

Intermediary Elasticity^{*}

Yu An[†]

Amy Wang Huber[‡]

This version: April 2024

Download most recent version [here](#).

Abstract

We study the limited risk-bearing capacity of intermediaries and its implication on asset prices. We measure intermediaries' risk-bearing capacity with a new measure: “intermediary elasticity”, which is defined as the price response to a marginal unit of risk induced by trading demand shocks. We apply our framework to the foreign exchange (FX) market and identify three key *traded* risk factors — the Dollar, the Carry, and the Pan-European — that account for 90% of the risk borne by intermediaries during FX trading. Through instrumental variable analysis, we quantify the intermediary elasticity for these factors. We then use the estimated FX-factor elasticity to recover the own- and cross-elasticity among currencies and provide novel estimates of cross-elasticity between different asset markets.

JEL Classifications: G11, G12, G15, G2

Keywords: Demand, Elasticity, Factor, Intermediary, Risk

^{*}We thank seminar participants at Temple University. We gratefully acknowledge funding from the Wharton Dean's Research Fund, the Jacobs Levy Equity Management Center for Quantitative Financial Research at the Wharton School of the University of Pennsylvania, and the General Research Support Fund at Johns Hopkins Carey Business School. All remaining errors are our own.

[†]Johns Hopkins Carey Business School. Email: yua@jhu.edu.

[‡]The Wharton School of the University of Pennsylvania. Email: amyhuber@wharton.upenn.edu.

1 Introduction

A growing literature offers evidence that financial intermediaries are central to asset pricing (for a survey, see [He and Krishnamurthy \(2017\)](#)). Liquidity, regulatory, and other constraints facing financial intermediaries lead to limited risk-bearing capacity (e.g., [Kondor and Vayanos \(2019\)](#), [Du, Hébert, and Huber \(2022\)](#)). As a result, in contrast to the traditional asset pricing paradigm, trading demand can affect asset prices in markets that are heavily intermediated (e.g., [Du and Huber \(2024\)](#)). In this paper, we study intermediaries’ limited risk-bearing capacity to risk factors that are impacted by trading demand shocks. Our results underscore the role that intermediaries play in driving cross-asset pricing dynamics.

To study intermediaries’ risk-bearing capacity, we introduce two conceptual innovations. First, we define “intermediary inverse elasticity” as the price response to a marginal unit of risk induced by trading demand shocks. For simplicity, we abbreviate it as “intermediary elasticity”. This concept is distinct from the “(inverse) elasticity of demand” in industrial organization (IO), as the latter measures price responses due to changes in the quantity of a *good* demanded. The classic asset pricing framework states that the risk premium is the product of the price of risk and the quantity of risk. An elasticity concept that is relevant to asset pricing should therefore be defined with respect to the quantity of *risk*. Our intermediary elasticity has intuitive interpretations. If the intermediary elasticity is 0, then intermediaries are able to perfectly share risks from accommodating trading and there is no limited risk-bearing capacity. Conversely, the larger the intermediary elasticity, the more limited the risk-bearing capacity.

Our second innovation involves viewing the trading of individual financial products as

transactions of underlying risk factors, thus giving us a way to quantify the risk that stems from accommodating trading shocks. Returns in many financial markets have a factor structure, and these common risk factors drive cross-sectional pricing dynamics (e.g., [Fama and French \(1993\)](#), [Lustig, Roussanov, and Verdelhan \(2011\)](#)). This suggests that if trading demand shocks mattered, they matter because these shocks alter the intermediaries' exposure to underlying risk factors. Accordingly, we use a panel data of investors' trading on individual financial products to back out the underlying risk factors that are actually traded. By combining the amount of trading to specific factors and the amount of risk inherent in these factors, we obtain the quantity of risk that intermediaries bear when accommodating trading shocks.

We study limited risk-bearing capacity in the foreign exchange (FX) market, where we obtain daily trading data from the CLS Group, the largest single source of FX executed data available to the market. We first identify three important traded risk factors: the Dollar, the Carry, and the Pan-European. These factors jointly account for 90% of the risk that intermediaries bear when accommodating FX trading flows. We then use instrumental variables to estimate the intermediary elasticity for each of the three factors, and we apply the factor-specific intermediary elasticity to recover the cross-elasticity between currencies. Finally, we show that returns in CDS, Commodity, Corporate bonds, and U.S. Treasury bonds can also be explained by the three traded FX risk factors, and we apply the estimated FX-factor elasticity to obtain novel estimates of cross-elasticity between asset markets.

We start by identifying FX risk factors that are most affected by trading shocks in 17 different non-U.S. dollar (USD) currencies. Using a weekly panel of trading flows and returns, we employ a modified Principal Component Analysis (PCA) to find portfolios that explain the largest amount of trading shocks, while simultaneously having uncorrelated returns,

endowing these portfolios with the interpretation of risk factors. Our approach contrasts with the standard PCA that can rationalize either FX trading or FX return, but not both simultaneously. A standard PCA on FX trading simply points to portfolios with the most traded currencies because it neglects the covariance in currency returns. A standard PCA on FX return, on the other hand, can surface the important risk factors priced in FX (Lustig, Roussanov, and Verdelhan (2011)). Yet it is silent on whether investors trade these factors. In fact, the risk premium of the traditional Dollar and Carry return factors is typically founded on consumption-based models with a standard stochastic discount factor (SDF) that does not rely on investor trading (Lustig and Verdelhan (2007)). If there is no trading, then there is also no role for limited risk-bearing capacity on the margin. It is therefore remarkable that, without imposing any prior knowledge on FX factors, we find the three most important traded risk factors traded by FX investors to be indeed the Dollar, the Carry, and the Pan-European factors. Moreover, the trading shocks of these three factors are uncorrelated, suggesting that investors perceive these factors as independent.

Having discovered the traded FX factors, we estimate the intermediary elasticity of these factors using instrumental variables. By construction, our traded factors have uncorrelated flows and uncorrelated returns. This allows us to estimate the intermediary elasticity factor-by-factor without worrying about cross-factor substitution. However, because we are interested in intermediaries' risk-bearing capacity, we need to instrument for trading shocks: the part of trading that is not motivated by changes in fundamentals such as the arrival of new information. We use announcements of the offering amount at upcoming sovereign bond auctions in the U.S., Australia, the U.K., and Germany to instrument for trading shocks in each of the three traded factors. These sovereign auctions often attract foreign investors who need to convert currencies to participate, making the instruments relevant. By using

offering amounts at auctions whose fundraising objectives are typically dictated by fiscal needs, we have instruments that are plausibly exogenous and meet the exclusion restriction. We estimate that the intermediaries raise the factor return by about 1% in response to a \$25 billion demand shock to the Dollar factor and a roughly \$10 billion demand shock to either the Carry or the Pan-European factor.

Using estimated intermediary elasticity to traded risk factors, we compute the own- and cross-elasticity between any pairs of currencies. Because FX trading can be highly correlated across currencies, finding the price impact of FX trading can be challenging. For example, a \$1 trading inflow into, say, the Canadian dollar (CAD), can be correlated with a commensurate *inflow* into the Japanese yen (JPY) because the investor wants to trade the Dollar factor, but the same trading into CAD could also be correlated with an *outflow* from JPY if the investor wants to trade the Carry factor. In short, there likely exists complex cross-elasticity across currencies. Our insight lies in mapping the cross-elasticity of currencies traded to the impact on the underlying risk factors. The cross-elasticity between any two currencies then, depends on how much each currency loads on the three traded FX factors and on the intermediary elasticity of the traded FX factors. Focusing on the six commonly traded advanced economy currencies, the Australian dollar (AUD), the Canadian dollar, the Swiss franc (CHF), the Euro (EUR), the British pound (GBP), and the Japanese yen, we find that their own-elasticity ranges from 6 bps to 13 bps in return impact from \$1 billion of inflow. More interestingly, we find large cross-elasticity between AUD and CAD because both currencies are traded in the same direction in the Dollar, the Carry, and the Pan-European factors. In contrast, the cross-elasticity between JPY and common Carry currencies such as AUD, CAD, and GBP is small or even negative. Negative cross-elasticity implies that two currencies are “complementary”: for example, because JPY and AUD are on the opposite

legs of the Carry trade, they hedge each other in exposures to the Carry factor.

Finally, we show that the FX traded risk factors are, in fact, not unique to the FX market. Intermediaries' presence across different asset markets therefore introduces substantial cross-substitution between assets; we provide estimates for this cross-elasticity. We find that a \$1 billion demand shock to Corporate bonds trading raises its own return by 5 bps and raises returns in CDS and Commodity by similar magnitudes. In contrast, a \$1 billion demand shock to US Treasury bonds reduces returns on CDS and Corporate bonds because US Treasury bonds have opposite loadings on the Carry factor from other assets.

We caution that our estimates only capture the cross-asset elasticity channeled through our three traded FX factors. These factors explain about 80% of the return variation for FX currencies and about 30% of the return variation for non-FX assets. This means that we may miss other factors contributing to return variations and the cross-elasticity arising due to common exposure to these missing factors. Nevertheless, our estimates highlight that although intermediaries are active in several markets, these markets do not necessarily move together. Rather, understanding how asset markets are interconnected requires understanding different assets' exposure to common risk factors and the intermediary elasticity of these factors.

More generally, this paper advances the literature on intermediary-based asset pricing on two fronts. First, we offer a way to quantify intermediaries' risk-bearing capacity. Constraints such as regulatory, liquidity, and segmentation, have all been proposed to limit intermediaries' risk-bearing capacity (e.g., [Gabaix and Maggiori \(2015\)](#), [He and Krishnamurthy \(2017\)](#), [Kondor and Vayanos \(2019\)](#)). Empirical evidence points to these constraints being priced (e.g., [Du, Tepper, and Verdelhan \(2018\)](#), [Du, Hébert, and Huber \(2022\)](#), [Duffie, Fleming, Keane, Nelson, Shachar, and Van Tassel \(2023\)](#)) but stops short of measuring the

impact of intermediaries’ risk-bearing capacity at the margin. We propose intermediary elasticity as a way to measure intermediaries’ risk-bearing capacity. We then estimate this elasticity for three most-traded FX risk factors to quantify the impact on asset prices from having intermediaries absorb risks arising from trading shocks. Second, we illustrate the nuanced cross-asset and cross-market pricing dynamics in heavily intermediated financial products. Intermediaries have been shown to matter for prices of many asset classes (e.g., [Adrian, Etula, and Muir \(2014\)](#), [He, Kelly, and Manela \(2017\)](#), [Haddad and Muir \(2021\)](#)). Because intermediaries are simultaneously active in many markets, trading shocks in one market could propagate through other markets. We provide the first set of estimates that quantifies such cross-market elasticity and highlights the potentially negative correlation across markets. Our framework of thinking about asset market connectedness through exposure to traded risk factors can have broad applications, including in policy designs such as taxes on financial transactions ([Tobin \(1978\)](#)).

Many findings in this paper relate directly to the literature on exchange rate determination. Trading flows are known to affect exchange rate because they convey information ([Evans and Lyons \(2002\)](#) and [Pasquariello \(2007\)](#)). We show that shocks to trading flows also move exchange rate, not because they reveal information but because they push intermediaries against their risk-taking capacity. In fact, we find that the risk factors that are sensitive to trading shocks are the same ones that have been shown to price the unconditional exchange rate returns ([Lustig, Roussanov, and Verdelhan \(2011\)](#)). By showing that these risk factors are traded, we enrich the understanding of why these risks are priced (e.g., [Bansal and Dahlquist \(2000\)](#), [Lustig and Verdelhan \(2007\)](#), [Ready, Roussanov, and Ward \(2017\)](#)). Finally, we add to the recent stream of literature that explores new drivers of exchange rate such as portfolio rebalancing, safe asset demand, and hedging demand (e.g., [Liao and Zhang](#)

(2020), Jiang, Krishnamurthy, and Lustig (2021), Bräuer and Hau (2022), Camanho, Hau, and Rey (2022)).

At the heart of our results is the concept of “intermediary elasticity”, which stresses that prices move in response to changes in the quantity of risk, not necessarily changes in the quantity of the traded security. The direct connection that we draw between risk factors and asset prices distinguishes our work and complements the growing literature applying the IO framework to understanding trading impacts on prices (e.g., Koijen and Yogo (2019) for the stock market, Koijen and Yogo (2020) and Jiang, Richmond, and Zhang (2024) for exchange rates, Bretscher, Schmid, Sen, and Sharma (2022) for corporate bonds). In particular, our framework emphasizes factor exposure as drivers of asset substitution, which contrasts with logit or nested logit models that characterize substitution directly at the security level. Our approach in part derives from An (2023) and is related to An, Su, and Wang (2024), who use the factor model to estimate price impacts in the equity markets. Our paper differs by focusing on the role of intermediaries in pricing risk factors, which leads to cross-elasticity between different asset markets. Our paper moreover employs a novel IV strategy and uses a unique dataset on FX trading. The FX flows data from CLS provides a rare view into market-wide currency trading, and its spot transactions have recently been used in papers that examine topics ranging from market microstructure to the impact of Fed policies (e.g. Rinaldo and Somogyi (2021), Roussanov and Wang (2023)).¹ The key distinction of our paper is the view that what matters for currency return is not necessarily the quantity of currencies traded but the amount of risk that is induced by the trading.

In the next section, we lay out our theoretical framework. We introduce the various

¹We focus not simply on spot transactions but also forward and swap transactions to obtain the full picture of the amount of risks that dealers bear. There are also papers that use CLS *unsigned* total trading volume data (e.g., Cespa, Gargano, Riddiough, and Sarno (2021), Rinaldo and Santucci de Magistris (2022)), which is in contrast to the buy versus sell differentiation in the trading order flow data that we use.

sources of data we use in Section 3 and proceed to recover the traded FX factors in Section 4. We employ an instrumental variable approach to estimate the intermediary elasticity of the traded FX factors in Section 5, and apply these estimates to recover the cross-elasticity between currency pairs. We explore the connection between the FX market and four other asset markets in Section 6, where we also present the cross-market elasticity. We conclude in Section 7.

2 Theoretical Framework

This section presents the theoretical framework of our study. In particular, we describe the construction of traded risk factors and the solution for intermediary elasticity. We also discuss potential issues in bridging the model to empirical observations.

2.1 Model Setup

There are three periods: $t = 0$, $t = 0^+$, and $t = 1$. The trading demand shock occurs from $t = 0$ to $t = 0^+$. We empirically analyze these shocks at the weekly frequency. Time $t = 1$ represents the long term, where the currency price is no longer affected by the short-term demand shock. In reality, reaching this stage can take years.

We have N foreign currencies and a domestic currency (USD). The gross risk-free rate of foreign currency n from $t = 0$ to $t = 1$ is a constant $R_{F,n}$, and the USD risk-free rate is a constant $R_{F,0}$. The time-0 price of one share of foreign currency n in USD is denoted as P_n , and the time-1 price of foreign currency n is denoted as X_n . These $X_1, X_2, \dots, X_N$ are jointly normally distributed. Consider the return of borrowing \$1 USD at the domestic risk-free rate, exchanging it to foreign currency n at time 0, investing at the foreign risk-free rate between time 0 and 1, and exchanging back to USD at time 1. This return is given by

$R_{F,n}X_n/P_n - R_{F,0}$, and we stack it as an $N \times 1$ vector:

$$\mathbf{R} = (R_{F,1}X_1/P_1 - R_{F,0}, R_{F,2}X_2/P_2 - R_{F,0}, \dots, R_{F,N}X_N/P_N - R_{F,0})^\top. \quad (1)$$

We assume, without loss of generality, that matrix $\text{var}(\mathbf{R})$ has full rank.

From time 0 to 0^+ , there is a net flow of $\$f_n$ USD into currency n , measured at the time 0 pre-flow price P_n and which we represent as an $N \times 1$ vector $\mathbf{f} = (f_1, f_2, \dots, f_N)^\top$. This flow $\mathbf{f}$ is an uninformed demand shock in that it does not influence the long-term price X_n at time 1. The short-term impact of this shock on the currency prices at time $t = 0^+$, denoted by $P_n(\mathbf{f})$, is the primary focus of our modeling.

2.2 Factor Construction

On the one hand, the returns $\mathbf{R}$ of different currencies may be correlated due to common risk factors. On the other hand, the flows $\mathbf{f}$ into different currencies might also exhibit correlations, as investors often engage in portfolio rebalancing trades involving multiple currencies. Consequently, we define two general $N \times N$ covariance matrices: $\text{var}(\mathbf{R})$ for returns and $\text{var}(\mathbf{f})$ for flows, noting that these matrices may differ. Proposition 1 asserts that, regardless of the correlations among returns and flows across different currencies, it is always possible to construct K portfolios with both uncorrelated returns and uncorrelated flows, where K is the rank of matrix $\text{var}(\mathbf{f})$. Appendix A.1 provides a proof.

PROPOSITION 1 (Factor construction). *There exist K portfolios $\mathbf{b}_k = (b_{1,k}, b_{2,k}, \dots, b_{N,k})^\top$ for $k = 1, 2, \dots, K$, satisfying:*

1. *Factor decomposition of flow:*

$$\mathbf{f} = \sum_{k=1}^K \mathbf{b}_k q_k, \text{ i.e., } \begin{pmatrix} f_1 \\ f_2 \\ \dots \\ f_N \end{pmatrix} = \begin{pmatrix} b_{1,1} \\ b_{2,1} \\ \dots \\ b_{N,1} \end{pmatrix} q_1 + \begin{pmatrix} b_{1,2} \\ b_{2,2} \\ \dots \\ b_{N,2} \end{pmatrix} q_2 + \dots + \begin{pmatrix} b_{1,K} \\ b_{2,K} \\ \dots \\ b_{N,K} \end{pmatrix} q_K, \quad (2)$$

where q_k is the flow into portfolio k .

2. *Uncorrelated return:*

$$\text{cov}(\mathbf{b}_k^\top \mathbf{R}, \mathbf{b}_l^\top \mathbf{R}) = 0 \text{ for all } k \neq l, \text{ and } \text{var}(\mathbf{b}_k^\top \mathbf{R}) = 1 \text{ for all } k. \quad (3)$$

3. *Uncorrelated flow:*

$$\text{cov}(q_k, q_l) = 0 \text{ for all } k \neq l, \text{ and } \text{var}(q_k) = \pi_k > 0 \text{ for all } k. \quad (4)$$

The K portfolios constructed by Proposition 1, each defined by its portfolio weights $\mathbf{b}_k = (b_{1,k}, b_{2,k}, \dots, b_{N,k})^\top$: investing \$1 in portfolio k results in buying $\$b_{n,k}$ of currency n . Consequently, a $\$q_k$ flow into portfolio k generates a $\$q_k b_{n,k}$ flow into currency n . This relationship is summarized by the equation $f_n = \sum_{k=1}^K q_k b_{n,k}$, presented in vector form as equation (2). Importantly, the returns to the K portfolios are by construction uncorrelated. We therefore interpret each portfolio to be a unique factor. The orthogonality conditions in equations (3) and (4) jointly signify that, from the covariance of returns and flows, we can construct K portfolios, which are K traded factors that also have uncorrelated flows.

To better understand the factors constructed in Proposition 1, we compare them with

the standard principal component analysis (PCA) factors for the flows $\mathbf{f} = \sum_{k=1}^K \mathbf{b}_k q_k$. Both methods aim for uncorrelated flows as specified in equation (4). However, the standard PCA requires the portfolio weights to be orthogonal, imposed through the condition $\mathbf{b}_k^\top \mathbf{b}_l = 0$ for all $k \neq l$, which lacks economic significance.² In contrast, the factors in Proposition 1 are constructed using a more economically meaningful condition: $\text{cov}(\mathbf{b}_k^\top \mathbf{R}, \mathbf{b}_l^\top \mathbf{R}) = 0$ for all $k \neq l$, which ensures that the returns of different factors are uncorrelated. Furthermore, the factors defined in Proposition 1 are generally unique, subject to standard issues common in PCA such as potential reordering, sign switching of factors, and duplicate eigenvalues.

Next, we provide a more economically meaningful linkage between the factor flow q_k and underlying currency flow f_n . Equation (1) shows that to go from factor flow q_k to currency flow f_n , one uses the weight $b_{n,k}$ of currency n in factor k . Conversely, to go from currency flow f_n to factor flow q_k , one should use the inverse of portfolio weights, which concerns how many factors k are held in currency n . This is precisely what the return beta $\beta_{n,k} = \text{cov}(R_n, \mathbf{b}_k^\top \mathbf{R}) / \text{var}(\mathbf{b}_k^\top \mathbf{R})$ of currency n to factor k measures. This insight of betas and portfolio weights being inverses was first discovered by Fama and MacBeth (1973), who used the inverse of betas as the mimicking portfolio weights for non-tradable factors. Hence, we have³

$$q_k = \sum_{n=1}^N \beta_{n,k} f_n. \quad (5)$$

That is, the factor flow q_k sums the flow into all individual currencies f_n , weighted by their respective risk exposures $\beta_{n,k}$ to the factor. Because we have standardized each factor's return variance to be one, $\text{var}(q_k) = \pi_k$ quantifies the total amount of flow-induced risk

²PCA imposes this restriction through the sequential maximal explanation of variance (Jolliffe (1986)).

³We denote the portfolio weights as an $N \times K$ matrix $\mathbf{B} = (\mathbf{b}_1, \mathbf{b}_2, \dots, \mathbf{b}_K)$ and factor flows as a $K \times 1$ vector $\mathbf{q} = (q_1, q_2, \dots, q_K)^\top$. Then, in matrix form, equation (2) reads $\mathbf{f} = \mathbf{B}\mathbf{q}$, and equation (3) reads $\mathbf{B}^\top \text{var}(\mathbf{R})\mathbf{B} = \mathbf{I}_K$. Therefore, we have $\mathbf{q} = \mathbf{B}^\top \text{var}(\mathbf{R})\mathbf{f} = \text{cov}(\mathbf{B}^\top \mathbf{R}, \mathbf{R})\mathbf{f}$, which implies equation (5).

explained by factor k . Empirically, we find that a few largest π_k account for the majority of $\sum_{k=1}^K \pi_k$, which allows us to use a small number of factors.

2.3 Intermediary Elasticity

By constructing factors with uncorrelated returns and flows, we can determine the price equilibrium for each factor independently, without worrying about potential interactions with other factors. We consider a scenario where each factor k has a continuum of intermediaries characterized by a total mass μ_k and a CARA risk-aversion parameter γ_k . These intermediaries collectively hold a total of $\$S_k$ in factor k at time $t = 0$ and absorb the flow q_k at time $t = 0^+$; as a result, the factor- k price changes from $P_k(0)$ at time 0 to $P_k(q_k)$ at time 0^+ . On a per-capita basis, each intermediary sells $\$q_k/\mu_k$ and retains $\$(S_k - q_k)/\mu_k$ of factor k after accommodating the flow. The equilibrium price $P_k(q_k)$ for factor k must therefore be set such that it is optimal for each intermediary to sell $y = q_k/\mu_k$ dollars or $y/P_k(0)$ units of factor k at the new price $P_k(q_k)$,

$$q_k/\mu_k = \arg \max_y \mathbb{E}[-\exp(-\gamma_k((S_k/\mu_k - y)\mathbf{b}_k^\top \mathbf{R} + R_{F,0}P_k(q_k)y/P_k(0)))]. \quad (6)$$

Here, $S_k/\mu_k - y$ multiplied by $\mathbf{b}_k^\top \mathbf{R}$ represents the time-1 payoff from holding $S_k/\mu_k - y$ dollars of factor k . Meanwhile, $R_{F,0}P_k(q_k)y/P_k(0)$ is the time- 0^+ proceeds from selling y dollars of factor k , compounded to time 1 at the gross risk-free rate $R_{F,0}$. Applying the first-order condition to (6), Proposition 2 determines the equilibrium price impact for each factor. Appendix A.2 provides a proof.

PROPOSITION 2 (Intermediary elasticity). *The price impact of factor k satisfies*

$$\Delta p_k := \frac{P_k(q_k) - P_k(0)}{P_k(0)} = \lambda_k q_k \text{var}(\mathbf{b}_k^\top \mathbf{R}). \quad (7)$$

Here, $\lambda_k = \gamma_k/(\mu_k R_{F,0})$ is approximately the per-capita risk aversion of intermediaries for factor k , because the USD gross risk-free rate $R_{F,0}$ is close to one.

The parameter λ_k is termed the “intermediary elasticity” of factor k . By equation (7), we can express λ_k as follows:

$$\lambda_k = \frac{\Delta p_k}{q_k \text{var}(\mathbf{b}_k^\top \mathbf{R})} = \frac{\Delta \text{ of risk premium}}{\Delta \text{ of quantity of risk}}. \quad (8)$$

Here, Δp_k represents the price impact of factor k from time 0 to 0^+ , and it reflects changes in the factor’s risk premium induced by the flow. The denominator, $q_k \text{var}(\mathbf{b}_k^\top \mathbf{R})$, measures the change in the quantity of risk due to the marginal flow into the factor.

The intermediary elasticity λ_k precisely measures the sensitivity of risk premium to changes in risk quantity when intermediaries absorb an incremental unit of flow. This concept extends the canonical price of risk, which is defined as the unconditional ratio of risk premium to the quantity of risk. We note that this intermediary elasticity differs from the (inverse) elasticity used in industrial organization, which is $(\Delta P/P)/(\Delta Q/Q)$ and focuses on the quantity of securities rather than the quantity of risk. One nice feature of the intermediary elasticity λ_k is that it is invariant to factor scaling because, economically, it reflects the per-capita risk aversion of intermediaries for the factor.⁴

⁴Suppose we double the portfolio weight $\mathbf{b}_k$, then by equation (2), the factor flow q_k halves. Moreover, by the law of one price, the factor-level price impact Δp_k and the return variance $\text{var}(\mathbf{b}_k^\top \mathbf{R})$ double and quadruple, respectively. Hence, equation (7) implies that λ_k does not change.

2.4 Cross-Elasticity

Having solved for factor prices, we can apply the law of one price to determine the price impact of individual currency n , denoted as⁵

$$\Delta p_n := \frac{P_n(\mathbf{f}) - P_n}{P_n}. \quad (9)$$

Proposition 3 computes the model-implied cross-elasticity, which quantifies how a \$1 flow into currency m impacts the price of currency n . Note that this formula also covers the case where m and n are the same, thereby calculating the currency's price elasticity to its own flow. Appendix A.3 provides a proof.

PROPOSITION 3 (Cross-elasticity). *Elasticity between currencies n and m is:*

$$\frac{\partial \Delta p_n}{\partial f_m} = \sum_{k=1}^K \frac{\partial q_k}{\partial f_m} \times \frac{\partial \Delta p_k}{\partial q_k} \times \frac{\partial \Delta p_n}{\partial \Delta p_k} = \sum_{k=1}^K \beta_{m,k} \times \lambda_k \text{var}(\mathbf{b}_k^\top \mathbf{R}) \times \beta_{n,k}. \quad (10)$$

The elasticity $\partial \Delta p_n / \partial f_m$ calculates the impacts on asset- n price (Δp_n) of asset- m flow (f_m), while holding the flow into all other assets constant. Proposition 3 shows that such impacts are channeled through all factors k via three steps. First, the flow into asset m changes factor- k flow q_k , with the sensitivity given by the beta coefficient $\beta_{m,k}$, as shown in equation (5). Second, changes in factor- k flow impact its price Δp_k , where the price sensitivity is $\lambda_k \text{var}(\mathbf{b}_k^\top \mathbf{R})$ (Proposition 2). Finally, changes in factor- k price Δp_k influence asset- n price Δp_n through the law of one price, with the sensitivity again captured by $\beta_{n,k}$.

⁵With a slight abuse of notation, we use Δp_n to denote the price impacts of individual currencies and Δp_k to denote the price impacts of factors.

2.5 Implementation Issues

We now discuss several issues in finding empirical counterparts to model primitives. In practice, we do not observe R_n , the return of currency n from time 0 to 1 that is unaffected by demand shocks; nor do we separately observe the price impact Δp_n from 0 to 0^+ . Instead, we only observe the equilibrium return r_n from 0 to 0^+ , which we measure as the currency-specific return (explicitly defined in Section 3.2) over the course of a week.

With a slight abuse of notation, we use R_n to also denote the counterfactual currency return from time 0 to 0^+ in a scenario with no demand shock. The equilibrium return r_n from time 0 to 0^+ is then the sum of Δp_n and R_n . Accordingly, the equilibrium return of factor k from time 0 to 0^+ is also the sum of the price impact from Proposition 2 and the counterfactual return, $\mathbf{b}_k^\top \mathbf{R}$:

$$r_k = \lambda_k q_k \text{var}(\mathbf{b}_k^\top \mathbf{R}) + \mathbf{b}_k^\top \mathbf{R}. \quad (11)$$

Because Proposition 2 measures $\text{var}(\mathbf{R})$ using $\mathbf{R}$ from time 0 to 1 and we are now using $\mathbf{R}$ from time 0 to 0^+ , an assumption for equation (11) to hold is that $\text{var}(\mathbf{R})$ is proportional across these time horizons. This assumption holds if, for example, $\mathbf{R}$ is i.i.d. over time.

Equation (11) implies that the equilibrium returns of different factors are also uncorrelated, i.e., $\text{cov}(r_k, r_l) = 0$ for any $k \neq l$. This is because Proposition 1 ensures uncorrelated demands, i.e., $\text{cov}(q_k, q_l) = 0$, and uncorrelated counterfactual returns, i.e., $\text{cov}(\mathbf{b}_k^\top \mathbf{R}, \mathbf{b}_l^\top \mathbf{R}) = 0$. Hence, by orthogonalizing the equilibrium returns and flows, we empirically obtain the same set of factors (up to scaling) as those derived in Proposition 1.

Finally, because price impacts are not observable, λ_k is estimated by running a time-series regression of r_k on q_k , scaled by $\text{var}(\mathbf{b}_k^\top \mathbf{R})$. An unbiased estimate of λ_k requires that

$\text{cov}(q_k, \mathbf{b}_k^\top \mathbf{R}) = 0$; that is, the factor flow q_k must be a demand shock that is exogenous to the counterfactual factor return $\mathbf{b}_k^\top \mathbf{R}$. This condition is often violated in observed data, we thus adopt an instrumental variables (IV) strategy in Section 5 to estimate λ_k .

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 CLS Group (CLS). CLS provides settlement services to FX trades done by its 72 settlement members, who are mostly large multinational banks. As such, CLS is the largest single source of FX executed data available to the market, covering over 50% of global FX volumes.

We obtain FX order flow data from CLS. Specifically, we have the daily aggregate value of all buy orders and all sell orders done between banks and their customers in 18 currencies between September 2012 and December 2023. The currencies in our sample include 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), Hungarian florin (HUF), 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). Our sample consists of all orders involving one of three types of customers: Funds, which include mutual funds and pension funds, Non-bank Financials, which include insurance companies and clearing houses, and Corporate. Banks, or dealers affiliated with banks, are the customer counterparties for all

transactions in our sample.

From the CLS FX flow data, we construct the dollar-valued total daily net customer inflow into each currency. Buy and sell orders are defined for currency pairs, e.g., a customer may place an order to buy AU\$100 AUD and sell the spot-equivalent amount in JPY. We measure all flows relative to USD. In the example above, we would record a USD equivalent amount of AU\$100 *positive* AUD flow, and a USD equivalent amount of AU\$100 *negative* JPY flow.

Our accounting provides a consistent measure of dealers' risk exposure in individual currencies. To capture the *total* amount of FX risk exposure facing dealers, we include not only spot flows, but also forward flows and swap flows. CLS records forward and swap order flows by currency pairs and by maturity buckets. We discount future-settled forward and swap notionals back to spot FX exposure using forward rates.⁶

We analyze trading and return at the weekly frequency. We therefore add up daily flows in a week to obtain weekly flows that start every Thursday to the following Wednesday, inclusive.

Our final trading data is a panel, between 2012-09-06 and 2023-12-31, of weekly net inflow into 17 non-USD currencies, measured in USD across spot, forward, and swap transactions.

3.2 Return Data

We obtain most of the data needed to construct returns from Bloomberg. To calculate FX returns, we get forward and spot price data for the 17 non-USD currencies in our sample.

⁶Specifically, we use the 1-week forward rate to discount back forward and swap contracts with maturity of 1-7 days, the 1-month forward rate for contracts with maturity of 8-35 days, the 3-month forward rate for contracts with maturity of 36-95 days, and the 1-year forward rate for contracts with maturity of greater than 96 days. The choice of forward rate depends on the range of the maturity bucket and forward contract liquidity.

All prices are at London closing, consistent with our trading flow measure.⁷

We define the weekly currency return as the outcome from borrowing USD at the US risk-free rate today, converting to 1 unit of foreign currency at the spot exchange rate and earning the foreign risk-free rate, then in a week, converting the foreign proceeds back to USD at the future spot rate. That is, for currency n from week t to $t + 1$: $r_{t+1,n} = s_{t+1,n} - s_{t,n} + i_{t,n} - i_{t,USD} - x_{t,n} = s_{t+1,n} - f_{t,n}$, where s is the log spot rate, f is the log forward rate, i is the net risk-free rate, and x is the CIP deviation. Throughout, we define exchange rates as the number of USD per 1 unit of foreign currency; a higher s thus corresponds to a depreciation of USD. Note that our currency return includes CIP deviation ($x_{t,n} = f_{t,n} - s_{t,n} - i_{t,USD} + i_{t,n}$) so as to capture compensation for all risks that dealers take in absorbing customer flows, including possible inventory costs arising from balance sheet constraints.

3.3 Other Data

We collect data on various sovereign bond auctions to instrument for FX demand shocks. Specifically, we obtain auction announcement data from the U.S. Treasury auctions for notes and bonds, the Australian Treasury bond auctions, the U.K. Gilt auctions, and the German Bund auctions.

We also collect various data to construct excess return in four other asset markets. For US Treasury bonds, we get yields of the six maturity-sorted “Fama Bond Portfolios” from CRSP. We exclude the portfolio of Treasury bills due to correlation with the risk-free rate. For Corporate bonds, Commodities, and CDS, we obtain pricing data on various indices from Bloomberg. Finally, we use the 1-month U.S. Libor as a proxy for the risk-free rate.

⁷CLS records daily flow as all orders submitted during the FX business day, which follows the London FX market hours.

CDS data are available from 2007 onward. All other series are available starting in 2000.

4 Traded Risk Factors in FX

In this section, we identify traded FX factors from data. We first find risk factors that have uncorrelated flows. We then show that these risk factors correspond to the Dollar, the Carry, and the Pan-European factors, respectively. After illustrating the properties of these risk factors, we decompose flows and returns of individual currencies into these traded risk factors and show that these risk factors capture the preponderance of flow and return variations.

4.1 Baseline Traded FX Factors

Our objective is to find risk factors whose risk premia are affected by demand shocks. Such risk factors likely exist in the FX market because the FX market is heavily intermediated and intermediaries have limited risk-bearing capacity (e.g., [Du and Huber \(2024\)](#), [Du, Hébert, and Huber \(2022\)](#)). To understand the role of intermediaries and their risk-bearing capacity in asset prices, we thus aim to estimate how changes in the amount of risk affect risk premia. In other words, we seek to identify traded risk factors and their associated intermediary elasticity.

Following Proposition 1, we identify the traded risk factors using weekly net flows ($\mathbf{f}$) and log returns ($\mathbf{r}$) of 17 non-USD currencies. The three factors 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. For example, in Factor 1, for every \$1 bought, \$0.15-worth of Canadian dollars and \$0.5-worth of Euro are sold. As discussed in Section 2.3, we can freely scale each factor without affecting the elasticity

estimates, and we accordingly scale all factors to facilitate comparison.⁸ Because the factors that we identify are traded factors, they logically place more weights on currencies that are more widely traded. In particular, six developed economy currencies have consistently high weights across the top 3 factors, these currencies are AUD, CAD, CHF, EUR, GBP, and JPY, and we highlight them in red. Our three traded factors explain 65%, 16%, and 9% of the trading-induced variance, respectively.⁹ In other words, about 90% of the risk that intermediaries bear when accommodating trading flows is captured by these three factors.

Eigenvector decomposition, or principal component analysis (PCA), is often seen as sensitive to minor changes in data. Yet the traded factors identified through our modified PCA procedure are robust to changes in the sample period.¹⁰ In Table 2, we report the correlation between the traded factors identified using our modified PCA on the full sample and those identified using the pre- and post-2020 subsamples. The correlations for both returns and flows are notably high, approaching 1 for the first factor and exceeding 0.8 for the other two factors. This evidence suggests that the underlying data are well-behaved, and in particular, that the flow and return covariance structures are rather stable over time.

A tempting alternative approach to finding traded factors may be to perform a principal component analysis (PCA) directly on trading data. Such a standard PCA approach on trading data results in portfolios that simply place weight in one single major currency. As Appendix Table A1 illustrates, the first such portfolio would place a portfolio weight of -1 on EUR and 0 on all other non-USD currencies, and the second such portfolio would similarly place a portfolio weight of 1 on CAD and 0 on all other non-USD currencies. This simply

⁸Specifically, 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 the weights on EUR and GBP sum to 1.

⁹These explained variances are calculated as $\pi_k / \sum_{l=1}^K \pi_l$, with π_k defined in Proposition 1.

¹⁰As discussed in Proposition 1, the theoretical reason for the stability of our factors is that we use both the return and flow covariance to pin down the factors, whereas standard PCA uses only one covariance and relies on an orthogonality condition that arises from the sequential maximal explanation of variance.

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

Currency	Factor 1	Factor 2	Factor 3
AUD	-0.08	0.14	-0.06
CAD	-0.15	0.56	-0.7
CHF	-0.03	-0.07	-0.01
DKK	-0.01	0	0.01
EUR	-0.5	-0.43	0.93
GBP	-0.11	0.18	0.07
HKD	0	-0.01	0.01
HUF	0	0	0
ILS	0	0	0
JPY	-0.07	-0.49	-0.8
KRW	-0.01	0.01	-0.01
MXN	-0.01	0.02	-0.02
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	0.01
ZAR	-0.01	0.01	-0.01
USD	1	0.03	0.59
Var explained	65%	16%	9%

Notes: This table presents the portfolio weights of the top 3 traded FX factors, constructed per Proposition 1. We use weekly return and flow data for 17 non-USD currencies from September 2012 to December 2023. The portfolio weight of USD is computed as the negative sum of the weights of all other currencies.

reflects that EUR/USD is the most actively traded pair, followed by USD/CAD. This result arises because the standard PCA does not require that portfolios have uncorrelated returns. In contrast, the traded portfolios identified in Table 1 have uncorrelated returns in addition to having uncorrelated flows, thus endowing the resulting portfolios the interpretation of risk factors.

Having established the robustness and the risk factor interpretation of our traded factors, we proceed to analyzing the economic risks that these traded factors represent.

Table 2: **Correlation of Traded Factors Between Subsamples and Full Sample**

		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 factors constructed based on the subsamples and full sample.

4.2 Interpretation of Traded FX Factors

We conjecture that the top three traded FX factors represent the Dollar, Carry, and Pan-European factors, respectively. Examining Factor 1 in Table 1, we see that all non-USD currencies enter the portfolio with a negative weight. This pattern is reminiscent of the Dollar portfolio that goes long in, or shorts, all non-USD currencies simultaneously. We thus propose a Dollar traded factor that is long USD and shorts the six most traded currencies (AUD, CAD, CHF, EUR, GBP, and JPY) in equal weights. In contrast, Factor 2 in Table 1 shows the striking pattern of positive weights on high interest rate currencies, e.g., AUD, and negative weights on low interest rate currencies, e.g., JPY. This pattern coheres with the Carry portfolio, and motivates us to propose a Carry traded factor that goes long in AUD, CAD, and GBP, and shorts CHF, EUR, and JPY. Finally, Factor 3 in Table 1 have large, positive weights in EUR and GBP, and negative weights in almost all other non-USD currencies. We postulate a Pan-European factor that goes long in EUR and GBP with 3/4 and 1/4 weight, respectively, and shorts AUD, CAD, CHF, and JPY with equal weights.¹¹

The data support our economic interpretation of the traded FX factors. Using the Dollar,

¹¹The Pan-European factor is robust to changing the relative weights on EUR and GBP.

Table 3: **Correlation of Return and Flow to Traded Factors Based on PC versus Economic Weights**

	Factor 1	Factor 2	Factor 3
Return	0.99	0.94	0.84
Flow	1.00	0.99	0.95
Var explained	64%	14%	7%

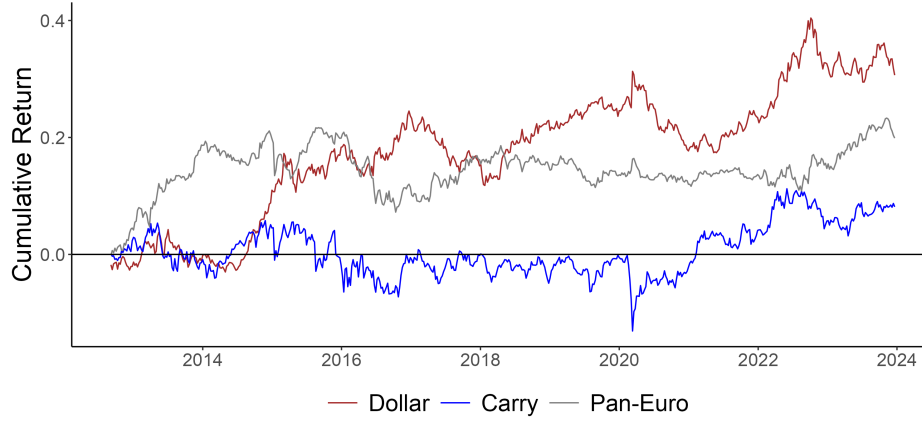
Notes: This table displays the correlation of return and flow to traded factors, using PC weights from Table 1 and the economic weights assigned to the Dollar, Carry, and Pan-European factors.

Carry, and Pan-European factor weights proposed above, we construct returns and flows to these proposed factors.¹² In Table 3, we show the correlation between traded factors identified following Proposition 1 and traded factors constructed from the economic weights described above. The correlations are highly positive in both returns and flows for all three factors. In particular, the correlations between factor flows are close to 1, and the correlations between factor returns are about 0.95 for the first two factors and 0.85 for the third factor.

It is remarkable that the three most important traded FX factors have clear economic interpretations. While the Dollar and the Carry factors are well-known risk factors in FX returns (e.g., [Lustig, Roussanov, and Verdelhan \(2011\)](#)), it is not previously known whether these are *traded* factors or unconditional risk premia that marginal investors price and hold but do not trade. Our analysis underscores two properties of the Dollar and the Carry factors. First, investors trade these two factors. Second, because trading flows into these two factors are uncorrelated, a revealed-preference argument implies that investors indeed perceive these factors as orthogonal. Finally, our analysis further identifies a third traded

¹²We orthogonalize the proposed economic weights using Proposition 1 to ensure that the orthogonalized factors exhibit uncorrelated flows and uncorrelated returns with respect to each other. We then scale each orthogonalized factor such that it holds exactly one unit of the corresponding proposed economic factor.

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



Notes: This figure displays the cumulative returns of the top three traded FX factors over our sample period, from September 2012 to December 2023.

factor, the Pan-European factor, which explains about 7% of risk in FX trading.

We now examine the properties of the traded Dollar, Carry, and Pan-European factors. We start with returns. Figure 1 plots the cumulative return to the three traded FX factors. Unsurprisingly, the Dollar return has been strong, as USD has appreciated against most currencies over the last decade. The Carry return has been around 0, but has taken off around 2022. Finally, the Pan-European factor experienced a good return before 2014, but has since languished.

Next, we examine flows. Figure 2 plots the cumulative flow to each of the three factors by different investor types. There are three types of dealer customers: Funds, which primarily consist of mutual funds; Corporates; and Non-Bank Financials, including clearing houses and insurance companies. In addition to these customer flows, we plot in dashes the Net Total, which represents the total net customer flows that dealers need to absorb. Panel (a) illustrates the flow to the Dollar factor. Over the sample period, Funds are persistently selling

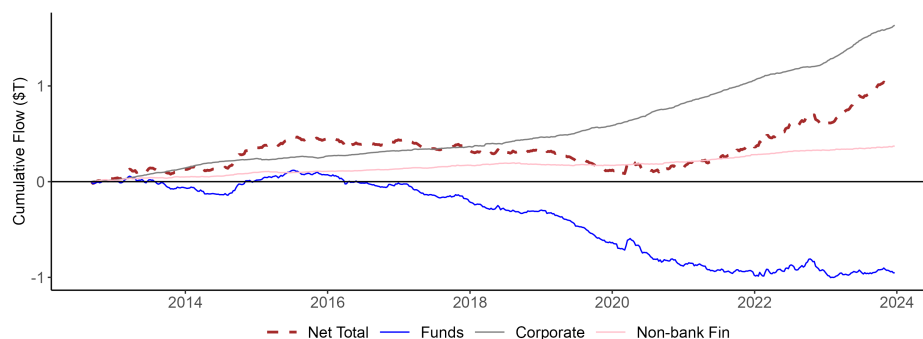
Dollars, whereas Corporates are persistently buying. In recent years, the buying pressure has been so strong that dealers have had to provide Dollars on net. We note that dealers may not be able to maintain a sustained inventory imbalance. The funding provision here likely reflects deposit or wholesale funding made available by banks to which the dealers are affiliated. The fact that dealers are providing Dollars on net to customers is then consistent with [Du and Huber \(2024\)](#)’s estimate that banks provide dollars on-net to non-US investors. Panel (b) illustrates the flow to the Carry factor. We observe that customers had not taken large directional bets with the Carry factor until 2022, but since then, they have sold off the Carry factor, an action almost exclusively undertaken by Funds. This sell-off may be motivated by empirical observations suggesting that the Carry tends to be unprofitable in times of high inflation.¹³ In fact, this outflow corresponded to a period of high returns to Carry, potentially because dealers had to be compensated for accommodating the sizeable outflow. Finally, from Panel (c)’s illustration of flows to the Pan-European factors, we see that this factor was sold by both Corporate and Funds right up to around the Covid-19 Crisis in 2020. Since then, Funds have bought back all of their short position to approximately neutral, while Corporate continues to sell the Pan-European factor. As a result, dealers have been net suppliers of EUR and GBP.

4.3 Factor Decomposition of Individual Currencies

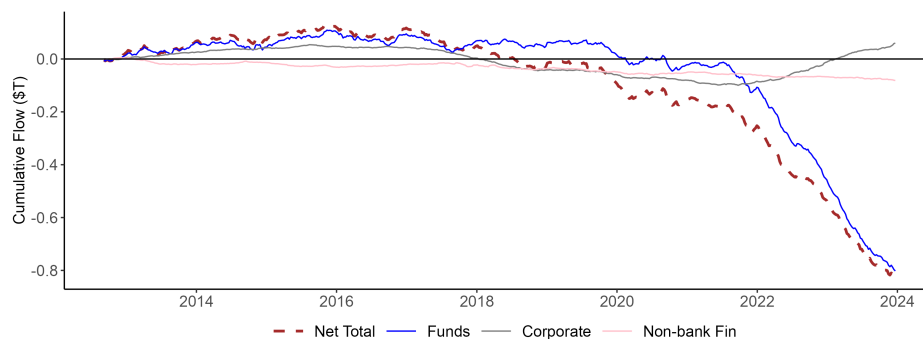
The top three traded FX factors that we identify explain a substantial amount of trading in individual currencies and almost all of the individual currency’s return. [Figure 3](#) illustrates the decomposition of individual currency’s trading flow and return into the Dollar, the Carry,

¹³[Bansal and Dahlquist \(2000\)](#) document that the uncovered interest-rate parity (UIP) holds better in developing countries with high levels of inflation and high inflation volatility. Carry is profitable when UIP is violated.

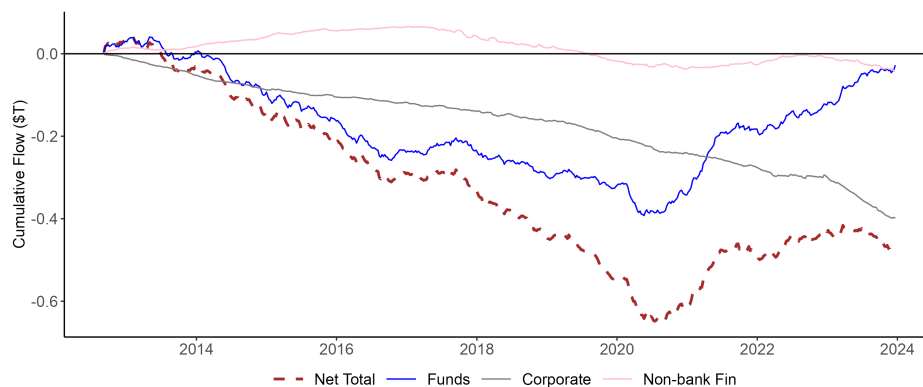
Figure 2: **Cumulative Flow by Investor Type to Top 3 Traded FX Factors**



(a) **Dollar Factor**



(b) **Carry Factor**



(c) **Pan-European Factor**

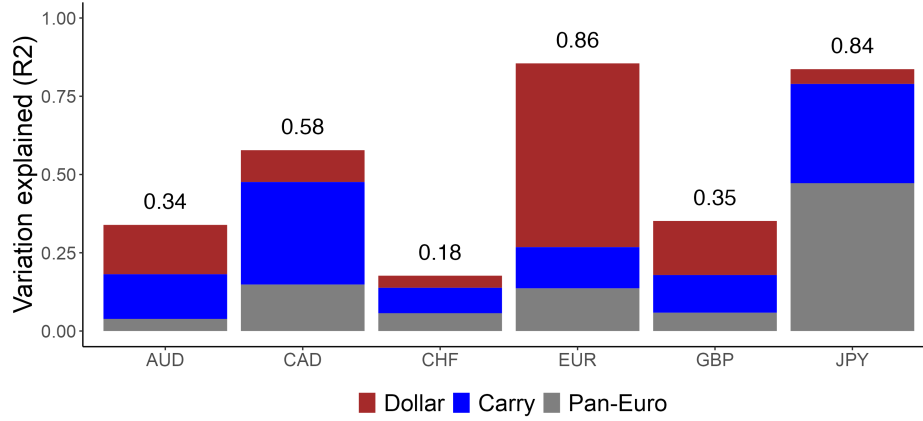
Notes: This figure displays the cumulative flows of the top three traded FX factors over our sample period, from September 2012 to December 2023. There are three types of dealer customers: Funds, Corporates, and Non-Bank Financials. In addition to these customer flows, we plot in dashes the Net Total, which represents the total net customer flows that dealers need to absorb.

and the Pan-European factors. This decomposition is achieved by regressing currency-level flows or returns on the flows or returns of traded risk factors in the time series. Because the returns and flows of different factors are uncorrelated by construction, the R^2 from each regression is additive. Starting with flows in Panel (a), the three factors account for almost all of the trading in EUR and JPY (86% and 84%), the majority of trading in CAD (58%), and a smaller fraction in AUD, CHF, and GBP. The unexplained flow results from investors trading idiosyncratic risk factors which, by construction, are uncorrelated with our three factors and hence do not affect the elasticity estimates of these factors.

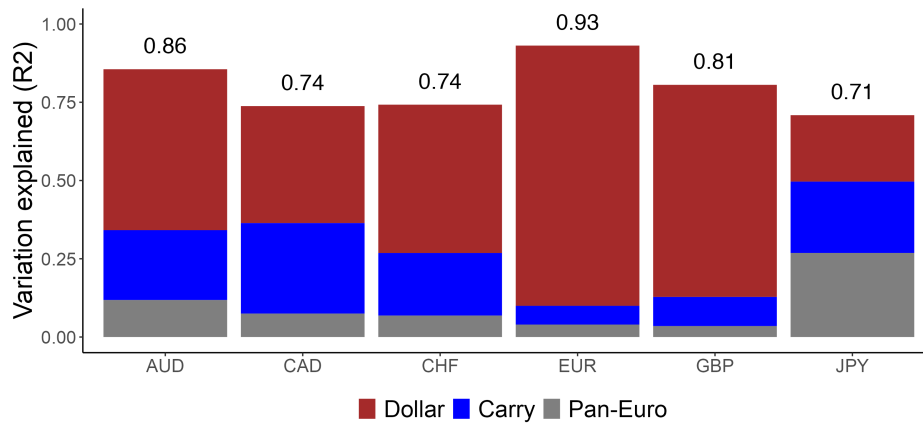
As Panel (b) illustrates, the Dollar, the Carry, and the Pan-European factors together account for between 71% and 93% of individual currency's unconditional return. The fact that the traded risk factors can explain a high fraction of currency return variations is not a foregone conclusion: the traded factors are only designed to rationalize changes in FX risk that are induced by trading, which are not necessarily all the risks that are priced in the FX markets. Reassuringly, these trade factors are also able to explain a significant amount of the total risk in FX returns.

Finally, we note that most of the individual currency returns are driven by the Dollar factor, yet flows to individual currency have more varied drivers. For example, trading of JPY and CAD are both largely motivated by Carry. While Carry also drives a significant amount of JPY FX return, the FX return of CAD is mostly driven by the Dollar factor. The large common variation with factors in both return and flow implies complex cross-elasticity between currencies. We tackle this question in the next section by first estimating the elasticity of individual traded factors and then applying the theory to derive cross-elasticity.

Figure 3: **Decomposition of Currency Variation Explained by Traded FX Factors**



(a) **Flow**



(b) **Return**

Notes: This figure decomposes the trading flows and returns of individual currencies into the Dollar, the Carry, and the Pan-European factors. The decomposition is achieved by regressing currency-level flows and returns against the flows and returns of all factors in the time series. It reports both the marginal R^2 values attributed to each factor and the total R^2 .

5 Elasticity in FX Markets

In this section, we estimate intermediary elasticity in FX markets. We first use instrumental variables to estimate the elasticity for each of the traded FX risk factors individually. We then apply the estimated factor-elasticity to recover the own- and cross-elasticity of currencies.

5.1 Instrument Construction

We are interested in estimating λ_k , the intermediary elasticity of traded FX factor k , in equation (7). However, as discussed in Section 2.5, we do not directly observe price responses induced by demand shocks (Δp_k); instead, we observe the equilibrium return (r_k) that reflects both Δp_k and the counterfactual return in the absence of demand shocks (R_k). Analogously, the factor flow that we construct, q_k , includes both flow due to demand shocks and flow due to fundamental changes, e.g., information. To isolate the impact of λ_k , we therefore must instrument for the demand shocks in q_k .

Because the factors are constructed to have uncorrelated returns and uncorrelated flows with each other, we can apply Proposition 2 to estimate λ_k for each factor individually without worrying about cross-substitution between these factors. Specifically, for each factor $k = \text{Dollar, Carry, Pan-European}$, we run a time-series regression of the factor's weekly equilibrium return $r_{k,t}$ on its instrumented weekly flow $\hat{q}_{k,t}$:

$$r_{k,t}/\text{var}(r_{k,t}) = \lambda_k \hat{q}_{k,t} + \epsilon_{k,t}, \text{ where} \quad (12)$$

$$q_{k,t} = \theta z_{k,t} + e_{k,t}, \quad (13)$$

$$\text{cov}(z_{k,t}, \epsilon_{k,t}) = 0. \quad (14)$$

The key is to find instruments (z_k) for observed factor flows (q_k) that are both relevant (equation (13)) and valid (equation (14)). We propose sovereign bond auction announcements as instruments. Government entities such as the U.S. Treasury periodically auction off long-term debt obligations, e.g., US Treasury notes and bonds. Foreign investors participate in auctions of advanced economies, making these auctions relevant instruments. For example, foreign investors directly purchased on average 14% of US Treasury notes and bonds sold at auctions between September 2012 and December 2023.¹⁴

We moreover argue that these auctions, and in particular, the *announcements* of the offered amount at upcoming auctions are valid instruments because they are plausibly exogenous and satisfy the exclusion restriction. First, the amount of securities planned to be sold at auctions is typically influenced by fiscal considerations such as tax receipt and expenditures, and because the majority of investors are domestic, offered amounts are likely not affected by FX market conditions. This makes the instrument possibly exogenous. Second, using the amount of securities *offered* to be auctioned as opposed to actually purchased lends credibility that the only way through which our instruments affect FX price is the purchase volume that they induce. This satisfies the exclusion restriction.

Specifically, we use the U.S. Treasury auction announcements as the instrument for the Dollar factor.¹⁵ We use the Australian Treasury auction announcements as the instrument for the Carry factor. We use the British gilt auction announcements and the German bund auction announcement as instruments for the Pan-European factor. We remove any linear trend in the size of the auctions over time. We also consider three time windows for each instrument: we tally the offering amount in all auction announcements in the same week

¹⁴Foreign investors' actual purchase of auctioned Treasury securities could be much higher, as purchases done via investment funds and dealers are not included in the 14%.

¹⁵We focus on auctions for Treasury notes and bonds as Treasury bills are mostly purchased by domestic investors such as money market funds.

that we measure flow (week t), in the same week and the previous week (week $t - 1$ to t), and in the same week and the last two weeks (week $t - 2$ to t). The three time windows trade off the power of the instrument (relevance) with the quality of the instrument (validity). The shorter the time window, the more likely that the induced flows are only from the auction announcement. However, the magnitude and the variation of the instrument can be modest. The longer time windows could lead to higher first-stage F -statistics. We also believe that FX trading in week t could be motivated by the trading of auctioned securities in the secondary market.¹⁶ For these reasons, our preferred specification is the IV from week $t - 2$ to t of the auction announcements.

5.2 Factor-Level Elasticity

Panels (a), (b), and (c) of Table 4 present the λ_k estimation results for the Dollar, Carry, and Pan-European factors, respectively, based on regression (12). Each panel includes four columns, detailing the OLS estimation results and the IV results, which utilize the auction announcement amount in week t , the average of week $t - 1$ to t , and the average of week $t - 2$ to t as instruments for the factor flow. We also exclude the first half of 2020 to be conservative, as the COVID period saw much greater price volatility and dislocation.

As we can see from Panel (a), the intermediary elasticity λ for the Dollar factor is about 0.1 and statistically significant in most specifications. The first-stage F -statistic for the IV regression is about 10, although some specifications yield larger values and others smaller. Using IV estimates in the last column, we can quantify the price impact of a \$1 billion

¹⁶Auction announcements are typically made one week before the actual auction.

Table 4: **Estimation Results for Factor-Level Elasticity**

Panel (a): Dollar factor				
	OLS	IV (week t)	IV (week $t - 1$ to t)	IV (week $t - 2$ to t)
λ	0.079	0.110	0.215	0.103
t-stats	(10.95)	(2.45)	(1.88)	(1.56)
IV F-stats		15.36	3.69	6.90
Observations	564	386	533	564
Panel (b): Carry factor				
	OLS	IV (week t)	IV (week $t - 1$ to t)	IV (week $t - 2$ to t)
λ	0.133	-0.088	0.268	0.210
t-stats	(8.87)	(-0.26)	(1.06)	(1.20)
IV F-stats		1.51	2.24	4.26
Observations	564	479	520	535
Panel (c): Pan-European factor				
	OLS	IV (week t)	IV (week $t - 1$ to t)	IV (week $t - 2$ to t)
λ	0.138	0.546	0.379	0.230
t-stats	(6.27)	(1.56)	(1.49)	(1.44)
IV F-stats		3.51	4.90	10.91
Observations	564	380	522	548

Notes: This table presents the λ_k estimation results for the Dollar, Carry, and Pan-European factors, based on regression (12). Each panel includes four columns, detailing the OLS estimation results and the IV results, which utilize the auction announcement amount in week t , the average of week $t - 1$ to t , and the average of week $t - 2$ to t as instruments for the factor flow. The sample is from September 2012 to December 2023, excluding the first half of 2020 to be conservative.

demand shock to the Dollar factor as follows:

$$\text{price impact} = \lambda \times \text{demand shock} \times \text{var}(\text{return}) = 0.103 \times 1 \times (6.3\%)^2 = 4.0 \text{ basis points (bps)}.$$

That is, a \$25 billion demand shock to the Dollar factor moves its return by 1%.

Panels (b) and (c) report the estimated intermediary elasticity λ for the Carry and Pan-

European factors, respectively. We observe that both the statistical significance and the first-stage F-statistics are weaker relative to the Dollar factor. Translating the estimates in the last column to the price impact of a \$1 billion demand shock, we have

$$\text{price impact of Carry factor} = \lambda \times \text{flow} \times \text{var}(\text{return}) = 0.210 \times 1 \times (7.0\%)^2 = 10.4 \text{ bps},$$

$$\text{price impact of Pan-Euro factor} = \lambda \times \text{flow} \times \text{var}(\text{return}) = 0.230 \times 1 \times (5.6\%)^2 = 7.2 \text{ bps}.$$

That is, a demand shock of \$10 billion and \$14 billion to the Carry or Euro factor respectively moves its return by 1%.

5.3 Cross-Currency Elasticity

Based on the estimated factor-level elasticity λ_k , we apply Proposition 3 to compute the cross-currency elasticity and report the results in Table 5. For clarity, we have arranged the six major currencies (AUD, CAD, GBP, CHF, EUR, JPY) in the upper left quadrant, followed by the other 11 currencies. The rows represent price impacts, and the columns correspond to demand shocks. For instance, the entry of 8.88 in the first row and second column implies that a \$1 billion demand shock to the CAD increases the return of AUD by 8.88 bps, holding the demand for all currencies equal.

The table reveals several interesting patterns of cross-currency elasticity. First, almost all entries are positive. This is because all currencies load on the Dollar factor in the same direction. Second, we note that cross-elasticity between currencies on the long leg of the Carry trade (AUD, CAD, GBP, MXN) and those on the short leg (CHF, EUR, JPY) is generally smaller, with some entries being even negative, such as GBP/JPY and MXN/JPY. This negative cross-elasticity is due to opposing beta loadings with respect to the Carry

Table 5: Cross-Currency Elasticity

	AUD	CAD	GBP	CHF	EUR	JPY	DKK	HKD	HUF	ILS	KRW	MXN	NOK	NZD	SEK	SGD	ZAR
AUD	13.08	8.88	7.32	2.59	2.19	2.58	2.19	0.18	4.57	4.50	6.41	8.95	10.91	10.69	5.65	4.04	12.10
CAD	8.88	6.18	5.13	0.63	0.99	0.52	1.00	0.13	2.70	2.94	4.18	6.32	7.26	7.15	3.52	2.53	8.20
GBP	7.32	5.13	8.73	1.64	5.28	-1.22	5.26	0.13	7.58	3.73	4.07	6.15	8.81	6.72	7.07	2.92	7.87
CHF	2.59	0.63	1.64	9.52	5.67	9.48	5.65	0.03	5.75	2.18	2.80	0.20	4.17	3.16	4.89	2.73	2.91
EUR	2.19	0.99	5.28	5.67	6.78	3.22	6.75	0.05	7.79	2.51	2.35	1.58	5.27	3.00	6.40	2.33	3.25
JPY	2.58	0.52	-1.22	9.48	3.22	11.20	3.21	0.02	2.70	1.44	2.52	-0.53	2.51	2.71	2.51	2.34	2.23
DKK	2.19	1.00	5.26	5.65	6.75	3.21	6.72	0.05	7.75	2.50	2.35	1.58	5.25	3.00	6.38	2.32	3.25
HKD	0.18	0.13	0.13	0.03	0.05	0.02	0.05	0.00	0.09	0.07	0.09	0.13	0.17	0.15	0.10	0.06	0.18
HUF	4.57	2.70	7.58	5.75	7.79	2.70	7.75	0.09	9.45	3.53	3.55	3.52	7.73	5.06	8.08	3.11	5.66
ILS	4.50	2.94	3.73	2.18	2.51	1.44	2.50	0.07	3.53	2.04	2.54	3.15	4.72	4.01	3.46	1.83	4.52
KRW	6.41	4.18	4.07	2.80	2.35	2.52	2.35	0.09	3.55	2.54	3.44	4.23	5.95	5.48	3.78	2.37	6.12
MXN	8.95	6.32	6.15	0.20	1.58	-0.53	1.58	0.13	3.52	3.15	4.23	6.69	7.79	7.31	4.18	2.58	8.46
NOK	10.91	7.26	8.81	4.17	5.27	2.51	5.25	0.17	7.73	4.72	5.95	7.79	11.08	9.56	7.76	4.16	10.83
NZD	10.69	7.15	6.72	3.16	3.00	2.71	3.00	0.15	5.06	4.01	5.48	7.31	9.56	8.96	5.65	3.62	10.11
SEK	5.65	3.52	7.07	4.89	6.40	2.51	6.38	0.10	8.08	3.46	3.78	4.18	7.76	5.65	7.19	3.07	6.34
SGD	4.04	2.53	2.92	2.73	2.33	2.34	2.32	0.06	3.11	1.83	2.37	2.58	4.16	3.62	3.07	1.75	3.99
ZAR	12.10	8.20	7.87	2.91	3.25	2.23	3.25	0.18	5.66	4.52	6.12	8.46	10.83	10.11	6.34	3.99	11.48

Notes: This table uses Proposition 3 and the estimated factor-level elasticity λ_k from the last column of Table 4 to compute cross-currency elasticity. Each entry represents the movement in bps of a row-currency's return, induced by a \$1 billion demand shock into a column-currency.

factor, so the two currencies hedge each other in risk exposures to the Carry factor. Third, despite belonging to opposite sides of the Carry factor, the cross-elasticity between the GBP and EUR is notably high, which can be attributed to both currencies loading positively on the Pan-European factor.

We also observe that the cross-elasticity matrix is symmetric, indicating that the impact of a demand shock from CAD on the price of AUD is identical to the impact of a demand shock from AUD on the price of CAD. As Proposition 3 explains, this symmetry arises because, for any factor k , the sensitivity of the AUD price to that factor’s price and the sensitivity of that factor’s trading demand to AUD’s trading demand are the same: both are the beta loading of AUD to that factor.

We note that although the economic factors are constructed based on the six major currencies and USD, significant cross-elasticity is observed in other currencies as well, due to their substantial loadings on the three traded risk factors. As a sanity check of our methodology, we examine the cross-elasticity for HKD, a currency pegged to USD within a narrow band of 1%. We do not use this pegged information in our estimation. We observe that the entire column and row associated with HKD are close to zero. The minimal impact vis-à-vis all other currencies reflects the nature of a pegged currency, whose own demand shifts have negligible risk implications for any currencies, and whose exchange rates relative to USD are not meaningfully impacted by demand shocks into any currencies.

6 Intermediary Elasticity Across Asset Markets

If the same set of intermediaries is active across different asset markets, then the traded factors in FX should also be relevant for trading and returns in other assets. In this section, we investigate the extent of common variation across markets and address two important

questions. First, is there a common component to the intermediary SDF that prices assets in different markets? Second, if intermediaries have limited risk-bearing capacity for the risks captured by this common component, what is the intermediary elasticity within and across asset markets? We explore these questions in turn.

6.1 Traded FX Factors in Other Assets

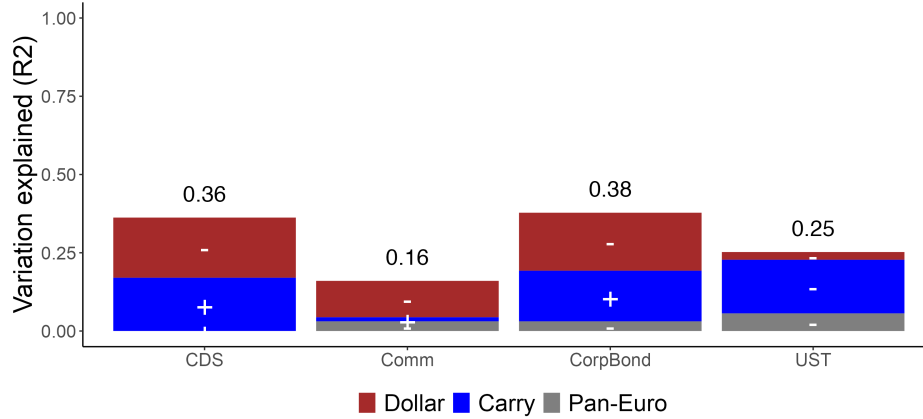
To assess if there is commonality in the intermediary SDFs across asset markets, we examine how much of the return variance in other assets can be explained by traded FX factors. We consider four asset markets that rely on dealer intermediation: CDS (CDS, five traded CDS indexes), Commodities (Comm, six Bloomberg commodity futures return indexes), Corporate bonds (CorpBond, five Bloomberg corporate bond indexes), and US Treasury bonds (UST, six maturity-sorted CRSP “Fama Bond Portfolios”). Figure 4 illustrates the variation in the return of each asset class that can be explained by the Dollar, the Carry, and the Pan-European factors.¹⁷ We measure this with the R^2 from regressing asset class monthly average excess return between 2000-02 and 2023-12 on returns from the three traded FX factors.¹⁸ Figure 4 also illustrates the sign of the asset class m ’s return loading on each of the three traded FX factors ($\beta_{m,k}$ in Proposition 3). All $\beta_{m,k}$ are reported in Appendix Table A2, and their magnitude is proportional to the square root of the incremental R^2 .

There exists a common component in intermediary SDFs. The three traded FX factors can jointly explain between 16% (Commodity) and 38% (Corporate bonds) of returns in other asset classes. The Dollar factor is present in the return of all four asset classes. Interestingly, the Dollar factor is least important in explaining the return of US Treasury bonds, suggesting

¹⁷We construct the return of each asset class as the equal-weighted average return of all available portfolios.

¹⁸The correlation among monthly factor returns is close to zero. We report the incremental R^2 by adding the three factors in the order of the Dollar, the Carry, and the Pan-European.

Figure 4: **Cross-Asset Return Variation Explained by Traded FX Factors**



Notes: This figure decomposes the returns of individual assets into the Dollar, the Carry, and the Pan-European 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. 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.

that movement in USD is not an important motivation for purchasing US Treasury bonds. This may be surprising considering that nearly a quarter of Treasury bonds are held by foreign investors, but as [Du and Huber \(2024\)](#) show, foreign investors hedge a substantial amount of USD FX risks associated with their security holdings. The common variation between the Carry factor return and asset class's return is large in CDS, Corporate bonds, and US Treasury bonds. [Burnside, Eichenbaum, Kleshchelski, and Rebelo \(2010\)](#) argue that the Carry return reflects investors' high marginal utility in a peso event. Our results suggest that what investors perceive as "peso events" are not simply crashes in the currency market, but bad states of the world that affect many asset markets. Finally, the Pan-European factor statistically significantly correlates with the return of Commodity, Corporate bonds, and US Treasury bonds; however, the fraction of return variance explained by this factor is small.

We acknowledge that the explanatory power of the Dollar, the Carry, and the Pan-European is lower for returns in non-FX asset classes (Figure 3 shows that the three factors explain on average 80% of return variations in six major currencies). In other words, markets are neither fully integrated, where only risks that are systematic across all markets are priced by intermediaries (extending Sharpe (1964) to the representative intermediary in He and Krishnamurthy (2013)), nor completely segmented such that risks priced in each market are idiosyncratic to that market (possibly due to reasons in Siriwardane, Sundaram, and Wallen (2022)). We note that our analysis provides a lower bound on the degree of integration between markets, as there could be non-traded common risk factors priced across markets.

Importantly, the presence of *traded* FX factors in other asset markets implies that intermediaries' limited risk-bearing capacity could also affect risk premia in these markets.

6.2 Intermediary Elasticity Across Markets

Following Proposition 3, we combine our IV estimates of intermediary elasticity in traded FX factors with asset markets' return loadings on these factors to arrive at the own- and cross-elasticity between four asset markets (Table 6). Similar to Table 5, each number in Table 6 represents a row-asset's return movement in bps that is induced by a \$1 billion flow into a column asset due to both assets' *exposure to the three traded FX factors*.

Consider a demand shock in corporate bonds that increases flows by \$1 billion. This influx exposes intermediaries to more risk associated with the three traded FX factors, pushing them against their limited risk-bearing capacity. Consequently, the return on corporate bonds increases by 4.94 bps. Moreover, because the same intermediaries are also active in CDS, the return to CDS increases by 3.71 bps. The difference in magnitude between the own- and the cross-elasticity owes to the smaller loading that CDS has on both the Dollar

Table 6: **Cross Elasticity Between Assets Due to Traded FX Factors**

	CDS	Comm	CorpBond	UST
CDS	3.23	3.39	3.71	-1.17
Comm	3.39	8.17	5.48	0.25
CorpBond	3.71	5.48	4.94	-0.91
UST	-1.17	0.25	-0.91	0.94

Notes: This table uses Proposition 3, the estimated factor-level elasticity λ_k from the last column of Table 4, and the beta loadings of assets to factors in Table A2 to compute cross-asset elasticity. Each entry represents the movement in bps of a row-asset’s return, induced by a \$1 billion demand shock into a column-asset.

and the Carry factors.

The same intermediaries are also active in US Treasury bonds. Therefore, demand shocks to Corporate bonds affect the returns on US Treasury bonds as well. However, because Corporate bonds and US Treasury bonds load on the Carry factor with opposite signs, a demand shock that increases intermediaries’ exposure to Carry actually lowers the return on US Treasury bonds. The net impact on Treasury returns is a decrease of 0.91 bps.

Cross-elasticity between assets arises because intermediaries are simultaneously active across many asset markets and these intermediaries have limited risk-bearing capacity for commonly traded risk factors. The degree of cross-elasticity thus depends on loadings of traded common risk factors across asset classes. Our analysis provides the first such cross-elasticity estimates. Yet we must underscore that our estimates capture only the intermediary elasticity due to exposure to traded FX risk factors. That is, our estimate should not be interpreted as the total return response to \$1 of trading into an asset market, as these assets can load on other risk factors that we do not capture. Moreover, while our paper connects cross-elasticity between assets to the elasticity of traded FX factors, we are silent on why

intermediaries are inelastic to these factors. Future research could explore the sources of such inelasticity. Nevertheless, our approach advances the understanding of how asset markets are linked, addressing an important question that has been elusive due to the limited availability of trading data and reliable instruments across markets.

7 Conclusion

In conclusion, this paper studies the limited risk-bearing capacity of intermediaries and its implication for asset prices. We measure intermediaries’ risk-bearing capacity with a new measure: “intermediary elasticity”, which is defined as the price response to a marginal unit of risk induced by trading demand shocks. We apply our framework to the FX market and identify three key *traded* risk factors — the Dollar, the Carry, and the Pan-European — that account for 90% of the risk borne by intermediaries during FX trading. Through instrumental variable analysis, we quantify the intermediary elasticity for these factors. We then use the estimated FX-factor elasticity to recover the own- and cross-elasticity among currencies. Consistent with intermediaries being active across multiple asset markets, the three traded FX risk factors also price CDS, Commodity, Corporate bonds, and US Treasury bonds. We are thus able to provide novel estimates of cross-elasticity between different asset markets.

At the heart of our cross-market demand transmission are three elements: assets’ exposure to common risk factors, the amount of factor risks assumed by intermediaries when accommodating demand shocks, and the price intermediaries charge for absorbing these risks. Combining these three elements generates novel transmission patterns, where trading demand shocks in one market could affect prices in other markets by differential magnitudes and even directions. As intermediaries function at the juncture of multiple financial markets

and real sectors, how intermediaries transmit demand shocks to asset prices across different markets is essential to understanding intermediaries' role in the broader economy.

Bibliography

- Adrian, T., E. Etula, and T. Muir. 2014. Financial intermediaries and the cross-section of asset returns. *The Journal of Finance* 69:2557–96.
- An, Y. 2023. Flow-based arbitrage pricing theory. Working paper, Johns Hopkins University.
- An, Y., Y. Su, and C. Wang. 2024. A factor framework for cross-sectional price impacts. Working paper, Johns Hopkins University.
- Bansal, R., and M. Dahlquist. 2000. The forward premium puzzle: different tales from developed and emerging economies. *Journal of International Economics* 51:115–44.
- Bräuer, L., and H. Hau. 2022. Can time-varying currency risk hedging explain exchange rates? .
- Bretscher, L., L. Schmid, I. Sen, and V. Sharma. 2022. Institutional corporate bond pricing. Working Paper.
- Burnside, C., M. Eichenbaum, I. Kleshchelski, and S. Rebelo. 2010. Do Peso Problems Explain the Returns to the Carry Trade? *The Review of Financial Studies* 24:853–91.
- Camanho, N., H. Hau, and H. Rey. 2022. Global portfolio rebalancing and exchange rates. *The Review of Financial Studies* 35:5228–74.
- Cespa, G., A. Gargano, S. J. Riddiough, and L. Sarno. 2021. Foreign Exchange Volume. *The Review of Financial Studies* 35:2386–427.
- Du, W., B. Hébert, and A. W. Huber. 2022. Are intermediary constraints priced? *Review of Financial Studies* .
- Du, W., and A. Huber. 2024. Dollar asset holding and hedging around the globe. Working Paper.
- Du, W., A. Tepper, and A. Verdelhan. 2018. Deviations from covered interest rate parity. *Journal of Finance* 73:915–57.
- Duffie, D., M. J. Fleming, F. M. Keane, C. Nelson, O. Shachar, and P. Van Tassel. 2023. Dealer capacity and us treasury market functionality. *FRB of New York Staff Report* .
- Evans, M., and R. Lyons. 2002. Order flow and exchange rate dynamics. *Journal of Political Economy* 110:170–80.
- Fama, E. F., and K. R. French. 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33:3–56.
- Fama, E. F., and J. D. MacBeth. 1973. Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy* 81:607–36.
- Gabaix, X., and M. Maggiori. 2015. International liquidity and exchange rate dynamics. *Quarterly Journal of Economics* 130:1369–420.
- Haddad, V., and T. Muir. 2021. Do intermediaries matter for aggregate asset prices? *The Journal of Finance* 76:2719–61.
- He, Z., B. Kelly, and A. Manela. 2017. Intermediary asset pricing: New evidence from many

- asset classes. *Journal of Financial Economics* 126:1–35.
- He, Z., and A. Krishnamurthy. 2013. Intermediary Asset Pricing. *American Economic Review* 103:732–70.
- . 2017. Intermediary asset pricing and the financial crisis. *Annual Review of Financial Economics* 173–97.
- Jiang, Z., A. Krishnamurthy, and H. Lustig. 2021. Foreign safe asset demand and the dollar exchange rate. *The Journal of Finance* 76:1049–89.
- Jiang, Z., R. J. Richmond, and T. Zhang. 2024. A portfolio approach to global imbalances. *Journal of Finance* Forthcoming.
- Jolliffe, I. 1986. *Principal component analysis*. Springer Series in Statistics.
- Koijen, R. S., and M. Yogo. 2020. Exchange rates and asset prices in a global demand system. Working Paper, National Bureau of Economic Research.
- Koijen, R. S. J., and M. Yogo. 2019. A demand system approach to asset pricing. *Journal of Political Economy* 127:1475–515.
- Kondor, P., and D. Vayanos. 2019. Liquidity risk and the dynamics of arbitrage capital. *Journal of Finance* 74:1139–73.
- Liao, G., and T. Zhang. 2020. The hedging channel of exchange rate determination. *International finance discussion paper* .
- Lustig, H., N. Roussanov, and A. Verdelhan. 2011. Common Risk Factors in Currency Markets. *The Review of Financial Studies* 24:3731–77.
- Lustig, H., and A. Verdelhan. 2007. The cross section of foreign currency risk premia and consumption growth risk. *American Economic Review* 97:89–117.
- Pasquariello, P. 2007. Informative trading or just costly noise? an analysis of central bank interventions. *Journal of Financial Markets* 10:107–43.
- Ranaldo, A., and P. Santucci de Magistris. 2022. Liquidity in the global currency market. *Journal of Financial Economics* 146:859–83.
- Ranaldo, A., and F. Somogyi. 2021. Asymmetric information risk in fx markets. *Journal of Financial Economics* 140:391–411.
- Ready, R., N. Roussanov, and C. Ward. 2017. Commodity trade and the carry trade: A tale of two countries. *The Journal of Finance* 72:2629–84.
- Roussanov, N., and X. Wang. 2023. Following the fed: Limits of arbitrage and the dollar. Working Paper.
- Sharpe, W. F. 1964. Capital asset prices: A theory of market equilibrium under conditions of risk. *The Journal of Finance* 19:425–42.
- Siriwardane, E., A. Sundaram, and J. Wallen. 2022. Segmented arbitrage. Working Paper.
- Tobin, J. 1978. A proposal for international monetary reform. *Eastern Economic Journal* 4:153–9.

A Proofs

This appendix provides proofs omitted in the main text.

A.1 Proof of Proposition 1

We carry out Cholesky decomposition and obtain $\text{var}(\mathbf{R}) = \mathbf{U}^\top \mathbf{U}$. Because the matrix $\text{var}(\mathbf{f})$ has rank K , the symmetric matrix $\mathbf{U}\text{var}(\mathbf{f})\mathbf{U}^\top$ also has rank K . Hence, $\mathbf{U}\text{var}(\mathbf{f})\mathbf{U}^\top$ has exactly K positive eigenvalues and $N - K$ zero eigenvalues (counting multiplicity). Hence, we carry out eigenvalue decomposition of $\mathbf{U}\text{var}(\mathbf{f})\mathbf{U}^\top$ to obtain

$$\mathbf{U}\text{var}(\mathbf{f})\mathbf{U}^\top \mathbf{G} = \mathbf{G}\mathbf{\Pi}, \quad (\text{A1})$$

where $\mathbf{\Pi} = \text{diag}(\pi_1, \pi_2, \dots, \pi_K)$ with $\pi_k > 0$ for all k and $\mathbf{G}$ is an $N \times K$ orthonormal matrix satisfying $\mathbf{G}^\top \mathbf{G} = \mathbf{I}_K$.

We now define $\mathbf{B} = \mathbf{U}^{-1}\mathbf{G}$, and show that the constructed $\mathbf{B} = (\mathbf{b}_1, \mathbf{b}_2, \dots, \mathbf{b}_K)$ satisfies the conditions (3) and (4). First, we have

$$\mathbf{B}^\top \text{var}(\mathbf{R}) \mathbf{B} = \mathbf{G}^\top (\mathbf{U}^\top)^{-1} \mathbf{U}^\top \mathbf{U} \mathbf{U}^{-1} \mathbf{G} = \mathbf{I}_K. \quad (\text{A2})$$

Second, equation (2) implies $\mathbf{f} = \mathbf{B}\mathbf{q}$, where $\mathbf{q} = (q_1, q_2, \dots, q_K)^\top$. Therefore,

$$\text{var}(\mathbf{f}) = \mathbf{B}\text{var}(\mathbf{q})\mathbf{B}^\top. \quad (\text{A3})$$

Then, using equations (A1), (A2), $\mathbf{B} = \mathbf{U}^{-1}\mathbf{G}$, and $\text{var}(\mathbf{R}) = \mathbf{U}^\top \mathbf{U}$, we have

$$\text{var}(\mathbf{q}) = \mathbf{B}^\top \text{var}(\mathbf{R}) \text{var}(\mathbf{f}) \text{var}(\mathbf{R}) \mathbf{B} = \mathbf{G}^\top \mathbf{U} \text{var}(\mathbf{f}) \mathbf{U}^\top \mathbf{G} = \mathbf{\Pi}. \quad (\text{A4})$$

A.2 Proof of Proposition 2

Simplifying equation (6), we have

$$\begin{aligned} & \mathbb{E}[-\exp(-\gamma_k((S_k/\mu_k - y)\mathbf{b}_k^\top \mathbf{R} + P_k(q_k)y/P_k(0)))] \\ &= -\exp(-\gamma_k(S_k/\mu_k - y)\mathbb{E}[\mathbf{b}_k^\top \mathbf{R}] - \gamma_k P_k(q_k)y/P_k(0) + \gamma_k^2(S_k/\mu_k - y)^2 \text{var}(\mathbf{b}_k^\top \mathbf{R})/2). \end{aligned} \quad (\text{A5})$$

Taking the first-order condition against y , we obtain

$$0 = \gamma_k \mathbb{E}[\mathbf{b}_k^\top \mathbf{R}] - \gamma_k P_k(q_k)/P_k(0) - \gamma_k^2(S_k/\mu_k - y) \text{var}(\mathbf{b}_k^\top \mathbf{R}). \quad (\text{A6})$$

Because the optimal $y = q_k/\mu_k$, we obtain

$$P_k(q_k)/P_k(0) = \lambda_k(q_k - S_k) \text{var}(\mathbf{b}_k^\top \mathbf{R}) + \mathbb{E}[\mathbf{b}_k^\top \mathbf{R}], \quad (\text{A7})$$

where $\lambda_k = \gamma_k/\mu_k$. Specifically, we know that

$$P_k(0)/P_k(0) = -\lambda_k S_k \text{var}(\mathbf{b}_k^\top \mathbf{R}) + \mathbb{E}[\mathbf{b}_k^\top \mathbf{R}]. \quad (\text{A8})$$

Taking the difference, we obtain equation (7).

A.3 Proof of Proposition 3

Because factors have uncorrelated returns by Proposition 1, we can project the return of any currency n onto the factors and obtain

$$\mathbf{R}(n) = \sum_{k=1}^K \beta_{n,k} \mathbf{b}_k^\top \mathbf{R} + e_n, \quad (\text{A9})$$

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 (7), the price impact of currency n is

$$\Delta p_n = \sum_{k=1}^K \beta_{n,k} \Delta p_k = \sum_{k=1}^K \lambda_k q_k \text{var}(\mathbf{b}_k^\top \mathbf{R}) \beta_{n,k}. \quad (\text{A10})$$

Therefore, we have

$$\frac{\partial \Delta p_n}{\partial q_k} = \frac{\partial \Delta p_k}{\partial q_k} \times \frac{\partial \Delta p_n}{\partial \Delta p_k} = \lambda_k \text{var}(\mathbf{b}_k^\top \mathbf{R}) \times \beta_{n,k}. \quad (\text{A11})$$

Next, equation (5) implies that $\partial q_k / \partial f_m = \beta_{m,k}$. Hence, we have

$$\frac{\partial \Delta p_n}{\partial f_m} = \sum_{k=1}^K \frac{\partial q_k}{\partial f_m} \times \frac{\partial \Delta p_n}{\partial q_k} = \sum_{k=1}^K \beta_{m,k} \times \lambda_k \text{var}(\mathbf{b}_k^\top \mathbf{R}) \times \beta_{n,k}, \quad (\text{A12})$$

which is equation (10).

B Additional Figures and Tables

Table A1: **Top 3 PCs from FX Trading Flows**

Currency	PC 1	PC 2	PC 3
AUD	-0.03	0.03	0.12
CAD	-0.04	1.00	-0.06
CHF	-0.01	-0.02	-0.06
DKK	-0.00	-0.00	0.01
EUR	-1.00	-0.03	0.03
GBP	-0.02	-0.01	0.26
HKD	-0.00	-0.02	-0.00
HUF	-0.00	-0.00	-0.00
ILS	-0.00	-0.01	-0.00
JPY	-0.04	-0.06	-0.95
KRW	-0.00	0.01	-0.00
MXN	-0.01	0.01	-0.00
NOK	0.00	0.01	0.01
NZD	-0.01	0.01	0.01
SEK	0.01	0.00	0.00
SGD	-0.01	-0.01	0.01
ZAR	-0.01	0.00	0.01
USD	1.17	-0.92	0.62
Var explained	60%	27%	16%

Notes: This table presents the portfolio weights of the top 3 traded FX factors, constructed using a standard PCA of FX trading flows. We use weekly flow data for 17 non-USD currencies from September 2012 to December 2023. The portfolio weight of USD is computed as the negative sum of the weights of all other currencies.

Table A2: Asset Market's Loading on Traded FX Factors

	CDS (1)	Comm (2)	CorpBond (3)	UST (4)
Dollar Factor	-0.40*** (0.07)	-0.92*** (0.17)	-0.51*** (0.09)	-0.09** (0.04)
Carry Factor	0.46*** (0.08)	0.32* (0.17)	0.51*** (0.09)	-0.24*** (0.03)
Pan-European	0.02 (0.10)	-0.67*** (0.21)	-0.30*** (0.09)	-0.18*** (0.04)
Observations	201	283	277	287
R ²	0.36	0.16	0.38	0.25

Notes: This table reports the beta loadings from regressing asset class monthly average excess return between 2000-02 and 2023-12 on returns from the three traded FX factors. Standard errors are presented in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.