U.S. Populism and Currency Risk Premia

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Abstract

We develop a novel measure of media attention to U.S. populism. Our Aggregate Populist Rhetoric (APR) Index spikes around well-known events that spur populist sentiment and exposure to APR is linked to financial globalization. We show that the APR Index is priced in the cross-section of currency excess returns. Currencies that perform well (badly) when attention to U.S. populism is high yield low (high) expected excess returns. Investors require a risk premium for holding currencies that underperform in times of rising attention to U.S. populism. Financial segmentation explains why friction to globalization in the form of populism affects the cross-section of currency returns.

Keywords: populism, foreign exchange market, textual analysis.

JEL Classification: F31, F37, G11, G12, G14, G32.

"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!" Nigel Farage (2020)

1 Introduction

'Populism' was the Cambridge Dictionary Word of the Year in 2017, based on the number of word searches (Cambridge Dictionary, 2017; Nichols and Lawyer, 2021). This confirms the enormous public attention surrounding this topic in the past decade following a range of recent unexpected political events worldwide, such as the election of Donald Trump as the 45th president of the U.S. or the U.K.'s vote to exit from the European Union. A rapidly growing number of papers have investigated populism and its consequences, mostly in the political science and economics literature (see, for example, Guriev and Papaioannou, 2022). However, its effect on financial markets remains unexplored.[1] One of the key challenges to conducting empirical work lies in quantifying this somewhat elusive concept in a relatively high-frequency (e.g., monthly data) environment in order to assess the asset pricing implications.

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).[2] 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 the U.S. Dollar (USD) as a vehicle currency (Maggiori, Neiman, and Schreger, 2019). The victory of Donald Trump in the 2016 U.S. presidential election

[1] One exception is the theory proposed by Pástor and Veronesi (2021), which we discuss in detail to motivate our empirical analysis.

[2] The foreign exchange market is the biggest asset market in the world in terms of trading volume. More than 7.5 trillion USD are traded on average every day based on the BIS (2022) survey.

provides a perfect example showing the extent to which U.S. politics, in general, and contemporary U.S. populism (Hawkins and Littvay, 2019), 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 the British Pound, showed resilience against the USD, reaching its best fortnight performance in eight years at one point during that period. This motivates us to investigate the question as to how U.S. populism, which is a growing political tendency and arguably with a broader audience thanks to the use of social media, is linked to the cross-section of currency excess returns.

The main contribution of our paper to the literature is twofold. First, we construct a novel index of U.S. populism that captures the attention to populism by leading U.S. newspapers. Some ongoing large-scale projects are currently attempting to quantify populism by measuring populist characteristics of specific political leaders based on campaign speeches (Hawkins, Aguilar, Silva, Jenne, Kocijan, and Kaltwasser, 2019; TeamPopulism, 2023) or the demand for populism based on vote shares for populist leaders or parties (Bayerlein, Funke, and Trebesch, 2019; Rooduijn, Van Kessel, Froio, Pirro, De Lange, Halikiopoulou, Lewis, Mudde, and Taggart, 2019). We differentiate our work from those projects as we aim to assess the media attention to populism in U.S. politics using leading newspapers over a longer time series, not the populist characteristics of any particular political leader or party. Although "populism" has become a catchword in current global affairs, it is not easy to define (Mudde, 2004), and it can be found in all ideological cleavages, including both left or right-wing politics. In more recent work, Müller (2017) highlights a prominent feature of populism, namely its rejection of pluralism and, indeed, its general tendency towards being 'anti', as in anti-establishment, anti-globalization, and anti-immigration. Several papers propose some limitations of defining populism as an ideology (Gidron and Bonikowski, 2013; Aslanidis, 2016), including the point that populist characteristics of political actors or parties are 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, we consider populism as a political style or rhetoric (Jagers and Walgrave, 2007; Bonikowski and Gidron, 2015).

We follow the methodology in Baker, Bloom, and Davis (2016) to construct our Aggregate Populist Rhetoric (APR) Index. In particular, we start with an existing dictionary containing populist terms constructed by Bonikowski and Gidron (2015) to identify populist articles, which contain terms in this dictionary from the New York Times (Jan 1984 - Dec 2020) and four other major newspapers, including the Washington Post, the New York Daily News, the New York Post and USA Today (Jan 2000 - Dec 2020). We extend the populist dictionary using bi-term topic modeling (Yan, Guo, Lan, and Cheng, 2013; Filippou, Gozluklu, T Nguyen, and Viswanath-Natraj, 2021) with Donald Trump's Twitter data both during his candidacy and presidency. We label the populist rhetoric index based on the dictionary containing terms from tweets as 'Populism 2.0' following the literature on the interaction of populism and the use of social media (Gerbaudo, 2018; Kioupkiolis, 2019). The APR index is based on the augmented dictionary containing terms from both the Bonikowski and Gidron (2015) dictionary and the terms we identify from Trump tweets. We construct the populist rhetoric indices by scaling the raw count of populist articles by the number of politics and economics articles reported by the New York Times (and the four other newspapers in the recent sample). Our APR Index spikes around key events featuring populism in U.S. politics, such as Ross Perot's presidential campaign, Seattle protests against the World Trade Organization, the Tea Party movement, and Donald Trump's presidency.

Second, our paper is the first major empirical work to investigate the link between populist media attention, financial globalization, and the foreign exchange market to the best of our knowledge. Our empirical analysis is guided by the theory put forward by Pástor and Veronesi (2021). According to that model, an expectation of a populist regime, that is a shift from globalization to autarky, results in higher valuations in U.S. stock and bond markets through a risk channel. However, the model in its original form has no predictions about the foreign exchange market. We extend the idea of these valuation effects to the currency market and explore the channels, e.g., exposure to different dimensions of globalization, through which changes in the attention to populism in the U.S. media affect foreign exchange markets. We show that exposure to U.S. populism media attention depends on countries' level of financial globalization. Following the recent literature on international asset pricing (Sandulescu, Trojani, and Vedolin, 2021; Chernov and Creal, 2023), we link the permanent component of a country's stochastic discount factor (SDF) (in relation to the U.S. SDF) to U.S. populism as it poses a threat to globalization and thus is an important source of risk for exchange rates.

Currencies with negative APR beta are found to yield low excess returns in times of rising attention to U.S. populism. Hence, they are considered relatively risky assets by U.S. investors. By contrast, currencies with positive exposure to the U.S. populism beta are found to yield high excess returns when the attention to U.S. populism is high so that investors see them as a hedge against U.S. populism. Therefore investors demand higher expected returns for holding currencies with low APR beta and are willing to pay higher prices and accept lower returns from currencies with high U.S. populism beta. We demonstrate the economic value of such exposure via a trading strategy that buys (sells) currencies with low (high) exposure to U.S. populism. We rationalize our findings within the models that highlight the important role of gravity effects in determining the currency return factor structure (Hassan, Loualiche, Reggi Pecora, and Ward, 2022; Lustig and Richmond, 2020; Richmond, 2019). In particular, we show that APR betas are positively correlated with countries' financial globalization and financial segmentation from the U.S. market. Peripheral countries are most vulnerable to an increase in attention to populism in the U.S. media and hence offer a higher currency risk premium.

We also examine the robustness of our results after controlling for other determinants of currency premia and find similar results. In particular, portfolio sorts are nonparametric as we do not impose a functional form in the relation between the APR 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, Brown, and Tang, 2017). To this end, we also investigate the cross-sectional predictive ability of the U.S. populism betas for expected currency returns at the currency level by applying Fama and MacBeth (1973) regressions. We control for foreign exchange (FX) volatility and FX illiquidity. Consistent with our previous findings, we find that the U.S. populism beta is a strong negative predictor of the cross-section of currency returns.

Using CLS FX order flow data, we examine the relationship between populism betas and the trading activity of different market participants. Specifically, we run a fixed effects panel regression of U.S. populism betas on FX volume of funds, non-bank financials, and corporates. We find that only the volume of funds demonstrates a strong negative relationship with populism betas. This finding indicates that funds tend to decrease their trading volume for currencies with high exposure to U.S. populism.

We also perform additional robustness tests, and our results still hold. In particular, we 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. We also conduct Fama-Macbeth asset pricing tests and three-pass Fama-Macbeth regressions (Giglio and Xiu, 2021) and find that the APR factor is priced in the cross-section of currency returns. A three-factor model (Nucera, Sarno, and Zinna, 2023) including APR, carry, and momentum improves the pricing performance of the benchmark three-factor model consisting of the dollar, carry, and momentum factors. Our results are robust when we consider transaction costs.

The rest of the paper is structured as follows. Section 2 summarizes related literature. Section 3 outlines the theoretical framework for our empirical work in detail. Section 4 describes the methodology implemented to extend the dictionary to 'Populism 2.0' and to construct the APR Index Section 5 describes the data and portfolio construction. Section 6 discusses the empirical findings. Section 7 discussed the relationship between globalization and U.S. populism. Section 8 offers robustness checks. Section 9 concludes.

2 Literature Review

Our paper is related to several strands of the research literature. First, it is closely related to research in political science investigating different methodologies to measure populism. One fairly standard approach has been to apply the populist label without any systematic empirical justifications (Hawkins, 2009). Alternatively, one can assess populism on a scale rather than classifying political parties or actors as *populist*. Textual analysis has been a popular method to measure populism because the input is usually in the form of 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 nature of manual coding, both labor-intensive and subject to human error and subjectivity, then 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 newspaper articles. Caldara and Iacoviello (2022) follow a similar methodology, but their interest is in a different type of risk, namely geopolitical risk. None of these papers focuses on the rising political tendency in the form of populism.

Rhodes and Johnson (2017) use a dictionary to identify statements mentioning the wealthy in Democratic presidential campaign speeches, then create an index of frequency of these statements over time, and analyze the tone of these statements; the limitation of this approach 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, developed 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 starting point for our purpose of searching for newspaper articles with populist rhetoric. However, one shortcoming of the dictionary is that it does not include in its corpus short texts from a new form of campaigning through social media (Gerbaudo, 2018; Kioupkiolis, 2019). Therefore we extend the populist dictionary using bi-term topic modeling (Yan et al., 2013; Filippou et al., 2021) with Donald Trump's Twitter data both during his candidacy and presidency. Our index of populism deviates from previous works using the dictionary-based method in several ways. We do not aim to measure the populism of any particular party or leader but the overall populist rhetoric used in U.S. politics. We also choose newspaper articles 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.

Our paper is also related to papers studying populism in the economics literature investigating the reasons for the rise of populism (Guriev and Papaioannou (2022)). For example, Rodrik (2018) suggests that the shock of globalization is one of the reasons for political backlash because it is viewed as increasing domestic inequality by creating gaps in society, e.g., between skilled and unskilled workers, between globally mobile professionals and local producers, between elites and ordinary people. This explanation has been supported by empirical evidence (Guiso, Herrera, Morelli, and Sonno, 2018; 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, Pástor and Veronesi (2021) establishes the link between populism and asset prices in a model containing elements from both strands of economic literature regarding inequality and the macroeconomic implications of populism. We discuss the details of the model in the next section as part of the motivation for our empirical study.

Our paper is also related to research investigating the effects of politics on asset prices. Sattler (2013) suggests that stock prices decrease considerably after a left-wing party's election and increase after a right-wing party's election in countries with low political constraints. Santa-Clara and Valkanov (2003), examine the stock market's performance during Democratic and Republican presidencies between 1927 and 1998, and observe a "presidential puzzle" in that the excess return of stocks is significantly higher when a Democratic president is in power. Booth and Booth (2003) also confirm this pattern for a small stock portfolio, but find that it is not the case for a large stock portfolio. Other studies find that a similar presidential puzzle exists in other countries outside the U.S., such as Germany (Döpke and Pierdzioch, 2006), New Zealand (Cahan, Malone, Powell, and Choti, 2005), and Australia (Worthington, 2009). Our study differs from these existing papers since our focus is on the effect of media attention to U.S. populism on currency markets rather than the bipartisan effect on stock returns.

Last but not least, a vast literature has examined foreign exchange predictability in the cross-section of currency excess returns. Predictability has been shown using investment strategies, such as carry (Koijen, Moskowitz, Pedersen, and Vrugt, 2018; Lustig, Roussanov, and Verdelhan, 2011), momentum (Asness, Moskowitz, and Pedersen, 2013; Menkhoff, Sarno, Schmeling, and Schrimpf, 2012b), and value (Asness et al., 2013; Menkhoff, Sarno, Schmeling, and Schrimpf, 2017). Although these papers document the predictability of currency excess returns, the fundamental forces behind them are still unclear. Della Corte, Riddiough, and Sarno (2016) suggest that global imbalance is a risk factor that can be used to explain returns to carry trade. Also, taking a macroeconomic perspective, Colacito, Riddiough, and Sarno (2020) suggest the output gap as the risk factor. Filippou and Taylor (2023) find that forward-looking policy rules are priced in the cross-section of currency returns. Some papers suggest risk factors based on properties of FX returns, such as correlation risk (Mueller, Stathopoulos, and Vedolin, 2017) and global FX volatility risk (Menkhoff, Sarno, Schmeling, and Schrimpf, 2012a). Nucera et al. (2023) show that the currency pricing kernel consists of at least three latent factors, including a strong U.S. dollar factor. On the other hand, nascent literature highlights the importance of the gravity effect in currency return factor structure (Hassan et al., 2022; Lustig and Richmond, 2020; Richmond, 2019). Filippou, Taylor, and Wang (2023) show that media sentiment is a strong negative predictor of the cross-section of currency returns. Linking political risk to currency returns, Filippou, Gozluklu, and Taylor (2018) suggest that global political risk explains returns to momentum strategy.

3 Testable Hypotheses

Our starting point is the theoretical framework established in Pástor and Veronesi (2021). In their model, agents in two countries, the U.S. and the rest of the world (RoW), dislike inequality within their countries. U.S. agents are less risk-averse (capturing the fact that the U.S. markets are more financially developed) than RoW agents. Under globalization, agents in the two countries trade freely, increasing aggregate consumption in the U.S. and its domestic inequality. The reverse is the case under financial autarky, where U.S. aggregate consumption 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. An important prediction from the model regarding the anticipation of a populist victory is on asset valuations.

According to this model, as the probability of a populist victory increases, the U.S. market price of risk goes down. As a result, U.S. asset market valuations increase. The intuition is as follows: Under autarky, the risk associated with U.S. output is borne by U.S. agents only, while under globalization, this risk is shared by U.S. and RoW agents. As U.S. agents are assumed to be less risk-averse, they demand a lower compensation for risk regardless of the global output level. The model also predicts that U.S. bond yields could be lower, even possibly negative, as anticipation for populist victory escalates. However, that prediction depends on the global output level. The intuition underlying this prediction is that as moving to autarky decreases U.S. agents' consumption, marginal utility to U.S. agents is high in this case.

How does U.S. populism affect currency markets?

Pástor and Veronesi (2021) model does not make any specific prediction on the currency valuation. Under the asset market view (AMV) of exchange rates (Chernov and Creal, 2023; Burnside and Graveline, 2020), the no-arbitrage condition implies the following equation for the domestic and foreign stochastic discount factors (SDFs):

$$\mathbb{E}_t(M^*_{t,t+1}R^*_{t+1}) = \mathbb{E}_t(M_{t,t+1}\frac{S_{t+1}}{S_t}R^*_{t+1}) \tag{1}$$

where R^*_{t+1} is the foreign currency-denominated gross return on a risky asset, $M_{t,t+1}$ and $M^*_{t,t+1}$ are the domestic (U.S) and the foreign SDFs, respectively and S_t the USD value of one unit of foreign currency.

International asset markets are integrated if

$$span(R_{t+1}) = span(R^*_{t+1}\frac{S_{t+1}}{S_t}) \tag{2}$$

where R_{t+1} is the domestic currency-denominated gross return on a risky asset and $span(R_{t+1})$ ($span(R^*_{t+1}\frac{S_{t+1}}{S_t})$) is the linear span of payoffs generated by domestic (foreign returns expressed in domestic) returns.

If international markets are complete:

$$\frac{S_{t+1}}{S_t} = \frac{M^*_{t,t+1}}{M_{t,t+1}} \tag{3}$$

one can recover the (gross) exchange rate return by the ratio of foreign and domestic SDFs.

Sandulescu et al. (2021) show that one can obtain the same recovery under incomplete markets with minimum entropy SDFs unless the markets are segmented. Importantly, market segmentation, defined as the lack of access to international long-term securities – which represents a friction to financial globalization – is the key driver of the low cross-country SDF correlations. Market segmentation thus helps resolve the international finance puzzles related to low exchange volatility and FX-macro disconnect. Therefore we assume markets are complete but financial segmentation limits perfect risk-sharing across countries.

Following extant literature (Chernov and Creal, 2023; Sandulescu et al., 2021; Alvarez and Jermann, 2005), we conjecture that two types of shocks drive the SDFs, i) persistent (common) shocks ii) temporary (country-specific) shocks:

$$M_{t,t+1} = M^P_{t,t+1} M^T_{t,t+1} \tag{4}$$

where the permanent component $M^P_{t,t+1}$ satisfies the martingale condition $\mathbb{E}[M^P_i] = 1$ and the transient component $M^T_{t,t+1}$ is the inverse of the return of an infinite-maturity bond. Sandulescu et al. (2021) show that the permanent component is the main driver of FX variation, while Chernov and Creal (2023) solve the FX bond disconnect puzzle by identifying the permanent component that only affects the exchange rates without an impact on bond yields.

In light of the predictions of Pástor and Veronesi (2021) model, we interpret a threat to globalization as a common (global) shock. We then test whether exposure to such a shock proxied by the U.S. populist rhetoric index (APR) captures the threat of a U.S. populist victory, which ultimately leads to more segmentation in international markets measured by cross-country correlations of permanent SDF components. Given that media coverage, and in particular through newspaper and social media, is an important source of information for investors, when there is a rise in populism – as reported by leading newspapers and used on Twitter – U.S. investors are likely to consider it as a signal that the U.S. economy is moving from an integrated world to autarky.

Does U.S. populism have the same effect on individual currencies?

Lustig and Richmond (2020) demonstrate the importance of gravity effects in the factor structure of exchange rates. Using different distance measures (e.g., cultural, physical, or institutional) across countries, they find distant countries are more exposed to systematic currency risks and hence offer higher expected currency returns. We conjecture that a threat to financial globalization is a systematic risk channel through which U.S. populism drives the cross-section of currency returns.[3]

Hypothesis 1 (H1)**.** *Rising U.S. populism reflects a threat to financial globalization. Less financially integrated countries demonstrate, on average, higher exposure to U.S. populism.*

We test the first hypothesis by running cross-country regressions of average loadings (betas) to our APR Index (Lustig and Richmond, 2020) on a direct measure of the financial globalization index (e.g., Dreher, 2006; Gygli, Haelg, Potrafke, and Sturm, 2019) and on the correlation of the permanent components of U.S. and foreign (model-free) SDFs (Sandulescu et al., 2021) as a proxy for financial segmentation in international asset markets and control for other distance measures (Lustig and Richmond, 2020).

We expect the media attention to U.S. populism, captured by our APR Index, to negatively affect the cross-section of currency excess returns. This hypothesis is based on

[3]For a detailed exposition of a model that generates heterogeneity in exposure to common shocks, see, for example, Lustig et al. (2011).

the intuition that U.S. populism leads to lower U.S. consumption, increasing marginal utility consumption to U.S. agents, linking consumption growth to the priced component of currency returns (Chernov, Dahlquist, and Lochstoer, 2023). Investors value currencies that give U.S. investors high excess returns in times of rising populism. 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 the rise of populism. Therefore we expect the exposure to the APR index to be negatively priced in the cross-section of currency excess returns.

Hypothesis 2 (H2)**.** *Countries with high exposure to U.S. populism experience currency depreciation when there is an increase in the perceived threat of a populist victory.*
(a.) Media attention to U.S. populism is a strong negative predictor of the cross-section of currency returns.
(b.) Investors require a risk premium for holding currencies that underperform in times of rising U.S. populism.

We test the second hypothesis by evaluating the performance of populism-sorted portfolios, running cross-sectional predictive regressions of excess returns on past loadings to APR index, and measuring the market price of risk associated with APR index while taking into account traditional risk factors such as dollar, carry and momentum (e.g., Lustig et al., 2011; Asness et al., 2013; Koijen et al., 2018; Menkhoff et al., 2017; Nucera et al., 2023) and controlling for FX volatility and liquidity as in Menkhoff et al. (2012a).

4 U.S. Populist Rhetoric Index

This section introduces the bi-term topic modeling algorithm to extend an existing populist dictionary to capture the new form of populism via social media and describes the methodology we use to construct our Aggregate Populist Rhetoric Index from several leading U.S. newspapers.

4.1 Newspapers

We rely on digital archives of the New York Times from Factiva. The New York Times has been regarded as a national 'newspaper of record,' so our index should encompass a large section of U.S. readers. This is also the only leading U.S. newspaper to which we have access to the data from January 1984 to December 2020. However, we also constructed a shorter time series index based on five newspapers, including the Washington Post, the New York Daily News, the New York Post, and USA Today, as well as the New York Times, from January 2000 through to December 2020.[4]

4.2 Populist Dictionary by Bonikowski and Gidron (2015)

An existing populist dictionary was constructed by Bonikowski and Gidron (2015). To minimize the risk of finding articles incorrectly classified as populist by the algorithm (false positives), we rely on the short version of their dictionary. The authors have eliminated all underperforming terms. The final dictionary used in this paper thus contains 26 terms ranging from uni-grams to four-grams+. There may be potential concerns that there are populist articles not detected as they do not contain any terms in the populist dictionary (false negatives). However, Bonikowski and Gidron (2015) claim in their paper that this number is expected to be low due to their extensive search for relevant populist terms. The

[4]While the news from NYT may contain liberal bias (Levy, 2021), the inclusion of newspapers with more moderate (e.g., USA Today) and conservative (e.g., New York Daily News, New York Post) media slants, should reduce such bias.

list of populist terms from this dictionary is in Panel A of Table 1. One might argue that the dictionary does not contain some economically relevant terms, e.g., tariffs, tax cuts, and immigration which one would expect in a populist narrative (Rodrik, 2021).

[TABLE 1 ABOUT HERE]

4.3 New Dictionary of Populism 2.0

4.3.1 Donald Trump's Tweets

Bonikowski and Gidron (2015) construct their dictionary using texts from an archival presidential campaign discourse dataset. However, social media has been extensively used as a campaign tool in modern U.S. politics, especially by populist candidates (Bode, Budak, Ladd, Newport, Pasek, Singh, Soroka, and Traugott, 2020). To capture this new form of communication of populist presidential candidates, Populism 2.0 (Gerbaudo, 2018; Kioupkiolis, 2019), we obtain an archive of Donald Trump's tweets from thetrumparchive, which collects all tweets from the account @realDonaldTrump. We are interested in the period starting from June 16^{th} 2015, as that was the day when Donald Trump announced his presidential campaign. Our sample ends on August 20^{th} 2019.

4.3.2 Bi-term topic modeling (BTM) approach

Bi-term topic modeling (BTM) is a word co-occurrence-based topic model that learns topics by modeling word-by-word co-occurrence patterns (e.g., bi-terms). It was developed by Yan et al. (2013) to address shortcomings associated with conventional topic modeling approaches, such as Latent Dirichlet Allocation (LDA) and Latent Semantic Indexing (LSI) when it comes to discovering the content of short texts.

Two sets of input are required from the BTM approach. The first is the collection of words, which is the corpus. We apply the BTM approach to our full sample of tweets after these tweets are cleaned with standard text-cleaning procedures, such as lower capitalization and removing numbers and English stop words. The second input required is the number of topics, which we set as 10.

Two sets of output are generated from the BTM algorithm. The first set of outputs 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 ten topics can be found in Figure A2 and Figure A3 in the Appendix. We summarise the keywords for the five topics we identify as having populism-related content in Figure 1.

[FIGURE 1 ABOUT HERE]

We pick the populism keywords from these five topics by filtering out those with many false positives. For example, we remove words such as news, fake, and media and keep bigrams 'fake news' and trigrams 'fake news media' instead. The list of populist terms from this dictionary can be found in Panel B of Table 1. As one can see, the new terms include "tariffs", "border security," or "illegal immigration," which are tightly linked to (frictions to) globalization. Another common term is "make America great again (maga)." Although Donald Trump has extensively used the phrase, it is hardly novel. Previous presidents such as Ronald Reagan and Bill Clinton have also used the same slogan (NBC News, 2016).

4.4 U.S. Aggregate Populist Rhetoric Index

We aim to search for articles containing populist rhetoric published in the New York Times. We define an article as populist if it falls under the U.S. politics or economics category and contains at least one term in the populist dictionary constructed by Bonikowski and Gidron (2015) and the 'Populism 2.0' dictionary either in its title or main content. We search for populist articles from five newspapers on the Factiva database by entering 26 populist terms in the search box and applying restrictions to filter out non-U.S. politics and economics articles. This allows us to obtain the count of populist articles from newspapers over our sample period.

Previous studies following similar methodologies, 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, we are interested in the ratio of the raw counts of populist articles divided by the total number of U.S. political and economic articles published monthly. This ratio gives us the Aggregate Populist Rhetoric (APR) Index. Figure 2 shows our APR Index plot.

[FIGURE 2 ABOUT HERE]

We evaluate our APR Index by uncovering events underlying their patterns. The plot of our APR Index displays several spikes over this sample period. The first spike was recorded in the late 1980s, featuring Reagan's presidency. The index then goes up around the 2000s, reflecting two notable political events featuring populism surrounding this time frame. The first event was 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. Our 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, our 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, explains the rise in the index even after the election in November 2016.

We also show plots of the index (PR BG index) constructed using the populist dictionary by Bonikowski and Gidron (2015) and the 'Populism 2.0' dictionary (PR P2.0 Index) separately in Figure 3. We note that both series have different time-series dynamics confirming that they capture different dimensions of populist rhetoric. Notably, the PR BG index spiked around Seattle WTO protests in the late nineties, while the PR P2.0 Index spiked earlier during the rise of populist conservative personalities (history.com, 2018) in mid-nineties and reached its peak during Donald Trump's presidency.

[FIGURE 3 ABOUT HERE]

We report summary statistics of the APR index, its sub-indices, and their changes (i.e., ΔAPR) in Panel A of Table 2. Both the APR index and the sub-indices are similar in terms of the first two moments, while the PR P2.0 index exhibits larger skewness and kurtosis. All indices and their changes are stationary according to the augmented Dickey-Fuller test.

In *Panel B* of Table 2, we report the correlation between our populist rhetoric indices and some (geo-)political risk and uncertainty measures in the literature. The APR index and the sub-indices show a mild negative correlation with the Geopolitical Risk Index constructed by Caldara and Iacoviello (2022). The reason behind this negative correlation is likely to be due to the fundamental differences in index construction. The Geopolitical Risk Index captures events associated with wars, terrorist acts, and some events that do not feature U.S. involvement.

Our populist rhetoric indices are unrelated to the Macroeconomics Uncertainty Index (Jurado, Ludvigson, and Ng, 2015) and Economic Policy Uncertainty Index (Baker et al., 2016), while the APR index has some positive correlation with the VIX Index, Trade Policy Uncertainty (TPU) Index (Caldara, Iacoviello, Molligo, Prestipino, and Raffo, 2020) and the government policy sentiment (GPS) measured by the University of Michigan Surveys of Consumers (Liu and Shaliastovich, 2022). However, it is interesting to note that the BG PR and P2.0 PR indices are correlated with these uncertainty measures, namely VIX, EPU, and TPU, showing opposite signs, confirming the distinct information content of both indices.[5] Panel B of Table 2 shows similar results for the changes of the APR index. Overall, correlation results suggest that our APR Index captures a different dimension than the existing economic and political uncertainty indices.

[TABLE 2 ABOUT HERE]

5 Currency Data and Portfolio Construction

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

5.1 Currency Data

Our data focuses on a rich set of developed and developing economies. Our sample includes **Australia**, Austria, Belgium, **Brazil**, **Bulgaria**, **Canada**, Croatia, Cyprus, **Czech Republic**, **Denmark**, Egypt, Europe, Finland, France, **Germany**, Greece, **Hong Kong**, **Hungary**, Iceland, **India**, Indonesia, Ireland, **Israel**, Italy, **Japan**, Kuwait, Malaysia, **Mexico**, Netherlands, **New Zealand**, **Norway**, **Philippines**, **Poland**, Portugal, Russia, Saudi Arabia, **Singapore**, **South Africa**, **South Korea**, Slovakia, Slovenia, Spain, **Sweden**, **Switzerland**, **Taiwan**, **Thailand**, Ukraine and **United Kingdom**.[6] We remove the euro-area countries after they adopt the euro. Our monthly data covers the period from January 1984 to December 2020.[7]

[5] P2.0 PR and TPU indices have a relatively high correlation of 0.74. However, in Appendix A1, we show that TPU does not have the same asset pricing implications for currency returns.

[6] We also eliminate observations of currencies that exhibit significant deviations from CIP.

[7] We use the 25 countries in bold to estimate the model-free foreign SDF in the post-2007 sample. We thank Mirela Sandulescu for sharing the replication codes.

5.2 Currency Excess Returns

Our exchange rate data are collected from Barclays and Reuters *via* Thompson Reuters Datastream (Eikon). We denote by S_t (F_t) the level of the spot exchange rate and the 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:

$$rx_{t+1} = f_t - s_{t+1}, \tag{5}$$

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.[8]

[8] We include the Euro in our sample following its launch in January 1999.

5.3 Portfolios sorted on APR betas

One way to test the role of U.S. populism 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. populism. If media attention to U.S. populism 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. Our proxy of media attention to U.S. populism is the APR Index. To measure the exposure of each currency to U.S. populism, we regress individual currency excess returns at time t on a constant and the APR Index.

$$rx_{i,t} = \alpha_{i,t} + \beta_{i,t}^{APR} APR_t + \epsilon_{i,t} \tag{6}$$

where $rx_{i,t}$ is the realised excess return on currency i in month t, and APR_t is the APR Index in month t.

The estimation is based on a 60-month rolling window (with a minimum of 36 observations). The time-varying slope coefficient (loadings) obtained from this regression is $\beta_{i,t}^{APR}$. Intuitively, currencies with more negative betas exhibit higher exposure to U.S. populism, as an increase in populism is associated with negative currency excess returns.

Populism Portfolios. At time t, we sort currencies into portfolios based on their past (i.e. $t-1$) betas with APR Index. We limit the number of portfolios to five to have a reasonable number of currencies in each portfolio. We rebalance our portfolios monthly. The first portfolio (P_1) includes currencies with the lowest betas, while the fifth portfolio (P_5) covers currencies with the highest betas. We then construct a zero-cost portfolio (LMH), which goes long the first portfolio (P_1) and short the high beta portfolio (P_5).

6 Empirical Results

In this section, we empirically investigate the link between U.S. populism and financial globalization. We then run the cross-sectional predictive regressions of currency excess returns on loadings to APR index. Finally, we show the results of the country-level asset pricing tests.

6.1 Globalization and U.S. Populism

We first explore the channels through which U.S. populism – a strong signal on the switch from globalization to autarky – could affect currency returns. We follow the recent literature on the gravity effect in the factor structure of exchange rates (Lustig and Richmond, 2020). The key insight from this literature is that peripheral countries in a network of global economies are more vulnerable to systematic currency risk and hence offer higher expected currency returns.

Globalization is a complex term with many dimensions, including economic, social, and political globalization (Dreher, 2006; Gygli et al., 2019). Dreher (2006) construct an index of globalization which is further developed by Gygli et al. (2019) to capture different layers of globalization. For instance, economic globalization can be measured either through the trade channel (trade in goods and services) or financial channel (e.g., foreign direct investment, portfolio investment, and international debt). We test the link between average APR betas and different dimensions of globalization.[9]

Figure 4 shows that the average APR betas are mostly correlated with the countries' financial globalization index (we report other dimensions of globalization in Appendix Figure A5). The positive and statistically significant slope coefficient – with a cross-sectional

[9]We also show scatter plots between average APR betas and other country characteristics such as geographic distance to the U.S. (Lustig and Richmond, 2020), country size (Hassan, 2013) and different dimensions of institutional quality (accountability, regulatory quality, government effectiveness and the rule of law) in Appendix A.

R-squared of 0.20 – suggests that less financially globalized countries have lower (higher) APR betas (in magnitude); that is, they depreciate most in times of rising U.S. populism. This finding is in line with our hypothesis H1, which states that U.S. populism is a friction to globalization and has a larger impact on the currencies of peripheral economies.

[FIGURE 4 ABOUT HERE]

Table 3 verifies this result in a multi-variate setting with country-specific controls such as country size (Hassan, 2013) and geographic distance to the U.S. (Lustig and Richmond, 2020). The cross-country regressions confirm the important role of financial globalization as an important mechanism behind the cross-sectional differences in exposure to U.S. populism.

Specifically, our first proxy for financial globalization is the KOF financial globalization index, which is a weighted average measure of foreign direct investment, portfolio investment, international debt, international reserves, and international income payments using annual data (e.g., Gygli et al., 2019). To this end, a contemporaneous cross-sectional regression of the sensitivity of each currency to the APR index on the KOF financial globalization index and a set of controls. The model takes the form:

$$\hat{\beta}_i^{APR} = \delta_1 + \delta_2 \text{KOF Financial Globalization}_i + \delta_{3,t}\mathbf{X}_i + \varepsilon_i, \tag{7}$$

where $\hat{\beta}_i^{APR}$ denotes the time-series average of APR rolling betas for each country i. The APR betas ($\hat{\beta}_{i,t}^{APR}$) are estimated in equation 6 based on a 60-month rolling window. The set of controls $\mathbf{X}_i$ includes the time-series average of log GDP share, log distance to the U.S., and Government effectiveness for country i. Table 3 reports the slope coefficients (δ) over the period of January 1984 to December 2020 for all countries in our sample. We report heteroskedasticity robust White (1980) t-statistics in parenthesis. We find a strong positive association between the APR betas and the globalization index, which illustrates the strong link between the currency exposures to U.S. populism and financial segmentation. This result is robust to the presence of control variables. In terms of goodness of fit, the adjusted R-squares range from 17% to 49% which implies that our proxy of financial globalization captures a large part of the cross-sectional variation of the APR betas.

[Table 3 ABOUT HERE]

The KOF financial globalization index reflects how integrated each country is based on its transactions with the rest of the world. However, it does not show how integrated a foreign country is with the U.S. financial system. Following the recent international asset pricing literature (Sandulescu et al., 2021; Chernov and Creal, 2023), we construct an alternative proxy for financial segmentation relative to the U.S., that is, the correlation between the permanent components of U.S. and foreign SDFs. We use the model-free measures of SDFs using asset returns, that is, stock market returns, long and short-term government bond returns, and exchange rate returns deflated by each Country's CPI index following (Sandulescu et al., 2021) and obtain the permanent SDF components as described in equation 4. Specifically, Sandulescu et al. (2021) relax the complete market assumption and obtain the minimum dispersion SDF as

$$\begin{aligned} \underline{M_i}(\alpha) = \underset{M_i}{\operatorname{argmin}} & \frac{1}{\alpha(\alpha-1)} log \mathbb{E}[M_i^{\alpha}] \\ s.t. \qquad & \mathbb{E}[M_i \mathbf{R_i}] = 1 \\ & M_i > 0, \end{aligned} \tag{8}$$

where the first constraint ensures that M_i prices all available assets ($\mathbf{R_i}$) in country i and the second constraint implies M_i is an SDF. Sandulescu et al. (2021) solves this problem by mapping it into a portfolio problem (Orłowski, Sali, and Trojani, 2018) and focus on two special cases, $\alpha = 0$ (minimum entropy SDF) and $\alpha = 2$ (minimum variance SDF). They allow for financial segmentation by excluding the investors in a country i from foreign stock and long-term bond markets. Figure 5 shows the average APR betas mostly correlated with the countries' financial segmentation from the U.S. market, proxied by the correlation of the permanent components of U.S. and foreign (minimum entropy) SDFs.[10] In line with the previous finding, we show that the alternative proxy for financial segmentation captures a significant part of the cross-sectional variation of the APR betas.

[FIGURE 5 ABOUT HERE]

Table 4 shows this result in a multi-variate setting with country-specific controls such as country size (Hassan, 2013) and geographic distance to the U.S. (Lustig and Richmond, 2020). The model takes the form:

$$\hat{\beta}_i^{APR} = \delta_1 + \delta_2 corr(M_{US}^P, M_i^P) + \delta_3 \mathbf{X}_i + \varepsilon_i, \tag{9}$$

where $corr(M_{US}^P, M_i^P)$ denotes the correlation of permanent components of U.S. and foreign model-free (minimum entropy) SDF. Table 4 reports the slope coefficients (δ) over the period of January 2007 to December 2020 for a subset of countries in our sample that we describe in Section 5.1. The positive slope coefficient of the correlation variable with a similar R^2=0.17 confirms our earlier result, lending further support to our hypothesis H1.

[Table 4 ABOUT HERE]

6.2 Populism-sorted Currency Portfolios

We next attempt to understand the role of U.S. populism in the foreign exchange market. We allocate currencies into portfolios based on their exposure to populism in the media, as was analyzed in the previous section. Table 5 reports summary statistics of portfolios sorted on Full Sample (*Panel A*) and Recent Sample (*Panel B*).

[TABLE 5 ABOUT HERE]

[10] Minimum variance SDFs provide very similar results.

Panel A shows that there is a significant dispersion with a monotonic pattern in terms of average betas when moving from P_1 to P_5. It increases from -0.47% to 0.30% 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 (3.09%) and statistically significant with a Newey and West (1987) t-statistic. The average excess returns to LMH portfolio is of particular interest, which is also positive and statistically significant with a Newey and West (1987) t-statistic of 2.19. The populism portfolio yields an annualized average excess return of 3.19% with a Sharpe ratio of 0.38. When we decompose the portfolio return into the exchange rate and forward discount components, we see that the portfolio return is entirely driven by exchange rate changes in line with our conjecture that the APR index captures only the risks associated with the currency markets.

These results can be interpreted as follows. Currencies in P_1 have negative APR betas, meaning their returns decrease when APR Index increases. An increase in U.S. populism, which is proxied by the APR index, is a bad state variable in terms of aggregate consumption for U.S. investors (Pástor and Veronesi, 2021). 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_5 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. This finding aligns with our hypothesis H2, which states that U.S. populism should be a negative predictor of the cross-section of currency returns and that investors require a risk premium for holding currencies that are exposed to U.S. populism.

Panel B also suggests a negative link between average portfolio excess returns and APR betas for the recent sample from 2000. Average excess returns are monotonically decreasing from P_1 to P_5. The LMH portfolio now generates even better performance than in *Panel A* in terms of Sharpe ratio. This portfolio yields 3.19% excess returns annually on average (with a Newey and West (1987) t-statistic of 2.63) and a Sharpe ratio of 0.62. The decomposition of the excess portfolio returns, however, suggests that only half of the portfolio return comes from exchange rate changes. We can also interpret this result through the lenses of Pástor and Veronesi (2021) model, which suggests that a threat of a populist regime implies both a lower market price of risk for U.S. investors and a lower U.S. bond yield beyond a certain threshold of global output. This is likely to be the case only in the recent sample.

As we would like to explore further which currencies drive the profit of the populism portfolio strategy found in Table 5, we plot each currency's frequency at the two extreme portfolios in Figure A1 of the Internet Appendix.

Panel A and of Figure A1 suggest that the top 3 currencies that are frequently entering the low beta portfolios based on APR Index betas are Hungary, Iceland, and New Zealand. These currencies typically have negative betas, so they tend to generate low excess returns when U.S. populism is high. By contrast, *Panel B* of the same figure reveals the top 3 currencies in high beta portfolios based on APR Index. These currencies include Japan, Australia, and Hong Kong. Due to their positive betas on average, they generally yield high excess returns when there is an increase in U.S. populism.

We show the plot of cumulative return to LMH portfolio in Figure 6. The cumulative return is adjusted by volatility. In particular, the return to the LMH portfolio is multiplied by the ratio of annual S&P500 Index volatility and LMH portfolio volatility. It is worth noticing that the APR strategy generates better performance during Republican presidencies, in particular when George W. Bush and Donald Trump were in power.

[Figure 6 ABOUT HERE]

6.3 Populism-sorted Portfolios and Other Investment Strategies

We investigate the link between other conventional investment strategies (i.e., market, carry trade, and momentum) and Populism-sorted portfolios. In particular, we examine whether the LMH Populism portfolio can generate significant alphas after controlling for these strategies. We run contemporaneous regressions of the LMH Populism portfolio on the market, carry trade, and momentum portfolios to see if these conventional investment portfolios can explain the returns generated by the LMH Populism portfolio.

The first column in Panel A of Table 6 shows results for univariate regression in which market portfolio is the only independent variable. The coefficient of the market portfolio is negative but statistically insignificant, whereas the alpha is 0.3% and statistically significant with a t-statistic of 2.08. These findings suggest that the market factor cannot explain our LMH Populism portfolios. In the next column, we add the carry trade factor to the regression and find the same pattern. The coefficient of the market is statistically significant, whereas the coefficient of the carry trade factor is only marginally significant. On the other hand, the regression's alpha remains economically and statistically significant at a 1% significance level. In the last regression, we augment the previous model with the momentum factor, and the coefficient of this factor is not significant. The alpha in this regression maintains its positive sign with a t-statistic of 3.44. Overall, we find that the LMH Populism strategy can generate a positive and statistically significant alpha even after considering conventional asset pricing factors. We find similar results for the Recent Sample in Panel B.

[TABLE 6 ABOUT HERE]

6.4 Country-level asset pricing tests

After documenting the significant excess returns of LMH portfolios sorted on currency exposures to U.S. populism, we now investigate the risk price of this factor.

Test assets. Our test assets are individual currencies rather than portfolios. Ang, Liu, and Schwarz (2018) suggest that grouping stocks into portfolios shrinks the betas' cross-sectional dispersion, 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, Kho, Rouxelin, and Yang (2018) test the risk price of global imbalances using individual currencies.

Cross-sectional Predictive Regressions. Having estimated $\hat{\beta}_{APR,i}$ in equation 6, we 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, we run monthly cross-sectional regressions at each time t:

$$rx_{i,t+1} = \lambda_{0,t} + \lambda_{1,t}\hat{\beta}^{APR}_{i,t} + \lambda_{2,t}X_{i,t} + \epsilon_{i,t+1} \tag{10}$$

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). We 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 7 summarises results regarding the estimation of risk prices of the APR Index betas from regressions (2) and (3).

In this table, we report results for Full Sample in *Panel A*. The univariate regression results shown in the first column suggest a negatively significant link between the APR betas and the cross-section of future currency excess returns. The market price of risk λ

associated with the APR beta is -0.006, with a t-statistic of -2.94. This negative coefficient for APR betas 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, we compute the difference in average β^{APR} between P_1 and P_5 from Table 5, which is 0.77% [=0.30% - 0.47%]. If a currency were to move from P_1 to P_5, its expected return would decrease by 0.46% [=0.77% × -0.006] per month. Therefore, the risk price of the APR Index betas is not only statistically significant but also economically significant.

In the second column, when we 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 -2.64, and the risk price of volatility factor is negative and marginally statistically significant. The third column controls for the illiquidity of individual currencies, and it still gives us a negative and statistically significant risk price of APR beta. On the other hand, the illiquidity factor's risk price is statistically insignificant. In the fourth column, when controlling for both illiquidity and volatility of individual currencies simultaneously, we still get a strongly significant risk price of APR betas with a Newey and West (1987) t-statistic of -2.64.

In the same table, we report results for the Recent Sample in *Panel B*. 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 separately and simultaneously, even though its statistical significance is weaker.

[TABLE 7 ABOUT HERE]

7 Robustness

Firms' Exposure to Globalization and APR Index. In the Pástor and Veronesi (2021) model, a shift to a populist regime is captured by a move to autarky from globalization. Therefore, if our measure of populism is well identified, it should be sensitive to exposure to globalization. We use an alternative of exposure to globalization using equity data following Barrot, Loualiche, and Sauvagnat (2019), 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. We then examine the correlation between these portfolios and our APR Index and show results in Table A4.

In *Panel A*, we report the pairwise correlations between the returns of 5 portfolios and the LMH portfolio and APR Index. A positive correlation exists between the low shipping cost portfolio and the APR Index for equally weighted portfolios. This is consistent with the rationale that an increase in the APR Index signals a switch from integrated to the autarkic regime for the U.S., so firms with low shipping costs (i.e. those with high exposure to globalization) should be positively correlated with our index. We also find an almost monotonically decreasing pattern in terms of this correlation as we go from P_1 to P_5. The negative correlation between P_5 with our index suggests that this portfolio of firms with low exposure to globalization can be a hedge in times of rising U.S. populism. This result is consistent for value-weighted portfolios and when we control for Fama-French 3 factors in *Panel B* and Fama-French 5 factors in *Panel C*. It is important to note that this result indicates firms' exposure to trade globalization where FX returns are mostly sensitive to financial globalization driven by cross-border capital mobility as documented in Figure 4.

Alternative pricing factors. To test for the robustness of our findings, we 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, our regressions (2) and (3) become:

$$rx_{i,t} = \alpha_{i,t} + \beta_{i,t}^{APR} APR_t + \beta_{i,t}^{DOL} DOL_t + \beta_{i,t}^{CAR} CAR_t + \epsilon_{i,t} \tag{11}$$

$$rx_{i,t+1} = \lambda_{0,t} + \lambda_{1,t}\hat{\beta}_{i,t}^{APR} + \lambda_{2,t}\hat{\beta}_{i,t}^{DOL} + \lambda_{3,t}\hat{\beta}_{i,t}^{CAR} + \epsilon_{i,t+1} \tag{12}$$

We report our regression results for APR Index in Table 8.

[TABLE 8 ABOUT HERE]

The results for Full Sample are reported in *Panel A*. The first column's result with univariate regression suggests a negative and statistically significant link between APR beta and future currency excess returns. The risk price of APR beta is -0.007 with a Newey and West (1987) t-statistic of -2.44. In the second column, when we 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 -2.67. The 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 -3.37. This highlights an important finding. APR beta predicts future currency excess returns beyond DOL and CAR factors.

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

Filtered Sample. A potential concern associated with our broad sample is that market frictions may impede investors from trading particular currencies, affecting the validity of our findings. To address this problem, we follow Della Corte, Sarno, Schmeling, and Wagner (2022) and apply two filters. In particular, we start with a large sample of 48 countries and eliminate month/country observations of countries that implement fixed or quasi-fixed exchange rate regimes and those imposing restrictions on their capital account (e.g., a negative Chin Ito index). Portfolio sorting results for this filtered sample are reported in Table A6. The average excess return to the LMH portfolio is positive and statistically significant both in Panel A (Full Sample) and Panel B (Recent Sample).

Fama-Macbeth Asset Pricing Test. Table 9 provides asset pricing results for a two-factor model that consists of the dollar factor (DOL) and the APR factor and three-factor model consisting of the dollar, carry (HML) and momentum factors versus APR, carry and momentum factors. We use as test assets six currency portfolios sorted based on lagged APR. Thus, in the case of the two-factor model, we employ an SDF of the following form:

$$M_{t+1} = 1 - b_{DOL}(DOL_{t+1} - \mu_{DOL}) - b_F(F_{t+1} - \mu_F) \tag{13}$$

where DOL represents the dollar factor and F is the APR risk factor (HML_{APR}). In the case of the three-factor model, we compare two specifications

$$M_{t+1} = 1 - b_{HML}(HML_{t+1} - \mu_{HML}) - b_{MOM}(MOM_{t+1} - \mu_{DOL}) - b_F(F_{t+1} - \mu_F) \tag{14}$$

where HML (MOM) represents the carry (momentum) factor, and F is either the dollar or the APR risk factor (HML_{APR}).

The table provides results for the second pass of the FMB regression. We provide estimates for the implied risk factor (λ) and the corresponding Newey and West (1987) t-statistic. The cross-sectional performance of the models is also evaluated based on root mean square error (RMSE), cross-sectional R-squared, and GRS. In Panel A, we report the results for the two-factor model in the Full Sample. We find that the APR factor strongly predicts the cross-section of currency returns, while the dollar factor is insignificant.

In Panel B, we compare two asset pricing models, DOL-HML-MOM and APR-HML-MOM. It can be seen from this panel replacing the APR factor for DOL in the benchmark three-factor model (Nucera et al., 2023) improves the results, both in terms of better R^2 and lower GRS. The results are even stronger in the Recent Sample reported in Panel C and Panel D.

[TABLE 9 ABOUT HERE]

Three-pass Fama-Macbeth Asset Pricing Test. We also follow the methodology by Giglio and Xiu (2021) to run a three-pass Fama-Mabeth Asset Pricing Test to deal with potential measurement error and omitted variable problems in our asset pricing tests (Nucera et al., 2023). Our 48 test assets include six carry portfolios, six short-term momentum portfolios, six long-term momentum portfolios, six APR portfolios, six value portfolios, six global volatility portfolios, six global liquidity portfolios, and six uncertainty portfolios. We report the two-factor (three-factor) model results based on the Full Sample in Panel A (Panel B). We find that the APR factor is a significant predictor of the cross-section of FX portfolio returns. In Panel B, we compare two asset pricing models, DOL-HML-MOM and APR-HML-MOM. We find that the dollar factor only is marginally significant, whereas the APR factor does a much better job with an R^2_{FPR} equal to 0.96 compared to R^2_{DOL} of 0.07. We also report the results for the Recent Sample in Panel C and Panel D. The APR factor results are stronger than the Full Sample results.

[TABLE 10 ABOUT HERE]

Transaction Costs. We also consider the implementation cost of the strategy. Earlier papers highlight that quoted spreads are much higher than the effective spreads actually paid in the FX market. To guard against this issue, researchers employ arbitrary scaling of the quoted bid-ask spread to obtain a more realistic value for the effective spread (Menkhoff et al., 2012b, 2017). Gilmore and Hayashi (2011) show that bid-ask spreads are likely much lower than 50% of the quoted spread for emerging market currencies. Cespa, Gargano, Riddiough, and Sarno (2022) show that even a 50% scaling of the WM/R spread is still around twice the actual market spread. This finding suggests that a 25% scaling provides a good approximation of the effective spread. Thus, we calculate transaction costs based on the 25% of the quoted spread.

Panel A of Table 11 shows results of cross-sectional regressions of currency excess returns at time $t+1$ on the APR Index beta at time t. In line with our previous findings, the APR Index beta is a strong negative predictor of currency excess returns. We find a similar pattern in *Panel B* where we show spread portfolios that go long currencies with low APR betas and short currencies with low APR betas. We find very positive and significant payoffs.

[TABLE 11 ABOUT HERE]

CLS FX Order Flows. We utilize the CLS FX flows dataset provided by Quandl. CLS Group handles more than 50% of global FX transaction volume, including spot, swap, and forward transactions, for up to 14 bilateral currency pairs.[11] The advantage of the CLS data is that it provides aggregated spot FX flows at an hourly frequency, in contrast to the BIS Survey. The dataset records transaction volumes for four groups of market participants: banks, funds, non-bank financial institutions, and corporations. Market makers, typically banks, interact with price takers in the market, which are divided into three categories: funds, non-bank financials, and corporates. Our data focuses on the time period starting from

[11]The included currency pairs represent bilateral exchange rates of the U.S. with Australia, Canada, the Euro Area, Japan, New Zealand, Norway, Sweden, Switzerland, the United Kingdom, Hungary, South Africa, Iceland, Mexico, Korea, Hong Kong, Singapore dollars, and Denmark.

September 2012 to August 2019. To control for persistence in FX volume, we construct a measure of abnormal FX trading volume. Our measure of abnormal volume for currency pair i at time t is the deviation from the moving average of FX trading volume over the last 12 months. We pool all observations from all currency pairs and run country fixed-effects panel regressions with monthly data. Our fixed-effects panel regression specification is in Equation (15).

$$\hat{\beta}_{i,t}^{APR} = \delta_1 + \delta_2 \text{Abnormal trading volume}_{i,t} + \mu_y + \sigma_m + \epsilon_{i,t} \tag{15}$$

where $\hat{\beta}_{i,t}^{APR}$ denotes the time-series of rolling APR betas for each country i at month t. Abnormal trading volume is defined as the difference in trading volume of each country i at month t and its average trading volume over the last 12 months. μ_y and σ_m are time fixed effects that control for the year and month, respectively. Standard errors are clustered at the level of the currency pair.

We show in Table 12 the coefficients of the abnormal trading volume for different market participants. The results in the first column indicate a significant negative association between β^{APR} and spot FX trading volume (total buy side) during that month. The coefficient of the independent variable is -0.01, with a t-statistic of -2.54. In the next four columns, we break down the trading volume and investigate the effects for different groups of participants. We can see that the results are mostly driven by the fund group, and the coefficient is negative and significant for this group of participants. This finding indicates that funds tend to reduce their trading activity for currencies with higher exposures to U.S. populism.

[TABLE 12 ABOUT HERE]

8 Conclusions

In this paper, we have constructed a novel index of U.S. populism based on an improved dictionary, including populist terms from social media. The proposed aggregate populist index captures the overall populism reported by the New York Times (1985-2020) and four other leading U.S. newspapers (2000-2020). Our Aggregate Populist Rhetoric (APR) Index spikes around a range of well-known populist events in the U.S. and captures friction to financial globalization. Specifically, countries that are more financially segmented from the U.S. financial system tend to have a larger exposure to this type of friction. Sorting currencies into portfolios based on their exposure to the media attention to U.S. populism, proxied by our APR Index, we find a positive and significant spread between low and high-beta portfolios. This trading strategy can generate highly statistically significant average excess returns highlighting the economic value offered to investors. We then find solid empirical evidence that media attention to U.S. populism, proxied by the APR 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. populism 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. Therefore, assets that generate high excess returns during this state of the world are valued by U.S. investors, and they 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, so investors demand higher expected returns for holding them. Our results can be extended to construct a similar index in different countries, which are particularly relevant to the current political climate of rising populism in many parts of the world.

References

Alvarez, F. and U. J. Jermann (2005). Using asset prices to measure the persistence of the marginal utility of wealth. *Econometrica 73*(6), 1977–2016.

Ang, A., J. Liu, and K. Schwarz (2018). Using stocks or portfolios in tests of factor models. In *AFA 2009 San Francisco Meetings Paper*.

Aslanidis, P. (2016). Is populism an ideology? a refutation and a new perspective. *Political Studies 64*(1), 88–104.

Asness, C. S., T. J. Moskowitz, and L. H. Pedersen (2013). Value and momentum everywhere. *The journal of finance 68*(3), 929–985.

Baker, S. R., N. Bloom, and S. J. Davis (2016). Measuring economic policy uncertainty. *The Quarterly Journal of Economics 131*(4), 1593–1636.

Balcere, I. (2014). Populism in the manifestos of latvian political parties: Increasingly used but ineffective? *Journal of Baltic Studies 45*(4), 477–497.

Bali, T. G., S. J. Brown, and Y. Tang (2017). Is economic uncertainty priced in the cross-section of stock returns? *Journal of Financial Economics 126*(3), 471–489.

Barroso, P., F. Kho, F. Rouxelin, and L. Yang (2018). Do external imbalances matter in explaining the cross-section of currency excess returns? *Available at SSRN 3232396*.

Barrot, J.-N., E. Loualiche, and J. Sauvagnat (2019). The globalization risk premium. *The Journal of Finance 74*(5), 2391–2439.

Bayerlein, M., M. Funke, and C. Trebesch (2019). Populism and economic upheavals since 1870: A quantitative analysis.

BIS (2022, Nov). Triennial central bank survey of foreign exchange and over-the-counter (otc) derivatives markets in 2022.

Bode, L., C. Budak, J. M. Ladd, F. Newport, J. Pasek, L. O. Singh, S. N. Soroka, and M. W. Traugott (2020). *Words that matter: How the news and social media shaped the 2016 Presidential campaign*. Brookings Institution Press.

Bonikowski, B. and N. Gidron (2015). The populist style in american politics: Presidential campaign discourse, 1952–1996. *Social Forces 94*(4), 1593–1621.

Booth, J. R. and L. C. Booth (2003). Is presidential cycle in security returns merely a reflection of business conditions? *Review of Financial Economics 12*(2), 131–159.

Bos, L. and K. Brants (2014). Populist rhetoric in politics and media: A longitudinal study of the netherlands. *European Journal of Communication 29*(6), 703–719.

Burnside, A. C. and J. J. Graveline (2020). On the asset market view of exchange rates. *The Review of Financial Studies 33*(1), 239–260.

Cahan, J., C. B. Malone, J. G. Powell, and U. W. Choti (2005). Stock market political cycles in a small, two-party democracy. *Applied Economics Letters 12*(12), 735–740.

Caldara, D. and M. Iacoviello (2022). Measuring geopolitical risk. *American Economic Review 112*(4), 1194–1225.

Caldara, D., M. Iacoviello, P. Molligo, A. Prestipino, and A. Raffo (2020). The economic effects of trade policy uncertainty. *Journal of Monetary Economics 109*, 38–59.

Cambridge Dictionary (2017). Cambridge Words, Cambridge Dictionary's Word of the Year 2017. https://dictionaryblog.cambridge.org/2017/11/29/cambridge-dictionarys-word-of-the-year-2017/.

Cespa, G., A. Gargano, S. J. Riddiough, and L. Sarno (2022). Foreign exchange volume. *The Review of Financial Studies 35*(5), 2386–2427.

Chernov, M. and D. Creal (2023). International yield curves and currency puzzles. *The Journal of Finance 78*(1), 209–245.

Chernov, M., M. Dahlquist, and L. Lochstoer (2023). Pricing currency risks. *The Journal of Finance*.

Colacito, R., S. J. Riddiough, and L. Sarno (2020). Business cycles and currency returns. *Journal of Financial Economics 137*(3), 659–678.

Colantone, I. and P. Stanig (2018). The trade origins of economic nationalism: Import competition and voting behavior in western europe. *American Journal of Political Science 62*(4), 936–953.

Della Corte, P., S. J. Riddiough, and L. Sarno (2016). Currency premia and global imbalances. *The Review of Financial Studies 29*(8), 2161–2193.

Della Corte, P., L. Sarno, M. Schmeling, and C. Wagner (2022). Exchange rates and sovereign risk. *Management Science 68*(8), 5591–5617.

Döpke, J. and C. Pierdzioch (2006). Politics and the stock market: Evidence from germany. *European Journal of Political Economy 22*(4), 925–943.

Dornbusch, R. and S. Edwards (2007). *The macroeconomics of populism in Latin America*. University of Chicago Press.

Dreher, A. (2006). Does globalization affect growth? evidence from a new index of globalization. *Applied economics 38*(10), 1091–1110.

Fama, E. F. and J. D. MacBeth (1973). Risk, return, and equilibrium: Empirical tests. *Journal of political economy 81*(3), 607–636.

Filippou, I., A. E. Gozluklu, M. T Nguyen, and G. Viswanath-Natraj (2021). The information content of trump tweets and the currency market. *Available at SSRN 3754991*.

Filippou, I., A. E. Gozluklu, and M. P. Taylor (2018). Global political risk and currency momentum. *Journal of Financial and Quantitative Analysis 53*(5), 2227–2259.

Filippou, I. and M. P. Taylor (2023). Forward-looking policy rules and currency premia. *Journal of Financial and Quantitative Analysis 58*(1), 449–483.

Filippou, I., M. P. Taylor, and Z. Wang (2023). Media sentiment and currency reversals. *Journal of Financial and Quantitative Analysis*.

Gerbaudo, P. (2018). Social media and populism: an elective affinity? *Media, culture & society 40*(5), 745–753.

Gidron, N. and B. Bonikowski (2013). Varieties of populism: Literature review and research agenda.

Giglio, S. and D. Xiu (2021). Asset pricing with omitted factors. *Journal of Political Economy 129*(7), 1947–1990.

Gilmore, S. and F. Hayashi (2011). Emerging market currency excess returns. *American Economic Journal: Macroeconomics 3*(4), 85–111.

Guiso, L., H. Herrera, M. Morelli, and T. Sonno (2018). Populism: Demand and supply. *Essays on Globalisation and Conflicts, Populism and Firm Heterogeneity*, 59.

Guriev, S. and E. Papaioannou (2022). The political economy of populism. *Journal of Economic Literature 60*(3), 753–832.

Gygli, S., F. Haelg, N. Potrafke, and J.-E. Sturm (2019). The kof globalisation index–revisited. *The Review of International Organizations 14*, 543–574.

Hassan, R., E. Loualiche, A. Reggi Pecora, and C. Ward (2022). International trade and the risk in bilateral exchange rates. *Available at SSRN 3745935*.

Hassan, T. A. (2013). Country size, currency unions, and international asset returns. *The Journal of Finance 68*(6), 2269–2308.

Hawkins, K. and L. Littvay (2019). *Contemporary US populism in comparative perspective*. Cambridge University Press.

Hawkins, K. A. (2009). Is chávez populist? measuring populist discourse in comparative perspective. *Comparative Political Studies 42*(8), 1040–1067.

Hawkins, K. A., R. Aguilar, B. C. Silva, E. K. Jenne, B. Kocijan, and C. R. Kaltwasser (2019). Measuring populist discourse: The global populism database. In *EPSA Annual Conference in Belfast, UK, June*, pp. 20–22.

Jagers, J. and S. Walgrave (2007). Populism as political communication style: An empirical study of political parties' discourse in belgium. *European Journal of Political Research 46*(3), 319–345.

Jurado, K., S. C. Ludvigson, and S. Ng (2015). Measuring uncertainty. *American Economic Review 105*(3), 1177–1216.

Kioupkiolis, A. (2019). Populism 2.0: New movements towards progressive populism 1. In *The Populist Radical Left in Europe*, pp. 168–193. Routledge.

Koijen, R. S., T. J. Moskowitz, L. H. Pedersen, and E. B. Vrugt (2018). Carry. *Journal of Financial Economics 127*(2), 197–225.

Levy, R. (2021). Social media, news consumption, and polarization: Evidence from a field experiment. *American economic review 111*(3), 831–870.

Liu, Y. and I. Shaliastovich (2022). Government policy approval and exchange rates. *Journal of Financial Economics 143*(1), 303–331.

Lustig, H. and R. J. Richmond (2020). Gravity in the exchange rate factor structure. *The Review of Financial Studies 33*(8), 3492–3540.

Lustig, H., N. Roussanov, and A. Verdelhan (2011). Common risk factors in currency markets. *The Review of Financial Studies 24*(11), 3731–3777.

Maggiori, M., B. Neiman, and J. Schreger (2019). The rise of the dollar and fall of the euro as international currencies. In *AEA Papers and Proceedings*, Volume 109, pp. 521–26.

Menkhoff, L., L. Sarno, M. Schmeling, and A. Schrimpf (2012a). Carry trades and global foreign exchange volatility. *The Journal of Finance 67*(2), 681–718.

Menkhoff, L., L. Sarno, M. Schmeling, and A. Schrimpf (2012b). Currency momentum strategies. *Journal of Financial Economics 106*(3), 660–684.

Menkhoff, L., L. Sarno, M. Schmeling, and A. Schrimpf (2017). Currency value. *The Review of Financial Studies 30*(2), 416–441.

Mudde, C. (2004). The populist zeitgeist. *Government and opposition 39*(4), 541–563.

Mueller, P., A. Stathopoulos, and A. Vedolin (2017). International correlation risk. *Journal of Financial Economics 126*(2), 270–299.

Müller, J.-W. (2017). *What is populism?* Penguin UK.

Newey, W. K. and K. D. West (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica 55*(3), 703–708.

Nichols, W. and L. C. Lawyer (2021). Identifying emergent meanings via the word of the year process: A case study. *Dictionaries: Journal of the Dictionary Society of North America 42*(2), 57–69.

Nucera, F., L. Sarno, and G. Zinna (2023). Currency risk premiums redux. *The Review of Financial Studies*, hhad049.

Orłowski, P., A. Sali, and F. Trojani (2018). Arbitrage free dispersion. *Swiss Finance Institute Research Paper* (19-20).

Pástor, L. and P. Veronesi (2021). Inequality aversion, populism, and the backlash against globalization. *The Journal of Finance 76*(6), 2857–2906.

Rhodes, J. H. and K. T. Johnson (2017). Welcoming their hatred: Class populism in democratic rhetoric in american presidential campaigns, 1932–2012. *Presidential Studies Quarterly 47*(1), 92–121.

Richmond, R. J. (2019). Trade network centrality and currency risk premia. *The Journal of Finance 74*(3), 1315–1361.

Rodrik, D. (2018). Populism and the economics of globalization. *Journal of International Business Policy*, 1–22.

Rodrik, D. (2021). Why does globalization fuel populism? economics, culture, and the rise of right-wing populism. *Annual Review of Economics 13*, 133–170.

Rooduijn, M. and T. Pauwels (2011). Measuring populism: Comparing two methods of content analysis. *West European Politics 34*(6), 1272–1283.

Rooduijn, M., S. Van Kessel, C. Froio, A. Pirro, S. De Lange, D. Halikiopoulou, P. Lewis, C. Mudde, and P. Taggart (2019). The populist: An overview of populist, far right, far left and eurosceptic parties in europe.

Sachs, J. D. (1989). Social conflict and populist policies in latin america.

Sandulescu, M., F. Trojani, and A. Vedolin (2021). Model-free international stochastic discount factors. *The Journal of Finance 76*(2), 935–976.

Santa-Clara, P. and R. Valkanov (2003). The presidential puzzle: Political cycles and the stock market. *The Journal of Finance 58*(5), 1841–1872.

Sattler, T. (2013). Do markets punish left governments? *The Journal of Politics 75*(2), 343–356.

TeamPopulism (2023, April). Team populism. Accessed: 2023-01-21.

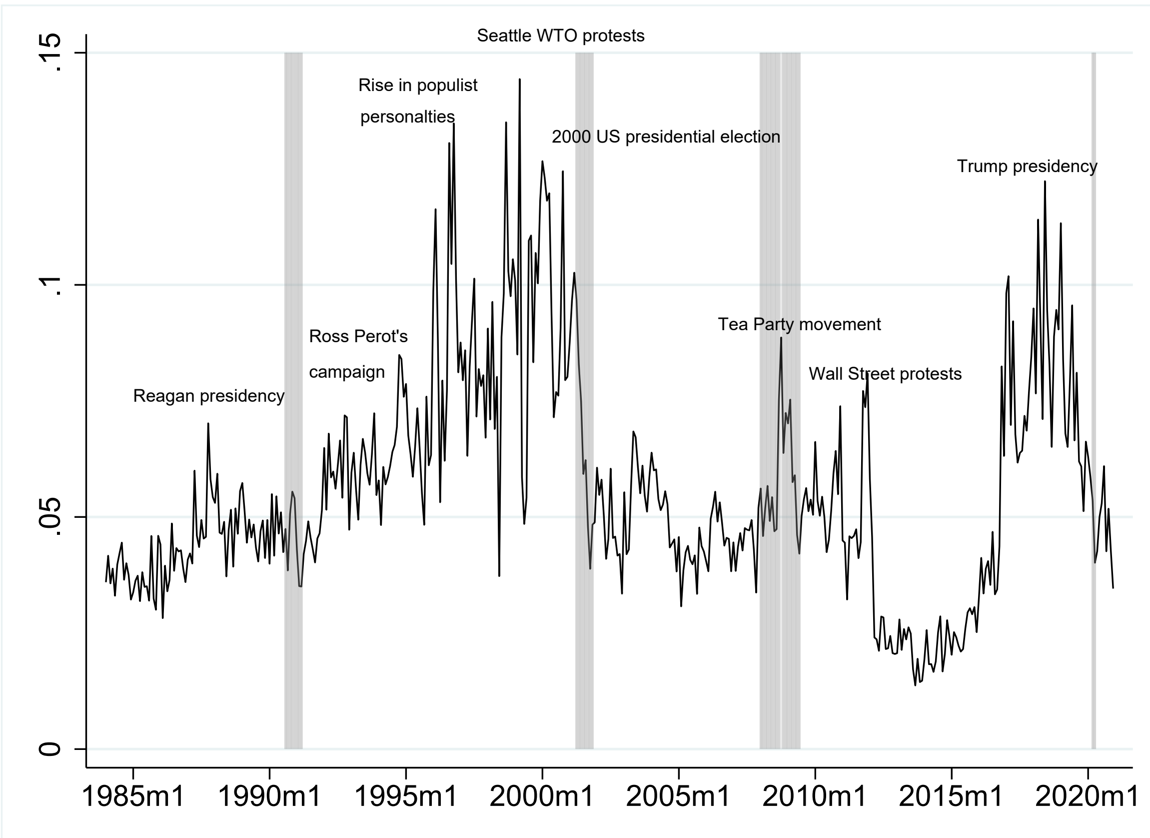
White, H. (1980). A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica: journal of the Econometric Society*, 817–838.

Worthington, A. C. (2009). Political cycles in the australian stock market since federation. *Australian Economic Review 42*(4), 397–409.

Yan, X., J. Guo, Y. Lan, and X. Cheng (2013). A biterm topic model for short texts. In *Proceedings of the 22nd international conference on World Wide Web*, pp. 1445–1456.

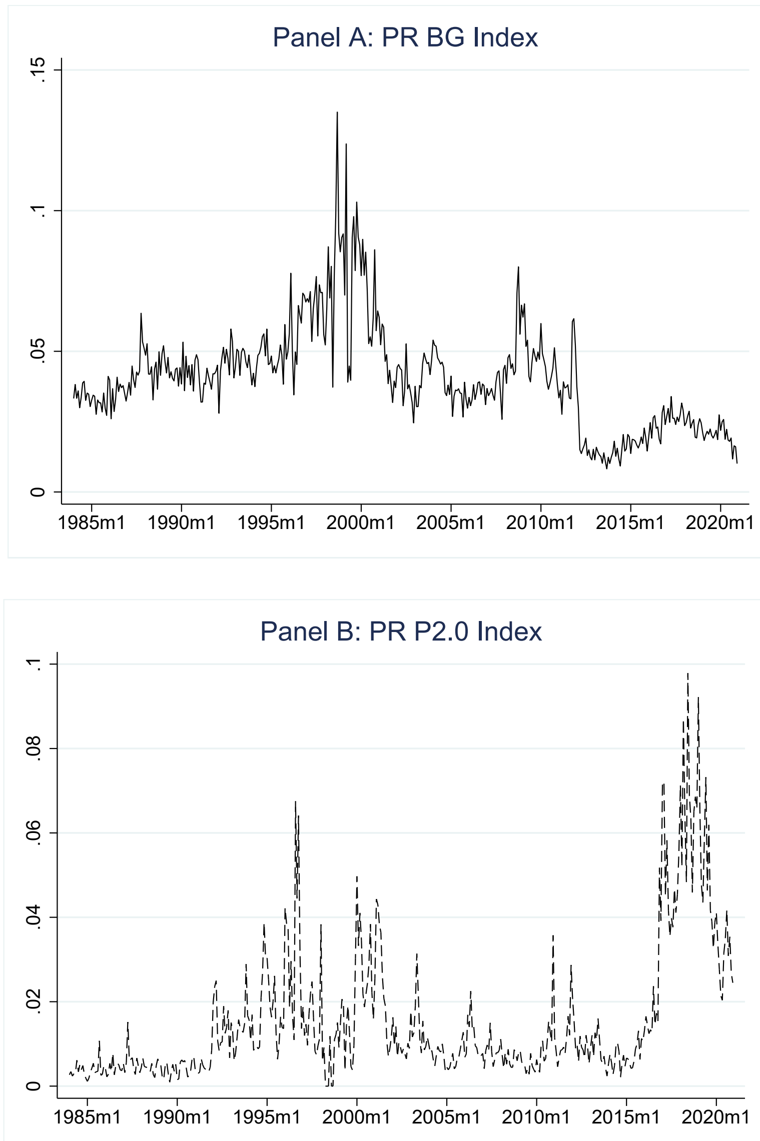
Figure 1. Top Keywords from Populism Topics

Figure 2. U.S. Aggregate Populist Rhetoric (APR) Index



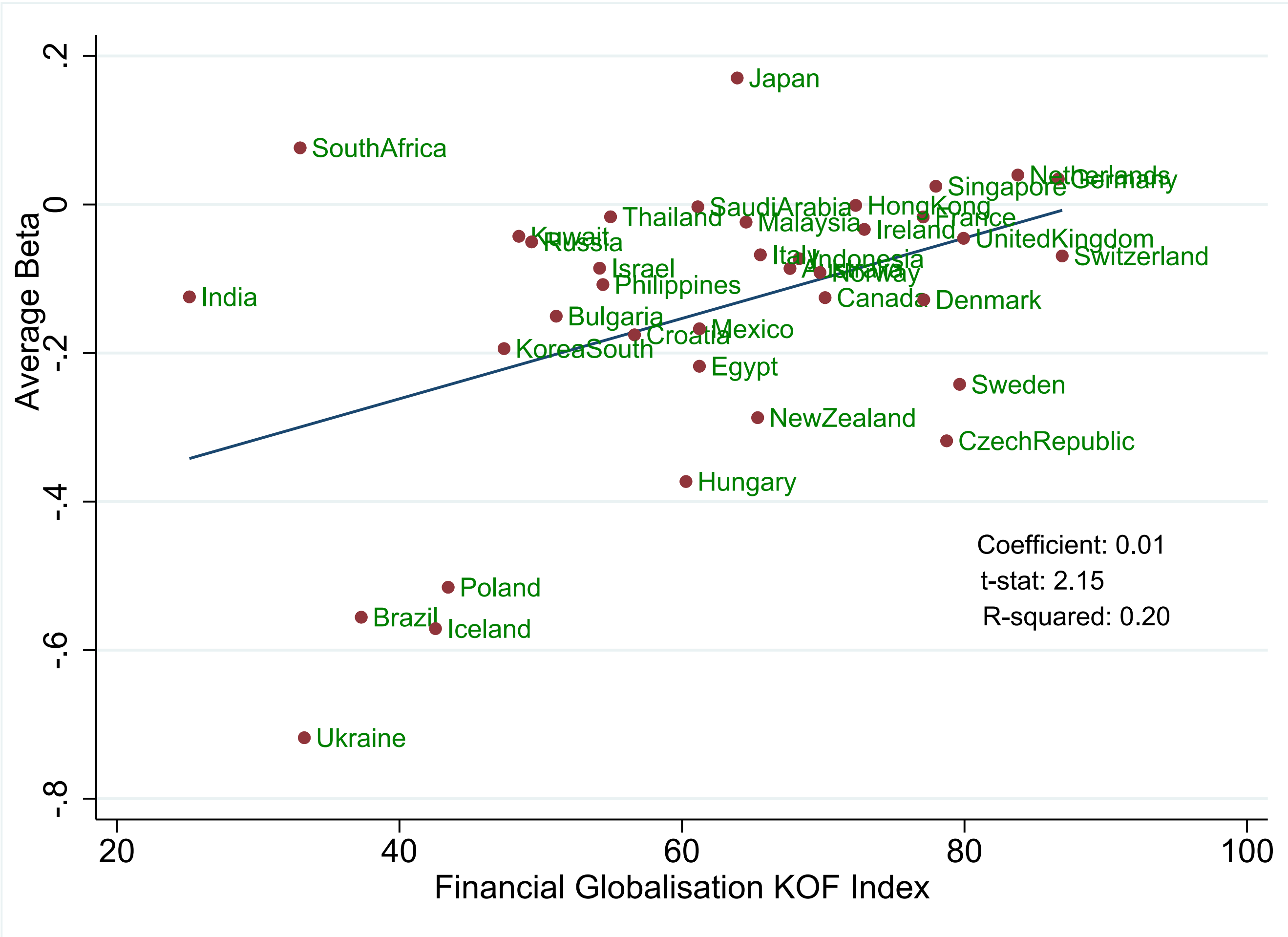
The figure reports our U.S. Aggregate Populist Rhetoric (APR) Index. The index is based on scaled monthly counts of articles containing populist rhetoric reported by The New York Times between 1984 and December 2020.

Figure 3. Populist Rhetoric Index based on Bonikowski and Gidron (2015) dictionary (PR BG Index) and the new dictionary based on Tweets (PR P2.0 Index)



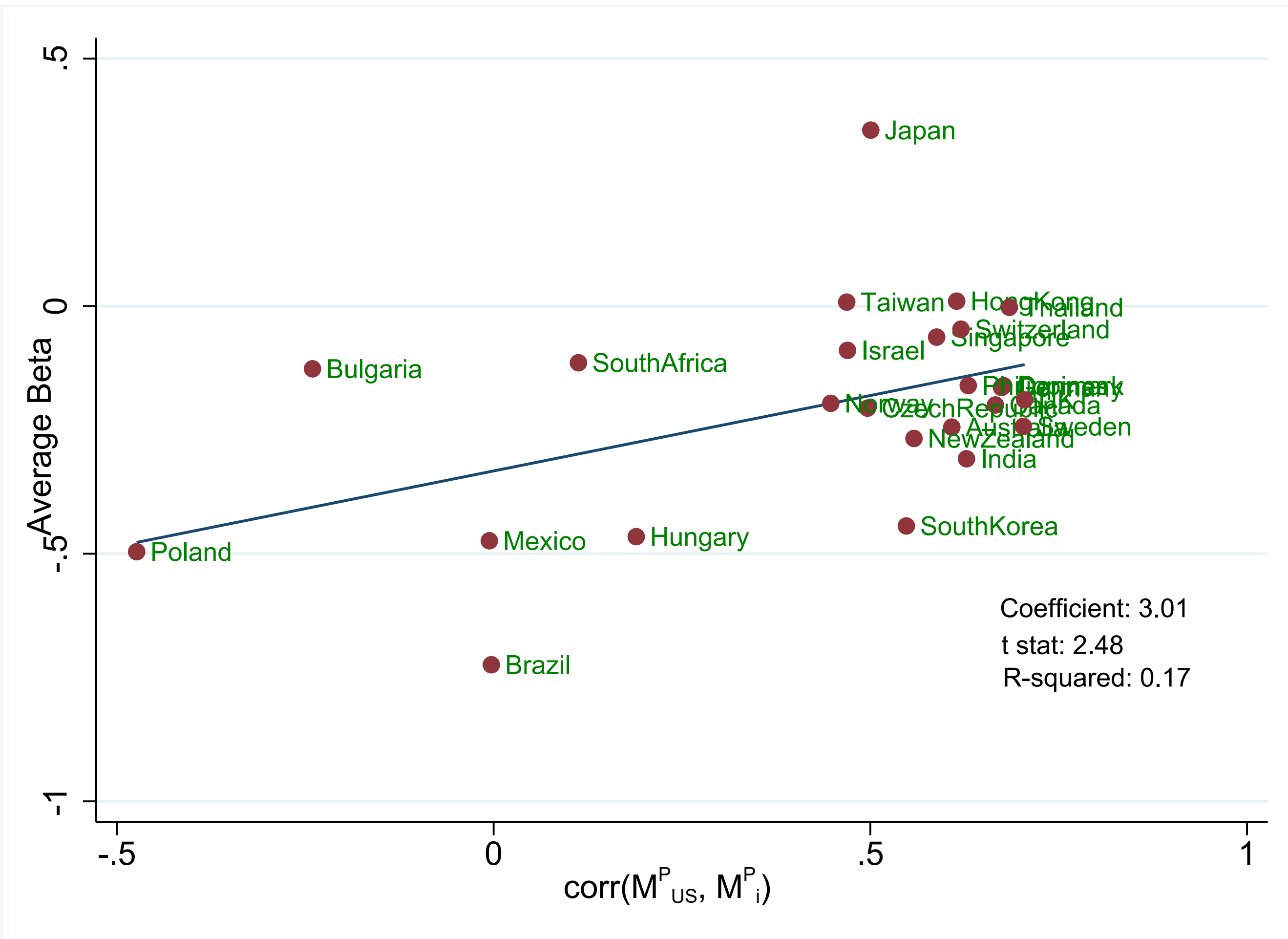
Populist Rhetoric Index based on Bonikowski and Gidron (2015) dictionary (PR BG Index) (Panel A) and the new dictionary based on Tweets (PR P2.0 Index) (Panel B). The data are from January 1984 to December 2020.

Figure 4. Average APR Betas and Financial Globalization



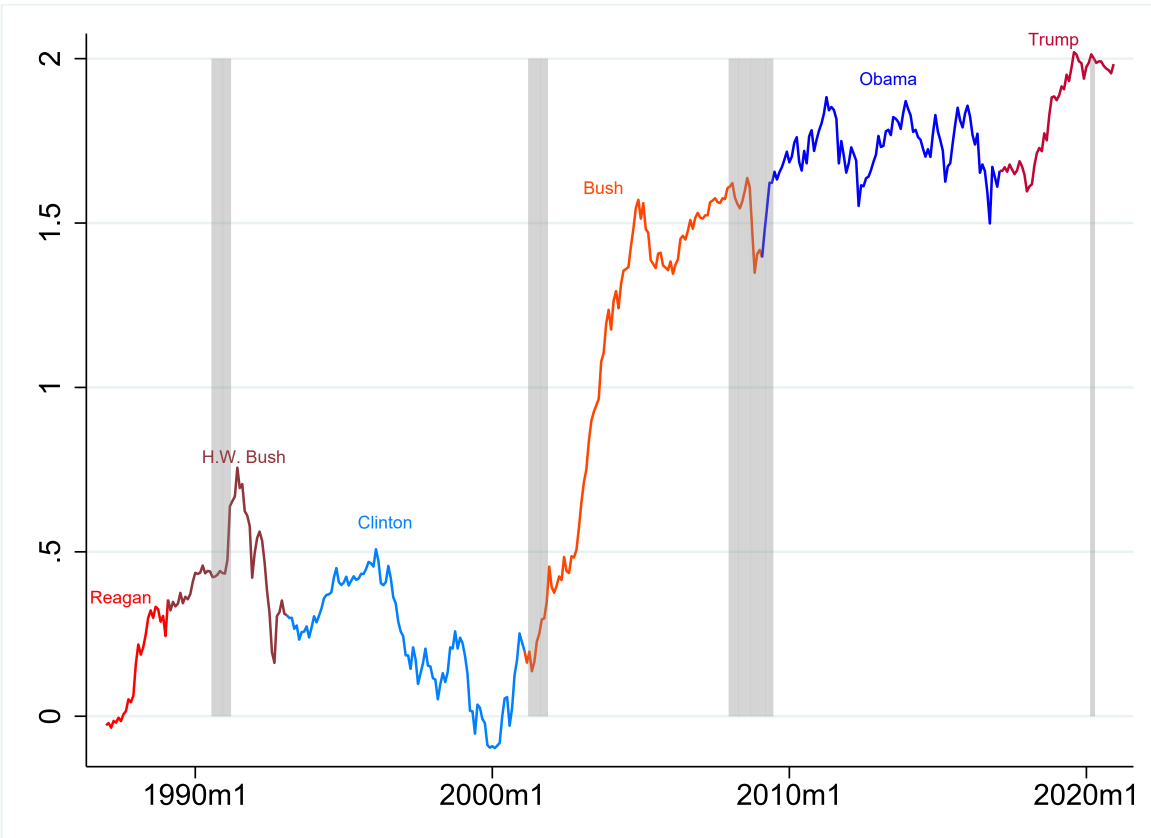
The figure shows the scatter plot of the average beta APR (New York Times) and KOF financial Globalization Index (Dreher, 2006; Gygli et al., 2019). The data from 37 countries are from January 1984 to December 2020.

Figure 5. Average APR Betas and Financial Segmentation



The figure shows the scatter plot of the average beta APR (five newspapers) and a proxy for financial segmentation from the U.S. market, that is, correlation of the permanent components of U.S. and foreign model-free (minimum entropy) SDFs (Sandulescu et al., 2021). The data from 25 countries are from January 2007 to December 2020.

Figure 6. Cumulative return of the APR portfolio



The figure shows the cumulative return of the APR portfolio adjusted for volatility. In particular, we multiply the raw return of the APR portfolio by the ratio of annual market stock return to the annual APR portfolio volatility. The data are from January 1984 to December 2020.

Table 1. Populist Dictionary

This table reports the populist terms identified in the dictionary by Bonikowski and Gidron (2015) (Panel A), and the new populist terms used in social media, which we extract from Trump tweets. We label the latter as Populism 2.0 dictionary (Panel B). We use this dictionary to identify newspaper articles containing populist rhetoric.

Bonikowski and Gidron (2015)'s 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

(New) Populism 2.0 Dictionary	
N-grams	Words
Unigrams	tariffs OR maga
Bigrams	tax cuts OR fake news OR border security OR illegal immigration OR American first
Trigrams	fake news media
Four-grams+	make America great again

Table 2. Summary Statistics of APR Index and PR Sub-Indices

This table reports summary statistics of Aggregate Populist Rhetoric Index (APR) and its sub-indices based Bonikowski and Gidron (2015) dictionary (BG dictionary) and the new dictionary based on tweets (P2.0 dictionary). Panel A reports the mean, standard deviation, minimum and maximum values, skewness, kurtosis, autocorrelation (AC(1)) and augmented Dickey-Fuller t-statistic of APR, changes in APR (i.e.ΔAPR). Panel B displays correlations between the APR Index and various indices capturing 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 (2022), VIX is the CBOE Volatility Index, TPU is the Trade Policy Uncertainty from Caldara et al. (2020) and GPS is the government policy sentiment, part of the Surveys of Consumers conducted by the University of Michigan (Liu and Shaliastovich, 2022). Panel B shows correlations for percentage changes in the populism index. *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. Monthly data are from January 1984 to December 2020.

Panel A: Populism Indices

	APR Index	ΔAPR Index	PR BG Index	ΔPR BG Index	PR P2.0 Index	ΔPR P2.0 Index
Mean	0.05	0.02	0.04	0.02	0.01	0.13
Std	0.02	0.22	0.02	0.22	0.02	0.63
Min	0.01	-0.59	0.01	-0.68	0.00	-1.00
Max	0.14	1.38	0.14	1.28	0.10	5.17
Skewness	1.03	1.21	1.20	1.14	2.25	2.39
Kurtosis	4.14	7.03	5.97	7.02	8.40	13.87
AC(1)	0.82	-0.32	0.82	-0.35	0.85	-0.23
Dickey Fuller t-statistic	-3.58***	-12.52***	-3.64***	-13.24***	-3.47***	-15.80***

Panel B: Index Level

	APR index	P2.0 PR Index	BG PR Index	EPU	UNC^m	UNC^m	UNC^y	GPR	VIX	TPU
APR index	1									
P2.0 PR Index	0.59***	1								
BG PR Index	0.73***	-0.10*	1							
EPU	-0.05	0.26***	-0.29***	1						
UNC^m	-0.05	-0.05	-0.02	0.56***	1					
UNC^q	-0.04	-0.05	-0.01	0.54***	0.53***	0.99***	1			
UNC^y	0.00	-0.03	0.03	0.50***	0.98***	0.98***	1			
GPR	-0.23***	-0.11*	-0.19***	0.14**	0.01	0.02	0.00	1		
VIX	0.18***	-0.14**	0.34***	0.42***	0.59***	0.60***	0.60***	0.05	1	
TPU	0.31***	0.74***	-0.24***	0.33***	-0.01	-0.02	0.00	-0.03	-0.14**	1
GPS	0.42***	0.13***	0.42***	-0.16***	-0.06	-0.06	-0.00	-0.04	0.19**	0.09*

Panel C: Index Change

	ΔAPR Index	ΔP2.0 PR Index	ΔBG PR Index	ΔEPU	Δ UNC^m	ΔUNC^q	Δ UNC^y	ΔGPR	ΔVIX	ΔTPU
Δ APR Index	1									
ΔP2.0 PR Index	0.55***	1								
ΔBG PR Index	0.76***	0.04	1							
ΔEPU	0.06	0.04	0.00	1						
ΔUNC^m	0.01	-0.01	0.04	0.23***	1					
ΔUNC^q	0.01	-0.02	0.06	0.24***	0.98***	1				
ΔUNC^y	0.02	-0.04	0.07	0.22***	0.93***	0.97***	1			
ΔGPR	-0.08	-0.06	-0.08	0.29***	0.12*	0.12*	0.08	1		
ΔVIX	0.06	-0.04	0.11*	0.23***	0.23***	0.26***	0.27***	0.08	1	
DeltaTPU	0.22***	0.19***	0.06	0.12*	-0.13*	-0.12*	-0.09	-0.09	0.05	1
ΔGPS	-0.10*	-0.10	-0.07	-0.06	-0.08*	-0.08*	-0.09*	-0.01	-0.03	-0.03

Table 3. Average APR Beta and Financial Globalization

This table reports contemporaneous cross-sectional regressions of average APR betas on KOF financial globalization with other controls. The model takes the form:

$$\hat{\beta}_i^{APR} = \delta_1 + \delta_2 \text{KOF Financial Globalization}_i + \delta_3 \mathbf{X}_i + \varepsilon_i, \tag{16}$$

where $\hat{\beta}_i^{APR}$ denotes the time-series average of rolling APR betas for each country i. The APR betas are estimated based on the model $rx_{i,t} = \alpha_{i,t} + \beta_{i,t}^{APR} APR_t + \epsilon_{i,t}$, where $rx_{i,t}$ is the realised excess return on currency i in month t, and APR_t is the APR Index in month t. The estimation of the APR betas is based on a 60-month rolling window. The set of controls $\mathbf{X}_{i,t}$ includes log GDP share, log distance to U.S. and Institutional Quality of country i. We report heteroskedasticity robust White (1980) t-statistics in parenthesis, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. The data are monthly from January 1984 to December 2020.

	(1)	(2)	(3)	(4)
KOF Financial Globalization$_i$	0.005**	0.004*	0.005**	0.008***
	(2.15)	(1.78)	(2.20)	(3.03)
Log GDP share$_i$		0.048**	0.055***	0.051**
		(2.09)	(2.79)	(2.34)
Log distance to U.S.$_i$			0.144**	0.089**
			(2.57)	(2.53)
Institutional Quality$_i$				-0.080***
				(-3.38)
Constant	-0.478***	-0.194	-1.508**	-1.161***
	(-2.73)	(-0.85)	(-2.63)	(-3.46)
Observations	37	37	37	34
Adj. R^2	0.17	0.25	0.35	0.49

Table 4. Average APR Betas and Financial Segmentation

This table reports contemporaneous cross-sectional regressions of average APR betas on the correlation of permanent components of U.S. and foreign model-free (minimum entropy) SDF ($corr(M_{US}^{P}, M_{i}^{P})$) with other controls. The model takes the form:

$$\hat{\beta}_i^{APR} = \delta_1 + \delta_2 corr(M_{US}^{P}, M_{i}^{P}) + \delta_3 \mathbf{X}_i + \varepsilon_i \tag{17}$$

where $\hat{\beta}_i^{APR}$ denotes the time-series average of rolling APR betas for each country i. The APR betas are estimated based on the model: $rx_{i,t} = \alpha_{i,t} + \beta_{i,t}^{APR} APR_t + \epsilon_{i,t}$, where $rx_{i,t}$ is the realised excess return on currency i in month t, and APR_t is the APR Index in month t. The estimation of the APR betas is based on a 60-month rolling window. The set of controls $\mathbf{X}_i$ includes log GDP share, log distance to U.S. and Institutional Quality of country i. We report heteroskedasticity robust White (1980) t-statistics in parenthesis, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. The data are monthly from January 2007 to December 2020.

	(1)	(2)	(3)	(4)
corr(M_{US}^{P}, M_{i}^{P})	0.305**	0.350**	0.313**	0.324**
	(2.48)	(2.84)	(2.24)	(2.21)
Log GDP share$_i$		-0.021	-0.011	-0.001
		(-0.44)	(-0.21)	(-0.02)
Log distance to U.S.$_i$			0.068	0.078
			(1.11)	(1.24)
Institutional Quality$_i$				-0.015
				(-0.44)
Constant	-0.333***	-0.507	-1.044***	-1.041***
	(-4.38)	(-1.44)	(-3.70)	(-3.34)
Observations	25	23	23	21
Adj. R^2	0.17	0.19	0.17	0.16

Table 5. Portfolios sorted on APR Betas

This table reports summary statistics for the excess returns of three currency portfolios sorted on exposure to APR Index for the Full sample (Jan 1984- Dec 2020, *Panel A*), Recent sample (Jan 2000- Dec 2020, *Panel B*). We construct the APR index in the full sample based on The New York Times articles, while the APR index in the recent sample is based on five newspapers, including The Washington Post, The New York Daily News, The New York Post, USA Today, and The New York Times. Portfolio 1 (P_1) contains currencies with the lowest APR Index betas, and Portfolio 5 (P_5) contains currencies with the highest APR Index betas. LMH represents the portfolios that have a short position in the high beta portfolio (P_5) and a long position in the low beta portfolio (P_1). For each portfolio, we report annualized mean and its t-statistics (reported in squared brackets), standard deviation (Std) and Sharpe ratios (SR), and average betas of individual currencies(β), all in percentage points. We also report skewness and kurtosis. The data are monthly from January 1984 (January 2000, Panel B) to December 2020.

Panel A: Full Sample: New York Times						
	P_1	P_2	P_3	P_4	P_5	LMH_{APR}
Mean	3.09	2.90	0.60	0.12	-0.10	3.19
	[2.19]	[2.11]	[0.43]	[0.10]	[-0.07]	[2.19]
Std	8.23	8.01	8.15	7.54	7.82	8.49
Skewness	-0.53	-0.09	-0.50	-0.56	-0.72	-0.16
Kurtosis	4.86	4.46	5.28	5.45	6.16	4.37
Exchange rate change	-0.36	-2.22	0.68	1.43	3.03	-3.40
	[-0.25]	[-1.56]	[0.46]	[1.04]	[2.15]	[-2.40]
Forward discount	2.72	0.68	1.28	1.56	2.94	-0.22
	[6.96]	[3.33]	[4.28]	[6.10]	[9.47]	[-0.37]
SR	0.38	0.36	0.07	0.02	-0.01	0.38
β^{APR}	-0.47	-0.20	-0.06	0.07	0.30	

Panel B: Recent Sample: Five Newspapers						
	P_1	P_2	P_3	P_4	P_5	LMH_{APR}
Mean	4.48	1.81	0.41	1.41	-0.73	5.21
	[2.20]	[0.89]	[0.22]	[0.87]	[-0.43]	[2.63]
Std	8.63	8.63	7.80	6.85	7.18	8.41
Skewness	-0.53	-0.09	-0.50	-0.56	-0.72	-0.16
Kurtosis	4.86	4.46	5.28	5.45	6.16	4.37
Exchange rate change	0.30	-1.00	0.47	0.06	2.93	-2.63
	[0.14]	[-0.49]	[0.25]	[0.03]	[1.76]	[-1.38]
Forward discount	4.79	0.81	0.87	1.47	2.24	2.55
	[7.79]	[3.85]	[3.75]	[4.42]	[5.31]	[2.98]
Exchange rate change	0.11	-1.82	0.22	1.63	2.62	-2.51
(New York Times)	[0.05]	[-0.92]	[0.12]	[0.98]	[1.40]	[-1.32]
Forward discount	4.43	0.79	1.11	1.25	2.66	1.78
(New York Times)	[7.17]	[4.57]	[4.49]	[4.91]	[6.04]	[2.57]
SR	0.52	0.21	0.05	0.21	-0.10	0.62
β^{APR}	-0.58	-0.33	-0.17	-0.01	0.24	

Table 6. Trading strategy based on U.S. Populism and Other Investment Strategies

This table reports contemporaneous time-series regressions of APR portfolio on the dollar, carry trade, and momentum factors. Newey and West (1987) t-statistics are reported in brackets, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. We report the Full (Recent) sample results in Panel A (B). The data are monthly from January 1984 (January 2000, in Panel B) to December 2020.

Panel A: Full Sample: New York Times			
	(1)	(2)	(3)
Constant	0.003**	0.004***	0.004***
	(2.08)	(2.61)	(3.44)
λ_{DOL}	-0.002	0.029	0.026
	(-0.03)	(0.43)	(0.42)
λ_{CAR}		-0.149**	-0.157**
		(-1.99)	(-2.22)
λ_{MOM}			0.122
			(1.54)
Obs	408	408	408
Adj R^2	0.00	0.02	0.04
Panel B: Recent Sample: Five Newspapers			
	(1)	(2)	(3)
Constant	0.004**	0.004*	0.005**
	(2.50)	(1.85)	(2.41)
λ_{DOL}	0.057	0.052	0.047
	(0.56)	(0.55)	(0.58)
λ_{CAR}		0.037	-0.002
		(0.24)	(-0.02)
λ_{MOM}			0.259**
			(2.02)
Obs	216	216	216
Adj R^2	0.00	0.00	0.07

Table 7. Cross-sectional FX Asset Pricing with U.S. Populism

This table reports regression results for the estimation of the market price of APR index betas. 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 brackets, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. We report the Full (Recent) sample results in Panel A (B). The data are monthly from January 1984 (January 2000, in Panel B) to December 2020.

Panel A: Full Sample: New York Times

	(1)	(2)	(3)	(4)
λ_{APR}	-0.006***	-0.006***	-0.005**	-0.006***
	(-2.94)	(-2.64)	(-2.23)	(-2.64)
$\lambda_{Volatility}$		0.238*		0.274*
		(1.85)		(1.94)
$\lambda_{Illiquidity}$			-0.000	-0.000
			(-0.77)	(-0.16)
Constant	0.001	0.000	-0.000	-0.000
	(0.69)	(0.48)	(-0.23)	(-0.50)
Obs	9,868	9,020	9,025	9,020
R^2	0.16	0.22	0.27	0.32

Panel B: Recent Sample: Five Newspapers

	(1)	(2)	(3)	(4)
λ_{APR}	-0.012***	-0.008**	-0.007**	-0.007**
	(-3.12)	(-2.18)	(-2.06)	(-2.04)
$\lambda_{Volatility}$		0.131		0.143
		(1.06)		(1.14)
$\lambda_{Illiquidity}$			0.000	0.000
			(0.09)	(0.49)
Constant	0.001	0.001	0.000	0.000
	(0.53)	(0.56)	(0.32)	(0.14)
Obs	6,665	5,843	5,845	5,843
R^2	0.13	0.17	0.21	0.25

Table 8. Cross-sectional FX Asset Pricing with U.S. Populism: DOL, CAR and MOM

This table reports regressions results for the estimation of the market price of APR index betas (λ_{APR}). The control variables are Dollar factor (λ_{DOL}), Carry factor (λ_{CAR}) as in Lustig et al. (2011). Newey and West (1987) t-statistics are reported in brackets, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. We report the Full (Recent) sample results in Panel A (B). The data are monthly from January 1984 (January 2000, in Panel B) to December 2020.

Panel A: Full Sample: New York Times				
	(1)	(2)	(3)	(4)
λ_{APR}	-0.007**	-0.008***	-0.008***	-0.008***
	(-2.44)	(-2.67)	(-2.85)	(-3.37)
λ_{DOL}		0.004	0.001	0.001
		(1.46)	(0.56)	(0.52)
λ_{CAR}			0.003*	0.002
			(1.84)	(1.34)
λ_{MOM}				0.003
				(-0.72)
Constant	0.001	0.001	0.001	0.000
	(1.15)	(0.98)	(0.93)	(0.55)
Obs	9,810	9,810	9,810	9,810
R^2	0.16	0.24	0.37	0.45

Panel B: Recent Sample: Five Newspapers				
	(1)	(2)	(3)	(4)
λ_{APR}	-0.012***	-0.012***	-0.011***	-0.012***
	(-2.83)	(-2.87)	(-2.61)	(-2.83)
λ_{DOL}		0.003	0.001	0.001
		(0.99)	(0.20)	(0.23)
λ_{CAR}			0.003*	0.003*
			(1.76)	(1.74)
λ_{MOM}				0.005*
				(1.84)
Constant	0.001	0.001	0.001	0.001
	(0.82)	(0.80)	(0.85)	(1.12)
Obs	6711	6711	6711	6711
R^2	0.14	0.20	0.33	0.39

Table 9. FX Asset Pricing Tests

This table reports regressions results for the two-factor model, including the DOL and APR risk factors. Test assets used are 6 APR portfolios. Portfolios are rebalanced monthly. 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. We also report R^2, Root Mean Squared Error (RMSE). We report the Full (Recent) sample results in Panel A,B (C,D). The data are monthly from January 1984 (January 2000, in Panel C,D) to December 2020.

Panel A: Two-factor model: Full Sample: New York Times						
	λ_{DOL}	λ_{APR}		RMSE	R^2	GRS
FMB	0.003	-0.003**		0.000	0.68	7.87
(NW)	[0.43]	[-2.04]				
Panel B: : Three-factor model: Full Sample: New York Times						
	λ_{DOL}	λ_{HML}	λ_{MOM}	RMSE	R^2	GRS
FMB	0.026	-0.012	-0.000	0.000	0.60	18.95
(NW)	[0.99]	[-1.09]	[-0.03]			
	λ_{APR}	λ_{HML}	λ_{MOM}	RMSE	R^2	GRS
FMB	-0.003**	0.003	-0.01	0.001	0.72	9.31
(NW)	[2.07]	[0.61]	[-1.05]			
Panel C: Two-factor model: Recent Sample: Five Newspapers						
	λ_{DOL}	λ_{APR}		RMSE	R^2	GRS
FMB	0.015	-0.005**		0.000	0.99	6.39
(NW)	[1.44]	[-2.36]				
Panel D: : Three-factor model: Recent Sample: Five Newspapers						
	λ_{DOL}	λ_{HML}	λ_{MOM}	RMSE	R^2	GRS
FMB	0.011	0.004	0.014	0.000	0.93	7.58
(NW)	[0.99]	[-1.09]	[-0.03]			
	λ_{APR}	λ_{HML}	λ_{MOM}	RMSE	R^2	GRS
FMB	-0.004**	0.007*	0.006	0.000	0.95	2.62
(NW)	[2.28]	[1.64]	[0.45]			

Table 10. Three Pass Fama Macbeth FX Asset Pricing Tests

This table reports three pass Fama Macbeth regressions (Giglio and Xiu, 2021) results for the two-factor model, including the DOL and FPR risk factors. 48 test assets used are six carry portfolios, six short-term momentum portfolios, six long-term momentum portfolios, six APR portfolios, six value portfolios, six global volatility portfolios, six global liquidity portfolios, and six uncertainty portfolios. Portfolios are rebalanced monthly. 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. We also report R^2_{DOL} and R^2_{FRP}. We report the Full (Recent) sample results in Panel A, B (C, D). The data are monthly from January 1984 (January 2000, in Panel C, D) to December 2020.

Panel A: Two-factor model: Full Sample: New York Times						
	λ_{DOL}	λ_{APR}			R^2_{DOL}	R^2_{APR}
FMB	0.001	-0.003**			0.07	0.96
(NW)	[1.67]	[-2.00]				
Panel B: Three-factor model: Full Sample: New York Times						
	λ_{DOL}	λ_{HML}	λ_{MOM}	R^2_{DOL}	R^2_{HML}	R^2_{MOM}
FMB	0.001*	0.005***	-0.006***	0.07	0.94	0.89
(NW)	[1.67]	[3.31]	[-3.56]			
	λ_{APR}	λ_{HML}	λ_{MOM}	R^2_{APR}	R^2_{HML}	R^2_{MOM}
FMB	-0.003**	0.005***	-0.006***	0.96	0.94	0.89
(NW)	[-2.00]	[3.31]	[-3.56]			
Panel C: Two-factor model: Recent Sample: Five Newspapers						
	λ_{DOL}	λ_{FPR}			R^2_{DOL}	R^2_{FPR}
FMB	0.008	-0.005**			0.13	0.93
(NW)	[0.72]	[-2.27]				
Panel D: Three-factor model: Recent Sample: Five Newspapers						
	λ_{DOL}	λ_{HML}	λ_{MOM}	R^2_{DOL}	R^2_{HML}	R^2_{MOM}
FMB	0.001	0.005***	-0.003	0.14	0.93	0.88
(NW)	[0.72]	[2.84]	[-1.47]			
	λ_{FRP}	λ_{HML}	λ_{MOM}	R^2_{FPR}	R^2_{HML}	R^2_{MOM}
FMB	-0.005**	0.005***	-0.003	0.93	0.93	0.88
(NW)	[-2.27]	[2.84]	[-1.47]			

Table 11. Cross-section FX Asset Pricing with Transaction Costs

This table reports regressions results and portfolio sorts for the estimation of the price of APR index betas (λ_{APR}) and LMH Portfolio. *Panel A* shows cross-sectional regressions of currency excess returns at time $t+1$ on the APR index at time t. *Panel B* displays the spread of portfolios that are sorted based on APR betas. We consider as transaction cost 25% of the quoted spread. Newey and West (1987) t-statistics are reported in brackets, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. We report the results for the Full and Recent samples. The data are monthly from January 1984 (January 2000, in Panel B) to December 2020.

Panel A: Cross-sectional Regressions		
	Full Sample Risk premium (1)	Recent Sample Risk premium (2)
λ_{APR}	-0.006**	-0.010***
	(-2.07)	(-2.69)
Constant	0.00	0.00
	(0.01)	(0.65)
Obs	8,405	5,441
R^2	0.17	0.12

Panel B: Portfolio Sorts		
	Full Sample LMH (1)	Recent Sample LMH (2)
Mean	2.96*	4.23**
	(1.66)	(2.14)
SR	0.34	0.50

Table 12. APR Beta and CLS Trading Volume

This table reports contemporaneous panel regressions with country fixed effects of average APR betas on the abnormal volume of buy side, bank, non-bank financials, funds and corporates. The model takes the form:

$$\hat{\beta}_{i,t}^{APR} = \delta_1 + \delta_2 \text{Abnormal trading volume}_{i,t} + \varepsilon_i, \tag{18}$$

where $\hat{\beta}_{i,t}^{APR}$ denotes the time-series of rolling APR betas for each country i at month t. The APR betas are estimated based on the model $rx_{i,t} = \alpha_{i,t} + \beta_{i,t}^{APR} APR_t + \epsilon_{i,t}$, where $rx_{i,t}$ is the realised excess return on currency i in month t, and APR_t is the APR Index in month t. The estimation of the APR betas is based on a 60-month rolling window. Abnormal trading volume is defined as the difference in trading volume of each country i at month t and its average trading volume over the last 12 months. We report t-statistics clustered by currency in parenthesis, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. The data are monthly from September 2012 to August 2019.

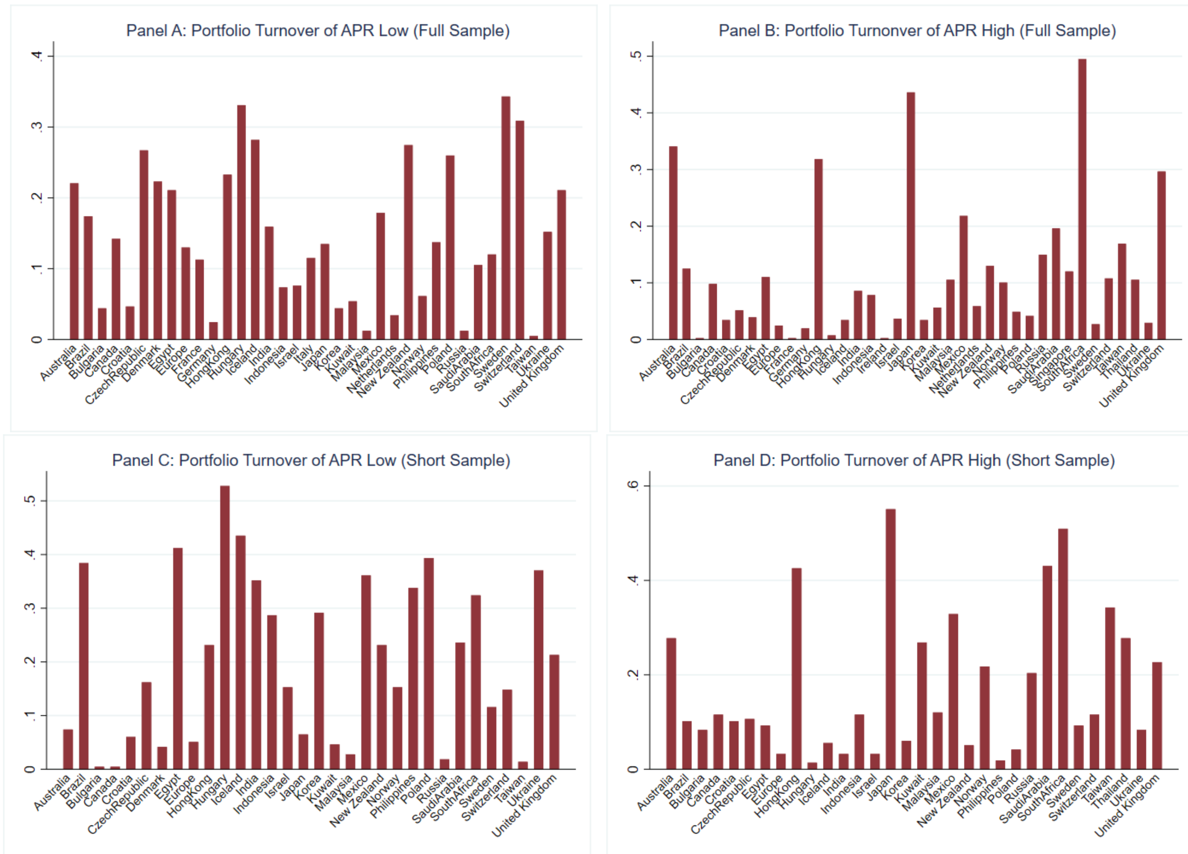
	(1) Buy Side	(2) Bank	(3) Non-bank Financials	(4) Fund	(5) Corporates
Abnormal trading volume$_{i,t}$	-0.010***	-0.002	0.008	-0.002***	-0.000
	(-2.54)	(-1.46)	(0.85)	(-4.41)	(-0.96)
Constant	-0.088**	-0.088**	-0.086**	-0.087**	-0.086**
	(-2.32)	(-2.31)	(-2.31)	(-2.29)	(-2.30)
Observations	1,049	1,049	1,008	1,047	1,005
Adj. R^2	0.15	0.15	0.14	0.15	0.15
Currency FE	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES

Internet Appendix to

"U.S. Populism and Currency Risk Premia"

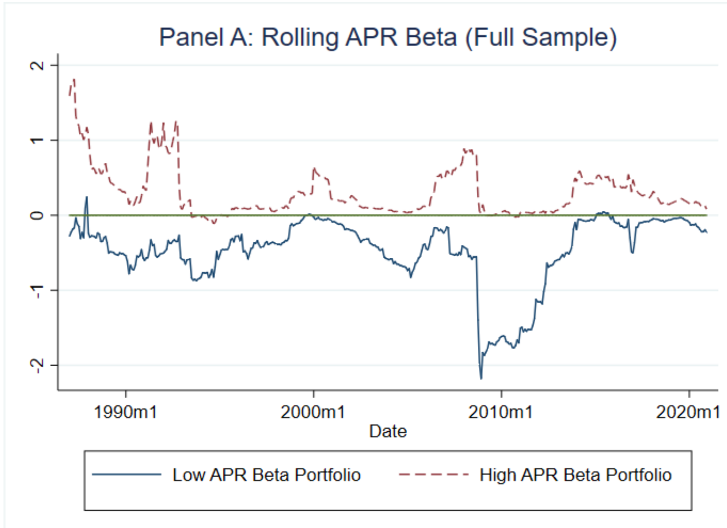
(Not for publication)

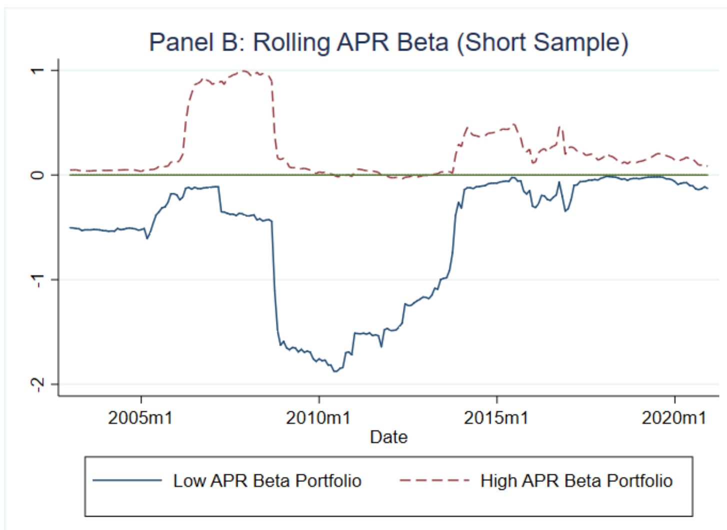
Figure A1. Portfolio Turnover



The figure shows the portfolio turnover of currency portfolios sorted on APR Index for the Full Sample (*Panel A* and *Panel B*), and for the Short Sample (*Panel C* and *Panel D*). The monthly data are from January 1984 to December 2020 (Panel A, Panel B) and from January 2000 to December 2020 (Panel C, Panel D).

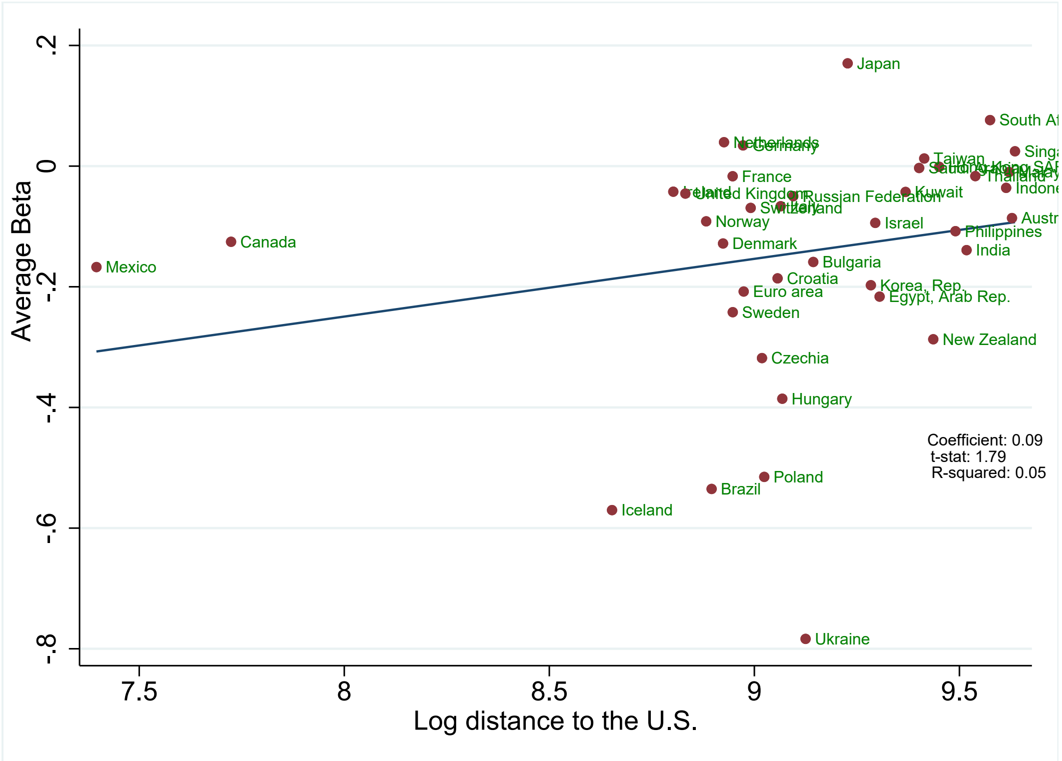
Figure A2. Rolling APR Betas of Portfolios





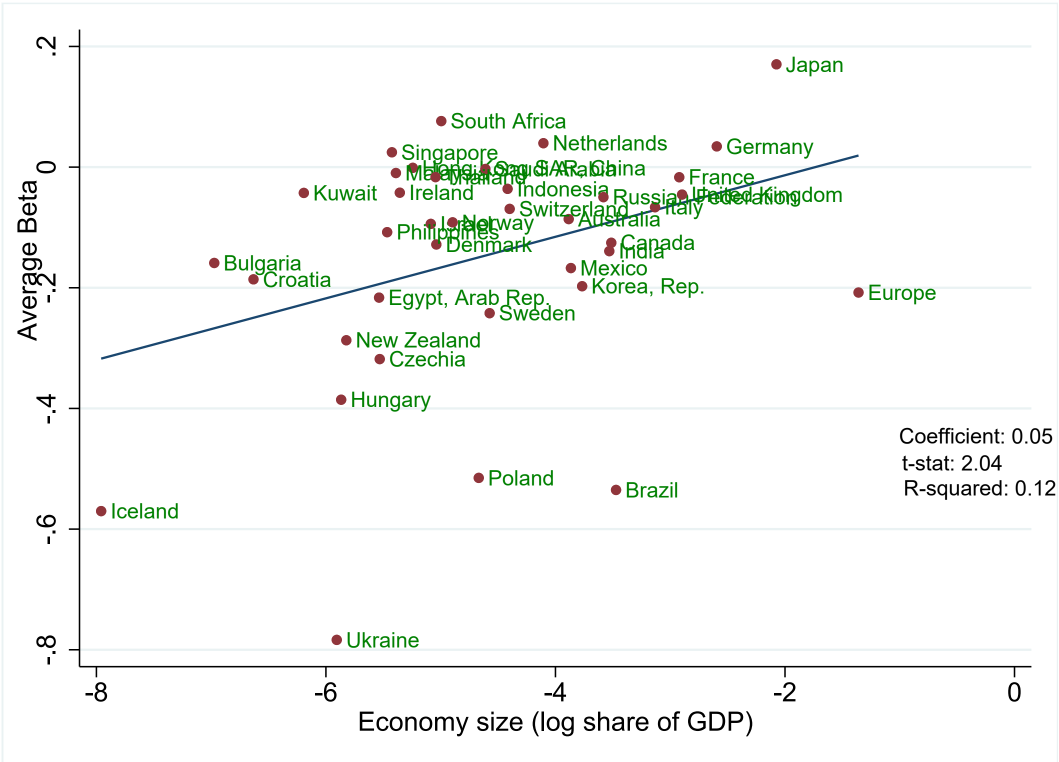
The figure shows the rolling betas of APR Full Sample (*Panel A*) and APR Short Sample (*Panel B*). In each panel, we plot the rolling betas of the low and high beta portfolios.The monthly data are from January 1984 to December 2020 (Panel A, Panel B) and from January 2000 to December 2020 (Panel C, Panel D).

Figure A3. Average APR Beta and Distance to the U.S.



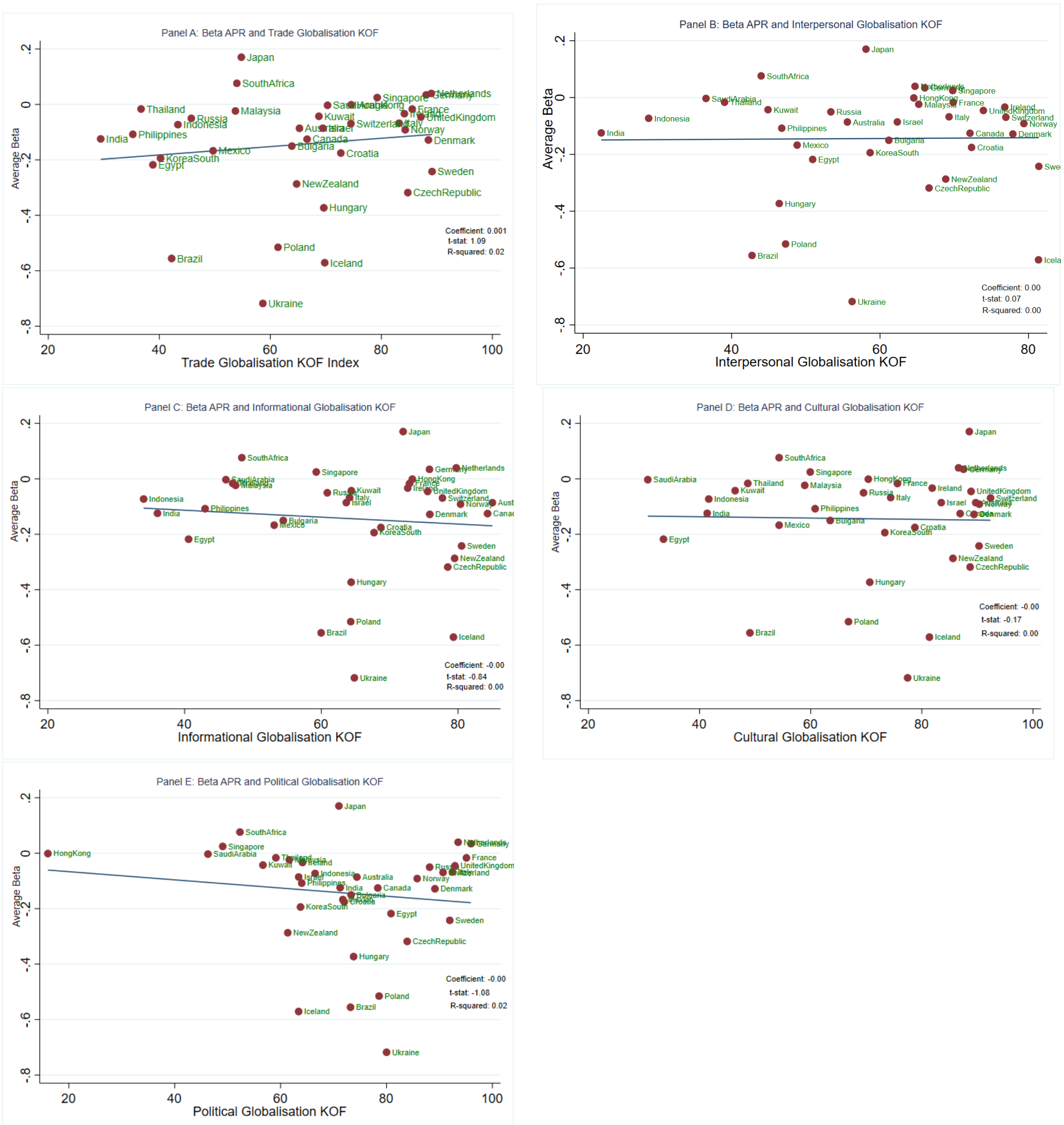
The figure shows the average beta APR and geographic distance to the U.S. (log kilometers). The data are from January 1984 to December 2020.

Figure A4. Average APR Beta and Country Size



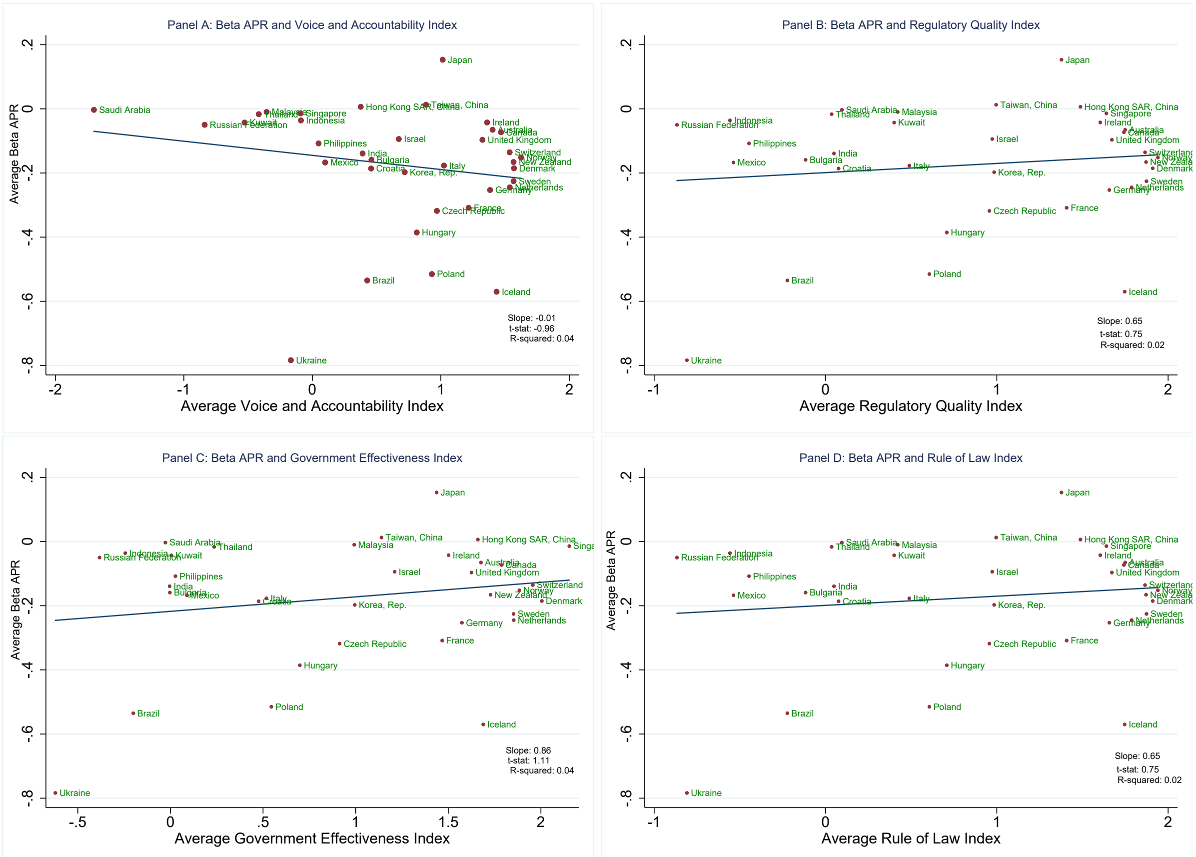
The figure shows average beta APR and country size (log share of GDP). The data are from January 1984 to December 2020.

Figure A5. Average APR Beta and KOF Globalization Index



The figure shows average APR beta and a range of Globalization KOF Index (*Panel A*: Trade, *Panel B*: Interpersonal, *Panel C*: Information, *Panel D*: Cultural),*Panel E*: Political). The monthly data are from January 1998 to December 2020.

Figure A6. 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). The monthly data are from January 1998 to December 2020.

Table A2. Distribution of Populism Topic Keywords by Bi-term Topic Modelling

The table reports results from Bi-term topic modelling implemented on Trump Twitter. These are the 5 populism topics. For each topic, the top 20 key words are reported.

Topic 1	Topic 2	Topic 3	Topic 4	Topic 5
american again	tax	news	china	border
america	jobs	fake	trade	wall
join	american	media	deal	democrats
vote	economy	fake news	president	security
maga	cuts	news media	korea	country
crowd	obamacare	fake news media	united	immigration
carolina	republicans	story	north	illegal
floria	senate	jobs	north korea	mexico
rally	court	country	tariffs	border security
love	democrats	failing	meeting	southern
iowa	tax cuts	house	country	crime
amazing	country	election	iran	southern border
south	america	cnn	dollars	stop
live	healthcare	dishonest	prime	borders
day	supreme	president	minister	laws
ohio	supreme court	press	billion	republicans
hshire	bill	market	prime minister	strong
forward	vote	stock	deals	national
poll	house	white	farmers	dems
south carolina	taxes	bad	world	illegal immigration

Table A3. Distribution of Non-Populism Topic Keywords by Bi-term Topic Modelling

The table reports results from Bi-term topic modelling implemented on Trump Twitter. These are the 5 non-populism topics. For each topic, the top 20 key words are reported.

Topic 1	Topic 2	Topic 3	Topic 4	Topic 5
hillary	party	honor	cruz	collusion
clinton	republicans	american	ted	fbi
crooked	america	law	poll	hunt
crooked hillary	job	america	president	witch
hillary clinton	republican party	happy	bush	witch hunt
endorsement	congratulations	world	ted cruz	democrats
interviewed	democrat	enforcement	jeb	russia
win	money	nation	wow	mueller
enjoy	president	women	rubio	caign
vote	record	law enforcement	john	hillary
job	country	day	debate	clinton
crime	governor	country	nice	comey
bernie	leadership	gold	caign	report
crooked hillary clinton	puerto rico	united	joe	russian
total	rico	attach	radical	crooked
bad	york	americans	failed	election
strong	jobs	heros	marco	obama
president	dollars	national	money	investigation
governer	left	prayers	watch	obstruction

Table A1. Portfolios sorted on Trade Policy Uncertainty Betas

This table reports summary statistics for the excess returns of three currency portfolios sorted on exposure to APR Index for the Full sample (Jan 1984- Dec 2020, *Panel A*), Trade Policy Uncertainty from Caldara et al. (2020) *Panel B*). We construct the APR index in the full sample based on The New York Times articles, while the APR index in the recent sample is based on five newspapers, including The Washington Post, The New York Daily News, The New York Post, USA Today, and The New York Times. Portfolio 1 (P_1) contains currencies with the lowest APR Index betas, and Portfolio 5 (P_5) contains currencies with the highest APR Index betas. LMH represents the portfolios that have a short position in the high beta portfolio (P_5) and a long position in the low beta portfolio (P_1). For each portfolio, we report annualized mean and its t-statistics (reported in squared brackets), standard deviation (Std) and Sharpe ratios (SR), and average betas of individual currencies(β), all in percentage points. We also report skewness and kurtosis. The data are monthly from January 1984 (January 2000, Panel B) to December 2020.

Panel A: PR P2.0 Index						
	P_1	P_2	P_3	P_4	P_5	LMH_{APR}
Mean	3.08	2.14	1.58	0.31	-0.47	3.55
	[2.38]	[1.67]	[1.22]	[0.22]	[-0.31]	[2.50]
Std	7.52	7.47	7.51	8.26	8.88	8.26
Skewness	-0.39	0.04	-0.15	-0.51	-0.67	0.12
Kurtosis	5.12	3.92	4.25	4.95	5.72	4.71
SR	0.41	0.29	0.21	0.04	-0.05	0.43
β^{APR}	-0.53	0.02	0.24	0.49	0.87	
Panel B: Trade Policy Uncertainty						
	P_1	P_2	P_3	P_4	P_5	LMH_{TPU}
Mean	2.51	1.46	0.40	0.88	1.60	0.91
	[1.99]	[1.10]	[0.283]	[0.58]	[0.97]	[0.70]
Std	6.79	7.47	8.04	8.31	9.13	7.56
Skewness	-0.51	0.05	-0.19	-0.58	-0.79	-0.35
Kurtosis	5.68	4.14	4.47	5.26	6.07	4.59
SR	0.38	0.37	0.20	0.11	0.18	0.12

Table A4. 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 have a long position in the low shipping cost portfolio (P_1) and a short position in the high shipping cost portfolio (P_5). We report p-values in parenthesis. The data are monthly from January 1984 to December 2020.

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	0.04	0.03	-0.02	-0.04	-0.05	0.14	0.10	0.04	0.05	-0.01	-0.01	0.15
						(0.00)						(0.00)

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	0.13	0.11	0.00	-0.06	-0.10	0.18	0.23	0.09	0.12	0.004	0.00	0.18
						(0.00)						(0.00)

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	0.12	0.10	-0.00	-0.07	-0.10	0.19	0.23	0.09	0.12	0.00	-0.01	0.18
						(0.00)						(0.00)

Table A5. FX Asset Pricing Tests: Time-series Betas

This table reports time-series beta results for the two-factor model, including the DOL and APR risk factors. Test assets used are 6 APR portfolios. Portfolios are rebalanced monthly. 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. We also report R^2, Root Mean Squared Error (RMSE). We report the Full (Recent) sample results in Panel A (Panel B). The data are monthly from January 1984 (January 2000, in Panel C,D) to December 2020.

Panel A: : Two-factor model: Full Sample: New York Times

	$\beta_1 DOL$	$\beta_2 DOL$	$\beta_3 DOL$	$\beta_4 DOL$	$\beta_5 DOL$	$\beta_6 DOL$	$\beta_1 FRP$	$\beta_2 FRP$	$\beta_3 FRP$	$\beta_4 FRP$	$\beta_5 FRP$	$\beta_6 FRP$
FMB	0.16***	0.07	0.08	0.09*	0.09**	0.16***	-0.55***	-0.27***	-0.15*	-0.05	0.08	0.45***
(NW)	[2.93]	[1.34]	[1.34]	[1.93]	[2.12]	[2.93]	[-7.37]	[-3.47]	[-1.68]	[-0.56]	[1.04]	[6.09]

Panel C: Two-factor model: Recent Sample: Five Newspapers

	$\beta_1 DOL$	$\beta_2 DOL$	$\beta_3 DOL$	$\beta_4 DOL$	$\beta_5 DOL$	$\beta_6 DOL$	$\beta_1 FRP$	$\beta_2 FRP$	$\beta_3 FRP$	$\beta_4 FRP$	$\beta_5 FRP$	$\beta_6 FRP$
FMB	0.13*	0.02	-0.03	0.03	0.07	0.12	-0.63***	-0.41***	-0.34***	-0.20**	-0.11	0.37***
(NW)	[1.71]	[0.29]	[-0.43]	[0.49]	[1.19]	[1.71]	[-4.99]	[-3.08]	[-2.97]	[-2.35]	[-1.33]	[2.89]

Table A6. Portfolios sorted on APR Betas- Filtered Sample

This table reports summary statistics for the excess returns of three currency portfolios sorted on exposure to APR Index for the Full sample (Jan 1984- Dec 2020, *Panel A*), Recent sample (Jan 2000- Dec 2020, *Panel B*). We construct the APR index in the full sample based on The New York Times articles, while the APR index in the recent sample is based on five newspapers, including The Washington Post, The New York Daily News, The New York Post, USA Today, and The New York Times. Portfolio 1 (P_1) contains currencies with the lowest APR Index betas, and Portfolio 4 (P_4) contains currencies with the highest APR Index betas. LMH represents the portfolios that have a short position in the high beta portfolio (P_4) and a long position in the low beta portfolio (P_1). For each portfolio, we report annualized mean and its t-statistics (reported in squared brackets), standard deviation (Std), and Sharpe ratios (SR), all in percentage points. We also report skewness and kurtosis. The data are monthly from January 1984 (January 2000, Panel B) to December 2020.

Panel A: Full Sample: New York Times					
	P_1	P_2	P_3	P_4	LMH_{APR}
Mean	5.80	1.23	0.37	1.73	4.08
	[3.65]	[0.83]	[0.25]	[1.16]	[2.12]
Std	9.26	8.59	8.60	8.69	9.52
Skewness	-0.13	-0.17	-0.34	-0.70	0.15
Kurtosis	5.06	4.70	4.15	5.14	4.57
SR	0.63	0.14	0.04	0.20	0.43
Panel B: Recent Sample: Five Newspapers					
	P_1	P_2	P_3	P_4	LMH_{APR}
Mean	7.69	1.63	-0.05	2.15	5.54
	[3.34]	[0.75]	[-0.01]	[2.11]	[2.19]
Std	9.75	9.20	7.93	7.97	9.50
Skewness	-0.33	-0.68	-0.36	-0.35	-0.16
Kurtosis	5.95	5.32	3.81	4.41	4.49
SR	0.79	0.18	-0.01	0.27	0.58