

Understanding the Strength of the Dollar*

Zhengyang Jiang[†]

Robert Richmond[‡]

Tony Zhang[§]

August 2022

Abstract

We link the sustained appreciation of the U.S. dollar from 2011 to 2019 to international capital flows driven by primitive economic factors. We show that increases in foreign investors' net savings, increases in U.S. monetary policy rates relative to the rest of the world, and shifts in investor demand for U.S. financial assets contributed approximately equally to the dollar's appreciation. We then quantify the impact of potential future demand shifts for U.S. assets on the value of the dollar.

Key Words: Dollar, Exchange Rate, Capital Flows, Asset Demand System

*For comments and discussions we would like to thank Ralph Koijen and Alexi Savov. Cody Wan provided excellent research assistance. The views in this paper are solely the responsibility of the authors and should not be interpreted as reflecting the views of the Board of Governors of the Federal Reserve System or any other person associated with the Federal Reserve System.

[†]**Northwestern University, Kellogg School of Management, and NBER;**
E-mail: zhengyang.jiang@kellogg.northwestern.edu.

[‡]**New York University, Stern School of Business;** E-mail: rrichmon@stern.nyu.edu.

[§]**Federal Reserve Board;** E-mail: tony.zhang@frb.gov.

In 2022, the dollar reached its highest level since the early 2000s, after experiencing a decade-long period of sustained appreciation. The strength of the dollar has far-reaching consequences for global asset prices, economic conditions, and the health of the global financial sector. As such, it is important to understand the economic drivers of the strength of the dollar. In this paper, we use a portfolio-based approach to attribute the dollar’s appreciation to variations in asset supply and demand driven by primitive economic factors. Our key finding is that increases in investors’ net savings, rising U.S. monetary policy rates relative to the rest of the world, and shifts in investor demand for U.S. assets contributed approximately equally to the dollar’s appreciation.

We employ the demand system approach to asset pricing (Kojien and Yogo 2019a,b; Kojien, Richmond, and Yogo 2019) by adopting the specification of Jiang, Richmond, and Zhang (2022). In the presence of downward-sloping asset demand, our approach traces out how the dollar’s exchange rate responds to variations in asset supply and demand. For example, an increase in foreigners’ demand for U.S. assets leads to a capital inflow to the U.S. and a dollar appreciation, whereas an increase in the supply of the U.S. short-term debt assets dilutes the supply of dollar assets and leads to a dollar depreciation.

We estimate our model using a comprehensive dataset of bilateral equity and debt portfolio positions between 2011 and 2019. We focus on the trade-weighted index of the dollar against advanced foreign economies, referred to as the dollar AFE index. In this period, the dollar AFE index appreciated by 23%, which represents a substantial proportion of the 30% appreciation between January 2011 and August 2022.

We divide our model’s primitive demand and supply factors into three categories: (i) investors’ savings and asset issuances, (ii) central banks’ monetary policies, and (iii) changes in investors’ demand. We treat these variables as exogenous, and they jointly explain the endogenous exchange rates, asset prices, and portfolio allocations. From one year to the next, had the exogenous variables remained unchanged, the endogenous variables, including the dollar’s exchange rate, would have remained unchanged. By iteratively restoring changes in exogenous variables between years and recomputing equilibrium exchange rates, prices, and allocations, we are able to attribute variations in the dollar to different factors.

We first trace out the effect of investor savings in excess of domestic investment opportu-

nities, while holding investors' demand curves fixed. When investors save in financial assets, they allocate their savings according to their existing portfolio weights. Then, given that asset prices adjust in response to the additional demand, investors will adjust their portfolios by moving along their demand curves. As a result, savings and issuances can impact exchange rates even without shifts in investors' demand curves. We find that the increase in global savings accounts for an 8.7% of the dollar's appreciation between 2011 and 2019.

Second, we study the effects of monetary policies. Over the last decade, the Federal Reserve Bank (FRB) raised domestic interest rates faster than other central banks. This relatively high yield attracted foreign capital to the U.S., keeping investor savings and asset supply fixed. The rise in U.S. short-term interest rates explains an additional 5.8% dollar appreciation. The FRB's monetary policy is particularly important for explaining the rise of the dollar against the Euro due to the expansionary policy stance taken by the European Central Bank. Interestingly, the relation between dollar appreciation and the U.S. monetary policy implied by our model also matches the estimates from the literature that uses high-frequency shocks to identify the effects of monetary policy.

Finally, we study the effects of shifts in investor demand curves, and find that they explain a further 9.3% dollar appreciation. These demand shifts appreciated the dollar in two ways. First, foreign investors' demand for U.S. assets increased. This shift in demand towards U.S. financial assets, particularly towards U.S. equity, was also instrumental in explaining the returns on U.S. financial assets as shown by [Jiang, Richmond, and Zhang \(2022\)](#). Second, U.S. investors' demand for foreign assets declined over the last decade, putting downwards pressure on foreign currencies relative to the dollar.

In the final part of the paper, we study the consequences of hypothetical large-scale sales of U.S. financial assets on the dollar. We find that even if a large economy such as China *unilaterally* sells all of its holdings of U.S. assets, the impact on the dollar's value is surprisingly modest. The reason is that sales of U.S. financial assets by any single country are met by purchases by the other countries, as long as U.S. financial assets are highly desirable. We also study a decline in the specialness of U.S. assets and show that it would lead to a larger depreciation of the dollar. These results highlight the stability of the dollar as a global currency, and the support the literature on coordination on reserve currencies.

Our focus on the dollar is motivated by the literature that shows the dollar plays a critical role in trade and the international financial system (Maggiore, Neiman, and Schreger 2020; Jiang, Krishnamurthy, and Lustig 2020; Gopinath and Stein 2021). The dollar’s influence on foreign economies drives the global financial cycle (Rey 2015; Du 2019; Miranda-Agrippino and Rey 2020) and its strength is related to frictions in financial intermediation. Specifically, Avdjiev, Du, Koch, and Shin (2019) show that a stronger dollar coincides with larger deviations from covered interest rate parity (CIP) and less cross-border lending. Global financial conditions also affect the CIP deviation and the demand for safe assets (Du and Schreger 2021; Jiang, Krishnamurthy, and Lustig 2021).

Our paper builds on work that demonstrates how exchange rates are connected to international capital flows. Gabaix and Maggiori (2015) presents a model for how exchange rates and capital flows are related in segmented financial markets. Lilley, Maggiori, Neiman, and Schreger (2022) document that after the global financial crisis, the dollar’s value is closely tied to measures of global risk appetite and to U.S. foreign bond purchases. Hau and Rey (2006) present an equilibrium model of exchange rates and capital flows and show that changes in exchange rates are correlated with capital flows. Camanho, Hau, and Rey (2018) study mutual fund rebalancing and exchange rates. Our paper contributes to this literature by quantifying how factors that drive capital flows can jointly explain the dynamics of the dollar.

Finally, our paper contributes to the literature on reserve currencies and the dollar. Maggiori (2017) studies the emergence of and properties of a reserve currency in a model with countries with varying degrees of financial development. Farhi and Maggiori (2017); He, Krishnamurthy, and Milbradt (2019) study a model of the international financial system and the implications of supply and demand for reserve assets. Our study highlights the stability of the dollar regime based on the asset substitution patterns of different investors.

1 A Portfolio Approach to Dollar Valuation

Our model follows Jiang, Richmond, and Zhang (2022), which builds on Kojien and Yogo (2019b). There are three key ingredients: (1) investors’ asset demand curves, (2) investors’

wealth dynamics, and (3) market clearing. These ingredients constitute an asset demand system that relates exchange rates and asset prices to the demand and supply of financial assets.

1.1 International Asset Demand System

Time is discrete. There are I investor countries that each contain a representative investor who allocates wealth across the asset space. There are N countries that issue assets. These sets of countries can be overlapping. Issuer countries supply assets in asset classes indexed by ℓ : short-term debt ($\ell = 1$), long-term debt ($\ell = 2$), and equity ($\ell = 3$). Each asset class contains $N + 1$ assets — one for each issuer country plus an “outside” asset indexed $n = 0$. This outside asset contains holdings in small countries that are not in our main sample due to data limitations.

We denote investor country i 's portfolio weight on issuer country n in asset class ℓ by $w_{i,t}(n, \ell)$, which can be decomposed as:

$$w_{i,t}(n, \ell) = w_{i,t}(n|\ell) \cdot w_{i,t}(\ell), \quad (1)$$

where $w_{i,t}(n|\ell)$ is investor country i 's portfolio weight on issuer country n within asset class ℓ , and $w_{i,t}(\ell)$ is investor country i 's total portfolio weight on asset class ℓ .

Demand within Asset Class. Within an asset class ℓ , the portfolio weight for investor i at time t in country n is a logistic function¹:

$$w_{i,t}(n|\ell) = \frac{\delta_{i,t}(n, \ell)}{1 + \sum_{k=1}^N \delta_{i,t}(k, \ell)}, \quad (2)$$

where $\delta_{i,t}(n, \ell)$ captures the relative desirability of a country's asset in this asset class:

$$\delta_{i,t}(n, \ell) = \exp(\beta_\ell \mu_{i,t}(n, \ell) + \boldsymbol{\theta}'_\ell \mathbf{x}_{i,t}(n) + \kappa_{i,t}(n, \ell)). \quad (3)$$

¹By construction, the total weight in each asset class equals 1, $\sum_{n=0}^N w_{i,t}(n|\ell) = 1$. The portfolio weight in the outside asset in asset class ℓ is therefore $w_{i,t}(0|\ell) = 1/(1 + \sum_{n=1}^N \delta_{i,t}(n, \ell))$.

This desirability has three components. First, $\mu_{i,t}(n, \ell)$ denotes the expected return at time t for country i 's investor in country n 's asset of class ℓ . Second, $\mathbf{x}_{i,t}(n)$ denotes a set of observable asset characteristics that can be country-specific or bilateral in nature. The loadings, $\boldsymbol{\theta}_\ell$, capture the weight investors place on the characteristics within each asset class. Third, $\kappa_{i,t}(n, \ell)$, denotes latent demand and describes additional variation in the portfolio weights that is not captured by the expected return or observable asset characteristics.

For concreteness, consider the U.S. investor deciding on her portfolio weight on German long-term debt. Thus, i is the U.S., n is Germany, and $\ell = 2$ represents long-term debt. $\mu_{i,t}(n, \ell)$ captures the local currency return the U.S. investor expects to earn on German long-term debt. $\mathbf{x}_{i,t}(n)$ captures characteristics such as the size (GDP) of Germany and the geographic distance between the U.S. and Germany. Finally, $\boldsymbol{\theta}_\ell$ captures how characteristics matter for the long-term bond portfolio allocation.

Expected Returns. Investors care about expected returns in their own currency. We measure expected excess returns in dollars and convert them to each investor's currency. Let $r_{t+1}(n, \ell) = \log(R_{t+1}(n, \ell))$ denote the log return in dollars on asset class ℓ in country n from time t to $t + 1$. To measure expected returns, we use a forecasting regression as in [Kojien and Yogo \(2019b\)](#):

$$r_{t+1}(n, \ell) - r_{t+1}(US, 1) = \phi_\ell \cdot pb_t(n, \ell) + \psi_\ell \cdot (e_t(n) - z_t(n)) + \chi_{n,\ell} + \nu_{t+1}(n, \ell). \quad (4)$$

This regression projects the excess return at time $t + 1$ for a U.S. investor onto its log market-to-book ratio $pb_t(n, \ell)$ at time t and the log real exchange rate $(e_t(n) - z_t(n))$ between country n and the dollars. The book value in the market-to-book ratio is equity book value for equity and par value for debt. The log real exchange rate is the difference between the log nominal exchange rate $e_t(n) = \log E_t(n)$ and the log consumer price index $z_t(n)$. The exchange rate, $E_t(n)$, is in dollars per unit of foreign currency. The regression coefficients ϕ_ℓ and ψ_ℓ are specific to each asset class ℓ . Based on this regression, the expected log excess return on

asset n in investor i 's currency is

$$\begin{aligned}\mu_{i,t}(n, \ell) &= \mathbb{E}_t[r_{t+1}(n, \ell) - r_{t+1}(i, 1)] \\ &= \phi_\ell pb_t(n, \ell) + \psi_\ell(e_t(n) - z_t(n)) + \chi_{n,\ell} - \phi_1 pb_t(i, 1) - \psi_1(e_t(i) - z_t(i)) - \chi_{i,1}.\end{aligned}\quad (5)$$

Demand Across Asset Classes. To allow for substitution across asset classes, the asset class portfolio weight is specified as a nested logit. The portfolio weight for investor i at time t in asset class ℓ is

$$w_{i,t}(\ell) = \frac{(1 + \sum_{k=1}^N \delta_{i,t}(n, \ell))^{\lambda_\ell} \exp(\alpha_\ell + \xi_{i,t}(\ell))}{\sum_{m=1}^3 (1 + \sum_{k=1}^N \delta_{i,t}(k, m))^{\lambda_m} \exp(\alpha_m + \xi_{i,t}(m))}, \quad (6)$$

where α_ℓ captures asset class fixed effects and $\xi_{i,t}(\ell)$ captures asset class latent demand. The terms $(1 + \sum_{k=1}^N \delta_{i,t}(n, \ell))$ are referred to as inclusive values for a given asset class ℓ , which capture the relative attractiveness of investing in each asset class. For example, when relative prices of assets within an asset class increase, the asset class becomes less desirable as a whole, and investors may substitute away from the asset class accordingly.

Central Banks. We differentiate between demand of private investors and central banks. We use $B_{i,t}(n, \ell)$ to denote the quantity of country n 's assets held by country i 's central bank in local currency book value, which we take as exogenous.

Investor Wealth Dynamics. Investor wealth adjusts according to the returns on the assets the investor holds. The law of motion for the assets under management (AUM) for investor i in dollars is:

$$A_{i,t} = A_{i,t-1} \sum_{\ell=1}^3 \sum_{n=0}^N w_{i,t-1}(\ell) w_{i,t-1}(n|\ell) R_t(n, \ell) + F_{i,t}, \quad (7)$$

where $R_t(n, \ell)$ is the capital gains on asset n in asset class ℓ in time t in dollars, and $F_{i,t}$ is investor i 's net financial savings in dollars, including dividend yield.²

²We specify capital gains as a function of the market-to-book ratio of assets and the exchange rate in Appendix A.1.

Market Clearing. Let $Q_t(n, \ell)$ denote the book quantity supplied by country n in asset class ℓ in its local currency. Specifically, $Q_t(n, \ell)$ is the total book value in local currency for equity, and the par value in local currency for long-term and short-term debt. We assume the quantity of assets outstanding in each period is exogenously determined. Nevertheless, the dollar book value, $E_t(n)Q_t(n, \ell)$, and the dollar market value, $PB_t(n, \ell)E_t(n)Q_t(n, \ell)$, of any asset are endogenous, because exchange rates and market-to-book ratios are endogenously determined.

The market clearing condition for asset (n, ℓ) in dollars is

$$PB_t(n, \ell)E_t(n)Q_t(n, \ell) = \sum_{i=1}^N A_{i,t}w_{i,t}(\ell)w_{i,t}(n|\ell) + PB_t(n, \ell)E_t(n) \sum_{i=1}^N B_{i,t}(n, \ell). \quad (8)$$

The left-hand side is the total market value, and the right-hand side is the sum of the dollar value of investors' portfolio holdings of the asset plus the sum of the dollar value of central banks' reserve holdings.

Exchange Rate Determination. Exchange rates are determined by market clearing for short-term debt. Demand for equity and long-term debt also affect exchange rates due to substitution across asset classes. We assume the short-term interest rate is controlled by each country's monetary authority so its price $PB_t(n, 1)$ is exogenous. When there is a shock to investor demand on the right-hand side of equation (8), the exchange rate $E_t(n)$ adjusts.³ Intuitively, if demand for country n short-term debt increases in dollar terms, the country n currency appreciates in value to clear the short-term debt market ($E_t(n)$ increases).

In sum, there are 3 asset classes with N assets each, which leads to $3N$ market clearing conditions. Taking short-term bond prices as given, there are N long-term bond prices, N equity prices, $N - 1$ exchange rates with respect to the dollar, and the U.S. short-term bond supply. This leads to an exactly determined system.

³Pegged exchange rates are cleared by assuming that the country's central bank maintains the peg by adjusting the supply of short-term debt.

1.2 Data

We employ three types of data: (1) cross-country bilateral portfolio holdings, (2) asset/country characteristics, and (3) asset returns. At each stage of our data construction, we combine the best available data to get an accurate representation of cross-border portfolio holdings and asset returns. The data we use in this paper are the same as in [Jiang, Richmond, and Zhang \(2022\)](#). We summarize our data here and provide details in [Appendix B.1](#).

Our cross-border holdings data are based upon IMF CPIS and the Treasury TIC databases. We improve the quality of the cross-border holdings and returns data in three ways. First, we use the reallocation matrices from [Coppola, Maggiori, Neiman, and Schreger \(2020\)](#) to account for mis-attributed investments in offshore financial centers. Second, we estimate the reserve holdings of specific central banks to disaggregate the quantities attributed to official asset purchases at the region level. Third, we use detailed estimates of asset returns from the TIC data to construct reliable estimates of capital gains and net savings.

We measure asset characteristics, $\mathbf{x}_{i,t}(n)$, that investors likely use to proxy for expected returns and their riskiness. These characteristics include the market-to-book value of equity and the yields on short-term and long-term debt. We use yields on 3-month government debt to capture the yield on short-term debt, and the yield on 10-year government debt for long-term debt. The issuer country characteristics are its log GDP, log population, trade network centrality ([Richmond 2016](#)), sovereign default risk, volatility, real exchange rate, and inflation. Bilateral characteristics are import and export exposures and distance. We also include indicator variables for domestic investment, U.S. issuer, investor country, and year fixed effects.

Our sample runs from 2011 to 2019, and consists of 35 investor countries and 32 issuer countries. Holdings in issuer countries for which we do not observe a complete panel of characteristics and asset price data are aggregated into an “outside” country which comprises 3.5% of observed holdings.

1.3 Estimation and Identification

We now describe how we estimate investor’s demand curves. Equations (2) and (3) imply

$$\log \left(\frac{w_{i,t}(n, \ell)}{w_{i,t}(0, \ell)} \right) = \beta_\ell \mu_{i,t}(n, \ell) + \boldsymbol{\theta}'_\ell \mathbf{x}_{i,t}(n) + \kappa_{i,t}(n, \ell). \quad (9)$$

This equation determines the within-asset-class demand, which we estimate separately for each asset class ℓ . We obtain the estimation equation for across-asset-class demand by dividing equation (6) for short-term ($\ell = 1$) and long-term debt ($\ell = 2$) by the equation for equity ($\ell = 3$):

$$\log \left(\frac{w_{i,t}(\ell)}{w_{i,t}(3)} \right) = \lambda_\ell \log \left(1 + \sum_{n=1}^N \delta_{i,t}(n, \ell) \right) - \lambda_3 \log \left(1 + \sum_{n=1}^N \delta_{i,t}(n, 3) \right) + \alpha_\ell + \xi_{i,t}(\ell). \quad (10)$$

The main challenge to estimating equations (9) and (10) is that expected returns may be endogenous to latent demand. Consider the estimation of the within-asset-class demand curves, equation (9). If investors have high latent demand for a particular issuer’s asset, the price of this asset will be higher, which will impact this asset’s expected return and bias the estimated demand coefficient β_ℓ due to the correlation between the regressor, $\mu_{i,t}(n, \ell)$, and the residual, $\kappa_{i,t}(n, \ell)$. Similarly for the across asset demand curves in equation (10) — If a particular asset class has high latent demand, this will increase the price of this asset class and potentially bias the estimation since the inclusive value, $1 + \sum_{n=1}^N \delta_{i,t}(n, \ell)$, contains the price. To address these endogeneity concerns we construct instruments for both estimation equations, building on the identification strategy in [Kojien and Yogo \(2019b\)](#).

To construct instruments we need cross-sectional variation in country-level expected returns that is uncorrelated with latent demand. Country-level expected returns are related to prices and exchange rates through the return forecasting regression, equation (5). Therefore, we can use exogenous variation in prices and exchange rates as instruments for expected returns. To obtain such variation, we use our model to construct instruments for prices under the assumption that investor portfolios are determined by exogenous characteristics.

Formally, our identifying assumption is that asset characteristics, asset supply, and in-

vestment in outside assets (investor wealth) are exogenous to latent demand:

$$\mathbb{E} \begin{bmatrix} \kappa_{i,t}(n, \ell) \\ \xi_{i,t}(\ell) \end{bmatrix} \Bigg| \mathbf{x}_t, \mathbf{Q}_t, \mathbf{O}_t = \mathbf{0}, \quad (11)$$

where \mathbf{x}_t is a matrix of characteristics for all countries, \mathbf{Q}_t is the vector of asset supplies, and \mathbf{O}_t is the vector of holdings of outside assets.

We begin by constructing exogenous portfolio weights by estimating a simplified version of the within-asset-class demand:

$$\log \left(\frac{w_{i,t}(n, \ell)}{w_{i,t}(0, \ell)} \right) = \boldsymbol{\theta}'_{\ell} \mathbf{x}_{i,t}(n) + \kappa_{i,t}(n, \ell). \quad (12)$$

In this equation, we omit expected returns and use a set of exogenous characteristics: bilateral distance between countries, issuer country population, an own country dummy, and investor fixed effects. By including investor fixed effects we control for the cross-sectional variation in investor's weights in the outside asset, which uses the assumption that outside asset holdings are exogenous. We use predicted values from (12) to construct predicted desirabilities, $\hat{\delta}_{i,t}(n, \ell)$, which are driven entirely by variation in exogenous characteristics.

The across-asset-class equation determines how investors substitute across asset classes when the relative desirability of all assets in a particular asset class changes. For example, when equities become more desirable relative to long-term debt, investors may substitute toward equity and away from long-term debt. The amount of this substitution is determined by the elasticities λ_{ℓ} . To estimate this equation we need exogenous variation in the overall desirability of each asset class. With our exogenous asset desirabilities, $\hat{\delta}_{i,t}(n, \ell)$, we are able to compute instruments for the the overall asset level desirabilities, or inclusive values, in equation (10):

$$1 + \sum_{n=1}^N \hat{\delta}_{i,t}(n, \ell).$$

Using this instrument, we are able to identify the parameters in the across-asset-class demand curve, equation (10).

The full estimates for equation (10) are reported in Appendix B.2 in Table B.5. Here we note that all λ_ℓ values are between 0 and 1. This implies that there is some substitution between asset classes when the relative value of an asset class varies. This is in contrast to the case when $\lambda_\ell = 0$, in which the allocations across asset classes are independent of the relative desirabilities of individual assets. When $\lambda_\ell = 1$, the substitution between asset classes only depends on the desirabilities of individual issuer countries' assets, and the demand system collapses to one tier.

The next step is to estimate the within-asset-class demand curves, as given by equation (9). To do so, we use the estimated cross-asset demand parameters, the exogenous desirabilities, and market clearing to construct instruments for prices and exchange rates. Given exogenous asset desirabilities $\hat{\delta}_{i,t}(n, \ell)$, and estimated cross-asset demand parameters, $\hat{\lambda}_\ell$ and $\hat{\alpha}_\ell$, we compute the model implied portfolio weights:

$$\hat{w}_{i,t}(n, \ell) = \frac{\hat{\delta}_{i,t}(n, \ell)}{1 + \sum_{n=1}^N \hat{\delta}_{i,t}(n, \ell)} \frac{\left(1 + \sum_{n=1}^N \hat{\delta}_{i,t}(n, \ell)\right)^{\hat{\lambda}_\ell} \exp(\hat{\alpha}_\ell)}{\sum_{m=1}^3 \left(\left(1 + \sum_{n=1}^N \hat{\delta}_{i,t}(n, m)\right)^{\hat{\lambda}_m} \exp(\hat{\alpha}_m) \right)}. \quad (13)$$

These exogenous weights are calculated using Equations (1), (2), (3), and (6), but using the exogenous asset desirabilities. These weights can be thought of as counterfactual portfolio weights for issuer country n 's asset in class ℓ if portfolios were determined by the distance between countries, issuer country population, and home bias.

Given these exogenous portfolio weights, we use the market clearing equation (8) to calculate implied asset prices and exchange rates, which we then use as instruments to estimate the within-asset-class demand curve. Specifically, we set each investor country's total assets under management as

$$\hat{A}_{i,t} = \frac{O_{i,t}}{1 - \sum_{k=1}^3 \sum_{m=1}^N \hat{w}_{i,t}(m, k)},$$

where $O_{i,t}$ is investor i 's total investment into outside assets. Market clearing in the short-

term debt market yields our instruments for exchange rates:

$$\hat{E}_t(n) = \frac{1}{Q_t(n, 1)} \sum_{i=1}^N \hat{A}_{i,t} \hat{w}_{i,t}(n, \ell),$$

and market clearing in long-term bonds and equities yields our instruments for prices:

$$\hat{P}B_t(n, \ell) = \frac{1}{\hat{E}_t(n) Q_t(n, \ell)} \sum_{i=1}^N \hat{A}_{i,t} \hat{w}_{i,t}(n, \ell).$$

Intuitively, the above procedure identifies differences in expected returns that arise due to the fact that asset prices are higher in countries that are geographically closer to large investor countries, and countries that tend to issue fewer assets. In this way, we obtain instruments for exchange rates and asset prices, which we use to identify the within-asset-class demand curve, equation (9). For short-term debt, we instrument expected returns with $\hat{E}_t(n)$. For long-term debt and equity we instrument expected returns with $\hat{E}_t(n)$ and $\hat{P}_t(n, \ell)$ for $\ell = 2, 3$.

The full estimates for within-asset-class demand curves are presented in Appendix [Table B.7](#), here we discuss the key implications of these estimates. Our estimates imply average demand elasticities of 197 for short-term debt, 2.5 for long-term debt, and 1.8 for equities. Appendix [B.5](#) discusses the details of this conversion. These numbers are comparable to those found in [Kojen and Yogo \(2019b\)](#) which we would expect since we employ a variation on the estimation methodology. For short-term debt with a maturity of 3-months this elasticity implies that a 1% increase in annualized yield increases demand for short-term debt by 49%. For long-term debt with a maturity of 10-years this demand elasticity implies that a 1% increase in annualized yield increases demand for long-term debt by 25%.

To ensure the robustness of our findings to the estimation and identification procedure, we present results from a number of alternative procedures in Appendix [B.3](#).

2 What Explains the Dollar’s Current Value?

In this section, we decompose the dollar’s appreciation from 2011 to 2019 into primitive variables in the model. We first describe our decomposition methodology and then present our results.

2.1 Decomposition Methodology

To decompose changes in exchange rates between year $t - 1$ and t , we begin by setting all primitive exogenous variables in our model back to their values in year $t - 1$. We compute the equilibrium through the market clearing condition, and refer to this equilibrium as the *baseline* step. We then sequentially restore each primitive variable to its year- t values, and recompute equilibrium asset prices and portfolio holdings at each step. Appendix B.4 provides computational details. After restoring all variables, we arrive at the actual observed year- t value of the dollar in the data which we refer to as *observed* step.

Our focus is on understanding what drove the trend in the dollar’s value. To do so, we report the cumulative log change in the dollar AFE index, denoted USD , over the sample period at each step of the decomposition. Dollar AFE index weights are obtained from the Federal Reserve Board. Let $\Delta_{j,t}$ denote the difference in the log of the implied dollar index between the $(j - 1)$ -th step and the j -th step:

$$\Delta_{j,t} = \log (USD_t^j / USD_t^{j-1}). \quad (14)$$

We report the summation of each step’s incremental contribution across all years:

$$\bar{\Delta}_j = \sum_j \Delta_{j,t}. \quad (15)$$

The sum of $\Delta_{j,t}$ across all J steps is equal to the actual log change in the dollar: $\sum_j \Delta_{j,t} = \log USD_t - \log USD_{t-1}$, the sum of $\bar{\Delta}_j$ is equal to the actual cumulative change in the dollar.

Having specified our decomposition framework, we now describe the sequence of steps we use in our decomposition. Our choice of the primitive variables are inspired by various

literatures that study the drivers of international capital flows. In particular, these variables measure (1) investor savings and asset issuances, (2) monetary policies, and (3) shifts in investor demand and asset characteristics.

Savings and Issuances. We start by measuring the contribution of investors’ net savings, $F_{i,t}$, and asset issuances, $Q_t(n, \ell)$, in various geographic regions. In each step, we restore investors’ savings and issuances simultaneously for a given geographic region. In doing so, our exercise allows us evaluate the effects of private saving gluts, which are driven by an excess of foreign savings that are not satiated by local investment opportunities.

Monetary Policies. Next, we account for two forms of central bank monetary policies: (i) reserve accumulation and (ii) changes in nominal short-term interest rates. Reserve accumulation includes both foreign official reserve holdings and U.S. quantitative easing. Increases in official holdings of U.S. external liabilities increase the value of the dollar. Interest rate policies also directly impact exchange rates, because increases in policy rates tend to attract foreign capital inflows and result in an appreciation of the domestic currency.

Demand Shifts. Finally, we restore changes in country characteristics $\mathbf{x}_{i,t}(n)$, within-asset-class latent demand $\kappa_{i,t}(n, \ell)$, and across-asset-class latent demand $\xi_{i,t}(\ell)$. These steps accounts for changes in the relative desirability of assets that arise from changes in asset fundamentals (such as economic growth), as well as changes in the taste for assets and asset classes that are not captured by observed characteristics.

2.2 Explaining the Dollar’s Appreciation

We summarize our decomposition in [Figure 1](#) and present specific numbers in column (1) of [Table 1](#). From 2011 to 2019, the dollar AFE index appreciated by 22.5%. The left-hand panel of [Figure 1](#) decomposes this appreciation into four blocks of primitive variables. We find that investor savings and asset issuance, changes in monetary policy rates, and shifts in investor asset demand approximately equally explain the dollar’s appreciation over the past decade. Central bank reserve policies account for a minor 1% depreciation of the dollar.

The right panel of [Figure 1](#) presents the contribution of each component over time. There were large inflows of savings and significant shifts in investor preference towards U.S. assets between 2012 and 2015, both of which partially reversed afterwards. Central bank reserve holdings played a relatively minor role in explaining movements in the dollar. Foreign reserve accumulation of U.S. external liabilities slowed after the Global Financial Crisis, which largely explains the small impact of foreign reserve accumulation. In comparison, policy rates contributed to dollar appreciation later in our sample, largely from 2014 to 2018.

In [Figure 2](#) we illustrate the economic mechanism for the three key drivers of the dollar’s appreciation. First, investor savings and asset issuances explain an 8.7% appreciation of the dollar against the AFE currencies with developed market savings and emerging market savings contributing approximately equally. The growth in foreign savings tends to appreciate the value of the dollar, because foreign investors tend to allocate a large share of their wealth to U.S. assets. The upper-left panel of [Figure 2](#) plots relative savings flows to the U.S. against our model-implied AFE dollar appreciation by year. Relative savings flows to the U.S. are savings allocated to the U.S. based on contemporaneous portfolio weights, normalized by the U.S. market capitalization, relative to savings allocated to Non-U.S. countries normalized by the market capitalization of all Non-U.S. countries. More savings by countries that are heavily invested in the U.S. increases the relative flow of capital to the U.S., which results in dollar appreciation. In particular, the greatest savings flows into the U.S. occurred mostly in 2013—2015, as shown in the top-right panel.

Increases in U.S. monetary policy rates relative foreign policy rates explain a 6% appreciation of the AFE dollar index. Higher U.S. short-term interest rates made U.S. assets more attractive to foreign investors, which attracted inflows to the U.S. and a stronger dollar. In the top-right panel of [Figure 2](#), we plot the changes in the U.S. monetary policy rate against the model-implied dollar exchange rate movements. In particular, increases in the U.S. short-term rate from 2016 to 2018 are associated with the most dollar appreciation. The largest effect took place in 2018, when a 1% rate hike led to a 3% dollar exchange rate movement. Notably, our model-implied dollar response is consistent with research using a high-frequency identification strategy which also shows that the dollar appreciates around

3% against the basket of trade-weighted AFE currencies in response to a 1% U.S. monetary policy shock [Curcuru et al. \(2017\)](#).

Lastly, we find that the investor demand shifts played a major role in shaping the dollar’s exchange rate dynamics. There is a strong shift in demand towards U.S. assets, in particular from developed market investors. In the bottom-left panel of [Figure 2](#), we plot shifts in the U.S. investors’ demand for developed countries’ assets against model-implied dollar exchange rate movements. In the bottom-right panel, we plot the shifts in the developed countries’ investors’ demand for U.S. assets against the implied dollar exchange rate movements. As expected, weaker U.S. demand for foreign assets leads a depreciation of foreign currencies and therefore an appreciation of the dollar. On the other hand, stronger foreign demand for U.S. assets leads to a dollar appreciation. In the time series, we find that the largest shift in the U.S. demand away from foreign assets occurred in 2012-2015 indeed appreciated. Additionally, the largest shift in the foreign demand towards U.S. assets occurred in 2014 and 2015.

2.3 Decomposition By Currency

We next study how the dollar appreciated against specific foreign currencies. [Table 1](#) reports the dollar’s appreciation against five major currencies: the euro, the Canadian dollar, the Japanese yen, the British pound, and the Swiss franc. Our analysis shows notable variation in the way primitive economic variables explain each exchange rate ([Zhang 2021](#); [Lustig and Richmond 2020](#)).

First, while investor savings unambiguously appreciated the dollar against all these foreign currencies, the dollar appreciated less against the British pound relative to other major currencies. This disparity indicates that developed market savings flowed disproportionately more to both the U.S. and the United Kingdom, rather than just the U.S.

Second, foreign central banks’ reserve policies explain a modest dollar appreciation against the euro and British pound, and a larger dollar depreciation against the Japanese yen. Thus, since 2011, reserves tended to flow out of euro and pound assets and into yen assets.

Third, while U.S. monetary policy rates led to dollar appreciation across the board, foreign monetary stances were quite different. The ECB and the Swiss central bank engaged

in monetary easing, which led to further depreciation of the euro and the Swiss franc against the dollar. Meanwhile, the Canadian and the British central banks tightened policy and partially closed the gap between their currencies and the dollar.

Finally, there were large differences in investor demand shifts across these foreign countries. Beyond U.S. assets, investors also favored European and Swiss assets, despite their opposite monetary stances. As a result, the demand shifts partially offset the dollar's appreciation against the euro and the Swiss franc, while deepening the dollar's appreciation against the Canadian dollar, Japanese yen, and British pound.

2.4 What If Demand for U.S. Assets Changes?

We conclude with two exercises to understand the impact of potential changes in demand for U.S. assets on the value of the dollar. First, we study which countries holdings matter the most for explaining the strength of the dollar. To do so, we compute exchange rates assuming each countries' investors and central bank reallocated their U.S. asset holdings to other countries. Second, we study how a reduction in the specialness of U.S. assets would impact the dollar.

We first turn to studying the impact of different investor countries on the value of the dollar. We use our end-of-sample data and estimates from $t = 2019$ and set country i 's latent demand for all U.S. assets, $\kappa_{i,t}(US, \ell)$, to a large negative number. We also assume that the country's central bank liquidates its reserve holdings of U.S. assets and distributes the wealth to its domestic investors, who will reallocate this wealth towards non-U.S. assets. The top panel of [Figure 3](#) shows the change in the value of the AFE dollar as each country liquidates their dollar asset holdings. The European Monetary Union (EMU), Japan, Canada, China, and Switzerland stand out. If the EMU disposes of its U.S. assets, the dollar will depreciate by 2.5%. If Japan, Canada, China, or Switzerland disposes of its U.S. assets, the dollar will depreciate by a modest 0.2% to 0.7%.

These impacts on the dollar are perhaps surprisingly small and highlight the large global demand for U.S. issued assets. When any one country unilaterally sells U.S. assets, other countries are willing to absorb the excess supply of dollar assets at a minor price discount. This is true even when the region we are considering is as large as the EMU. In this case, as

the EMU sells their U.S. assets, we find that other countries increase their positions in the U.S. assets by 10% to 30%.

To further understand the impact of the specialness of U.S. assets, we reduce the specialness of U.S. assets in investor’s demand curves. To do so, we scale the U.S. asset dummy in investors’ demand curves down towards zero, while holding other demand parameters fixed. The bottom panel of [Figure 3](#) shows the change in the value of the AFE dollar for various scalings of the U.S. asset dummy variable. The first bar shows that when the specialness of U.S. issued assets is completely removed the dollar AFE index depreciates by over 4%.

Overall, these results demonstrate a source of the stability in dollar’s valuation. Our demand curve estimates based on 2002 to 2019 data suggest that investors in many countries stand ready to buy U.S. assets when other countries sell. From a theoretical perspective, this special demand for U.S. assets is precisely what is required to coordinate on the dollar as a reserve currency ([Farhi and Maggiori 2017](#); [He, Krishnamurthy, and Milbradt 2019](#)).

3 Conclusion

We use a portfolio-based demand system to decompose the dollar’s appreciation since 2011. We show this appreciation can be explained approximately equally by increases in global savings, relatively high U.S. monetary policy rates, and shifts in investor demand. Furthermore, we demonstrate how the asset demand system can be used to understand the impact of potential demand shifts on the dollar.

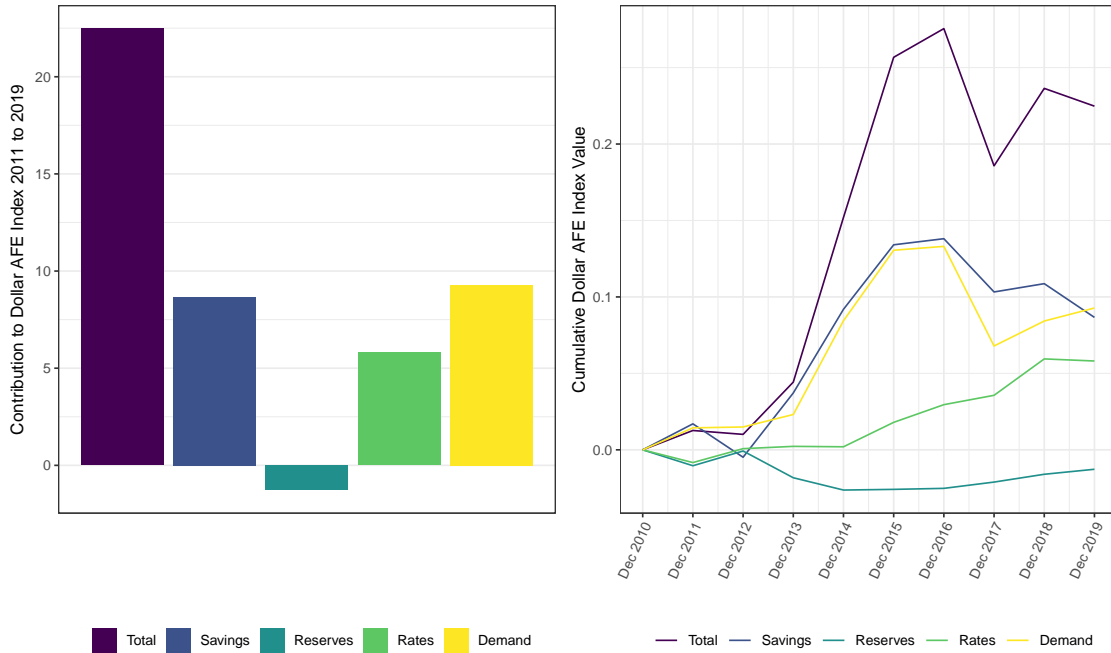
References

- Avdjiev, Stefan, Wenxin Du, Catherine Koch, and Hyun Song Shin, 2019, The dollar, bank leverage, and deviations from covered interest parity, *American Economic Review: Insights* 1, 193–208.
- Bertaut, Carol, and Ruth Judson, 2014, Estimating u.s. cross-border securities positions: New data and new methods, International Finance Discussion Paper 1113.
- Bertaut, Carol, and Ralph W. Tryon, 2007, Monthly estimates of u.s. cross-border securities positions, International Finance Discussion Papers 910.
- Camanho, Nelson, Harald Hau, and H elene Rey, 2018, Global portfolio rebalancing and exchange rates, Technical report, National Bureau of Economic Research.
- Coppola, Antonio, Matteo Maggiori, Brent Neiman, and Jesse Schreger, 2020, Redrawing the map of global capital flows: The role of cross-border financing and tax havens, Technical report, National Bureau of Economic Research.
- Curcuru, Stephanie, et al., 2017, The sensitivity of the us dollar exchange rate to changes in monetary policy expectations, *IFDP Notes, Board of Governors of the Federal Reserve System, September* .
- Du, Wenxin, 2019, Financial intermediation channel in the global dollar cycle, in *Jackson Hole Economic Policy Symposium Proceedings*.
- Du, Wenxin, and Jesse Schreger, 2021, Cip deviations, the dollar, and frictions in international capital markets, Technical report, National Bureau of Economic Research.
- Farhi, Emmanuel, and Matteo Maggiori, 2017, A model of the international monetary system, *The Quarterly Journal of Economics* 133, 295–355.
- Gabaix, Xavier, and Matteo Maggiori, 2015, International liquidity and exchange rate dynamics, *The Quarterly Journal of Economics* 130, 1369–1420.
- Gopinath, Gita, and Jeremy C Stein, 2021, Banking, trade, and the making of a dominant currency, *The Quarterly Journal of Economics* 136, 783–830.
- Hau, Harald, and Helene Rey, 2006, Exchange rates, equity prices, and capital flows, *The Review of Financial Studies* 19, 273–317.
- He, Zhiguo, Arvind Krishnamurthy, and Konstantin Milbradt, 2019, A model of safe asset determination, *American Economic Review* 109, 1230–62.
- Iancu, Alina, Gareth Anderson, Sakai Ando, Ethan Boswell, Andrea Gamba, Shushanik Hakobyan, Lusine Lusinyan, Neil Meads, and Yiqun Wu, 2020, Reserve currencies in an evolving international monetary system, IMF Departmental Paper No. 2020/002.
- Jiang, Zhengyang, Arvind Krishnamurthy, and Hanno Lustig, 2020, Dollar safety and the global financial cycle, Technical report, National Bureau of Economic Research.

- Jiang, Zhengyang, Arvind Krishnamurthy, and Hanno Lustig, 2021, Foreign safe asset demand and the dollar exchange rate, *The Journal of Finance* 76, 1049–1089.
- Jiang, Zhengyang, Robert J Richmond, and Tony Zhang, 2022, A portfolio approach to global imbalances, Technical report, National Bureau of Economic Research.
- Koijen, Ralph, Robert Richmond, and Motohiro Yogo, 2019, Which investors matter for equity valuations and expected returns?, Technical report.
- Koijen, Ralph S.J., and Motohiro Yogo, 2019a, A demand system approach to asset pricing, *Journal of Political Economy* 127, 1475–1515.
- Koijen, Ralph S.J., and Motohiro Yogo, 2019b, Exchange rates and asset prices in a global demand system, Technical report.
- Lilley, Andrew, Matteo Maggiori, Brent Neiman, and Jesse Schreger, 2022, Exchange rate reconnect, *Review of Economics and Statistics* 104, 845–855.
- Lustig, Hanno, and Robert J Richmond, 2020, Gravity in the exchange rate factor structure, *The Review of Financial Studies* 33, 3492–3540.
- Maggiori, Matteo, 2017, Financial intermediation, international risk sharing, and reserve currencies, *American Economic Review* 107, 3038–71.
- Maggiori, Matteo, Brent Neiman, and Jesse Schreger, 2020, International currencies and capital allocation, *Journal of Political Economy* 128, 2019–2066.
- Miranda-Agrippino, Silvia, and H elene Rey, 2020, Us monetary policy and the global financial cycle, *The Review of Economic Studies* 87, 2754–2776.
- Rey, H el ene, 2015, Dilemma not trilemma: the global financial cycle and monetary policy independence, Technical report, National Bureau of Economic Research.
- Richmond, Robert J, 2016, Trade network centrality and currency risk premia, *The Journal of Finance* .
- Stock, James H, and Motohiro Yogo, 2002, Testing for weak instruments in linear iv regression.
- Tabova, Alexandra, and Francis Warnock, 2021, Foreign investors and u.s. treasuries, NBER Working Paper 29313.
- Zhang, Tony, 2021, Monetary policy spillovers through invoicing currencies, *The Journal of Finance* 77, 129–161.

Tables and Figures

FIGURE 1
TREND DECOMPOSITION OF DOLLAR AFE INDEX



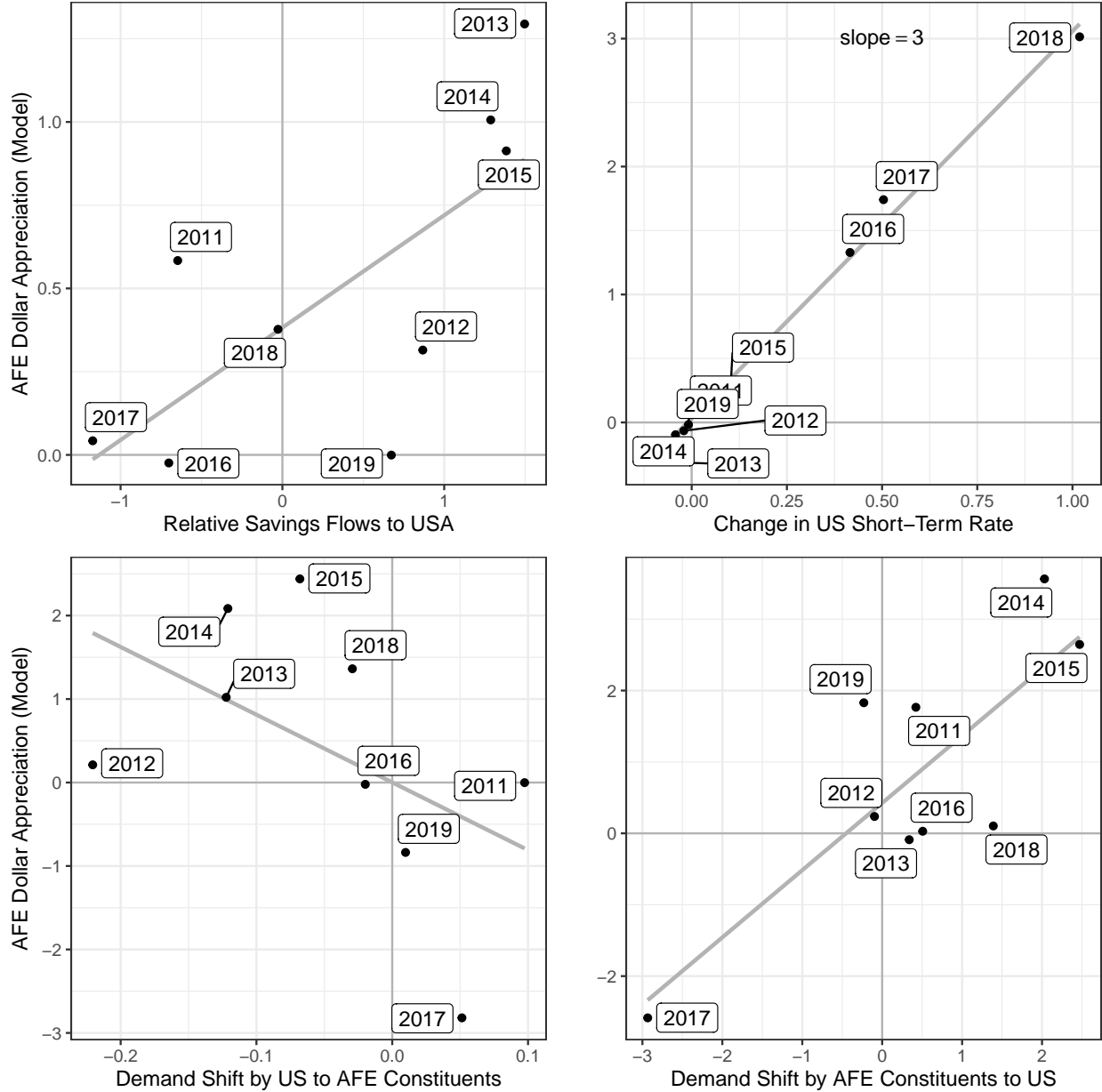
This figure presents the share of the dollar AFE index appreciation explained by each block of economic primitives. The left panel presents the decomposition of the cumulative change in the total dollar AFE index appreciation from 2011 to 2019. The right panel presents the time-series of the cumulative contribution of each block of variables to the dollar AFE index.

TABLE 1
DECOMPOSITION OF DOLLAR AFE INDEX AND CONSTITUENTS

	AFE	EUR	CAN	JPN	GBR	CHE
AFE Index Weight	18.6	14.5	6.7	5.3	5.3	2.5
Savings and Issuances						
DM Savings	4.2	4.5	5.2	4.4	1.1	5.1
EM Savings	4.5	4.7	4.1	5.0	4.8	4.2
Total Savings	8.7	9.2	9.3	9.5	5.9	9.3
Monetary Policies (Reserves)						
US Reserves	-1.2	-1.2	-1.3	-1.7	-1.0	-0.9
DM Reserves	-0.2	-0.2	-0.2	-0.2	-0.2	-0.1
EM Reserves	0.1	1.2	-0.6	-1.2	0.7	-0.3
Total Reserves	-1.3	-0.1	-2.1	-3.1	-0.4	-1.4
Monetary Policies (Rates)						
US Rates	6.0	5.7	7.0	5.3	5.0	5.7
EM/DM Rates	-0.1	4.1	-6.6	-0.1	-2.7	2.7
Total Rates	5.8	9.8	0.5	5.2	2.4	8.4
Demand Shifts						
DM Demand	8.1	-2.3	18.2	16.3	6.9	-13.9
EM Demand	1.1	1.0	0.8	1.4	1.9	1.5
Total Demand	9.3	-1.3	18.9	17.7	8.8	-12.5
Total	22.5	17.6	26.6	29.3	16.7	3.8

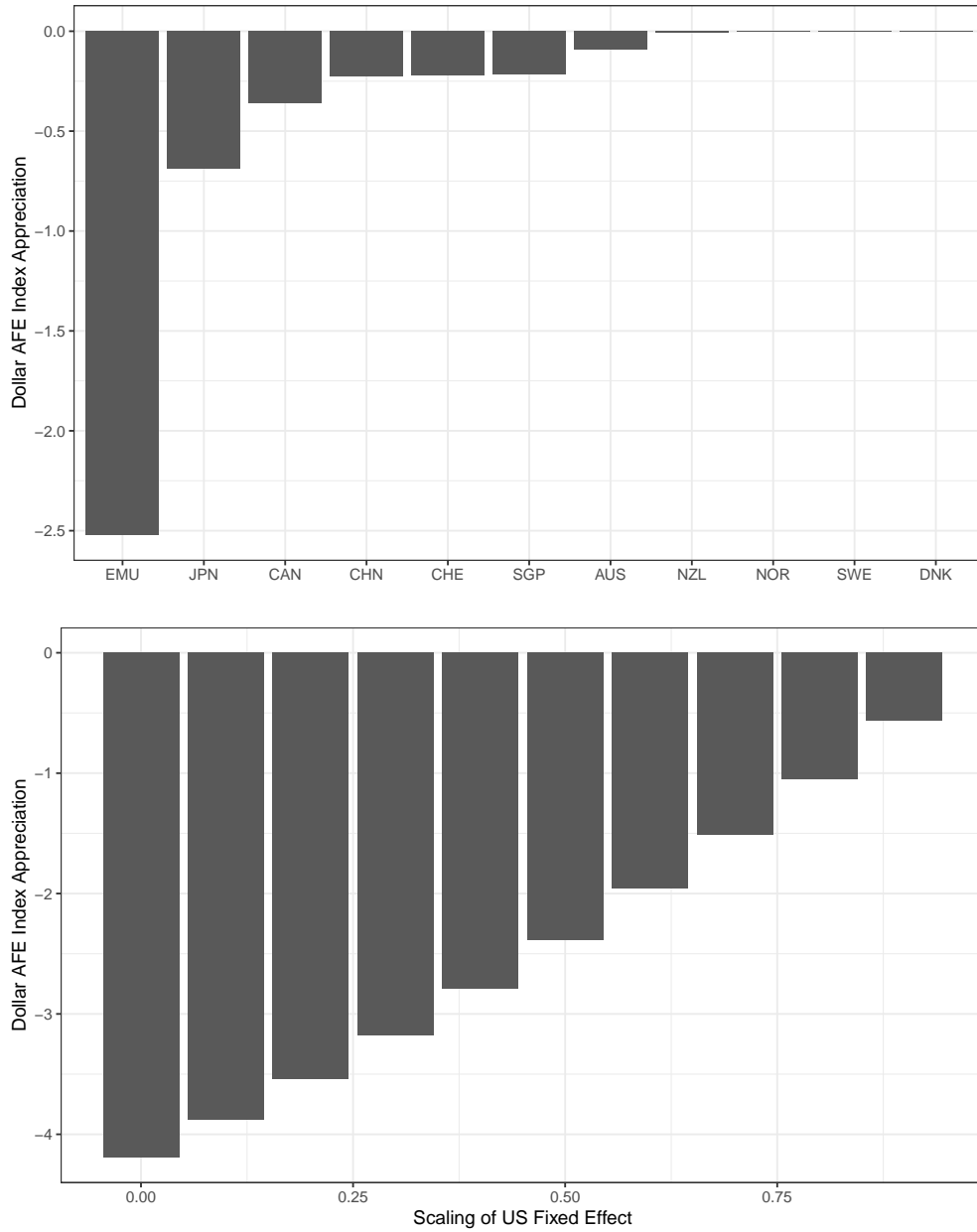
This table presents a detailed decomposition of the dollar’s appreciation against the trade-weighted basket of advanced economy currencies, as well as against five major currencies, between 2011 and 2019. All numbers represent the dollar’s exchange rate movement in percentage units. We group the economic factors explaining dollar appreciation into four blocks — the last row within each block presents the contribution of all variables within that block. The last row of the table presents the aggregate dollar appreciation (i.e., the dollar appreciated 22.5 percent against the trade weighted basket of AFE currencies between 2011 and 2019). “DM” refers to the developed market economies and “EM” refers to the emerging market economies.

FIGURE 2
DOLLAR AFE INDEX APPRECIATION MECHANISMS



This figure presents the various mechanisms captured by our framework that jointly explain movements in the dollar AFE index. In each panel, we plot changes in the dollar computed within our model (y-axis) against changes in various data inputs (x-axis). The top-left panel presents dollar appreciation explained by relative savings flows to the USA. The top-right panel presents dollar appreciation explained by changes in the U.S. short-term interest rate. The bottom-left panel presents dollar appreciation explained by shifts in U.S. investor demand towards AFE financial assets, and the bottom-right panel presents dollar appreciation explained by shifts in AFE investor demand towards U.S. financial assets. The y-axis is in percentage points.

FIGURE 3
CHANGE IN DOLLAR AFE INDEX IN COUNTERFACTUAL SCENARIOS



The figure presents the change in the dollar relative to the advanced foreign economy currencies in two hypothetical scenarios. In the top panel we assume each economy were to unilaterally sell all of their U.S. financial assets and reallocate to the other issuer countries in their portfolio. In the bottom panel we gradually decrease the U.S. fixed effect in all investors' demand curves to zero. We compute the counterfactual dollar movement taking the state of the world at the end of 2019 as given. The y-axes are in percentage points.

Appendix

A Theory Appendix

A.1 Capital Gains

The capital gains earned by the investor country is determined by changes in asset prices and changes in exchange rates, $E_t(k)$. Because we assume investors form expectations of asset returns based on market-to-book ratios, we explicitly model realized dollar returns as a function of market-to-book ratios:

$$R_t(k, \ell) = \frac{PB_t(k, \ell)E_t(k)S_t(k, \ell)}{PB_{t-1}(k, \ell)E_{t-1}(k)S_{t-1}(k, \ell)}, \quad (\text{A.1})$$

where $S_t(k, \ell)$ is the conversion factor between book value and share number (i.e. book-per-share) in local currency terms. When mapping our framework to equities data, we translate changes in market-to-book ratios into changes in prices, because the demand curve specification depends on the market-to-book ratio and the dynamics of countries' portfolios depend on capital gains. We compute the multiplicative factor $S_t(k, \ell)/S_{t-1}(k, \ell)$ that achieves this conversion using the return, market-book and exchange rate data.¹ Because $PB_t(k, \ell)$ denotes the market-to-book ratio, $PB_t(k, \ell)S_t(k, \ell)E_t(k, \ell)$ is the dollar price per asset share. For bonds, the book value is the par value, and the conversion factor $S_t(k, \ell)$ is 1.

B Empirical Appendix

B.1 Data Construction

To re-iterate, our analysis requires three types of data: cross-country portfolio holdings, country/asset characteristics, and realized returns in each asset class. [Table B.1](#) presents the specific set of countries in our sample and their classifications. [Table B.2](#) presents the list of central banks for which we are able to construct bilateral holdings. We discuss our measurement of these data, below. Afterwards, we also discuss how we use these data to impute net financial savings.

B.1.1 Cross-Country Portfolio Holdings

We observe cross-country portfolio holdings data for non-U.S. countries from the Coordinated Portfolio Investment Survey (CPIS) provided by the IMF, and for the U.S. from the Treasury International Capital System (TIC). The TIC data reports U.S. external assets and U.S. external liabilities only. Thus, for U.S. external assets and liabilities, we use all available data from TIC. For all external positions between non-U.S. countries, we use CPIS data. In the end, for each investor country i , we observe year-end holdings of foreign financial assets

¹Implicitly, the ratio $S_t(k, \ell)/S_{t-1}(k, \ell)$ captures changes in the shares of assets outstanding relative to the book value of assets outstanding.

in dollars by asset class and issuer country. The asset classes comprise short-term debt, long-term debt and equity. The asset holders include corporations, and individuals, government entities (such as sovereign wealth funds, but not including the central bank foreign reserve holdings).

A well-known issue with portfolio holdings data is that flows to and from offshore financial centers can present a highly distorted view of capital allocation. For example, [Coppola, Maggiori, Neiman, and Schreger \(2020\)](#) point out that investments by countries in the European Monetary Union are often funneled through Luxembourg. As a result, in the raw CPIS data, Luxembourg is in the top 10 investors for all asset classes. In order to mitigate this issue, after merging the CPIS and TIC data, we apply the reallocation matrices from [Coppola, Maggiori, Neiman, and Schreger \(2020\)](#) to re-attribute portfolio holdings to their investor nationality as much as possible. These reallocation matrices are provided from 2007 to 2017. We extend these matrices forwards and backwards in time to cover the full sample period from 2002 to 2019, by assuming a constant share of funds pass through each offshore center before 2007 and after 2017. Following [Coppola, Maggiori, Neiman, and Schreger \(2020\)](#), we also aggregate all investment holdings by Euro Area countries into a single European Monetary Union (EMU) investor entity, because the vast majority of investment in the euro area is funnelled through a small number of tax haven countries. After applying the reallocation matrices there remain some funds held by tax haven countries. We redistribute these remaining holdings proportionally to the countries which have inward investment into the tax havens.

We split off central bank and other official holdings, and treat changes in these official holdings as exogenous policy decisions when estimating our structural model. For all non-U.S. countries, we use the IMF Securities Held as Foreign Exchange Reserves (SEFER) survey to estimate the value of each country’s assets that are held as reserve assets by central banks.² For the United States, official and private holdings of U.S. liabilities are reported together in the TIC data.³ We parse out the value of foreign official holdings of U.S. liabilities using data describing the currency composition of countries’ reserve assets with data capturing the total size of countries’ reserve portfolio. The next Appendix Section [B.1.2](#) describes our procedure in detail.

Finally, the cross-country portfolio holdings data do not record domestic holdings of financial assets. Thus, we estimate domestic portfolio holdings by subtracting foreign holdings from total market capitalization data. We observe the country-level stock market capitalization from the World Bank, and we observe the aggregate value of outstanding short-term and long-term debt securities from the BIS.

B.1.2 Central Bank Reserve Holdings of U.S. Liabilities

As stated in Appendix [B.1.1](#), the TIC data report both private and official holdings of U.S. liabilities together. Our main challenge is to parse out official holdings from total holdings, because we would like to treat official holdings as an exogenous policy variable in

²The CPIS does not contain reserve holdings of central banks. Thus, the sum of the CPIS and SEFER holdings should capture all holdings held by foreign private and foreign official investors.

³For example, the publicly available TIC data only reports that Canadian private and official investors held a total of 1,262 billion dollars of U.S. portfolio liabilities in 2019.

the benchmark analysis of our structural model.

Our procedure involves three steps. First, we estimate the size of each country’s official dollar holdings. Then, we attribute each country’s official dollar holdings to official holdings into the three asset classes (i.e., short-term debt, long-term debt and equity). Finally, we subtract the estimated official holdings from the TIC holdings data to dis-aggregate the TIC holdings data into private and official holdings.

To estimate the size of each country’s official dollar holdings, we multiply the share of each country’s reserve portfolio held in dollars (Iancu et al. (2020)) with the total size of each country’s reserve portfolio. The total size of each country’s reserve portfolio is taken from its “Securities” position from the IMF’s International Reserves and Foreign Currency Liquidity Survey. We assume that all countries’ dollar reserves are U.S. issued liabilities. While it is true that non-U.S. entities can issue dollar liabilities, we think our assumption is reasonable given that the vast majority of dollar reserves are comprised of U.S. treasury securities.

To attribute total official dollar holdings to separate asset classes, we use the breakdown of the aggregate official holdings of U.S. liabilities from TIC. For each year, TIC reports the aggregate official holdings of U.S. short-term debt, long-term debt, and equity. We divide each country’s official U.S. holdings into these three sectors based on the distribution of the aggregate official holdings.

Finally, we subtract out the estimated official holdings by each investor country and in each asset class from the total TIC holdings of U.S. liabilities. Due to potential differences in sample coverage between the TIC data and the IMF data⁴, as well as potential measurement errors introduced by our estimation procedure, the total value of official holdings of U.S. liabilities for a given asset class ℓ and investor country n may be larger than the observed TIC holdings. In these instances, we attribute the entirety of the TIC holdings to official holdings and set private holdings for the investor to zero.

Ultimately, our procedure is able to parse out between 21 to 39 percent of the total official holdings for each year in our sample.⁵ Finally, we attribute all holdings of U.S. long-term debt by China to Chinese Central Bank reserves.

B.1.3 Country Characteristics

We observe country-level market-to-book values of equity, yields on short-term debt, and yields on long-term debt from Datastream. We observe GDP, GDP per capita, and population from the World Bank. We obtain trade network centrality measures from Richmond (2016). We observe S&P sovereign debt ratings and impute sovereign default probabilities using S&P 5-year default rates. Market volatility is annual volatility from each countries

⁴For example, the IMF data often rely on each country’s domestic statistical agency to report reserve assets, whereas the TIC holdings are built off of surveys of custodial bank in the U.S. For a detailed descriptions of various sources of reserves holdings data, see: <https://ticdata.treasury.gov/resource-center/data-chart-center/tic/Documents/fohdefs1.904.pdf>

⁵As mentioned previously, even though the TIC data do not provide a bilateral breakdown of official and private holdings of U.S. liabilities, the TIC data do report the aggregate value of U.S. liabilities held by foreign official sources. For example, in 2019, foreign official investors held 6.1 trillion dollars of U.S. liabilities. We are able to parse out 1.4 trillion dollars based on our reallocation methodology.

MSCI Equity market index in local currency. We obtain dollar exchange rates from Datastream, inflation rates from the IMF, and trade and distance variables from CEPII.

B.1.4 Realized Capital Gains

We want to decompose the changes holdings over time into changes in the valuation of existing assets (*capital gains*), and the net value of additional asset purchases (*capital flows*) between any two periods $t - 1$ and t . We therefore need the best possible measurement of realized capital gains and capital flows.

For all investments between two non-U.S. countries, we impute realized capital gains on equity by computing changes in country-level equity price return indexes obtained through Datastream, and we impute realized returns on debt using 3-month and 10-year yields. For short-term debt, the realized return is computed by compounding the four 3-month yields over the course of each year. For long-term debt, the realized return is the annualized 10-year yield from the previous year.

For the U.S. holdings of foreign assets and foreign holdings of U.S. assets, we provide a more accurate view of returns to equity and long-term debt assets by imputing the realized capital gains earned by foreign investors using granular capital flows and positions data from Bertaut and Tryon (2007) and Bertaut and Judson (2014). Tabova and Warnock (2021) show the capital flows data from these two papers are more representative and internally consistent than TIC S capital flows data.

Because the data from Bertaut and Tryon (2007) and Bertaut and Judson (2014) are provided at the monthly frequency, we simply need to aggregate the monthly flows and positions data to the annual frequency. We impute the realized capital gains from investing in country n in asset class ℓ , $R_t(n, \ell)$, from periods $t - 1$ and t using the valuation change in the data:

$$R_t(n, \ell) = 1 + \text{VALUATION CHANGE}_t(n, \ell) / \text{POSITION}_{t-1}(n, \ell).$$

Due to data quality concerns, we winsorize the lower bound of $R_t(n, \ell)$ at 1%. We compound the monthly returns into annual returns.

B.1.5 Net Financial Savings

Having obtained data on investor holdings and realized returns in each period, it is straightforward to back out net financial savings $F_{i,t}$ for each investor country using Eq. (7):

$$F_{i,t} = A_{i,t} - A_{i,t-1} \sum_{\ell=1}^3 \sum_{n=0}^N w_{i,t-1}(\ell) w_{i,t-1}(n|\ell) R_t(n, \ell).$$

When restoring the actual net savings $F_{i,t}$, we use a multiplicative growth rate $f_{i,t}$ equal to $F_{i,t}$ divided by time- t value of the portfolio from period $t - 1$, and plug in

$$\tilde{F}_{i,t}^j = f_{i,t} \cdot A_{i,t-1} \sum_{\ell=1}^3 \sum_{n=0}^N w_{i,t-1}(\ell) w_{i,t-1}(n|\ell) \tilde{R}_t^j(n, \ell)$$

at step j of the counterfactual.

B.2 Identification

In this Appendix we provide additional detail on the various steps of the estimation and identification in Section 1.3.

The results of estimating equation (12) are reported in Table B.4. Investors tend to have higher portfolio weights in countries which are larger and geographically closer. For all asset classes there is a large home bias in portfolio holdings. These characteristics explain a substantial amount of the variation in bilateral portfolio weights, with the R-squared ranging from 50 to 67% across the three asset classes. Furthermore, these characteristics explain a substantial share of the within investor country variation in portfolio weights, with a within R-squared of approximately 20%. We compute the predicted values from these regressions, which we refer to as exogenous asset desirabilities, $\hat{\delta}_{i,t}(n, \ell)$. These desirabilities are driven entirely by variation in these exogenous characteristics.

The results for estimating equation (10) are reported in Table B.5.⁶ The first thing to note is that the first-stage F-statistics in the bottom three rows of the table are all greater than 100 (Stock and Yogo 2002). These high first-stage F-statistics imply that the instruments for the inclusive value are all highly correlated with the asset-class level desirabilities, even though they are constructed entirely from exogenous asset characteristics. Next, all λ_ℓ values are between 0 and 1. This implies that there is some substitution between asset classes when the relative value of an asset class varies. This is in contrast to the case when $\lambda_\ell = 0$, in which the allocations across asset classes are independent of the relative desirabilities of individual assets. When $\lambda_\ell = 1$, the substitution between asset classes only depends on the desirabilities of individual issuer countries' assets, and the demand system collapses to one tier. Our estimates are between these two polar cases, implying that there is some segmentation across asset classes.⁷

The first stages for estimating equation (10) are presented in Table B.8. Consistent with the expected return regression (5), expected returns are negatively related to the instruments for prices and exchange rates. Furthermore the first-stage F-statistic for all three asset classes is high which implies these are strong instruments.

The full estimates for within-asset-class demand curves are presented in Appendix Table B.7. The coefficients on expected returns are all positive, which implies that conditional on our set of asset characteristics, assets with higher expected returns are preferred by investors. The coefficients on asset characteristics are all intuitive. Investors prefer assets that provide better hedges against systematic risks, such as the assets of larger countries (higher GDP). Conditional of countries having higher GDP, investors prefer countries with lower population, which implies they tend to prefer countries with higher GDP per capita. Investors also prefer assets from countries that are closer and with whom they have a stronger trade relationship. Finally, the next-to-last row of Appendix Table B.7 shows there is strong home bias in all asset classes.

⁶We normalize α and $\xi_{i,t}$ for equity to 0. The full first stages for this regression are reported in Table B.6.

⁷See Koijen and Yogo (2019b) for more discussion on the interpretation of these parameters. Our estimates here are consistent with their findings.

B.3 Robustness Under Different Instrument Construction

Section 1.3 presents our baseline instrument construction and estimation. In this section, we evaluate the robustness of our findings to variations in our estimated demand curves. A potential concern is that our findings may be sensitive to the specific estimation and identification procedure we used for our demand equations (9) and (10). To demonstrate the robustness of our findings we study the sensitivity of our decompositions to variations in our identification strategy.

Our baseline estimation constructs exogenous asset desirabilities using log population, log distance, investor fixed effects and an own country dummy. We then construct instruments using market clearing with actual asset supply and outside asset holdings. We study five variations on this instrument construction and estimation:

1. Instead of using actual supply, we predict supply in dollars from a regression of log asset supply on log issuer country population by asset type.⁸ Using instrumented supply alleviates any concerns about the endogeneity of supply to latent demand.
2. Instead of using actual holdings of outside assets, we predict holdings of outside assets from a regression of log holdings on log investor country population. We run this regression pooled across all countries and years, but separately by asset type. Using instrumented outside asset holdings alleviates any concerns about the endogeneity of wealth to latent demand.
3. We predict both supply and outside asset holdings using log population as in variants (1) and (2).
4. We use our baseline construction of instruments except instead of population for predicting exogenous asset desirabilities we use issuer country log GDP. This specification replicates that of [Kojen and Yogo \(2019b\)](#).
5. We relax the assumption that GDP is exogenous to latent demand. In particular, we allow for country-level GDP to depend on asset prices, as would be the case in settings where growth is related to capital flows.⁹ We model country-level GDP as a function year fixed effects and prices (which are potentially a function of latent demand):

$$\log GDP_t(n) = \alpha_t + \beta_2 pb_t(n, 2) + \beta_3 pb_t(n, 3) + \nu_t(n) \quad (\text{B.2})$$

We estimate this equation using our instruments for prices, where the instruments for prices are constructed as in our baseline procedure. Importantly, these instruments for prices do not use GDP to construct predicted weights. We then extract the residuals from this regression, which we refer to as GDP shocks. Finally, we estimate our within asset-class equation, but instead of directly including log GDP as a characteristic we instrument for log GDP with these GDP shocks.

⁸For short-term debt supply we convert to dollars at the exchange rate in 2001, since we use short-term debt to clear the exchange rate market. This is done simply to ensure that the supply across countries is in the same numeraire while avoiding using contemporaneous exchange rates.

⁹This procedure builds on a similar procedure to endogenize characteristics in [Kojen et al. \(2019\)](#).

The coefficients on expected returns and their standard errors for our baseline construction and these five variations can be found in Table B.9. The point estimates vary across the specifications, though most are not significantly different than each other.

To understand how these differing estimates might impact our key results we recompute our decomposition of the dollar AFE index for each of these variations. Table B.10 presents the results. The top panel presents the implied demand elasticities from these estimates.¹⁰ The second panel presents our trend decomposition.

The baseline column re-iterates our decomposition of the changes in the dollar AFE index position that we discussed in Section 2. Columns (1) through (5) present the alternative estimation and identification procedures along with the corresponding decompositions of the dollar AFE index. As we look across the columns in Table B.10, we observe that the decomposition does not vary substantially across the specifications.

Total savings and issuances appreciated the dollar AFE by 6.6% to 8.7%. Reserves had a minor impact across all specifications while policy rates appreciated the dollar AFE index by an additional 4.8% to 7.3%. Similarly, regardless of the specification, shifts in demand counteract appreciated the dollar AFE index by around 9% to 11.8%. Overall, we conclude that our key findings are robust to plausible variations on our identification and estimation strategy.

B.4 Solution Methodology

In the following appendix, we apply an approximation of Newton’s Method to calculate the equilibrium price in the counterfactual analysis. Our algorithm closely follows [Kojien and Yogo \(2019a\)](#). For each asset j in sector l at time t , we want to find the zero of the following function:

$$H(\mathcal{P}) = p_{j,t}^l + q_{j,t} - \log \left[\sum_{i=1}^N A_{i,t} w_{i,t}^l w_{i,j,t}^l \right],$$

where the vector of parameters:

$$\mathcal{P} = [e_{j,t}, q_{j,t}, p_{j,t}^{lt}, p_{j,t}^{eq}]$$

comprises nominal exchange rates, short-term debt quantities for issuers in fixed exchange rate regimes, prices of long-term debt, and prices of equity. To re-iterate, the share of investor i assets within asset type l that are allocated to country j at time t is:

$$w_{i,j,t}^l = \frac{\exp(\beta^l \mu_{i,j,t}^l + \Theta_{i,j,t}^l \mathbf{x}_{i,j,t} + \kappa_{i,j,t})}{1 + \sum_{n=1}^N \exp(\beta^l \mu_{i,n,t}^l + \Theta_{i,n,t}^l \mathbf{x}_{i,n,t} + \kappa_{i,n,t})}$$

¹⁰The details of the calculation of these elasticities can be found in Appendix B.5.

The share of investor i assets allocated to asset type l is:

$$w_{i,t}^l = \frac{\left(1 + \sum_{n=1}^N \exp(\beta^l \mu_{i,n,t}^l + \Theta_{i,n,t}^l \mathbf{x}_{i,n,t} + \kappa_{i,n,t})\right)^{\lambda^l} \exp(\alpha^l + \xi_{i,t}^l)}{\sum_{m=\{st,lt,eq\}} \left[\left(1 + \sum_{n=1}^N \exp(\beta^m \mu_{i,n,t}^m + \Theta_{i,n,t}^m \mathbf{x}_{i,n,t} + \kappa_{i,n,t})\right)^{\lambda^m} \exp(\alpha^m + \xi_{i,t}^m) \right]},$$

and the expected return of asset j of type l for investor i at time t is defined:

$$\mu_{i,j,t}^l = \gamma_p^l p_{j,t}^l + \gamma_e^l (e_{j,t} - \pi_{j,t}) - (\gamma_p^{st} p_{j,t}^{st} + \gamma_e^{st} (e_{i,t} - \pi_{j,t}))$$

Given any initial parameter vector \mathcal{P} , Newton's Method would update the price vector with:

$$\mathcal{P}' = \mathcal{P} - \mathcal{J}_H^{-1} H(\mathcal{P})$$

where \mathcal{J}_H represents the Jacobian of the multivariate function H . However, rather than calculate the full Jacobian, we approximate \mathcal{J}_H with its diagonal. Let $H_{j,t}^l$ denote the row of H that corresponds to the market clearing condition for asset j of asset type l in period t .

For an asset j in the short-term debt market with floating exchange rates, the diagonal element of \mathcal{J}_H is:

$$\frac{\partial H_{j,t}^{st}}{\partial e_{j,t}} = - \frac{\sum_{i=1}^N A_{i,t} \left(\frac{\partial w_{i,t}^{st}}{\partial e_{j,t}} \times w_{i,j,t}^{st} + \frac{\partial w_{i,j,t}^{st}}{\partial e_{j,t}} \times w_{i,t}^{st} \right)}{\sum_{i=1}^N (A_{i,t} w_{i,t}^{st} w_{i,j,t}^{st})} \quad (\text{B.3})$$

where

$$\frac{\partial w_{i,t}^{st}}{\partial e_{j,t}} = \begin{cases} \lambda^{st} \beta^{st} \gamma_e^{st} w_{i,t}^{st} w_{i,j,t}^{st} - w_{i,t}^{st} \left(\sum_{m=st,lt,eq} \lambda^m \beta^m \gamma_e^m w_{i,t}^m w_{i,j,t}^m \right) & \text{if } i \neq j \\ -\lambda^{st} \beta^{st} \gamma_e^{st} w_{i,t}^{st} \left(\sum_{k \neq i} w_{i,k,t}^{st} \right) + w_{i,t}^{st} \left(\sum_{m=st,lt,eq} \lambda^m \beta^m \gamma_e^m w_{i,t}^m \left(\sum_{k \neq i} w_{i,k,t}^m \right) \right) & \text{if } i = j \end{cases}$$

and

$$\frac{\partial w_{i,j,t}^{st}}{\partial e_{j,t}} = \begin{cases} \beta^{st} \gamma_e^{st} w_{i,j,t}^{st} (1 - w_{i,j,t}^{st}), & \text{if } i \neq j \\ -\beta^{st} \gamma_e^{st} w_{i,j,t}^{st} \left(\sum_{k \neq i} w_{i,k,t}^{st} \right), & \text{if } i = j \end{cases} \quad (\text{B.4})$$

For an asset j in the short-term debt market that is part of a currency union, the diagonal element of \mathcal{J}_H is:

$$\frac{\partial H_{j,t}^{st}}{\partial q_{j,t}} = 1, \quad (\text{B.5})$$

where we update the quantity $q_{j,t}$ of short-term debt outstanding.

For long-term debt and equity assets, the diagonal element of \mathcal{J}_H is:

$$\frac{\partial H_{j,t}^l}{\partial p_{j,t}^l} = 1 - \frac{\sum_{i=1}^N A_{i,t} \left(\frac{\partial w_{i,t}^l}{\partial p_{j,t}^l} \times w_{i,j,t}^l + \frac{\partial w_{i,j,t}^l}{\partial p_{j,t}^l} \times w_{i,t}^l \right)}{\sum_{i=1}^N (A_{i,t} w_{i,t}^l w_{i,j,t}^l)} \quad (\text{B.6})$$

where

$$\frac{\partial w_{i,t}^l}{\partial p_{j,t}^l} = \lambda^l \beta^l \gamma_p^l w_{i,j,t}^l w_{i,t}^l (1 - w_{i,t}^l) \quad (\text{B.7})$$

and

$$\frac{\partial w_{i,j,t}^l}{\partial p_{j,t}^l} = \beta^l \gamma_p^l w_{i,j,t}^l (1 - w_{i,j,t}^l) \quad (\text{B.8})$$

We start with an initial parameter vector \mathcal{P} equal to the observed market prices and quantities, and we update the parameter vector according to:

$$\mathcal{P}' = \mathcal{P} - (\text{diag}[\mathcal{J}_H])^{-1} H(\mathcal{P}).$$

We continue to iterate until convergence.

B.5 Demand Elasticities and the Price Impact Multiplier

In this section, we derive expressions for demand elasticities with respect to price. We first derive bilateral demand elasticities for each investor-issuer country pair and then we aggregate demand elasticities for each issuer country.

The log demand by country i for country n assets in sector ℓ is given by

$$\hat{q}_{i,t}(n, \ell) = \log(A_{i,t} w_{i,t}(\ell) w_{i,t}(n|\ell)) - p_t(n, \ell). \quad (\text{B.9})$$

Changes in the log price of assets affect the quantity of assets demanded through its influence on the across-sector weight $w_{i,t}(\ell)$, the within-sector weight $w_{i,t}(n|\ell)$, and the price of the loan itself $p_t(n, \ell)$.

To derive the elasticity of demand for a given investor i to asset n in sector ℓ , we plug equations (2), (3), (6) and (5) into equation (B.9), and differentiate with respect to price:

$$-\frac{\partial \hat{q}_{i,t}(n, \ell)}{\partial p_t(n, \ell)} = 1 - \underbrace{(1 - w_{i,t}(\ell)) w_{i,t}(n|\ell) \lambda_\ell \beta_\ell \phi_\ell}_{\frac{\partial \log(w_{i,t}(\ell))}{\partial p_t(n, \ell)}} - \underbrace{(1 - w_{i,t}(n|\ell)) \beta_\ell \phi_\ell}_{\frac{\partial \log(w_{i,t}(n|\ell))}{\partial p_t(n, \ell)}}. \quad (\text{B.10})$$

The aggregate log demand for country n assets in sector ℓ is equal to:

$$\hat{q}_t(n, \ell) = \log \left(\sum_i A_{i,t} w_{i,t}(\ell) w_{i,t}(n|\ell) \right) - p_t(n, \ell).$$

To derive the aggregate demand elasticity for sector ℓ of country n , we take the derivative of the above expression with respect to $p_t(m, \ell)$:

$$-\frac{\partial \hat{q}_t(n, \ell)}{\partial p_t(n, \ell)} = \sum_i \left(\frac{A_{i,t} w_{i,t}(n, \ell)}{\sum_j A_{j,t} w_{j,t}(n, \ell)} \right) \left(-\frac{\partial \hat{q}_{i,t}(n, \ell)}{\partial p_t(n, \ell)} \right) \quad (\text{B.11})$$

Equation (B.11) shows the aggregate demand elasticity for the country n sector ℓ asset is just a weighted sum of the bilateral demand elasticities of each individual investor country.

B.6 Additional Tables and Figures

TABLE B.1
LIST OF INVESTOR AND ISSUER COUNTRIES

Country	Region	Investor	Issuer
Australia	Asia-Pacific Developed	✓	✓
Austria	Europe Developed		✓
Belgium	Europe Developed		✓
Brazil	Other	✓	
Canada	Other	✓	✓
Chile	Other	✓	
China	Other	✓	✓
Czechia	Other	✓	✓
Denmark	Europe Developed	✓	✓
Estonia	Other	✓	
European Union	Europe Developed	✓	
Finland	Europe Developed		✓
France	Europe Developed		✓
Germany	Europe Developed		✓
Greece	Europe Developed		✓
Hungary	Other	✓	✓
Iceland	Other	✓	
India	Other	✓	✓
Indonesia	Other	✓	
Italy	Europe Developed		✓
Japan	Asia-Pacific Developed	✓	✓
Latvia	Other	✓	
Lithuania	Other	✓	
Malaysia	Other	✓	✓
Mexico	Other	✓	✓
New Zealand	Europe Developed	✓	✓
Norway	Europe Developed	✓	✓
Pakistan	Other	✓	
Philippines	Other	✓	✓
Poland	Europe Developed	✓	✓
Portugal	Europe Developed		✓
Romania	Other	✓	
Russia	Other	✓	✓
Singapore	Asia-Pacific Developed	✓	✓
Slovakia	Other	✓	
South Africa	Other	✓	✓
South Korea	Asia-Pacific Developed	✓	✓
Spain	Europe Developed		✓
Sweden	Europe Developed	✓	✓
Switzerland	Europe Developed	✓	✓
Thailand	Other	✓	✓
Turkey	Other	✓	
United Kingdom	Europe Developed	✓	✓
United States	United States	✓	✓

This table lists the countries in our sample, classifies them by region and marks whether each country enters as an investor or issuer country.

TABLE B.2
LIST OF CENTRAL BANKS IN SAMPLE

Central Bank	Region
Australia	Developed
Belgium	Developed
Brazil	Emerging
Canada	Developed
Chile	Emerging
China	Emerging
Colombia	Emerging
Croatia	Emerging
Czechia	Emerging
Denmark	Developed
Estonia	Emerging
European Central Bank	Developed
Federal Reserve	Emerging
Finland	Developed
Germany	Developed
Hong Kong SAR China	Emerging
Iceland	Emerging
Italy	Developed
Latvia	Emerging
Netherlands	Developed
New Zealand	Developed
Norway	Developed
Philippines	Emerging
Poland	Developed
Slovenia	Emerging
South Africa	Emerging
Spain	Developed
Sweden	Developed
Switzerland	Developed
Turkey	Emerging
United Kingdom	Developed

This table lists the Central Banks in our sample for which we can impute holdings data.

TABLE B.3
PREDICTING EXPECTED EXCESS RETURNS

	DebtLong (1)	DebtShort (2)	Equity (3)
Log market-to-book	-0.37*** (0.05)	-8.33*** (1.23)	-0.11*** (0.04)
Log real exchange rate	-0.42*** (0.06)	-0.35*** (0.03)	-0.80*** (0.09)
Observations	576	576	576
R ²	0.30	0.28	0.16
Country fixed effects	✓	✓	✓

This table displays results from estimating equation (4). For debt, the log market-to-book ratio is minus the maturity times the yield. All specifications include country fixed effects. Standard errors are clustered by year. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

TABLE B.4
PREDICTIVE MODEL FOR WEIGHTS

	ST Debt (1)	LT Debt (2)	Equity (3)
Log Population	0.95*** (0.06)	0.65*** (0.08)	0.98*** (0.09)
Distance	-0.95*** (0.13)	-1.25*** (0.16)	-1.51*** (0.22)
Indicator: Own Country	6.97*** (0.55)	5.23*** (0.56)	4.42*** (0.82)
Observations	17,393	20,087	20,142
R ²	0.49	0.62	0.67
Within R ²	0.19	0.20	0.21
Investor fixed effects	✓	✓	✓

This table displays results from estimating equation (4). For debt, the log market-to-book ratio is minus the maturity times the yield. All specifications include country fixed effects. Standard errors are clustered by year. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

TABLE B.5
DEMAND ESTIMATION ACROSS ASSET CLASSES

	(1)
λ (Short-Term Debt)	0.13** (0.06)
λ (Long-Term Debt)	0.15** (0.07)
λ (Equity)	0.25*** (0.07)
α (Long-Term Debt)	0.95*** (0.14)
α (Short-Term Debt)	-1.14*** (0.13)
Observations	1,228
F-test (1st stage), λ (Short-Term Debt)	775.8
F-test (1st stage), λ (Long-Term Debt)	316.6
F-test (1st stage), λ (Equity)	273.1

This table estimates equation (10). *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

TABLE B.6
DEMAND ESTIMATION ACROSS ASSET CLASS. FIRST STAGE.

	(1)	(2)	(3)
Inclusive Value Instrument (Short-Term Debt)	0.85*** (0.03)	-0.04 (0.03)	-0.35*** (0.05)
Inclusive Value Instrument (Long-Term Debt)	0.00 (0.03)	0.58*** (0.03)	-0.19*** (0.06)
Inclusive Value Instrument (Equity)	0.00 (0.03)	-0.05* (0.03)	0.41*** (0.05)
α (Long-Term Debt)	0.00 (0.09)	1.78*** (0.10)	-2.26*** (0.16)
α (Short-Term Debt)	1.27*** (0.10)	-0.07 (0.10)	-1.36*** (0.17)
Observations	1,228	1,228	1,228
F-test (1st stage)	775.8	316.6	273.1

This table reports the first stage of equation (10). *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

TABLE B.7
DEMAND ESTIMATION WITHIN ASSET CLASS

	ST Debt (1)	LT Debt (2)	Equity (3)
E[Excess Return]	43.67*** (13.42)	7.04 (5.63)	10.29** (3.71)
Log GDP	2.34*** (0.35)	1.95*** (0.20)	2.13*** (0.33)
Centrality	-0.04 (0.09)	-0.08 (0.06)	0.02 (0.10)
Log Population	-0.57* (0.30)	-0.63*** (0.19)	-0.58* (0.29)
Default	0.01 (0.11)	-0.19 (0.20)	-0.04 (0.09)
Distance	-0.87*** (0.19)	-1.14*** (0.17)	-1.25*** (0.23)
Import Exposure	0.10 (0.12)	0.13* (0.08)	0.10 (0.13)
Export Exposure	0.11 (0.12)	0.06 (0.09)	0.25 (0.15)
Inflation	-0.27 (0.21)	0.11 (0.10)	-0.03 (0.12)
Volatility	-0.15* (0.09)	-0.20*** (0.06)	-0.06 (0.07)
Indicator: Own Country	7.34*** (0.00)	5.76*** (0.77)	5.38*** (1.07)
Indicator: USA Issuance	1.86** (0.66)	2.31*** (0.57)	0.86 (0.59)
Observations	17,393	20,087	20,142
F-test (1st stage), E[Excess Return]	28.7	39.0	166.7
Investor fixed effects	✓	✓	✓
Year fixed effects	✓	✓	✓
Developed Market fixed effects	✓	✓	✓

This table estimates equation (9) separately for each asset class when we instrument for expected excess returns. The sample comprises annual data from 2002 to 2019. Default is the 5-year default probability for the sovereign debt category imputed by S&P. All specifications include investor country, year and issuer country MSCI market fixed effects. Standard errors are reported parentheses are double clustered by investor country and year. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

TABLE B.8
DEMAND ESTIMATION WITHIN ASSET CLASS. FIRST STAGE.

	ST Debt (1)	LT Debt (2)	Equity (3)
Log NER Instrument	-0.004*** (0.001)	-0.005*** (0.001)	-0.013*** (0.002)
Log Price Instrument		-0.011** (0.004)	-0.007* (0.003)
Log GDP	-0.027** (0.010)	-0.027* (0.014)	-0.097*** (0.022)
Log Population	0.018** (0.007)	0.002 (0.013)	0.076*** (0.018)
Centrality	0.004* (0.002)	0.010*** (0.002)	0.020*** (0.006)
Default	0.001 (0.002)	0.028*** (0.005)	-0.002 (0.006)
Distance	0.003 (0.003)	0.002 (0.002)	-0.003 (0.003)
Import Exposure	0.002 (0.003)	0.002 (0.003)	0.006 (0.003)
Export Exposure	0.001 (0.003)	-0.000 (0.003)	-0.005 (0.003)
Inflation	0.007* (0.003)	0.010** (0.005)	0.011** (0.005)
Volatility	0.001 (0.002)	0.007* (0.004)	0.004 (0.004)
Indicator: Own Country	0.013 (0.010)	0.008 (0.010)	0.002 (0.013)
Indicator: USA Issuance	0.019 (0.014)	0.003 (0.017)	0.124*** (0.033)
Observations	17,393	20,087	20,142
F-test (1st stage)	28.7	39.0	166.7
Investor fixed effects	✓	✓	✓
Year fixed effects	✓	✓	✓
Developed Market fixed effects	✓	✓	✓

This table reports the first stage of equation (9). *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

TABLE B.9
ESTIMATION VARIATIONS. COEFFICIENTS ON EXPECTED RETURNS

	Estimation Variation					
	Baseline	(1)	(2)	(3)	(4)	(5)
Short-Term Debt	43.7 (13.4)	41.8 (19.8)	45.4 (18.4)	43.8 (37.4)	29.0 (10.7)	74.4 (35.6)
Long-Term Debt	7.0 (5.6)	14.4 (14.3)	11.9 (5.7)	0.5 (9.4)	3.2 (4.6)	9.2 (5.8)
Equity	10.3 (3.7)	1.5 (2.3)	5.3 (3.7)	9.4 (3.0)	5.0 (2.0)	18.7 (7.3)

This table presents the coefficients on expected returns for each asset class under each of our alternative methodologies for constructing the instrumental variable. These variations are described in Appendix [B.3](#).

TABLE B.10
TREND DECOMPOSITION OF DOLLAR AFE INDEX. VARY ESTIMATION.

	Estimation Variation					
	Baseline	(1)	(2)	(3)	(4)	(5)
Demand Elasticity						
Short-Term Debt	197.4	189.0	205.3	198.0	118.1	335.7
Long-Term Debt	2.5	4.1	3.6	1.1	1.7	3.0
Equity	1.8	1.1	1.4	1.7	1.4	2.4
Trend Decomposition						
Savings and Issuances						
DM Savings	4.2	4.3	4.2	2.5	3.5	3.7
EM Savings	4.5	4.4	4.4	4.1	4.4	3.7
Total Savings	8.7	8.7	8.6	6.6	8.0	7.5
Monetary Policies (Reserves)						
US Reserves	-1.2	-1.5	-1.4	-0.9	-1.2	-1.1
DM Reserves	-0.2	-0.2	-0.2	-0.2	-0.2	-0.1
EM Reserves	0.1	0.1	0.1	0.1	0.2	0.0
Total Reserves	-1.3	-1.6	-1.5	-1.0	-1.2	-1.2
Monetary Policies (Rates)						
US Rates	6.0	6.2	6.3	5.4	4.9	7.2
EM/DM Rates	-0.1	0.2	0.1	-0.2	-0.1	0.2
Total Rates	5.8	6.4	6.4	5.2	4.8	7.3
Demand Shifts						
DM Demand	8.1	8.0	7.9	10.3	9.9	6.8
EM Demand	1.1	1.0	1.1	1.5	1.0	2.1
Total Demand	9.3	9.0	8.9	11.8	10.9	8.9
Total	22.5	22.5	22.5	22.5	22.5	22.5

The top panel presents the average elasticity of demand with respect to asset prices in each of the variations. The “Baseline” column re-iterates the trend decomposition shown in Table 1. The remaining columns present the results under alternative assumptions taken to construct the instrumental variables. These alternatives are described in Appendix B.3.