Demand Propagation Through Traded Risk Factors[*]

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Abstract

We propose that demand propagates across financial assets as they share exposure to non-diversifiable risks. Using a novel approach, we identify such risks in currency trading by jointly analyzing trading and returns. Three traded risk factors—Dollar, Carry, and Euro-Yen—explain 90% of trading-induced non-diversifiable risk and are priced unconditionally and conditionally on trading. By construction, demand shocks to one factor do not affect another's price. IV analysis shows factor prices rise 5–30 bps per $1 billion of own demand shocks. We combine factor-level price sensitivity with factor exposures to quantify cross-multipliers for 17 currencies and seven asset classes.

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1 Introduction

Demand shocks unrelated to information can drive significant fluctuations in asset prices (e.g., Lee, Shleifer, and Thaler, 1991; Froot and Ramadorai, 2008; Koijen and Yogo, 2019). Such shocks can propagate quickly, especially among financial assets that are tightly linked by arbitrage. Assets with similar risk exposures tend to co-move (Fama and French, 1993; Lustig, Roussanov, and Verdelhan, 2011). As a result, the price of a similarly risky asset can move as much as—or even more than—the price of the asset experiencing a demand shock. Consider a currency and a leveraged portfolio that holds a $2\times$ leveraged position in that currency: a demand shock to the currency should move the price of the leveraged portfolio by twice as much. Given this distinct arbitrage feature, how do demand shocks propagate across financial assets?

Empirically answering this question is challenging. An asset's price may respond not only to its own shock but also to shocks to other assets. Moreover, demand shocks often correlate across assets, limiting independent variation to identify cross-asset dynamics. To address this, the industrial organization (IO) literature has developed tailored structural models. However, these models may not be arbitrage-free, and ignoring arbitrage-implied cross-asset demand propagation can lead to substantial estimation biases for financial assets (Haddad, He, Huebner, Kondor, and Loualiche, 2025).[1]

In this paper, we develop an arbitrage-based approach to study demand propagation through traded risk factors. Our setting is the foreign exchange (FX) market, where customers' trades are almost exclusively accommodated by specialist intermediaries such as dealers and hedge funds. These risk-averse intermediaries require compensation for bearing trading-induced risks, thus demand shocks can lead to price adjustment in currencies and other correlated assets (Grossman and Miller, 1988; Duffie, 2010; Gabaix and Maggiori, 2015; Vayanos and Vila, 2021). Our innovation lies in using factors to characterize non-diversifiable risks induced by trading, and empirically quantify demand propagation. The advantage of factors arises because FX intermediaries simultaneously manage a portfolio of currencies, enabling them to diversify trading-induced risks across currencies.[2] For example, if customers buy one currency and sell another to intermediaries, the intermediaries can offset some risks if the returns of the two currencies are positively correlated. In other words, the relevant risk for intermediaries — and thus for asset pricing — is the portion of trading-induced risks that cannot be further diversified. Drawing on insights from Markowitz

[1] Fuchs, Fukuda, and Neuhann (2023) show that investor tastes can break no-arbitrage and some logit asset demand systems do not fully account for cross-asset demand propagation.

[2] This is particularly evident when considering the intermediary sector as a whole, where agents share risks of different currencies by trading through the deep and liquid inter-dealer network.

(1952) and Ross (1976), we characterize these trading-induced non-diversifiable risks using factors. We then use instrumental variables to estimate these factors' price sensitivity to trading-induced risks. Finally, combining these factor-level price sensitivity with individual assets' factor exposures, we uncover novel patterns of demand propagation across a panel of 17 currencies and seven asset classes.

We begin by identifying the non-diversifiable risks generated by FX trading. To achieve this, we jointly analyze a unique dataset of daily trading flows between customers and intermediaries across 17 major currencies and a panel of currency returns. We develop a novel approach that extends portfolio theory to extract "*traded* risk factors" that explain the largest variations in risk exposure driven by customer trading. Unlike merely *tradable* factors, these *traded* factors capture non-diversifiable risks that investors collectively deem important, as revealed by their actual trading. The two most prominent traded FX factors resemble the well-known Dollar and Carry factors (Lustig, Roussanov, and Verdelhan, 2011). Additionally, we identify a Euro-Yen factor that partially reflects risks stemming from substantial currency trading between the Euro area and Japan. This factor is orthogonal to the Dollar and Carry factors and delivers a Sharpe ratio comparable to that of the Carry factor. By simultaneously incorporating trading and return data, our approach identifies factors that differ from those derived solely from returns, where the Carry factor is not readily apparent and the Euro-Yen factor is entirely absent. Our approach also contrasts with analyses based solely on flows, which surface currency pairs with the highest trading volumes as "factors." Together, the top three traded FX factors explain 90% of the non-diversifiable risks intermediaries face in accommodating customer trading. Beyond explaining risks, these factors reveal intermediaries' otherwise unobserved risk exposures. For instance, using net trading flows into the Carry factor, we estimate that intermediaries accumulated $0.8 trillion in Carry trade exposure from 2012 to 2023.

Having identified the traded FX factors, we estimate each factor's price sensitivity to trading-induced risks. In general, demand shocks can propagate across factors, causing the price of one factor to respond to shocks to others. As a result, regressing a factor's price solely on its own shock is generally misspecified, even at the factor level (Haddad, He, Huebner, Kondor, and Loualiche, 2025). However, because our factors are constructed to be orthogonal, we can estimate price sensitivities factor-by-factor without concerns about cross-factor interactions. This orthogonality also enhances the interpretability of the estimated price sensitivity, as it directly reflects intermediaries' risk-bearing capacity.

To estimate each factor's price sensitivity from the observed equilibrium customer trading flows, we instrument for demand shocks to ensure the estimate is not contaminated by the effects of fundamentals (e.g., the arrival of new information) on price. We use as instrumental variables the announcements of the offering amount at upcoming sovereign bond auctions in the U.S., Australia, Canada, France, Germany, Italy, Japan, and the U.K. These sovereign auctions often attract foreign investors who need to convert currencies to participate, making the instruments relevant. At the same time, because these auctions are typically forward-guided,[3] the announcements contain limited new information, making the instruments plausibly exogenous and satisfying the exclusion restriction. Our estimates imply that inducing intermediaries to absorb a $1 billion non-diversifiable demand shock requires price increases of 5 basis points (bps) for the Dollar, 9 bps for the Carry, and 29 bps for the Euro-Yen. These are significantly larger price responses than those estimated for the U.S. equities market factor (Gabaix and Koijen, 2021),[4] suggesting that arbitrage capital is more limited in FX than in equities. The variation in price sensitivity to risks across traded FX factors may also reflect differences in available arbitrage capital, with lesser-known factors such as the Euro-Yen attracting less arbitrage capital and exhibiting greater price sensitivity. Furthermore, we find evidence of state-dependent price sensitivity to risks. Specifically, the Dollar factor's price sensitivity varies with the public equity returns of large intermediaries. As equity returns capture changes in wealth that affect intermediaries' risk-bearing capacities, our finding supports the interpretation that the observed price sensitivity arises from a risk-return trade-off.

Using the estimated factor-level price sensitivity to risks, we compute the currency-level cross-multiplier between any arbitrary pair. This cross-multiplier quantifies demand propagation by showing how a demand shock to one currency affects the price of another, holding the demand shocks to all other currencies constant. Estimating cross-multipliers for a panel of N currencies is challenging due to correlated demand shocks, which limits the independent variation needed to estimate the N^2 cross-multipliers. Our approach maps cross-multipliers to the risk exposures of the underlying currencies to traded FX factors. When intermediaries accommodate a demand shock to one currency, they bear additional non-diversifiable risks, as characterized by the traded FX factors. These risks affect the price of the traded FX factors and, via the law of one price, alter the prices of other currencies that load on the affected factors.

We uncover rich cross-substitution patterns among currencies, driven by variation in factor loadings. Currencies exhibit demand substitution when they share the same sign of

[3] For example, in the U.S., the Treasury Borrowing Advisory Committee (TBAC) releases two-quarter-ahead recommendation on auction amounts, and actual auctions exhibit little deviation from these recommendations (Rigon, 2024).

[4] Gabaix and Koijen (2021) find that a 1% larger trading demand shock to the entire U.S. stock market increases price by 5%. Such a shock can be interpreted as a shock to the market factor. The average market capitalization between 2012 and 2022 is about $31.7 trillion. A $1 billion demand shock in our sample period therefore raises the price of the market factor by about 2 bps.

loading to a factor and complementarity when they have opposite signs. For instance, we find a large cross-multiplier between the Australian dollar (AUD) and the Canadian dollar (CAD) because both currencies have the same sign of loadings on all three traded FX factors. In contrast, the cross-multiplier between the Japanese yen (JPY) and either AUD or CAD is small because JPY has the opposite loading on the Carry factor, allowing the currencies to hedge each other by reducing intermediaries' exposure to the Carry factor. Similarly, while the euro (EUR) and JPY are both low-interest-rate currencies and act as "substitutes" with respect to the Carry factor, they are on opposite sides of the Euro-Yen factor, making them "complements" for that factor. As a result, we estimate only a modest cross-multiplier between EUR and JPY.

Building on this logic, we compute cross-multipliers among FX and six non-FX asset classes: U.S. Treasury bonds (Treasurys), corporate bonds, U.S. public equities, options, CDS, and commodities. These asset classes meaningfully load on the traded FX factors, which explain approximately 30% of their return variance. Consequently, a demand shock to, say, corporate bonds generates non-diversifiable FX risks, as captured by the traded FX factors. These risks affect the prices of traded FX factors and, in turn, the prices of U.S. equities and other assets that load on the affected factors. Demand shocks transmitted through the traded FX factors have the smallest price effect on U.S. Treasurys, consistent with the depth and liquidity of the Treasurys market. Notably, Treasurys alone exhibit negative cross-multipliers with other assets, reflecting their "safe haven" status. In our framework, this safe haven property arises because Treasurys form the only asset class with a negative loading on the Carry factor.

Our paper extends the literature on exchange rates by developing a novel approach to quantify the price response of trading flows through risks. Beyond conveying information (e.g., Evans and Lyons, 2002; Pasquariello, 2007; Froot and Ramadorai, 2008), trading influences prices by increasing the non-diversifiable risks that marginal agents must bear. Our key contribution is to recover risk factors that investors empirically deem important by analyzing their trading behavior together with return data. This revealed-preference approach differs from, and complements, the literature's typical method of conjecturing relevant state variables based on economic intuition, constructing factors from those variables, and then testing these factors' cross-sectional pricing power.[5] We find that the two most significant traded FX factors, the Dollar and the Carry, are the same factors that price unconditional FX returns (Lustig, Roussanov, and Verdelhan, 2011). Furthermore, we introduce a new

[5] For example, Fama and French (1993) identify size and value as key state variables for determining expected returns, sort stocks by these variables to build the size and value factors, and then show that these factors price the cross-section of expected returns.

Euro-Yen factor, which is a priced risk both unconditionally over time and conditionally on demand shocks. We also uncover new evidence of intermediaries' time-varying exposure to these factors and demonstrate that intermediaries' risk-return trade-offs are pivotal for how risks are priced in trading. Our findings complement existing research on priced risk factors in FX markets (e.g., Bansal and Dahlquist, 2000; Lustig and Verdelhan, 2007; Hassan and Mano, 2018; Korsaye, Trojani, and Vedolin, 2023) and offer fresh insights into the role of trading-induced risks in driving price co-movements across currencies and between FX and other asset markets (e.g., Jiang, Krishnamurthy, and Lustig, 2021; Camanho, Hau, and Rey, 2022; Chernov and Creal, 2023; Gourinchas, Ray, and Vayanos, 2024; Liao and Zhang, 2025).

Our paper also contributes to the broader literature on demand propagation across assets. Estimating propagation among N assets using reduced-form regressions is impractical due to the sheer number of parameters. To address this, the literature has primarily adopted two structural approaches. One approach focuses on asset characteristics and ties demand propagation to microfounded functional forms (e.g., Koijen and Yogo, 2019; Koijen and Yogo, 2020; Bretscher, Schmid, Sen, and Sharma, 2022; Jiang, Richmond, and Zhang, 2024). The other appeals to mean-variance optimization and links propagation to return covariances between individual assets (e.g., Vayanos and Vila, 2021; Kodres and Pritsker, 2002; Pasquariello and Vega, 2015; Davis, Kargar, and Li, 2023; Greenwood, Hanson, and Vayanos, 2023; Jansen, Li, and Schmid, 2024).

We offer a distinct alternative inspired by the arbitrage pricing theory (APT) of Ross (1976): demand propagates through traded risk factors. This approach offers three key advantages. First, asset-level propagation is driven by exposures to these risk factors, allowing assets to be "complements" with respect to some factors but "substitutes" with respect to others. Second, because each factor can have a unique price sensitivity to risk, shocks of different natures can propagate differently. Third, because the traded risk factors capture non-diversifiable risks aggregated across assets, their price sensitivity to risk reflects the "macro-multiplier" in the spirit of Gabaix and Koijen (2021). Through the arbitrage mechanism between factors and assets, these factor-level "macro-multiplier" further inform the asset-level "micro-multiplier," much like how canonical asset pricing uses factor-level risk premium to determine asset-level risk premium. This arbitrage-based linkage between multipliers at different aggregation levels differs from, and complements, existing work that estimates price multipliers at distinct micro vs. macro levels (Li and Lin, 2022; Haddad, He, Huebner, Kondor, and Loualiche, 2025).

More generally, our paper augments the intermediary asset pricing and microstructure literatures, both of which emphasize intermediaries' limited risk-bearing or balance-sheet capacity as a driver of asset price responses to customers' demand shocks (e.g., Ho and Stoll, 1981; Grossman and Miller, 1988; Gabaix and Maggiori, 2015; He and Krishnamurthy, 2017; Kondor and Vayanos, 2019; Haddad and Muir, 2021; Du, Hébert, and Huber, 2023; Du, Hébert, and Li, 2023). While we share this focus on intermediaries and the frictions they face, our approach differs in emphasizing that intermediaries' pricing decisions are shaped by non-diversifiable risks aggregated across all assets, rather than analyzing the risks of individual assets in isolation. In this sense, our perspective aligns with the foundational insights of Markowitz (1952), Sharpe (1964), and Lintner (1965), where non-diversifiable risks are the primary concern in asset price determination.

The next section presents our theoretical framework. Section 3 introduces the data source and Section 4 identifies the traded FX factors. Section 5 examines the unconditional and conditional pricing properties of the traded FX factors. Section 6 explores how these factors propagate demand shocks across currencies and other asset classes. Section 7 concludes.

2 Theoretical Framework

This section begins by introducing the model setup. It then describes the construction of the traded risk factors, the solution for these factors' price sensitivity to trading-induced risks, and the mapping from factor-level price sensitivity to currency-level cross-multipliers.

2.1 Model Setup

There are three periods: $t = 0$, $t = 1$, and $t = 2$; and there are $N + 1$ currencies, where the last currency serves as the numeraire. Customers buy or sell any pair of the $N + 1$ currencies. These trades could be motivated by demand shocks (e.g., preference shocks) or private information. All customer trades are accommodated by a mass μ of competitive intermediaries. For $n = 1, \ldots, N$, the return of currency n from time 0 to time 1 is r_n, which is defined as the return from borrowing one unit of the numeraire at its risk-free rate, converting it to currency n at time 0, investing at currency n's risk-free rate from time 0 to 1, and then converting it back to the numeraire at time 1. We stack r_n into an $N \times 1$ vector as $\mathbf{r} = (r_1, r_2, \ldots, r_N)^\top$.[6] Similarly, R_n denotes the return of currency n between time 1 and time 2, which we stack into an $N \times 1$ vector $\mathbf{R} = (R_1, R_2, \ldots, R_N)^\top$. We assume there are no redundant currencies, so the matrix $\text{var}(\mathbf{r})$ has full rank, and we assume that the return covariance structure remains stable over time, such that $\text{var}(\mathbf{r}) = \text{var}(\mathbf{R})$.[7] Our goal is to study the price response of customer demand shocks between time 0 to time 1, holding fixed

[6] Throughout this paper, bold font is used to denote matrices and vectors, and $\mathbf{A}^\top$ represents the transpose of $\mathbf{A}$.

[7] All our theory holds if we instead assume the more general form $\text{var}(\mathbf{r}) = L\text{var}(\mathbf{R})$, for some positive constant L.

the trading between time 1 and time 2. We empirically map the interval between time 0 to time 1 to a week. Time $t = 2$ represents the long term, where currency prices are no longer affected by demand shocks between time 0 and time 1; reaching this stage may take months in reality.

2.2 Factor Construction

We want to study trading-induced risks that intermediaries bear at the margin. We thus aim to identify a few factors that maximally explain the non-diversifiable risks induced by the aggregate trading flow. Using the U.S. dollar (USD) as the numeraire currency, we first decompose all trades between time 0 and 1 into trades against USD, and express the aggregate trading flow as $\mathbf{f} = (f_1, f_2, \ldots, f_N)^\top$, where f_n is the net customer buying flow for currency n against USD.[8] For any given factor $\mathbf{b}_1 = (b_{1,1}, \ldots, b_{N,1})$, where $b_{n,1}$ represents the weight of currency n in this factor,[9] currency n loads on the factor with $\beta_{n,1} = \text{cov}(r_n, \mathbf{b}_1^\top \mathbf{r})/\text{var}(\mathbf{b}_1^\top \mathbf{r})$. When intermediaries accommodate a currency-level trading flow, f_n, they effectively bear a factor-level trading flow of size $f_n \beta_{n,1}$, along with other risks uncorrelated with the factor. Given that there are N currencies, intermediaries can offset the factor-level trading flow across different currencies, leaving a non-diversifiable factor-level flow of amount[10]

$$q_1 = \sum_{n=1}^{N} f_n \beta_{n,1} = \text{cov}(\mathbf{f}^\top \mathbf{r}, \mathbf{b}_1^\top \mathbf{r})/\text{var}(\mathbf{b}_1^\top \mathbf{r}). \tag{1}$$

Note that for any given factor (as defined by the portfolio weights $\mathbf{b}_1$), the factor-level trading flow q_1 varies in proportion to the currency-level trading flow f_n, and this relationship depends on the factor being considered, as varying $\mathbf{b}_1$ changes the beta ($\beta_{n,1}$) of a currency to a factor.

We next specify the problem that pins down the most traded risk factors. Because returns are defined per dollar, $\beta_{n,1}$ measures the additional factor exposure in *dollars* from one *dollar* invested in currency n. Thus, when summing the currency-level flows f_n using the beta weights in (1), these flows must be measured in dollars,[11] and the resulting factor flow q_1 is likewise expressed in dollars. Multiplying q_1 by the factor return variance $\text{var}(\mathbf{b}_1^\top \mathbf{r})$

[8] Specifically, if a customer buys currency n by selling currency m, we record it as a positive trading flow for currency n from USD and a negative trading flow for currency m from USD. In Supplemental Appendix A, we prove that the construction of traded risk factors remains invariant to the choice of the numeraire currency.

[9] By definition, the weight of USD in this factor is $-\sum_{n=1}^{N} b_{n,1}$.

[10] Our model assumes a representative intermediary who accommodates all customer trades. In practice, such netting across currencies could also occur through interdealer trading.

[11] For example, normalizing f_n by the aggregate trading volume of the currency and then applying equation (1), would result in an incorrect aggregation.

changes the unit to trading-induced risks. As our goal is to maximally explain the trading-induced risks, we construct the first factor $\mathbf{b}_1$ to maximize the variation of trading-induced risks,

$$\max_{\mathbf{b}_1} \frac{\text{var}(q_1 \text{var}(\mathbf{b}_1^\top \mathbf{r}))}{\text{var}(\mathbf{b}_1^\top \mathbf{r})} = \text{var}(q_1)\text{var}(\mathbf{b}_1^\top \mathbf{r}). \tag{2}$$

We normalize the variance of $q_1 \text{var}(\mathbf{b}_1^\top \mathbf{r})$ by the factor return variance so that scaling $\mathbf{b}_1$ does not affect the objective function.[12]

We construct the second factor $\mathbf{b}_2$ by requiring that the second factor has an uncorrelated return with the first and that the second factor maximizes the variation of trading-induced risks,

$$\begin{aligned} &\max_{\mathbf{b}_2} \text{var}(q_2)\text{var}(\mathbf{b}_2^\top \mathbf{r}) \\ &\text{s.t.} \operatorname{cov}(\mathbf{b}_1^\top \mathbf{r}, \mathbf{b}_2^\top \mathbf{r}) = 0, \end{aligned} \tag{3}$$

where $q_2 = \operatorname{cov}(\mathbf{f}^\top \mathbf{r}, \mathbf{b}_2^\top \mathbf{r})/\text{var}(\mathbf{b}_2^\top \mathbf{r})$.[13]

This sequential maximization procedure is similar to the standard principal component analysis (PCA) on *returns* alone, a common asset-pricing approach used to identify factors that maximally explain unconditional risks (Ross, 1976; Fama and French, 1993; Lustig, Roussanov, and Verdelhan, 2011).[14] However, our procedure extends the standard PCA framework by incorporating both trading and returns data to maximally explain conditional trading-induced risks. Appendix A.1 provides details on solving for these factors through eigenvalue decomposition. In theory, one can construct at most K factors, where K is the rank of the matrix $\text{var}(\mathbf{f})$. Empirically, a small number of factors are typically sufficient to explain the majority of trading-induced risks.

Our procedure can also be interpreted as a risk-based extension of the standard PCA on *flows* alone, an intuitive approach for analyzing trading data. Specifically, if the returns of different currencies are i.i.d. (i.e., $\text{var}(\mathbf{r})$ is proportional to the identity matrix), our procedure becomes identical to the standard PCA on flows.[15] Moreover, if the returns of different currencies are independent but each currency n has its own return volatility σ_n,

[12]Specifically, if $\mathbf{b}_1$ is doubled, $\beta_{n,1}$ in equation (1) is halved, causing q_1 to also halve, which leaves the objective function unchanged.

[13]Because the returns of different factors are uncorrelated by construction, the univariate beta defined here is equivalent to the multivariate beta.

[14]Specifically, the first factor $\mathbf{b}_1$ maximizes the variance of the factor return: $\text{var}(\mathbf{b}_1^\top \mathbf{r})$. The second factor $\mathbf{b}_2$, conditional on being uncorrelated with the first factor, i.e., $\operatorname{cov}(\mathbf{b}_1^\top \mathbf{r}, \mathbf{b}_2^\top \mathbf{r}) = 0$, again aims to maximize the variance of the factor return: $\text{var}(\mathbf{b}_2^\top \mathbf{r})$, and so on.

[15]Specifically, (2) simplifies to $\max_{\{b_{1,1}, b_{2,1}, \dots, b_{N,1}\}} \text{var}(\sum_{n=1}^N f_n b_{n,1})/(\sum_{n=1}^N b_{n,1}^2)$.

our procedure reduces to the standard PCA on $\sigma_n f_n$, the risk-weighted flows.[16] The most general form of the objective function (2) accommodates scenarios where different currencies may exhibit arbitrary correlations.

2.3 Price Sensitivity to Trading-Induced Risks

Having identified the traded risk factors, we now derive the price sensitivity to trading-induced risks of each factor through the portfolio optimization of a representative intermediary. Our model is kept deliberately simple to emphasize the relationship between trading and asset prices. We assume that the mass μ of intermediaries have CARA preference.[17] In addition to risk aversion, the only type of friction that the model features is possible factor-specific frictions in accommodating risks, leading to possibly different factor-specific risk-aversion, denoted by γ_k for factor k.[18]

The traded risk factors in Section 2.2 are constructed using observed, equilibrium trading flows and returns. As such, we have identified the factors with the largest amount of trading-induced risks in equilibrium, which are priced partly due to changes in fundamentals (e.g., the arrival of news, learning from trades) and partly due to intermediaries being pushed against their risk-bearing capacity. Our goal is to compute the sensitivity of price change to uninformed *demand shocks*. To achieve this, we examine the price response of hypothetical and marginal demand shocks $\hat{f}_1, \ldots, \hat{f}_N$, which occur between times 0 and 1 and are uninformed about currency prices at time 2. Due to intermediaries' limited risk-bearing capacity, the (percentage) price response of currency n at time 1 is

$$\Delta \hat{p}_n := \frac{P_n(\hat{f}_1, \ldots, \hat{f}_N) - P_n(0, \ldots, 0)}{P_n(0, \ldots, 0)}, \tag{4}$$

where $P_n(\hat{f}_1, \ldots, \hat{f}_N)$ is the exchange rate of currency n (measured as the number of USD per foreign currency) with demand shocks $\hat{f}_1, \hat{f}_2, \ldots, \hat{f}_N$. Then, for factor k that holds $\$b_{n,k}$ of currency n against the USD, the price response is

$$\Delta p_k = \sum_{n=1}^{N} b_{n,k} \Delta \hat{p}_n. \tag{5}$$

[16] Specifically, (2) simplifies to $\max_{\{g_1, g_2, \ldots, g_N\}} \operatorname{var}(\sum_{n=1}^N \sigma_n f_n g_n)/(\sum_{n=1}^N g_n^2)$, where g_n is defined as $\sigma_n b_{n,1}$.

[17] We can re-cast the absolute risk aversion as a function of wealth to mimic a CRRA preference.

[18] In practice, not all intermediaries may be willing to accommodate risks in every factor. If some intermediaries choose not to absorb risks of a certain factor k, this would manifest as a higher effective risk aversion, γ_k, in our model.

The factor-level demand shock is aggregated in the same way as equation (1),

$$\hat{q}_k = \sum_{n=1}^{N} \beta_{n,k} \hat{f}_n. \tag{6}$$

The equilibrium price responses are such that each intermediary finds it optimal to buy $y_k = -\hat{q}_k/\mu$ dollars of factor k. For each additional dollar of factor k purchased, intermediaries bear an extra payoff risk of $\mathbf{b}_k^\top \mathbf{R}$ at time 2. This factor is bought at the adjusted price Δp_k at time 1, which is compounded to time 2 by multiplying it by the USD gross risk-free rate R_F. Hence, the representative intermediary's optimization problem reads

$$\{-\hat{q}_1/\mu, \ldots, -\hat{q}_K/\mu\} = \arg \max_{\{y_1,\ldots,y_K\}} \mathbb{E}\left[-\exp\left(-\sum_{k=1}^{K} \gamma_k y_k (\mathbf{b}_k^\top \mathbf{R} - R_F \Delta p_k)\right)\right]. \tag{7}$$

Applying the first-order condition to (7) and using the assumption that $\text{var}(\mathbf{r}) = \text{var}(\mathbf{R})$, Proposition 1 determines the equilibrium price response for each factor.

PROPOSITION 1 (Price sensitivity to trading-induced risks). *Denoting $\lambda_k = \gamma_k/(\mu R_F)$, the price response of factor k is*

$$\Delta p_k = \lambda_k \hat{q}_k \text{var}(\mathbf{b}_k^\top \mathbf{r}). \tag{8}$$

The parameter λ_k is termed the "price sensitivity to trading-induced risks" of factor k, or simply "price sensitivity to risks." By equation (8), we can express λ_k as follows:

$$\lambda_k = \frac{\Delta p_k}{\hat{q}_k \text{var}(\mathbf{b}_k^\top \mathbf{r})}. \tag{9}$$

Here, Δp_k represents the price response of factor k at time 1. The denominator, $\hat{q}_k \text{var}(\mathbf{b}_k^\top \mathbf{r})$, measures the change in the quantity of risk due to the marginal demand shock to the factor. Consequently, λ_k captures the price compensation that intermediaries require for absorbing the marginal increase in *traded* risk. This concept extends the canonical price of risk that measures price compensation required for taking on an extra unit of *unconditional* risk. Note that in our simple model, λ_k is not a function of intermediaries' pre-existing holdings at time 1, as we do not model nonlinear constraints (e.g., position limits).

We highlight three features of the price sensitivity to risks λ_k. First, because the traded risk factors have uncorrelated returns by construction, the equilibrium solution from (7) implies that demand shocks $\hat{q}_k$ affect only the price of factor k, without influencing any other factors. Appendix A.2 provides a proof. Second, λ_k is invariant to scaling or sign reversal of a factor. This highlights that, economically, $\lambda_k \approx \gamma_k/\mu$ reflects the intermediaries' risk-bearing capacity, or their per-capita risk aversion to that factor. While λ_k is linked solely to γ_k and μ in our stylized model, the empirical estimate of λ_k may also reflect other constraints that intermediaries face when accommodating trading-induced risks for factor k. Calibrating to the estimated λ_k would require a more sophisticated macro-finance model that incorporates these additional features, which is beyond the scope of this paper. Third, the price sensitivity to risks is defined in terms of risks rather than securities, unlike the inverse demand elasticity $(\Delta P/P)/(\Delta Q/Q)$ commonly used in industrial organization. Although quantities of securities are readily observable, in markets where marginal agents optimize their portfolios to diversify risks, the quantities of risks are more relevant.

2.4 Cross-Multiplier

We now appeal to the law of one price and determine the cross-multiplier between individual currencies by using factor-level price sensitivities to risks. Consider the scenario where currency m experiences a \$1 demand shock (a one-dollar change to $\hat{f}_m$), while customers' demand for all other currencies remain constant. First, as in equation (6), this additional \$1 demand shock to currency m would increase the demand shock $\hat{q}_k$ to factor k by an amount $\beta_{m,k}$. Second, changes in factor-k demand shock affect its price by $\Delta p_k = \lambda_k \text{var}(\mathbf{b}_k^\top \mathbf{r})$ (Proposition 1). Finally, changes in factor-k price Δp_k affect currency-n price $\Delta \hat{p}_n$ through the law of one price, with the sensitivity being $\beta_{n,k}$. Following this logic, Proposition 2 computes the model-implied cross-multiplier. Appendix A.3 provides a proof.

PROPOSITION 2 (Cross-multiplier). *The cross-multiplier between currencies n and m is:*

$$\frac{\partial \Delta \hat{p}_n}{\partial \hat{f}_m} = \sum_{k=1}^{K} \frac{\partial \hat{q}_k}{\partial \hat{f}_m} \times \frac{\partial \Delta p_k}{\partial \hat{q}_k} \times \frac{\partial \Delta \hat{p}_n}{\partial \Delta p_k} = \sum_{k=1}^{K} \beta_{m,k} \times \lambda_k \text{var}(\mathbf{b}_k^\top \mathbf{r}) \times \beta_{n,k}. \tag{10}$$

The model-implied cross-multiplier has two features. First, the own-multiplier

$$\frac{\partial \Delta \hat{p}_n}{\partial \hat{f}_n} = \sum_{k=1}^{K} \beta_{n,k}^2 \times \lambda_k \text{var}(\mathbf{b}_k^\top \mathbf{r}) \tag{11}$$

is always positive as long as λ_k is positive. Positive λ_k indicates that intermediaries are averse to bearing trading-induced risks rather than risk-seeking. On the other hand, the cross-multiplier between two currencies could be negative, if the currencies have opposite signs of beta loading to a factor, which reflects complementarity. We return to this point empirically in Section 6.1.

Second, the cross-multiplier *as channeled through traded risk factors* is symmetric between any two currencies n and m, as shown by

$$\frac{\partial \Delta \hat{p}_n}{\partial \hat{f}_m} = \frac{\partial \Delta \hat{p}_m}{\partial \hat{f}_n}. \tag{12}$$

This symmetry arises because

$$\frac{\partial \hat{q}_k}{\partial \hat{f}_n} = \beta_{n,k} = \frac{\partial \Delta \hat{p}_n}{\partial \Delta p_k}. \tag{13}$$

The first equality, relating currency to factors in terms of quantity, follows from our portfolio theory (6), while the second equality, relating currency to factors in terms of price, results from the law of one price. Both relationships are governed by the beta of currency n to factor k, which gives rise to the symmetry.

3 Data

To identify traded risk factors, we need data on FX trading and returns. In this section, we outline the various data sources that we use.

3.1 Trading Data

Our FX trading data come from the CLS Group (CLS), which provides settlement services for FX trades conducted by its 72 settlement members, primarily large multinational banks.[19] As the largest single source of FX execution data, CLS covers over 50% of global FX volumes.

We use daily aggregate FX order flow data from CLS, which includes the total value of buy and sell orders between Banks and their customers in 17 currencies from September 2012 to December 2023. The currencies in our sample are: U.S. dollar (USD), Australian dollar (AUD), Canadian dollar (CAD), Swiss frank (CHF), Danish kroner (DKK), Euro (EUR), British pound (GBP), Hong Kong dollar (HKD), Israeli shekel (ISL), Japanese yen (JPY), Korean won (KRW), Mexican peso (MXN), Norwegian kroner (NOK), New Zealand dollar (NZD), Swedish kroner (SEK), Singaporean dollar (SGD), and South African rand (ZAR). All trades involve Banks as one counterparty, including trades by bank-affiliated dealers and hedge funds transacting through prime brokers. We interpret Banks' trading as representing the activities of the specialist intermediary in our model. Counterparties to Banks are grouped into three categories: Funds (e.g., mutual funds, pension funds, sovereign wealth funds), Non-bank Financials (e.g., insurance companies, clearing houses), and Corporates.

[19] A list of settlement members can be found at https://www.cls-group.com/communities/settlement-members/.

To measure the *total* FX risk borne by intermediaries, we are the first to jointly analyze the CLS flows data on FX spot (e.g. Ranaldo and Somogyi, 2021; Roussanov and Wang, 2023) alongside data on FX forwards and swaps.[20] Due to the pronounced negative correlation between flows into spot versus forward and swap, excluding either can underestimate the price sensitivity to risks (see Supplemental Appendix B). The CLS forward and swap data are organized by maturity buckets. We estimate FX spot exposure from these future-settled contracts by discounting the notional using forward rates.[21] Aggregating across spot, forward, and swap, we construct the USD-valued total daily net customer inflow for each currency.

To align with our instruments, we analyze trading and return at the weekly frequency. Weekly flows are calculated by summing daily flows from Thursday to the following Wednesday. Our final trading data is a panel spanning 2012-09-06 to 2023-12-31, consisting of weekly net inflow into 16 non-USD currencies, measured in USD, across spot, forward, and swap transactions.

3.2 Return Data

We obtain the forward and spot data for the 16 non-USD currencies in our sample from Bloomberg. All prices are recorded at the London close, consistent with CLS trading data, which also follow London FX market hours.

We define the weekly currency return as the result of borrowing USD at the US risk-free rate, converting to foreign currency at the spot exchange rate, earning the foreign risk-free rate, and converting back to USD at the future spot rate. For currency n from week t to $t+1$, we define $r_{t+1,n} = s_{t+1,n} - s_{t,n} + i_{t,n} - i_{t,USD} - x_{t,n} = s_{t+1,n} - f_{t,n}$, where s is the log spot rate, f is the log forward rate, i is the net risk-free rate, and x is the deviation from the covered interest-rate parity (CIP). Exchange rates are defined as USD per one unit of foreign currency, so a higher s corresponds to USD depreciation. Our currency return includes the CIP deviation, $x_{t,n} = f_{t,n} - s_{t,n} - i_{t,USD} + i_{t,n}$, to more accurately reflect the actual return that intermediaries have when absorbing customer flows, including inventory costs from balance sheet constraints.

[20]Conceptually, FX swaps should not expose intermediaries to currency risk, as the spot and forward legs offset each other. However, residual currency risk may remain. Our results are effectively unchanged if swaps are excluded.

[21]Specifically, we use the 1-week forward rate for contracts maturing in 1-7 days, the 1-month forward rate for contracts maturing in 8-35 days, the 3-month forward rate for contracts maturing in 36-95 days, and the 1-year forward rate for contracts maturing in more than 96 days. The choice for these rates reflects bucket maturity ranges and forward contract liquidity.

3.3 Other Data

We collect sovereign bond auction data to instrument for FX demand shocks. Specifically, we source announcement information on auctions of bonds with maturities of one year or longer from government websites in the U.S., Australia, Canada, France, Germany, Italy, Japan, and the U.K.

To construct excess returns in six non-FX asset classes, we use the following data. For credit default swaps (CDS), we obtain five Markit indices from Bloomberg (North America investment grade and high yield, Europe main and crossover, and Emerging Market), with returns defined from the seller's perspective. For commodities, we use six Bloomberg commodity futures return indices (energy, grains, industrial metals, livestock, precious metal, and softs). For corporate bonds, we use five Bloomberg indices on U.S. corporate bonds by credit rating (Aa, A, Baa, high yield; excluding AAA to avoid collinearity with the risk-free rate). For equities, we use the "Market" return from Ken French's website, which aggregates value-weighted returns of U.S. publicly traded firms in CRSP. For options, we calculate leverage-adjusted option portfolio returns on S&P 500 call and put prices from OptionMetrics, following Constantinides, Jackwerth, and Savov (2013). For US Treasury bonds, we use yields of the six maturity-sorted "Fama Bond Portfolios" from CRSP, excluding Treasury bills due to correlation with the risk-free rate. Finally, we use the 1-month U.S. Libor as a proxy for the risk-free rate.

The Bloomberg CDS data begin in 2007, OptionMetrics data end in December 2022, and all other asset classes data span January 2000 to December 2023.

4 Traded Risk Factors in FX

In this section, we identify the most important traded FX factors from data. We first find that three risk factors account for most of the non-diversifiable risks induced by FX trading. We then interpret these factors as the Dollar, the Carry, and the Euro-Yen. Finally, we show that these factors cannot be obtained by the standard PCA on returns or flows alone.

4.1 Baseline Traded FX Factors

Our objective is to identify risk factors that capture the effect of FX trading on currency prices in the cross-section. To this end, we focus on factors that maximally explain trading-induced risks. Using the procedure detailed in Section 2.2, we derive the traded FX factors from weekly net flows ($\mathbf{f}$) and log returns ($\mathbf{r}$) of 16 non-USD currencies.[22] The three factors

[22]We use aggregate flows across all customer types to identify total trading-induced risks from the intermediaries' perspective. Trades from different customers may carry different informational content but pose

that explain the most amount of trading-induced risk are reported in Table 1. Each column of Table 1 represents a factor, and the component values are the currency weights in this factor.[23] For example, in Factor 1, for every \$1 bought, \$0.15-worth of CAD and \$0.5-worth of EUR are sold.[24] Because the identified risk factors are traded, they place greater weight on widely traded currencies. Notably, six developed economy currencies — AUD, CAD, CHF, EUR, GBP, and JPY — have consistently high weights across the top three factors; they are highlighted in red along with USD. Of the total trading-induced non-diversifiable risks, $\sum_{k=1}^{K} \mathrm{var}(q_k)\mathrm{var}(\mathbf{b}_k^\top \mathbf{r})$, the top three traded FX factors individually account for 65%, 16%, and 9%, respectively. Jointly, these three factors explain approximately 90% of the risks intermediaries bear when accommodating trading flows.[25]

4.2 Interpretation of Traded FX Factors

To better understand the risks captured, we conjecture and verify that the top three traded FX factors represent the Dollar, the Carry, and the Euro-Yen, respectively. Factor 1 in Table 1 assigns negative weights to all non-USD currencies, resembling the proverbial Dollar portfolio that shorts all non-USD currencies to bet on the USD exchange rate. We therefore propose a traded Dollar factor that goes long in USD and shorts the six most traded currencies (AUD, CAD, CHF, EUR, GBP, and JPY) in equal weights. Factor 2 has positive weights on high-interest-rate currencies (e.g., AUD, CAD, GBP) and negative weights on low-interest-rate currencies (e.g., JPY, CHF, EUR), consistent with the proverbial Carry portfolio that exploits violations of uncovered interest-rate parity (UIP). We propose a traded Carry factor that goes long in AUD, CAD, and GBP, and shorts CHF, EUR, and JPY, all in equal weights. Factor 3 features a large positive weight on EUR and a large negative weight on JPY, motivating a traded Euro-Yen factor that goes long in EUR and shorts JPY in equal weights. The rationale is that, because EUR and JPY are traded in the same direction in both Dollar and Carry factors, these factors do not capture the bilateral trading flows between the Euro area and Japan, two of the world's largest economies.

These proposed factors are economically meaningful but may be correlated. To address this, we apply the procedure described in Section 2.2 to orthogonalize them. In particular, this process transforms the proposed EUR-JPY pair (long EUR, short JPY) into the Euro-Yen factor, which is uncorrelated with the Dollar and Carry factors. In other words, the

the same balance-sheet or inventory risk.

[23]The portfolio weight of USD is the negative sum of the weights of all other currencies.

[24]To facilitate comparison, we have scaled such that factor 1 has a weight of 1 for USD, factor 2 has all positive weights sum to 1 and all negative weights sum to -1, and factor 3 has a weight of -1 for JPY.

[25]The traded FX factors are robust to sample period changes. Table SA3 in the Supplemental Appendix shows high correlations in returns and flows between factors from the full sample and pre-/post-2020 subsamples: nearing 1 for the first factor and exceeding 0.8 for the other two.

Table 1: **Top 3 Traded FX Factors**

Currency	Factor 1	Factor 2	Factor 3
AUD	-0.08	0.14	-0.08
CAD	-0.15	0.56	-0.87
CHF	-0.03	-0.07	-0.02
DKK	-0.01	0	0.02
EUR	-0.5	-0.43	1.16
GBP	-0.11	0.18	0.09
HKD	0	-0.01	0.02
ILS	0	0	0
JPY	-0.07	-0.49	-1
KRW	-0.01	0.01	-0.01
MXN	-0.01	0.02	-0.03
NOK	-0.01	0.02	-0.01
NZD	-0.01	0.02	-0.01
SEK	-0.01	0.01	-0.01
SGD	-0.01	0	0.02
ZAR	-0.01	0.01	-0.01
USD	1	0.03	0.74
Var explained	65%	16%	9%

Notes: This table presents the portfolio weights of the top 3 traded FX factors, constructed following the procedure in Section 2.2. The return and flow data for 16 non-USD currencies are weekly from September 2012 to December 2023. The portfolio weight of USD is computed as the negative sum of the weights of all other currencies.

Euro-Yen factor captures the portion of non-diversifiable risk that intermediaries bear when absorbing EUR-JPY pair trading, after hedging out exposures to the Dollar and Carry factors. Empirically, for every dollar traded in the EUR-JPY pair, 13% of the risk is attributed to the Dollar factor, 25% to the Carry factor, and 62% to the Euro-Yen factor.

The data support our interpretation of the traded FX factors. Using data on individual currencies, we construct factor returns and factor flows. Table 2 shows the correlation between returns and flows of the baseline factors ("PC Factors") from Table 1 and returns and flows of the factors constructed from the proposed Dollar, Carry, and Euro-Yen weights ("Economic Factors"). The correlations are nearly 1 for both returns and flows across all three factors. Together, the three Economic Factors explain about 86% of trading-induced non-diversifiable risks, closely matching the risks accounted for by the PC Factors. Given this striking similarity and to avoid potential in-sample overfitting concerns with PC Factors, we focus on analyzing the more interpretable Economic Factors for the remainder of the paper.

Table 2: **Correlation between Return and Flow for Baseline PC Factors versus for Proposed Economic Factors**

	Factor 1	Factor 2	Factor 3
Return	0.98	0.95	0.92
Flow	1.00	0.99	0.95
Var explained by Economic Factors	63%	15%	8%

Notes: This table shows the correlation between return and flow for the baseline traded FX factors in Table 1 ("PC Factors") and for the traded FX factors constructed from the proposed factor weights of the Dollar, the Carry, and the Euro-Yen ("Economic Factors"). It also shows the fraction of trading-induced risks explained by the Economic Factors.

Panel (a) of Figure 1 plots the cumulative flows to the three traded FX factors.[26] During our sample period, customers purchased approximately \$1 trillion of the Dollar factor from intermediaries, primarily after the 2020 COVID crisis. This provision of USD by intermediaries likely reflects USD deposits or wholesale funding made available by (dealer-affiliated) banks (Du and Huber, 2024), as some intermediaries, especially dealers, may not be able to maintain a sustained inventory imbalance. For the Carry factors, customers initially refrained from large directional bets but began selling off the Carry factor post-2022. As a result, intermediaries including dealers and hedge funds accumulated \$0.8 trillion in Carry trade exposure between 2012 and 2023. Finally, customers sold the Euro-Yen factor up until the 2020 COVID crisis, after which they started repurchasing some, but not all, positions. This left the intermediaries with a net positive position in the Euro-Yen factor throughout the sample period. As JPY acts as a "funding currency" (negative weight) in both the Carry and Euro-Yen factors, our analysis highlights that the unwinding of intermediaries' short JPY positions cannot solely be attributed to the Carry trade.

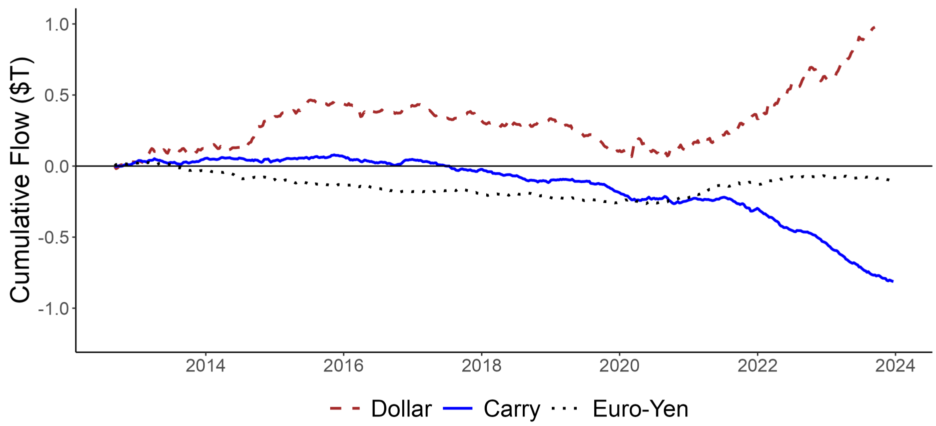
Panel (b) of Figure 1 plots the cumulative returns of the three factors over our sample period. We observe that all three factors enjoy positive returns, including the Euro-Yen factor. We formally investigate the unconditional risk premium of these factors in Section 5.1.

4.3 Standard PCA on Returns or Flows Fails to Identify Traded Risk Factors

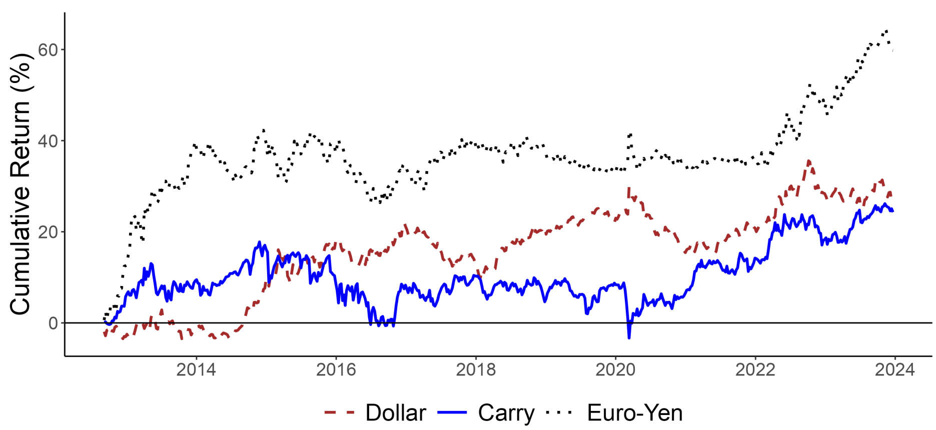
We demonstrate that a standard PCA applied solely to returns or flows fails to identify the traded FX factors. The results underscore the empirical value of using our approach to

[26]Figure SA2 in the Supplemental Appendix provides a breakdown of factor flows by customer type.

Figure 1: **Cumulative Flow and Return of Top 3 Traded FX Factors**



(a) **Cumulative Flow**



(b) **Cumulative Return**

Notes: This figure displays the cumulative flows and returns of the top three traded FX factors between September 2012 and December 2023. Flows are measured from the perspective of customer purchases (intermediary sales). For instance, the figure indicates that customers bought approximately $1 trillion of the Dollar factor from intermediaries during this period.

jointly analyze returns and flows.

The first three columns of Table 3 show the portfolio weights for the first three principal components of a standard PCA applied to returns.[27] The first factor resembles a Dollar factor, with negative loadings on all currencies. The second factor assigns large positive weights to some high-interest-rate currencies such as ZAR and MXN, and large negative

[27]The eigenvectors from a return PCA represent individual currencies' betas to the factors. We convert these betas into portfolio weights using the pseudoinverse of the beta matrix, following the factor-mimicking portfolio approach of Fama and MacBeth (1973).

Table 3: **Top 3 PCs from FX Returns or Flows**

Currency	Return PCA			Flow PCA		
	PC 1	PC 2	PC 3	PC 1	PC 2	PC 3
AUD	-0.08	0.04	0.27	-0.03	0.03	0.12
CAD	-0.05	0.05	0.32	-0.04	1	-0.06
CHF	-0.05	-0.21	-0.51	-0.01	-0.02	-0.06
DKK	-0.06	-0.15	-0.12	0	0	0.01
EUR	-0.06	-0.15	-0.13	-1	-0.03	0.03
GBP	-0.07	-0.08	0.47	-0.02	-0.01	0.26
HKD	0	0	0	0	-0.02	0
ILS	-0.04	-0.03	0.24	0	-0.01	0
JPY	-0.03	-0.17	-1	-0.04	-0.06	-0.95
KRW	-0.06	0.02	-0.15	0	0.01	0
MXN	-0.08	0.22	0.71	-0.01	0.01	0
NOK	-0.1	-0.05	0.72	0	0.01	0.01
NZD	-0.08	0.01	0.13	-0.01	0.01	0.01
SEK	-0.08	-0.13	0.22	0.01	0	0
SGD	-0.04	-0.03	-0.12	-0.01	-0.01	0.01
ZAR	-0.11	0.29	-1.35	-0.01	0	0.01
USD	1	0.37	0.29	1.17	-0.92	0.62

Notes: The first three columns display the portfolio weights for the first three principal components from a return PCA, while the second three columns show those from a flow PCA. The analysis uses weekly data for 16 non-USD currencies spanning September 2012 to December 2023. The USD portfolio weight is calculated as the negative sum of the weights of all other currencies.

weights to some low-interest-rate currencies like CHF, JPY, and EUR. However, it also assigns very small positive weights to other high-interest-rate currencies like AUD and NZD and even a negative weight to GBP and NOK.[28] The third factor lacks a clear economic interpretation. In contrast, our approach of jointly analyzing flows and returns yields a significant traded risk factor that is unambiguously the Carry and reveals an economically meaningful Euro-Yen factor.

The next three columns of Table 3 report the portfolio weights for the first three principal components of a standard PCA applied to flows. The resulting portfolios from this approach primarily allocate weight to a single major currency. For instance, the first factor assigns a portfolio weight of -1 to EUR and 0 to all other non-USD currencies, reflecting that EUR/USD is the most actively traded pair. The second and third principal components

[28] Lustig, Roussanov, and Verdelhan (2011) identify the Carry factor from the second principal component after sorting currencies into six portfolios based on interest rate levels.

Table 4: **Unconditional Risk Premium**

Panel A: Sep 2012 to Dec 2023			
	Dollar	Carry	Euro-Yen
Mean return (annualized %)	2.38	2.15	5.26
Sharpe ratio (annualized)	0.35	0.26	0.56
Fama-MacBeth premium (annualized %)	2.42	3.34	3.58
t-stats	(1.15)	(1.22)	(1.12)
Panel B: Jan 2000 to Dec 2023			
	Dollar	Carry	Euro-Yen
Mean return (annualized %)	-0.16	2.09	1.99
Sharpe ratio (annualized)	-0.02	0.23	0.20
Fama-MacBeth premium (annualized %)	-0.07	3.02	1.00
t-stats	(-0.04)	(1.41)	(0.40)

Notes: This table presents the annualized mean return and Sharpe ratio of the three traded FX factors. Additionally, it reports the Fama-MacBeth factor premium along with t-statistics calculated using Shanken-corrected standard errors. Panel A is based on weekly returns from September 2012 to December 2023, while Panel B uses weekly returns from January 2000 to December 2023.

correspond to the CAD/USD and JPY/USD pairs, respectively. This outcome occurs because the flow PCA identifies portfolios based solely on the largest trading volumes, entirely overlooking the strong factor structure in returns.

5 Pricing Properties of Traded FX Factors

In this section, we study the traded FX factors' unconditional risk premium and their price sensitivity to trading-induced risks.

5.1 Unconditional Risk Premium

Panel A of Table 4 reports the annualized mean returns and Sharpe ratios of the three traded FX factors based on weekly returns from September 2012 to December 2023. Notably, the newly proposed Euro-Yen factor achieves an annualized return exceeding 5% and a Sharpe ratio of 0.56, both meaningfully higher than those of the other two factors. To evaluate the cross-sectional pricing power of these factors, we estimate the Fama-MacBeth factor premia.[29] The Fama-MacBeth premia of the three factors are similar to their mean returns

[29]We follow the Fama-MacBeth two-step procedure: first, time-series regressions of each currency's return on factor returns estimate betas; second, cross-sectional regressions of average currency returns on these betas

estimated from the time series, though we caution that the estimated Fama-MacBeth premia are not statistically significant, which may partly reflect that the portfolios are static and not conditionally rebalanced as in Lustig, Roussanov, and Verdelhan (2011).

Our sample period begins in September 2012 due to the availability of CLS data. To further explore unconditional risk premia, we extend the sample to start in 2000 (introduction of the Euro) and report the results in Panel B. In this longer sample, the Euro-Yen factor exhibits a time-series mean return and Sharpe ratio comparable to the Carry factor. In the cross-section, the Carry factor demonstrates considerably stronger pricing power than the other two factors.

5.2 Price Sensitivity to Trading-Induced Risks

We aim to estimate λ_k, the price sensitivity to trading-induced risks of traded FX factor k in equation (8). Because the traded FX factors are constructed to have uncorrelated returns, we use Proposition 1 to estimate λ_k factor-by-factor without worrying about cross-factor substitution. However, for each factor, we must instrument for the unobserved demand shocks that are orthogonal to changes in fundamentals. Specifically, we regress each factor's risk-adjusted returns[30] on its instrumented weekly flows, $\hat{q}_{k,t}$:

$$r_{k,t}/\text{var}(r_{k,t}) = \lambda_k \hat{q}_{k,t} + \epsilon_{k,t}, \text{ where} \tag{14}$$

$$q_{k,t} = \theta_k z_{k,t} + e_{k,t}, \tag{15}$$

$$\text{cov}(z_{k,t}, \epsilon_{k,t}) = 0. \tag{16}$$

The instruments (z_k) for the observed factor flows (q_k) must be both relevant (equation (15)) and valid (equation (16)). We propose sovereign bond auction announcements as instruments.[31] Government entities, such as the U.S. Treasury, periodically auction off long-term debt obligations, e.g., U.S. Treasury notes and bonds. Foreign investors actively participate in these auctions; for instance, they directly purchased on average 14% of U.S. Treasury notes and bonds sold at auctions between September 2012 and December 2023.[32] Auction announcements prompt foreign investors to exchange domestic currencies for local currencies, making these instruments relevant.

(excluding the constant) recover the factor premium. Standard errors are corrected following Shanken (1992).

[30]Each factor's weekly observed return $r_{k,t}$ is normalized by its annualized return variance, $\text{var}(r_{k,t})$, so the regression coefficient estimates the price sensitivity to risk λ_k, as defined in Proposition 1.

[31]We focus on auctions for securities with maturities of longer than a year, as short-term securities are typically bought by domestic investors such as money market funds.

[32]This 14% excludes foreign purchases made indirectly through U.S. investment funds and dealers, so the actual figure may be higher.

We also argue that the instruments are valid. First, auction announcements are plausibly exogenous to FX trading because auctions follow strong fiscal cyclicality and are largely predetermined. For example, the U.S. Treasury Borrowing Advisory Committee (TBAC) issues two-quarter-ahead recommendations on debt issuance for upcoming auctions. Actual issuance of long-term debt (maturities of longer than a year) rarely deviates from these recommendations (Rigon, 2024).[33] Second, auction announcements plausibly satisfy the exclusion restriction that their effect on exchange rates arises solely through FX trading. One concern is that announcements might affect FX by changing fundamentals ($\epsilon_{k,t}$), but because auctions are heavily forward-guided, announcements likely contain limited new information. Another concern is that auction announcements might induce excess bond trading, affecting bond prices and spilling over to FX. However, empirically, Wachtel and Young (1990) find that while Treasury auction *results* move bond yield, the *announcements* have no detectable effect. Thus, any impact on FX is likely driven solely by announcement-induced FX demand shocks.

To validate that our instruments generate genuine demand shocks, we test whether the resulting price responses are temporary and revert over time. As discussed in Section 2, true demand shocks move currency prices initially (at time 1) but do not persist (at time 2). Figure SA3 in the Supplemental Appendix confirms that the contemporaneous price responses of all three factors fully revert within a month.

As the traded FX factors place weights on multiple currencies, we consider sovereign auction announcements from a panel of countries. Specifically, U.S. Treasury auction announcements instrument demand shocks to the Dollar factor; Australian, Canadian, British, and Japanese government bond auction announcements instrument shocks to the Carry factor, and Euro-Area government bond auctions (aggregating German, French, and Italian auctions) instrument for the Euro-Yen factor. For each auction, we aggregate the offered amount across all announcements in a week, consistent with FX trading flows. To instrument for factor flows in week t, we use same-week announcements for the Dollar and Carry factors and announcements from weeks $t-1$ and t for the Euro-Yen factor. This longer window accounts for potential delays in auction-induced currency conversion, as Germany, France, and Italy do not allow direct bids from foreign investors. Finally, we remove any linear trend in auction sizes over time.

Table 5 presents the λ_k estimation results for the Dollar, Carry, and Euro-Yen factors. For all three factors, the estimated price sensitivity to trading-induced risks is positive and statistically significant. Recall that the regression (14) normalizes each factor's return by

[33] Similarly, Germany's Finance Agency releases an annual auction calendar each December, specifying target amounts for each auction.

Table 5: **Estimated Price Sensitivity to Trading-Induced Risks**

	Dollar		Carry		Euro-Yen	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Factor flow	0.072***	0.107***	0.132***	0.138**	0.139***	0.335*
	(0.009)	(0.037)	(0.018)	(0.064)	(0.021)	(0.195)
Response per $B (bps)	3.4	5.0	8.9	9.3	12.2	29.3
1st stage F-stat		24.8		6.5		3.8
Anderson-Rubin CI				(0.01, 2.39)		(0.09, 1.91)
Observations	590	386	590	228	590	560

Notes: This table presents the λ_k estimation results for the Dollar, Carry, and Euro-Yen factors, based on regression (14). The response of factor prices to demand shocks, measured per billion dollars, is calculated as the product of λ_k and the annualized return variance. The IV regressions report the first-stage heteroscedasticity and autocorrelation consistent (HAC) effective F-statistics and the Anderson-Rubin confidence intervals at the 90% confidence level. The estimation period spans September 2012 to December 2023, excluding the first half of 2020. Newey-West standard errors are reported in parentheses, where the bandwidth is chosen by the Newey and West (1994) selection procedure. *$p<.1$; **$p<.05$; ***$p<.01$.

its variance. As a result, the estimated λ_k captures the price response to one unit of risk induced by $1 billion of factor flow and is directly comparable across factors. Both OLS and IV estimates show that the price sensitivity to risks is the smallest for the Dollar, higher for the Carry, and highest for the Euro-Yen. This indicates that intermediaries bear marginal risks most effectively in the Dollar factor, with their risk-bearing capacity progressively lower for the Carry and the Euro-Yen. Viewed through Proposition 1, the cross-factor variation in price sensitivity to risks may reflect differences in available arbitrage capital across risk factors, with lesser-known factors like Euro-Yen attracting less arbitrage capital.[34] The OLS estimates are slightly smaller than the IV estimates, reflecting the instrument's role in mitigating bias from the correlation between information-driven price changes $\epsilon_{k,t}$ and contemporaneous customer flows q_k. This correlation is negative because customers trade against fundamentals: they buy when news causes a currency to depreciate and sell when it appreciates. Such behavior is consistent with the profitability of momentum strategies in FX (Menkhoff, Sarno, Schmeling, and Schrimpf, 2012).[35]

To compare the magnitude of our estimated price sensitivity to risks with the literature,

[34]The annualized volatility of customer flows is $85 billion for the Dollar factor, $34 billion for the Carry factor, and $22 billion for the Euro-Yen factor.

[35]In a rational market, prices would adjust to fundamental news without trading (Milgrom and Stokey, 1982). However, when customers buy in response to negative fundamental news, prices under-react, leading to subsequent price drift and generating momentum.

we multiply each factor's λ_k by its return variance to calculate the factor-level price response per billion of demand shocks, as shown in the second row of Table 5. A \$1 billion demand shock increases the prices of the Dollar, Carry, and Euro-Yen factors by 5, 9, and 29 basis points, respectively.[36] These price responses are large compared to U.S. equities, where a \$1 billion demand shock to the entire U.S. stock market raises the aggregate price by about 1.7 bps (Gabaix and Koijen, 2021).[37] We think that the supply of FX arbitrage capital is likely limited due to the specialized nature of the FX market, where only sophisticated participants like bank dealers and hedge funds absorb demand shocks.[38] This may seem counterintuitive given the large turnover in FX, but up to 75% of trades occur between intermediaries (BIS, 2022), suggesting that the arbitrage capital available to absorb shocks is much smaller than the total turnover.[39]

Finally, the precision of IV estimation depends on the strength of the instrument. The heteroscedasticity and autocorrelation consistent (HAC) effective F-statistics for the Dollar, the Carry, and the Euro-Yen factors are 24.8, 6.5, and 3.8, respectively. The effective F-statistics for the Carry and the Euro-Yen are below the rule-of-the-thumb threshold of 10. To assess the implications of potentially weak instruments on IV inference, we compute the Anderson-Rubin confidence interval, which has the correct coverage regardless of the strength of the instrument (Andrews, Stock, and Sun, 2019). For both the Carry and the Euro-Yen, the Anderson-Rubin confidence interval is bounded away from zero, but is very wide in the positive direction. In other words, we are reasonably confident that the price sensitivity to risks is not zero but much less certain that the true value is not larger. A larger estimate would mean an even greater price sensitivity to risk.

5.3 Time-Varying λ and the Role of Risk

Our representative intermediary framework posits that price responses to trading stem from intermediaries' sensitivity to risk. In the previous subsection, we discussed patterns in the estimated λ consistent with this view — for instance, specialization may limit arbitrage

[36] In a dynamic setting, the persistence of demand shocks can influence price response, as intermediaries anticipate future demand (e.g., Campbell and Kyle, 1993; Wang, 1993; Jansen, Li, and Schmid, 2024). Our estimates reflect the average level of persistence over the sample period.

[37] Gabaix and Koijen (2021) find that a 1% greater demand shock to the entire US stock market increases price by 5%. Given an average market capitalization of \$31.7 trillion between 2012 and 2022, a \$1 billion demand shock raises the price of the market factor by 1.7 bps over our sample period.

[38] The limited FX arbitrage capital may also reflect slow-moving capital and the fact that our price sensitivity to risks is estimated based on a weekly horizon, shorter than the monthly or quarterly horizons typically considered in the literature. Asset markets tend to be more inelastic over shorter horizons as long-term investors are slower to react to price changes and provide arbitrage capital (Duffie, 2010).

[39] Of the FX trades accounted for in the BIS Triennial Central Bank Survey, 46% are between reporting dealers, 22% with non-reporting dealers, and 7% with hedge funds, all of which are intermediaries in our model and captured in Banks in the data.

capital and risk-bearing capacity, resulting in larger price responses. In this subsection, we seek more direct evidence that risk drives observed price responses to trading. Specifically, we examine whether λ depends on time-varying wealth or constraints that alter intermediaries' risk-return trade-off.

We consider two proxies. First, we use intermediary equity returns to capture intermediaries' wealth.[40] Second, we use deviations from covered interest-rate parity (CIP) to capture intermediaries' constraints, as such deviations indicate intermediaries' inability to exploit known profitable trades.[41]

Table 6 presents potential determinants of the Dollar factor's weekly return.[42] Column (1) suggests that the Dollar factor reflects variations in intermediary equity returns. However, Column (2) clarifies that intermediary equity returns do not directly affect the Dollar's return. Instead, they influence λ, consistent with a risk-based view of price response: as intermediaries' wealth increases, their effective risk aversion decreases, reducing the price response to absorbing demand shocks (instrumented using U.S. Treasury auction announcements). This state-dependent response is driven specifically by intermediaries' wealth, as Columns (3) and (4) show that broader stock market returns have no comparable effect on λ. Conceptually, intermediaries' constraints may also affect price response: when constraints prevent intermediaries from fully exploiting profitable investment opportunities, they become more selective, leading to higher effective risk aversion and lower risk-bearing capacity. Empirically, the effects of such constraints, proxied by CIP deviations, are directionally consistent with the risk-return trade-off but, as shown in Column (6), not statistically significant.

6 Cross-Currency and Cross-Asset-Class Multiplier

In this section, we use the traded FX factors' estimated price sensitivity to risks to study the propagation of demand shocks among currencies and asset classes. We quantify demand propagation with cross-multipliers: the effect of a shock to demand for one asset on the price of another, holding all other demand constant.

[40] Following He, Kelly, and Manela (2017), we construct the value-weighted weekly return of primary dealers' bank holding companies. This series is highly correlated (0.95) with the KBW NASDAQ bank index over our sample period and is equivalent to the intermediary capital ratio shock (0.98 correlation) in He, Kelly, and Manela (2017).

[41] We calculate the weekly average cross-currency basis using the AUD-JPY currency pair and 3-month IBOR.

[42] We focus on the state-dependency of the Dollar factor's λ because it is the most important traded FX factor, and its flow instrument has the highest statistical power.

Table 6: **Time-Varying λ for the Dollar Factor**

	Weekly Return of Dollar Factor					
	(1)	(2)	(3)	(4)	(5)	(6)
Intermed. ret	-0.490***	-0.109				
	(0.119)	(0.204)				
Flow × Intermed. ret		-0.091***				
		(0.033)				
S&P ret			-0.148	-0.077		
			(0.096)	(0.314)		
Flow × S&P ret				0.006		
				(0.074)		
CIP deviation					0.081	0.182
					(0.060)	(0.177)
Flow × CIP deviation						0.063
						(0.129)
Factor flow		0.096***		0.106***		0.160*
		(0.037)		(0.040)		(0.093)
Observations	559	385	559	385	559	385

Notes: This table reports the IV-estimated time-varying λ for the Dollar factor. "Interm. ret" is the value-weighted weekly equity return of primary dealers' bank holding company. "S&P ret" is the weekly return of the S&P 500 index. "CIP deviation" is measured by the weekly average AUD-JPY 3-month IBOR cross-currency basis. All three variables are demeaned and standardized. All factor flows are instrumented with U.S. Treasury auction announcements. Newey-West standard errors are reported in parentheses, where the bandwidth is chosen by the Newey and West (1994) selection procedure. *p <.1; **p <.05; ***p <.01.

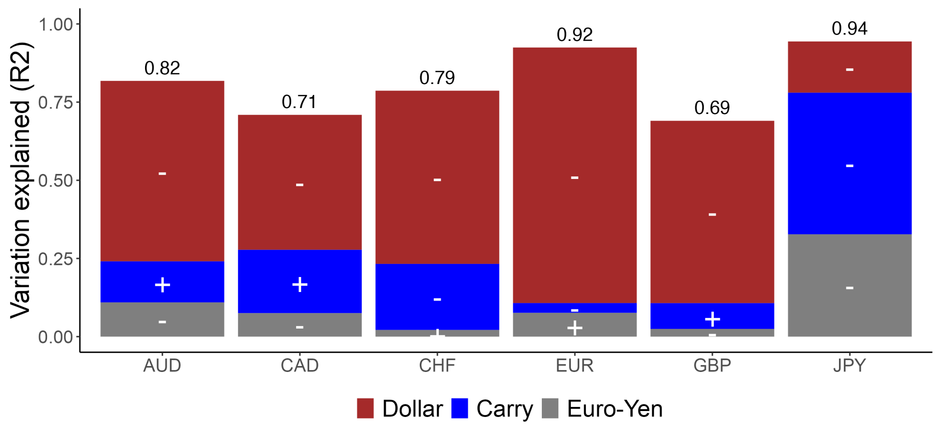
6.1 Cross-Currency Multiplier

For a traded FX factor to affect currency-level cross-multipliers, the currencies must load on the factor. Figure 2 demonstrates the relevance of the traded FX factors in explaining individual currency returns. Regressing currency-level returns on the returns of the Dollar, the Carry, and the Euro-Yen factors in the time series, we plot the marginal R^2 attributed to each factor and indicate the direction of the beta loadings.[43] Together, the three factors explain between 69% and 94% of individual currency returns.

The decomposition in Figure 2 provides a framework to analyze the risk implied in demand shocks. For instance, when a customer buys $1 of AUD from intermediaries, Figure 2 shows that intermediaries attribute 60% of the total risk to the Dollar factor, 10% each

[43] Because the returns of different factors are uncorrelated by construction, the regression R^2 from each factor is additive.

Figure 2: **Decomposition of Currency Returns Explained by Traded FX Factors**



Notes: This figure plots the R^2 of regressing currency-level returns against the returns of the Dollar, the Carry, and the Euro-Yen factors in the time series. It plots the marginal R^2 values attributed to each factor and labels the total R^2. The positive and negative signs illustrate the direction of the beta loadings.

to the Carry and Euro-Yen factors, and 20% to idiosyncratic risk unexplained by the three factors. The direction of factor loadings further reveals that intermediaries perceive the customer's $1 purchase (and their $1 sale) of AUD as the customer selling the Dollar and Euro-Yen factors while buying the Carry factor.

Combining the information in Figure 2 with the IV estimated price sensitivity to risks λ_k, we compute the cross-currency multipliers according to Proposition 2 and report the results in Table 7. For clarity, we have arranged the six major currencies (AUD, CAD, GBP, CHF, EUR, JPY) in the upper left quadrant, followed by the other ten currencies in the sample. Each entry shows the price response in one row (column) currency, in basis points, to a $1 billion demand shock to the corresponding column (row) currency. For instance, the entry of 7.9 in the first row and second column indicates that a $1 billion demand shock to the CAD (AUD) raises the price of AUD (CAD) by 7.9 bps (in percentage terms), holding the demand for all other currencies equal. Because the model-implied cross-multiplier is symmetric, we report only the upper half. The diagonal entries represent each currency's own multiplier. As USD is the numeraire, the own multiplier is also the currency's cross-multiplier with USD.

Table 7 reveals several interesting patterns of cross-currency multipliers. First, all entries are positive. This is because all currencies load on the Dollar factor in the same direction, which is the most important traded risk factor in the cross-section. Second, the cross-multiplier between currencies on the long leg of the Carry trade (e.g., AUD, CAD, GBP) and those on the short leg (e.g., CHF, EUR, JPY) is generally smaller. This modest cross-

Table 7: **Cross-Currency Multiplier**

	AUD	CAD	GBP	CHF	EUR	JPY	DKK	HKD	ILS	KRW	MXN	NOK	NZD	SEK	SGD	ZAR
AUD	12.0	7.9	9.0	2.1	2.8	5.9	2.8	0.2	4.7	6.3	7.8	10.4	10.4	5.9	4.3	11.0
CAD		5.3	5.9	0.7	1.6	2.6	1.6	0.1	3.0	4.0	5.3	6.8	6.7	3.7	2.6	7.2
GBP			7.4	3.1	4.0	3.2	3.9	0.1	3.9	5.0	6.2	8.9	8.0	6.1	3.5	8.8
CHF				8.6	7.3	4.1	7.3	0.0	2.4	2.4	1.1	5.1	2.7	6.5	2.4	3.2
EUR					7.4	0.2	7.4	0.1	2.5	2.4	2.5	6.1	3.1	7.1	2.3	4.2
JPY						16.2	0.2	0.0	2.3	4.0	0.9	3.5	5.7	1.1	3.1	4.0
DKK							7.4	0.1	2.5	2.4	2.5	6.0	3.1	7.1	2.3	4.2
HKD								0.0	0.1	0.1	0.1	0.2	0.1	0.1	0.1	0.2
ILS									2.1	2.7	3.1	4.8	4.2	3.5	2.0	4.6
KRW										3.6	4.0	5.9	5.6	3.9	2.5	5.9
MXN											5.7	7.3	6.6	4.6	2.6	7.5
NOK												11.1	9.4	8.2	4.3	10.5
NZD													9.1	5.7	3.9	9.6
SEK														7.7	3.1	6.8
SGD															1.9	4.1
ZAR																10.5

Notes: This table uses Proposition 2, the estimated factor-level price sensitivity to risks λ_k from Table 5, and the beta loadings of currencies to factors (signs illustrated in Figure 2) to compute currency-level cross-multiplier. Each entry represents the percentage price change in bps of a row (column) currency, as induced by a \$1 billion demand shock to a column (row) currency, holding the demand in all other currencies equal. As noted after Proposition 2, the model-implied cross-multiplier is symmetric, so we report only the upper half.

multiplier owes to opposite beta loadings with respect to the Carry factor, which makes currencies in one of these two groups hedge currencies in the other group in risk exposures to the Carry factor. In IO, such phenomena are typically referred to as complementarity. Third, we note that although EUR and JPY are both low-interest-rate currencies, we estimate a rather small cross-multiplier because the two currencies are on the opposite side of the Euro-Yen factor. This result suggests that EUR and JPY are not entirely substitutable.

Moreover, although we analyze traded FX factors constructed based on the six major currencies and USD, we recover meaningful cross-multiplier in other currencies due to these currencies' loadings on the three traded FX factors. As a sanity check of our methodology, we examine the cross-multiplier for HKD, a currency pegged to USD within a narrow band of 1%. While we do not use this pegged information in our estimation, the estimated cross-multipliers in the entire column and row associated with HKD are close to zero. This minimal impact reflects the nature of a pegged currency: its own demand shocks have negligible risk implications for other currencies, and its exchange rate relative to USD is largely unaffected by demand shocks to other currencies.

6.2 Cross-Asset-Class Multiplier

If other asset classes load on the traded FX factors, demand shocks can propagate through common exposures. We analyze six non-FX asset classes: credit default swap (CDS), commodities (Comm), corporate bonds (CorpBond), equities (Equity), equity options (Opt), and US Treasury bonds (UST).[44] Similar to Figure 2, we regress the monthly excess returns of each asset class from 2000-02 to 2023-12 on the Dollar, Carry, and Euro-Yen returns, and present the R^2 decomposition in Figure 3.[45,46]

The three traded FX factors jointly explain between 15% (commodities) and 41% (equities) of the returns in the six non-FX asset classes we examine. Interestingly, while the Dollar factor is statistically significant across all six asset classes, it is least important in explaining the return of U.S. Treasury bonds (Treasurys).[47] Moreover, while all other asset classes load positively on the Carry factor, Treasurys load negatively. This contrast suggests that large shocks to the Carry factor could drive divergent price movements between Treasurys and

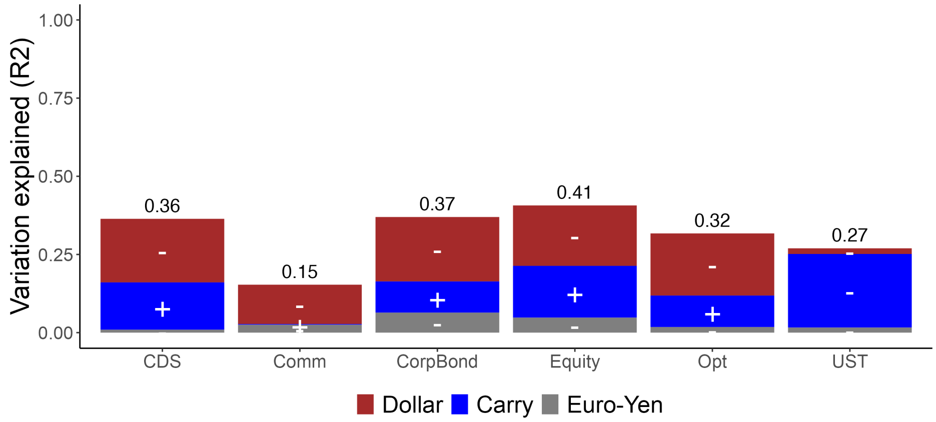
[44]We construct the return of each asset class as the equal-weighted average return of all available portfolios; see also Section 3.3.

[45]By construction, the correlation among weekly factor returns is zero. The correlation among monthly factor returns is close to zero. We report the incremental R^2 by adding the factors sequentially in the order of the Dollar, the Carry, and the Euro-Yen.

[46]We also explore the explanatory power of traded FX factors for other assets' returns outside crisis periods (e.g., GFC, Covid). The results, shown in Figure SA4 of the Supplemental Appendix, are largely similar.

[47]One possible reason for this attenuated connection is that foreign investors hedge a substantial amount of the USD FX risks associated with their securities holdings, especially bonds (Du and Huber, 2024).

Figure 3: **Decomposition of Asset-Class Returns Explained by Traded FX Factors**



Notes: This figure plots the R^2 of regressing individual asset's monthly excess returns against the returns of the Dollar, the Carry, and the Euro-Yen factors in the time series. It plots the marginal R^2 values attributed to each factor and labels the total R^2. The positive and negative signs illustrate the direction of the beta loadings. The estimation period is from 2000-02 to 2023-12. The returns from CDS are available starting in 2007-04. The returns from Opt end in 2022-12.

Table 8: **Cross multiplier Between Assets Due to Traded FX Factors**

	CDS	Comm	CorpBond	Equity	Opt	UST
CDS	2.4	3.5	3.2	5.8	4.7	-0.5
Comm		8.9	6.0	9.5	7.7	0.7
CorpBond			4.8	8.3	6.5	-0.2
Equity				14.6	11.4	-0.9
Opt					9.3	-0.6
UST						0.7

Notes: This table uses Proposition 2, the estimated factor-level price sensitivity to risks λ_k from Table 5, and the beta loadings of assets to factors (signs illustrated in Figure 3) to compute asset-level cross-multiplier. Each entry represents the percentage price change in bps of a row (column) asset, as induced by a \$1 billion demand shock to a column (row) asset, holding the demand for all other assets equal. As noted after Proposition 2, the model-implied cross-multiplier is symmetric, so we report only the upper half.

other assets. Finally, while the Euro-Yen factor is less prominent in non-FX asset classes, it explains a non-negligible share of returns in corporate bonds and equities.

Similar to Table 7, we report cross-multipliers between asset classes in Table 8.[48] Ex-

[48]The cross-multiplier between the traded FX factors and these six non-FX asset classes are reported in

amining the last column of Table 8, we recover two salient features of Treasurys while using only assets' factor loadings and factors' price sensitivity to risks. First, the price response to a demand shock is smallest for Treasurys, corroborating the observation that the Treasury market is deep and liquid. Second, Treasurys uniquely exhibit negative cross-multipliers with most other asset classes. A \$1 billion demand shock to Treasurys raises their price but depresses the price of other assets, reflecting Treasurys' "safe haven" property. Our estimation captures this behavior because only Treasurys load negatively on the commonly priced Carry factor.

We raise two cautions in interpreting our estimated cross-asset multiplier. First, our estimates capture only the price response driven by exposure to the three traded FX factors. They may not represent the total price response to a \$1 demand shock to an asset, as these assets may also load on other traded risk factors that we do not capture. Second, by using λ_k from the traded FX factors to inform multipliers in other asset markets, our analysis implicitly assumes that the marginal intermediaries are the same across different markets. Departures from this assumption may alter the magnitude but not the mechanism of demand propagation.

7 Conclusion

In conclusion, this paper studies the propagation of demand shocks through traded risk factors. If asset prices respond to risks and marginal agents can diversify risks across assets, then demand shocks transmit by affecting non-diversifiable risks, as captured by traded risk factors. We identify the most important traded risk factors by extending the concept of priced non-diversifiable risks (Ross, 1976) to a representative intermediary framework (He and Krishnamurthy, 2017) and developing a method that integrates trading and returns data. We find that three factors — the Dollar, Carry, and Euro-Yen — jointly account for 90% of non-diversifiable FX trading risks. These factors are priced unconditionally and, using instrumental variables, we estimate these factors' price sensitivity to trading-induced risk. Finally, combining factors' price sensitivity with assets' factor exposure, we link trading quantities to asset prices (Froot and Ramadorai, 2008; Koijen and Yogo, 2019) through *risks*, deriving novel cross-asset price multipliers for a panel of 17 currencies and across 7 major asset classes, underscoring the role of common risk exposure in driving cross-asset dynamics (Haddad and Muir, 2021; Du, Hébert, and Huber, 2023).

A distinguishing feature of our paper is the use of factor-level price sensitivity to inform cross-multipliers at both the currency and asset-class levels. At the heart of this cross-

Table SA4 of the Supplemental Appendix.

asset demand transmission are three key elements: how demand shocks alter the amount of non-diversifiable factor risks borne by marginal agents, how risk prices adjust to induce agents to absorb these incremental risks, and how different assets are exposed to these risks. By integrating these three elements, we uncover novel transmission patterns where demand shocks in one market propagate across others with varying magnitudes and even directions. As asset markets become increasingly interconnected, understanding how demand shocks propagate through common risk exposure is crucial for predicting and managing systemic market dynamics.

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A Appendix for Proofs

This appendix provides proofs omitted in the main text.

A.1 Solution for Traded Risk Factors

In this appendix, we present solutions for traded risk factors in Section 2.2.

We conduct Cholesky decomposition of $\text{var}(\mathbf{r})$ as $\mathbf{U}^\top\mathbf{U}$. Then, we define $\mathbf{g}_k = \mathbf{U}\mathbf{b}_k$ for each factor k. Equation (1) implies that the factor-level flow is

$$q_k = (\mathbf{b}_k^\top \text{var}(\mathbf{r})\mathbf{b}_k)^{-1}\mathbf{b}_k^\top \text{var}(\mathbf{r})\mathbf{f} = (\mathbf{g}_k^\top \mathbf{g}_k)^{-1}\mathbf{g}_k^\top \mathbf{U}\mathbf{f}. \tag{A1}$$

Moreover, the sequential optimization problem (3) becomes

$$\begin{aligned} &\max_{\mathbf{g}_k} (\mathbf{g}_k^\top \mathbf{g}_k)^{-1}\text{var}(\mathbf{g}_k^\top \mathbf{U}\mathbf{f}) \\ &\text{s.t.}\, \mathbf{g}_k^\top \mathbf{g}_j = 0 \text{ for } k \neq j. \end{aligned} \tag{A2}$$

This becomes a standard PCA problem that is solved by the eigenvalue decomposition of the matrix $\text{var}(\mathbf{U}\mathbf{f})$ (Jolliffe, 1986). The eigenvectors are $\mathbf{g}_k$ and the corresponding eigenvalues are proportional to the fraction of explained variance. Once we obtain $\mathbf{g}_k$, the portfolio weights are obtained by $\mathbf{b}_k = \mathbf{U}^{-1}\mathbf{g}_k$.

A.2 Proof of Proposition 1

Simplifying equation (7), we have

$$\begin{aligned} &\mathbb{E}\left[-\exp\left(-\sum_{k=1}^{K}\gamma_k y_k(\mathbf{b}_k^\top \mathbf{R} - R_F\Delta p_k\right)\right] \\ =& -\exp\left[-\sum_{k=1}^{K}\left(\gamma_k y_k \mathbb{E}[\mathbf{b}_k^\top \mathbf{R}] - \gamma_k R_F y_k \Delta p_k - \gamma_k^2 y_k^2 \text{var}(\mathbf{b}_k^\top \mathbf{R})/2\right)\right], \end{aligned} \tag{A3}$$

where the last equality uses the fact that $\text{cov}(\mathbf{b}_k^\top \mathbf{R}, \mathbf{b}_j^\top \mathbf{R}) = 0$ for $k \neq j$. Taking the first-order condition with respect to y_k and evaluating it at the optimal $y_k = -\hat{q}_k/\mu$, we obtain

$$\Delta p_k = \frac{\text{var}(\mathbf{b}_k^\top \mathbf{R})\gamma_k \hat{q}_k/\mu + \mathbb{E}[\mathbf{b}_k^\top \mathbf{R}]}{R_F}. \tag{A4}$$

Using the fact that $\Delta p_k = 0$ when $\hat{q}_k = 0$, along with the assumption that $\text{var}(\mathbf{r}) = \text{var}(\mathbf{R})$, we derive equation (8).

A.3 Proof of Proposition 2

Because factors have uncorrelated returns by equation (3), we can project the return of any currency n onto the factors and obtain

$$r_n = \sum_{k=1}^{K} \beta_{n,k} \mathbf{b}_k^\top \mathbf{r} + e_n, \tag{A5}$$

where e_n is the idiosyncratic return of currency n that is uncorrelated with any factor $\mathbf{b}_k^\top \mathbf{r}$. Hence, by the law of one price and equation (8), the price response of currency n is

$$\Delta \hat{p}_n = \sum_{k=1}^{K} \beta_{n,k} \Delta p_k = \sum_{k=1}^{K} \lambda_k \hat{q}_k \mathrm{var}(\mathbf{b}_k^\top \mathbf{r}) \beta_{n,k}. \tag{A6}$$

Therefore, we have

$$\frac{\partial \Delta \hat{p}_n}{\partial \hat{q}_k} = \frac{\partial \Delta p_k}{\partial \hat{q}_k} \times \frac{\partial \Delta \hat{p}_n}{\partial \Delta p_k} = \lambda_k \mathrm{var}(\mathbf{b}_k^\top \mathbf{r}) \times \beta_{n,k}. \tag{A7}$$

Next, equation (6) implies that $\partial \hat{q}_k / \partial \hat{f}_m = \beta_{m,k}$. Hence, we have proved

$$\frac{\partial \Delta \hat{p}_n}{\partial \hat{f}_m} = \sum_{k=1}^{K} \frac{\partial \hat{q}_k}{\partial \hat{f}_m} \times \frac{\partial \Delta \hat{p}_n}{\partial \hat{q}_k} = \sum_{k=1}^{K} \beta_{m,k} \times \lambda_k \mathrm{var}(\mathbf{b}_k^\top \mathbf{r}) \times \beta_{n,k}. \tag{A8}$$

Supplemental Appendix of
"Demand Propagation Through Traded Risk Factors"

A Invariance of Factors under Alternative Numeraire Currency

In this appendix, we prove that the factors constructed in Appendix A.1 remain unchanged when we alter the numeraire currency used to measure demand shocks and returns.

Suppose we switch from using USD to the N-th currency as the numeraire. We denote the demand shock from the N-th currency to the n-th currency as $\tilde{f}_n$ for $n = 1, 2, \ldots, N-1$, and the demand shock from the N-th currency to USD as $\tilde{f}_N$. Recall that f_n represents the demand shock from USD to the n-th currency. Because each demand shock f_n (for $n = 1, 2, \ldots, N-1$) can be broken down into a component from USD to the N-th currency and another from the N-th currency to the n-th currency, we can express this transformation as follows:

$$\tilde{\mathbf{f}} = (\tilde{f}_1, \tilde{f}_2, \ldots, \tilde{f}_{N-1}, \tilde{f}_N)^\top = \left(f_1, f_2, \ldots, f_{N-1}, -\sum_{n=1}^{N} f_n \right)^\top = \mathbf{C}\mathbf{f}, \tag{SA1}$$

where we define the matrix

$$\mathbf{C} := \begin{pmatrix} 1 & 0 & \ldots & 0 & 0 \\ 0 & 1 & \ldots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \ldots & 1 & 0 \\ -1 & -1 & \ldots & -1 & -1 \end{pmatrix}. \tag{SA2}$$

Similarly, returns are now measured relative to the N-th currency. Specifically, $\tilde{r}_n$ for $n = 1, 2, \ldots, N-1$ represents the return from borrowing at the N-th currency's riskfree rate to invest in the n-th currency's riskfree rate. Similarly, $\tilde{r}_N$ denotes the return from borrowing at the N-th currency's riskfree rate to invest in the USD riskfree rate. The transformation of returns can thus be described as follows:

$$\tilde{\mathbf{r}} = (\tilde{r}_1, \tilde{r}_2, \ldots, \tilde{r}_{N-1}, \tilde{r}_N)^\top = (r_1 - r_N, r_2 - r_N, \ldots, r_{N-1} - r_N, -r_N)^\top = \mathbf{C}^\top \mathbf{r}. \tag{SA3}$$

Now, we apply Appendix A.1 to analyze the factors using $\tilde{\mathbf{r}}$ and $\tilde{\mathbf{f}}$. Specifically, the variance of $\tilde{\mathbf{r}}$, given by $\mathrm{var}(\tilde{\mathbf{r}}) = \mathbf{C}^\top \mathrm{var}(\mathbf{r})\mathbf{C}$, can be decomposed as $\mathbf{C}^\top \mathbf{U}^\top \mathbf{U}\mathbf{C} = \tilde{\mathbf{U}}^\top \tilde{\mathbf{U}}$, where $\tilde{\mathbf{U}} := \mathbf{UC}$. Subsequently, the eigenvalue decomposition is transformed to

$$\tilde{\mathbf{U}}\text{var}(\tilde{\mathbf{f}})\tilde{\mathbf{U}}^\top = \mathbf{UCC}\text{var}(\mathbf{f})\mathbf{C}^\top\mathbf{C}^\top\mathbf{U}^\top = \mathbf{U}\text{var}(\mathbf{f})\mathbf{U}^\top, \tag{SA4}$$

where we use the fact that $\mathbf{CC} = \mathbf{I}_N$. This derivation reveals that the eigenvectors $\mathbf{g}_k$ and eigenvalues are invariant. The resulting portfolio weights under the new numeraire currency are given by $\tilde{\mathbf{b}}_k = \tilde{\mathbf{U}}^{-1}\mathbf{g}_k = \mathbf{C}^{-1}\mathbf{U}^{-1}\mathbf{g}_k = \mathbf{C}^{-1}\mathbf{b}_k$. Hence, the factor returns also remain invariant, because $\tilde{\mathbf{b}}_k^\top\tilde{\mathbf{r}} = \mathbf{b}_k^\top(\mathbf{C}^{-1})^\top\mathbf{C}^\top\mathbf{r} = \mathbf{b}_k^\top\mathbf{r}$.

B Inclusion of Non-spot FX Derivatives Trading Flows

Foreign exchange trades can be executed in the spot market and in the derivatives market of forwards and swaps. Trading in the derivatives market can expose the intermediary to foreign exchange risk. Consider a customer-initiated trade of selling \$100-worth of JPY 1-month forward against USD. In the absence of other trades, an intermediary who has no capital, maintains a net neutral FX exposure, and serves as the counterparty in this trade, must satisfy the obligation to deliver \$100 in a month by setting aside $\$100/(1+r^{\$}_{1M})$ today, where $r^{\$}_{1M}$ is the 1-month USD risk-free rate. Similarly, the intermediary will sell $100/(1+r^{JPY}_{1M})$ of JPY today to both fund his USD purchase and to ensure FX neutrality when he receives the promised delivery from the customer. To the intermediary, therefore, a forward contract is no different from a spot transaction but for the fact that the amount of implied FX exposure in a forward is less than its notional.

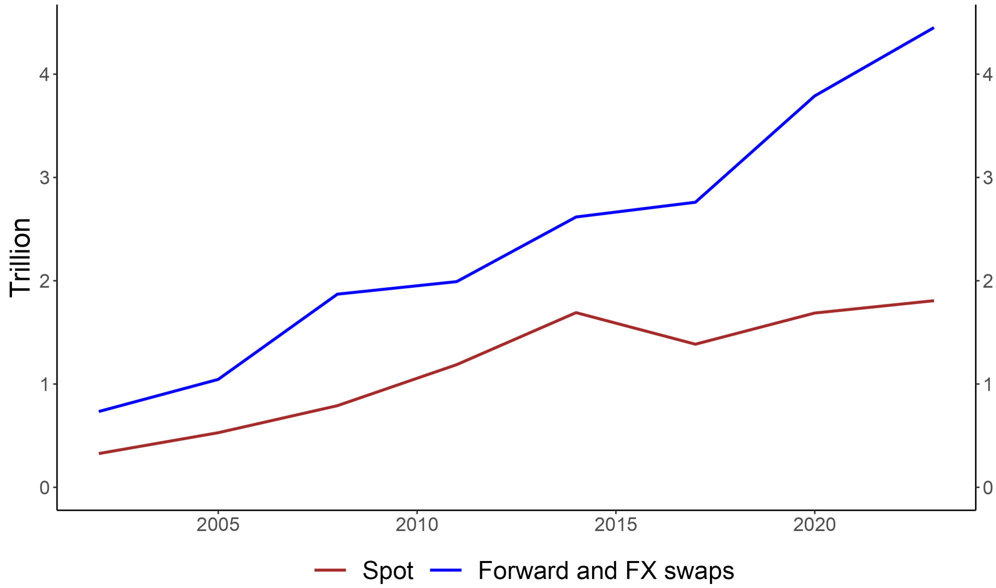
Because we are interested in measuring all the FX risks that intermediaries have to bear by accommodating customer trading flows, we need to consider trading flows in both the spot and the derivatives market.[49] In this appendix, we explore the difference between trading flows into the spot versus the derivatives market and the implications of using trading data in only one of the two markets in our analysis.

We start by examining the observed trading flows into individual currencies. The triennial survey conducted by the Bank of International Settlement (BIS) indicates that there is twice as much trading flow in the FX derivatives market as in the spot market (Appendix Figure SA1). Appendix Table SA1 reports the correlation between the net flow into the spot versus the derivatives market for each of the six major currencies in our sample. The absolute strength of the correlation ranges between 0.17 and 0.62, suggesting sizeable comovements in trading flows between the spot and the derivatives FX market.

Comovements in observed trading flows could be induced by common risk factors that

[49] We treat swaps as a spot transaction plus a forward contract.

Figure SA1: **FX Daily Turnover Against USD**



Notes: This figure plots the global daily volume of foreign exchange spot versus forward and FX swaps transactions involving USD. Daily volume is calculated as the average of all trading days in April of the survey year. The survey is conducted triennially from 2001 to 2022 by BIS.

Table SA1: **Currency-Specific Correlation between Net Trading Flow in Spot vs. Non-Spot Derivatives**

AUD	CAD	CHF	EUR	GBP	JPY
-0.48	0.17	-0.54	-0.39	-0.62	-0.35

Notes: This table reports the correlation between net flows into individual currencies in the spot market and in the non-spot derivatives market.

are present in both the spot and the derivatives market. If so, trading data from either market alone should be sufficient to recover the traded FX risk factors. At the same time, if there are strong comovements in trading flows to the traded FX factors, then relying on data from only one market risks introducing measurement error in the estimation of price sensitivity to risks.

In Appendix Table SA2, we compare the traded FX factors recovered separately from the spot market and the non-spot derivatives market. The top row shows the correlation between *returns* of factors estimated using only one of the individual markets. For the first factor, the return correlation is close to 1, and this correlation is 77% for the second factor and 73% for the third factor. Such pronounced relationships underscore the robustness of the underlying factors and suggest that the same risk factors drive trading across the spot

Table SA2: **Correlation between Returns and Flows to Factors Estimated in Different Samples**

	Factor 1	Factor 2	Factor 3
Return	0.99	0.77	0.73
Flow	-0.51	-0.13	-0.35

Notes: This table reports the correlation between the returns and flows to each of the top three traded risk factors as estimated in the spot market versus in the non-spot derivatives market.

and the derivatives market. The bottom row shows the correlation between *flows* to factors estimated using only one of the individual markets. The correlations are -0.51, -0.13, and -0.35 for the three factors, respectively.

The marked association between factor returns and factor flows points to the strength and limitation of using only data in the spot market. On the one hand, the tight correlation between factor returns constructed using data from individual markets shows that the spot market alone is sufficient to recover the underlying risk factors because these factors drive trading in both the spot and derivatives markets. On the other hand, using only data from the spot market is likely insufficient for estimating these factors' price sensitivity to risks because the spot market data alone may not provide an appropriate measure of the flow changes. Estimating price sensitivity to risks requires instrumenting for the flow that induces the observed price change. As spot flows and derivatives flows are highly correlated, it is empirically difficult to isolate variations in just the spot flow. Specifically, because factor flows in the spot market are negatively correlated with factor flows in the derivatives market, instrumenting for just the spot market will overestimate factor flows, biasing the estimate to imply smaller price sensitivity to risks.

C Additional Figures and Tables

Table SA3: **Correlation Between Traded FX Factors in Full Sample vs. Subsamples**

		Factor 1	Factor 2	Factor 3
Return	Pre 2020	0.97	0.83	0.83
	Post 2020	1.00	0.97	0.89
Flow	Pre 2020	0.98	0.82	0.81
	Post 2020	0.99	0.96	0.81

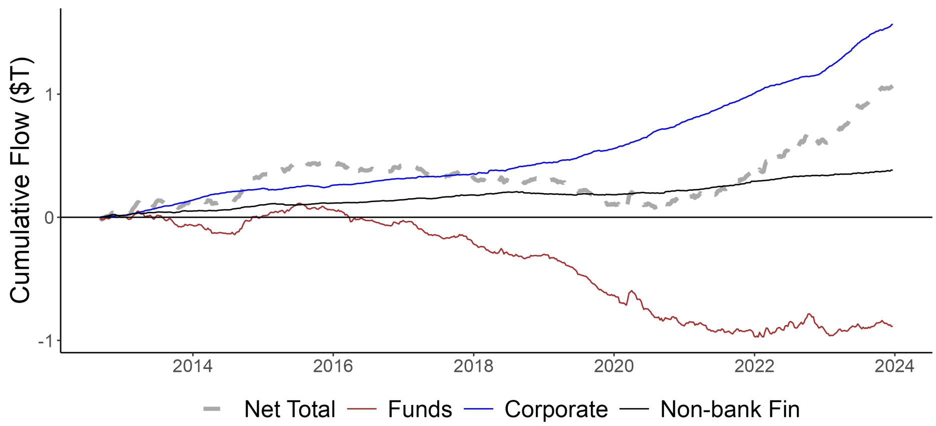
Notes: In this table, we report the correlation between returns and flows of the traded FX factors constructed based on the full sample versus returns and flows of the traded FX factors constructed based on different subsamples. Pre-2020 refers to the sample period from September 2012 to December 2019, while post-2020 refers to the sample period from January 2020 to December 2023.

Table SA4: **Cross-Multiplier between Traded FX Factors and Non-FX Asset Classes**

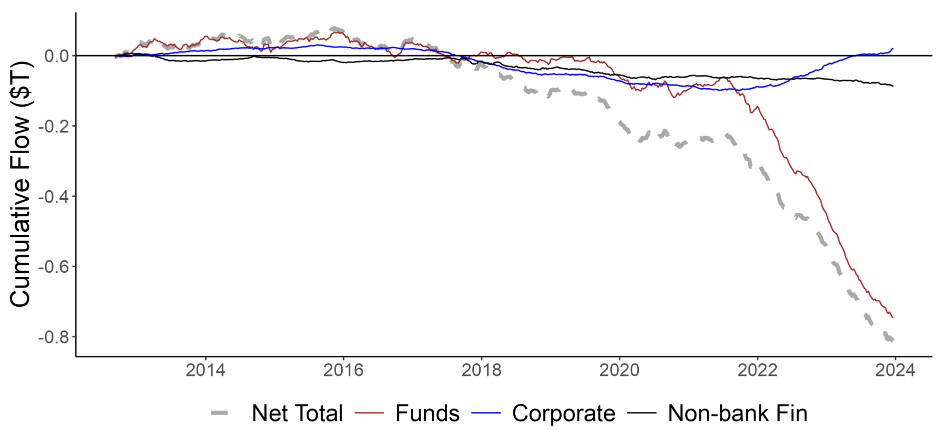
	CDS	Comm	CorpBond	Equity	Opt	UST
Dollar	-2.0	-5.0	-2.8	-4.4	-4.4	-0.5
Carry	3.7	1.6	3.7	7.9	6.1	-2.3
Euro-Yen	-2.5	-10.3	-7.3	-10.8	-6.6	-1.6

Notes: This table uses Proposition 2, the estimated factor-level price sensitivity to risks λ_k from Table 5, and the beta loadings of assets to factors (signs illustrated in Figure 3) to compute cross-multiplier between traded FX factors and six non-FX asset classes. Each entry represents the price movement in bps of a column asset, as induced by a $1 billion demand shock into a traded FX factor.

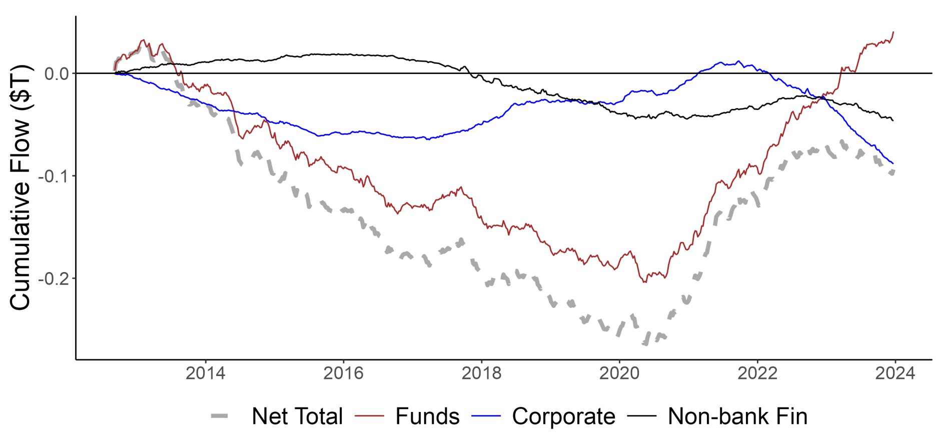
Figure SA2: **Cumulative Flow by Investor Type to Traded FX Factors**



(a) **Dollar Factor**



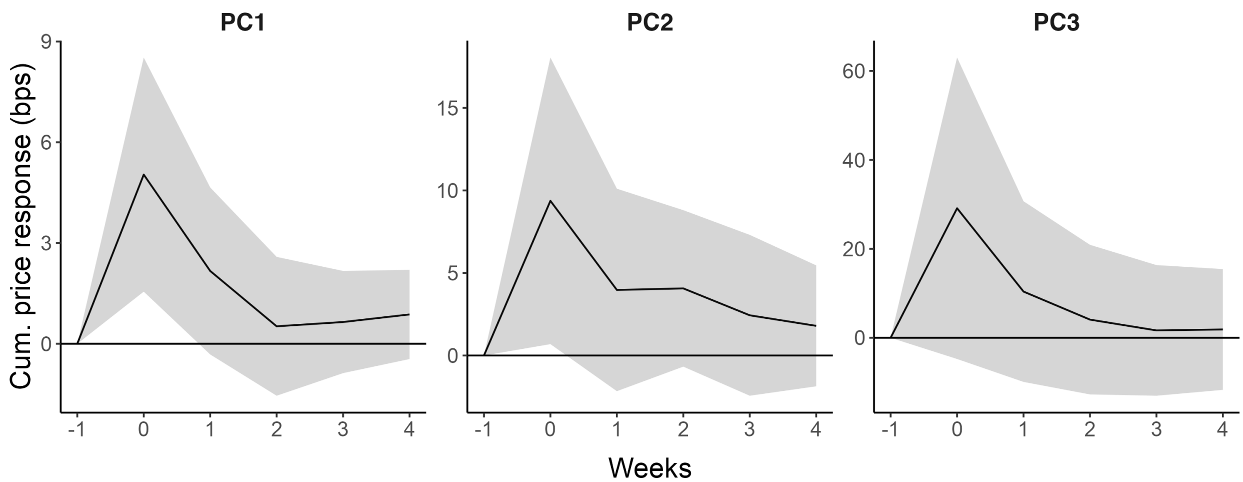
(b) **Carry Factor**



(c) **Euro-Yen Factor**

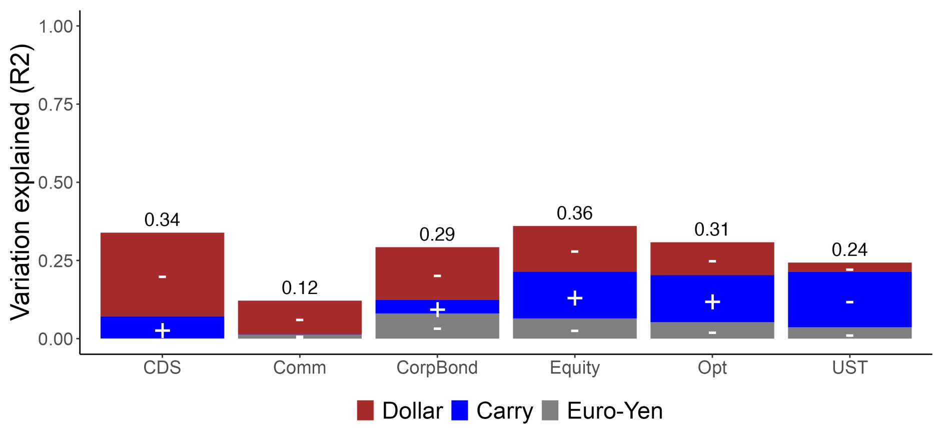
Notes: This figure displays the cumulative flows by customer type into the top three traded FX factors between September 2012 and December 2023. The Net Total represents the net customer flows that Banks (intermediaries) need to absorb.

Figure SA3: **Reversion of Contemporaneous Price Response**



Notes: This figure shows the cumulative price responses for the traded FX factors. These responses, measured per billion of demand shocks, are estimated by regressing the return from week $t-1$ to $t+h$ (for $h = 0, 1, 2, 3, 4$) on the instrumented flow from week $t-1$ to t. The shaded area represents the 95% confidence interval based on Newey-West standard errors with the bandwidth selected according to the Newey and West (1994) procedure.

Figure SA4: **Decomposition of Asset-Class Returns Explained by Traded FX Factors Outside of Crises**



Notes: This figure decomposes the returns of individual assets into the Dollar, the Carry, and the Euro-Yen factors. The decomposition is achieved by regressing asset class monthly average excess return between 2000-02 and 2023-12 on returns from the three traded FX factors. We exclude the GFC (2007-07 through 2010-07) and COVID (2020-01 through 2020-06) period. The returns from CDS are available starting 2007-04. The returns from Opt end in 2022-12. It reports both the marginal R^2 values attributed to each factor and the total R^2. The positive and negative signs illustrate the direction of the beta loadings.