negative sentiment, and in line with my hypothesis, the coefficient on the tweet dummy is negative and strongly significant. In the last column, the coefficient of this variable is -0.007 with *t*-statistic of -4.85. The analysis suggests that the sentiment of tweets matters for currency returns. Positive tweets are linked with USD's appreciation, whereas negative tweets are linked with USD's depreciation. This is consistent with my model prediction on the bias between Trump expectations and private information. Examining the distribution of sentiment, I find two thirds of the sample are classified as positive sentiment, which explains why the unconditional effects of Trump tweets are to cause a USD appreciation in the hour of the tweet.

3.5.4.3 Intra-hour impacts of Tweets on currency returns

The results so far are based on hourly spot returns. I now investigate the impact of Trump tweets on spot returns within the hours. In particular, I implement an event study at the minute level and show the cumulative returns for the average returns of 16 currency pairs (Panel A) and the USD ETF (Panel B) in Figure 3.7, following a similar methodology of investigating minute-level ETF returns on the stock market in Abdi et al. (2021). Consistent with my panel specification, I find a cumulative USD appreciation for both the average returns of 16 currency pairs and the USD ETF, the post-event cumulative returns (up to 2 hours after a tweet is posted) are both statistically significant, whereas the corresponding figures in the pre-event period are not statistically significant. This result suggests that Trump's tweets do not just temporarily distort prices due to behavioural biases but carry additional information. This is consitent with our assumption of unbiasedness in our theoretical model.

3.5.4.4 Trading Strategy: Event Study

To test if the impact of Trump tweets on spot returns persist over the trading day, I implement the following trading strategy based on tweet hours. Currencies are sorted into terciles based on its spot changes during the tweet hours, with portfolio 3 containing currencies with the highest positive spot changes during tweet hours and portfolio 1 containing currencies with the most negative spot changes during tweet hours. Figure 3.8 shows the average returns of the high minus low (HML) portfolio of going long in Portfolio 1 and going short in Portfolio 3 around the hour of Trump tweets.

A striking feature observed from Figure 3.8 is that the average returns of the HML portfolio decreases significantly during the tweet hours, but it immediately bounces back the hour after the tweet occurs. The results suggest that returns from the tradable strategy are short-lived and corrected in the hour following the Trump tweet.[25]

[25]While the effect of Trump tweets on FX spot returns is short-lived from the perspective of long-term investors, one can argue that one hour is a relatively long window for a market populated by algorithmic traders (e.g., Chaboud et al. (2014)).

3.5.5 Robustness Exercises

3.5.5.1 Trump Tweets and Macro Announcements

A potential concern with my estimation is an omitted variable bias due to Trump tweets coinciding with macroeconomic releases. An alternative view posits that Trump tweets are echoing macroeconomic news released that day. For example, shortly after a macroeconomic release on job openings, Trump tweets "*Incredible number just out, 7,036,000 job openings. Astonishing - it's all working! Stock Market up big on tremendous potential of USA. Also, Strong Profits. We are Number One in World, by far!*". If Trump tweets are responding to macroeconomic news, then the effects we find may be attributed to agents updating their signals based on macroeconomic releases instead of the Trump tweet.[26]

I control for the omitted variable by including dummies for macroeconomic releases on output, employment and trading activity. In particular, I add an additional control that is a dummy variable which is equal to 1 if there is at least one macro announcement on that day and 0 otherwise. The list of macro releases are based on Gürkaynak et al. (2005). These include capacity utilization, Consumer confidence, inflation, employment costs, GDP, initial claims, leading indicators, new home sales, non-farm payrolls, PPI, retail sales, and the unemployment rate. To address the concern that the coefficient estimates on the tweet hour dummy would capture the effect of Trump tweets independent of macro announcements, I control for macro announcements in the regressions. Results of baseline regressions with this new dummy variable are shown in Table 3.9. The coefficient on the tweet hour dummy is robust to including a variable that captures macroeconomic releases, with significant declines in volatility and FX volume, a decline in bid-ask spreads and an appreciation in spot returns.

3.5.5.2 Trump tweets during his presidency

As my sample covers all tweets since Trump announced his presidential campaign, I further analyse the effects of those tweets that are posted during his presidency. In order to do so, I include an interaction variable between Tweet hour dummy and Presidency dummy (*Tweet*Presidency*) in all baseline regressions. Results are reported in Table 3.10. The effects of informative tweets during Trump presidency on FX market outcomes would be the summation of three coefficients: Tweet hour, Presidency dummy, and Presidency*Tweet. Overall, results from regressions suggest that those tweets during

[26] While tweets with macroeconomic content can follow a macroeconomic release, there is research that shows that Trump tweets on macroeconomic issues as a diversion to political coverage on the Mueller report and other political news during the presidency (Lewandowsky et al., 2020). Tweeting on macroeconomic topics as a diversion is more consistent with our story of the timing of Trump signals being plausibly exogenous.

his presidency have similar effects on the FX market as found in previous sections of the paper. In other words, informative Trump tweets during his presidency also reduce FX trading volume, volatility, bid-ask spreads, and are associated with U.S. Dollar appreciation. The effect of tweets during his presidency is found strongest for the returns.

3.5.5.3 Placebo Test: Uninformative tweets and the FX market

My analysis has used a set of tweets on the macroeconomic outlook and trade, which I perceive as tweets that have relevant information content for exchange rates. I hypothesize that a set of uninformative tweets should not have any information relevant for FX trading. To select a placebo group, I define a set of uninformative tweets as a complementary set that satisfies two criteria. First, these tweets have the lowest probability of belonging to the trade and macroeconomics topics based on the BTM method.[27] Second, I choose a number of uninformative tweets to match the number of informative tweets. I then replicate the panel regressions with the independent variable being the uninformative tweet hour dummy. Results are reported in Table 3.11.

In the first column of this table, I can see that uninformative tweets hour is negatively linked with FX trading volume. Although the coefficient of uninformative tweet hour dummy is statistically significant, the magnitude of this coefficient is -0.562, which is an order of magnitude smaller than the coefficient of the informative tweet hour dummy shown in Table 3.2. The marginal negative effect of FX volume can be due to two reasons. First, errors in classifying tweets as informative or uninformative through the BTM algorithm can create false negatives. Second, the model framework suggests that if the set of irrational agents, "Trump followers", adopt uninformative tweets for FX trading, the model predicts a decline in FX volume. In the next three columns, the estimates of uninformative tweets on volatility, bid-ask spread, and returns are statistically insignificant, suggesting that there is no evidence of uninformative tweets affecting FX volatility, the bid-ask spread, and returns. The results are broadly consistent with my hypothesis that only tweets that have relevant information for FX trading will impact trading, volatility and spot returns. This highlights the importance of implementing textual analysis to filter the informative tweets carrying relevant information for the FX market. My results are consistent with related work in Abdi et al. (2021) on the effects of Trump tweets on the stock market. The authors find evidence that Trump tweets are responding to information earlier in the day. They do however find evidence of information effects for Trump tweets on the NAFTA trade agreement

[27] Formally, the BTM method gives me a set of weights that measures the proportion of topics for each tweet. For example, for each tweet, the following vector $\hat{\gamma}_{t,n}$ measures the proportion of tweet t that is made up of topic n. Based on the weight vector, I select tweets with the lowest weights for topics with macroeconomic or trade content.

and the US China trade war, which is consistent with my hypothesis that Trump tweets with macroeconomic and trade content are more informative.

3.5.6 Tweets and Disagreement in the FX market

I have shown a decline in volume, volatility and a bias in spot returns. The channel I put forward in the model is that the Trump tweet acts as a common public signal which reduces the dispersion of speculator expectations of the future spot rate. Therefore, I expect a decline in investor disagreement following the Trump tweet. In order to test this channel I construct a proxy for investors' disagreement using FX options. Following Salomé 2020, I use the moneyness ratio of option prices as a proxy for investor disagreement in the options market. I focus on put options for EUR/USD currency pair.[28] The moneyness of an option is provided in equation 3.28, which is defined as follows:

$$Moneyness = \frac{\ln(\frac{K}{S})}{\sigma\sqrt{\tau}} \tag{3.28}$$

In the above equation, the numerator expresses the ratio of strike price (K) to underlying price (S). The denominator is the multiplication of yearly volatility of an option (σ) and time to expiration in years (τ). Therefore, the absolute value of moneyness can be considered as a proxy for disagreement as it captures the dispersion between the strike price and the current spot price, after adjusting for the time to expiry and implied volatility of the EUR/USD returns. I examine the link between Tweets and disagreement among investors by running the following time-series regressions:

$$x_{i,t} = \alpha_i + \beta_1 Tweet_t + \beta_2 X_t + \mu_d + \sigma_h + \epsilon_{i,t} \tag{3.29}$$

in which x_t is the absolute value of moneyness for EUR/USD currency pair put options. I use a similar set of controls X_t to the panel specification in equation 3.27. Regression results are shown in Table 3.12.

In the first column, the coefficient of Tweet hour dummy is negative and statistically significant with a *t*-statistic of -2.41. The negative relationship between Trump tweet hours and the absolute value of moneyness suggests disagreement among investors decreases during hours of Trump tweets. In the next three columns, when I add more control variables, the statistical power of Tweet hour dummy remains mostly unchanged. In the last column with full set of control variables, the coefficient of our variable of interest is still significantly negative with a *t*-statistic of -1.98. These empirical findings

[28] I clean the data by removing trades with bid price being larger than ask price, and those with ask price and ask size being zero.

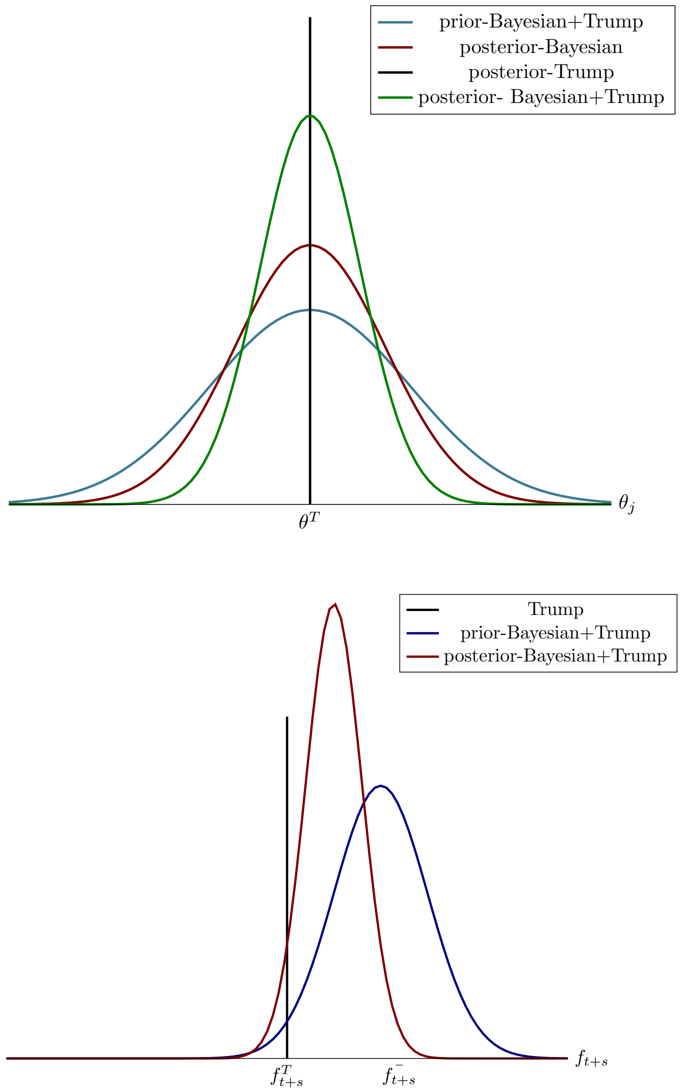
suggest that the potential channel through which Trump tweets reduce volume and volatility in the market is through a reduction in investor disagreement.

3.6 Conclusion

In this paper, I combine two approaches of textual analysis, the dictionary approach and bi-term topic modelling approach, to identify the information content of tweets posted by Donald Trump. I hypothesize that Trump tweets about the macroeconomics outlook, trade policy, and FX policy are relevant for trading in the foreign exchange market. Through a model, I show that Trump tweets act as a common public signal in a market of heterogeneous private information. A common public signal with sufficient information content reduces investor disagreement on expectations of the future spot rate, and a decline in trading volume and intra-day volatility. In a framework where the spot exchange rate conveys information on future macroeconomic fundamentals, differences between Trump's expectations of future macroeconomic fundamentals and speculators can induce a bias in currency returns.

I test my model predictions using a rich dataset of Trump tweets, FX volume and price data for up to 16 bilateral pairs with respect to the USD. Supporting the model, I find empirical evidence that these tweets have an impact on FX trading activity. I find a statistically significant decline in the volume of trading during Trump tweets with macro and trade content, both in the aggregate and for specific market participants (banks, funds and non-financial firms). I find a decline in exchange rate volatility, and a decline in asymmetric information in the FX market as dealers quote narrower bid-ask spreads during tweet hours. Turning to spot returns, I find Trump tweets on average lead to an appreciation of the USD reflecting the generally optimistic views of Trump on the U.S. economy. Finally, using the options market to construct a proxy for investor disagreement, I find evidence that the decline in trading volume and volatility is associated with a decline in investor disagreement in the currency market.

Figure 3.1: Top: Prior and Posterior Distributions following Trump Tweet, Bottom: Bias between Trump and other agents on expectations of future fundamentals



Top: The figure shows the prior and posterior distributions of agent expectations of the future spot rate. Bayesian agents update their prior to give a positive weight to the Trump tweet, which is centered at θ^T. Trump followers adopt the public signal completely, causing a reduction in the dispersion of investor expectations. Bottom: Trump expectations of future fundamentals differ from agent expectations. Bayesian agents update their signal, causing spot returns to change that is proportional to the bias.

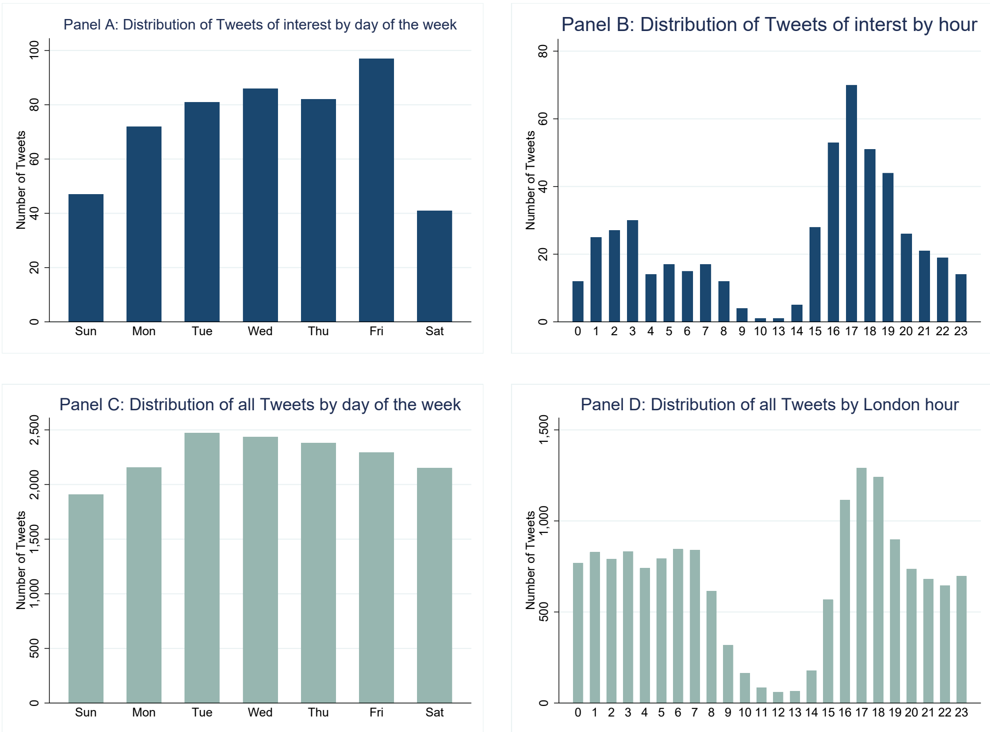
Figure 3.2: Trade and macroeconomics Topics from BTM

(a) Trade Topic

(b) Macroeconomics Topic

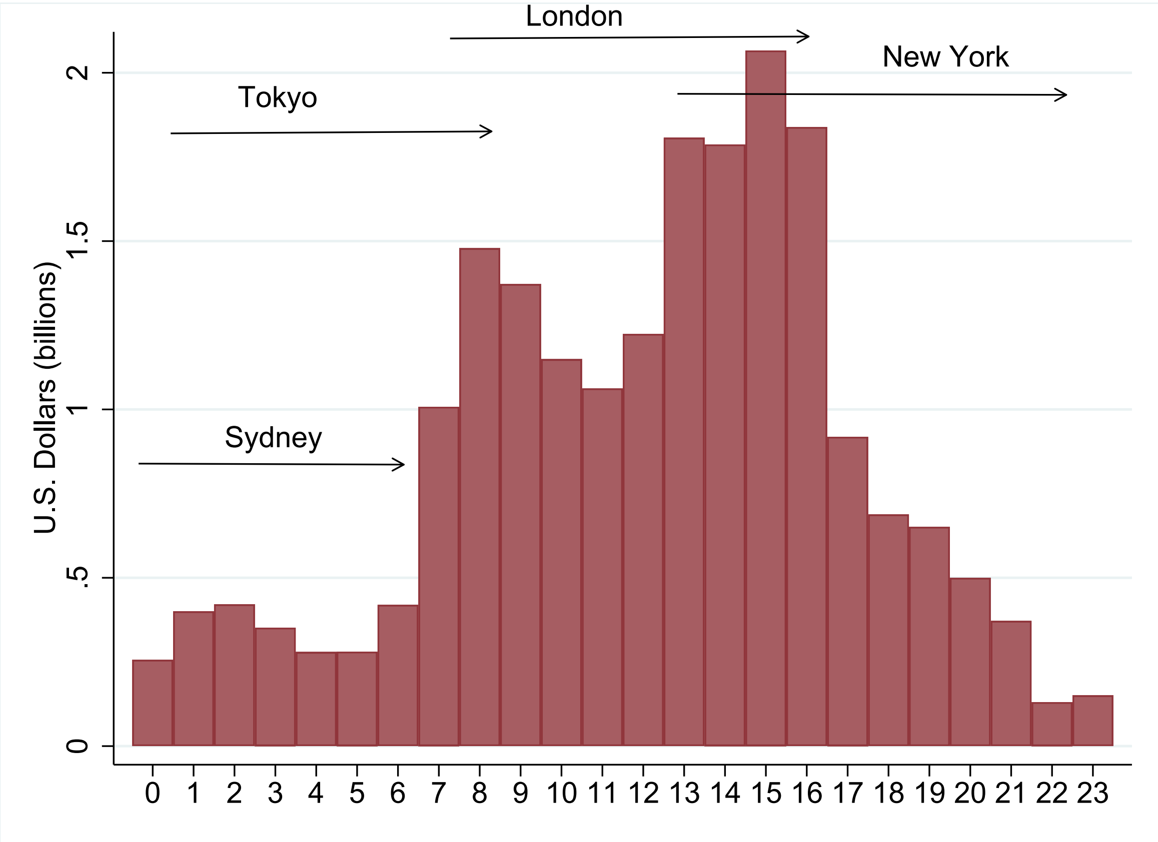
The figure shows the top keywords for Trade topic (a) and Macroeconomics topioc (b) based on results from BTM algorithm. The data are between 16th June 2015 and 20th August 2019.

Figure 3.3: Time distribution of Tweets



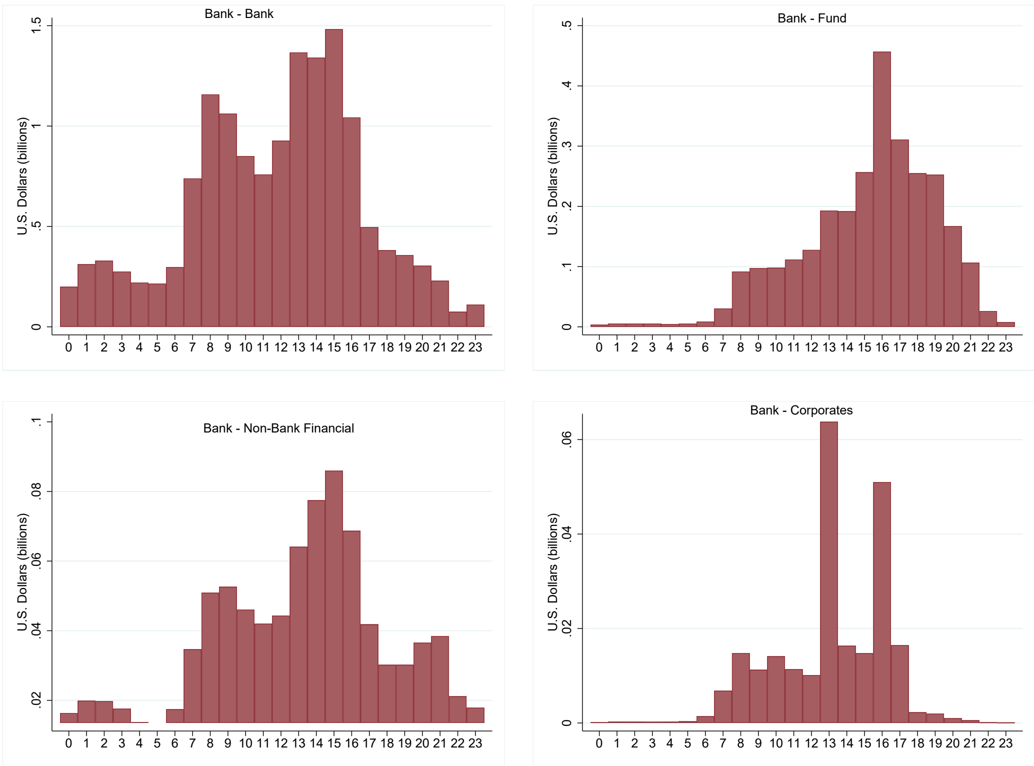
The figure shows time distribution of Tweets belonging to Macroeconomics, Trade Policy, and Exchange Rate categories in Panel A and Panel B. Time distribution of all Tweets is shown in Panel C and Panel D. The number shown on the x-axis is the closing time based on London time. The data are between 16th June 2015 and 20th August 2019.

Figure 3.4: Spot FX Trading Volume



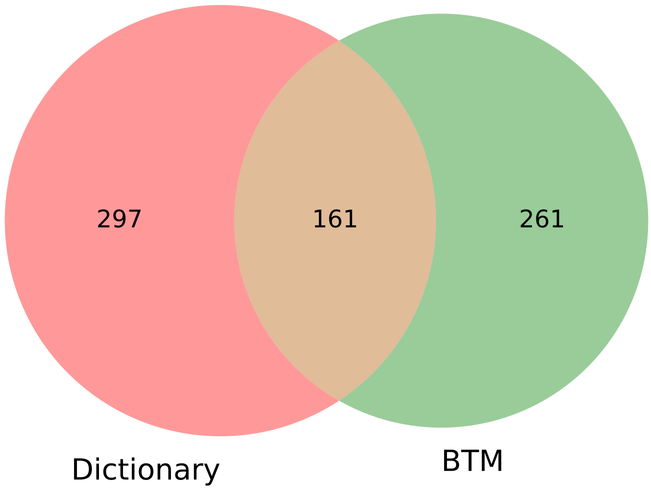
The figure reports the average hourly FX spot volume (in USDs) throughout a business trading day (London Time). The average is constructed across all trading days in our sample, from 16th June 2015 to 20th August 2019. Volume is the sum of 16 pairs of currency included in our sample. The number shown on the x-axis is the closing time based on London time. Arrows show market trading hours in London (from 7am to 4pm), New York (from 12pm to 9pm), Sydney (from 9pm to 6am) and Tokyo (from 11pm to 8am).

Figure 3.5: Spot FX Trading Volume by participants



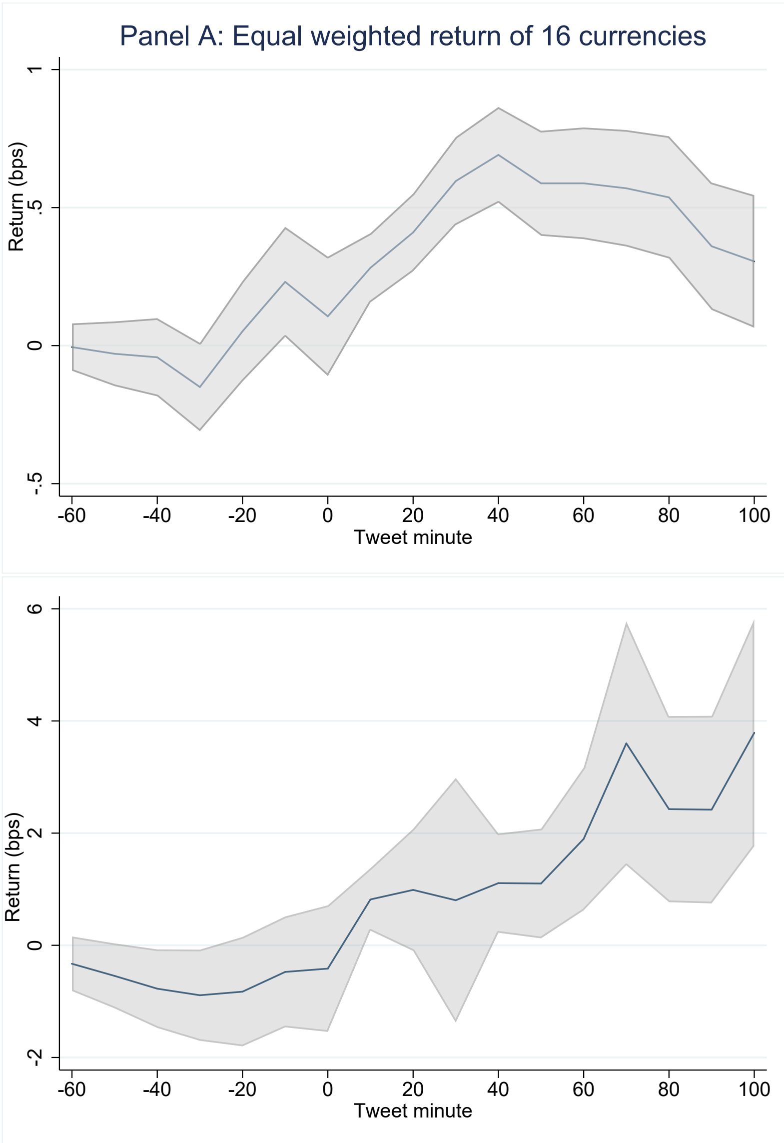
The figure reports the average hourly FX spot volume (in USDs) throughout a business trading day (London Time) by different groups of market participant. The average is constructed across all trading days in our sample, from 16th June 2015 to 20th August 2019. Volume is the sum of 16 pairs of currency included in our sample. The number shown on the x-axis is the closing time based on London time.

Figure 3.6: Tweets identified by Dictionary approach and BTM approach



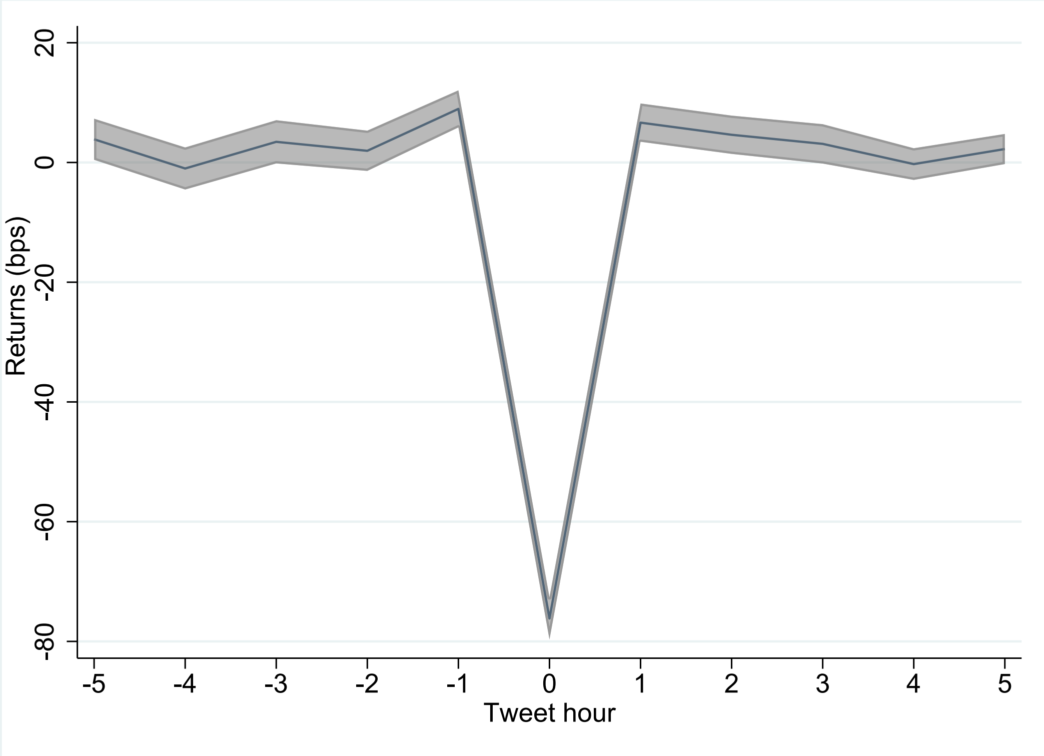
The figure reports the number of relevant Tweets (trade, macro, and FX tweets) identified by dictionary and bi-term topic modelling (BTM) approach.

Figure 3.7: Event study of spot returns during the Tweet hour



This graph shows the average cumulative spot returns in bps during the tweet hours for the equal weighted return of 16 currencies (Panel A) and the USD ETF (Panel B). The shaded area shows 95% confidence interval. The y-axis shows the minutes during the event, with 0 being the minute in which a tweet is posted. The negative values in the y-axis are the number of minutes before tweets.

Figure 3.8: Event study of spot returns around the Tweet hours



This graph shows the average spot returns in bps around the tweet hours for HML portfolio going long currencies in Portfolio 1 and going short currencies in Portfolio 3. I carry out this strategy for all tweets with relevant content (trade and macro tweets). The shaded area shows 90% confidence interval. Currencies are sorted based on the magnitude of its spot returns during tweet hours, with Portfolio 3 containing currencies with highest spot returns. The y-axis shows the hours during the event, with 0 being the end of the hour in which a tweet is posted. The negative values in the y-axis are the number of hours before tweets.

Table 3.1: Category Specific Dictionary

This table reports the terms used to identify Tweets related to Macroeconomics Outlook, Exchange Rate, and Trade Policy. These term sets are based on Baker et al. (2019)

Dictionary	
Category	Words
Macroeconomics Outlook	gold, silver, gdp, economic growth, depression, recession, economic crisis, macroeconomic indicators, macroeconomic news, rail loadings, railroad loadings, cpi, inflation, consumer prices, ppi, producer prices, housing prices, home prices, homebuilding, homebuilders, housing starts, home sales, building permits, residential sales, mortgages, residential construction, commercial construction, commercial real estate, real estate, labor force, workforce, unemployment, employment, unemployment, insurance, ui claims, jobs report, jobless claims, payroll, underemployment, quits, hires, weekly hours, wages, labor income, labor earnings, corporate bonds, bank loans, interest rates, trade news, trade surplus, trade deficit, national exports, national imports, business investment business inventories, consumer spending, retail sales, consumer purchases, consumer confidence, consumer sentiment, macro outlook, business sentiment, business confidence, industrial production, ism report, manufacturing index, household credit, household savings, household debt, household borrowing, consumer credit
Exchange Rate	exchange rate, currency crisis, currency devaluation, currency depreciation currency revaluation, currency appreciation, crawling peg, managed float, currency manipulation currency intervention
Trade Policy	trade policy, tariff, import duty, import barrier, import restriction, trade quota, dumping, export tax, export duty, trade treaty, trade agreement, trade act, wto world trade organization, Doha round, Uruguay round, gatt, export restriction, investment restriction, Nafta, North American Free Trade Agreement, Trans-Pacific partnership, TransPacific Partnership, Federal Maritime Commission, International Trade Commission, Jones Act, trade adjustment assistance

Table 3.2: Tweets and Spot FX Trading Volume (Total Sell Side - Total Buy Side)

This table reports panel regressions results for the estimation of Tweets hour dummy on FX Trading Volume. The control variables are presidency dummy, FOMC dummy, VIX, TED Spread, and Economic Policy Uncertainty (EPU) from Baker et al. (2016). Hour-of-the-day and day-of-the-week dummies are included in all regressions. Standard errors are clustered by currency. t-statistics are reported in squared brackets, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. The data are hourly between 16th June 2015 and 20th August 2019.

Dependent variable: Trading Volume between Sell Side and Buy Side						
	(1)	(2)	(3)	(4)	(5)	(6)
Tweet hour	-0.647***	-0.710***	-0.711***	-0.712***	-0.715***	-0.701***
	[-4.12]	[-4.10]	[-4.10]	[-4.16]	[-4.25]	[-4.26]
Presidency dummy		0.283***	0.283***	0.343***	0.332***	0.331***
		[3.16]	[3.16]	[3.41]	[3.36]	[3.36]
FOMC dummy			0.231***	0.244***	0.246***	0.248***
			[2.62]	[2.87]	[2.92]	[2.93]
VIX				0.023***	0.021***	0.021***
				[3.65]	[3.54]	[3.55]
TED Spread					-0.327**	-0.326**
					[-2.44]	[-2.43]
EPU						-0.581**
						[-3.95]
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	367,168	367,168	367,168	363,350	357,423	357,410
R^2	3.65%	3.67%	3.67%	3.78%	3.78%	3.80%

Table 3.3: Tweets and FX Trading Volume by groups of market participant

This table reports panel regressions results for the estimation of Tweets hour dummy on FX Trading Volume. The control variables are presidency dummy, FOMC dummy, VIX, TED Spread, and Economic Policy Uncertainty (EPU) from Baker et al. (2016). Hour-of-the-day and day-of-the-week dummies are included in all regressions. In Panel A, dependent variable is trading volume between market maker bank and price taker bank. In Panel B, dependent variable is trading volume between market maker bank and price taker fund. In Panel C, dependent variable is trading volume between market maker bank and price taker non-bank financials. In Panel D, dependent variable is trading volume between market maker bank and price taker corporates. Standard errors are clustered by currency. t-statistics are reported in squared brackets, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. The data are hourly between 16th June 2015 and 20th August 2019.

	Panel A. Dependent variable: Bank - Bank Trading Volume						*Panel B. Dependent variable*: Bank - Fund Volume					
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
Tweet hour	-0.711***	-0.768***	-0.768***	-0.767***	-0.771**	-0.757**	-0.631***	-0.779***	-0.779***	-0.803***	-0.839***	-0.830***
	[-3.70]	[-3.71]	[-3.71]	[-3.73]	[-3.80]	[-3.80]	[-3.71]	[-5.06]	[-5.07]	[-5.48]	[-5.75]	[-5.76]
Presidency dummy		0.247***	0.247***	0.318***	0.309***	0.309***		0.642***	0.642***	0.718**	0.711***	0.710***
		[3.16]	[3.16]	[3.43]	[3.41]	[3.40]		[4.88]	[4.89]	[5.30]	[5.35]	[5.35]
FOMC dummy			0.105**8	0.121**	0.362	0.124**			0.364	0.370	0.368	0.370
			[2.02]	[2.38]	[2.41]	[2.44]			[1.39]	[1.46]	[1.47]	[1.48]
VIX				0.025***	0.024***	0.024***				0.031***	0.030***	0.030***
				[3.50]	[3.41]	[3.42]				[5.69]	[5.75]	[5.77]
TED Spread					-0.302**	-0.301*					-0.040	-0.040
					[-2.06]	[-2.05]					[-0.11]	[-0.11]
EPU						-0.056***						-0.391***
						[-3.82]						[-3.35]
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	310,724	310,724	310,724	307,507	302,395	302,384	291,342	291,342	291,342	288,319	283,640	283,627
R^2	3.91%	3.89%	3.89%	4.00%	4.00%	4.02%	22.63%	22.76%	22.76%	22.97%	23.07%	23.07%
	Panel C. Dependent variable: Bank - Non-Bank Trading Volume						*Panel D. Dependent variable*: Bank - Corporate Volume					
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
Tweet hour	-0.422***	-0.866***	-0.866***	-0.868***	-0.871***	-0.862***	0.342**	0.174	0.174	0.135	0.098	0.098
	[-3.14]	[-6.65]	[-6.66]	[-6.98]	[-7.10]	[-7.14]	[2.09]	[1.38]	[1.38]	[1.09]	[0.79]	[0.79]
Presidency dummy		2.002***	2.002***	2.085***	2.049***	2.048***		0.865***	0.865***	1.032***	0.943*** *	0.943***
		[5.99]	[5.99]	[6.19]	[6.08]	[6.08]		[2.94]	[2.94]	[3.06]	[2.80]	[2.80]
FOMC dummy			0.389	0.405	0.409	0.410			-0.122	-0.0918	-0.073	-0.073
			[1.41]	[1.48]	[1.50]	[1.50]			[-0.14]	[-0.10]	[-0.08]	[-0.08]
VIX				0.034***	0.034***	0.034***				0.069***	0.068***	0.068***
				[5.00]	[4.92]	[4.92]				[3.41]	[3.36]	[3.36]
TED Spread					-0.601**	-0.602**					-1.915**	-1.915**
					[-2.26]	[-2.26]					[-2.59]	[-2.59]
EPU						-0.444***						0.078
						[-4.23]						[0.38]
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	299,828	299,828	299,828	296,758	291,885	291,873	102,917	102,917	102,917	101,901	100,292	100,290
R^2	2.76%	4.97%	4.97%	5.01%	4.98%	4.98%	0.99%	1.15%	1.15%	1.25%	1.30%	1.30%

Table 3.4: Tweets and FX Hourly Realised Volatility

This table reports panel regressions results for the estimation of Tweets hour dummy on FX hourly realised volatility. The control variables are presidency dummy, FOMC dummy, VIX, TED Spread, and Economic Policy Uncertainty (EPU) from Baker et al. (2016). Hour-of-the-day and day-of-the-week dummies are included in all regressions. Standard errors are clustered by currency. t-statistics are reported in squared brackets, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. The data are hourly between 16th June 2015 and 20th August 2019.

	Dependent variable: Realised Volatility					
	(1)	(2)	(3)	(4)	(5)	(6)
Tweet hour	-0.006***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***
	[-5.07]	[-2.77]	[-2.75]	[-3.60]	[-2.90]	[-2.94]
Presidency dummy		-0.014***	-0.014***	-0.012***	-0.011***	-0.011***
		[-7.05]	[-7.05]	[-6.38]	[-5.93]	[-5.93]
FOMC dummy			0.070***	0.070***	0.070***	0.069***
			[8.82]	[8.82]	[8.81]	[8.81]
VIX				0.001***	0.001***	0.001***
				[8.39]	[10.99]	[8.82]
TED Spread					0.017***	0.017***
					[3.49]	[3.49]
EPU						0.001*
						[2.05]
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	397,708	397,708	397,708	393,251	387,708	387,058
R^2	6.17%	7.22%	7.38%	7.64%	7.77%	7.77%

Table 3.5: Tweets and FX Hourly Bid-Ask Spreads

This table reports panel regressions results for the estimation of Tweets hour dummy on FX hourly bid-ask spreads quoted by big banks based on the 2016 G-SIB Classification. The control variables are presidency dummy, FOMC dummy, VIX, TED Spread, and Economic Policy Uncertainty (EPU) from Baker et al. (2016). Hour-of-the-day and day-of-the-week dummies are included in all regressions. Standard errors are clustered by currency. t-statistics are reported in squared brackets, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. The data are hourly between 16th June 2015 and 20th August 2019.

	Dependent variable: Bid-Ask Spreads					
	(1)	(2)	(3)	(4)	(5)	(6)
Tweet hour	-0.372***	-0.137***	-0.137***	-0.148***	-0.144***	-0.145***
	[-3.11]	[-2.62]	[-2.62]	[-2.75]	[-2.72]	[-2.73]
Presidency dummy		-1.022***	-1.022***	-1.012***	-1.010***	-1.009***
		[-2.79]	[-2.79]	[-2.89]	[-2.77]	[-2.77]
FOMC dummy			0.261*	0.266*	0.260*	0.260*
			[1.74]	[1.78]	[1.77]	[1.77]
VIX				0.003	0.003	0.003
				[0.45]	[0.47]	[0.46]
TED Spread					0.009	0.009
					[0.13]	[0.13]
EPU						0.059
						[1.32]
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	382,894	382,894	382,894	378,715	372,638	372,622
R^2	0.62%	1.86%	1.86%	1.85%	1.85%	1.85%

Table 3.6: Tweets and FX Hourly Returns

This table reports panel regressions results for the estimation of Tweets hour dummy on FX hourly returns. The control variables are presidency dummy, FOMC dummy, VIX, TED Spread, and Economic Policy Uncertainty (EPU) from Baker et al. (2016). Hour-of-the-day and day-of-the-week dummies are included in all regressions. Standard errors are clustered by currency. t-statistics are reported in squared brackets, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. The data are hourly between 16th June 2015 and 20th August 2019.

	Dependent variable: Returns					
	(1)	(2)	(3)	(4)	(5)	(6)
Tweet hour	0.005***	0.005***	0.005***	0.005***	0.005***	0.005***
	[3.45]	[3.42]	[3.42]	[3.53]	[3.69]	[3.60]
Presidency dummy		-0.000	-0.000	0.000	0.000	0.000
		[-0.23]	[-0.24]	[1.42]	[0.63]	[0.63]
FOMC dummy			-0.023***	-0.023***	-0.023***	-0.023***
			[-4.79]	[-4.77]	[-4.76]	[-4.76]
VIX				0.000*	0.000*	0.000
				[1.85]	[1.68]	[1.68]
TED Spread					-0.001	-0.001
					[-1.09]	[-1.09]
EPU						0.003*
						[1.90]
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	401,864	401,864	401,864	397,266	390,806	390,790
R^2	0.06%	0.06%	0.07%	0.07%	0.07%	0.07%

Table 3.7: Tweets and FX Hourly Returns

This table reports panel regressions results for the estimation of Tweets hour dummy on FX hourly returns. The control variables are presidency dummy, FOMC dummy, VIX, TED Spread, and Economic Policy Uncertainty (EPU) from Baker et al. (2016). Hour-of-the-day and day-of-the-week dummies are included in all regressions. In Panel A, independent variable of interest is Trade Tweet. In Panel B, independent variable of interest is Macro Tweet. Standard errors are clustered by currency. t-statistics are reported in squared brackets, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. The data are hourly between 16th June 2015 and 20th August 2019.

Panel A: Trade Tweet
Dependent variable: Returns

	(1)	(2)	(3)	(4)	(5)	(6)
Trade Tweet	0.003*	0.003*	0.003*	0.003	0.003*	0.003*
	[1.67]	[1.64]	[1.61]	[1.62]	[1.67]	[1.64]
Presidency dummy		-0.000	-0.000	0.000	0.000	0.000
		[-0.01]	[-0.02]	[1.61]	[0.85]	[0.85]
FOMC dummy			-0.023***	-0.023***	-0.023***	-0.023***
			[-4.77]	[-4.75]	[-4.75]	[-4.75]
VIX				0.000*	0.000*	0.000*
				[1.86]	[1.69]	[1.68]
TED Spread					-0.001	-0.001
					[-1.22]	[-1.22]
EPU						0.003*
						[2.08]
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	401,864	401,864	401,864	397,266	390,806	390,790
R^2	0.06%	0.06%	0.07%	0.07%	0.07%	0.07%

Panel B: Macro Tweet
Dependent variable: Returns

	(1)	(2)	(3)	(4)	(5)	(6)
Macro Tweet	0.005***	0.005***	0.005***	0.005***	0.005***	0.005***
	[3.91]	[3.94]	[3.94]	[3.94]	[4.19]	[4.08]
Presidency dummy		-0.000	-0.000	0.000	0.000	0.000
		[-0.24]	[-0.25]	[1.46]	[0.67]	[0.68]
FOMC dummy			-0.023***	-0.023***	-0.023***	-0.023***
			[-4.79]	[-4.77]	[-4.76]	[-4.77]
VIX				0.000*	0.000*	0.000*
				[1.88]	[1.71]	[1.71]
TED Spread					-0.001	-0.001
					[-1.04]	[-1.05]
EPU						0.003*
						[1.80]
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	401,864	401,864	401,864	397,266	390,806	390,790
R^2	0.06%	0.06%	0.07%	0.07%	0.07%	0.07%

Table 3.8: Tweets and FX Hourly Returns

This table reports panel regressions results for the estimation of Tweets hour dummy on FX hourly returns. The control variables are presidency dummy, FOMC dummy, VIX, TED Spread, and Economic Policy Uncertainty (EPU) from Baker et al. (2016). Hour-of-the-day and day-of-the-week dummies are included in all regressions. In Panel A, independent variable of interest is Positive Tweet. In Panel B, independent variable of interest is Negative Tweet. Standard errors are clustered by currency. *t*-statistics are reported in squared brackets, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. The data are hourly between 16th June 2015 and 20th August 2019.

Panel A: Positive Tweet
Dependent variable: Returns

	(1)	(2)	(3)	(4)	(5)	(6)
Positive Tweet	0.005***	0.005***	0.005***	0.005***	0.005***	0.005***
	[4.58]	[4.46]	[4.43]	[4.84]	[5.21]	[5.18]
Presidency dummy		-0.000	-0.000	0.000	0.000	0.000
		[-0.29]	[-0.29]	[1.32]	[0.55]	[0.55]
FOMC dummy			-0.023***	-0.023***	-0.023***	-0.023***
			[-4.77]	[-4.75]	[-4.75]	[-4.75]
VIX				0.000*	0.000*	0.000*
				[1.85]	[1.68]	[1.68]
TED Spread					-0.001	-0.001
					[-1.07]	[-1.08]
EPU						0.003
						[2.06]
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	401,864	401,864	401,864	397,266	390,806	390,790
R^2	0.06%	0.06%	0.07%	0.07%	0.00%	0.07%

Panel B: Negative Tweet
Dependent variable: Returns

	(1)	(2)	(3)	(4)	(5)	(6)
Negative Tweet	-0.006***	-0.006***	-0.006***	-0.008***	-0.008***	-0.007***
	[-2.94]	[-2.91]	[-2.93]	[-4.16]	[-5.07]	[-4.85]
Presidency dummy		0.000	0.000	0.001*	0.000	0.000
		[0.12]	[0.11]	[1.81]	[1.05]	[1.05]
FOMC dummy			-0.023***	-0.023***	-0.023***	-0.023***
			[-4.79]	[-4.78]	[-4.77]	[-4.77]
VIX				0.000*	0.000*	0.000*
				[1.90]	[1.74]	[1.73]
TED Spread					-0.001	-0.001
					[-1.30]	[-1.30]
EPU						0.003*
						[2.10]
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	401,864	401,864	401,864	397,266	390,806	390,790
R^2	0.06%	0.06%	0.07%	0.07%	0.07%	0.07%

Table 3.9: Tweets and FX market controlling for macro announcements

This table reports panel regressions results for the estimation of Tweets hour dummy on FX market characteristics. Dependent variables in regressions (1), (2), (3), and (4) and hourly total trading volume, hourly volatility, hourly bid-ask spread, and hourly returns respectively. The control variables are presidency dummy, FOMC dummy, VIX, TED Spread, and Economic Policy Uncertainty (EPU) from Baker et al. (2016). Macro Announcements is a dummy variable which is equal to 1 if there is at least one macro announcement on that day and 0 otherwise. Hour-of-the-day and day-of-the-week dummies are included in all regressions. Standard errors are clustered by currency. t-statistics are reported in squared brackets, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. The data are hourly between 16th June 2015 and 20th August 2019.

	Dependent variable: FX market characteristics			
	(1) Volume	(2) Volatility	(3) Bid-Ask Spread	(4) Returns
Tweet hour	-0.702***	-0.003***	-0.143***	0.005***
	[-4.26]	[-2.98]	[-2.71]	[3.61]
Presidency dummy	0.321***	-0.011***	-0.996***	0.000
	[3.28]	[-6.15]	[-2.80]	[1.47]
FOMC dummy	0.247***	0.069***	0.263*	-0.023***
	[2.92]	[8.82]	[1.79]	[-4.75]
VIX	0.021***	0.001***	0.004	0.000*
	[3.49]	[8.78]	[0.53]	[1.80]
TED Spread	-0.356***	0.017***	0.133	-0.000
	[-2.56]	[3.62]	[0.20]	[-0.33]
EPU	-0.560***	0.001**	0.058	0.003*
	[-3.95]	[2.07]	[1.30]	[1.89]
Macro Announcements	0.105***	0.001	-0.128	-0.003***
	[4.31]	[1.10]	[-0.98]	[-5.34]
Country FE	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Obs	375,410	387,058	372,622	390,790
R^2	3.81%	7.77%	1.86%	0.07%

Table 3.10: Tweets and FX market during presidency

This table reports panel regressions results for the estimation of Tweets hour dummy on FX market characteristics. Dependent variables in regressions (1), (2), (3), and (4) and hourly total trading volume, hourly volatility, hourly bid-ask spread, and hourly returns respectively. The control variables are presidency dummy, FOMC dummy, VIX, TED Spread, and Economic Policy Uncertainty (EPU) from Baker et al. (2016). Hour-of-the-day and day-of-the-week dummies are included in all regressions. Standard errors are clustered by currency. t-statistics are reported in squared brackets, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. The data are hourly between 16th June 2015 and 20th August 2019.

	Dependent variable: FX market characteristics			
	(1) Volume	(2) Volatility	(3) Bid-Ask Spread	(4) Returns
Tweet hour	-1.005***	-0.008***	0.131	-0.005*
	[-3.65]	[-3.15]	[1.00]	[-3.96]
Presidency dummy	0.329***	-0.011***	-1.007***	0.000
	[3.37]	[-5.95]	[-2.76]	[0.29]
FOMC dummy	0.247***	0.069***	0.261*	-0.023***
	[2.92]	[8.81]	[1.77]	[-4.76]
VIX	0.021***	0.001***	0.003	0.000*
	[3.55]	[8.83]	[0.47]	[1.67]
TED Spread	-0.324**	0.017***	0.093	-0.000
	[-2.42]	[3.49]	[0.13]	[-1.04]
EPU	-0.580***	0.001**	0.058	0.003*
	[-3.96]	[2.05]	[1.31]	[1.93]
Presidency*Tweet	0.345***	0.006**	-0.314**	0.012***
	[2.59]	[2.33]	[-2.02]	[3.11]
Country FE	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Obs	375,410	387,058	372,622	390,790
R^2	3.81%	7.77%	1.85%	0.07%

Table 3.11: Uninformative Tweets and FX market

This table reports panel regressions results for the estimation of uninformative Tweets hour dummy on FX market characteristics. Dependent variables in regressions (1), (2), (3), and (4) and hourly total trading volume, hourly volatility, hourly bid-ask spread, and hourly returns respectively. The control variables are presidency dummy, FOMC dummy, VIX, TED Spread, and Economic Policy Uncertainty (EPU) from Baker et al. (2016). Hour-of-the-day and day-of-the-week dummies are included in all regressions. Standard errors are clustered by currency. t-statistics are reported in squared brackets, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. The data are hourly between 16th June 2015 and 20th August 2019.

Dependent variable: FX market characteristics				
	(1) Volume	(2) Volatility	(3) Bid-Ask Spread	(4) Returns
Uninformative Tweet hour	-0.562***	-0.001	0.097	0.001
	[-3.86]	[-1.08]	[1.38]	[0.89]
Presidency dummy	0.327***	-0.011***	-1.011***	0.000
	[3.38]	[-5.95]	[-2.77]	[1.01]
FOMC dummy	0.183**	0.070***	0.260*	-0.023***
	[2.27]	[8.81]	[1.78]	[-4.76]
VIX	0.022***	0.001***	0.003	0.000
	[3.58]	[8.82]	[0.46]	[1.70]
TED Spread	-0.284**	0.017***	0.098	-0.002
	[-2.25]	[3.51]	[0.14]	[0.97]
EPU	-0.581***	0.001**	0.051	0.003*
	[-3.96]	[2.02]	[1.20]	[2.05]
Country FE	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Obs	358,002	387,058	372,622	390,790
R^2	3.86%	7.77%	1.84%	0.06%

Table 3.12: Tweets and FX Options Moneyness

This table reports time series regressions results for the estimation of Tweets hour dummy on FX options moneyness. The control variables are presidency dummy, FOMC dummy, VIX, TED Spread, and Economic Policy Uncertainty (EPU) from Baker et al. (2016). Hour-of-the-day and day-of-the-week dummies are included in all regressions. Standard errors are adjusted by Newey-West with number of lags based on AIC. t-statistics are reported in squared brackets, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. The data are hourly between 16th June 2015 and 20th August 2019.

	Dependent variable: Moneyness					
	(1)	(2)	(3)	(4)	(5)	(6)
Tweet hour	-0.142**	-0.148**	-0.148**	-0.146**	-0.139**	-0.129**
	[-2.41]	[-2.38]	[-2.38]	[-2.36]	[-2.15]	[-1.98]
Presidency dummy		0.067	0.067	0.060	-0.008	-0.009
		[1.10]	[1.10]	[1.04]	[-0.28]	[-0.20]
FOMC dummy			-0.019	-0.179	-0.022	-0.020
			[-0.26]	[-0.24]	[-0.28]	[-0.26]
VIX				-0.003	-0.003	-0.004
				[-0.62]	[-0.80]	[-0.80]
TED Spread					-0.725*	-0.728*
					[-1.71]	[-1.72]
EPU						-0.097
						[-0.83]
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	9,855	9,855	9,855	9,541	9,378	9,377
R^2	0.10%	0.09%	0.08%	0.02%	0.00%	0.00%

Chapter 4

U.S. Presidential Fiscal News and Cross-section of Stock Returns

4.1 Introduction

Statements made by political actors, especially the President of the U.S. are closely followed by the public as well as investors, and can impact the financial markets[1] . There are various ways through which politicians can influence the financial markets either by changing the 'rules of the game' or intervening on a case by case basis (Pagano and Volpin 2001). Among the content delivered by the president in the speeches, news regarding fiscal policy should be of particular importance and attract enormous attention, given the important role that fiscal policy plays in the economy. On 25th June 2013, President Obama's speech proposing new regulations for companies to tackle climate change made share price of energy companies such as Peadbody Energy and Walter Energy drop by up to 11.6%[2]. On 15th January 2021, President Biden announced a massive stimulus package of $1.9 trillion to save the economy hit by the pandemic. Following his announcement, the broad S&P 500 index increased by 3%, 10-year government bond yields also reached their highest levels in nearly one year [3]. Despite this evidence, to the best of my knowledge, there is no research paper extracting the fiscal policy content of a large historical collection of U.S. Presidents' speeches and examine their impacts on the stock returns. This research question is worth investigating, especially in the recent economic situation in which the conduct of monetary policy is constrained as interest rate reaches zero bound so the role of fiscal policy is becoming increasingly important to support the economy.

Regarding the economic channels, there are at least two potential ways through which political statements in general, and fiscal policy specifically can influence asset prices identified in the literature. As statements made by the Presidents may contain signals regarding future government actions, they are an information source of political uncertainty. Pástor and Veronesi (2013) suggest that political uncertainty increases the discount rates as investors demand a risk premium. On the other hand, Alesina et al. (1997), and Baker et al. (2016) provide empirical evidence suggesting the effects of political uncertainty on the macroeconomy, suggesting the cash flow channel. The combination of these two effects is documented in the theoretical framework of Pastor and Veronesi (2012), and empirically supported in Gala et al. (2020).

The main contribution of this paper to the literature is twofold. First, I construct a novel historical time-series Fiscal News Index, which can be considered as a dimension of political risks. Quantifying political risk poses a challenge for researchers (Bremmer 2005). In terms of finance literature, a number of papers use elections as a proxy for

[1]The number of audience of a U.S. President's Speech can be as high as 66.9 million based on https://www.npr.org/sections/thetwo-way/2018/02/01/582414052/trump-claims-his-sotu-had-the-highest-ratings-in-history-it-didnt?t=1615987187913

[2]https://eu.usatoday.com/story/money/markets/2013/06/25/obama-emissions-energy-stocks/2455167/

[3]https://finance.yahoo.com/news/analysis-wall-street-cheers-biden-214245955.html

political risk (Belo et al. 2013, Brogaard et al. 2020). A limitation associated with this approach is that elections only last for a relatively short period of time so it is mostly suitable for event studies only. Moreover, it would ignore the impacts of potential policy changes outside election time, which is also an important aspect of political risk. When it comes to quantitative index of political risk, most of the widely used indicators such as ICRG Index, and World Bank Governance Indicators are based on subjective assessments of experts[4]. An exception is the news based Economic Policy Uncertainty constructed by Baker et al. (2016) and this index is widely used as a proxy for political uncertainty. In this paper, I propose an alternative methodology of measuring a dimension of political risk. Collecting an archive of U.S. Presidents' speeches, I implement textual analysis to extract the fiscal policy content. This allows me to construct a historical time-series Fiscal News index going back as far as 1929. Most of the existing political risk indicators previously mentioned are only available from 1980s. Baker et al. (2016) construct a historical index starting from 1900s, however Rule et al. (2015) point out a limitation of using dictionary approach when studying language evolving over long time, which is also acknowledged by the authors themselves. Dictionary approach assumes that categories display a stable textual characteristic, whereas in reality language usage changes over time. My index also differs from the Tax Changes by Romer and Romer (2010) as their focus is on the tax aspect whereas my index takes into account all aspects of fiscal policy. Second, my paper is the first one to study the impacts of fiscal policy News on the cross-section of stock returns. My empirical findings suggest that Fiscal News factor is positively priced in the cross-section of stock returns. Investors demand higher expected returns for stocks with high exposure to Fiscal News.

I implement textual analysis to construct the Fiscal News Index. In particular, I first collect a large sample of speeches (i.e., news conferences, interviews, state of union speeches, remarks, radio speeches, oral addresses) of U.S. Presidents from February 1929 to December 2020. LDA Algorithm is employed to discover the information content that U.S. Presidents convey to the public. The fiscal policy can be clearly identified based on the keywords provided by LDA Algorithm. I then construct the monthly Fiscal News Index as the average of fiscal topic delivered during the month. Fiscal News Index spikes during recessions, as the president is more likely to announce changes in fiscal policy to support the economy when the economic conditions are unfavourable. Results from logit regressions also suggest that Fiscal News Index is a leading indicator of economic recession, as an increase in this index is associated with an increased likelihood of a recession in the next quarter.

I then find pricing implications of Fiscal News Index for the cross-section of stock returns. My empirical findings suggest that Fiscal News is positively priced in the cross-section of stock returns. Investors demand higher expected returns for stocks with

[4] Many finance research papers use these indices such as Filippou et al. (2018)

high exposure to Fiscal News. Decomposing the expected return into Cash flow news return and Discount rate return, I find that the pricing implications of Fiscal News for cross-sectional stock returns is mainly through the Discount rate news channel. I also show the economic value of the exposure to this risk factor though a trading strategy that goes long stocks with high exposure to Fiscal News and short stocks with low exposure to Fiscal News. An equal-weighted portfolio following this strategy generates an average excess returns of 8.2% annually with a Sharpe ratio of 0.86. This outperforms an alternative strategy of investing in the S&P500 Index. During the same time , investing in the S&P500 Index yields an average excess return of 4.5% annually with a Sharpe ratio of 0.25. In addition, the excess return of this portfolio cannot be explained by conventional risk factors.

I also carry out a number of robustness checks, and my empirical results remain strong. In particular, I first do a placebo test with the exposure of stocks to other topics identified by LDA Algorithm. Trading strategy based on the exposure to all of those topics shows no significant average returns or weaker performance than the Fiscal News trading strategy. In addition, the pricing results remain strong when I categorise stocks in the sample into five industries and do the asset pricing tests for each of them individually. Finally, the results are also robust for the sample during the 1964-2020 period.

The rest of the paper is structured as follows. Section 2 summarises related literature. Section 3 describes the methodology implemented to construct the Fiscal News Index. Section 4 summarises the stock data and the construction of Fiscal News sorted portfolio. Section 5 discusses empirical findings between Fiscal News Index and cross-section of stock returns. Section 6 offers robustness checks. Section 7 concludes.

4.2 Literature review

This paper is related to several strands of literature. First, it provides empirical evidence supporting existing theoretical framework linking political news and asset prices. In Pastor and Veronesi (2012) theoretical model, there are two types of government uncertainty: policy uncertainty (the uncertain impact of a given policy on the profit of the private sector) and political uncertainty (the uncertainty as to whether the current government policy will change). The announcement of a policy change typically increases the firms' expected future profit due to the government's optimal decision rule, and increases the discount rates as the impact of the policy on profit is more uncertain (as investors now need to update their beliefs about the new policy's impact, and it undoes the gains from learning about the old policy). The discount effect is typically stronger than the cash flow effect unless the old policy is perceived as sufficiently harmful to profit. It results in the stock prices falling at the announcement of a policy change. Pástor and Veronesi (2013) develop a related model, with investors now learning about the political costs of the potential new policies. Political uncertainty, which is defined as uncertainty about the government's future actions commands a risk premium, especially in weak economy. Political uncertainty also makes stocks more volatile and more correlated.

This paper is also related to papers empirically examining the effects of political uncertainty and asset prices, although the proxy for political risk in these papers is rather simple. Kelly et al. (2016) use national elections and global summits as proxy for political uncertainty and find that political uncertainty is priced in the equity option market. Hou et al. (2020) show that commodity prices and inventories decline in the quarter leading up to the U.S. presidential election, whereas the opposite effect is found when national elections in major commodity producing countries are used. Several papers examine the effects of political uncertainty on the international financial markets. Gala et al. (2020) construct an index of politics policy uncertainty based on Ifo World Economic Survey and find that this factor predicts variation in stock market returns across countries.

There is a number of papers deviating from general political risk and focusing on fiscal policy instead. The risk premium embeded in fiscal policy has been found in some theoretical models. Croce et al. (2012) find that in a production-based general equilibrium model, fiscal policies impact corporate investment and financing decisions through corporate taxes, which generate a sizable risk premia. In Gomes et al. (2013), the authors analyse the impacts of fiscal policy changes in a model with incomplete markets, and find that when public debt accounts for 64% of GDP, it leads to a 77-basis-point increase in the riskless rate, and a 38-basis-point decrease in the equity premium. Empirical papers linking fiscal policy and asset prices focus on various asset classes. Several papers show the empirical evidence that higher fiscal deficits result in changes in long-term interest rate in a panel of countries (Baldacci and Kumar 2010, Akitoby and Stratmann 2008, Baldacci et al. 2011, Barro 1987, Fisher and Peters 2010). Regarding the currency market, Ravn et al. (2012), Enders et al. (2011) find empirical evidence suggesting that increased government spending leads to a depreciation of the real exchange rate, and Jiang (2019) finds that government surplus cyclically is a priced factor explaining currency returns. The most closely related work to my paper is Belo et al. (2013), who investigate the effects of government spending policies in the cross section of stock returns. They find that during Democratic presidencies, firms with high government spending exposure experience higher cash flows and stock return, and the opposite feature is true during Republican presidencies.

This paper contributes to the literature focusing on the announcement of fiscal policy specifically. The announcement of a future increase in VAT as a form of discretionary fiscal policy to push up aggregate demand without having negative impacts on the size of the budget deficit in liquidity traps was first introduced in Feldstein (2002). The notion of unconventional fiscal policy was then formalised in Correia et al. (2013), suggesting it as a potential solution when monetary policy reaches zero bound. A decrease in current consumption taxes (or increase in future consumption taxes) leads to higher expected inflation, which brings down real interest rates. Similarly, a recent work by D'Acunto et al. (2018) defines unconventional fiscal policies as those generating an increasing path of consumption taxes that result in household's higher inflation expectations and negative real interest rates. They then use data from Poland and find supporting evidence for the effectiveness of the unconventional fiscal policy. D'Acunto et al. (2016) use the unexpected announcement of an increase in VAT in German in 2005 as a natural experiment, and that it increases German households' inflation expectations. What differentiates my paper is that my focus is on News of fiscal policy in general, not just unconventional fiscal policy.

This paper is also related to those studying the impacts of political communications on asset prices. The general overview is that most papers linking political statements and asset prices focus on a limited sample of speeches, and employ event studies approach. Mohl and Sondermann (2013) find that statements about restructuring, bailout and the involvement of the European Financial Stability Facility have impacts on bond yields of eurozone countries. Using 25,000 news media releases between January 2009 and October 2011, Gade et al. (2013) find that political communication regarding fiscal policy and public finances by political actors has an impact on the sovereign bond spreads of 3 euro area countries over the Germand Bund, depending on the type of communication Specifically, more positive words in the communication is associated with a reduction in the yield spread, and vice versa. Wisniewski and Moro (2014) use closing statements from European Council meetings and find that their sentiment affects the stock market index. The difference between positive and negative communications expressed in terms of cumulative abnormal returns over a 12-day event window is 3.9% and 3.4% for the European Index and the World Index, respectively. Conrad and Zumbach (2016) collect data regarding all statements by major European politicians about the debt crisis between August and December 2011, and find that it impacts the EUR/USD exchange rate, eight national stocks and bond markets in the window of 15 minutes following each statement. Positive statements lead to an appreciation of the EURO against USD, and better performance of the stock market indices. German and Italian bond yields are also affected, with negative statements regarding economic outlook in Italy resulting in an increase in Italian bond yields and decrease in German bond yields. Sazedj and Tavares (2011) use speeches relevant for the economy by President Obama in the 11 month period following his inauguration as president and find that certain words such as 'Dreams' and 'Crisis' have impacts on the stock market returns proxied by Dow Jones, S&P 500, and NASDAQ indicies, at 3 and 7 day time horizons. Durnev et al. (2013) show that political rhetoric in 388 speeches given by governor carries information for the market. These speeches are classified into positive and negative tone, and the authors find that there is a positive link between the level of optimism in a Governor's speech and the abnormal returns of firms headquartered in that Governor's state. They also find that firms having state-government contracts and those more dependant on skilled human capital, and therefore education spending, significantly increase investments if the content of budget-related and education-related sections of the speech are more optimistic.

Last but not least, this paper relates to the major literature examining the risk factors predicting stock returns (e.g., La Porta 1996 , Chang et al. 2013, Bali et al. 2017). My Fiscal News Index starts from February 1929, which allows me to study a much larger sample (including both Great Depression and Great Recession) than most other papers in the existing literature.

4.3 Content of U.S. President Speeches

In this section, I describe the methodology implemented to analyse the content of speeches, and to construct the Fiscal News Index based on the latent Dirichlet Allocation (LDA) algorithm.

4.3.1 U.S Presidential Speeches

I collect an archive of U.S. Presidential speeches, including interviews, spoken remarks, news conferences, oral addresses, Saturday Weekly Addresses, and State of the Union Addresses from The American Presidency Project website[5]. My data sample starts from February 1929 until December 2020. During this time period, there are 15 presidents in power, and their party affiliation is almost evenly distributed. In particular 8 presidents are Republicans and 7 presidents are Democrats. The collection of documents sums up to 9,524 speeches in total. Summary statistics regarding the number of speeches made by each president per term is shown in Table 4.1.

Based on the graph, the number of speeches delivered vary from president to president. Presidents in the past, such as President Roosevelt and President Ford are relatively less active in terms of communications to the public. Since President Carter was in power, the number of speeches per president has increased significantly. President Bill Clinton and President George W. Bush have the most average number of speeches. Both of them conducted around 800 speeches per term during their presidency. Interestingly, despite being extremely active on Twitter [6], President Trump still delivered around 600 speeches during his term. It suggests that speeches remain an important channel of communication from the President to the public.

4.3.2 Topic Distribution of U.S Presidential Speeches

I choose the LDA topic modelling algorithm, which is one of the most popular latent topic models, to analyse the data. The LDA algorithm is developed by Blei et al. (2003), and it has been applied in various contexts, including finance (Jegadeesh and Wu 2017, Hansen et al. 2017). This method employs hierarchical Bayesian analysis to discover the semantic structure of textual documents. The intuition behind this method is that each document is represented as combinations of latent topics, and each latent topic is characterised by a distribution over words. Latent topic models infer these two hidden distributional properties based on the corpus. LDA assumes that these two distributions follow Dirichlet distribution. As the base unit of my analysis is a paragraph, which

[5] https://www.presidency.ucsb.edu/documents

[6] The information content of Trump Tweets and their impacts on the currency market has been studied in Filippou et al. (2021)

means that I have a collection of T paragraphs. Each paragraph is a mixture of a list of words. I denote V as the number of unique words across all T paragraphs. Two inputs required when fitting LDA model are the corpus of documents, and the number of topics N. In order to minimise researcher's subjectivity when choosing number of topics for LDA model, a topic coherence score matrix is computed for number of topics being in the range between 5 and 20. A topic coherence score matrix is an indicator of how well the LDA model fits the data with that particular number of topics. The coherence score suggests that the optimal number of topics given the data is when N = 9. The coherence score graph is shown in Figure C.1 in the Appendix.

The methodology implemented by LDA can be described briefly as follows. Each paragraph t is constituted by a mixture of N topics. $\theta_d = [\theta_{d,1},...,\theta_{d,N}]'$, in which $\theta_{d,n}$ is the proportion of topic n in paragraph t. This mixture of topic proportions is assumed to follow an order -N Dirichlet distribution over the N topics.

Each topic n is a mixture of v words, and it is also assumed to follow an order-V Dirichlet distribution over the V words.

The probability of each words contributing to paragraph t can be expressed as follows:

$$\prod_{n=1}^{N} \sum_{zn} \Pr[z_n | \theta] \Pr[w_n | \beta_{zn}]$$

The probability of each paragraph t is therefore:

$$\int ... \int \prod_{k=1}^{K} \Pr[\beta_k | \ \eta] \Pr[\theta | \alpha] (\prod_{n=1}^{N} \Pr[z_n | \theta] \Pr[w_n | \ \beta_{z,n}]) \ t\theta t\beta_1 ... t\beta_K$$

Two important sets of results are the output from the LDA algorithm. The first one is the top keywords and their distribution for each topic, and the second one is the proportion of each topic in each paragraph.

I implement LDA algorithm with the corpus being the collection of U.S. Presidential speeches described in the previous subsection. I analyse the data at the paragraph level. This amounts to 452,551 paragraphs in total. I first remove short paragraphs (those with less than 20 words) and then follow standard text cleaning procedures. In particular, all words are converted to lowercase, then all punctuation marks are removed. I also remove English stop words [7], words with length less than 2 characters, 100 most common words, and 500 least common words in my sample. After being tokenised into unigrams, the words are stemmed using Porter Stemmer (Porter 1980), which is implemented through Python's Natural Language Toolkit.

[7]Full list of stop words removed is available upon request

4.3.2.1 Results from LDA Algorithm

The first set of results obtained from LDA algorithm is the top keywords and their distributions in each topic. For each topic n, there is a set of vectors $\hat{\beta}_n = [\hat{\beta}_{n,1},..., \hat{\beta}_{n,J}]$', in which $\hat{\beta}_{n,j}$ is the probability that the word j defines topic n.

The full list of top key words for all 9 topics can be found in Table 4.1.

Based on those keywords, we can identify what each topic is about. For example, topic 1 contains words such as militari, defens, union, war, polic..., which suggests that this topic is about Military Defense. Based on key words of topic 3 such as china, deal, iraq, leader..., we can identify this topic as International Relations. Topic of particular interest in this paper is Topic 0, which is the Fiscal Topic as its top keywords include job, tax, busi, economi, percent...Top keywords with the highest occurrence in Fiscal topic are shown in the word cloud in Figure 4.2. During the long sample period examined, there are substantial technological and economic changes in the U.S. so the nature of fiscal issues varies over time. We can see that the keywords capture various fiscal issues in the U.S. over this long sample period. For example, carbon tax did not become a prominent issue until 1990s, and the word 'carbon' appears in the list of keywords too.

The second set of output is the proportion of topics for each paragraph. In particular, for each paragraph t there is a set of vectors $\hat{\theta}_t = [\hat{\theta}_{t,0}, \hat{\theta}_{t,1}, \hat{\theta}_{t,2}, \hat{\theta}_{t,3}, \hat{\theta}_{t,4}, \hat{\theta}_{t,5}]$', in which $\hat{\theta}_{t,n}$ is the proportion of paragraph t that is made up of topic n. Some samples of paragraphs and their corresponding classification results from LDA can be found in Appendix C.

4.3.3 Fiscal News Index

Fiscal News Index is constructed as the average of the proportion of Topic 0 (Fiscal Topic) in all paragraphs during the month. A plot of the monthly index between February 1929 and December 2020 is shown in Figure 4.3.

In the plot, grey shaded areas represent the recession periods based on NBER recession indicators. As can be seen from the plot, the index spikes mostly during recessions times, which is expected as the president should be more likely to announce changes in fiscal policy to support the economy when the economic conditions are unfavourable. The peak of the index is recorded during the beginning of the sample, which is also the worst economic downturn observed in the sample - the Great Depression. Summary statistics of Fiscal News Index (i.e. FN) and its change (i.e. ΔFN) are shown in Table 4.2.

In Panel A of Table 4.3, I check for the correlation between Fiscal News and other prominent economic and political uncertainty indexes in the literature[8].

The most closely related index to my Fiscal News is the Fiscal Policy Uncertainty Index from Baker et al. (2016), therefore it is reasonable that the correlation between my index and the Fiscal Policy Uncertainty Index is the highest (0.33). Although Fiscal News show positive correlations with Macroeconomic Uncertainty Indices from Jurado et al. (2015), Economic Risk index from International Country Risk Guide, and the Aggregate Populist Rhetoric index from Filippou et al. (2020b), the magnitude of the correlation is very mild. In general, these results suggest that my Fiscal News captures a novel aspect of political risk on top of the existing indexes.

It would be interesting to address the question as to whether my Fiscal News Index captures the surprise component. In the literature, the conventional method to extract the unexpected news component is to subtract the forecast element from the actual element (e.g., Chatrath et al. 2014). In the context of fiscal variables, it would be challenging to find a forecast fiscal proxy available from the beginning of my Fiscal News Index (February 1929). The most relevant data is the Government Consumption Expenditures and Gross Investment from Survey of Professional Forecasters. This variable starts from Quarter 3 in 1981. During this sample period (from Quarter 3 in 1981 to Quarter 4 in 2020), I extract the unexpected Fiscal News element by finding the difference between Fiscal News and the forecast government consumption expenditures and gross investment. I then find that the correlation between this unexpected Fiscal News element and the Fiscal News Index is 0.97 (with p-value of 0), suggesting that Fiscal News Index actually captures the surprise element.

[8] The sample varies depending on data availability of each index. EPU and EPU^F are from January 1985 to December 2020. UNC^m, UNC^q, UNC^y. ICRG ER is between January 1985 and January 2014. APR is between January 1998 and October 2018.

4.3.4 Fiscal News Index and Macroeconomics Variables

Having identifed the pattern between Fiscal News Index and NBER recession in Figure 4.5, it would be interesting to explore the correlation between these two variables further. I investigate the contemporaneous and predictive links between Fiscal News Index and the economic conditions by running the following logit regressions:

$$Recession_t = \alpha_{i,t} + \beta_{1,t} FN_t + \epsilon_{i,t} \tag{4.1}$$

$$Recession_t = \alpha_{i,t} + \beta_{1,t} FN_{t-1} + \epsilon_{i,t} \tag{4.2}$$

where $Recession_t$ is the dummy variable which is equal to 1 if quarter t is the recession quarter defined by NBER and 0 otherwise, FN_t is the Fiscal News Index in quarter t, and FN_{t-1} is the Fiscal News Index in quarter *t-1*. There are some reliable recession predictor discussed in the literature, including the slope of the yield curve (Estrella and Mishkin 1996), and unemployment trough (Kliesen 2018). Therefore I also control for these variables. $Spread_{t-1}$ is the spread between 10-year interest rate and 3-month interest rate data [9]. $Unemployment_{t-1}$ is the unemployment rate. I report the results of regressions in Table 4.4. Panel A of Table 4.4 shows results for the contemporaneous link between Fiscal News Index and the recession. In the first column, Fiscal News is the only independent variable and the coefficient of this variable is positive and statistically significant with *t-statistics* of 2.48. It suggests that there is a positive link between Fiscal News and the probability of recession in that quarter. This result is due to the fact that the president is likely to announce changes in the fiscal policy when the economy is in recession. In the next two column, when I add slope of yield curve and unemployment in the regressions, the coefficient of Fiscal News loses its statistical significance. However, in the last specification in which I also control for lagged recession, the coefficient of Fiscal News is positive and statistically significant with *t-statistics* of 2.17.

Panel B of Table 4.4 shows results for the predictive link between Fiscal News Index and the recession. The first column shows the univariate results in which Fiscal News is the independent variable. The coefficient of Fiscal News is positive and statistically significant with *t-statistics* of 2.56. This result implies that an increase in Fiscal News Index is associated with an increased likelihood of a recession in the next quarter. In the next column I control for slope of the yield curve in the regressions. The coefficient of this variable is negative and strongly significant in all specifications as expected. Fiscal News Index remains a leading indicator for recession the the next quarter although its statistical power is weaker. The result is similar in the next column when I control for unemployment rate. In the full specification in which lagged dependent variable is also added to the regression, the coefficient of Fiscal News is still positive and statistically

[9] Spread data is collected from the Federal Reserve Bank of Cleveland

significant with *t-statistics* of 2.28. The reason as to why Fiscal News Index is a leading indicator of an economic recession can be explained as follows. When the economy starts to show signs of slowdown, the president is likely to outline more fiscal policy changes to boost the economy. As there are some time lag effects of fiscal policy changes, the economic conditions will be likely to go into recession within a short-term horizon before it gets better.

I also attempt to examine the link between Fiscal News Index and the economic conditions at a longer time horizon by running the following regressions:

$$\Delta Y_t = \alpha + \sum_{i=0}^{M} \beta_{1,i} FN_{t-i} + \sum_{j=1}^{N} \beta_{2,i} \Delta Y_{t-j} + \epsilon_t \tag{4.3}$$

where ΔY_t is the GDP growth at quarter t. I follow the methodology outlined in Romer and Romer (2010) to include various lags of the Fiscal News Index and the GDP growth in the regression. In particular, I include 5 lags of these two variables. The effects of an increase in Fiscal News Index on the GDP growth in the next 5 quarters are shown in Figure 4.6

As can be seen from this graph, an increase in Fiscal New Index is associated with a decrease in GDP growth in the next quarter. This is consistent with the result that in the short term economic conditions are likely to get worse following an increase in Fiscal News Index. The effect changes from 2 quarters ahead. An increase in Fiscal News Index is associated with positive growth of GDP instead. The effect fades away after 2 quarters.

4.4 Stock Data and Portfolio Construction

This section discusses the stock data and the construction of portfolios based on exposure to Fiscal News Index.

4.4.1 Stock Data

I collect the stock data between February 1929 and December 2020 from CRSP. My sample covers common stocks listed on NYSE, AMEX, and the Nasdaq stock exchanges based on the share code and exchange code. I remove stocks with price below $5 and those above $1000. In addtion, as in the standard empirical asset pricing literature, stocks in the financial and utilities industries (CRSP SIC Code between 6000-6999 and 4900-4999) are removed. These filters leave the final sample with 1,399,305 stock-month observations.

4.4.2 Portfolios sorted on Fiscal News betas

As the first attempt to examine the role of Fiscal News Index as a risk factor priced in the cross-section of stock returns, I sort stocks based on exposure to Fiscal News Index. If it is a pricing factor for the cross-section of stock returns, there should be a significant dispersion in terms of excess returns between portfolios of low-betas and those of high-betas, and HML portfolio which goes long and short two extreme portfolios should generate statistically significant excess returns.

Rolling Betas. In order to obtain the exposure of each stock to the fiscal announcements, proxied by my Fiscal News Index, I run the following time-series regressions using a 60-month rolling window (with a minimum of 24 observations):

$$rx_{i,t} = \alpha_{i,t} + \beta_{i,t}^{FN} FN_t + \beta_{i,t}^{Mkt} Mkt_t + \beta_{i,t}^{SMB} SMB_t + \beta_{i,t}^{HML} HML_t + \beta_{i,t}^{Mom} Mom_t + \epsilon_{i,t} \tag{4.4}$$

where $rx_{i,t}$ is the excess return on stock i in month t, and FN_t is the Fiscal News Index in month t. I also control for the market factor (Mkt), small minus big factor (SMB), high minus low factor (HML), and momentum factor (Mom) of Carhart (1997). Data of market factor, small minus big factor, high minus low factor, and momentum factor are from Kenneth R. French data library. The slope coefficient of interest obtained from this regression is $\beta_{i,t}^{FA}$.

Fiscal News Portfolios. I first sort stocks into quintiles based on their raw exposure to Fiscal News (i.e., $\beta_{i,t}^{FN}$). In particular, at time t, I sort stocks into portfolios based on their past (i.e. *t-1*) betas with Fiscal News Index. Portfolios are rebalanced monthly. What is interesting is that the excess returns form a V-shape when moving from portfolios of low $\beta_{i,t}^{FN}$ to portfolios of high $\beta_{i,t}^{FN}$, which implies that it is the magnitude of the exposure (absolute value of $\beta_{i,t}^{FN}$) that matters for the cross-section of stock returns[10]. This pattern of beta has also been found in Kolari et al. (2008). Therefore, stocks are then sorted into quintiles based on their absolute value of $\beta_{i,t}^{FN}$ estimated from equation (1).The first portfolio (P1) includes stocks with the lowest absolute betas, while the fifth portfolio (P5) contains stocks with the highest absolute betas. A HML portfolio is constructed by going short the low absolute beta portfolio (P1) and long the high absolute beta portfolio (P5).

[10]Results are available upon request

4.5 Empirical Results

In this section, the role of Fiscal News Index as a priced risk factor in the cross-section of stock returns is empirically examined.

4.5.1 Fiscal News-sorted Portfolios

I sort stocks into portfolios based on their absolute exposure to Fiscal News as discussed in the previous section. Table 4.5 shows summary statistics of equal-weighted portfolios (Panel A) and value-weighted portfolios (Panel B).

Panel A shows results for equal-weighted portfolios. It can be seen that average betas reported in the third column increase monotonically from P1 to P5, and there is a significant dispersion in terms of average betas between two extreme portfolios. In particular, average beta of P1 is 0.02%, whereas average beta of P5 is 0.48%. Average excess returns also display the same pattern as they are monotonically increasing in the beta. Average excess return to P1 is 0.93% with a Newey-West *t-statistics* of 4.32, and average excess return to P5 is 1.61% with a Newey-West *t-statistics* of 5.7. Of particular interest is the average excess returns to HML portfolio, which is positive and statistically significant with a Newey-West *t-statistics* of 7.1. This HML portfolio generates an average excess returns of 8.2% annually with a Sharpe ratio of 0.86.

Apart from the raw excess returns of portfolios, I also check for their risk-adjusted returns (alphas) from different factor models in the last three columns. The first model is the CAPM model, and α_{Mkt} is the constant from the regression of the excess portfolio returns on the market factor (Mkt). The second model is the Fama and French (1993) three-factor model, and α_{FM3} is the constant from the regression of the excess portfolio returns on the market factor (Mkt), small-minus-big factor (SMB), and high-minus-low factor (HML). The third model is the Carhart (1997) four-factor model, and α_{CH4} is the constant from the regression of the excess portfolio returns on the market factor (Mkt), small-minus-big factor (SMB), high-minus-low factor (HML), and momentum factor (Mom). Based on the results of the third column, α_{Mkt} also increases monotonically as we go from P1 to P5. Risk adjusted returns of all these portfolios relative to the market model are also all significant. The risk adjusted return to HML portfolio is 0.5% with a Newey-West *t-statistics* of 6.18. In the next two columns, α_{FM3} and α_{CH4} increase monotonically from low portfolio to high portfolio in most cases. Importantly, the HML strategy generates positive and statistically significant returns regardless of the risk factor models used. These results suggest that excess returns from beta sorted strategy based on Fiscal News cannot be explained by conventional risk factors.

Panel B shows results for value-weighted portfolios. The findings are similar with the equal-weighted portfolio results found in Panel A. There is a significant dispersion in terms of excess returns between P1 and P5, as P1 earns an excess returns of 0.35% per month, whereas P5 generates 0.85% per month. It implies that the HML portfolio generates an average excess returns of 0.5% with a Newey-West *t-statistics* of 3.82. The risk-adjusted returns of HML strategy in the next three columns are also positive and statistically significant.

These results from beta sorted portfolios can be interpreted as follows. Stocks in the low betas portfolios by construction have low exposure to Fiscal News, whereas the reverse is the case for stocks in the high betas portfolios. Those stocks with high exposure to Fiscal News generate higher expected returns in the next period.

It is also worth examining the performance of HML strategy throughout the sample. Figure 4.4 reports the average returns of the (value-weighted) HML portfolio per each presidency term.

Trading strategy based on the exposure to Fiscal News shows the best performance at the beginning of the sample, during the first term of President Roosevelt in particular. During this 4-year period, average annual return generated from the strategy reached around 40%. There are only several occasions in which the average return of HML strategy per president term is negative, however the loss is always negligible. The average returns during President Trump time is around 25%.

4.5.2 Average stock characteristics

Having found the significant dispersion in terms of average excess returns between low and high Fiscal News exposure beta, I examine the link between Fiscal News exposure and stock characterstics. The following monthly cross-sectional regressions are run:

$$\beta_{i,t}^{FN} = \alpha_i + \lambda_{1,t} X_{i,t} + \epsilon_{i,t} \tag{4.5}$$

where $\beta_{i,t}^{FN}$ is the absolute Fiscal News beta of stock i in month t and $X_{i,t}$ is the set of individual characteristics of stock i in month t. These characteristics include market beta, size, short-term reversal, momentum factor, return skewness, and idiosyncratic volatility. The time-series averages of the slope coefficients from the regressions are reported in Table 4.8.

The first univariate regression in the first column shows that the slope coefficient of $\beta_{i,t}^{Mkt}$ is positive and statistically significant. It suggests that stocks with high exposure to Fiscal News have high market beta. The next columns reveal more characteristics of stocks with high exposure to Fiscal News. Those stocks are small, illiquid, and they have high skewness and high idiosyncratic volatility. In the last column, when I include all characteristics in the regression, the results mostly hold, apart from skewness as this variable loses its statistical significance.

4.5.3 Asset Pricing Tests

In this section, I carry out asset pricing tests to address the question as to whether Fiscal News Index is a priced risk factor in the cross-section of stock returns. I choose individual stocks as test assets rather than portfolios due to the limitations associated with portfolio approach recently identified in the literature. Ang et al. (2018) suggest that grouping stocks into portfolios make the cross-sectional dispersion of the betas shrink, which leads to less efficient estimate of factor risk premia. Therefore, I follow Bali et al. (2017) and Barroso et al. (2018) to estimate the risk price using individual assets. In particular, I run monthly cross-sectional regressions at each time t:

$$rx_{i,t+1} = \alpha_i + \lambda_{1,t}\beta_{i,t}^{FN} + \lambda_{i,t}X_t + \epsilon_{i,t} \tag{4.6}$$

where $rx_{i,t+1}$ is the excess return on stock i in month $t+1$, and $\beta_{i,t}^{FN}$ is the absolute value of the exposure of stock i in month t to Fiscal News Index in month t estimated from equation (1). I also control for a set of firm characteristics in the regressions, including market beta (Fama and French 1993), size (Eugene and French 1992), lag return (Jegadeesh 1990), momentum (Jegadeesh and Titman 1993), illiquidity (Amihud 2002), return skewness (Harvey and Siddique 2000), and idiosyncratic risk (Ang et al. 2006). I then take the time-series average of slope coefficients $\lambda_{1,t}$ and report its Newey-West t-statistic and average adjusted R^2. Results of these regressions are reported in Table 4.6.

In Panel A of Table 4.6, I do not include industry fixed effect in the regressions. The first column reports the univariate regression, in which Fiscal News is the only risk factor. The coefficient of this risk factor is positive and highly significant with a *t-statistics* of 6.43. This suggests a positive link between exposure to Fiscal News and the expected returns in the next period. I also investigate the economic significance of this risk factor. Based on the results from Table 4.5, the difference in $\beta_{i,t}^{FN}$ between average stocks in the two extreme portfolios is 0.45[=0.47- 0.02]. I can then estimate the difference in expected return if a stock were to move from the first quintile to the fifth quintile of $\beta_{i,t}^{FN}$. As the coefficient of $\lambda_{i,t}^{FN}$ is 0.01 in the cross-sectional regression, this figure should be 0.45% per month [=0.01 x 0.45 = 0.45%]. This shift in the expected return between stock in the two extreme portfolios is therefore economically significant. In the next column, the market beta $\beta_{i,t}^{Mkt}$ is added to the regression, and the coefficient of $\beta_{i,t}^{FN}$ is still positive and remains its strong statistical significance. The next column controls for both the market beta $\beta_{i,t}^{Mkt}$ and size. The result of $\beta_{i,t}^{FN}$ coefficient remains similar. The next column adds an additional control variable, which is the lag return. In this regression, the coefficient of $\beta_{i,t}^{FN}$ is still 0.01. With the full set of control variables, Fiscal Announcement Index factor has a *t-statistics* of 5.7. Harvey et al. (2016) suggest that the risk factor found to be priced in the cross-section of stock returns should pass the threshold of *t-statistics* of 3. The results found in this table therefore well pass that hurdle.

In Panel B, I control for industry fixed effect. For each month, I sort each stock to one of the five industries based on the four-digit SIC code and control for this variable in all regressions in Panel A. Results in all regressions in Panel B suggest that taking into account industry fixed effect generally does not have any significant impact on the significance of the risk price of $\beta_{i,t}^{FN}$ and future expected stock return. Both the magnitude and statistical significance of $\beta_{i,t}^{FN}$ coefficients remain mostly similar to the results obtained in Panel A.

Overall, results from Table 4.6 provide evidence that investors demand higher expected returns for stocks with high exposure to the Fiscal News or $\beta_{i,t}^{FN}$.

4.5.4 Fiscal News Beta factor

Having found empirical evidence that the Fiscal News is priced in the cross-section of individual stock returns, it is worth checking the risk premium associated with this index for equity portfolios as test assets. Therefore, I create a factor associated with the Fiscal News beta and examine whether this factor also generates statistically significant returns, as well as whether well-known risk factors can explain the returns captured by Fiscal News beta factor. This factor is constructed using the factor-forming technique following Fama and French (1993), and Bali et al. (2017). In particular, I first sort stocks into two groups based on size, with the threshold being the median market capitalisation of stocks traded on the NYSE[11]. In the next step, I independently sort stocks into three groups based on their exposure to Fiscal News (i.e. absolute β^{FN}). Six portfolios are generated as the intersection of these two size groups and three absolute β^{FN} groups. The equal-weighted (value-weighted) β^{FN} factor is constructed as the mean returns of the two equal-weighted (value-weighted) low β^{FN} portfolios minus the two equal-weighted (value-weighted) high β^{FN} portfolios. Summary statistics of this factor are reported in Table 4.7.

As can be seen from the table, the equal-weighted Fiscal News factor generates an average monthly return of 0.56%, and it is strongly significant with a Newey-West *t-statistics* of 6.77. The return of this factor remains significant when I check for the alphas of this factor with respect to different factor models. α_{Mkt} , which is the alpha relative to the market factor is 0.43% with a Newey-West *t-statistics* of 5.41. Similarly, α_{FM3} and α_{CH4} are also positive and strongly significant with their Newey-West *t-statistics* being 6.21, and 6.61 respectively.

[11]This data is from Kenneth R. French data library.

The next row shows summary statistics of the value-weighted Fiscal News factor. Although the average returns of the value-weighted factor is slightly lower (0.41% monthly), it is still strongly significant with a Newey-West *t-statistics* of 3.91. Alphas range between 0.22% to 0.26%, and all of them are statistically significant.

These results suggest that Fiscal News index is not only priced in the cross-section of stock returns. I also find pricing implications at the portfolio-level by examining the equal-weighted and value-weighted factor captured by the bivariate portfolios of size and absolute β^{FN}. Not only do these two equal-weighted and value-weighted factors generate significant positive returns, the returns are also not explained by well-known risk factors.

4.5.5 Channels of Fiscal News risk premium

Based on existing theoretical guidance, there are two potential channels through which Fiscal News can influence the stock returns, including the expected cashflow and discount rate channels. In order to identify the relevant channel for Fiscal News, I decompose the returns components into two components: changes in cash flow expectations (i.e., cash flow news) and changes in discount rates (i.e., expected returns news) within the Campbell-Shiller-Vuolteenaho framework. The methodology is described in details in Chen et al. (2013) and Vuolteenaho (2002).

I then replicate cross-sectional regressions in column (8) of Panel A and Panel B in Table 4.6 with the dependent variable being the cash flow news and expected returns news respectively. Results of these regressions are reported in Table 4.9.

The first two columns examine the link between exposure to Fiscal News and the cash flow news. The slope coefficient of β^{FN} is not statistically significant. It indicates that exposure to Fiscal News does not impact the expected cash flow of stocks. The last two columns show the link between exposure to Fiscal News and the expected returns news. The slope coefficients of β^{FN} are positive and statistically significant, regardless of whether industry fixed effect is included. This result can be interpreted as follows. For stocks with high exposure to Fiscal News, investors consider it as negative news for discount rate (i.e. it increases the discount rate), therefore they require higher expected returns for these stocks. Overall, empirical findings suggest the channel that Fiscal News Index predicts stock expected return is through the discount rate. My results therefore provide evidence supporting theoretical framework by Pástor and Veronesi (2013), which suggest that political uncertainty increases the discount rates as investors command a risk premium associated with this factor.

4.6 Robustness

In this section, I carry out a number of further tests to check for robustness of my findings.

Placebo tests. In order to ensure that my findings with regard to risk price of Fiscal News Index are not due to data mining, I replace Fiscal News with other 8 topics identified by LDA Algorithm and investigate whether the results also hold. In particular, I also sort stocks into quintiles based on their exposure (i.e. absolute value of β) to each of these topics. There should not be a significant dispersion in terms of excess returns of the extreme portfolios, therefore HML portfolio should not also generate statistically significant average returns. The results regarding HML portfolio performance should be even weaker for topics that are not closely related to the economy. Summary statistics showing Carhart (1997) four-factor model alpha of these portfolios can be found in Table 4.10.

The last row shows the returns of HML portfolio, which are all insignificant for Topic 1 to Topic 7. The last column draws some attention as the return of HML portfolio is positive (0.18%) and statistically significant with a Newey-West *t-statistics* of 2.08. This is reasonable given that the Immigration content should also be relevant for stock return as shown in Sharifkhani (2018). However, the result is weaker than Fiscal News both economically and statistically, as the corresponding result for Fiscal News is an average return of 0.22% with a Newey-West *t-statistics* of 2.34. Therefore, overall these results indicate that Fiscal News is the topic that contain the most relevant information for the cross-section of stock returns.

Other business cycle indicators. The strength of Fiscal News compared with other business cycle indicators is the long time period that it covers. I also test whether Fiscal News outperforms other business cycle indicators in terms of asset pricing. In particular, I also implement trading strategies based on other different business cycle indicators, including Fiscal Policy Uncertainty from Baker et al. (2016) (FB), 1-month-ahead, 3-month-ahead, and 12-month-ahead macroeconomic uncertainty indices respectively from Jurado et al. (2015)(UNC^m, UNC^q, UNC^y). Summary statistics showing Carhart (1997) four-factor model alpha of these portfolios can be found in Table 4.11. The result for HML portfolio is positive and statistically significant for Fiscal News, whereas it is not significant for UNC^m and UNC^q. HML portfolio of UNC^y, and FB is marginally significant, and its magnitude is also smaller than the portfolio of Fiscal News. These results imply better ability of Fiscal News compared to other business cycle indicators in terms of pricing cross-section of stock returns.

Risk premium in different industries. One way to confirm the role of Fiscal News as a priced factor in the stock returns is to check the risk premium of Fiscal News in each of the industries rather than the full universe of CRSP stocks. Stocks are categoried into industries based on 5-industry SIC Code classification from Kenneth French data library. These industries include consumer, manufacturing, hi tech, healthcare, and others. Stocks are then sorted into quintiles based on exposure to Fiscal News, and alphas with respect to Carhart (1997) four factor model are reported in Table 4.12 .

The α_{CH4} of HML portfolio are positive and strongly significant for all 5 industries. It suggests the role of Fiscal News as a risk factor for stock returns of all industries beyond conventional risk factors. The result is strongest for hi tech and manufacturing industry as the risk adjust returns of HML portfolio of these two industries are 0.5% and 0.46% respectively.

Sub-sample. One potential particular concern with empirical results of this paper is that the sample starts from 1920s, which is much earlier than most other empirical asset pricing papers, so it poses the question as to whether the results hold for the sample starting from 1960s as commonly used in other papers. To address this concern, I check the role of Fiscal News as a risk factor for the sample from July 1963. With the sample starting at this date, data of other risk factors are available. Therefore I can also do another robustness check of estimating Fiscal News beta by adding investment (CMA), and profitability (RMW) factors (Fama and French 2015)[12] to Eq. (4.4). I then replicate the Fiscal News beta sorted portfolios and cross-sectional asset pricing tests for this sample. Results can be found in Table C.1 and Table C.2 in the Online Appendix. In general, all results hold and they are even stronger than what is found with the full sample in the main paper. The equal-weighted HML portfolio exploiting the return predictability of Fiscal News can generate an average return of of 8.9% annually with Sharpe ratio of 0.93. This indicates the robustness of my empirical findings regardless of the sample choice.

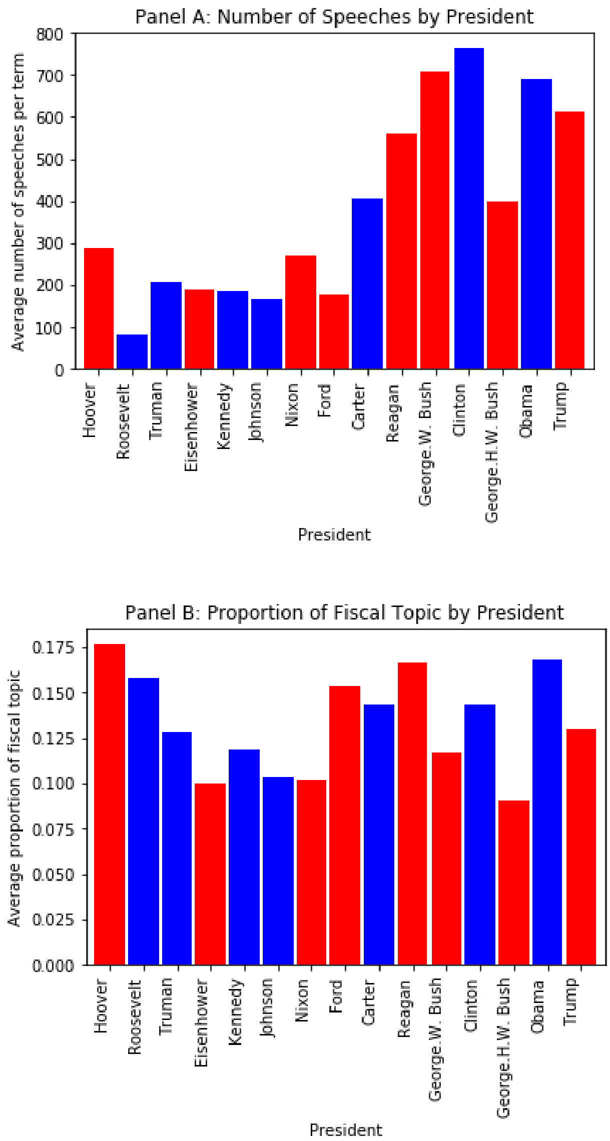
[12] Data of CMA and RMW factors are from Kenneth French data library.

4.7 Conclusion

In this paper, I have implemented textual analysis to construct Fiscal News Index based on large historical sample of U.S. President speeches. This novel long time-series Fiscal News Index can be considered as a dimension of political risk and it spikes around the economic recessions as the president is likely to propose fiscal policy changes during unfavourable economic conditions. An increase in Fiscal News Index is also linked with an increased likelihood of a recession in the next quarter.

I then sort stocks into portfolios based on their exposure to Fiscal News Index. There is a significant dispersion in terms of excess returns between two extreme portfolios. A trading strategy that goes long portfolio with high exposure to Fiscal News and short portfolio with low exposure to Fiscal News generates an average excess returns of 8.2% annually. Empirical findings suggest that this index is a risk factor priced in the cross-section of stock returns. Decomposing the expected return into Cash flow news return and Discount rate return, I find that the pricing implications of Fiscal News for cross-sectional stock returns is mainly through the Discount rate news channel. Investors demand higher expected excess returns for stocks with high exposure to Fiscal News as they are deemed riskier.

Figure 4.1: Frequency of U.S. President Speeches

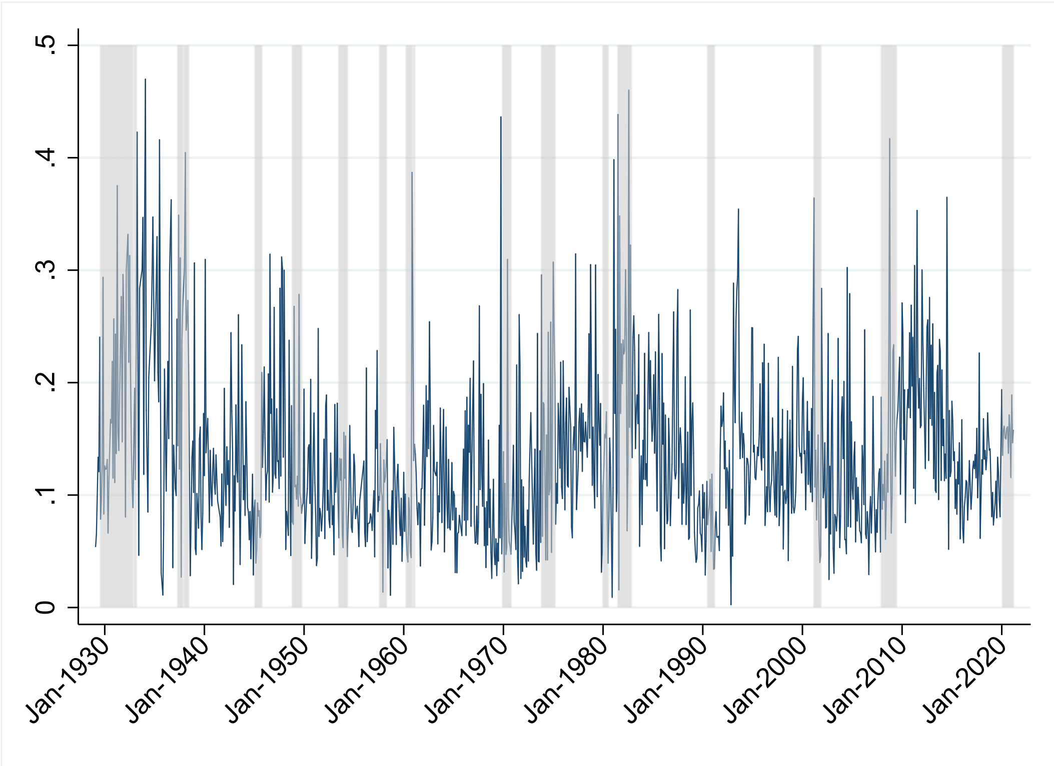


The figure reports the number of speeches by president (Panel A), and the porportion of fiscal topic mentioned by president (Panel B). Blue bars represent presidents from Democratic party, and red bars represent presidents from Republican party. The data is between February 1929 and December 2020.

Figure 4.2: Fiscal Topic

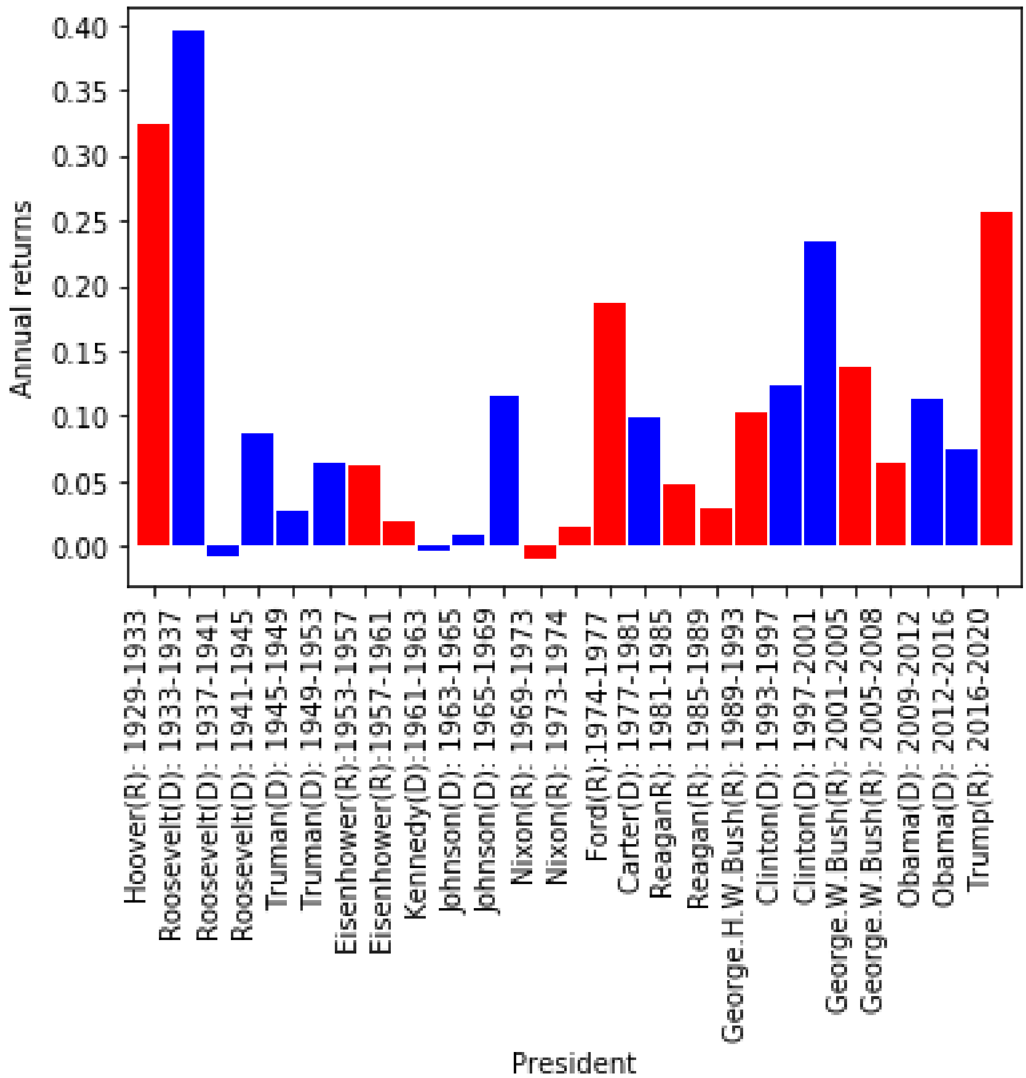
The figure reports most important words for the Fiscal Topic. The data is between February 1929 and December 2020.

Figure 4.3: Fiscal News Index



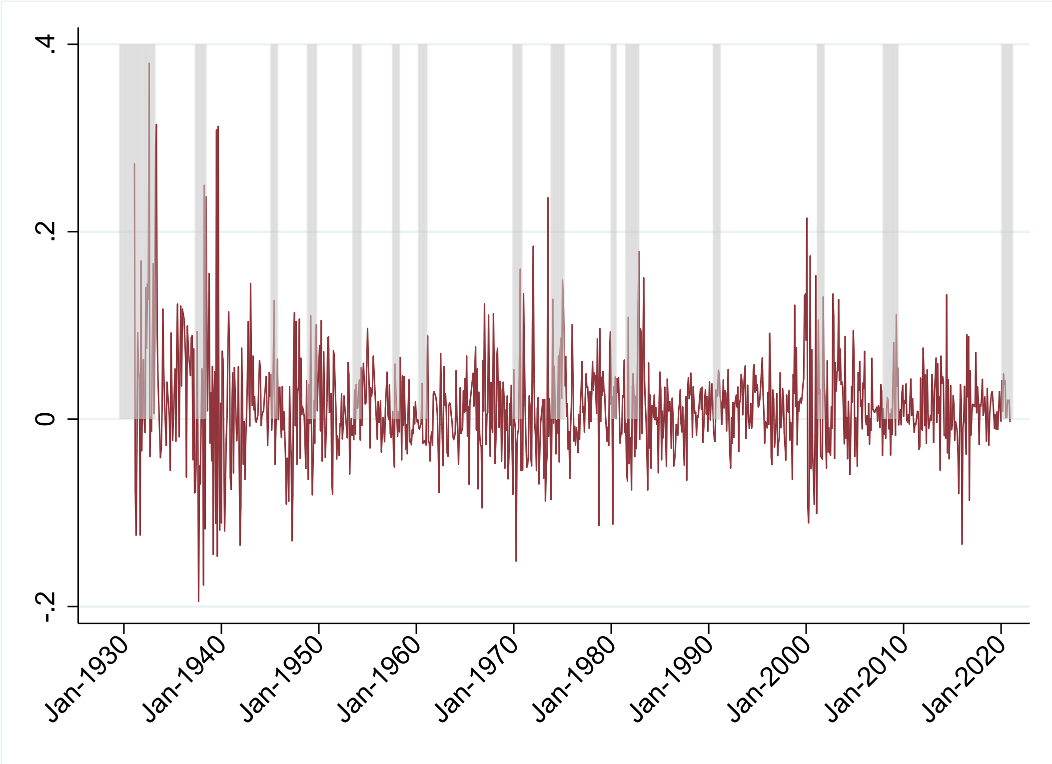
The figure reports Fiscal News Index. This is the average proportion of Fiscal topic across all paragraphs during the month. NBER recession months are shaded in grey color. The data is monthly between February 1929 and December 2020.

Figure 4.4: Trading Strategy based on Fiscal News Index Profit by President



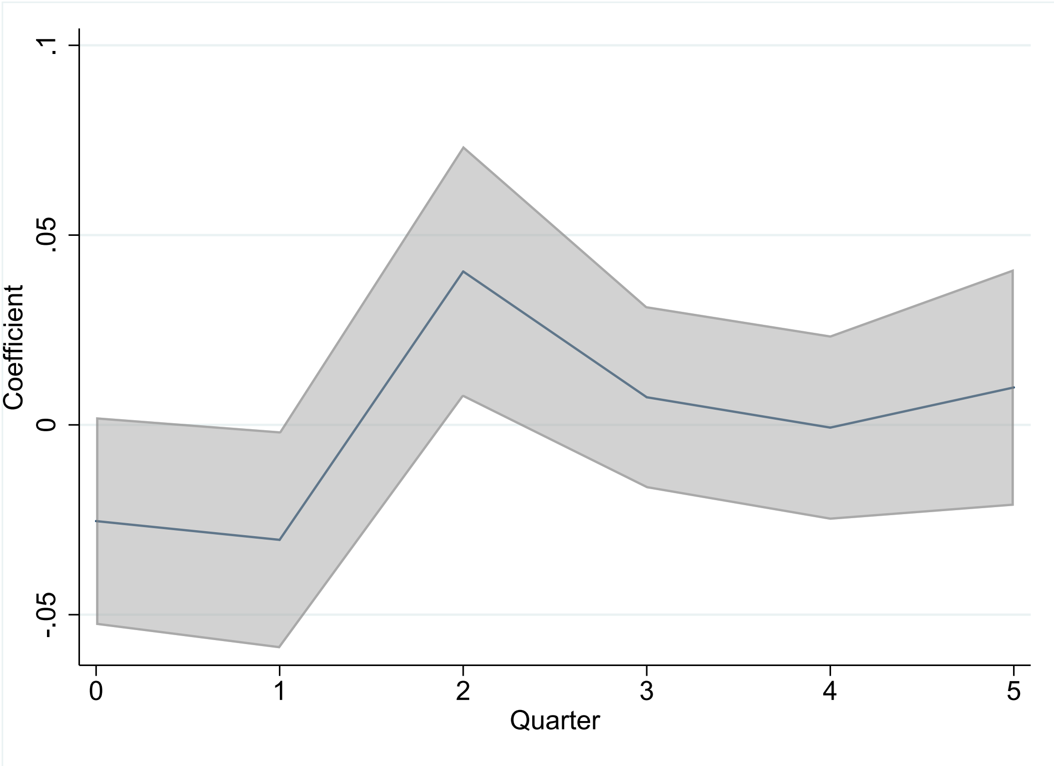
The figure reports the average annual returns by president term of the portfolio based on Fiscal News sorted strategy. Blue bars represent presidents from Democratic party, and red bars represent presidents from Republican party. The data is monthly between February 1929 and December 2020.

Figure 4.5: Time-varying Fiscal News Index Risk Premium



The figure reports the time-varying risk premium of Fiscal News risk factor in the cross-section of stock returns. NBER recession months are shaded in grey color. The data is monthly between February 1929 and December 2020.

Figure 4.6: Estimated impact of Fiscal News Index on GDP growth



The figure reports the estimated impact of Fiscal News Index on GDP growth in the next 5 quarters. Shaded areas represent the 90% confidence interval. The data is quarterly between Quarter 1 1947 and Quarter 4 2020.

Table 4.1: Distribution of LDA Topic Keywords

The table reports topics identified by LDA Algorithm implemented on 452,551 paragraphs from U.S presidential speeches from February 1929 to December 2020. For each topic, the top key words and their associated probability are reported.

Topic 0		**Topic 1**		**Topic 2**	
Weight	Word	Weight	Word	Weight	Word
0.03	job	0.002	militari	0.004	congress
0.002	tax	0.002	defens	0.003	vote
0.002	busi	0.001	union	0.002	pass
0.002	economi	0.001	war	0.002	democrat
0.002	percent	0.001	polic	0.002	senat
0.01	pay	0.001	child	0.002	reform
0.001	billion	0.001	weapon	0.002	republican
0.001	cut	0.001	threat	0.002	elect
0.001	increas	0.001	europ	0.002	bill
Topic 3		**Topic 4**		**Topic 5**	
Weight	Word	Weight	Word	Weight	Word
0.003	china	0.002	care	0.001	student
0.001	deal	0.002	health	0.001	pandem
0.001	iraq	0.002	school	0.001	start
0.001	leader	0.002	test	0.001	team
0.001	discuss	0.002	vaccin	0.001	win
0.01	global	0.001	edu	0.001	news
0.01	minist	0.001	feder	0.001	guess
0.01	prime	0.001	drug	0.001	pretti
0.08	relationship	0.001	children	0.001	mission
Topic 6		**Topic 7**		**Topic 8**	
Weight	Word	Weight	Word	Weight	Word
0.02	famili	0.02	free	0.02	border
0.01	hospit	0.02	freedom	0.02	decad
0.01	women	0.01	futur	0.01	north
0.01	friend	0.01	challeng	0.01	oil
0.01	dream	0.01	build	0.01	south
0.01	children	0.01	opportun	0.01	war
0.01	beauti	0.01	human	0.01	shot
0.01	fight	0.01	power	0.01	korea
0.01	lost	0.01	citizen	0.01	air

Table 4.2: Summary Statistics of Fiscal News Index

This table reports summary statistics of Fiscal News Index. I report mean, standard deviation, minimum and maximum values, skewness, kurtosis, and first order autocorrelations of the index and its changes (i.e.Δ). The data is monthly between February 1929 and December 2020.

Panel A: Fiscal News Index (1929-2020)		
	Fiscal News Index	ΔFiscal News Index
Mean	0.14	0.00
Std	0.07	0.75
Min	0.00	-4.04
Max	0.47	3.77
Skewness	1.22	-0.09
Kurtosis	4.83	5.74
AC (1)	0.22	-0.46
Panel B: Fiscal News Index (1929-1963)		
	Fiscal News Index	ΔFiscal News Index
Mean	0.13	0.00
Std	0.07	0.72
Min	0.02	-4.04
Max	0.46	3.75
Skewness	1.10	-0.09
Kurtosis	4.88	6.74
AC (1)	0.27	-0.40
Panel C: Fiscal News Index (1964-2020)		
	Fiscal News Index	ΔFiscal News Index
Mean	0.14	0.00
Std	0.08	0.73
Min	0.01	-2.60
Max	0.47	2.26
Skewness	1.32	-0.10
Kurtosis	4.55	4.09
AC (1)	0.19	-0.50

Table 4.3: Correlations with Economic Uncertainty and Political Risk Indices

This table reports correlations between Fiscal News Index and some indices for economic uncertainty and political risks. EPU, and EPU^F are the Economic Policy Uncertainty and Fiscal Policy Uncertainty from Baker et al. (2016); UNC^m, UNC^q, UNC^y are 1-month-ahead, 3-month-ahead, and 12-month-ahead macroeconomic uncertainty indices respectively from Jurado et al. (2015), ICRG ER is the Economic Risk index from International Country Risk Guide (ICRG), APR is the Aggregate Populist Rhetoric index from Filippou et al. (2020b). Figures in parentheses are p-values. I report results for both index level (Panel A) and its percentage change (Panel B). The data is monthly and subject to data availability.

			Panel A: Index Level				
	EPU	EPU^F	UNC^m	UNC^q	UNC^y	ICRG ER	APR
Fiscal News Index	0.30	0.33	0.13	0.13	0.15	0.17	0.24
	(0.03)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
			Panel B: Index Change				
	ΔEPU	ΔEPU^F	ΔUNC^m	ΔUNC^q	ΔUNC^y	ΔICRG ER	ΔAPR
ΔFiscal News Index	0.05	0.14	0.06	0.04	0.02	0.02	0.09
	(0.34)	(0.00)	(0.13)	(0.28)	(0.56)	(0.73)	(0.41)

Table 4.4: Fiscal News Index and Recessions

This table reports the results from logit regression. Dependent variable is a dummy variable which takes the value of 1 if the quarter is a recession based on NBER recession indicator, and 0 otherwise . Independent variables are Fiscal News Index, and Spread (the difference between 3-month interest rate and 10-year interest rate), and Unemployment rate. Robust t-statistics are reported in squared brackets. The data is monthly between February 1929 and December 2020.

Panel A: Contemporaneous Fiscal News and Recession

	(1)	(2)	(3)	(4)
Fiscal News Index	6.25**	6.52	5.51	12.94**
	[2.48]	[1.51]	[1.06]	[2.17]
Slope		-0.27*	-0.29*	-0.62***
		[-1.84]	[-1.87]	[-2.62]
Unemployment			-0.07	-0.57***
			[-0.51]	[-2.93]
Lagged recession				5.76***
				[6.91]
Constant	-2.44***	-2.47***	-1.76*	-1.34
	[-6.15]	[-3.91]	[-1.89]	[-1.22]
Obs	367	247	203	203
Adj R^2	1.62%	1.73%	1.79%	52.09%

Panel B: Predictive Fiscal News and Recession

	(1)	(2)	(3)	(4)
Fiscal News Index	6.43**	8.81*	8.81*	23.79**
	[2.56]	[1.95]	[1.89]	[2.28]
Slope		-0.32**	-0.34**	-0.89**
		[-2.16]	[-2.15]	[-2.71]
Unemployment			-0.11	-0.74***
			[-2.15]	[-3.55]
Lagged recession				6.55***
				[4.95]
Constant	-2.46***	-2.73***	-1.98**	-1.91
	[-6.21]	[-4.21]	[-2.09]	[-1.45]
Obs	366	247	203	203
Adj R^2	2.02%	3.25%	4.09%	53.82%

Table 4.5: Univariate portfolio of stocks sorted by Fiscal News Index beta

In each month, stocks are sorted into quintiles based on their exposure to Fiscal News Index (absolute value of $\beta_{i,t}^{FN}$), where quintile 1 (5) contains stocks with lowest (highest) $\beta_{i,t}^{FN}$ in the previous month. Panel A reports the equal-weighted portfolios, whereas Panel B reports the value-weighted portfolios. The first column shows the average excess return RET-RF in percentage. The next columns shows the average $\beta_{i,t}^{FN}$. α_{Mkt} is the alpha relative to market factor, α_{FM3} is the alpha relative to market, size, book-to-market factors, α_{FM4} is the alpha relative to market, size, book-to-market, and momentum factors. High-Low is the portfolio that has a long position in P5 and a short position in P1. The annualised Sharpe ratio (SR) of the High-Low portfolio is reported. Newey and West (1986) t-statistics are reported in squared brackets. The data is monthly between February 1929 and December 2020.

Panel A: Equal-weighted portfolios					
Quintile	RET-RF	β	α_{Mkt}	α_{FM3}	α_{CH4}
1 (Low)	0.93	0.02	0.16	0.03	0.10
	[4.32]		[2.20]	[0.57]	[2.21]
2	0.95	0.07	0.16	0.01	0.09
	[4.26]		[2.11]	[0.25]	[2.02]
3	1.04	0.13	0.23	0.09	0.16
	[4.51]		[2.85]	[1.79]	[2.99]
4	1.22	0.22	0.35	0.18	0.27
	[4.86]		[3.72]	[3.18]	[4.84]
5 (High)	1.61	0.48	0.66	0.48	0.59
	[5.70]		[5.52]	[6.65]	[7.57]
High-Low	0.68		0.50	0.45	0.49
	[7.10]		[6.18]	[7.18]	[6.97]
SR	0.86				

Panel B: Value-weighted portfolios					
Quintile	RET-RF	β	α_{Mkt}	α_{FM3}	α_{CH4}
1 (Low)	0.35	0.02	-0.27	-0.24	-0.24
	[2.17]		[-6.52]	[-6.50]	[-6.15]
2	0.36	0.07	-0.27	-0.25	-0.26
	[2.16]		[-7.03]	[-6.82]	[-6.82]
3	0.49	0.13	-0.20	-0.20	-0.20
	[2.67]		[-4.85]	[-4.95]	[-5.06]
4	0.59	0.22	-0.19	-0.20	-0.16
	[2.81]		[-2.82]	[-3.18]	[-2.44]
5 (High)	0.85	0.48	-0.46	-0.08	-0.02
	[3.34]		[-0.47]	[-0.98]	[-0.21]
High-Low	0.50		0.22	0.02	0.22
	[3.82]		[1.97]	[1.80]	[2.34]
SR	0.41				

Table 4.6: Cross-section Asset Pricing with Fiscal News Index

This table reports regressions results for the estimation of the market price of Fiscal News Index (λ_{FN}). The control variables are market beta (λ_{Mkt}), size, reversal, momentum, liquidity, skewness, and idiosyncratic risk. Constants are not reported due to brevity. Panel A reports regressions without industry fixed effect, and Panel B reports regressions with industry fixed effect. Newey and West (1986) t-statistics are reported in squared brackets, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. The data is monthly between February 1929 and December 2020.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Without industry fixed effect								
λ_{FN}	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***
	[6.43]	[6.48]	[6.41]	[6.60]	[5.70]	[3.88]	[3.93]	[3.12]
λ_{Mkt}		0.00**	0.00**	0.00**	0.00**	0.00***	0.00***	0.00***
		[2.13]	[2.01]	[2.38]	[2.22]	[3.22]	[3.25]	[3.0]
Size			-0.00***	-0.00**	-0.00**	-0.00**	-0.00**	-0.00*
			[-2.34]	[-2.30]	[-2.25]	[-2.03]	[-1.99]	[-1.65]
Reversal				-0.04***	-0.04***	-0.04***	-0.05***	-0.05***
				[-11.33]	[-11.35]	[-11.78]	[-12.24]	[-12.86]
Momentum					0.01***	0.01***	0.01***	0.01***
					[3.22]	[3.15]	[3.18]	[3.57]
Liquidity						0.21***	0.21***	0.20***
						[9.38]	[9.37]	[9.27]
Skewness							0.00***	0.00***
							[4.12]	[3.35]
Idiosyncratic risk								0.18***
								[3.38]
Obs	1,399,305	1,399,305	1,399,305	1,399,305	1,399,305	1,398,148	1,398,140	1,398,140
Adj R^2	0.7%	1.9%	2.3%	3.33%	4.78%	5.68%	5.88%	6.76%
Panel B: With industry fixed effect								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
λ_{FN}	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***
	[6.40]	[6.45]	[6.37]	[6.52]	[5.64]	[3.72]	[3.70]	[2.92]
λ_{Mkt}		0.00**	0.00**	0.00***	0.00**	0.00***	0.00***	0.00***
		[2.26]	[2.10]	[2.43]	[2.28]	[3.72]	[3.34]	[3.12]
Size			-0.00**	-0.00**	-0.00**	-0.00*	-0.00*	-0.00
			[-2.32]	[-2.28]	[-2.23]	[-1.96]	[-1.92]	[-1.52]
Reversal				-0.05***	-0.05***	-0.05***	-0.05***	-0.05***
				[-12.57]	[-12.44]	[-12.87]	[-13.44]	[-13.84]
Momentum					0.00***	0.00***	0.00***	0.00***
					[2.77]	[2.70]	[2.73]	[3.10]
Liquidity						0.21***	0.21***	0.20***
						[9.47]	[9.46]	[9.45]
Skewness							0.00***	0.00***
							[4.27]	[3.56]
Idiosyncratic risk								0.17***
								[3.41]
Obs	1,399,305	1,399,305	1,399,305	1,399,305	1,399,305	1,398,148	1,398,140	1,398,140
Adj R^2	3.19%	4.22%	4.58%	5.57%	6.81%	8.08%	7.85%	9.03%

Table 4.7: Fiscal News Index Beta Factors

At the end of each month, all stocks in the sample are sorted into two groups based on the size using the NYSE size breakpoint and three Fiscal News absolute beta groups using the 30th and 70th percentile values of absolute Fiscal News beta. Six portfolios are formed by the intersection of the two size groups and the thee absolute Fiscal News beta groups. The equal-weighted (value-weighted) return of the Fiscal News beta factor is the mean return of the two equal-weighted (value-weighted) high absolute Fiscal News beta portfolios minus the two equal-weighted (value-weighted) low absolute Fiscal News beta portfolios. The alphas relative to different factor models are also reported. α_{Mkt} is the alpha relative to market factor, α_{FM3} is the alpha relative to market, size, book-to-market factors, α_{CH4} is the alpha relative to market, size, book-to-market, and momentum factors. Newey and West (1986) t-statistics are reported in squared brackets. The data is monthly between February 1929 and December 2020.

Average monthly returns and alphas of the Fiscal News beta factors				
	Average returns	α_{Mkt}	α_{FM3}	α_{CH4}
EW β_{FN} factor	0.56%	0.43%	0.42%	0.44%
	[6.77]	[5.41]	[6.21]	[6.61]
VW β_{FN} factor	0.41%	0.23%	0.22%	0.26%
	[3.91]	[2.28]	[2.38]	[2.76]

Table 4.8: Average stock characteristics

This table reports the time-series averages of the slope coefficients from the regressions of the exposure to Fiscal News Index (absolute value of $\beta_{i,t}^{FN}$) on the stock-level characteristics. The independent variables are market beta (λ_{Mkt}), size, reversal, momentum, illiquidity, skewness, and idiosyncratic volatility. Newey and West (1986) t-statistics are reported in squared brackets, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. The data is monthly between February 1929 and December 2020.

	Stock characteristics							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
λ_{Mkt}	0.03**							0.02***
	[12.56]							[10.78]
Size		-0.00**						-0.00***
		[-9.32]						[-8.84]
Reversal			0.04***					-0.03***
			[7.58]					[-7.51]
Momentum				0.06***				0.05***
				[16.14]				[17.79]
Illiquidity					10.51***			61.38***
					[14.22]			[10.97]
Skewness						0.01***		0.00
						[18.72]		[1.01]
Idiosyncratic volatility							4.37***	3.69***
							[36.88]	[33.48]
Obs	1,399,040	1,399,040	1,399,040	1,399,040	1,399,040	1,399,040	1,399,040	1,399,040
Adj R^2	1.86%	1.22%	0.76%	2.13%	2.37%	0.33%	7.77%	10.90%

Table 4.9: Decomposing stock-level return innovations

This table reports regressions results for the estimation of the market price of Fiscal News Index (λ_{FN}) when returns are decomposed into the cashflow and expected returns components based on the Campbell and Shiller (1988). Dependent variables are the cashflow news component in the first two columns, and expected returns news component in the next two columns. The control variables are market beta (λ_{Mkt}), size, reversal, momentum, liquidity, skewness, and idiosyncratic risk. Fixed effects refer to industry fixed effects. Newey and West (1986) t-statistics are reported in squared brackets, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. The data is monthly between February 1929 and December 2020.

Return innovation decomposition				
	Cashflow news		Expected returns news	
	(1)	(2)	(3)	(4)
λ_{FN}	-0.00	-0.00	0.02**	0.02**
	[-0.88]	[-0.95]	[2.11]	[2.15]
Controls	Yes	Yes	Yes	Yes
Fixed effects	No	Yes	No	Yes
Obs	726,054	726,054	726,054	726,054
Adj R^2	13.8%	14.8%	15.8%	16.7%

Table 4.10: Placebo Tests

In each month, stocks are sorted into quintiles based on the absolute value of their exposure to each of 8 topics identified by LDA Algorithm, where quintile 1 (5) contains stocks with lowest (highest) exposure in the previous month. Carhart (1997) four-factor model alpha for each portfolio is reported. High-Low reports the average returns of a strategy that goes long the high portfolio (P5) and short the low portfolio (P1). Newey and West (1986) t-statistics are reported in squared brackets. The data is monthly between February 1929 and December 2020.

Quintile	Topic 1	Topic 2	Topic 3	Topic 4	Topic 5	Topic 6	Topic 7	Topic 8
1 (Low)	-0.23	-0.28	-0.21	-0.22	- 0.23	-0.26	-0.16	-0.21
	[-6.01]	[-4.94]	[-5.66]	[-5.80]	[-5.88]	[-6.63]	[-4.53]	[-5.11]
2	-0.24	-0.22	-0.26	-0.23	-0.23	-0.19	-0.25	-0.29
	[-6.39]	[-5.20]	[-6.51]	[-5.78]	[-5.44]	[-4.66]	[-6.73]	[-6.91]
3	-0.30	-0.22	-0.16	-0.20	-0.16	-0.24	-0.31	0.10
	[-6.49]	[-5.20]	[-3.17]	[-4.77]	[-3.04]	[-5.10]	[-8.51]	[-4.57]
4	-0.49	-0.10	-0.10	-0.25	-0.23	-0.21	-0.21	0.10
	[-0.71]	[-1.69]	[-4.81]	[-4.35]	[-3.69]	[-3.63]	[-3.67]	[-3.30]
5 (High)	-0.11	-0.17	-0.18	-0.13	-0.11	-0.10	-0.03	-0.03
	[-1.49]	[-2.37]	[-2.24]	[-1.47]	[-1.25]	[-1.29]	[-0.43]	[-0.42]
High-Low	0.12	0.11	0.04	0.09	0.13	0.16	0.12	0.18
	[1.38]	[1.36]	[0.40]	[0.99]	[1.34]	[1.68]	[1.40]	[2.08]

Table 4.11: Trading strategies based on other business cycle indicators

In each month, stocks are sorted into quintiles based on the absolute value of their exposure to each of the business cycle indicators, where quintile 1 (5) contains stocks with lowest (highest) exposure in the previous month. FB is the Fiscal Policy Uncertainty from Baker et al. (2016); UNC^m, UNC^q, UNC^y are 1-month-ahead, 3-month-ahead, and 12-month-ahead macroeconomic uncertainty indices respectively from Jurado et al. (2015). Carhart (1997) four-factor model alpha for each portfolio is reported. High-Low reports the average returns of a strategy that goes long the high portfolio (P5) and short the low portfolio (P1). Newey and West (1986) t-statistics are reported in squared brackets. The data is monthly between July 1960 and December 2020 for FN, UNC^m, UNC^q, UNC^y, and between January 1985 and December 2020 for FB.

Quintile	FN	UNC^m	UNC^q	UNC^y	FB
1 (Low)	-0.14	-0.09	-0.10	-0.13	- 0.00
	[-3.83]	[-2.13]	[-2.38]	[-3.15]	[-0.17]
2	-0.16	-0.20	-0.18	-0.12	-0.07
	[-3.40]	[-4.63]	[-4.12]	[-2.91]	[-1.06]
3	-0.13	-0.06	-0.07	-0.15	-0.17
	[-2.87]	[-1.13]	[-1.16]	[-3.01]	[-2.69]
4	-0.06	-0.13	-0.11	-0.04	0.02
	[-0.77]	[-2.03]	[-1.63]	[-0.56]	[0.25]
5 (High)	0.18	0.08	0.03	0.07	0.26
	[1.80]	[0.78]	[0.33]	[0.68]	[2.04]
High-Low	0.32	0.17	0.14	0.20	0.27
	[2.89]	[1.53]	[1.21]	[1.69]	[1.87]

Table 4.12: Fiscal News premium of stocks in five industries

In each month, stocks in each of the five industries are sorted into quintiles based on their exposure to Fiscal News Index (absolute value of $\beta_{i,t}^{FN}$), where quintile 1 (5) contains stocks with lowest (highest) $\beta_{i,t}^{FN}$ in the previous month. Carhart (1997) four-factor model alpha for each portfolio is reported. High-Low reports the average returns of a strategy that goes long the high portfolio (P5) and short the low portfolio (P1). Newey and West (1986) t-statistics are reported in squared brackets. The data is monthly between February 1929 and December 2020.

Quintile	Consumer	Manufacturing	Hi tech	Healthcare	Others
1 (Low)	0.11	0.05	0.22	0.50	0.13
	[1.45]	[0.83]	[2.02]	[3.66]	[1.20]
2	0.11	0.04	0.30	0.52	0.01
	[1.41]	[0.69]	[2.96]	[3.81]	[0.07]
3	0.12	0.09	0.36	0.53	0.01
	[1.37]	[1.34]	[2.81]	[3.25]	[0.60]
4	0.23	0.28	0.54	0.74	0.09
	[2.55]	[3.48]	[3.87]	[4.47]	[0.78]
5 (High)	0.47	0.51	0.76	1.11	0.53
	[4.62]	[4.82]	[4.71]	[5.31]	[3.55]
High-Low	0.35	0.46	0.55	0.46	0.40
	[4.24]	[5.27]	[4.41]	[2.54]	[2.99]

Appendix to

"Textual Analysis in Empirical Asset Pricing"

Appendix A

U.S. Populist Rhetoric and Currrency Returns

1 Populist Articles and LDA Classification

Two sample populist rhetoric articles and their LDA classification results are provided. The populist terms in the articles are in bold.

Article 1: (99% Fiscal topic)
Republicans trying to limit tax cuts' benefits for rich
BYLINE: Damian Paletta
Details are in flux, but some GOP lawmakers are wary of a backlash
White House officials and Republican leaders are preparing a set of broad income and corporate tax cuts while also looking for a way to keep their plan from being a massive windfall for the wealthiest Americans, two people familiar with the plan said.
Party leaders are quietly circulating proposals to lower the corporate tax rate to 20 percent from 35 percent and to lower the top individual income tax rate to 35 percent from 39.6 percent, according to the people familiar with the plan.
White House advisers are divided over whether to cut the top individual tax rate, and Republican leaders, aware the plan could be construed as a huge giveaway to the wealthy, are trying to design features in the package that would ensure that the rich don't get too large a share of the plan's tax relief.
Top White House negotiators and key GOP leaders have agreed on those targets, but apparently President Trump has not. On Sunday, as he was about to board Air Force One in New Jersey, Trump told reporters that he hoped to see the corporate tax rate lowered to 15 percent, a level that his own negotiators had privately dismissed weeks ago.
"We'll see what happens, but I hope it's going to be 15 percent," he told reporters. "But it's going to be substantially lower so we bring jobs back to the country."

The lack of agreement, even days before the plan is set to be unveiled more broadly, underscores the difficulty Republicans face in uniting behind a tax bill. GOP leaders, including House Speaker Paul D. Ryan (Wis.), have said it is impossible to cut the corporate rate to 15 percent without adding too much to the federal debt. As it stands, the tax cut is expected to add at least $1 trillion to the debt, and potentially much more.
As part of the package of tax cuts, the White House and GOP leaders are hoping to persuade their Republican colleagues to cut the rate paid by thousands of businesses that pay taxes through the individual income tax code to 25 percent from 39.6 percent, said the people, who spoke on the condition of anonymity because they were not authorized to speak about the private discussions.
GOP leaders plan to unveil specifics of their targets to their colleagues on Capitol Hill this week, and the details could change as negotiations go forward.
Republicans plan to push for collapsing the seven existing income tax rates to three new brackets, with a top bracket of 35 percent. It is unclear what income level they want to qualify for that tax bracket.
Trump made additional comments on the tax brackets on the tarmac Sunday, but it wasn't clear exactly what he was referring to, and the White House didn't immediately clarify his intention.
"We're going to bring the individual rate to 10 percent or 12 percent, much lower than it is right now," he said.
Among details that have become public, the plan's benefits would accrue largely to the wealthy - an awkward position for a president who promised that his administration would be an economic boon for working-class and middle-class households.
Even the tax cut Trump is hoping to advance for companies that pay individual taxes would help thousands of upper-income business owners in a way that critics have said could be gamed to lower their taxes even more. White House officials have said they would create "guardrails" to prevent against this but have not explained how.
Many contours of the talks are similar to what Trump proposed in April. The Tax Policy Center, a nonpartisan group that reviews tax proposals, found that roughly 50 percent of the cuts from that plan would benefit the **top 1 percent** of U.S. households. The Tax Policy Center found that those households would get an average annual tax cut of $175,000.
External estimates, based on initial reports of the plan and not full details, found that it would cut taxes by $5.5 trillion over 10 years. Some Senate Republicans are trying to tailor the tax cut so that it reduces revenue only by $1.5 trillion over 10 years.
That means the White House and congressional Republicans would have to find $4 trillion in tax breaks to eliminate, something that could prove difficult if they insist on keeping tax rates low for the wealthy.

While rate cuts are broadly popular, many tax breaks are either also popular - such as deductions for charitable giving or for interest paid on a home mortgage - or enjoy support from powerful industries and lobbying groups.
Some details of the plan were reported Friday night by The Washington Post, and others were first reported Saturday by Axios.

Article 2: (39% Election topic, 61% International Relations topic)

In China, wake of Trump's Super Tuesday wins churns up unlikely supporters
BYLINE: Simon Denyer
BEIJING - There was an element of schadenfreude - the pleasure derived from another's misfortune. And then there was the principle that the enemy of my enemy is my friend. The view from here of Super Tuesday highlighted both. But plenty of Chinese people who tuned in just seemed to be enjoying the show.
Donald Trump's latest victories in the race for the Republican nomination unleashed a wave of surprisingly positive comments across Chinese social media, from admiration of his credentials as a "strongman" to hopes he will lift the world economy "out of its quagmire" - and one assertion that he really is not "crazy and stupid."
Last week, Chinese Foreign Ministry spokeswoman Hua Chunying said her country was watching the U.S. presidential race with "bemused interest," and there was a strong current of opinion on social media delighting in America's seemingly chaotic political system.
"It's great fun watching the dogfight in the United States," one user wrote. "This is their democracy."
Other Netizens enjoyed what they saw as their great superpower rival pressing the self-destruct button. "Trump is very cute with a big mouth," one user wrote. "I hope he reigns [over] the United States and makes it as messed up as the Middle East."
Another said he hoped with his "whole heart" that Trump wins the presidential election: "That way I can watch the comedy that is the United States for several years."
But as the nationalist Global Times tabloid noted in an op-ed Thursday, the leading GOP candidate "has surprisingly earned himself a few fans in China."
As the paper noted, it is surprising because Trump has not always had good things to say about China. Although he says he "loves China," and "people from China love me," he also accuses it of stealing American jobs. He promises to immediately declare it a currency manipulator. He rails against its "Great Wall of Protectionism" and pledges to stand firm against its "cheating" and "financial blackmail."
"Many of his ideas are far from heartwarming," columnist Ai Jun wrote in the Global Times piece. "In the normal run of events, China should reject an **arrogant**, hawkish candidate like him out of hand."
But Trump has one thing in common with Chinese people, the columnist suggested: "His winning streak is solid proof that U.S. voters are tired of Washington politics."

"The Chinese people also have had enough of U.S. politicians' deeds betraying their words," Jun wrote.

In an article posted on the party-controlled website, the Paper, and widely circulated online, Shen Xincheng, a doctoral candidate at the Georgia Institute of Technology, urged Chinese people not to rush to judgment, even if the Republican Party and observers alike see Trump as "crazy and stupid."

"To the public, he is the most human among the GOP candidates," Shen wrote. "What he says is truth, as even GOP voters know very well themselves."

Trump has another attraction to the nationalists who often dominate the debate on Chinese social media: He isn't Hillary Clinton.

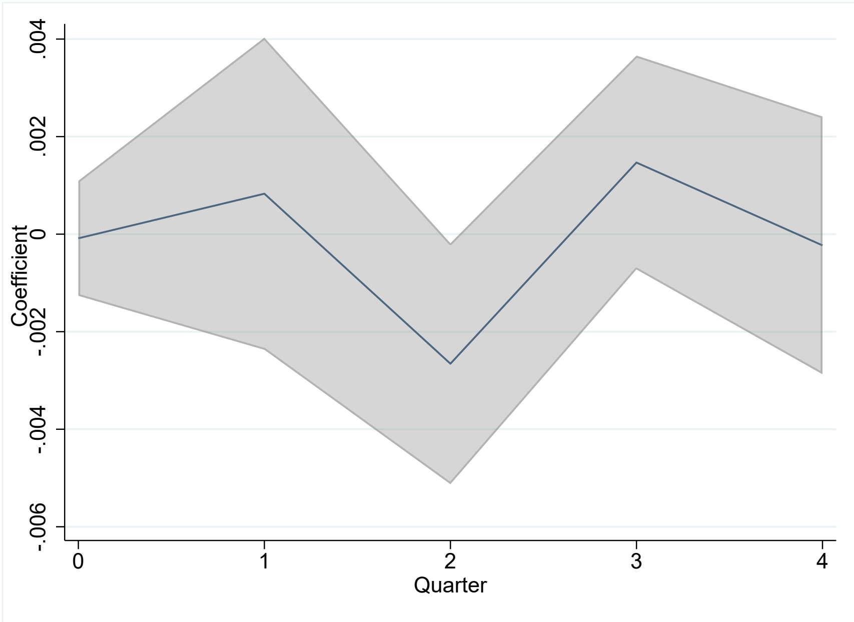
He would be a better president than Clinton "no matter what," one user commented.

"She seems to be less welcomed," the Global Times wrote, "given her tough attitude toward Beijing, incessant accusations about China's human rights record, and her push for the U.S. re-balance to the Asia-Pacific strategy as secretary of state."

Trump sometimes seems fixated on China. But he uses it as a foil to reflect on the relative decline and weakness of the United States. If China can build a Great Wall, he observed this week, without tractors or cranes, then he can build one along the Mexican frontier.

Of course, Chinese social media is a poor reflection of public opinion. Perhaps the approving comments directed at Trump merely reflect the notion that a strongman, and a businessman, in the White House might not be such bad news for a one-party authoritarian regime that commands tremendous economic power.

Figure A.1: Estimated impact of APR Index on GDP growth

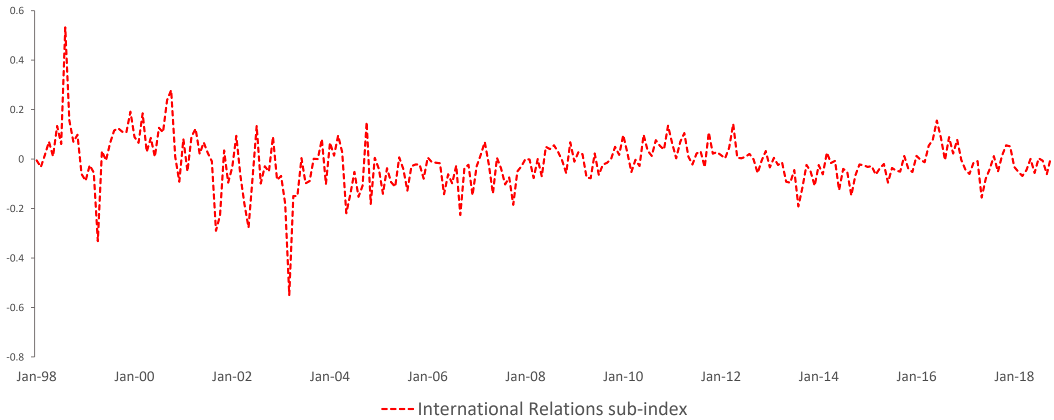


The figure reports the estimated impact of APR Index on GDP growth in the next 4 quarters by running the following regression:

$$\Delta Y_t = \alpha + \sum_{i=0}^{M} \beta_{1,i} APR_{t-i} + \sum_{j=1}^{N} \beta_{2,i} \Delta Y_{t-j} + \epsilon_t \tag{A.1}$$

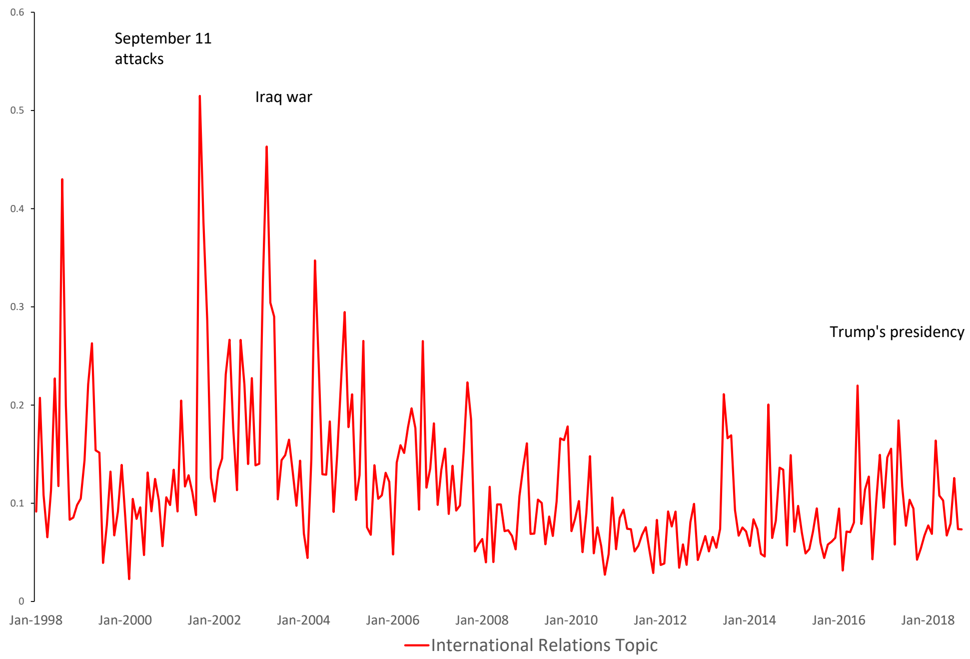
4 lags of both variables are included as independent variables. Shaded areas represent the 90% confidence interval. The data is quarterly between Quarter 1 1998 and Quarter 3 2018..

Figure A.2: International Relations Sub-index



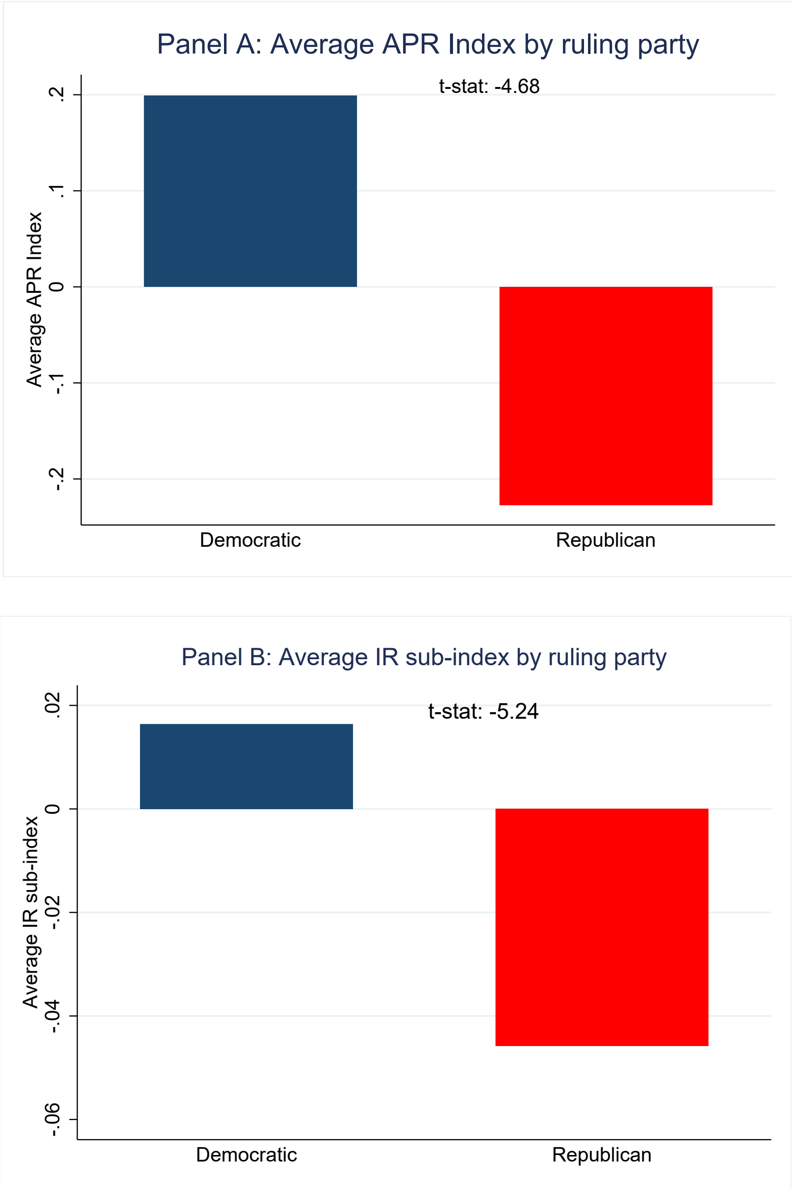
The figure reports International Relations Sub-index. This sub-index is constructed by multiplying the average proportion of International Relations topic across all populist rhetoric newspapers articles from 5 newspapers with the Aggregate Populist Rhetoric Index. The monthly data are between January 1998 and October 2018.

Figure A.3: International Relations Topic Proportion



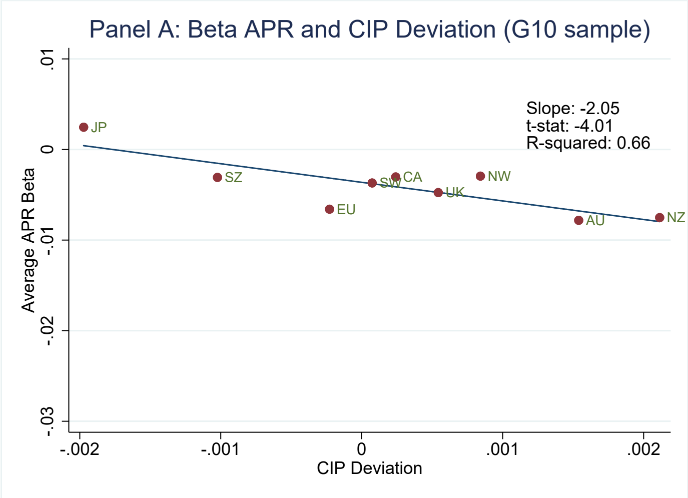
The figure reports International Relations Topic Proportion. This is the proportion of International Relations topic averaged across all articles containing populist rhetoric from The New York Daily News, The New York Post, USA Today, The Washington Post, and The New York Times. The data are between January 1998 and October 2018.

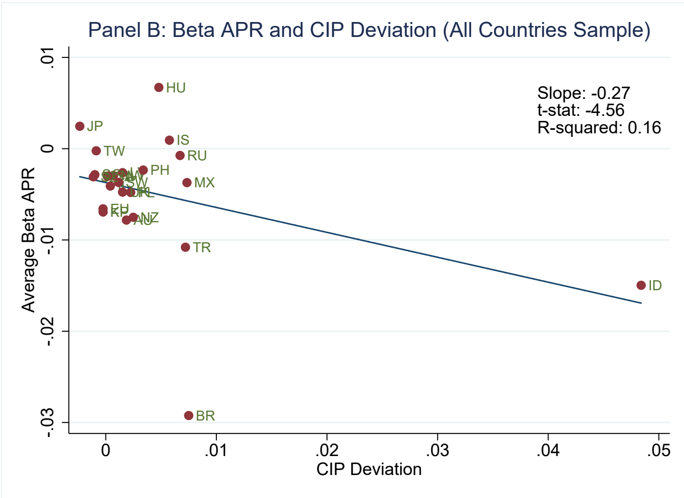
Figure A.4: Average Index by ruling party



The figure shows average APR Index (*Panel A*), and IR sub-index (*Panel B*) by ruling party. The monthly data are between January 1998 and October 2018.

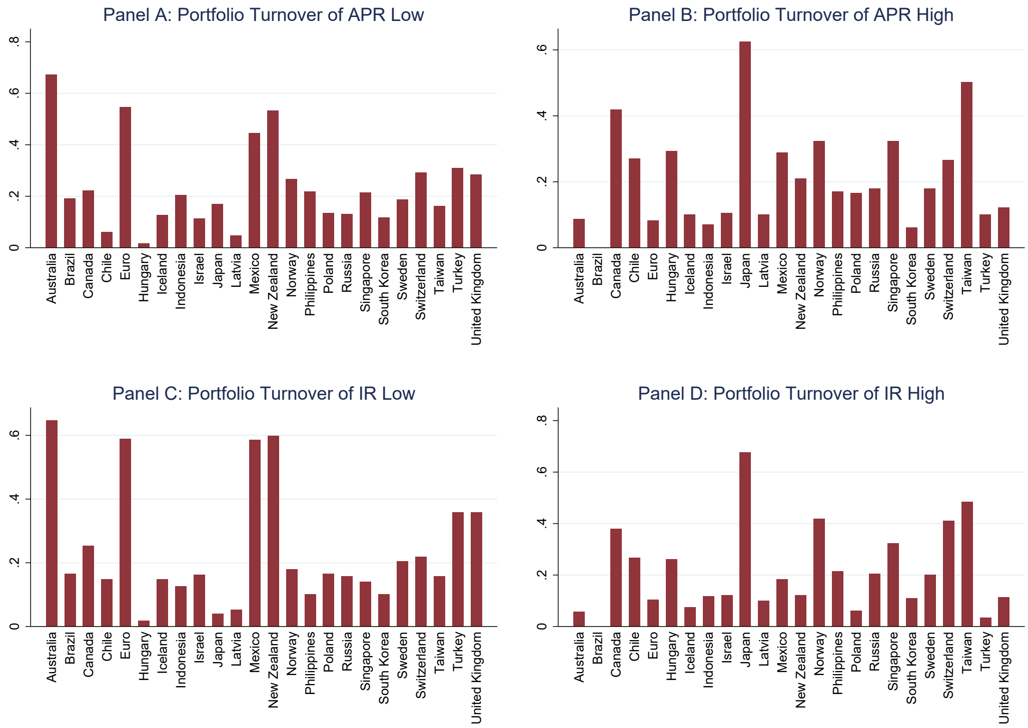
Figure A.5: Average Beta APR and CIP Deviation





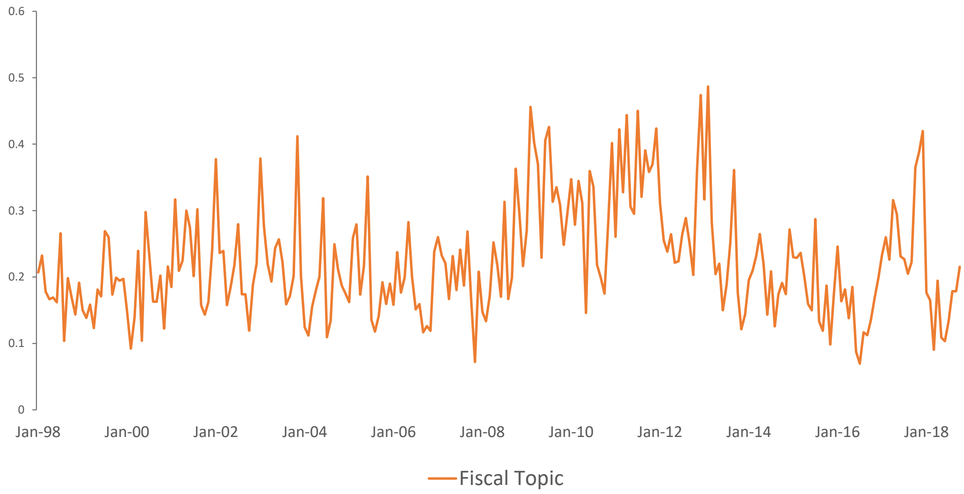
The figure shows average beta APR and CIP Deviation for G10 sample (*Panel A*), All countries sample (*Panel B*). The monthly data are between January 1998 and October 2018.

Figure A.6: Portfolio Turnover



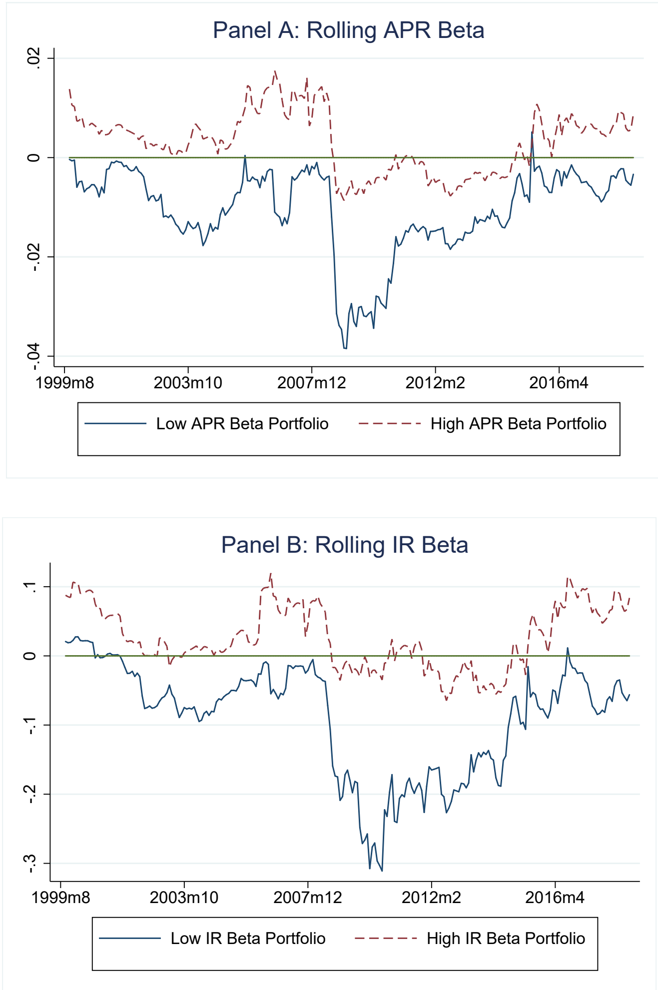
The figure shows the portfolio turnover of currency portfolios sorted on APR Index (*Panel A* and *Panel B*), and on IR sub-index (*Panel C* and *Panel D*). The monthly data are between January 1998 and October 2018.

Figure A.7: Fiscal Topic Proportion



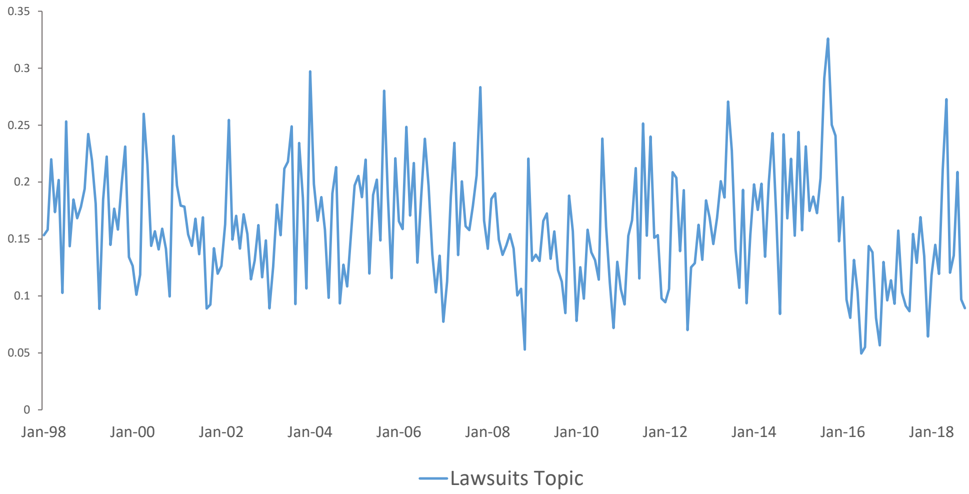
Fiscal Topic Proportion. The monthly average proportion of Fiscal topic in populist rhetoric articles across 5 newspapers the New York Daily News, The New York Post, USA Today, The Washington Post, and The New York Times between January 1998 and October 2018.

Figure A.8: Rolling APR and IR Betas of Porfolios



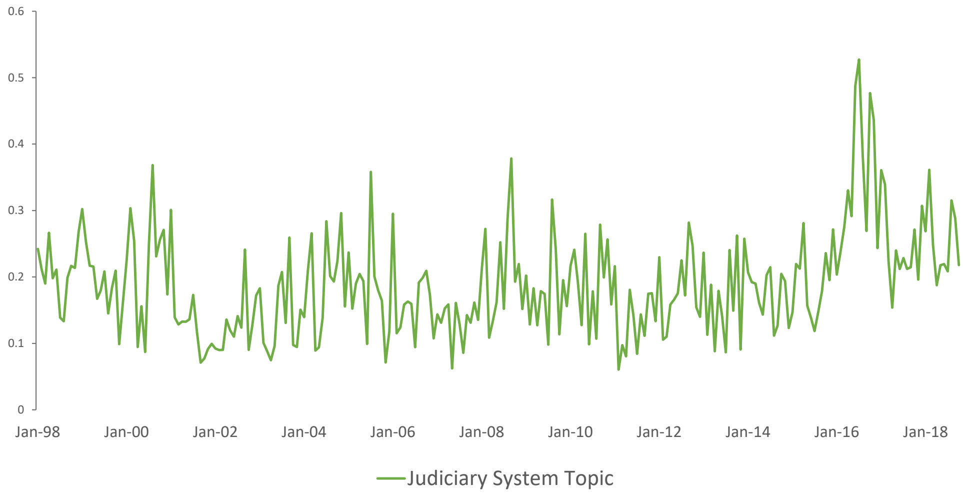
The figure shows the rolling betas of APR (*Panel A*), and IR (*Panel B*). In each panel, we plot the rolling betas of low beta portfolio and high beta portfolio. The monthly data are between January 1998 and October 2018.

Figure A.9: Lawsuits Topic Proportion



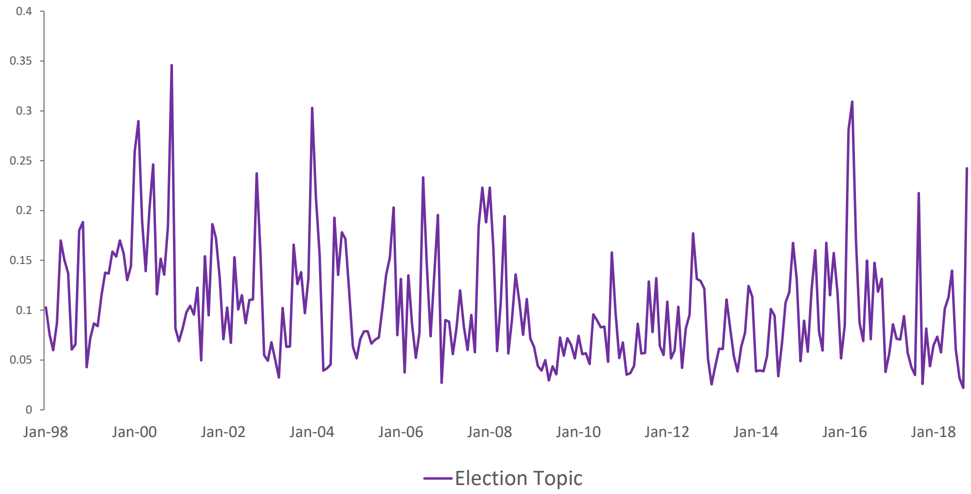
Lawsuits Topic Proportion. The monthly average proportion of Lawsuits topic in populist rhetoric articles across 5 newspapers the New York Daily News, The New York Post, USA Today, The Washington Post, and The New York Times between January 1998 and October 2018.

Figure A.10: Judiciary System Topic Proportion



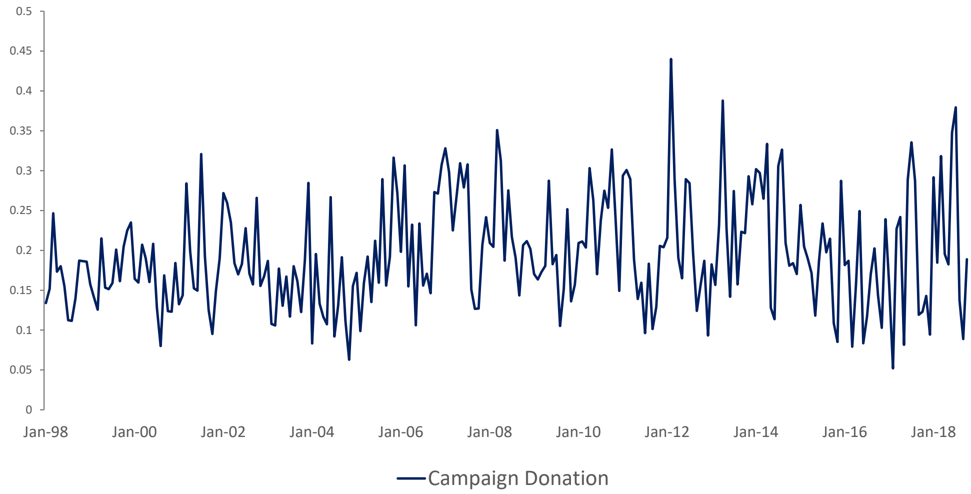
Judiciary System Topic Proportion. The monthly average proportion of Judiciary System topic in populist rhetoric articles across 5 newspapers the New York Daily News, The New York Post, USA Today, The Washington Post, and The New York Times between January 1998 and October 2018.

Figure A.11: Election Proportion



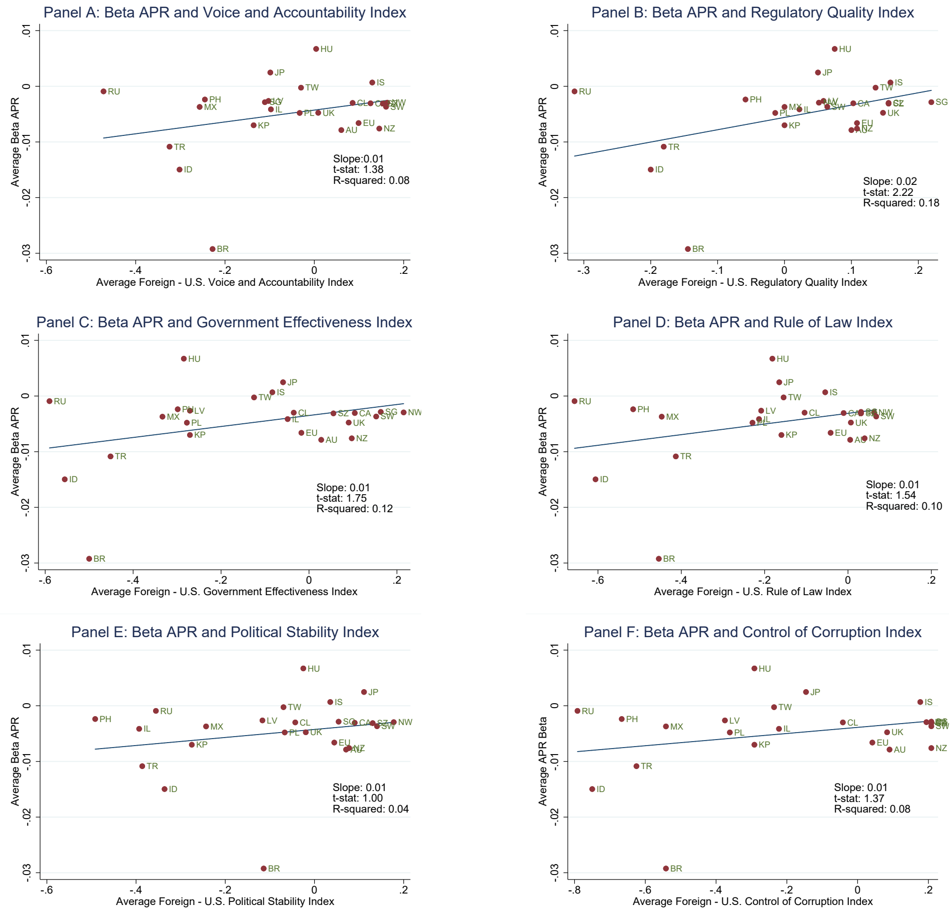
Election Topic Proportion. The monthly average proportion of Election topic in populist rhetoric articles across 5 newspapers the New York Daily News, The New York Post, USA Today, The Washington Post, and The New York Times between January 1998 and October 2018.

Figure A.12: Campaign Donation Proportion



Campaign Donation Topic Proportion. The monthly average proportion of Campaign Donation topic in populist rhetoric articles across 5 newspapers the New York Daily News, The New York Post, USA Today, The Washington Post, and The New York Times between January 1998 and October 2018.

Figure A.13: Average APR Beta and Institutional Quality



The figure shows average APR beta and a range of institutional quality dimensions provided by World Bank (*Panel A*: Voice and Accountability, *Panel B*: Regulatory Quality, *Panel C*: Government Effectiveness, *Panel D*: Rule Of Law, *Panel E*: Political Stability, *Panel F*: Control of Corruption). The monthly data are between January 1998 and December 2017.

Table A.1: Distribution of LDA Topic Keywords

The table reports results from LDA implemented on articles containing populist rhetoric. For each topic, the top 15 key words and their associated probability are reported.

Topic 0 (Lawsuits)		**Topic 1 (Judiciary System)**		**Topic 2 (Fiscal)**	
Weight	Word	Weight	Word	Weight	Word
0.003	park	0.003	suprem	0.004	insur
0.003	william	0.002	nomin	0.003	price
0.003	site	0.002	reagan	0.003	medicar
0.002	town	0.002	nomine	0.003	reduc
0.002	prosecutor	0.002	convent	0.003	debt
0.02	crime	0.002	constitut	0.003	growth
0.002	area	0.002	media	0.003	credit
0.002	mail	0.002	women	0.003	save
0.002	web	0.002	abort	0.003	taxpay
0.002	age	0.002	vice	0.003	deficit
0.002	car	0.002	gun	0.003	consum
0.002	trial	0.002	robert	0.003	energi
0.002	room	0.002	civil	0.002	capit
0.002	stori	0.002	appeal	0.002	revenu
0.002	activ	0.002	messag	0.002	stock
Topic 3 (Election)		**Topic 4 (Campaign Donation)**		**Topic 5 (International Relations)**	
Weight	Word	Weight	Word	Weight	Word
0.004	iowa	0.005	donor	0.005	china
0.004	seat	0.005	donat	0.003	terrorist
0.003	rep	0.005	fundrais	0.003	terror
0.003	hampshir	0.004	lobbi	0.003	iraqi
0.003	south	0.004	maryland	0.003	intellig
0.003	immigr	0.004	romney	0.003	japan
0.003	gilmor	0.003	pack	0.003	minist
0.002	davi	0.003	gov	0.003	nuclear
0.002	tuesday	0.003	legislatur	0.003	bomb
0.002	carolina	0.003	bradley	0.002	weapon
0.002	edward	0.003	soft	0.002	european
0.002	night	0.003	influenc	0.002	armi
0.002	gov	0.003	dean	0.002	afghanistan
0.002	contest	0.003	rep	0.002	troop
0.002	floria	0.003	mail	0.002	pentagon

Table A.2: Correlation Coefficients of Currency Trading Strategies

This table reports correlation coefficients across a set of currency trading strategies for G10 sample (Panel A), All currencies sample (Panel B). The portfolios are rebalanced monthly on the basis of APR Index (LMH_{APR}), IR sub-Index (LMH_{IR}) forward discounts (*CAR*), momentum (MOM). The DOL portfolio is a portfolio that buys all currencies against the U.S. Dollar. In each panel, portfolios are split between two periods, including pre-crisis (January 1998 to November 2007), and post-crisis (June 2009 to October 2018).

Panel A: G10 sample

	Pre-crisis						Post-crisis				
	LMH_{APR}	LMH_{IR}	*CAR*	MOM	DOL		LMH_{APR}	LMH_{IR}	*CAR*	MOM	DOL
LMH_{APR}	1					LMH_{APR}	1				
LMH_{IR}	0.73	1				LMH_{IR}	0.83	1			
CAR	0.38	0.59	1			*CAR*	0.27	0.33	1		
MOM	0.05	0.21	0.24	1		MOM	0.11	0.04	-0.19	1	
DOL	-0.07	0.01	0.13	-0.01	1	DOL	0.31	0.31	0.52	-0.27	1

Panel B: All countries sample

	Pre-crisis						Post-crisis				
	LMH_{APR}	LMH_{IR}	*CAR*	MOM	DOL		LMH_{APR}	LMH_{IR}	*CAR*	MOM	DOL
LMH_{APR}	1					LMH_{APR}	1				
LMH_{IR}	0.65	1				LMH_{IR}	0.79	1			
CAR	0.53	0.34	1			*CAR*	0.17	0.33	1		
MOM	0.25	0.15	0.23	1		MOM	0.19	0.05	-0.37	1	
DOL	0.07	-0.07	0.11	0.20	1	DOL	0.38	0.34	0.58	-0.34	1

Table A.3: Cross-section FX Asset Pricing with U.S. Populist Rhetoric and Fiscal News

This table reports regressions results for the estimation of the market price of APR index and IR sub-index (λ_{PR}). The control variables are Fiscal News as in Nguyen (2021). Panel A (Panel B) reports results for All Countries (G10 Countries). Newey and West (1987) t-statistics are reported in squared brackets, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. The data are monthly between January 1998 and October 2018.

Panel A: All Countries				
	APR Index		IR Sub-index	
	(1)	(2)	(3)	(4)
λ_{PR}	-0.42***	-0.32***	-0.06***	-0.06**
	[-3.02]	[-2.96]	[-2.96]	[-3.50]
λ_{FN}		-0.02**		-0.02**
		[-2.45]		[-2.12]
Constant	0.00	-0.00	0.00	-0.00
	[0.05]	[-0.54]	[0.65]	[-0.18]
Obs	3,649	3,649	3,649	3,649
Adj R^2	0.16	0.26	0.15	0.27

Panel B: G10				
	APR Index		IR Sub-index	
	(1)	(2)	(3)	(4)
λ_{PR}	-0.26**	-0.30***	-0.04***	-0.05***
	[-2.32]	[-2.75]	[-2.53]	[-2.97]
λ_{FN}		-0.01		-0.01
		[-1.00]		[-0.84]
Constant	-0.00	-0.00	0.00	-0.00
	[-0.07]	[-0.21]	[0.12]	[-0.3]
Obs	2,0480	2,0480	2,0480	2,0480
Adj R^2	0.20	0.34	0.19	0.35

Table A.4: FX Asset Pricing with U.S. Populist Rhetoric - Sub-indices

This table reports regressions results for the estimation of the market price of sub-indices identified by LDA Algorithm (λ_{PR}). The control variables are volatility ($\lambda_{Volatility}$) and illiquidity ($\lambda_{Illiquidity}$) as in Menkhoff et al. (2012a). Newey and West (1987) t-statistics are reported in squared brackets, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. The data are monthly between January 1998 and October 2018.

Panel A: All Countries					
	Lawsuits	Judiciary System	Fiscal	Election	Campaign Donation
λ_{PR}	-0.07***	-0.10***	-0.10***	-0.07***	-0.08***
	[-3.57]	[-3.42]	[-4.02]	[-2.95]	[-3.40]
$\lambda_{Volatility}$	-0.01	-0.01	-0.01	-0.01	-0.01
	[-1.20]	[-0.72]	[-0.96]	[-1.02]	[-0.76]
$\lambda_{Illiquidity}$	0.02	0.01	0.02	0.02	0.00
	[0.57]	[0.17]	[0.38]	[0.40]	[0.00]
Constant	-0.00	-0.00	-0.00	-0.00	-0.00
	[-0.64]	[-0.72]	[-0.25]	[-0.33]	[-0.16]
Obs	3,648	3,648	3,648	3,648	3,648
Adj R^2	0.36	0.34	0.34	0.34	0.35
Panel B: G10					
	Lawsuits	Judiciary System	Fiscal	Election	Campaign Donation
λ_{PR}	-0.01	-0.04*	-0.04	-0.02	-0.03
	[-0.73]	[-1.80]	[-1.45]	[-1.49]	[-0.84]
$\lambda_{Volatility}$	0.00	-0.00	-0.01	-0.00	0.00
	[0.11]	[-0.19]	[-0.17]	[-0.43]	[0.21]
$\lambda_{Illiquidity}$	-0.31	-0.28	-0.34	-0.34	-0.34
	[-2.41]	[-1.98]	[-2.53]	[-2.40]	[-2.49]
Constant	-0.00	-0.00	-0.00	-0.00	-0.00
	[-1.01]	[-1.33]	[-0.52]	[-0.81]	[-1.24]
Obs	2,048	2,048	2,048	2,048	2,048
Adj R^2	0.50	0.49	0.49	0.50	0.51

Table A.5: FX Asset Pricing with U.S. Populist Rhetoric - Individual newspapers

This table reports regressions results for the estimation of the market price of U.S. populist rhetoric constructed by individual newspapers (λ_{PR}). UST is the USA Today, WSP is the Washington Post, NYT is the New York Times, NYP is the New York Post, DNY is the Daily News New York. The control variables are volatility ($\lambda_{Volatility}$) and illiquidity ($\lambda_{Illiquidity}$) as in Menkhoff et al. (2012a). Newey and West (1987) t-statistics are reported in squared brackets, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. The data are monthly between January 1998 and October 2018.

Panel A: All Countries

	UST	WSP	NYT	NYP	DNY
λ_{PR}	-0.53***	-0.23*	-0.68***	-0.30	-0.59***
	[-3.09]	[-1.81]	[-3.76]	[-1.58]	[-2.66]
$\lambda_{Volatility}$	-0.01	-0.01**	-0.01	- 0.01	-0.01
	[-1.08]	[-2.01]	[-0.92]	[-0.74]	[-1.32]
$\lambda_{Illiquidity}$	0.04	0.02	-0.00	0.00	-0.01
	[0.90]	[0.47]	[-0.03]	[0.08]	[-1.28]
Constant	-0.00	0.00	-0.00	-0.00	0.00
	[-0.52]	[0.49]	[-0.18]	[1.06]	[0.30]
Obs	3,648	3,648	3,648	3,648	3,595
Adj R^2	0.36	0.34	0.34	0.33	0.31

Panel B: G10

	UST	WSP	NYT	NYP	DNY
λ_{PR}	-0.26*	-0.08	-0.26	0.01	0.11
	[-1.96]	[-0.48]	[-1.19]	[0.06]	[0.49]
$\lambda_{Volatility}$	-0.01	-0.01	0.00	- 0.00	-0.01
	[-0.79]	[-0.98]	[0.00]	[-0.48]	[-0.94]
$\lambda_{Illiquidity}$	-0.30**	-0.35**	-0.37***	-0.39***	-0.42***
	[-2.22]	[-2.54]	[-2.96]	[-3.07]	[-3.30]
Constant	-0.00	-0.00	-0.00	-0.00	0.00
	[-0.69]	[-0.15]	[-1.15]	[-0.14]	[0.16]
Obs	2,048	2,048	2,048	2,048	2,022
Adj R^2	0.48	0.50	0.51	0.48	0.47

Table A.6: FX Asset Pricing Tests: Factor-Mimicking Portfolio

This table reports regressions results for the two-factor model including the DOL and FPR risk factors. Test assets used are 6 carry portfolios for All Countries sample and 5 carry portfolios for G10 sample. Portfolios are rebalanced monthly. Newey and West (1987) and Shanken (1985) t-statistics are reported in squared brackets, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. We also report χ^2. Figures in parentheses are p-values. The data are monthly between January 1998 and October 2018.

	Panel A: All Countries							
	APR Index				IR Sub-index			
	λ_{DOL}	λ_{FPR}	χ^2_{NW}	χ^2_{SH}	λ_{DOL}	λ_{FPR}	χ^2_{NW}	χ^2_{SH}
FMB	0.31**	4.86***	37.79***	33.45***	0.29**	1.13***	35.33***	29.99***
(Sh)	[2.24]	[3.77]	(0.00)	(0.00)	[2.06]	[4.76]	(0.00)	(0.00)
(NW)	[2.24]	[3.87]			[2.07]	[4.94]		

	Panel B: G10							
	APR Index				IR Sub-index			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	λ_{DOL}	λ_{FPR}	χ^2_{NW}	χ^2_{SH}	λ_{DOL}	λ_{FPR}	χ^2_{NW}	χ^2_{SH}
FMB	0.06	1.55*	1.96	1.93	0.06	0.29*	1.95	1.91
(Sh)	[0.37]	[1.67]	(0.74)	(0.75)	[0.37]	[1.82]	(0.75)	(0.75)
(NW)	[0.37]	[1.67]			[0.37]	[1.83]		

Appendix B

The Information Content of Trump Tweets and the Currency Markets

1 Model Solution

Proof of Model Weights

A Bayesian agent will update their prior based on the relative precision of the public and private signal.

$$\mathbb{E}[s^j_{t+1}|I_j, I_T] = \omega^B_j \theta^T + (1-\omega^B_j)\theta^j \tag{B.1}$$

Proof of optimal weights:
We use the following property of the conditional expectation of normally distributed random variables:
consider $x_1, x_2 ... x_n$ which are signals of y.

$$x_i = y + \epsilon_i, i = 1, ..., n$$

Each ϵ_i is distributed independently with $\epsilon_i \sim N(0, \sigma^2_i)$
Then the expectation of y conditional on $x_1, x_2, ... x_n$ is given by:

$$E[y|x_1, x_2, ... x_n] = \frac{x_1 \sigma^-_1 2 + ... + x_n \sigma^{-2}_n}{\sigma^{-2}_1 + ... + \sigma^{-2}_n}$$

where σ^{-2}_i measures the precision of signal i. Using this property, we can express the expectation of the future spot rate conditional on the public and private signal as:

$$\mathbb{E}[s^j_{t+1}|I_j, I_T] = \frac{\theta^T \sigma^{-2}_T + \theta^j \sigma^{-2}_j}{\sigma^{-2}_T + \sigma^{-2}_j} \tag{B.2}$$

$$= \frac{\sigma^2_j}{\sigma^2_T + \sigma^2_j}\theta^T + \frac{\sigma^2_T}{\sigma^2_T + \sigma^2_j}\theta^j \tag{B.3}$$

Therefore, we define the optimal weight on the public signal, $\omega^B_j = \frac{\sigma^2_j}{\sigma^2_T + \sigma^2_j}$, in equation B.1.

Solution of optimal weight and bond holdings

Bayesian Agent

$$\max_{b^j_t, \omega^j_t} \qquad L = \mathbb{E}[W^j_{t+1}] - \frac{1}{2}\gamma Var(W^j_{t+1})$$

subject to:

$$W_t^j = \rho_t^j b_t^j$$

We can rewrite the maximization problem as follows:

$$\max_{b_t^j} \qquad L = \mathbb{E}[\rho_t^j]b_t^j - \frac{\gamma}{2} b_t^{j2}(\omega_j^{B2}\sigma_T^2 + (1-\omega_j^B)^2\sigma_j^2)$$

Taking first order conditions:
FOC w.r.t b_t^j

$$E[\rho_t^j] - \gamma b_t^j[\omega_j^{B2}\sigma_T^2 + (1-\omega_j^B)^2\sigma_j^2] = 0$$

This gives solution for bond holdings, using the fact that
$E[\rho_t^j] = \omega_j^B\theta^T + (1-\omega_j^B)\theta^j - s_t + i_t^* - i_t$

$$b_t^j = \frac{\omega_j^B\theta^T + (1-\omega_j^B)\theta^j - s_t + i_t^* - i_t}{\gamma(\omega_j^{B2}\sigma_T^2 + (1-\omega_j^B)^2\sigma_j^2)}$$

Trump follower

$$\max_{b_t^j} \qquad L = \mathbb{E}[W_{t+1}^j] - \frac{1}{2}\gamma Var(W_{t+1}^j)$$

subject to:

$$W_t^j = \rho_t^j b_t^j$$

We can rewrite the maximization problem as follows:

$$\max_{b_t^j} \qquad L = \mathbb{E}[\rho_t^j]b_t^j - \frac{\gamma}{2} b_t^{j2}\sigma_T^2$$

Taking first order conditions:
FOC w.r.t b_t^j

$$E[\rho_t^j] - \gamma b_t^j\sigma_T^2 = 0$$

This gives the solution for bond holdings, using the fact that $E[\rho_t^j] = \theta^T - s_t + i_t^* - i_t$

$$b_t^j = \frac{\theta^T - s_t + i_t^* - i_t}{\gamma\sigma_T^2}$$

Proof of Market Clearing Spot Rate

$$\sum_{j\in N_B} \frac{\omega_j^B \theta^T + (1-\omega_j^B)\theta^j - s_t + i_t^* - i_t}{\omega_j^{B\,2}\sigma_T^2 + (1-\omega_j^B)^2\sigma_j^2} + \sum_{j\in N_T} \frac{\theta^T - s_t + i_t^* - i_t}{\sigma_T^2} = 0$$

Rearranging terms,

$$\sum_{j\in N_B} \frac{s_t}{\omega_j^{B\,2}\sigma_T^2 + (1-\omega_j^B)^2\sigma_j^2} + \sum_{j\in N_T} \frac{s_t}{\sigma_T^2} = \sum_{j\in N_B} \frac{\omega_j^B \theta^T + (1-\omega_j^B)\theta^j + i_t^* - i_t}{\omega_j^{B\,2}\sigma_T^2 + (1-\omega_j^B)^2\sigma_j^2} + \sum_{j\in N_T} \frac{\theta^T + i_t^* - i_t}{\sigma_T^2}$$

$$s_t = i_t^* - i_t + \frac{1}{\left(\frac{N_B}{\omega_j^{B\,2}\sigma_T^2 + (1-\omega_j^B)^2\sigma_j^2} + \frac{N_T}{\sigma_T^2}\right)} \left(\frac{N_B \bar{\theta}^j}{\omega_j^{B\,2}\sigma_T^2 + (1-\omega_j^B)^2\sigma_j^2} + \frac{N_T \theta^T}{\sigma_T^2} + \frac{\omega_j^B N_B}{\omega_j^{B\,2}\sigma_T^2 + (1-\omega_j^B)^2\sigma_j^2}(\theta^T - \bar{\theta}^j) \right)$$

Under the simplifying assumption that $\theta^T = \bar{\theta}^j$, the Trump tweet is an unbiased signal, we obtain:

$$s_t = i_t^* - i_t + \theta^T$$

Proof of Prediction 1

Bayesian Agent

The market clearing exchange rate is given by:

$$s_t = \theta^T + i_t^* - i_t$$

The excess return for a bayesian agent,

$$\begin{aligned}
\mathbb{E}_t[\rho_t^j] &= \omega_j^B \theta^T + (1-\omega_j^B)\theta^j - s_t + i_t^* - i_t \\
&= \omega_j^B \theta^T + (1-\omega_j^B)\theta^j - (\theta^T + i_t^* - i_t) + i_t^* - i_t \\
&= (1-\omega_j^B)(\theta_j - \theta^T)
\end{aligned}$$

Therefore we can write the bond holdings of investor j of the Bayesian agent (conditioning on public to private information) as follows:

$$
\begin{aligned}
b_t^j|I_j, I_T &= \frac{(1-\omega_j^B)(\theta^j - \theta^T)}{\gamma({\omega_j^B}^2\sigma_T^2 + (1-\omega_j^B)^2\sigma_j^2)} \\
&= \frac{(1-\omega_j^B)(\theta^j - \theta^T)}{\gamma({\omega_j^B}^2(\sigma_T^2 + \sigma_j^2) + \sigma_j^2 - 2\omega_j^B\sigma_j^2)} \\
&= \frac{\theta^j - \theta^T}{\gamma\sigma_j^2} \times \frac{(1-\omega_j^B)}{{\omega_j^B}^2\frac{\sigma_T^2+\sigma_j^2}{\sigma_j^2} + 1 - 2\omega_j^B}
\end{aligned}
$$

Using the fact that bond holdings of investor j conditional on private information is $b_t^j|I_j = \frac{\theta^j-\theta^T}{\gamma\sigma_j^2}$, and $\omega_j^B = \frac{\sigma_j^2}{\sigma_T^2+\sigma_j^2}$, simplifies the bond holdings of investor j to be the same as bond holdings without the Trump tweet (i.e. conditioned only on private information).

$$
\begin{aligned}
b_t^j|I_j, I_T &= \frac{\theta^j - \theta^T}{\gamma\sigma_j^2} \times \frac{(1-\omega_j^B)}{1-\omega_j^B} \\
&= \frac{\theta^j - \theta^T}{\gamma\sigma_j^2} = b_t^j|I_j
\end{aligned}
$$

Trump Follower

The excess return for a bayesian agent,

$$
\begin{aligned}
\mathbb{E}_t[\rho_t^j] &= \theta^T - s_t + i_t^* - i_t \\
&= \theta^T - (\theta^T + i_t^* - i_t) + i_t^* - i_t \\
&= 0
\end{aligned}
$$

Therefore, as expected excess returns of a Trump follower is zero, optimal bond holdings are zero.

Total Volume Traded

The total volume traded is given by $V_{FX} = \frac{1}{2}\sum_{j=1}^{N}|b_t^j|$. We have shown that bond holdings of Bayesian agents are unchanged relative to an equilibrium without public information. Trump followers, on the other hand, do not trade conditional on public information as they earn zero excess returns in equilibrium. Based on this information, we can compute the ratio of trading with the public signal to the original equilibrium as follows:

$$\frac{V_{FX}|I_j, I_T}{V_{FX}|I_j} = \frac{\frac{1}{2}\sum_{j\in N_B}|b_t^j|}{\frac{1}{2}\left(\sum_{j\in N_B}|b_t^j| + \sum_{j\in N_T}|b_t^j|\right)}$$
$$= \frac{\sum_{j\in N_B}|\frac{\theta^j-\theta^T}{\sigma_j^2}|}{\sum_{j\in N_B}|\frac{\theta^j-\theta^T}{\sigma_j^2}| + \sum_{j\in N_T}|\frac{\theta^j-\theta^T}{\sigma_j^2}|} < 1$$

Proof of Prediction 2

$$\begin{aligned}
var(s_{t+1|I_j,I_T}) &= \frac{\sum_{j=1}^{N} var(s_{t+1}^j)}{N} \\
&= \frac{\sum_{j\in N_B} var(s_{t+1}^j) + \sum_{j\in N_T} var(s_{t+1}^j)}{N} \\
&= \frac{N_B}{N}(\omega_j^{B2}\sigma_T^2 + (1-\omega_j^B)\sigma_j^2) + \frac{N_T}{N}\sigma_T^2 \\
&= \frac{N_B}{N}(1-\omega_j^B{}_{\sigma}{}_j^2 + (1-\frac{N_B}{N})\sigma_T^2 \\
&= \sigma_T^2 + \frac{N_B}{N}\left((1-\omega_j^B)\sigma_j^2 + \sigma_T^2\right)
\end{aligned}$$

Using the fact that the variance conditional on private information is $var(s_{t+1|I_j}) = \sigma_j^2$, the ratio of variance with the public signal to the equilibrium without the public signal is, using $R = \frac{\sigma_T^2}{\sigma_j^2}$

$$\begin{aligned}
\frac{var(s_{t+1|I_j,I_T})}{var(s_{t+1|I_j})} &= \frac{\sigma_T^2}{\sigma_j^2} + \frac{N_B}{N}\left(1-\omega_j^B - \frac{\sigma_T^2}{\sigma_j^2}\right) \\
&= R + \frac{N_B}{N}\left(\frac{R}{1+R} - R\right) \\
&= R\left(1 + \frac{N_B}{N}\left(\frac{1}{1+R} - 1\right)\right) \\
&= R\left(1 - \frac{N_B}{N}\frac{R}{1+R}\right)
\end{aligned}$$

For a decline in the volatility conditional on public information, we require $\frac{var(s_{t+1|I_j,I_T})}{var(s_{t+1|I_j})} < 1$, this imposes the following restriction on the share of Bayesian agents.

$$R\left(1-\frac{N_B}{N}\frac{R}{1+R}\right) < 1$$
$$\frac{N_B}{N}\frac{R}{1+R} > 1-\frac{1}{R}$$
$$\frac{N_B}{N} > \frac{R^2-1}{R^2} \implies \frac{var(s_{t+1|I_j,I_T})}{var(s_{t+1|I_j})} < 1$$

Proof of Prediction 3

Using an asset pricing view of the exchange rate to link it to macroeconomic fundamentals, the spot exchange rate conditional on private information is given by (where $f_t = \frac{m_t-m_t^*}{1+\alpha} - \frac{\eta(y_t-y_t^*)}{1+\alpha}$

$$s_t|I_j = f_t + \sum_{s=1}^{\infty}\left(\frac{\alpha}{1+\alpha}\right)^s \frac{1}{N}\sum_{j=1}^{N}\mathbb{E}_t[f_{t+s}^j]$$

The spot exchange rate conditional on public and private information is given by

$$\begin{aligned} s_t|I_j, I_T &= f_t + \sum_{s=1}^{\infty}\left(\frac{\alpha}{1+\alpha}\right)^s \frac{1}{N}\left(\sum_{j\in N_B}^{N}\left(\omega_B E[f_{t+s}^T] + (1-\omega_B)E[f_{t+s}^j]\right) + \sum_{j\in N_T}^{N} E[f_{t+s}^T]\right) \\ &= f_t + \sum_{s=1}^{\infty}\left(\frac{\alpha}{1+\alpha}\right)^s \left(\frac{\omega_B N_B + N_T}{N}E[f_{t+s}^T] + (1-\omega_B)\frac{1}{N}\sum_{j\in N_B} E[f_{t+s}^j]\right) \end{aligned}$$

Taking the difference between the spot rate conditional on public information and the spot rate in the equilibrium without the public signal,

$$s_t|I_j, I_T - s_t|I_j = \sum_{s=1}^{\infty}\left(\frac{\alpha}{1+\alpha}\right)^s \left(\frac{\omega_B N_B + N_T}{N}E[f_{t+s}^T] + (1-\omega_B)\frac{1}{N}\sum_{j\in N_B} E[f_{t+s}^j]\right) - \frac{1}{N}\sum_{j=1}^{N}\mathbb{E}_t[f_{t+s}^j]$$

Assuming that $\frac{1}{N_B}\sum_{j\in N_B} E[f_{t+s}^j] = \frac{1}{N}\sum_{j\in N} E[f_{t+s}^j]$, we can simplify the above expression as follows:

$$
\begin{aligned}
s_t|I_j, I_T - s_t|I_j &= \sum_{s=1}^{\infty}\left(\frac{\alpha}{1+\alpha}\right)^s \left(\frac{\omega_B N_B + N_T}{N} E[f_{t+s}^T] + \frac{N_B}{N}\omega_B \sum_{j=1}^{N} E[f_{t+s}^j]\right) \\
&= \sum_{s=1}^{\infty}\left(\frac{\alpha}{1+\alpha}\right)^s \left(\frac{\omega_B N_B + N_T}{N} E[f_{t+s}^T] + \left((1-\omega_B)\frac{N_B}{N} - 1\right)\sum_{j=1}^{N} E[f_{t+s}^j]\right) \\
&= \sum_{s=1}^{\infty}\left(\frac{\alpha}{1+\alpha}\right)^s \left(\frac{\omega_B N_B + N_T}{N} E[f_{t+s}^T] - \frac{\omega_B N_B + N_T}{N}\frac{1}{N}\sum_{j=1}^{N} E[f_{t+s}^j]\right) \\
&= \frac{\omega_B N_B + N_T}{N}\sum_{s=1}^{\infty}\left(\frac{\alpha}{1+\alpha}\right)^s \left(E[f_{t+s}^T] - \frac{1}{N}\sum_{j=1}^{N} E[f_{t+s}^j]\right)
\end{aligned}
$$

2 Sample of Tweets

Some Tweets belonging to 3 categories (Macroeconomics Outlook, Exchange Rate, and Trade Policy) are listed

Macroeconomics Outlook

"*Somebody please inform Jay-Z that because of my policies, Black Unemployment has just been reported to be at the LOWEST RATE EVER RECORDED!*"

"*Beautiful weather all over our great country, a perfect day for all Women to March. Get out there now to celebrate the historic milestones and unprecedented economic success and wealth creation that has taken place over the last 12 months. Lowest female unemployment in 18 years!*"

"*HAPPY THANKSGIVING, your Country is starting to do really well. Jobs coming back, highest Stock Market EVER, Military getting really strong, we will build the WALL, V.A. taking care of our Vets, great Supreme Court Justice, RECORD CUT IN REGS, lowest unemployment in 17 years....!*"

Trade Policy

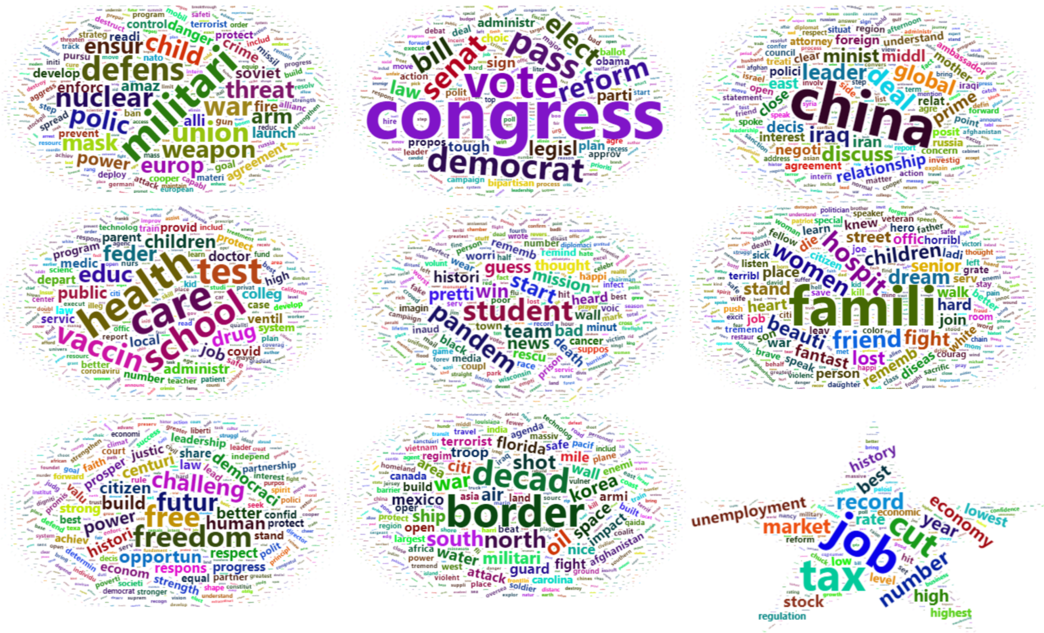
"*I am pleased to inform you that The United States of America has reached a signed agreement with Mexico. The Tariffs scheduled to be implemented by the U.S. on Monday, against Mexico, are hereby indefinitely suspended,*"

"*When a car is sent to the United States from China, there is a Tariff to be paid of 2 1/2%. When a car is sent to China from the United States, there is a Tariff to be paid of 25%, Does that sound like free or fair trade. No, it sounds like STUPID TRADE - going on for years!*"

Exchange Rate

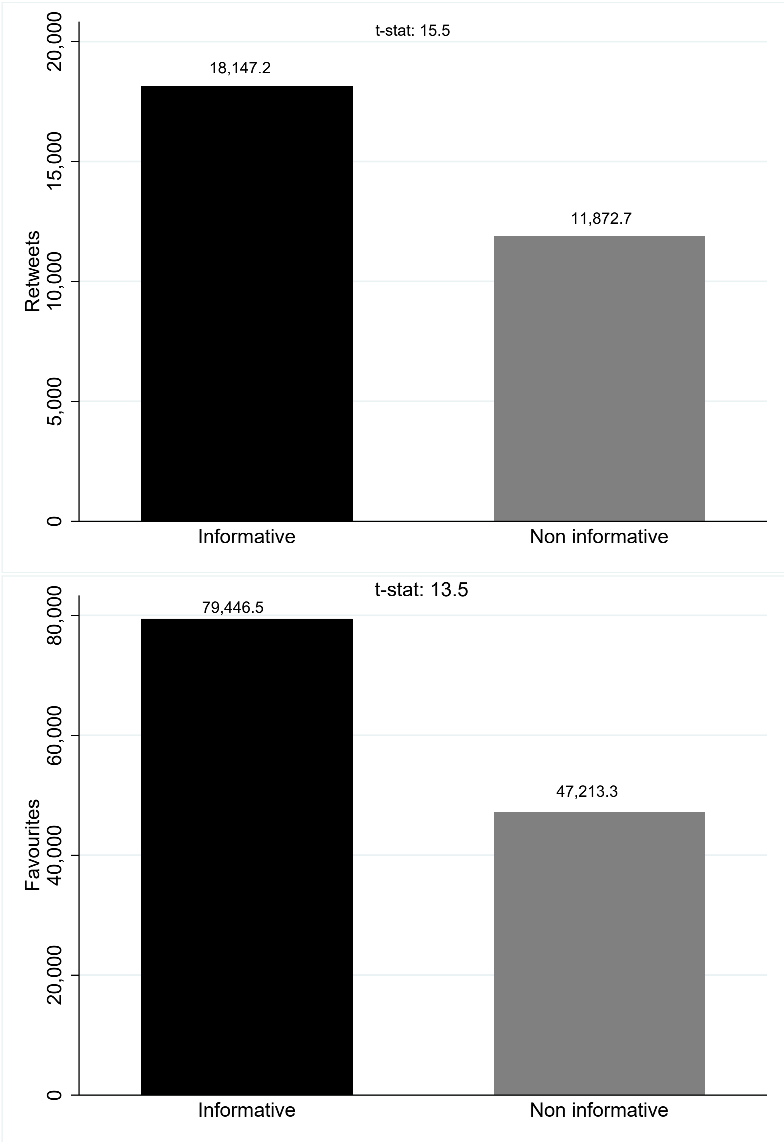
"*Based on the historic currency manipulation by China, it is now even more obvious to everyone that Americans are not paying for the Tariffs – they are being paid for compliments of China, and the U.S. is taking in tens of Billions of Dollars! China has always....*"

Figure B.1: BTM Topic Keywords



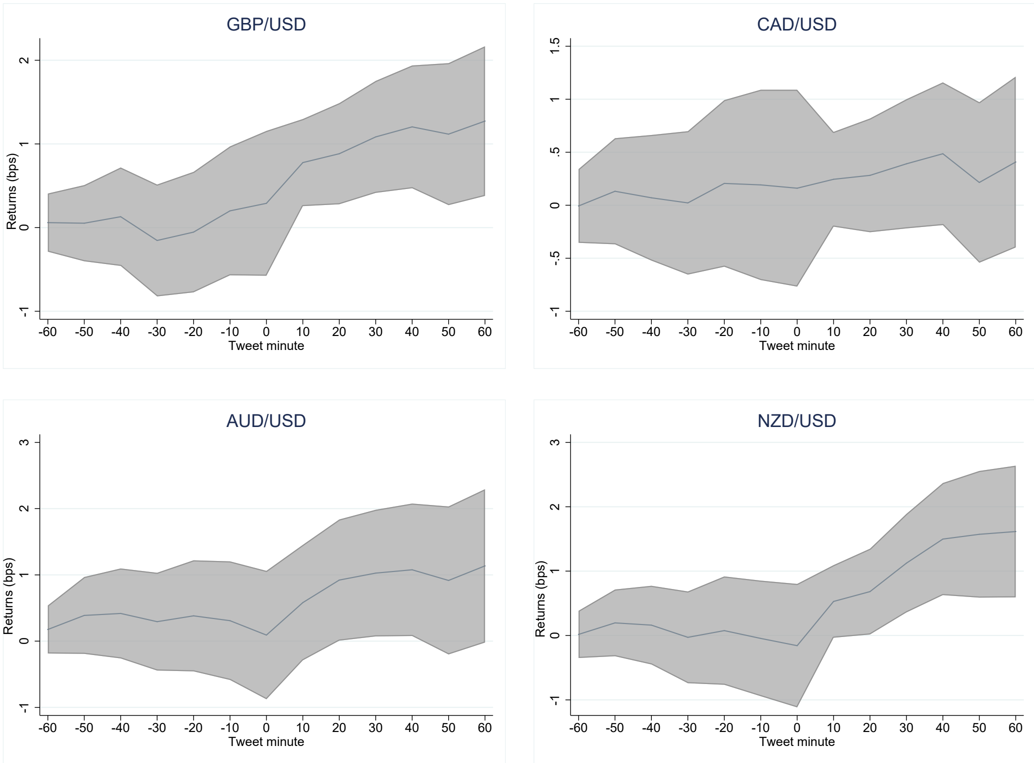
The graph reports results from BTM implemented on Tweets. For each topic, the top keywords are reported.

Figure B.2: Informative Tweets and Non-informative Tweets



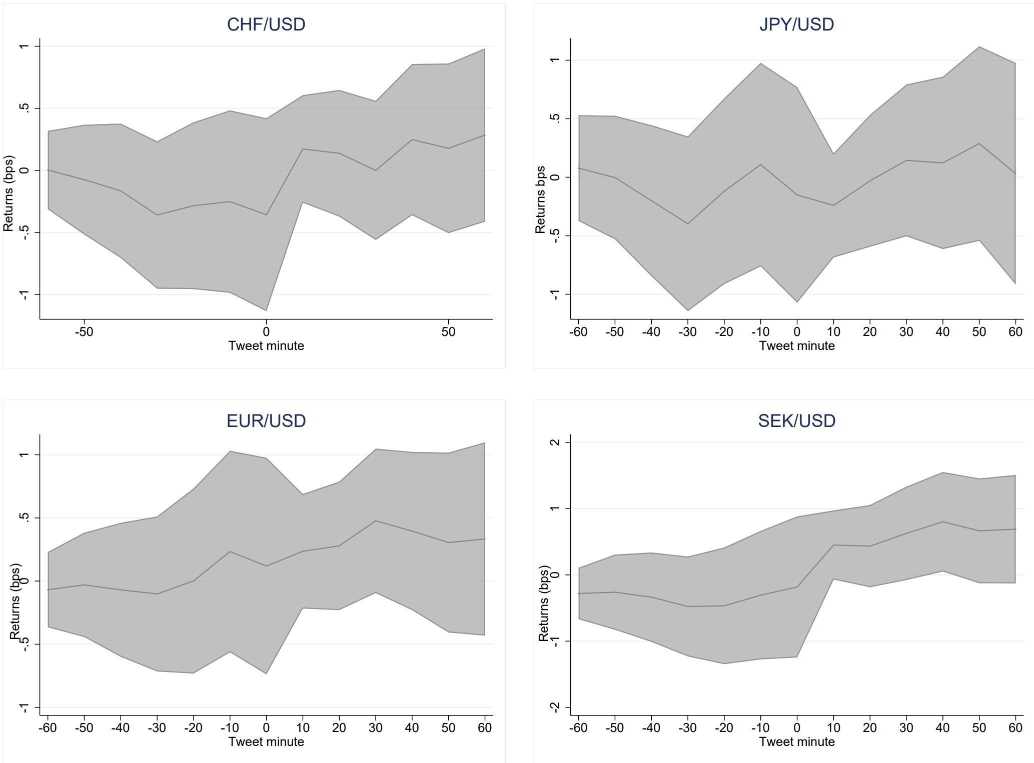
The figure shows the average number of Retweets (Panel A) and favorite (Panel B) for Informative Tweets and Non-informative Tweets. Informative Tweets and Non-informative Tweets are matched by VIX Index and hour-of-day. The data is between 16th June 2015 and 20th August 2019.

Figure B.3: Event study: Cumulative returns by currency



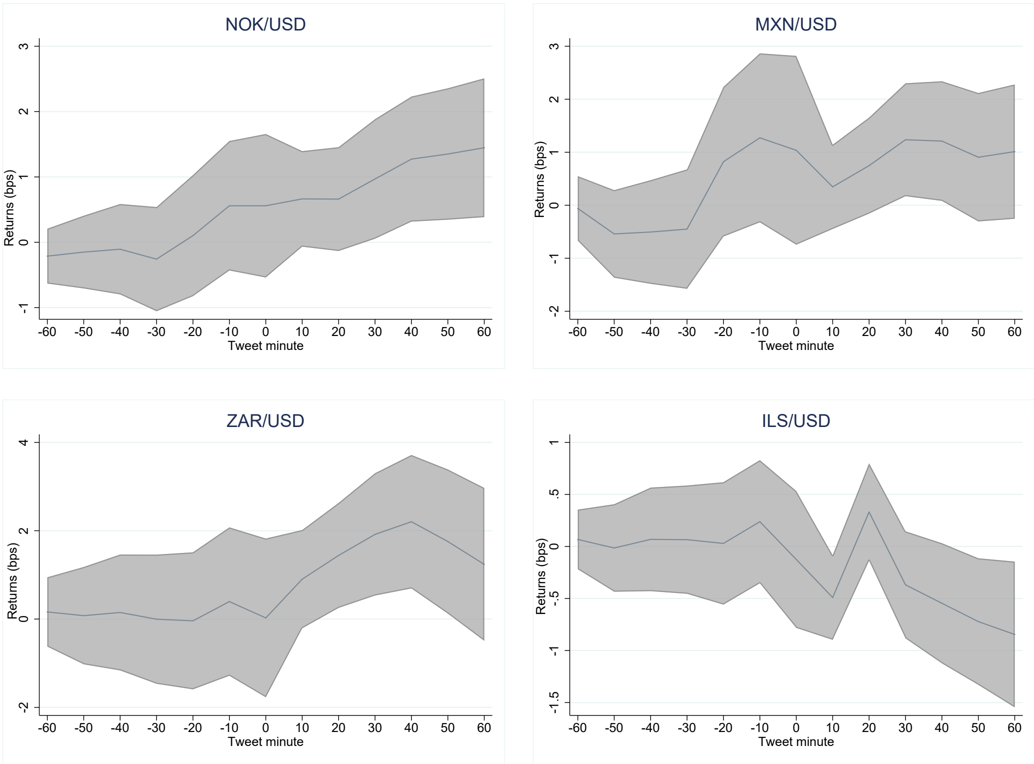
The figure reports the cumulative returns for individual currencies. The y-axis shows the minutes during the event, with 0 being the minute in which a tweet is posted. The negative values in the y-axis are the number of minutes before tweets. The shaded area shows 95% confidence interval

Figure B.4: Event study: Cumulative returns by currency



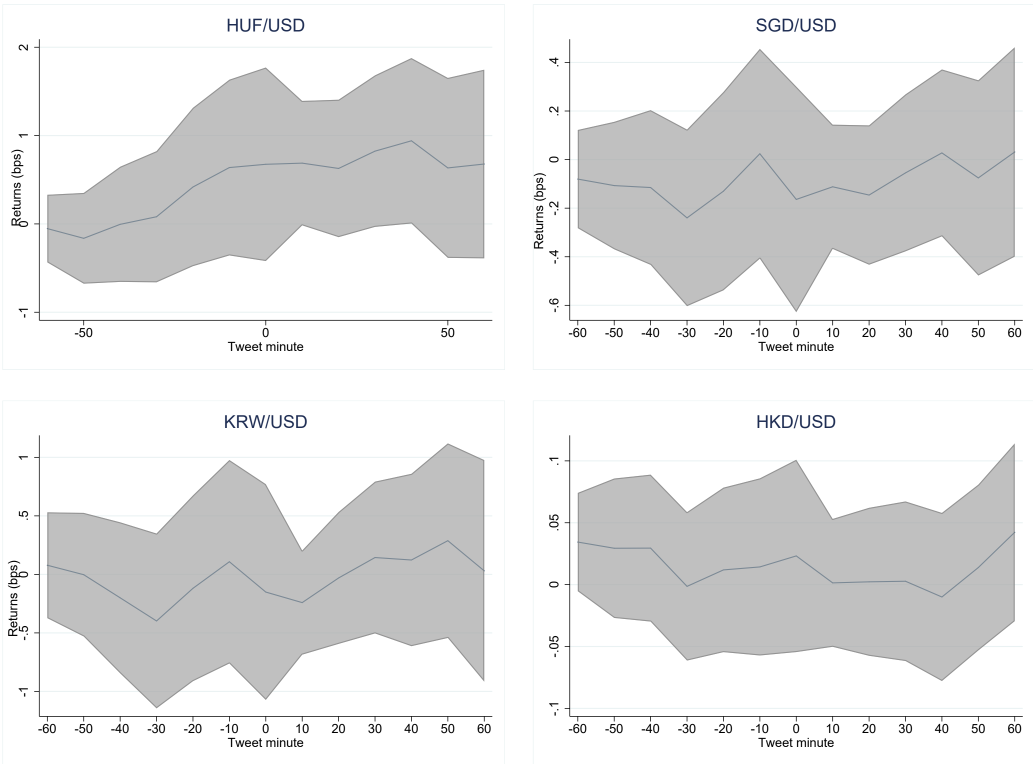
The figure reports the cumulative returns for individual currencies. The y-axis shows the minutes during the event, with 0 being the minute in which a tweet is posted. The negative values in the y-axis are the number of minutes before tweets. The shaded area shows 95% confidence interval

Figure B.5: Event study: Cumulative returns by currency



The figure reports the cumulative returns for individual currencies. The y-axis shows the minutes during the event, with 0 being the minute in which a tweet is posted. The negative values in the y-axis are the number of minutes before tweets. The shaded area shows 95% confidence interval

Figure B.6: Event study: Cumulative returns by currency



The figure reports the cumulative returns for individual currencies. The y-axis shows the minutes during the event, with 0 being the minute in which a tweet is posted. The negative values in the y-axis are the number of minutes before tweets. The shaded area shows 95% confidence interval

Table B.1: Tweets (based on dictionary method) and Spot FX Trading Volume (Total Sell Side - Total Buy Side)

This table reports panel regressions results for the estimation of Tweets hour dummy on FX Trading Volume The control variables are presidency dummy, FOMC dummy, VIX, TED Spread, and Economic Policy Uncertainty (EPU) from Baker et al. (2016). Hour-of-the-day and day-of-the-week dummies are included in all regressions. Standard errors are clustered by currency. t-statistics are reported in squared brackets, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. The data are hourly between 16th June 2015 and 20th August 2019.

	Dependent variable: Trading Volume between Sell Side and Buy Side					
	(1)	(2)	(3)	(4)	(5)	(6)
Tweet hour	-0.649***	-0.710***	-0.710***	-0.739***	-0.744***	-0.726***
	[-4.35]	[-4.30]	[-4.30]	[-4.38]	[-4.51]	[-4.52]
Presidency dummy		0.279***	0.280***	0.340***	0.328***	0.328***
		[3.14]	[3.14]	[3.40]	[3.35]	[3.35]
FOMC dummy			0.209***	0.222***	0.224***	0.226***
			[2.42]	[2.66]	[2.71]	[2.73]
VIX				0.023***	0.022***	0.022***
				[3.66]	[3.55]	[3.56]
TED Spread					-0.324**	-0.323**
					[-2.40]	[-2.40]
EPU						-0.580***
						[-3.94]
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	367,333	367,333	367,333	363,515	357,588	357,588
R^2	4.57%	4.64%	4.64%	4.76%	4.75%	4.75%

Table B.2: Tweets (based on dictionary method) and FX Trading Volume by groups of market participant

This table reports panel regressions results for the estimation of Tweets hour dummy on FX Trading Volume. The control variables are presidency dummy, FOMC dummy, VIX, TED Spread, and Economic Policy Uncertainty (EPU) from Baker et al. (2016). Hour-of-the-day and day-of-the-week dummies are included in all regressions. In Panel A, dependent variable is trading volume between market maker bank and price taker bank. In Panel B, dependent variable is trading volume between market maker bank and price taker fund. In Panel C, dependent variable is trading volume between market maker bank and price taker non-bank financials. In Panel D, dependent variable is trading volume between market maker bank and price taker corporates. Standard errors are clustered by currency. t-statistics are reported in squared brackets, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. The data are hourly between 16th June 2015 and 20th August 2019.

	Panel A. Dependent variable: Bank - Bank Trading Volume						*Panel B. Dependent variable*: Bank - Fund Volume					
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
Tweet hour	-0.706***	-0.761***	-0.761***	-0.793***	-0.797**	-0.777***	-0.626***	-0.770***	-0.769***	-0.835***	-0.862***	-0.850***
	[-3.87]	[-3.86]	[-3.86]	[-3.94]	[-4.04]	[-4.04]	[-3.79]	[-5.07]	[-5.06]	[-5.67]	[-5.82]	[-5.82]
Presidency dummy		0.243***	0.243***	0.315***	0.305***	0.305***		0.637***	0.638***	0.714***	0.706***	0.706***
		[3.14]	[3.14]	[3.41]	[3.40]	[3.39]		[4.82]	[4.83]	[5.25]	[5.30]	[5.29]
FOMC dummy			0.077	0.092*	0.094*	0.096*			0.340	0.345	0.343	0.344
			[1.45]	[1.78]	[1.81]	[1.85]			[1.30]	[1.35]	[1.36]	[1.37]
VIX				0.025***	0.024***	0.024***				0.032***	0.030***	0.030***
				[3.51]	[3.42]	[3.43]				[5.71]	[5.77]	[5.78]
TED Spread					-0.298**	-0.297**					0.035	0.035
					[-2.03]	[-2.02]					[-0.09]	[-0.09]
EPU						-0.443**						0.093
						[-4.16]						[-0.46]
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	310,888	310,888	310,888	307,671	302,559	302,559	291,541	291,541	291,541	288,518	283,839	283,839
R^2	4.80%	4.81%	4.81%	4.94%	4.93% 4.93%	22.06%	22.23%	22.23%	22.46%	22.55%	22.55%	

	Panel C. Dependent variable: Bank - Non-Bank Trading Volume						*Panel D. Dependent variable*: Bank - Corporate Volume					
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
Tweet hour	-0.444***	-0.877***	-0.875***	-0.919***	-0.928***	-0.915***	0.0738	-0.081	-0.081	-0.154	-0.226	-0.226
	[-3.87]	[-8.02]	[-8.02]	[-8.90]	[-8.77]	[-8.84]	[0.35]	[-0.49]	[-0.49]	[-1.02]	[-1.51]	[-1.51]
Presidency dummy		2.000***	2.000***	2.081***	2.045***	2.044***		0.869***	0.869***	1.036***	0.947***	0.947***
		[5.985]	[5.98]	[6.19]	[6.08]	[6.08]		[2.96]	[2.95]	[3.08]	[2.81]	[2.81]
FOMC dummy			0.354	0.368	0.372	0.374			-0.122	-0.0938	-0.078	-0.078
			[1.28]	[1.34]	[1.36]	[1.37]			[-0.14]	[-0.11]	[-0.09]	[-0.09]
VIX				0.035***	0.034***	0.034***				0.069***	0.068***	0.068***
				[5.02]	[4.94]	[4.94]				[3.43]	[3.38]	[3.38]
TED Spread					-0.597**	-0.597**					-1.92***	-1.92***
					[-2.25]	[-2.25]					[-2.61]	[-2.61]
EPU						-0.443***						-0.093***
						[-4.16]						[-0.46]
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	300,093	300,093	300,093	297,023	292,150	292,150	103,508	103,508	103,508	102,492	100,883	100,883
R^2	2.32%	4.28%	4.28%	4.31%	4.27%	4.27%	0.95%	1.11%	1.14%	1.24%	1.30%	1.30%

Table B.3: Tweets (based on dictionary method) and FX Hourly Realised Volatility

This table reports panel regressions results for the estimation of Tweets hour dummy on FX hourly realised volatility. The control variables are presidency dummy, FOMC dummy, VIX, TED Spread, and Economic Policy Uncertainty (EPU) from Baker et al. (2016). Hour-of-the-day and day-of-the-week dummies are included in all regressions. Standard errors are clustered by currency. t-statistics are reported in squared brackets, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. The data are hourly between 16th June 2015 and 20th August 2019.

	Dependent variable: Realised Volatility					
	(1)	(2)	(3)	(4)	(5)	(6)
Tweet hour	-0.006***	-0.003***	-0.003***	-0.004***	-0.003***	-0.003***
	[-5.36]	[-3.20]	[-3.03]	[-3.49]	[-2.93]	[-2.98]
Presidency dummy		-0.014***	-0.014***	-0.012***	-0.011***	-0.011***
		[-7.06]	[-7.06]	[-6.38]	[-5.94]	[-5.94]
FOMC dummy			0.070***	0.070***	0.069***	0.069***
			[8.81]	[8.81]	[8.80]	[8.80]
VIX				0.001***	0.001***	0.001***
				[8.81]	[8.82]	[8.82]
TED Spread					0.017***	0.017***
					[3.49]	[3.49]
EPU						0.001**
						[2.06]
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	397,708	397,708	397,708	393,251	387,708	387,708
R^2	6.17%	7.22%	7.38%	7.64%	7.77%	7.77%

Table B.4: Tweets (based on dictionary method) and FX Hourly Bid-Ask Spreads

This table reports panel regressions results for the estimation of Tweets hour dummy on FX hourly bid-ask spreads. The control variables are presidency dummy, FOMC dummy, VIX, TED Spread, and Economic Policy Uncertainty (EPU) from Baker et al. (2016). Hour-of-the-day and day-of-the-week dummies are included in all regressions. Standard errors are clustered by currency. t-statistics are reported in squared brackets, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. The data are hourly between 16th June 2015 and 20th August 2019.

	Dependent variable: Bid-Ask Spreads					
	(1)	(2)	(3)	(4)	(5)	(6)
Tweet hour	-0.439***	-0.208***	-0.208***	-0.210***	-0.202***	-0.203***
	[-3.49]	[-3.51]	[-3.51]	[-3.56]	[-3.51]	[-3.52]
Presidency dummy		-1.022***	-1.022***	-1.012***	-1.010***	-1.009***
		[-2.79]	[-2.79]	[-2.89]	[-2.77]	[-2.77]
FOMC dummy			0.257*	0.262*	0.256*	0.256*
			[1.72]	[1.76]	[1.75]	[1.75]
VIX				0.003	0.003	0.003
				[0.45]	[0.47]	[0.47]
TED Spread					0.094	0.094
					[0.13]	[0.13]
EPU						0.061
						[1.36]
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	382,894	382,894	382,894	378,715	372,638	372,638
R^2	1.58%	3.32%	3.33%	3.34%	3.45%	3.45%

Table B.5: Tweets (based on dictionary method) and FX Hourly Returns

This table reports panel regressions results for the estimation of Tweets hour dummy on FX hourly returns. The control variables are presidency dummy, FOMC dummy, VIX, TED Spread, and Economic Policy Uncertainty (EPU) from Baker et al. (2016). Hour-of-the-day and day-of-the-week dummies are included in all regressions. Standard errors are clustered by currency. t-statistics are reported in squared brackets, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. The data are hourly between 16th June 2015 and 20th August 2019.

	Dependent variable: Returns					
	(1)	(2)	(3)	(4)	(5)	(6)
Tweet hour	0.005***	0.005***	0.005***	0.005***	0.005***	0.005***
	[3.84]	[3.78]	[3.74]	[3.64]	[3.93]	[3.80]
Presidency dummy		-0.000	-0.000	0.000	0.000	0.000
		[-0.16]	[-0.17]	[1.49]	[0.72]	[0.72]
FOMC dummy			-0.023***	-0.023***	-0.023***	-0.023***
			[-4.76]	[-4.74]	[-4.74]	[-4.74]
VIX				0.000*	0.000*	0.000*
				[1.85]	[1.67]	[1.67]
TED Spread					-0.001	-0.001
					[-1.11]	[-1.11]
EPU						0.003*
						[1.91]
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	376,850	376,850	376,850	372,534	366,474	366,474
R^2	0.07%	0.07%	0.07%	0.07%	0.07%	0.07%

Table B.6: Tweets (based on BTM method) and Spot FX Trading Volume (Total Sell Side - Total Buy Side)

This table reports panel regressions results for the estimation of Tweets hour dummy on FX Trading Volume The control variables are presidency dummy, FOMC dummy, VIX, TED Spread, and Economic Policy Uncertainty (EPU) from Baker et al. (2016). Hour-of-the-day and day-of-the-week dummies are included in all regressions. Standard errors are clustered by currency. t-statistics are reported in squared brackets, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. The data are hourly between 16th June 2015 and 20th August 2019.

	Dependent variable: Trading Volume between Sell Side and Buy Side					
	(1)	(2)	(3)	(4)	(5)	(6)
Tweet hour	-0.743***	-0.822***	-0.823***	-0.812***	-0.805***	-0.790***
	[-3.98]	[-3.99]	[-3.99]	[-4.01]	[-4.11]	[-4.11]
Presidency dummy		0.284***	0.284***	0.342***	0.331***	0.331***
		[3.16]	[3.16]	[3.41]	[3.37]	[3.36]
FOMC dummy			0.243**	0.256**	0.258***	0.259***
			[2.73]	[2.97]	[3.02]	[3.03]
VIX				0.023***	0.021***	0.021***
				[3.62]	[3.51]	[3.52]
TED Spread					-0.321***	-0.320***
					[-2.40]	[-2.39]
EPU						-0.584***
						[-3.95]
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	367,333	367,333	367,333	363,515	357,588	357,588
R^2	4.59%	4.65%	4.65%	4.76%	4.75%	4.75%

Table B.7: Tweets (based on BTM method) and FX Trading Volume by groups of market participant

This table reports panel regressions results for the estimation of Tweets hour dummy on FX Trading Volume. The control variables are presidency dummy, FOMC dummy, VIX, TED Spread, and Economic Policy Uncertainty (EPU) from Baker et al. (2016). Hour-of-the-day and day-of-the-week dummies are included in all regressions. In Panel A, dependent variable is trading volume between market maker bank and price taker bank. In Panel B, dependent variable is trading volume between market maker bank and price taker fund. In Panel C, dependent variable is trading volume between market maker bank and price taker non-bank financials. In Panel D, dependent variable is trading volume between market maker bank and price taker corporates. Standard errors are clustered by currency. t-statistics are reported in squared brackets, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. The data are hourly between 16th June 2015 and 20th August 2019.

	Panel A. Dependent variable: Bank - Bank Trading Volume						*Panel B. Dependent variable*: Bank - Fund Volume					
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
Tweet hour	-0.758***	-0.9459***	-0.946***	-0.956***	-0.982** *	-0.972***	-0.533***	-1.086***	-1.087***	-1.077***	-1.057***	-1.047***
	[-3.82]	[-5.39]	[-5.40]	[-5.74]	[-6.10]	[-6.13]	[-3.14]	[-6.24]	[-6.25]	[-6.30]	[-6.42]	[-6.44]
Presidency dummy		0.643***	0.644***	0.718***	0.711***	0.710***	20.004***	2.0042***	2.085***	2.049***	2.048***	
		[4.90]	[4.90]	[5.31]	[5.37]]	[5.36]		[5.99]	[5.99]	[6.19]	[6.08]	[6.08]
FOMC dummy			0.377	0.383	0.382	0.383			0.408	0.422	0.426	0.427
			[1.45]	[1.52]	[1.53]	[1.54]			[1.48]	[1.55]	[1.56]	[1.56]
VIX				0.031***	0.029***	0.029***				0.034***	0.033***	0.033***
				[5.63]	[5.69]	[5.71]				[4.94]	[4.86]	[4.86]
TED Spread					-0.033	-0.033					-0.596**	-0.597**
					[-0.09]	[-0.09]					[-2.25]	[-2.25]
EPU						-0.584						-0.568**
						[-3.95]						[-3.82]
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	310,888	310,888	310,888	307,671	302,559	302,559	291,541	291,541	291,541	288,518	283,839	283,839
R^2	4.81%	4.83%	4.83%	4.94%	4.93%	4.93%	22.07%	22.24%	22.24%	22.47%	22.55%	22.55%
	Panel C. Dependent variable: Bank - Non-Bank Trading Volume						*Panel D. Dependent variable*: Bank - Corporate Volume					
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
Tweet hour	-0.533***	-1.086***	-1.087***	-1.077***	-1.057***	-1.047***	0.497***	0.282**	0.282**	0.275**	0.262*	0.262*
	[-3.14]	[-6.24]	[-6.25]	[-6.30]	[-6.42]	[-6.44]	[4.58]	[2.06]	[2.06]	[2.13]	[1.90]	[1.90]
Presidency dummy		2.004***	2.004***	2.085***	2.049***	2.048***		0.864***	0.864***	1.031***	0.941***	0.941***
		[5.99]	[5.99]	[6.19]	[6.08]	[6.08]		[2.92]	[2.92]	[3.04]	[2.78]	[2.78]
FOMC dummy			0.408	0.422	0.426	0.427			-0.13	-0.108	-0.10	-0.10
			[1.48]	[1.55]	[1.56]	[1.56]			[-0.15]	[-0.11]	[-0.09]	[-0.09]
VIX				0.0341***	0.033***	0.033***				0.070***	0.068***	0.068***
				[4.94]	[4.86]	[4.86]				[3.42]	[3.37]	[3.37]
TED Spread					-0.596**	-0.597**					-1.912***	-1.912***
					[-2.25]	[-2.25]					[-2.59]	[-2.59]
EPU						-0.444**						0.072***
						[-4.23]						[-0.34]
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	300,093	300,093	300,093	297,023	292,150	292,150	103,508	103,508	103,508	102,492	100,883	100,883
R^2	2.33%	4.29%	4.29%	4.32%	4.28%	4.28%	0.96%	1.14%	1.14%	1.24%	1.30%	1.30%

Table B.8: Tweets (based on BTM method) and FX Hourly Realised Volatility

This table reports panel regressions results for the estimation of Tweets hour dummy on FX hourly realised volatility. The control variables are presidency dummy, FOMC dummy, VIX, TED Spread, and Economic Policy Uncertainty (EPU) from Baker et al. (2016). Hour-of-the-day and day-of-the-week dummies are included in all regressions. Standard errors are clustered by currency. t-statistics are reported in squared brackets, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. The data are hourly between 16th June 2015 and 20th August 2019.

	Dependent variable: Realised Volatility					
	(1)	(2)	(3)	(4)	(5)	(6)
Tweet hour	-0.006***	-0.003***	-0.003***	-0.004***	-0.003***	-0.003***
	[-5.36]	[-3.20]	[-3.03]	[-3.49]	[-2.93]	[-2.98]
Presidency dummy		-0.014***	-0.014***	-0.012***	-0.011***	-0.011***
		[-7.06]	[-7.06]	[-6.38]	[-5.94]	[-5.94]
FOMC dummy			0.070***	0.070***	0.069***	0.069***
			[8.81]	[8.81]	[8.80]	[8.80]
VIX				0.001***	0.001***	0.001***
				[8.81]	[8.82]	[8.82]
TED Spread					0.017***	0.017***
					[3.49]	[3.49]
EPU						0.001**
						[2.06]
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	397,708	397,708	397,708	393,251	387,708	387,708
R^2	6.17%	7.22%	7.38%	7.64%	7.77%	7.77%

Table B.9: Tweets (based on BTM method) and FX Hourly Bid-Ask Spreads

This table reports panel regressions results for the estimation of Tweets hour dummy on FX hourly bid-ask spreads. The control variables are presidency dummy, FOMC dummy, VIX, TED Spread, and Economic Policy Uncertainty (EPU) from Baker et al. (2016). Hour-of-the-day and day-of-the-week dummies are included in all regressions. Standard errors are clustered by currency. t-statistics are reported in squared brackets, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. The data are hourly between 16th June 2015 and 20th August 2019.

	Dependent variable: Bid-Ask Spreads					
	(1)	(2)	(3)	(4)	(5)	(6)
Tweet hour	-0.406***	-0.111**	-0.111**	-0.126**	-0.124**	-0.125**
	[-2.91]	[-2.07]	[-2.07]	[-2.21]	[-2.28]	[-2.30]
Presidency dummy		-1.023***	-1.023***	-1.013***	-1.010***	-1.010***
		[-2.79]	[-2.79]	[-2.89]	[-2.77]	[-2.77]
FOMC dummy			0.263*	0.268*	0.262*	0.262*
			[1.75]	[1.79]	[1.78]	[1.78]
VIX				0.003	0.003	0.003
				[0.44]	[0.46]	[0.46]
TED Spread					0.096	0.096
					[0.14]	[0.14]
EPU						0.057
						[1.30]
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	382,894	382,894	382,894	378,715	372,638	372,638
R^2	1.57%	3.32%	3.33%	3.34%	3.45%	3.45%

Table B.10: Tweets (based on BTM method) and FX Hourly Returns

This table reports panel regressions results for the estimation of Tweets hour dummy on FX hourly returns. The control variables are presidency dummy, FOMC dummy, VIX, TED Spread, and Economic Policy Uncertainty (EPU) from Baker et al. (2016). Hour-of-the-day and day-of-the-week dummies are included in all regressions. Standard errors are clustered by currency. t-statistics are reported in squared brackets, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. The data are hourly between 16th June 2015 and 20th August 2019.

	Dependent variable: Returns					
	(1)	(2)	(3)	(4)	(5)	(6)
Tweet hour	0.006***	0.006***	0.006***	0.007***	0.007***	0.006***
	[3.59]	[3.58]	[3.59]	[3.83]	[3.92]	[3.85]
Presidency dummy		-0.000	-0.000	0.000	0.000	0.000
		[-0.24]	[-0.25]	[1.42]	[0.64]	[0.64]
FOMC dummy			-0.023***	-0.023***	-0.023***	-0.023***
			[-4.80]	[-4.78]	[-4.77]	[-4.77]
VIX				0.000*	0.000*	0.000*
				[1.87]	[1.70]	[1.70]
TED Spread					-0.001	-0.001
					[-1.12]	[-1.12]
EPU						0.003*
						[1.94]
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	376,850	376,850	376,850	372,534	366,474	366,474
R^2	0.07%	0.07%	0.07%	0.07%	0.07%	0.07%

Table B.11: Log ReTweets and Spot FX Trading Volume (Total Sell Side - Total Buy Side)

This table reports panel regressions results for the estimation of Tweets hour dummy on FX Trading Volume The control variables are presidency dummy, FOMC dummy, VIX, TED Spread, and Economic Policy Uncertainty (EPU) from Baker et al. (2016). Hour-of-the-day and day-of-the-week dummies are included in all regressions. Standard errors are clustered by currency. t-statistics are reported in squared brackets, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. The data are hourly between 16th June 2015 and 20th August 2019.

Dependent variable: Trading Volume between Sell Side and Buy Side						
	(1)	(2)	(3)	(4)	(5)	(6)
Log Retweets	-0.068***	-0.076***	-0.076***	-0.076***	-0.076***	-0.076***
	[-4.18]	[-4.16]	[-4.16]	[-4.23]	[-4.32]	[-4.32]
Presidency dummy		0.298***	0.299***	0.360***	0.350***	0.350***
		[3.25]	[3.25]	[3.49]	[3.46]	[3.46]
FOMC dummy			0.184**	0.198**	0.201***	0.200***
			[2.16]	[2.39]	[2.44]	[2.43]
VIX				0.024***	0.022***	0.022***
				[3.66]	[3.55]	[3.64]
TED Spread					-0.305**	-0.304**
					[-2.41]	[-2.40]
EPU						-0.012
						[-1.44]
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	367,333	367,333	367,333	369,492	358,013	358,013
R^2	4.59%	4.66%	4.66%	4.77%	4.77%	4.77%

Table B.12: Log ReTweets and FX Hourly Returns

This table reports panel regressions results for the estimation of Tweets hour dummy on FX hourly returns. The control variables are presidency dummy, FOMC dummy, VIX, TED Spread, and Economic Policy Uncertainty (EPU) from Baker et al. (2016). Hour-of-the-day and day-of-the-week dummies are included in all regressions. Standard errors are clustered by currency. t-statistics are reported in squared brackets, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. The data are hourly between 16th June 2015 and 20th August 2019.

	Dependent variable: Returns					
	(1)	(2)	(3)	(4)	(5)	(6)
Log ReTweets	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	[3.64]	[3.60]	[3.60]	[3.65]	[3.74]	[3.66]
Presidency dummy		-0.000	-0.000	0.000	0.000	0.000
		[-0.29]	[-0.30]	[1.21]	[0.53]	[0.54]
FOMC dummy			-0.029***	-0.028***	-0.023***	-0.023***
			[-4.46]	[-4.44]	[-4.43]	[-4.43]
VIX				0.000*	0.000	0.000
				[1.65]	[1.52]	[1.50]
TED Spread					-0.001	-0.001
					[-0.84]	[-0.84]
EPU						0.002*
						[1.68]
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	376,850	376,850	376,850	372,534	366,474	366,474
R^2	0.07%	0.07%	0.07%	0.07%	0.07%	0.07%

Table B.13: Log ReTweets and FX Hourly Realised Volatility

This table reports panel regressions results for the estimation of Tweets hour dummy on FX hourly realised volatility. The control variables are presidency dummy, FOMC dummy, VIX, TED Spread, and Economic Policy Uncertainty (EPU) from Baker et al. (2016). Hour-of-the-day and day-of-the-week dummies are included in all regressions. Standard errors are clustered by currency. t-statistics are reported in squared brackets, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. The data are hourly between 16th June 2015 and 20th August 2019.

	Dependent variable: Realised Volatility					
	(1)	(2)	(3)	(4)	(5)	(6)
Log Retweets	-0.001***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	[-5.04]	[-2.62]	[-2.59]	[-3.36]	[-2.68]	[-2.72]
Presidency dummy		-0.014***	-0.014***	-0.012***	-0.011***	-0.011***
		[-7.06]	[-7.05]	[-6.38]	[-5.93]	[-5.93]
FOMC dummy			0.070***	0.070***	0.070***	0.069***
			[8.82]	[8.82]	[8.81]	[8.81]
VIX				0.001***	0.001***	0.001***
				[8.81]	[8.82]	[8.82]
TED Spread					0.017***	0.017***
					[3.49]	[3.49]
EPU						0.001*
						[2.05]
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	397,708	397,708	397,708	393,251	387,708	387,708
R^2	6.18%	7.22%	7.38%	7.64%	7.77%	7.77%

Table B.14: Log ReTweets and FX Options Moneyness

This table reports time series regressions results for the estimation of Tweets hour dummy on FX options moneyness. The control variables are presidency dummy, FOMC dummy, VIX, TED Spread, and Economic Policy Uncertainty (EPU) from Baker et al. (2016). Hour-of-the-day and day-of-the-week dummies are included in all regressions. Standard errors are adjusted by Newey-West with number of lags based on AIC. t-statistics are reported in squared brackets, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. The data are hourly between 16th June 2015 and 20th August 2019.

	Dependent variable: Moneyness					
	(1)	(2)	(3)	(4)	(5)	(6)
Log Retweets	-0.013**	-0.014**	-0.014**	-0.014**	-0.013*	-0.013*
	[-2.18]	[-2.16]	[-2.16]	[-2.14]	[-1.93]	[-1.93]
Presidency dummy		0.066	0.066	0.059	-0.009	-0.010
		[1.09]	[1.09]	[1.03]	[-0.20]	[-0.22]
FOMC dummy			-0.019	-0.019	-0.023	-0.021
			[-0.27]	[-0.26]	[-0.29]	[-0.27]
VIX				-0.003	-0.004	-0.004
				[-0.63]	[-0.81]	[-0.81]
TED Spread					-0.727*	-0.730*
					[-1.72]	[-1.73]
EPU						-0.100*
						[-0.83]
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	9,855	9,855	9,855	9,541	9,378	9,378
R^2	0.10%	0.09%	0.08%	0.02%	0.00%	0.00%

Appendix C

U.S. Presidential Fiscal News and Cross-section of Stock Returns

1 Paragraphs in speeches and LDA Classification

Two sample populist rhetoric articles and their LDA classification results are provided. The populist terms in the articles are in bold.

Paragraph 1: (58% Fiscal topic)
In the matter of tax legislation, we must face the plain and unpalatable fact that due to the degeneration in the economic situation during the past month the estimates of fertility of taxes which have been made from time to time based upon the then current prospects of business must be readjusted to take account of the decreasing business activity and shrinking values. The Finance Committee has been advised that the setbacks of the past month now make it evident that if we are to have absolute assurance of the needed income with breadth of base which would make a certainty of the collections we must face additional taxes to those now proposed by the Senate Finance Committee

Paragraph 2: (85% Fiscal topic)
There is a third reason for believing that business can afford to pay wage increases–namely, increased output per hour of work or what is generally called increased productivity. While increased production rests ultimately with labor, the time will soon come when improvements in machinery and manufacturing know-how developed in the war can certainly result in more goods per hour and additional room for wage increases

Paragraph 3: (89% Fiscal topic)
The economy was running at a high level when this untimely tax cut was made. People then could pay the taxes necessary to balance the budget and to provide a surplus for debt reduction. Today, because profits and incomes have fallen, taxes bring in less

money. An increase in taxes now might bear too heavily on business and discourage the investment necessary to full production and full employment.

3.0 Paragraphs in speeches and LDA Classification

Two sample populist rhetoric articles and their LDA classification results are provided. The populist terms in the articles are in bold.

Paragraph 1: (58% Fiscal topic)

In the matter of tax legislation, we must face the plain and unpalatable fact that due to the degeneration in the economic situation during the past month the estimates of fertility of taxes which have been made from time to time based upon the then current prospects of business must be readjusted to take account of the decreasing business activity and shrinking values. The Finance Committee has been advised that the setbacks of the past month now make it evident that if we are to have absolute assurance of the needed income with breadth of base which would make a certainty of the collections we must face additional taxes to those now proposed by the Senate Finance Committee

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There is a third reason for believing that business can afford to pay wage increases–namely, increased output per hour of work or what is generally called increased productivity. While increased production rests ultimately with labor, the time will soon come when improvements in machinery and manufacturing know-how developed in the war can certainly result in more goods per hour and additional room for wage increases

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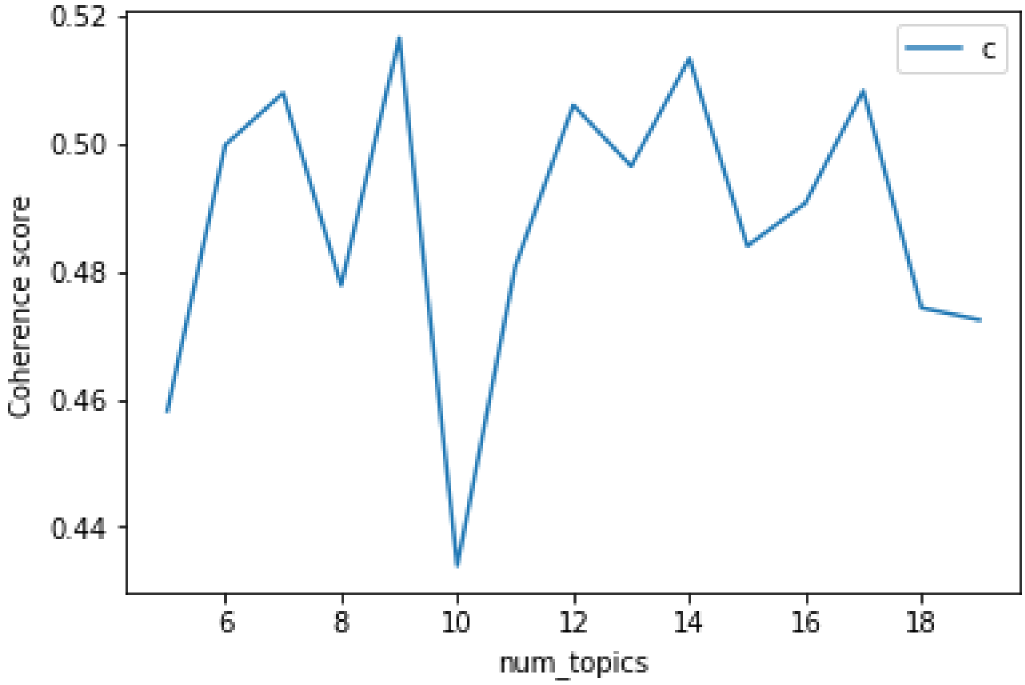
The economy was running at a high level when this untimely tax cut was made. People then could pay the taxes necessary to balance the budget and to provide a surplus for debt reduction. Today, because profits and incomes have fallen, taxes bring in less money. An increase in taxes now might bear too heavily on business and discourage the investment necessary to full production and full employment.

Figure C.1: Coherence Score Graph



Coherence score graph showing the optimal number of topics for LDA Algorithm based on the data.

Table C.1: Univariate portfolio of stocks sorted by Fiscal News Index beta

In each month, stocks are sorted into quintiles based on the absolute value of their Fiscal News Index $\beta^{FA}_{i,t}$, where quintile 1 (5) contains stocks with lowest (highest) $\beta^{FA}_{i,t}$ in the previous month. Panel A reports the equal-weighted portfolios, whereas Panel B reports the value-weighted portfolios. The first column shows the average excess return RET-RF in percentage. The next columns shows the average $\beta^{FA}_{i,t}$. α_{Mkt} is the alpha relative to market factor, α_{FM3} is the alpha relative to market, size, book-to-market factors, α_{FM4} is the alpha relative to market, size, book-to-market, and momentum factors. High-Low is the portfolio that has a long position in P5 and a short position in P1. The annualised Sharpe ratio (SR) of the High-Low portfolio is reported. Newey and West (1986) t-statistics are reported in squared brackets. The data is between July 1963 and December 2020.

Panel A: Equal-weighted portfolios						
Quintile	RET-RF	β	α_{Mkt}	α_{FM3}	α_{CH4}	α_{FF5}
1 (Low)	0.94	0.023	0.35	0.20	0.27	0.10
	[4.15]		[3.84]	[3.92]	[5.17]	[2.21]
2	0.98	0.08	0.38	0.22	0.30	0.12
	[4.19]		[3.95]	[4.23]	[5.70]	[2.64]
3	1.07	0.15	0.44	0.28	0.38	0.21
	[4.36]		[4.21]	[4.91]	[6.28]	[3.76]
4	1.23	0.25	0.41	0.51	0.27	0.37
	[4.66]		[4.85]	[7.06]	[8.32]	[6.47]
5 (High)	1.69	0.57	0.95	0.83	0.92	0.90
	[5.53]		[6.26]	[10.56]	[10.88]	[11.37]
High-Low	0.75		0.60	0.63	0.65	0.80
	[6.38]		[5.86]	[7.91]	[7.62]	[10.45]
SR	0.93					

Panel B: Value-weighted portfolios						
Quintile	RET-RF	β	α_{Mkt}	α_{FM3}	α_{CH4}	α_{FF5}
1 (Low)	0.30	0.03	-0.20	-0.19	-0.18	-0.26
	[1.76]		[-4.79]	[-4.79]	[-4.44]	[-6.73]
2	0.37	0.08	-0.14	-0.11	-0.12	0.19
	[2.15]		[-2.99]	[-2.56]	[-2.66]	[-4.53]
3	0.40	0.15	-0.14	-0.11	-0.12	-0.15
	[2.16]		[-2.80]	[-2.15]	[-2.26]	[-2.87]
4	0.41	0.25	-0.20	-0.15	-0.14	-0.08
	[1.86]		[-2.76]	[-2.28]	[-2.01]	[-1.23]
5 (High)	0.89	0.57	0.14	0.19	0.20	0.43
	[3.17]		[1.05]	[1.84]	[1.94]	[4.24]
High-Low	0.59		0.35	0.38	0.38	0.67
	[3.47]		[2.25]	[3.33]	[3.31]	[5.83]
SR	0.45					

Table C.2: Cross-section Asset Pricing with Fiscal News Index

This table reports regressions results for the estimation of the market price of Fiscal News Index (λ_{FA}). The control variables are market beta (λ_{Mkt}), size, reversal, momentum, liquidity, skewness, and idiosyncratic risk. Constants are not reported due to brevity. Newey and West (1986) t-statistics are reported in squared brackets, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. The data is between July 1963 and December 2020.

Panel A: Without industry fixed effect

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
λ_{FA}	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***
	[6.56]	[6.65]	[6.52]	[6.73]	[6.24]	[4.40]	[4.38]	[3.94]
λ_{Mkt}		-0.00	-0.00	-0.00	-0.00	0.00**	0.00**	0.00
		[-0.26]	[-0.36]	[-0.01]	[0.16]	[1.97]	[1.99]	[1.45]
Size			-0.00***	-0.00**	-0.00**	-0.00**	-0.00**	-0.00*
			[-3.94]	[-3.85]	[-3.82]	[-2.99]	[-2.97]	[-3.06]
Reversal				-0.04***	-0.04***	-0.04***	-0.04***	-0.05***
				[-9.65]	[-9.66]	[-9.88]	[-10.66]	[-11.32]
Momentum					0.00	0.00	0.00*	0.00
					[1.29]	[1.19]	[1.22]	[1.57]
Liquidity						0.27***	0.27***	0.25***
						[9.34]	[9.34]	[8.78]
Skewness							0.00***	0.00***
							[5.57]	[5.19]
Idiosyncratic risk								0.19***
								[3.45]
Obs	1,181,295	1,181,295	1,181,295	1,181,295	1,181,295	1,180,295	1,180,291	1,180,291
Adj R^2	0.6%	1.1%	1.4%	2.17%	3.30%	3.93%	4.06%	4.83%

Panel B: With industry fixed effect

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
λ_{FA}	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***
	[6.74]	[6.82]	[6.74]	[6.87]	[6.26]	[4.33]	[4.32]	[3.84]
λ_{Mkt}		0.00	-0.00	0.00	0.00	0.00**	0.00**	0.00*
		[0.00]	[-0.13]	[0.24]	[0.38]	[2.33]	[2.34]	[1.83]
Size			-0.00**	-0.00**	-0.00**	-0.00*	-0.00*	-0.00
			[-4.03]	[-3.94]	[-3.90]	[-3.10]	[-3.08]	[-3.26]
Reversal				-0.04***	-0.04***	-0.04***	-0.05***	-0.05***
				[-11.33]	[-11.13]	[-11.25]	[-12.15]	[-12.48]
Momentum					0.00	0.00	0.00	0.00
					[0.95]	[0.85]	[0.87]	[1.20]
Liquidity						0.27***	0.27***	0.25***
						[9.49]	[9.50]	[9.11]
Skewness							0.00***	0.00***
							[5.72]	[5.48]
Idiosyncratic risk								0.18***
								[3.39]
Obs	1,181,295	1,181,295	1,181,295	1,181,295	1,181,295	1,180,295	1,180,291	1,180,291
Adj R^2	2.48%	2.90%	3.15%	3.90%	4.90%	5.52%	5.64%	6.30%

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