Demand Propagation Through Traded Risk Factors[*]

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Abstract

We develop a risk-driven framework to quantify how demand shocks to one asset reprice others. Applied to FX, intermediaries' aversion to non-diversifiable risk emerges as the key friction transmitting shocks. Using a novel technique that jointly analyzes trading flows and returns, we identify three traded risk factors—Dollar, Carry, and a new Euro-Yen Residual factor linked to active euro-yen trading—that explain 90% of the non-diversifiable risk intermediaries bear. These factors are orthogonal in both trading flows and returns, capturing independent channels of propagation. We estimate each factor's price sensitivity using an instrumental-variable strategy enabled by our factor construction. We find that factor prices rise by 5-30 basis points per $1 billion of net demand, highlighting intermediaries' limited risk-bearing capacity. This friction causes demand shocks to first reprice non-diversifiable risks and then all assets exposed to these risks. We map how interventions in one currency move 16 other exchange rates and 5 non-FX assets through traded risk factors.

Keywords: Demand Propagation, Traded Risk Factors, Diversification, Intermediary, FX

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1 Introduction

A defining feature of modern financial markets is their tight interlinkages. Episodes such as the Global Financial Crisis of 2007-2009 serve as stark reminders that shocks originating in one corner of the market can rapidly propagate across the globe (e.g., Allen and Gale, 2000; Pavlova and Rigobon, 2008). One class of shocks that arises frequently in asset markets are demand shocks. Although they do not reflect new fundamental information, demand shocks nonetheless move prices powerfully (e.g., Lee, Shleifer, and Thaler, 1991; Froot and Ramadorai, 2008; Koijen and Yogo, 2019). In an interconnected system, these shocks rarely affect only a single asset. For example, when a central bank intervenes in the foreign exchange market, the target currency moves—but so do many others. Which currencies react, and by how much? Answering these questions and, more broadly, understanding how shocks propagate are essential for designing effective policy interventions and responses.

In this paper, we propose a risk-driven framework for quantifying demand propagation, and find that intermediaries' aversion to absorbing non-diversifiable risk is a key friction underlying shock transmission. We argue that when a given asset is hit by a demand shock, marginal investors—often intermediaries—end up carrying additional exposure in a small set of traded, non-diversifiable risk, which can be represented as factor portfolios or "factors." Intermediaries' limited risk-taking capacity means that shifts in factor demand result in factor price changes, which in turn reprice all assets that are exposed to those factors.

The focus on non-diversifiable risks is motivated by the tight connections across financial assets. In principle, every asset could be affected by shocks to every other, thus flexibly capturing propagation between N assets would require estimating $N(N-1)$ cross-impact coefficients. However, genuine asset-specific demand variation is scarce: investor flows often arrive in correlated baskets, rebalancing typically affects multiple assets at once, and index-linked trades tend to move many markets together. Progress therefore hinges on imposing structure. Our structure is rooted in non-diversifiable risks because these are known to drive co-movements in asset prices (Markowitz, 1952; Ross, 1976; Kozak, Nagel, and Santosh, 2018). Moreover, recent studies show that the price of these risks responds to quantity changes (Gabaix and Koijen, 2021; Li and Lin, 2022). Our contribution is three-fold. Conceptually, we combine factor's price sensitivity with each asset's factor loading to quantify demand propagation. Methodologically, we develop new tools to implement the framework, including constructing empirically traded risk factors and isolating independent factor-specific variation from correlated currencies. Empirically, we devise a novel instrumental variable strategy to identify intermediaries' limited risk-bearing capacity as a key friction underlying the transmission of shocks.

We apply our framework to study demand propagation in foreign exchange (FX). Demand shocks from central-bank interventions, corporate hedging, and index rebalancing occur almost daily. Moreover, because triangular arbitrage holds, currencies are tightly interconnected.[1] This makes the FX market a natural setting for our framework, which addresses such interlinkages by focusing on non-diversifiable risks—precisely the risks around which FX markets are organized. Indeed, sophisticated FX intermediaries absorb customer trades and pass any resulting inventory risk among themselves through a dense inter-dealer network. This constant reshuffling leaves returns to align with a handful of common factors (Lustig, Roussanov, and Verdelhan, 2011), underscoring the role of non-diversifiable risks in driving currency co-movement. What has been missing is data on the underlying trading flows. A novel dataset that records the net positions handled by more than 70 major intermediaries between 17 currencies fills this gap, which we harness to study the risks FX intermediaries truly bear.

Our inquiry starts with identifying the risk factors that can transmit demand shocks. Risk factors are typically proposed to explain common variation in returns (Ross, 1976). But a singular focus on returns ignores quantities, and the resulting risk factors need not correspond to those that investors actually trade. A trading-only analysis (e.g., Lo and Wang, 2000; Hasbrouck and Seppi, 2001), by contrast, would identify portfolios that are actively traded. In equities, these portfolios can be economically meaningful, capturing risks linked to agency frictions in delegated asset management (Dou, Kogan, and Wu, 2022). In FX, however, they merely uncover the most liquid currency pairs. We therefore develop a new method that jointly analyzes the weekly trading flows between customers and intermediaries and the corresponding panel of currency returns, uncovering what we call "*traded risk factors*": portfolios that explain the preponderance of non-diversifiable risk borne by intermediaries when absorbing trading flows, and that therefore serve as the principal conduits for demand-shock propagation.[2]

[1] Across any three currencies A, B, and C, no-arbitrage implies that the cross rate equals the product of the other two: $S_{A/C} = S_{A/B} \times S_{B/C}$.

[2] Our notion of "traded" risk factors differs from the conventional idea of "tradable" factors. Tradable

Our method reveals that the top three traded risk factors in FX account for 90% of the trading-induced non-diversifiable risks in our sample, are economically interpretable, and remain stable over time. The two most traded risk factors resemble the well-known Dollar and Carry factors, yet our method recovers the Carry factor without first sorting currencies by interest rates, as in Lustig, Roussanov, and Verdelhan (2011), and further shows that intermediaries accumulated about $0.8 trillion of Carry exposure between 2012 and 2023. The third factor, the Euro-Yen Residual, captures the risk intermediaries bear when accommodating active customer trading between the euro area and Japan, after hedging Dollar and Carry exposures. This new factor delivers a Sharpe ratio comparable to that of the Carry factor.

Next, we investigate how the price of each traded risk factor responds to its own trading-induced risks. To estimate this price sensitivity from observed trading flows and returns, we use instrumental variables (IVs). In our context, the ideal instrument should affect trading demand without carrying information about fundamentals, and crucially, the instrument should affect a factor's price only though demand for that factor. This last requirement is difficult to satisfy in general. As financial assets are tightly linked, any instrument that shifts demand for one asset is likely to shift demand for others that are not included in the regression. Such spill-overs of demands feed back into the original asset's price via cross-impacts, contaminating the estimate of own price sensitivity. To address this issue, we orthogonalize our traded risk factors so that *both* factor returns and factor trading flows are mutually uncorrelated. Put differently, each factor is an independent source of risk that investors also trade independently in equilibrium. This joint orthogonality ensures that each factor behaves like an independent asset, so that a demand shock to one leaves the prices of the rest unchanged. A consistent estimate of each factor's price sensitivity thus follows simply from regressing that factor's return on its own instrumented demand.[3]

factors correspond to risks that are replicable by portfolios that investors could buy or sell. Non-tradable factors, by contrast, reflect risks that are observable but for which no direct trading vehicle exists—global macroeconomic conditions are a typical example. Crucially, labeling a factor "tradable" does not imply that the associated replicating portfolio is, in fact, actively traded by investors.

[3]Fuchs, Fukuda, and Neuhann (2025) and Haddad, He, Huebner, Kondor, and Loualiche (2025) both point out that cross-asset linkages can complicate IV estimation. Haddad, He, Huebner, Kondor, and Loualiche (2025) propose regressing each factor's return on demands for all factors simultaneously, with factors chosen from the prior literature. We let price and quantity data reveal the most important risk factors that transmit demand shocks and orthogonalize the factors, thereby achieving identification without pre-specifying the full factor universe.

We find that FX intermediaries require substantial price compensation to absorb non-diversifiable risks: a \$1 billion net demand shock raises factor prices by 5 basis points for the Dollar, 9 basis points for the Carry, and 29 basis points for the Euro-Yen Residual. These estimates directly reflect intermediaries' limited risk-bearing capacity and form the central friction driving the propagation of demand shocks across currencies. Supporting this interpretation, we find strong state-dependence: the Dollar factor's price sensitivity is lower when FX intermediaries' public equity returns are high. As equity returns likely capture variations in intermediaries' wealth, our findings are consistent with greater wealth leading to greater willingness to bear risk (He and Krishnamurthy, 2013; Brunnermeier and Sannikov, 2014).

To identify these effects, we use as demand instruments the week-ahead 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. Importantly, because these auctions are typically forward-guided, the week-ahead announcements contain limited new information, making the instruments plausibly exogenous and satisfying the exclusion restriction. For instance, in the U.S., the Treasury Borrowing Advisory Committee (TBAC) releases two-quarter-ahead recommendation on auction amounts; the subsequent week-ahead announcements and the eventual auctions exhibit little deviation from these recommendations (Rigon, 2024). Although the timing and the amount of bonds auctioned are well anticipated, the associated demand shocks could still affect prices when realized (Vayanos, 2021; Hartzmark and Solomon, 2024). Consistent with these shocks being uninformed and temporary, we show that the associated price responses fully revert within a month. This mean reversion also implies that trading flow explains a sizable share of short-term return variance—about 10-35% of the 1-week return, but considerably less at longer horizons—5-15% of the 1-month return.

Price reversion implies return predictability. Although our estimated factor price sensitivities appear large, the attainable Sharpe ratio from trading against demand shocks in any of the three factors is below 0.1 annualized. These modest ratios reflect the high volatility of FX returns. In such a market, only sophisticated and specialized intermediaries absorb demand shocks, leaving a relatively thin layer of arbitrage capital. This may seem counterintuitive given the large turnover in FX, but up to 75% of trades occur between intermediaries

(BIS, 2022). The limited arbitrage capital may be why price sensitivity is higher in FX than in equities. Based on Gabaix and Koijen (2021), a $1 billion demand shock raises the price of the U.S. market factor by only 2 basis points.[4] Differences in arbitrage capital may also explain cross-factor variation, with lesser-known factors such as the Euro-Yen Residual attracting less arbitrage capital and thus exhibiting greater price sensitivity.

Having identified the most traded risk factors and each factor's price sensitivity to risk, we use these findings to trace out demand propagation across currencies. When intermediaries accommodate a demand shock to one currency, they bear additional non-diversifiable risks captured by the traded risk factors. These risks then affect the prices of the traded risk factors in proportion to these factors' price sensitivities. Finally, the law of one price ensures that prices of other currencies that share those exposures also adjust and such exposures can be measured as betas or factor loadings. We quantify this demand propagation through cross-multipliers, which measure how a demand shock to one currency affects the price of another, holding the demand shocks to all other currencies constant.

We uncover rich patterns of cross-currency substitution arising from exposures to the three traded risk factors. Currencies exhibit strong demand propagation when they share the same sign of loading to a factor and modest propagation 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 risk factors, making them close "substitutes" whose prices co-move strongly. 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 these 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 Residual factor, making them "complements" for that factor. As a result, we estimate only a modest cross-multiplier, implying muted demand propagation between EUR and JPY.

Additionally, we find that five major non-currency assets also load on the traded risk factors in FX, allowing demand shocks to propagate across markets through shared cur-

[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 basis points.

rency risk. We study U.S. Treasury bonds (Treasurys), corporate bonds, options, CDS, and commodities. The traded risk factors in FX explain approximately 30% of each non-FX asset's return variance. Consequently, a demand shock to, say, corporate bonds generates non-diversifiable risks as captured by the traded risk factors. These risks affect the prices of traded risk factors and, in turn, the prices of options and other assets that load on the affected factors. We find that Treasurys are the only asset whose demand shocks can reduce, rather than raise, other assets' price, reflecting Treasurys' "safe haven" status. In our framework, this safe-haven property arises because Treasurys load on the Carry factor with a uniquely negative sign, making them an effective hedge against other assets during shifts between "risk-on" and "risk-off" regimes.

Our paper contributes to the understanding of demand propagation across assets marked by high degree of interconnection. In essence, we introduce a new structure for cross-asset demand propagation by mapping it to a small set of independent risk factors that govern price co-movement. This risk-based structure follows naturally from the canonical asset-pricing insight that risk drives returns (Markowitz, 1952; Ross, 1976). In doing so, our approach complements and contrasts with other structural approaches of studying demand shocks. One existing approach maps the effect of demand to asset characteristics via micro-founded demand systems (e.g., Koijen and Yogo, 2019, 2020; Bretscher, Schmid, Sen, and Sharma, 2022; Chaudhary, Fu, and Li, 2023; Jiang, Richmond, and Zhang, 2024; Haddad, He, Huebner, Kondor, and Loualiche, 2025). Another approach links the price effect of demand shocks to pairwise return covariances (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). Similar to these approaches, we take seriously the factor structure in asset returns, which is shown to be empirically important even in the presence of demand shocks (Kozak, Nagel, and Santosh, 2018). At the same time, we innovate on two key dimensions. First, because we are interested in propagation across assets, we directly study the effect of demand shocks to traded, non-diversifiable risks. These risk factors are constructed to be independent, allowing for easy-to-implement factor-by-factor demand estimation that is free of cross-impact biases. Second, we allow possibly different risk-bearing capacity, and thereby price sensitivity, toward different risks. Consequently, we are able to generate flexible cross-asset dynamics that allow assets to be substitutes with respect to one risk but complements with respect to another.

Our paper also extends the literature on exchange rates by developing a novel approach to quantifying the price impact 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 investors must bear. Our 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 traded risk factors, the Dollar and the Carry, are similar to what price unconditional FX returns (Lustig, Roussanov, and Verdelhan, 2011). We moreover introduce a new Euro-Yen Residual factor, which delivers a Sharpe ratio comparable to that of the Carry factor and is priced conditionally on demand shocks. Finally, we uncover new evidence demonstrating the pivotal role of intermediation friction in how risks are priced in FX (e.g., Gabaix and Maggiori, 2015; Itskhoki and Mukhin, 2021). 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, between FX and other asset markets, as well as in transmitting monetary policy shocks (e.g., Jiang, Krishnamurthy, and Lustig, 2021; Camanho, Hau, and Rey, 2022; Chernov and Creal, 2023; Gourinchas, Ray, and Vayanos, 2024; Loualiche, Pecora, Somogyi, and Ward, 2024).

More generally, our paper augments the intermediary asset pricing and the microstructure literature, 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 assets, rather than analyzing the risks of individual

[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.

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 sources and Section 4 identifies the traded risk factors. Section 5 examines the pricing properties of the traded risk factors. Section 6 explores how these factors propagate demand shocks across currencies and asset classes. Section 7 concludes.

2 Theoretical Framework

Our goal is to provide a parsimonious empirical characterization of cross-currency impacts. To anchor this characterization in a risk-driven framework, we start with a standard equilibrium model and show that, in this benchmark, cross-currency impacts are determined by a single price-sensitivity parameter, which maps to intermediaries' per-capita risk aversion and captures the marginal risk-return trade-off conditional on trading. This one-parameter characterization can be too restrictive for modeling cross-currency impacts, so we extend the model to allow factor-specific price sensitivities. To implement our model, we construct a small number of independent, traded risk factors that are orthogonal in both returns and flows. These traded risk factors serve as distinct channels for demand propagation and permit factor-by-factor estimation. Propositions 1 and 2 detail the construction of these factors and show how their price sensitivities recover the full cross-currency impacts.

2.1 Standard Equilibrium Model

Consider a two-period setting, $t = 0$ and $t = 1$, with $N + 1$ currencies. The last currency serves as the numeraire, so all exchange rates are denominated in its units. Appendix A.3 shows that our model is invariant to the numeraire choice; hence, without loss of generality, we take the U.S. dollar (USD) as the numeraire throughout. At $t = 0$ customers can buy or sell any pair of currencies. A continuum of competitive intermediaries with mass μ absorbs all customer orders and clears the market. Each intermediary has constant absolute risk aversion (CARA) utility with coefficient γ. For each non-USD currency $n = 1, \dots, N$, let r_n denote its excess return from $t = 0$ to $t = 1$. Formally, r_n is the payoff from borrowing one unit of the USD at the risk-free rate, exchanging the proceeds into currency n at $t = 0$, investing at currency n's risk-free rate until $t = 1$, and then exchanging the position back into the USD at $t = 1$.

We study customer demand shocks that arrive at $t = 0$. These shocks are uninformed: they are independent of exchange rates that materialize at $t = 1$. Because intermediaries have limited risk-bearing capacity, the exchange rate of currency n at time 0 moves from P_n to $P_n(1 + \Delta p_n)$, where Δp_n is the percentage price change, or price impact, on currency n. For accounting purposes we rewrite every transaction as a net flow between each non-USD currency and the USD, such that if a customer buys currency n by selling currency m, we record a positive flow for currency n and a negative flow for currency m. The resulting net purchase equals $\Delta Q_n/P_n$ units of currency n, or, equivalently, ΔQ_n dollars. Throughout, we measure demand shocks relative to the pre-shock exchange rate P_n, consistent with standard empirical practice.

The equilibrium prices at $t = 0$ must adjust so that competitive intermediaries are willing to absorb the net customer demand. Let each intermediary take a position y_n dollars in currency n, which in equilibrium equals $-\Delta Q_n/\mu$. Holding one additional USD's worth of currency n exposes the intermediary to an extra payoff r_n at $t = 1$. The cost of making this purchase at time 0 has increased by Δp_n. Compounding that price change forward to time 1 at the USD's gross risk-free rate R_F gives the intermediary's objective

$$\{-\Delta Q_1/\mu, \dots, -\Delta Q_N/\mu\} = \arg\max_{\{y_1,\dots,y_N\}} \mathbb{E}\left[-\exp\left(-\gamma \sum_{n=1}^{N} y_n(r_n - R_F\Delta p_n)\right)\right]. \tag{1}$$

The first-order condition to (1) implies that the price impact of currency n satisfies[6]

$$\Delta p_n = \lambda\left[\text{cov}(r_n, r_1)\Delta Q_1 + \text{cov}(r_n, r_2)\Delta Q_2 + \cdots + \text{cov}(r_n, r_N)\Delta Q_N\right], \tag{2}$$

where $\lambda := \gamma/(\mu R_F)$ approximates the per-capita risk aversion of intermediaries.[7] Equation (2) shows that the price impact of asset n is a return-covariance-weighted linear combination of demand shocks across all currencies, which is the standard mean-variance bench-

[6]Define the $N \times 1$ vectors $\Delta\mathbf{Q} = (\Delta Q_1, \dots, \Delta Q_N)^\top$, $\mathbf{r} = (r_1, \dots, r_N)^\top$, and $\Delta\mathbf{p} = (\Delta p_1, \dots, \Delta p_N)^\top$. The first-order condition of (1) then takes the form $R_F\Delta\mathbf{p} - \mathbb{E}[\mathbf{r}] = \gamma\text{var}(\mathbf{r})\Delta\mathbf{Q}/\mu$. Note that $\Delta\mathbf{Q} = \mathbf{0}$ gives $\Delta\mathbf{p} = \mathbf{0}$. Taking the difference then gives $\Delta\mathbf{p} = (\gamma/(R_F\mu))\text{var}(\mathbf{r})\Delta\mathbf{Q}$, which elementwise corresponds to (2).

[7]The division by the gross risk-free rate R_F appears only because the model is discrete; in continuous time it disappears.

mark for price impact (see Kozak, Nagel, and Santosh, 2018 and the literature review by Rostek and Yoon, 2023).

The equilibrium price-impact formula in (2) extends from single currencies to any portfolio of currencies, i.e., to any factor. Fix a factor k with currency weights $w_{n,k}$ for $n = 1, \ldots, N$.[8] Let $\Delta p_k^{\text{factor}}$ and r_k^{factor} denote, respectively, the factor's price impact at $t = 0$ and its return from $t = 0$ to $t = 1$. Then

$$\Delta p_k^{\text{factor}} = w_{1,k}\Delta p_1 + \cdots + w_{N,k}\Delta p_N \tag{3}$$

$$= \lambda \left[\text{cov}\left(\sum_{n=1}^{N} w_{n,k} r_n, r_1 \right) \Delta Q_1 + \cdots + \text{cov}\left(\sum_{n=1}^{N} w_{n,k} r_n, r_N \right) \Delta Q_N \right] \tag{4}$$

$$= \lambda \left[\text{cov}\left(r_k^{\text{factor}}, r_1 \right) \Delta Q_1 + \cdots + \text{cov}\left(r_k^{\text{factor}}, r_N \right) \Delta Q_N \right]. \tag{5}$$

Equation (3) uses the Law Of One Price (LOOP) to express the factor's price impact as the weighted sum of its constituent currencies' impacts. Substituting the currency-level expression from (2) yields (4). Finally, recognizing that $r_k^{\text{factor}} = \sum_{n=1}^{N} w_{n,k} r_n$ from the LOOP gives (5).

2.2 Factor-Level Generalization

The standard equilibrium benchmark (2) above captures all cross-currency impacts with one parameter, λ. In this subsection, we relax this restriction by allowing a small set of factor-specific price sensitivities. This generalization delivers the empirical flexibility needed to match the data while keeping the analysis firmly grounded in equilibrium theory.

We first simplify the equilibrium condition in (5) by restricting attention to K risk factors whose returns are mutually uncorrelated, $\text{cov}\left(r_k^{\text{factor}}, r_j^{\text{factor}} \right) = 0$ for every $k \neq j$. These factors capture the independent risk dimensions actively traded by customers; Section 2.4 describes their construction in detail. Under this orthogonality, the coefficient from a univariate regression of a currency's return on one factor equals the corresponding coefficient in a full multiple-factor regression. Thus the beta of currency n on factor k is simply

[8] Because every trade is financed in the USD, the implied portfolio weight on the USD is $-\sum_{n=1}^{N} w_{n,k}$.

$\beta_{n,k} = \text{var}\left(r_k^{\text{factor}}\right)^{-1} \text{cov}\left(r_k^{\text{factor}}, r_n\right)$. Substituting this expression into equation (5) yields

$$\Delta p_k^{\text{factor}} = \lambda \text{var}\left(r_k^{\text{factor}}\right) \left[\beta_{1,k}\Delta Q_1 + \cdots + \beta_{N,k}\Delta Q_N\right]. \tag{6}$$

Note that the linear combination $\beta_{1,k}\Delta Q_1 + \cdots + \beta_{N,k}\Delta Q_N$ represents the net customer demand for factor k. When intermediaries absorb a currency-level demand shock, ΔQ_n, their exposure to factor k rises by $\Delta Q_n \beta_{n,k}$, while the residual risk is orthogonal to that factor. Summing these beta-scaled exposures across all N currencies[9] therefore leaves a *non-diversifiable* demand shock of magnitude $\beta_{1,k}\Delta Q_1 + \cdots + \beta_{N,k}\Delta Q_N$.

This weighting scheme is exactly the portfolio-beta calculation used in risk management: each position is multiplied by its factor loading, and the results are added up to obtain the book's aggregate factor exposure. It is also identical to the cross-hedging ratio that standard texts derive for offsetting the risk in a single asset with an index future (see section 3.6 of Hull, 2022). Accordingly, define

$$\Delta Q_k^{\text{factor}} := \beta_{1,k}\Delta Q_1 + \cdots + \beta_{N,k}\Delta Q_N \tag{7}$$

as demand for factor k, and rewrite (6) as

$$\Delta p_k^{\text{factor}} = \lambda \text{var}\left(r_k^{\text{factor}}\right) \Delta Q_k^{\text{factor}}. \tag{8}$$

Rearranging equation (8) gives

$$\frac{\Delta p_k^{\text{factor}}}{\text{var}\left(r_k^{\text{factor}}\right) \Delta Q_k^{\text{factor}}} = \lambda = \frac{\gamma}{\mu R_F}. \tag{9}$$

Here, $\Delta p_k^{\text{factor}}$ represents the price impact of factor k at time 0. The denominator, $\text{var}\left(r_k^{\text{factor}}\right) \Delta Q_k^{\text{factor}}$ is the incremental quantity of risk created by the marginal demand shock. Consequently, the ratio measures the price sensitivity to risks induced by demand shocks and captures the *marginal* risk-return tradeoff conditional on trading. This concept extends the canonical price of risk, which reflects the *unconditional* risk-return tradeoff. Equation (9) further shows that the ratio equals intermediaries' per-capita risk aversion and is therefore invariant

[9] Our model uses a representative intermediary to accommodate all customer trades. In practice, such netting across currencies could also occur through interdealer trading.

to portfolio leverage.[10]

By employing orthogonal factors, we have simplified equation (5) to (9), so each factor responds only to its own demand shocks. However, (9) also implies that for any two different factors $k \neq j$, their price sensitivity to risk must be the same, i.e.,

$$\frac{\Delta p_k^{\text{factor}}}{\text{var}\left(r_k^{\text{factor}}\right) \Delta Q_k^{\text{factor}}} = \frac{\Delta p_j^{\text{factor}}}{\text{var}\left(r_j^{\text{factor}}\right) \Delta Q_j^{\text{factor}}}. \tag{10}$$

The restriction follows from mean-variance utility: a representative intermediary has the same marginal utility of wealth no matter which factor delivers that wealth. This property holds not only under the CARA specification we adopt, but more generally under CRRA or recursive preferences, as such utilities can generate time-varying risk aversion through state variables, but they preserve the cross-sectional equality implied by mean-variance pricing.

This single-lambda characterization of cross-currency impacts can be too restrictive. Theoretically, modern asset-pricing research permits distinct unconditional risk-return trade-offs across factors (Fama and MacBeth, 1973). If unconditional trade-offs differ, it is natural to permit the conditional trade-offs in (10) to differ as well. Specifically, here, $\lambda = \gamma/(\mu R_F)$, heterogeneous trade-offs can potentially arise if the pricing kernel varies by risk dimension (different γ) or if intermediaries are segmented across risks (different μ).[11] Empirically, a single degree of freedom in λ predicts the same price sensitivity whether the shock is to the aggregate market risk, a long-short style factor, or pure idiosyncratic risk. This stark implication conflicts with a large demand-based literature that finds markedly different price sensitivities for different portfolios (see Table 1 in Gabaix and Koijen, 2021 for a review).

We therefore relax (10) by allowing factor-specific sensitivities,

$$\frac{\Delta p_k^{\text{factor}}}{\text{var}\left(r_k^{\text{factor}}\right) \Delta Q_k^{\text{factor}}} = \lambda_k. \tag{11}$$

Moreover, as we show in Section 2.4, the K factors can be constructed such that there are no cross-factor impacts. Consequently, specification (11) contains K sensitivity parameters,

[10] For instance, doubling every position—i.e., multiplying the weights $w_{n,k}$ by 2—doubles the factor's price impact $\Delta p_k^{\text{factor}}$, halves the factor demand $\Delta Q_k^{\text{factor}}$ (because each asset's beta to the levered factor is halved), and quadruples the return variance $\text{var}\big(r_k^{\text{factor}}\big)$, leaving the ratio in (9) unchanged.

[11] Dynamic models can also produce distinct λ_k's endogenously; An and Zheng (2025) show this for CARA agents when trading demand is predictable.

one λ_k per factor.

2.3 Demand Propagation Across Currencies

We now use the LOOP to derive demand propagation across individual currencies from factor-level price sensitivities. Consider the scenario where currency m experiences a \$1 demand shock (a one-dollar increase in ΔQ_m), while customers' demand for all other currencies remains constant. First, as in equation (7), this additional \$1 demand shock to currency m raises the demand shock $\Delta Q_k^{\text{factor}}$ to factor k by an amount $\beta_{m,k}$. Second, the change in factor-k demand alters its price by $\Delta p_k^{\text{factor}} = \lambda_k \text{var}\left(r_k^{\text{factor}}\right)$, as in equation (11). Finally, changes in factor-k price $\Delta p_k^{\text{factor}}$ affect currency-n price Δp_n through the LOOP, with the sensitivity being $\beta_{n,k}$. The partial derivative $\partial \Delta p_n / \partial \Delta Q_m$ measures this demand propagation and is referred to as the "cross-multiplier." Proposition 1 derives the model-implied cross-multiplier, and Appendix A.1 provides a proof.

PROPOSITION 1 (Demand propagation). *The cross-multiplier between currencies n and m is:*

$$\frac{\partial \Delta p_n}{\partial \Delta Q_m} = \sum_{k=1}^{K} \frac{\partial \Delta Q_k^{\text{factor}}}{\partial \Delta Q_m} \times \frac{\partial \Delta p_k^{\text{factor}}}{\partial \Delta Q_k^{\text{factor}}} \times \frac{\partial \Delta p_n}{\partial \Delta p_k^{\text{factor}}} = \sum_{k=1}^{K} \beta_{m,k} \times \lambda_k \, \text{var}\left(r_k^{\text{factor}}\right) \times \beta_{n,k}. \tag{12}$$

The cross-multiplier as channeled through traded risk factors is symmetric:

$$\frac{\partial \Delta p_n}{\partial \Delta Q_m} = \frac{\partial \Delta p_m}{\partial \Delta Q_n}. \tag{13}$$

This symmetry arises because

$$\frac{\partial \Delta Q_k^{\text{factor}}}{\partial \Delta Q_n} = \beta_{n,k} = \frac{\partial \Delta p_n}{\partial \Delta p_k^{\text{factor}}}. \tag{14}$$

The first equality, relating currency to factors in terms of quantity, follows from our portfolio theory (7), while the second equality, relating currency to factors in terms of price, results from the law of one price.

Under the standard equilibrium benchmark (2), the cross-impact between two currencies is

$$\frac{\partial \Delta p_n}{\partial \Delta Q_m} = \lambda \operatorname{cov}(r_n, r_m), \tag{15}$$

which depends on a single parameter λ and the pairwise return covariance. In contrast, our cross-multiplier in (12) makes use of currencies' covariance with each factor (β) because we allow factor-specific price sensitivity to risk (λ_k).

2.4 Constructing Traded Risk Factors

The discussion thus far is about how demand shocks propagate through traded risk factors. We now construct these factors from observed equilibrium returns and trading flows. Henceforth, we use ΔQ to denote observed equilibrium trading flows and $\Delta \hat{Q}$ to denote uninformed demand shocks, obtained possibly from instrumental variables.

The factors we choose should have two properties. First, although the complete set of systematic risks is unknown and potentially large (Cochrane, 2011), our chosen factors must capture a substantial share of trading-induced risk, so that they act as the primary channels through which demand shocks propagate across currencies. Second, because investors often transact in baskets that load on several uncorrelated risks at once,[12] our factors must correspond to independent sources of risk that customers also trade independently to eliminate cross-factor impact.

Our "traded risk factors" satisfy these two properties. We estimate them with a new procedure that jointly uses returns and flows, letting actual trading patterns reveal the risks investors care about; we then rank candidate factors by the share of trading-induced risk they explain and select the top few that capture a large share. We also construct the factors to have both uncorrelated returns and uncorrelated trading flows, ensuring independence and avoiding cross-factor impact.[13]

[12]This practice has been bolstered by the growth of portfolio trades and exchange-traded funds (ETFs). Evidence includes the strong commonality in order flow across assets (Hasbrouck and Seppi, 2001; Balasubramaniam, Campbell, Ramadorai, and Ranish, 2023), the sizable price effects that follow index inclusions (Shleifer, 1986; Chang, Hong, and Liskovich, 2015; Pavlova and Sikorskaya, 2023), and theoretical work linking asset price co-movements to institutional demand (Basak and Pavlova, 2013; Buffa and Hodor, 2023).

[13]The relevant return r in the intermediaries' optimization in Section 2.1 is the counterfactual currency return that would prevail in the absence of customer trading, which cannot be observed directly. The imperative to work with equilibrium return further underscores the need to simultaneously orthogonalize returns and trading. By definition, the equilibrium return equals the counterfactual return plus the trading-induced component. Under mild technical conditions, requiring both equilibrium returns and trading flows

The following proposition formalizes the idea and, together with Appendix A.2, provides an explicit algorithm for constructing the factors.

PROPOSITION 2. *There exists a set of K factors that spans all non-diversifiable risk induced by customer trading and satisfies*

1. *Uncorrelated factor returns:*

$$\mathrm{cov}\big(r_k^{\text{factor}}, r_j^{\text{factor}}\big) = 0, \ \textit{for any } k \neq j. \tag{16}$$

2. *Uncorrelated factor flows:*

$$\mathrm{cov}\big(\Delta Q_k^{\text{factor}}, \Delta Q_j^{\text{factor}}\big) = 0, \ \textit{for any } k \neq j. \tag{17}$$

The factors are ordered by descending $\mathrm{var}(\Delta Q_k^{\text{factor}})\,\mathrm{var}(r_k^{\text{factor}})$*, the amount of trading-induced risk each one explains.*

Proposition 2 is effectively a modified principal-component analysis (PCA) that operates *jointly* on asset returns and trading flows. By contrast, the standard return-only PCA is typically used to isolate factors that explain unconditional risk (Ross, 1976; Fama and French, 1993; Lustig, Roussanov, and Verdelhan, 2011). Concretely, the return-only PCA enforces (16), replaces (17) with orthogonal factor loadings, and sorts factors by descending unconditional return variance, $\mathrm{var}(r_k^{\text{factor}})$. By incorporating both returns and flows, our procedure pinpoints the risk factors that customers trade most actively and quantifies each factor's contribution to trading-induced risks via the product $\mathrm{var}(\Delta Q_k^{\text{factor}})\,\mathrm{var}(r_k^{\text{factor}})$. Empirically, we select the number of factors, K, so that (i) they explain the bulk of trading-induced risk; (ii) they remain robust across different sample periods; and (iii) each factor admits a clear economic interpretation.

Our procedure also differs from a PCA applied solely to trading flows (Lo and Wang, 2000; Hasbrouck and Seppi, 2001; Balasubramaniam, Campbell, Ramadorai, and Ranish, 2023). The flow-only PCA enforces (17), replaces (16) with orthogonal portfolio weights, and sorts factors by descending unconditional quantity variance, $\mathrm{var}(\Delta Q_k^{\text{factor}})$. When currency returns

to be orthogonal is equivalent to imposing orthogonality on the counterfactual returns and on the flows.

are independent and identically distributed, uncorrelated factor returns (16) are equivalent to orthogonal weights because

$$0 = \mathrm{cov}\big(r_k^{\mathrm{factor}}, r_j^{\mathrm{factor}}\big) = \mathrm{cov}\left(\sum_{n=1}^{N} w_{n,k} r_n, \sum_{n=1}^{N} w_{n,j} r_n\right) = \sum_{n=1}^{N} w_{n,k} w_{n,j} \mathrm{var}(r_n). \tag{18}$$

In this case, the flow-only and our modified PCA coincide, as all cross-sectional structure resides in the flow data. In general, combining flows with returns enables our method to recover the *risk factors* that customers actually trade, not merely the *portfolios* they trade. Section 4 empirically contrasts our approach with both return-only and flow-only PCA.

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.[14] 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, where Banks include bank-affiliated dealers and hedge funds transacting through prime brokers. We interpret Banks' trading as representing the activities of the intermediary in our model. Counterparties to Banks

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

fall into three categories: Funds (e.g., mutual funds, pension funds, sovereign wealth funds), Non-bank Financials (e.g., insurance companies, clearing houses), and Corporates.

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. Due to the pronounced negative correlation between flows into spot versus forward and swap, excluding either can underestimate the price sensitivity to risks (see 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.[15,16] 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. The CLS trading data also follow London business 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

[15] Conceptually, FX swaps should not expose intermediaries to currency risk, as the spot and forward legs offset each other in notional amounts. Empirically, a negligible amount of currency risk remains after discounting the forward leg. Our results are effectively unchanged if swaps are excluded.

[16] 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.

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.

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 five 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 four 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 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 traded risk factors in FX 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 Residual. Finally, we show that these factors cannot be obtained by the standard PCA on returns or flows alone.

4.1 Baseline Traded Risk 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 2.4, we derive the traded risk factors from weekly net flows and log returns of 16 non-USD currencies.[17] 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 CAD and $0.5-worth of EUR are sold.[18] 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, the top three traded risk 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. The traded risk factors are stable over time. Appendix Table A3 shows that the returns and flows of factors recovered from the full sample are highly correlated with those recovered from the pre-2020 or the post-2020 subsamples: the correlations are nearing 1 for the first factor and exceeding 0.8 for the other two.

4.2 Interpretation of Traded Risk Factors

To better understand the risks captured, we conjecture and verify that the top three traded risk factors represent the Dollar, the Carry, and the Euro-Yen Residual, 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. As Appendix A.3 proves, factors constructed from our procedure are invariant to the choice of numeraire. The Dollar's emergence as the first factor is thus not mechanical but reflective of its economic status as the world's reserve currency. We propose a traded Dollar factor

[17] 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 the same balance-sheet or inventory risk.

[18] 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. Note that the portfolio weight of USD is the negative sum of the weights of all other currencies.

Table 1: **Top 3 Traded Risk 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 risk factors, constructed following the procedure in Section 2.4. 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.

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 Residual factor that goes long in EUR and shorts JPY in equal weights. This factor could be capturing the large bilateral trading flows between the euro area and

Table 2: **Correlation between Return and Flow for Baseline PC Factors vs. 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 risk factors in Table 1 ("PC Factors") and for the traded risk factors constructed from the proposed factor weights of the Dollar, the Carry, and the Euro-Yen Residual ("Economic Factors"). It also shows the fraction of trading-induced risks explained by the Economic Factors.

Japan. Such flows are not reflected in either the Dollar or the Carry factors, because those factors trade EUR and JPY in the same direction.

These proposed factors are economically meaningful but may be correlated. To address this, we apply the procedure described in Section 2.4 to orthogonalize them. In particular, this process transforms the proposed EUR-JPY pair (long EUR, short JPY) into the Euro-Yen Residual factor, which is uncorrelated with the Dollar and Carry factors. In other words, the Euro-Yen Residual 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 Residual factor.

The data support our interpretation of the traded risk factors. 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 Residual ("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.

We emphasize that although the factors place little to no weight on currencies from small or emerging economies, all currencies can nonetheless have meaningful exposure to the non-diversifiable risks represented by these factors. The intuition mirrors the market factor in equities: a diversified portfolio holding only a small number of stocks can approximate the market, and all stocks load on this factor. Accordingly, the Economic Factors serve as conduits for demand propagation across all currencies, including those of small or emerging economies. We return to this point empirically in Section 6.

Panel (a) of Figure 1 plots the cumulative trading flows from customers to the three traded risk factors; Appendix Figure A3 provides a breakdown of factor flows by customer type. 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). For the Carry factors, customers initially refrained from large directional bets but began selling off the Carry factor post-2022. As a result, intermediaries accumulated $0.8 trillion in Carry trade exposure between 2012 and 2023. Finally, customers sold the Euro-Yen Residual 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 Residual factor throughout the sample period. As JPY acts as a "funding currency" (negative weight) in all traded risk factors, our analysis highlights that unwinding of JPY positions cannot be equated with a change in Carry exposure without analyzing adjustments in the overall portfolio.

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 Residual factor. We formally investigate the unconditional risk premium of these factors in Section 5.1.

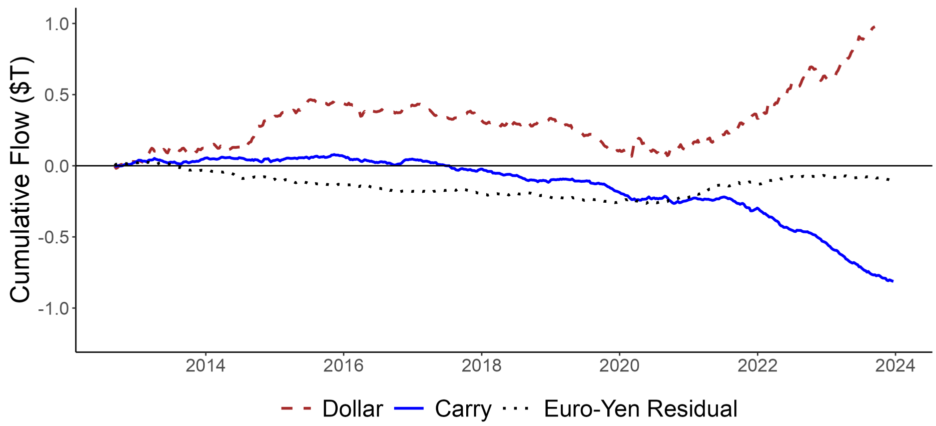
4.3 Standard PCA on Returns or Flows Fails to Identify Traded Risk Factors

We demonstrate that a standard PCA applied solely to returns or flows fails to identify the traded risk factors.

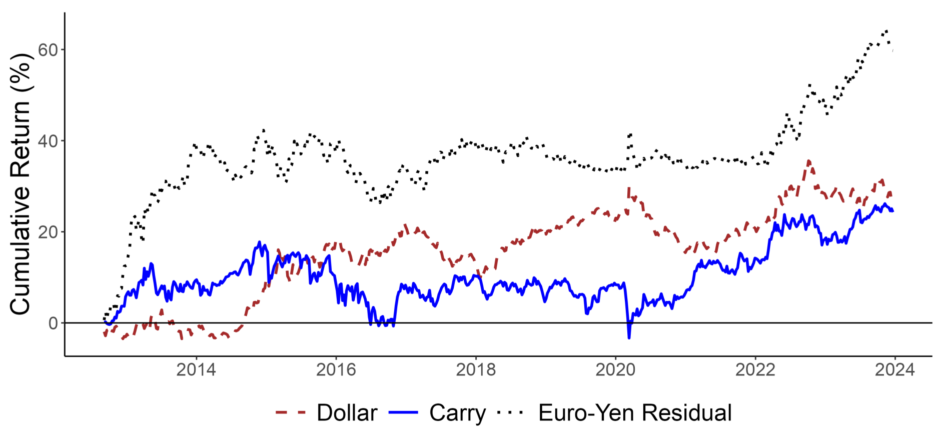
The first three columns of Table 3 show the portfolio weights for the first three principal

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

(a) **Cumulative Flow**



(b) **Cumulative Return**



Notes: This figure displays the cumulative flows and returns of the top three traded risk 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.

components of a standard PCA applied to returns.[19] The first factor resembles a Dollar factor, with negative loadings on all non-USD currencies. The second factor assigns large

[19]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 next 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.

positive weights to some high-interest-rate currencies such as ZAR and MXN, and large negative 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.[20] 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 Residual factor.

[20] 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.

The next three columns of Table 3 report the portfolio weights for the first three principal components of a standard PCA applied to trading 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 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 Risk Factors

In this section, we study the traded risk 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 risk factors based on weekly returns from September 2012 to December 2023. Notably, the newly proposed Euro-Yen Residual 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.[21] The Fama-MacBeth premia of the three factors are similar to their mean returns 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 Residual 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

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

Table 4: **Unconditional Risk Premium**

	Dollar	Carry	Euro-Yen Residual
Panel A: Sep 2012 to Dec 2023			
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 Residual
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 risk 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.

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 risk factor k in equation (11). Accordingly, we normalize each factor's return by its annualized return variance, $\text{var}(r_{k,t}^{\text{factor}})$, and regress this risk-adjusted return on the factor's instrumented demand shock, $\Delta\hat{Q}_{k,t}^{\text{factor}}$:

$$r_{k,t}^{\text{factor}}/\text{var}(r_{k,t}^{\text{factor}}) = \lambda_k \Delta\hat{Q}_{k,t}^{\text{factor}} + \epsilon_{k,t}, \text{ where} \tag{19}$$

$$\Delta Q_{k,t}^{\text{factor}} = \theta_k z_{k,t} + e_{k,t}, \tag{20}$$

$$\text{cov}(z_{k,t}, \epsilon_{k,t}) = 0. \tag{21}$$

To obtain $\Delta\hat{Q}_{k,t}^{\text{factor}}$, the instruments ($z_k$) for the observed factor flows ($\Delta Q_{k,t}^{\text{factor}}$) must be both relevant (equation (20)) and valid (equation (21)). We propose sovereign bond auction *announcements* as instruments.[22] 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.[23] When auctions are announced about a week in advance, these announcements can prompt foreign investors to exchange domestic currencies for local currencies, making these instruments relevant.

We also argue that the instruments are valid. Factor prices may be influenced by multiple unmodeled determinants ($\epsilon_{k,t}$). Our instruments are unlikely to be correlated with these determinants for two reasons: institutional features of sovereign auctions and the way we construct the traded risk factors.

The key institutional feature is that sovereign 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. Subsequent announcements and the eventual issuance of notes and bonds rarely deviate from these recommendations (Rigon, 2024).[24] Such heavy forward guidance makes announcements unlikely to contain new information about fundamentals, and ensures that the instrumented shocks are not responding to short-term FX market conditions. At the same time, these predictable auction-induced demands can still move prices when they materialize. Hartzmark and Solomon (2024) show that anticipated dividend payments move stock prices, and Vayanos (2021) explain why sophisticated investors may not find it optimal to front-run the entire expected demand.

How we construct traded risk factors is also crucial. Because currencies are tightly interconnected, the regression residual $\epsilon_{k,t}$ generally contains cross-impacts on factor k from demand shocks to other currencies. By construction, however, our traded risk factors have uncorrelated returns and uncorrelated flows. They therefore behave like independent assets: they are insulated from cross-impacts from one another and respond only to their own de-

[22]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.

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

[24]As another example, Germany's Finance Agency releases an annual auction calendar each December, specifying target amounts for each auction.

mand shocks, as shown in equation (11). A further concern is that auction announcements could induce excess bond trading, affecting bond prices and spilling over into FX. Yet empirically, Wachtel and Young (1990) find that while Treasury auction *results* move bond yields, the week-ahead *announcements* have no detectable effect. In short, our IV strategy likely captures effects on factor prices driven solely by announcement-induced demand shocks to that factor.

As the traded risk 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 factor, we aggregate the offered amount across all announcements in a week, consistent with FX trading flows.[25] 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 Residual factors. For all three factors, the estimated price sensitivity to trading-induced risks is positive and statistically significant. Recall that the regression (19) normalizes each factor's return by 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 Residual. 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 Residual. Viewed through the model in Section 2.2, 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 Residual attracting less arbitrage capital. Indeed, the annualized volatility of trading flows absorbed by intermediaries is highest for the Dollar factor (\$85 billion), followed by the Carry factor (\$34 billion), and lowest for the Euro-Yen Residual factor (\$22 billion). The OLS estimates are slightly smaller than the IV estimates, reflecting the instrument's

[25]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.

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)
Impact per \$B ($\lambda_k \sigma^2(r_{k,t})$)	3.4 bps	5.0 bps	8.9 bps	9.3 bps	12.2 bps	29.3 bps
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

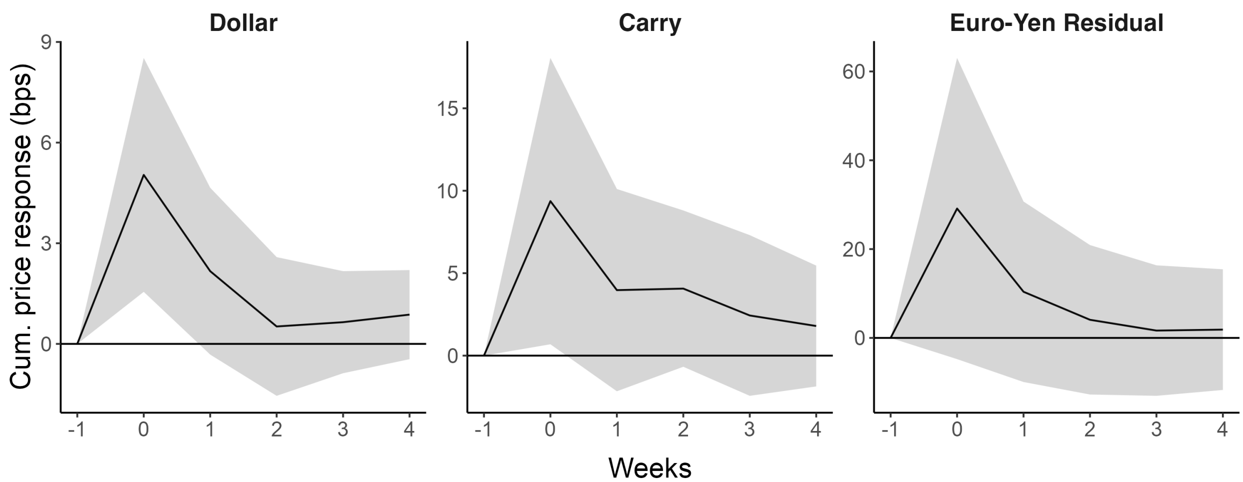
Notes: This table presents the λ_k estimation results for the Dollar, Carry, and Euro-Yen Residual factors, based on regression (19). The response of factor prices to demand shocks, measured per billion dollars, is calculated as the product of λ_k and the annualized return variance. The IV regressions 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. $^*p < .1$; $^{**}p < .05$; $^{***}p < .01$.

role in mitigating bias from the correlation between information-driven price changes $\epsilon_{k,t}$ and contemporaneous customer flows $\Delta Q_{k,t}^{\text{factor}}$. This correlation is negative, likely because customers trade against fundamental movements: 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).[26]

The behavior of asset prices provides an important test for the validity of our IV strategy. As discussed in Section 2, valid demand shocks move currency prices initially (at time 0), but these price effects should eventually revert (at time 1). In contrast, if the instrumented demand shocks contained new information, the resulting price response would be permanent and not revert. Empirically, Figure 2 shows that the contemporaneous price responses of

[26] 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.

Figure 2: **Reversion of Contemporaneous Price Response**



Notes: This figure shows the cumulative price responses for the traded risk 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.

all three factors fully revert within a month. One implication of this price reversion is that trading flows' contribution to return variance differs across horizons. We derive an expression for this contribution in Appendix C and find that flows account for about 10-35% of return variance at the 1-week horizon, 5-15% at one month, and fade quickly thereafter.

Price reversion also implies return predictability. In the same Appendix C, we estimate the annualized Sharpe ratios from exploiting these demand shocks, which are 0.04 for the Dollar factor, 0.05 for the Carry, and 0.09 for the Euro-Yen Residual. These values are modest, reflecting the high return volatility in FX. In such a market, only sophisticated and specialized participants like bank dealers and hedge funds absorb demand shocks, leaving a relatively thin layer of capital. 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.[27]

[27] 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.

Indeed, our estimated price sensitivity in FX is higher than comparable measures in equity. To facilitate this comparison, 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 Residual factors by 5, 9, and 29 basis points, respectively.[28] 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).[29]

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 Residual factors are 24.8, 6.5, and 3.8, respectively. The effective F-statistics for the Carry and the Euro-Yen Residual 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 Residual, 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_k consistent with this view: for instance, specialization may limit arbitrage 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_k depends on time-varying wealth or constraints that alter intermediaries'

[28] 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; van Binsbergen, David, and Opp, 2025; He, Kondor, and Li, 2025). Our estimates reflect the average level of persistence over the sample period.

[29] 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.

risk-return trade-off.

We consider two proxies. First, we use intermediary equity returns to capture intermediaries' wealth.[30] 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.[31]

Table 6 presents potential determinants of the Dollar factor's weekly return. We focus on the state-dependency of the Dollar factor's λ_k because the Dollar is the most traded risk factor and its flow instrument exhibits the highest statistical power. Column (1) suggests that the Dollar factor's return 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_k, 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_k. 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 not statistically significant (Column (6)).

6 Demand Propagation Across Currencies and Asset Classes

In this section, we use the traded risk factors' estimated price sensitivity 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.

[30] 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).

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

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

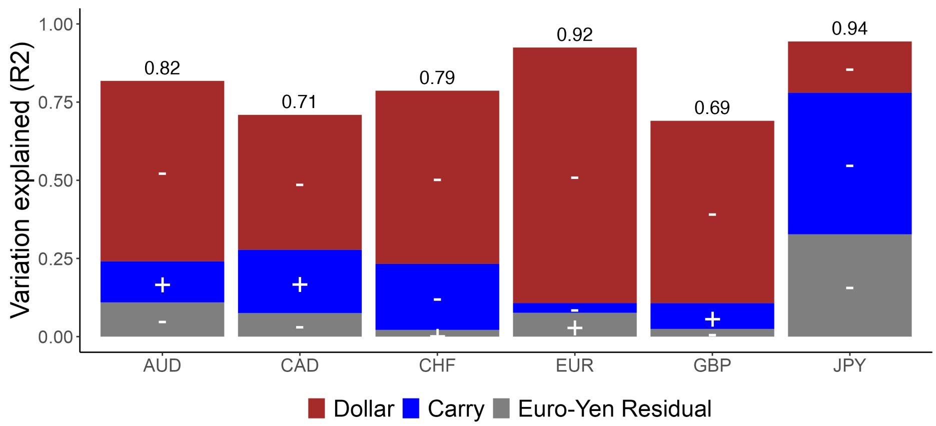
	Weekly Return of Dollar Factor					
	(1)	(2)	(3)	(4)	(5)	(6)
Intermed. equity ret	-0.490***	-0.109				
	(0.119)	(0.204)				
Flow × Intermed. equity ret		-0.091***				
		(0.033)				
S&P equity ret			-0.148	-0.077		
			(0.096)	(0.314)		
Flow × S&P equity ret				0.006		
				(0.074)		
CIP deviation					0.081	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 Demand Propagation Across Currencies

For a traded risk factor to affect currency-level cross-multipliers, the currencies must load on the factor. Figure 3 demonstrates the relevance of the traded risk factors in explaining individual currency returns. Regressing currency-level returns on the returns of the Dollar, the Carry, and the Euro-Yen Residual factors in the time series, we plot the marginal R^2 attributed to each factor, which are additive because the factor returns are orthogonal by construction. The positive and negative signs in the plot indicate the direction of each

Figure 3: **Decomposition of Currency Returns Explained by Traded Risk 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 Residual 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.

currency's beta loading on each factor. Together, the three factors explain between 69% and 94% of individual currency returns.

The decomposition in Figure 3 provides a framework to analyze the risk implied in demand shocks. For instance, when a customer buys \$1 of AUD from intermediaries, Figure 3 shows that intermediaries attribute 60% of the total risk to the Dollar factor, 10% each to the Carry and Euro-Yen Residual factors, and 20% to residual 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 Residual factors while buying the Carry factor.

Combining the information in Figure 3 with the IV estimated price sensitivity to risks λ_k, we compute the cross-currency multipliers according to Proposition 1 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 another column (row) currency. For instance, the entry of 7.9 in the first row and first column indicates that a \$1 billion demand shock to the CAD (AUD)

Table 7: **Demand Propagation Across Currencies Through the Three Most Traded Risk Factors**

	CAD	GBP	CHF	EUR	JPY	DKK	HKD	ILS	KRW	MXN	NOK	NZD	SEK	SGD	ZAR
AUD	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		5.9	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			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				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					0.2	7.4	0.1	2.5	2.4	2.5	6.1	3.1	7.1	2.3	4.2
JPY						0.2	0.0	2.3	4.0	0.9	3.5	5.7	1.1	3.1	4.0
DKK							0.1	2.5	2.4	2.5	6.0	3.1	7.1	2.3	4.2
HKD								0.1	0.1	0.1	0.2	0.1	0.1	0.1	0.2
ILS									2.7	3.1	4.8	4.2	3.5	2.0	4.6
KRW										4.0	5.9	5.6	3.9	2.5	5.9
MXN											7.3	6.6	4.6	2.6	7.5
NOK												9.4	8.2	4.3	10.5
NZD													5.7	3.9	9.6
SEK														3.1	6.8
SGD															4.1

Notes: This table uses Proposition 1, 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 3) 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. The model-implied cross-multiplier is symmetric, so we report only the upper half.

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.

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 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. The modest cross-multipliers reflect opposite beta loadings with respect to the Carry factor, which makes currencies in one group effective hedges for the Carry risk exposure of the other group. In short, these two groups are "complements" in their exposure to the Carry risk factor. 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 Residual factor. This result suggests that EUR and JPY are not entirely substitutable.

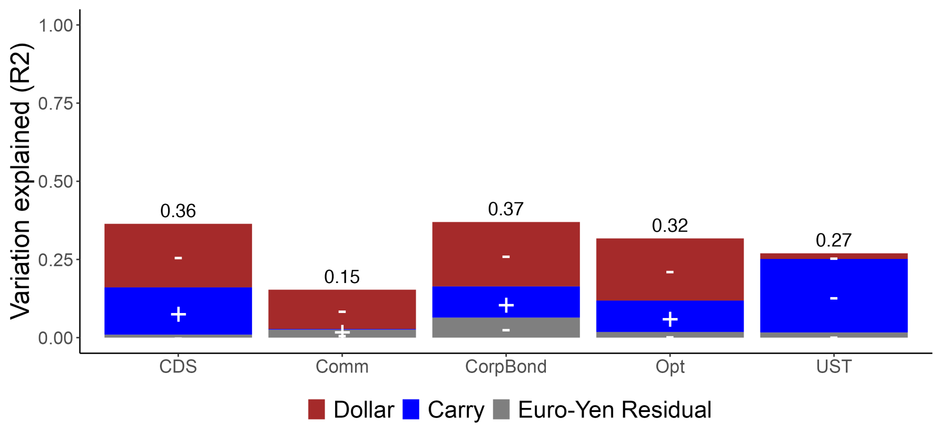
Moreover, although we analyze traded risk factors constructed using the six major currencies and USD, we still recover meaningful cross-multipliers for other currencies. This is because the non-diversifiable risks represented by these factors matter for all currencies. Take MXN as an example: its exposure to the three traded risk factors implies strong propagation to other high-interest-rate currencies. These include AUD and CAD, which enter the construction of the traded factors, as well as NOK, NZD, and ZAR, which do not. In short, we naturally recover that all high-interest-rate currencies behave more like substitutes for one another.

Finally, 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 Demand Propagation Across Asset Classes

If other asset classes load on the traded risk factors in FX, demand shocks can propagate through shared FX exposures. We analyze five non-FX asset classes: credit default swap

Figure 4: **Decomposition of Asset-Class Returns Explained by Traded Risk Factors in FX**



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 Residual 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.

(CDS), commodities (Comm), corporate bonds (CorpBond), options (Opt), and US Treasury bonds (UST).[32] Similar to Figure 3, 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 4.[33,34]

The three traded risk factors in FX jointly explain between 15% (commodities) and 37% (corporate bonds) of the returns in the five non-FX asset classes we examine. The high explanatory power of traded risk factors is not an artifact of crisis-period comovements. Appendix Figure A4 shows that results based on returns excluding the 2007-09 Financial

[32]We exclude equities because Haddad and Muir (2021) show that intermediation in equities differs considerably from FX, suggesting different marginal investors. While traded risk factors in FX may partially explain equities returns, their price sensitivities are likely different in equities.

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

[34]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 Residual.

Table 8: **Demand Propagation Across Asset Classes Through Shared FX Risks**

	Comm	CorpBond	Opt	UST
CDS	3.5	3.2	4.7	-0.5
Comm		6.0	7.7	0.7
CorpBond			6.5	-0.2
Opt				-0.6

Notes: This table uses Proposition 1, 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 4) 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. The model-implied cross-multiplier is symmetric, so we report only the upper half.

Crisis and the COVID-19 period are largely similar. Interestingly, while the Dollar factor is statistically significant across all five asset classes, it is least important in explaining the return of U.S. Treasury bonds (Treasurys).[35] 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 other assets. Finally, while the Euro-Yen Residual factor is less prominent in non-FX asset classes, it explains a non-negligible fraction of returns in corporate bonds.

Similar to Table 7, we report cross-multipliers between asset classes in Table 8.[36] Examining the last column of Table 8, we find that Treasurys uniquely exhibit negative cross-multipliers with most other asset classes. A demand shock to Treasurys hence 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, making them an effective hedge against other asset classes during shifts between "risk-on" and "risk-off" regimes.

We raise two cautions in interpreting our estimated cross-asset multipliers. First, our

[35] 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).

[36] The cross-multiplier between the traded risk factors in FX and these five non-FX asset classes are reported in Appendix Table A4.

estimates capture only demand propagation across asset classes through exposure to the three traded risk factors in FX. Demand shocks across these assets may also propagate through other shared risks that we do not capture. Second, by using λ_k from the traded risk factors in FX 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 how demand shocks propagate through traded risk factors. If asset prices respond to risks and marginal investors diversify across assets, then demand shocks propagate by shifting non-diversifiable risks, as captured by traded risk factors. We identify the most traded risk factors by extending the concept of priced non-diversifiable risks (Ross, 1976) to a representative intermediary framework (He and Krishnamurthy, 2017), and by developing a method that integrates trading and returns data.

Applying this method to FX, we uncover three factors: the Dollar, the Carry, and the Euro-Yen Residual. Together, they explain 90% of the non-diversifiable risk intermediaries absorb in FX trading. These factors are orthogonal in both trading flows and returns, and thus represent independent channels of demand propagation. IV estimates show that factor prices rise by 5-30 basis points per $1 billion of factor demand, highlighting intermediaries' limited risk-bearing capacity.

By combining traded risk factors with IV estimates, our framework quantifies demand propagation by mapping complex inter-asset linkages to three measurable objects: (i) how demand shocks change non-diversifiable risks ($\Delta\hat{Q}_k^{\text{factor}}$), (ii) how prices adjust to compensate intermediaries for absorbing those risks (λ_k), and (iii) how each asset is exposed to these risks ($\beta_{n,k}$). Integrating these elements reveals rich transmission patterns across 17 currencies and 5 major non-FX asset classes, where demand shocks propagate with varying magnitudes and even directions.

At the heart of our framework is the idea of linking trading quantities and asset prices (Froot and Ramadorai, 2008; Koijen and Yogo, 2019) through common risks. This emphasis underscores the role of shared exposures in cross-asset dynamics (Haddad and Muir, 2021; Du, Hébert, and Huber, 2023). As markets become increasingly interconnected, understanding how demand shocks propagate through common risks is crucial for predicting and managing systematic dynamics.

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A Appendix for Proofs

This appendix provides proofs omitted in the main text.

A.1 Proof of Proposition 1

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

$$r_n = \sum_{k=1}^{K} \beta_{n,k} r_k^{\text{factor}} + e_n, \tag{A1}$$

where e_n is the idiosyncratic return of currency n that is uncorrelated with any factors. Hence, by the law of one price and equation (11), the price impact of currency n is

$$\Delta p_n = \sum_{k=1}^{K} \beta_{n,k} \Delta p_k^{\text{factor}} = \sum_{k=1}^{K} \lambda_k \Delta Q_k^{\text{factor}} \text{var}(r_k^{\text{factor}}) \beta_{n,k}. \tag{A2}$$

Therefore, we have

$$\frac{\partial \Delta p_n}{\partial \Delta Q_k^{\text{factor}}} = \frac{\partial \Delta p_k^{\text{factor}}}{\partial \Delta Q_k^{\text{factor}}} \times \frac{\partial \Delta p_n}{\partial \Delta p_k^{\text{factor}}} = \lambda_k \text{var}(r_k^{\text{factor}}) \times \beta_{n,k}. \tag{A3}$$

Next, equation (7) implies that $\partial \Delta Q_k^{\text{factor}} / \partial \Delta Q_m = \beta_{m,k}$. Hence, we have proved

$$\frac{\partial \Delta p_n}{\partial \Delta Q_m} = \sum_{k=1}^{K} \frac{\partial \Delta Q_k^{\text{factor}}}{\partial \Delta Q_m} \times \frac{\partial \Delta p_n}{\partial \Delta Q_k^{\text{factor}}} = \sum_{k=1}^{K} \beta_{m,k} \times \lambda_k \text{var}(r_k^{\text{factor}}) \times \beta_{n,k}. \tag{A4}$$

A.2 Proof of Proposition 2

Let the return vector be $\mathbf{r} = (r_1, r_2, \ldots, r_N)^\top$ and the vector of currency flows $\Delta\mathbf{Q} = (\Delta Q_1, \Delta Q_2, \ldots, \Delta Q_N)^\top$.

First, take the spectral decomposition $\text{var}(\mathbf{r}) = \mathbf{V}\mathbf{D}\mathbf{V}^\top$, where $\mathbf{D}$ is an $L \times L$ diagonal matrix with $L = \text{rank}\big(\text{var}(\mathbf{r})\big)$, and $\mathbf{V}$ is an $N \times L$ orthonormal matrix ($\mathbf{V}^\top\mathbf{V} = \mathbf{I}_L$). Next, perform another spectral decomposition:

$$\mathbf{D}^{1/2}\mathbf{V}^\top \, \text{var}(\Delta\mathbf{Q}) \, \mathbf{V}\mathbf{D}^{1/2}\mathbf{G} = \mathbf{G}\mathbf{\Pi}, \tag{A5}$$

where $\mathbf{\Pi}$ is a $K \times K$ diagonal matrix with entries ordered from largest to smallest, and $\mathbf{G}$ is an $L \times K$ orthogonal matrix ($\mathbf{G}^\top \mathbf{G} = \mathbf{I}_K$). Define the portfolio-weight matrix $\mathbf{W} = \mathbf{V}\mathbf{D}^{-1/2}\mathbf{G}$.

We claim that the factors constructed by the portfolio weight matrix $\mathbf{W}$ satisfy the conditions (16) and (17). First,

$$\mathrm{var}(\mathbf{W}^\top \mathbf{r}) = \mathbf{G}^\top \mathbf{D}^{-\frac{1}{2}} \mathbf{V}^\top \mathbf{V}\mathbf{D}\mathbf{V}^\top \mathbf{V}\mathbf{D}^{-\frac{1}{2}}\mathbf{G} = \mathbf{I}_K. \tag{A6}$$

Thus each factor return is uncorrelated with the others and has unit variance.

Second, equation (7) in matrix form yields

$$\Delta\mathbf{Q}^{\text{factor}} = \mathrm{var}(\mathbf{W}^\top \mathbf{r})^{-1} \mathrm{cov}(\mathbf{W}^\top \mathbf{r}, \Delta\mathbf{Q}^\top \mathbf{r}) = \mathbf{G}^\top \mathbf{D}^{\frac{1}{2}} \mathbf{V}^\top \Delta\mathbf{Q}, \tag{A7}$$

where we use $\mathbf{W}^\top \mathbf{r} = \mathbf{I}_K$, $\mathbf{W} = \mathbf{V}\mathbf{D}^{-\frac{1}{2}}\mathbf{G}$, and $\mathrm{var}(\mathbf{r}) = \mathbf{V}\mathbf{D}\mathbf{V}^\top$. Hence,

$$\mathrm{var}(\Delta\mathbf{Q}^{\text{factor}}) = \mathbf{G}^\top \mathbf{D}^{\frac{1}{2}} \mathbf{V}^\top \mathrm{var}(\Delta\mathbf{Q}) \mathbf{V}\mathbf{D}^{\frac{1}{2}}\mathbf{G} = \mathbf{\Pi}, \tag{A8}$$

which is diagonal; factor flows are therefore uncorrelated, and each diagonal element of $\mathbf{\Pi}$ is its variance.

The factors can be scaled arbitrarily, but the product $\mathrm{var}(\Delta\mathbf{Q}^{\text{factor}})\,\mathrm{var}(\mathbf{W}^\top \mathbf{r})$ is invariant, because doubling a factor's weights doubles its return while halving its flow. The proof has adopted the convenient normalization $\mathrm{var}(\mathbf{W}^\top \mathbf{r}) = \mathbf{I}_K$; ordering the factors by the diagonal elements of $\mathrm{var}(\Delta\mathbf{Q}^{\text{factor}}) = \mathbf{\Pi}$ therefore guarantees that the leading factors explain the largest share of trading-induced risk.

A.3 Invariance of Factors under Alternative Numeraire Currency

This appendix shows that the factors constructed in Appendix A.2 are invariant to the numeraire currency used to measure returns and flows.

Assume we switch the numeraire from USD to currency N. Let $\Delta\tilde{Q}_n$ be the flow from currency N into currency n for $n = 1, \ldots, N-1$, and let $\Delta\tilde{Q}_N$ be the flow from currency N into USD. Recall that ΔQ_n denotes the flow from USD into currency n. Because each USD-based trade decomposes into a leg from USD to currency N and a leg from currency

N to the target currency, the flows transform according to

$$\Delta\tilde{\mathbf{Q}} = (\Delta\tilde{Q}_1, \Delta\tilde{Q}_2, \ldots, \Delta\tilde{Q}_{N-1}, \Delta\tilde{Q}_N)^\top = \left(\Delta Q_1, \Delta Q_2, \ldots, \Delta Q_{N-1}, -\sum_{n=1}^{N} \Delta Q_n\right)^\top = \mathbf{C}\Delta\mathbf{Q}, \tag{A9}$$

where we define the matrix

$$\mathbf{C} := \begin{pmatrix} 1 & 0 & \ldots & 0 & 0 \\ 0 & 1 & \ldots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \ldots & 1 & 0 \\ -1 & -1 & \ldots & -1 & -1 \end{pmatrix}. \tag{A10}$$

Returns transform analogously. For $n = 1, \ldots, N-1$, define $\tilde{r}_n$ as the excess return from borrowing at currency N's risk-free rate and investing at currency n's risk-free rate; let $\tilde{r}_N$ be the corresponding return on USD funding. Then,

$$\tilde{\mathbf{r}} = (\tilde{r}_1, \tilde{r}_2, \ldots, \tilde{r}_{N-1}, \tilde{r}_N)^\top = (r_1 - r_N, r_2 - r_N, \ldots, r_{N-1} - r_N, -r_N)^\top = \mathbf{C}^\top \mathbf{r}. \tag{A11}$$

A crucial property of $\mathbf{C}$ is $\mathbf{CC} = \mathbf{I}_N$, which follows directly from the definition above. Intuitively, changing the numeraire from USD to currency N and then back again leaves all quantities unchanged, so multiplying $\mathbf{C}$ by itself must be identity.

Next, we apply the procedure in Appendix A.2 to the transformed data $\tilde{\mathbf{r}}$ and $\Delta\tilde{\mathbf{Q}}$ and show that it produces the same factors obtained from $\mathbf{r}$ and $\Delta\mathbf{Q}$. Let the spectral decomposition be $\text{var}(\tilde{\mathbf{r}}) = \tilde{\mathbf{V}}\tilde{\mathbf{D}}\tilde{\mathbf{V}}^\top$ and $\text{var}(\mathbf{r}) = \mathbf{VDV}^\top$. From (A11) we also have $\text{var}(\tilde{\mathbf{r}}) = \mathbf{C}^\top \text{var}(\mathbf{r})\mathbf{C}$. Hence there exists an $L \times L$ orthogonal matrix $\mathbf{O}$ ($\mathbf{O}^\top\mathbf{O} = \mathbf{I}_L$) such that

$$\mathbf{C}^\top \mathbf{V}\mathbf{D}^{\frac{1}{2}} = \tilde{\mathbf{V}}\tilde{\mathbf{D}}^{\frac{1}{2}}\mathbf{O}. \tag{A12}$$

Using (A9) and the fact that $\mathbf{CC} = \mathbf{I}_N$,

$$\tilde{\mathbf{D}}^{1/2}\tilde{\mathbf{V}}^\top \,\text{var}(\Delta\tilde{\mathbf{Q}})\, \tilde{\mathbf{V}}\tilde{\mathbf{D}}^{1/2} = \mathbf{O}\mathbf{D}^{\frac{1}{2}}\mathbf{V}^\top\mathbf{CC}\,\text{var}(\Delta\mathbf{Q})\,\mathbf{C}^\top\mathbf{C}^\top\mathbf{V}\mathbf{D}^{\frac{1}{2}}\mathbf{O}^\top = \mathbf{O}\mathbf{D}^{\frac{1}{2}}\mathbf{V}^\top\,\text{var}(\Delta\mathbf{Q})\,\mathbf{V}\mathbf{D}^{\frac{1}{2}}\mathbf{O}^\top. \tag{A13}$$

The spectral decomposition in equation (A5) therefore read

$$\tilde{\mathbf{D}}^{1/2}\tilde{\mathbf{V}}^\top \operatorname{var}(\Delta\tilde{\mathbf{Q}})\,\tilde{\mathbf{V}}\tilde{\mathbf{D}}^{1/2}\tilde{\mathbf{G}} = \tilde{\mathbf{G}}\tilde{\mathbf{\Pi}}, \tag{A14}$$

$$\mathbf{D}^{\frac{1}{2}}\mathbf{V}^\top \operatorname{var}(\Delta\mathbf{Q})\,\mathbf{V}\mathbf{D}^{\frac{1}{2}}\mathbf{G} = \mathbf{G}\mathbf{\Pi}, \tag{A15}$$

which implies $\mathbf{G} = \mathbf{O}^\top\tilde{\mathbf{G}}$ and $\tilde{\mathbf{\Pi}} = \mathbf{\Pi}$. Thus, the eigenvalues are identical and the eigenvectors differ only by an orthogonal rotation.

Hence the factor-portfolio weights under the new numeraire are $\tilde{\mathbf{W}} = \tilde{\mathbf{V}}\tilde{\mathbf{D}}^{-1/2}\tilde{\mathbf{G}}$, and the corresponding factor returns satisfy

$$\tilde{\mathbf{W}}^\top\tilde{\mathbf{r}} = (\mathbf{C}\tilde{\mathbf{V}}\tilde{\mathbf{D}}^{-\frac{1}{2}}\tilde{\mathbf{G}})^\top\mathbf{r} = (\mathbf{C}\tilde{\mathbf{V}}\tilde{\mathbf{D}}^{-\frac{1}{2}}\mathbf{O}\mathbf{G})^\top\mathbf{r} = (\mathbf{V}^\top\mathbf{C}\tilde{\mathbf{V}}\tilde{\mathbf{D}}^{-\frac{1}{2}}\mathbf{O}\mathbf{G})^\top\mathbf{f}, \tag{A16}$$

where the last step uses $\mathbf{r} = \mathbf{V}\mathbf{f}$ for some L-dimensional vector $\mathbf{f}$, because $\operatorname{rank}\big(\operatorname{var}(\mathbf{r})\big) = L$.

We left-multiply both sides of equation (A12) by $\tilde{\mathbf{D}}^{-\frac{1}{2}}\tilde{\mathbf{V}}^\top$ to obtain $\tilde{\mathbf{D}}^{-\frac{1}{2}}\tilde{\mathbf{V}}^\top\mathbf{C}^\top\mathbf{V}\mathbf{D}^{\frac{1}{2}} = \mathbf{O}$ (recall that $\tilde{\mathbf{V}}^\top\tilde{\mathbf{V}} = \mathbf{I}_L$). Taking transposes gives $\mathbf{D}^{\frac{1}{2}}\mathbf{V}^\top\mathbf{C}\tilde{\mathbf{V}}\tilde{\mathbf{D}}^{-\frac{1}{2}} = \mathbf{O}^\top$. Left-multiplying by $\mathbf{D}^{-1/2}$ and right-multiplying by $\mathbf{O}$ yields $\mathbf{V}^\top\mathbf{C}\tilde{\mathbf{V}}\tilde{\mathbf{D}}^{-\frac{1}{2}}\mathbf{O} = \mathbf{D}^{-\frac{1}{2}}$ (recall that $\mathbf{O}^\top\mathbf{O} = \mathbf{I}_L$).

Substituting this identity into (A16) gives

$$\tilde{\mathbf{W}}^\top\tilde{\mathbf{r}} = (\mathbf{D}^{-\frac{1}{2}}\mathbf{G})^\top\mathbf{f} = (\mathbf{V}\mathbf{D}^{-1/2}\mathbf{G})^\top\mathbf{V}\mathbf{f} = \mathbf{W}^\top\mathbf{r}, \tag{A17}$$

where we used $\mathbf{V}^\top\mathbf{V} = \mathbf{I}_L$. Therefore the factor returns—and hence the factors themselves—are identical under either numeraire.

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 $\$100/(1+r^{\$}_{1\text{M}})$ today, where $r^{\$}_{1\text{M}}$ is the 1-month USD risk-free rate. Similarly, the intermediary will sell $100/(1+r^{\text{JPY}}_{1\text{M}})$ of JPY today to both fund his USD purchase and to ensure FX neutrality

Table A1: **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.

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 due to discounting.

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.[37] 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.

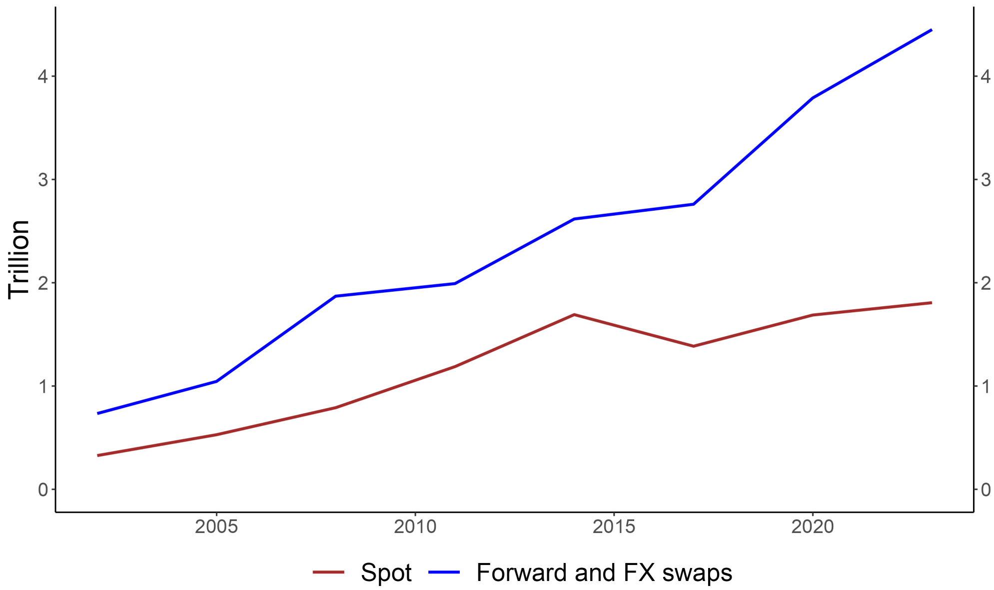
We start by examining the observed trading flows into individual currencies. The triennial survey conducted by the Bank of International Settlement (BIS) indicates that there is twice as much trading flow in the FX derivatives market as in the spot market (Appendix Figure A1). Appendix Table A1 reports 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 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 risk risk factors. At the same time, if there are strong comovements in trading flows to the traded risk factors, then relying on data from only one market risks introducing measurement error in aggregate flows and, therefore, in the estimation of price sensitivity to risks.

In Appendix Table A2, we compare the traded risk factors recovered separately from

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

Figure A1: **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.

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 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

Table A2: **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.

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.

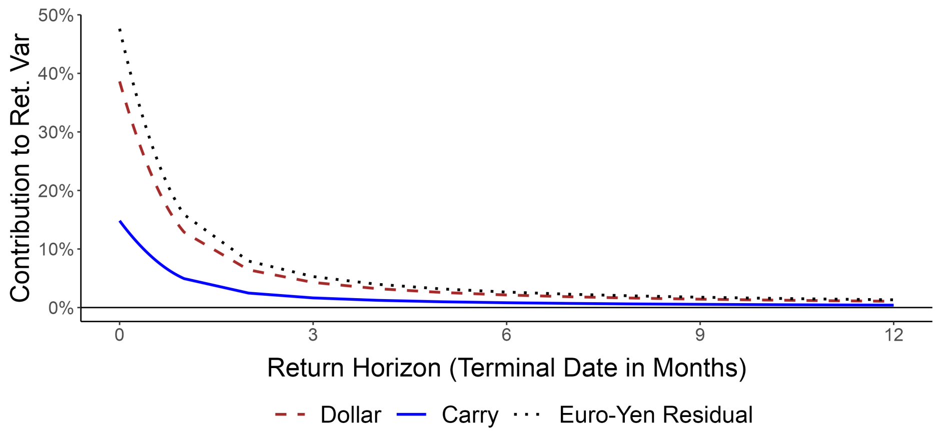
C Implications of Reversal in Demand-Induced Price Response

This appendix considers the implication of price reversal on two issues. First, how much of each factor's return variance comes from trading flows? Second, with predictable return, what is the implied Sharpe ratio?

We start with the first issue. Equilibrium flows may carry information, so any associated price impacts have two parts: a permanent information component and a temporary demand component. Our estimate λ_k captures the demand component. Figure 2 moreover shows that the contemporaneous price impact reverts over roughly four weeks, approximately linearly. We now compute, across different horizons, the share of return variance explained by this temporary effect. As the horizon lengthens, the temporary impact decays and accounts for a smaller fraction of total variance.

Consider stochastic trading flow over the horizon $[0, T]$. During an infinitesimal interval dt, the flow shock for factor k has standard deviation $\sigma(\Delta Q_{k,t}^{\text{factor}})\sqrt{dt}$, where $\sigma(\Delta Q_{k,t}^{\text{factor}})$ is the annualized flow volatility. Each unit of flow moves the price by $\lambda_k \sigma^2(r_{k,t}^{\text{factor}})$, with $\sigma(r_{k,t}^{\text{factor}})$

Figure A2: **Factor Flow Contribution to Return Variance**



Notes: This figure displays the share of return variance that comes from the impact of flow, which is derived in equation (A19).

denoting the annualized return volatility. Hence the contemporaneous price change generated by the flow shock equals $\lambda_k \, \sigma^2(r_{k,t}^{\text{factor}}) \, \sigma(\Delta Q_{k,t}^{\text{factor}})\sqrt{dt}$. Assuming this impact decays linearly to zero within one month (1/12 years), a flow shock arriving at time t still affects the price at the terminal date T by the factor $\max\{0,\, 1 - 12(T-t)\}$. Accordingly, the proportion of the terminal price variance attributable to flow is

$$\frac{\int_0^T \left(\max\{0,\, 1-12(T-t)\}\lambda_k \sigma^2(r_{k,t}^{\text{factor}})\sigma(\Delta Q_{k,t}^{\text{factor}})\right)^2 dt}{\int_0^T \sigma^2(r_{k,t}^{\text{factor}})dt}, \tag{A18}$$

which measures the share of total variance over $[0, T]$ that arises from temporary price impacts of flow shocks. This fraction simplifies to

$$\begin{cases} \lambda_k^2 \sigma^2(r_{k,t}^{\text{factor}})\sigma^2(\Delta Q_{k,t}^{\text{factor}})(1-12T+48T^2) & 0 < T \leq \dfrac{1}{12}, \\ \dfrac{\lambda_k^2 \sigma^2(r_{k,t}^{\text{factor}})\sigma^2(\Delta Q_{k,t}^{\text{factor}})}{36T} & T > \dfrac{1}{12}. \end{cases} \tag{A19}$$

Figure A2 shows that for the three factors, flows explain roughly 10-35% of return variance at the 1-week horizon, 5-15% at one month, and rapidly less at longer horizons.

Table A3: **Correlation Between Traded Risk 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 risk factors constructed based on the full sample versus returns and flows of the traded risk 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.

The second issue relates to the Sharpe ratio associated with this predictable price reversion. Let $\sigma(\Delta\hat{Q}^{\text{factor}}_{k,t})$ denote the annualized volatility of factor k's demand shock. Because the demand-shock induced price impact reverts roughly linearly over four weeks, the predictable return next week reflects one-quarter of the reversal from each of the past four shocks. With i.i.d. demand shocks, each shock's standard deviation scales by $\sqrt{4}/4 = 1/2$, and the predictable one-week price reversion is $\lambda_k\, \sigma^2(r^{\text{factor}}_{k,t})\, \sigma(\Delta\hat{Q}^{\text{factor}}_{k,t})\sqrt{1/52}/2$. The factor's weekly return volatility is $\sigma(r^{\text{factor}}_{k,t})\sqrt{1/52}$. Hence, the annualized Sharpe ratio implied by this reversion is

$$\frac{\lambda_k\, \sigma^2(r^{\text{factor}}_{k,t})\, \sigma(\Delta\hat{Q}^{\text{factor}}_{k,t})\sqrt{1/52}/2}{\sigma(r^{\text{factor}}_{k,t})\sqrt{1/52}} \times \sqrt{52} = \lambda_k\, \sigma(r^{\text{factor}}_{k,t})\, \sigma(\Delta\hat{Q}^{\text{factor}}_{k,t})\sqrt{13}. \tag{A20}$$

Empirically, the annualized Sharpe ratios are 0.044, 0.050, and 0.086 for the Dollar, Carry, and Euro-Yen Residual factors, respectively. These values are not trivially small but also not very compelling. The modest Sharpe ratio may be one reason why arbitrage capital and, consequently, risk-bearing capacity, are rather limited.

D Additional Figures and Tables

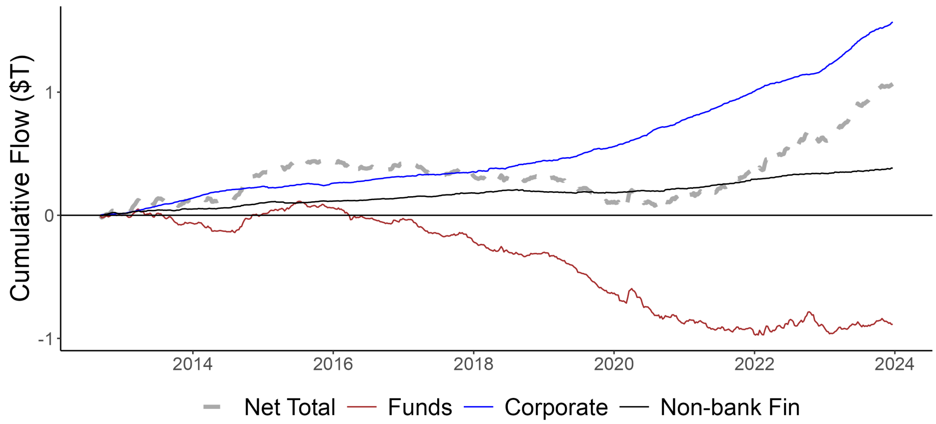
Table A4: **Demand Propagation Between Traded Risk Factors in FX and Non-FX Asset Classes**

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

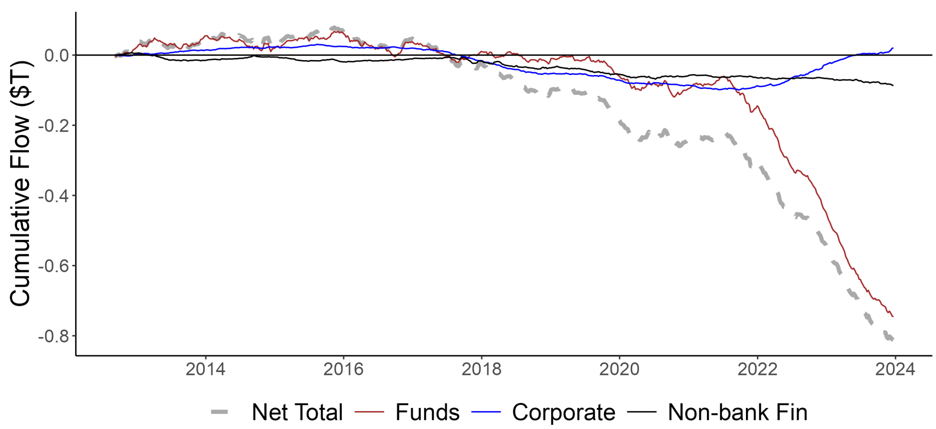
Notes: This table uses Proposition 1, the estimated factor-level price sensitivity to risks λ_k from Table 5, and the beta loadings of assets to factors (signs illustrated in Figure 4) to compute cross-multiplier between traded risk factors in FX and five non-FX asset classes. Each entry represents the price movement in bps of a column asset, as induced by a $1 billion demand shock into a traded risk factor.

Figure A3: **Cumulative Flow by Investor Type to Traded Risk Factors**

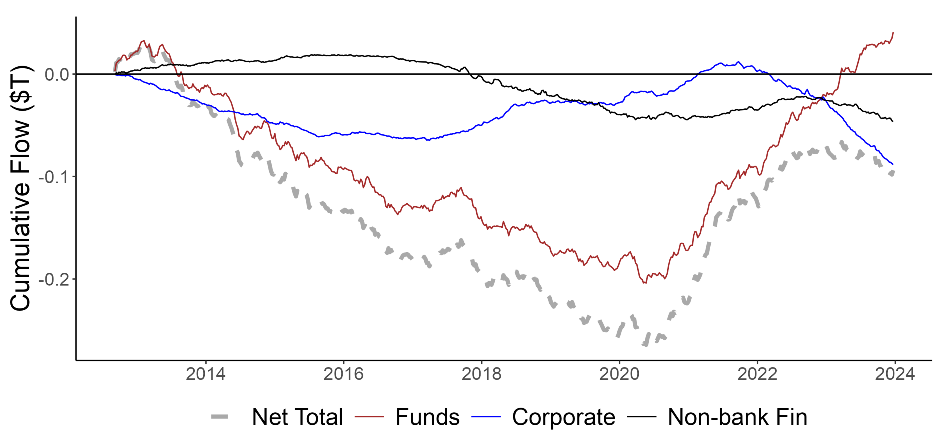
(a) **Dollar Factor**



(b) **Carry Factor**

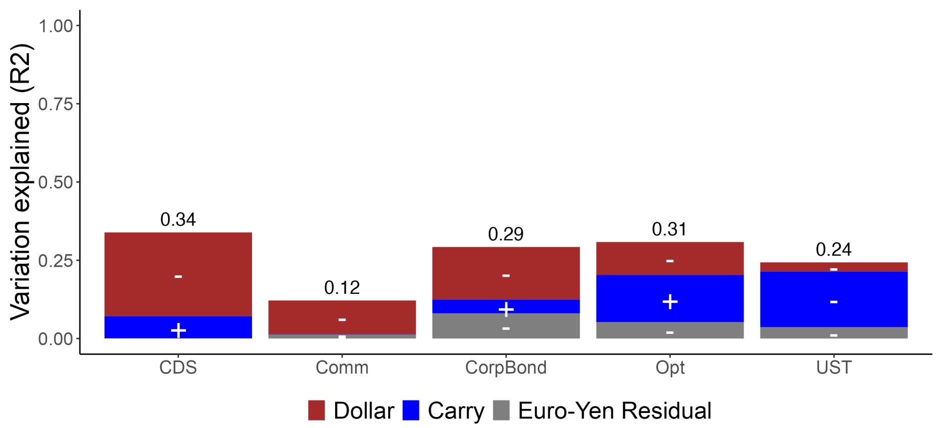


(c) **Euro-Yen Residual Factor**



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

Figure A4: **Decomposition of Asset-Class Returns Explained by Traded Risk Factors in FX Outside of Crises**



Notes: This figure decomposes the returns of individual assets into the Dollar, the Carry, and the Euro-Yen Residual 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 risk 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.