Intermediary Elasticity and Limited Risk-Bearing Capacity*

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Abstract

We study intermediaries' limited risk-bearing capacity and its implications for asset prices. We introduce a new measure, "intermediary elasticity", defined as the price response to a marginal unit of risk induced by trading demand shocks. We apply our framework to the foreign exchange (FX) market and find that just three traded risk factors can jointly account for 90% of the non-diversifiable risks borne by intermediaries when accommodating FX trading flows. These three traded risk factors resemble the Dollar, the Carry, and the Euro-Yen, and reveal that intermediaries accumulated \$0.8 trillion in exposure to the Carry over the last decade. Through instrumental variable analysis, we show that intermediaries raise prices by 5 to 30 bps in response to \$1 billion net trading demand shock to these factors. We use our estimated FX-factor elasticity to quantify the cross-elasticity of a panel of currencies and across 7 major asset classes.

JEL Classifications: G11, G12, G15, G2
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1 Introduction

A growing literature offers evidence that financial intermediaries are central to asset pricing (for a survey, see He and Krishnamurthy (2017)). Liquidity, regulation, and other constraints facing financial intermediaries lead to limited risk-bearing capacity (e.g., Kondor and Vayanos (2019), Du, Hébert, and Huber (2022)). As a result, in contrast to the traditional asset pricing paradigm, trading demand can affect asset prices (e.g., Du and Huber (2024)). In this paper, we study intermediaries' risk-bearing capacity by first identifying risks that trading demand shocks induce and then quantifying intermediaries' price sensitivity to these risks. Our results underscore the role that intermediaries play in driving cross-asset pricing dynamics.

Central to our investigation is the concept of "intermediary inverse elasticity", which we define as the price response to a marginal unit of risk induced by trading demand shocks. For simplicity, we abbreviate it as "intermediary elasticity."[1] Our concept follows directly from the classic asset pricing framework that views risk premium as the product of the price of risk and the quantity of risk. An elasticity concept that is relevant to asset pricing should therefore be defined with respect to the quantity of *risk*. Intermediary elasticity thus contrasts with the "(inverse) elasticity of demand" in industrial organization (IO), which measures price responses due to changes in the quantity of a *good* demanded. Our concept has intuitive interpretations. If intermediary elasticity is zero, then intermediaries are able to perfectly share risks from accommodating trading demand shocks and there is no limited risk-bearing capacity. Conversely, the larger the intermediary elasticity, the more limited the risk-bearing capacity.

[1] "Price multiplier" is another term that is sometimes used to refer to inverse elasticity, e.g., Gabaix and Koijen (2021).

To quantify intermediary elasticity, we develop a novel technique that extends the classic arbitrage pricing theory to identifying risks from trading. The classic theory builds on diversification of risk, whereby only common variations in asset returns constitute risk factors that explain unconditional expected returns (Markowitz (1952) and Ross (1976)). In this spirit, we argue that should trading demand shocks affect asset prices, they do so by altering the amount of non-diversifiable risks that intermediaries must bear. Consider an intermediary taking customer buy orders of the same size for two assets. If the two assets' returns are perfectly negatively correlated, the buy orders offset each other, and the intermediary bears no risk. Conversely, if the two assets are positively correlated, the intermediary is left with some non-diversifiable risk and requires compensation. The effect of trading demand shocks on asset prices thus depends on intermediary elasticity to trading-induced non-diversifiable risks. As in the canonical theory, *traded* non-diversifiable risks give rise to *traded* risk factors. Empirically, such factors can be identified through a modified principal component analysis (PCA) that incorporates both customer trading and asset return data. Our approach contrasts with the standard PCA done using asset returns only, which uncovers *unconditional* risk factors but is silent on whether these risk factors are affected by trading.

We study intermediaries' risk-bearing capacity in the foreign exchange (FX) market, where we obtain daily trading data in FX spot, FX forward, and FX swap from the CLS Group, the largest single source of FX executed data available to the market. We first show that FX trading-induced risks follow a strong factor structure: the three most important traded FX risk factors ("traded FX factors") jointly account for 90% of the non-diversifiable risks that intermediaries bear when accommodating FX trading flows. Decomposing observed trading flows to these three traded FX factors, which resemble the Dollar, the Carry, and the Euro-Yen,[2] provides a method for measuring intermediaries' otherwise unobserved net risk positions from trading. We then use instrumental variables to estimate the intermediary elasticity of the three traded FX factors. The factor-specific intermediary elasticity allows us to recover the cross-elasticity between the whole panel of currencies, a first in the literature. Finally, we show that returns in CDS, commodities, corporate bonds, equities, options, and U.S. Treasury bonds can also be explained by the three traded FX risk factors, and we apply the estimated FX-factor elasticity to obtain novel estimates of cross-elasticity between these asset classes.

We start by identifying FX risk factors that are most affected by trading demand shocks in 16 non-U.S. dollar (USD) currencies. We employ a modified PCA procedure on a weekly panel of trading flows and returns to recover risk factors most affected by customer trading. By accounting for variations in trading and returns simultaneously, our procedure contrasts with the standard PCA found in the literature. A standard PCA on FX trading simply points to portfolios with the most traded currencies because it neglects the covariance in currency returns. A standard PCA on FX return, on the other hand, can surface unconditional risk factors priced in FX (Lustig, Roussanov, and Verdelhan (2011)), but is silent on whether these factors are traded.[3] If there is no trading, then there is also no role for limited risk-bearing capacity at the margin. Remarkably, we find that the three most important traded FX risk factors are the Dollar, the Carry, and the Euro-Yen, where the first two are also the most important unconditional risk factors. As these factors capture the non-diversifiable risks in FX trading, net flows into these factors measure the intermediaries' risk exposure

[2]The Euro-Yen factor is constructed by longing the Euro (EUR) and shorting the Japanese yen (JPY), while being neutral on all other currencies.

[3]In fact, the risk premium of these unconditional risk factors is typically microfounded on consumption-based models with stochastic discount factors (SDFs) that do not rely on investor trading (Lustig and Verdelhan (2007)).

from FX trading. For example, we find that intermediaries accumulated \$0.8 trillion in exposure to the Carry between 2012 and 2023.

Having identified the traded FX factors, we proceed to estimate the intermediary elasticity of these factors. By construction, our traded FX factors have uncorrelated returns and uncorrelated flows, meaning that both intermediaries and customers view these factors as uncorrelated; we thus estimate the intermediary elasticity factor-by-factor without worrying about cross-factor substitution. At the same time, we must instrument for trading demand shocks in each of the factors because we are interested in intermediaries' price response to trading that is not motivated by changes in fundamentals (e.g., the arrival of new information). We employ as instrumental variables the announcements of the offering amount at upcoming sovereign bond auctions in the U.S., Australia, Canada, the U.K., Japan, Italy, France, and Germany. These sovereign auctions often attract foreign investors who need to convert currencies to participate, making the instruments relevant. By using *offering* amounts at auctions whose size is typically dictated by fiscal needs, we have instruments that are plausibly exogenous and meet the exclusion restriction. We estimate that the intermediaries raise the factor price by about 1% in response to net trading demand shocks of approximately \$20 billion in the Dollar, \$11 billion in the Carry, and \$3.5 billion in the Euro-Yen. Compared to the estimated price response to trading demand shocks in the aggregate U.S. equities market, intermediaries' price response to shocks to the traded FX factors is high.[4] Viewed through the lens of our model, the high intermediary elasticity in the FX markets reflects intermediaries' greater aversion to liquidity provision. This aversion is especially pronounced for less well-known factors like Euro-Yen, and could arise due to limited

[4] Gabaix and Koijen (2021) find that a 1% higher trading demand shock to the entire U.S. stock market increases price by 5%. The average market capitalization between 2012 and 2022 is about \$31.7 trillion. To raise the stock market price by 1% over our sample period therefore requires about \$63 billion.

FX arbitrage capital.

The estimated intermediary elasticity allows us to compute the cross-(inverse) elasticity between any pair of currencies. We use "cross-elasticity" to measure the impact of a trading demand shock to currency A on the price of currency B, while holding the trading demand shocks of all other currencies constant. Estimating such cross-elasticities for a whole panel of currencies can be challenging, as currencies are substitutable and trading demand shocks are likely correlated across currencies. Our insight lies in mapping the cross-elasticity of currencies to trading's impact on common risk factors. When intermediaries accommodate trading demand shocks to currency A, they bear additional non-diversifiable factor-level risks. These risks influence factor prices through the estimated intermediary elasticity and ultimately affect the price of currency B via the law of one price. We find that the own-elasticity to $1 billion of inflow ranges from 5 bps to 16 bps for six commonly traded advanced economy currencies.[5] More interestingly, we find large cross-elasticity between AUD and CAD because these two currencies are traded in the same direction in all three traded FX factors. In contrast, the cross-elasticity between JPY and either AUD or CAD is small because JPY and these two currencies are on opposite sides of the Carry trade and hedge each other in exposure to the Carry factor. In IO, such phenomena are typically referred to as complementarity. Accordingly, although EUR and JPY are both low interest-rate currencies, our estimates suggest that they have only modest cross-elasticity because they "complement" each other in reducing the intermediary's exposure to the Euro-Yen factor.

Finally, we use the traded FX factors to inform cross-elasticity between asset classes. We show that returns in six other asset classes load on the traded FX factors. Consequently, intermediaries' limited risk-bearing capacity means that trading demand shocks

[5]The six currencies are the Australian dollar (AUD), the Canadian dollar, the Swiss franc (CHF), the Euro (EUR), the British pound (GBP), and the Japanese yen (JPY).

originating in FX can affect prices in other asset classes, as these shocks generate additional non-diversifiable trading risks and alter the price of traded FX factors. Similarly, a trading demand shock in, say, corporate bonds also exposes intermediaries to incremental non-diversifiable FX risks. Such risks change the price of the traded FX factors, which then affect corporate bonds' own price and the price in other asset classes through common exposure to the traded FX factors. For own elasticity, we find that trading demand shocks move the price the least in U.S. Treasury bonds, corroborating the observation that the Treasurys market is deep and liquid. U.S. Treasury bonds also stand out as the only asset class that has negative cross-elasticity with other assets. For example, a $1 billion trading demand shock to Treasurys depresses the price of corporate bonds by 0.2 bps.

We caution that our estimates only capture the cross-elasticity channeled through the three traded FX factors. These factors explain about 80% of the unconditional return variation for FX currencies and about 30% of the unconditional return variation for non-FX assets. Our estimates thus miss potential cross-elasticity arising due to common exposure to factors other than the three traded FX factors. Nevertheless, our estimates highlight that even though intermediaries are active in several markets, these markets do not necessarily move in tandem. Rather, understanding how asset markets are interconnected requires understanding different assets' exposure to common risk factors and the intermediary elasticity of these factors.

More generally, this paper advances the literature on intermediary-based asset pricing on two fronts. First, we present a novel way to measure the impact of intermediaries' risk-bearing capacity on asset prices. Constraints such as regulation, liquidity, and segmentation, have all been proposed to limit intermediaries' risk-bearing capacity (e.g., Gabaix and Maggiori (2015), He and Krishnamurthy (2017), Kondor and Vayanos (2019)). Empirical evidence points to these constraints being priced (e.g., Du, Tepper, and Verdelhan (2018), Du, Hébert, and Huber (2022), Duffie, Fleming, Keane, Nelson, Shachar, and Van Tassel (2023)) but offers limited insight into how these constraints matter at the margin. We extend the portfolio theories of Markowitz (1952) and Ross (1976) to a representative intermediary (He and Krishnamurthy (2013)) to show that trading-induced non-diversifiable risks are priced by the intermediary at the margin. We propose intermediary elasticity as a measure for intermediary's risk-bearing capacity, and we estimate the intermediary elasticity of traded FX factors to quantify the impact of trading demand shocks' on price. Second, we illustrate the nuanced cross-asset and cross-market pricing dynamics in intermediated financial products. Intermediaries have been shown to matter for prices of many asset classes (e.g., Adrian, Etula, and Muir (2014), He, Kelly, and Manela (2017), Haddad and Muir (2021)). Because intermediaries are simultaneously active in many markets, trading demand shocks in one market could propagate to other markets. We provide the first set of cross-market elasticity estimates by examining different asset markets' exposure to a common set of traded risk factors. Understanding cross-product and cross-market dynamics through exposure to common factors is a framework that can be broadly applied. For example, tying the tax burden of financial transactions to risk exposure rather than to specific transactions is likely more effective (Tobin (1978)).

Many findings in this paper relate directly to the literature on exchange rate determination. In particular, FX trading flows affect exchange rate. Flows matter in part because they convey information (e.g., Evans and Lyons (2002), Pasquariello (2007)), but uninformed flows also move exchange rates (Froot and Ramadorai (2008)). We emphasize that uninformed flows matter because these trading demand shocks push intermediaries against their risk-bearing capacity. Exchange rates can also affect and be affected by asset demands in other markets: Camanho, Hau, and Rey (2022) examine the connection to the equity market through portfolio rebalancing, and Liao and Zhang (2020), Jiang, Krishnamurthy, and Lustig (2021), and Gourinchas, Ray, and Vayanos (2024), among others, study the relationship with the bond markets due to hedging, safe asset demand, and preferred-habitat investors. The distinguishing feature of our paper is that we let the data inform the specific risk factors that link FX trading with other asset markets. In fact, we find that the risk factors affected by FX trading demand shocks are the same as those shown to price the unconditional exchange rate returns (Lustig, Roussanov, and Verdelhan (2011)). By showing that these risk factors are traded, we enrich the understanding of why these risks are priced (e.g., Bansal and Dahlquist (2000), Lustig and Verdelhan (2007), Ready, Roussanov, and Ward (2017)).

Finally, this paper adds to the growing literature that connects trading demand with asset prices. Early empirical works such as Coval and Stafford (2007) and Lou (2012) highlight the importance of demand on asset prices. More recently, several papers document reduced-form evidence that prices respond to trading demand because of perceived risks (e.g., Li and Lin (2022), Albuquerque, Cardoso-Costa, and Faias (2024)). We similarly focus on risk as the channel through which trading affects prices, but we use a theory-based procedure to identify the pertinent risk factors and translate the elasticity of risk factors to the elasticity of underlying assets. Our focus on trading-induced *risks* sets our "intermediary elasticity" apart from the IO-inspired price elasticity with respect to traded *securities* (e.g., Koijen and Yogo (2019) for the stock market, Koijen and Yogo (2020) and Jiang, Richmond, and Zhang (2024) for exchange rates, Bretscher, Schmid, Sen, and Sharma (2022) for corporate bonds). Our approach in part derives from An (2023) and is related to An, Su, and Wang (2024), who use a factor model to estimate price impacts in the equity markets. In emphasizing factor exposure as the driver of asset substitution, we complement recent papers that rationalize inelastic demand of individual asset through cross-substitution (e.g., Chaudhary, Fu, and Li (2023), Davis, Kargar, and Li (2023), Fuchs, Fukuda, and Neuhann (2023)). Indeed, we show that intermediaries' limited risk-bearing capacity leads to large price responses to non-diversifiable risks at the factor level, which in turn drives the inelasticity of individual securities and asset markets.

In the next section, we lay out our theoretical framework. We introduce the various sources of data we use in Section 3 and proceed to recover the traded FX factors in Section 4. We employ an instrumental variable approach to estimate the intermediary elasticity of the traded FX factors in Section 5, and apply these estimates to recover the cross-elasticity between currency pairs. We explore the connection between the FX market and six other asset classes in Section 6, and derive cross-elasticity between asset classes. We conclude in Section 7.

2 Theoretical Framework

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

2.1 Model Setup and Conceptual Framework

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

We have $N+1$ currencies, where the last currency is the numeraire currency. The gross risk-free rate of currency n from $t=0$ to $t=1$ is a constant $R_{F,n}$. The time-0 price of one unit of currency n in the numeraire currency is denoted as P_n, and the time-1 price of currency n is denoted as X_n. These $X_1, X_2, \ldots, X_N$ are jointly normally distributed. Consider the return of borrowing one unit of the numeraire currency at its risk-free rate, exchanging it to currency n at time 0, investing at currency n's risk-free rate between time 0 and 1, and exchanging back to the numeraire currency at time 1. This return is given by $R_{F,n}X_n/P_n - R_{F,N+1}$, and we stack it as an $N \times 1$ vector:

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

We assume that there are no redundant currencies such that the matrix $\text{var}(\mathbf{R})$ has full rank.[6]

Customers can buy or sell any pair of the $N+1$ currencies between time 0 to 0^+. These trading demand shocks are accommodated by a unit mass of representative intermediaries, who set the trading price competitively. These trading demand shocks are uninformed and do not impact the long-term price X_n at time 1. Hence, if intermediaries had unlimited risk-bearing capacity, the asset price P_n at time 0^+ would not be affected by the trading demand shocks. However, intermediaries may not freely bear all risks.

As in the classic asset pricing theory, intermediaries in our model require compensation for any non-diversifiable risks, including those resulting from accommodating customers' trading demand shocks. The key idea here is that intermediaries can diversify risks not only within the same currency but also across different currencies. Consider two customers trading with an intermediary (e.g., a dealer), where one customer is buying and the other is

[6] Throughout the paper, we use bold font to denote matrices and vectors.

selling. In the simplest case, the two customers are buying and selling the same currency, so the intermediary can easily offset the risks. However, even if the customers are trading different currencies, as long as the returns of these trades are not perfectly correlated, the intermediary can still offset some risks. Just as in the classic theory, diversification across currencies requires the intermediaries to consider portfolios of currencies (i.e., risk factors). Once the trading demand shocks from different currencies are aggregated, the remaining risks are non-diversifiable and the intermediaries require price compensation for bearing such risks. Hence, we aim to find the risk factors that represent the largest amount of non-diversifiable trading risks; these traded risk factors capture the most important shocks in the cross-section. Section 2.2 shows how to achieve this. Then, in Section 2.3, we compute the price equilibrium at the factor level to determine the intermediary elasticity of these non-diversifiable trading risks. Finally, as these non-diversifiable trading risks influence factor prices, individual currency prices must also adjust to maintain the law of one price in the cross-section; Section 2.4 completes the analysis by computing cross-elasticity, whereby trading demand shocks to one currency generate factor-level non-diversifiable risks, thus affecting factor prices and, in turn, the price of other currencies.

In what follows, we use the U.S. dollar (USD) as the numeraire currency and decompose all trades into trades against USD. In Appendix A.2, we prove that the construction of traded risk factors remains invariant to the choice of the numeraire currency. Accordingly, if a customer buys currency n by selling currency m, we record it as a positive trading demand shock for currency n from USD and a negative trading demand shock for currency m from USD.[7] Consequently, the trading demand shocks between the $N+1$ currencies can

[7]Triangular arbitrage implies that the time-0 exchange rate between currency n and currency m is P_n/P_m. Hence, if a customer buys $f_{n,m}$ units of currency n by selling $f_{n,m}P_n/P_m$ units of currency m, we can decompose it into two trades against the USD. First, the customer buys $\$f_{n,m}P_n$ of currency n and sells $\$f_{n,m}P_n$ of USD. Second, the customer sells $\$f_{n,m}P_n$ of currency m and buys $\$f_{n,m}P_n$ of USD.

be represented as an $N \times 1$ vector $\mathbf{f} = (f_1, f_2, \ldots, f_N)^\top$, where f_n is the net customer buying demand for currency n against USD.

2.2 Factor Construction

In this section, we construct the traded risk factors most affected by trading demand shocks by using a modified PCA on both customer trading and asset return data.

To fix idea, we first review how the standard PCA on asset returns alone implements the classic Ross (1976) Arbitrage Pricing Theory (APT) logic. The goal is to find a few factors that can be used to model the unconditional expected returns in the cross-section. The standard PCA procedure identifies these factors as those that maximally explain the variance of the (unconditional) returns. Specifically, the first factor is defined by a vector of N-currency portfolio weights $\mathbf{b}_1 = (b_{1,1}, b_{2,1}, \ldots, b_{N,1})^\top$ that maximizes the variance of the factor return: $\text{var}(\mathbf{b}_1^\top \mathbf{R})$. The second factor $\mathbf{b}_2$, conditional on being uncorrelated with the first factor, i.e., $\text{cov}(\mathbf{b}_1^\top \mathbf{R}, \mathbf{b}_2^\top \mathbf{R}) = 0$, again aims to maximize the variance of the factor return: $\text{var}(\mathbf{b}_2^\top \mathbf{R})$, and so on.

We want to study trading-induced risks that intermediaries bear at the margin. Thus, similar to the APT, we aim to identify a few factors that maximally explain the risks induced by the trading demand shock $\mathbf{f} = (f_1, f_2, \ldots, f_N)^\top$ and then use these factors to model how $\mathbf{f}$ impacts currency prices in the cross-section. For any given factor $\mathbf{b}_1$, currency n loads on the factor with a beta $\beta_{n,1} = \text{cov}(R_n, \mathbf{b}_1^\top \mathbf{R}) / \text{var}(\mathbf{b}_1^\top \mathbf{R})$. When there is a currency-level trading demand shock, f_n, that the intermediary must accommodate, the intermediary effectively bears a factor-level trading demand shock of size $f_n \beta_{n,1}$, along with other risks uncorrelated with the factor. Given that there are N currencies, intermediaries can offset the factor-level trading demand shock across different currencies, leaving a non-diversifiable factor-level shock of amount[8]

$$q_1 = \sum_{n=1}^{N} f_n \beta_{n,1}. \tag{2}$$

Note that for any given factor (as defined by the portfolio weights $\mathbf{b}_1$), the factor-level trading demand shock q_1 varies in proportion to the currency-level trading demand shock f_n. The relationship between q_1 and f_n depends on the factor being considered, as varying $\mathbf{b}_1$ changes the beta $\beta_{n,1}$ of the same currency to the factor. Because our goal is to maximally explain the trading-induced risks using a few factors, we construct the first factor $\mathbf{b}_1$ to maximize the variation of trading demand shock q_1 multiplied by the factor's return variance,[9]

$$\max_{\mathbf{b}_1} \text{var}(q_1)\text{var}(\mathbf{b}_1^\top \mathbf{R}). \tag{3}$$

We then construct the second factor $\mathbf{b}_2$ by requiring that the second factor has an uncorrelated return with the first and that the second factor maximizes the variation of q_2 multiplied by the return variance,

$$\begin{aligned} &\max_{\mathbf{b}_2} \text{var}(q_2)\text{var}(\mathbf{b}_2^\top \mathbf{R}) \\ &\text{s.t.}\ \text{cov}(\mathbf{b}_1^\top \mathbf{R}, \mathbf{b}_2^\top \mathbf{R}) = 0, \end{aligned} \tag{4}$$

where $q_2 = \sum_{n=1}^{N} f_n \beta_{n,2}$, with the beta $\beta_{n,2} = \text{cov}(R_n, \mathbf{b}_2^\top \mathbf{R})/\text{var}(\mathbf{b}_2^\top \mathbf{R})$.[10]

Such a sequential maximization procedure bears a resemblance to the standard PCA. Because we seek to maximally explain trading-induced risks using a few factors, and these

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

[9] Note that scaling $\mathbf{b}_1$ does not affect the objective function. If $\mathbf{b}_1$ doubles, then q_1 halves according to (2), and $\mathbf{b}_1^\top \mathbf{R}$ also doubles. Empirically, we choose a convenient scaling for economic interpretation.

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

risks depend on both currency-level trading demand shocks and currency returns, our construction is effectively a modified PCA on both trading and returns data. Appendix A.1 provides details on solving for these factors through eigenvalue decomposition. Additionally, we prove that our constructed risk factors also have uncorrelated trading demand shocks, i.e., $\text{cov}(q_k, q_j) = 0$ for $k \neq j$. Shocks to different q_k can thus be interpreted as uncorrelated shocks to uncorrelated risk factors.

2.3 Intermediary Elasticity

Having identified the traded risk factors that are most affected by trading demand shocks, we now determine the intermediary elasticity of each factor. We assume that there is a unit mass of intermediaries who have CARA preference. Because the intermediaries may face factor-specific frictions in accommodating risks, they have possibly factor-specific risk-aversion, denoted by γ_k.[11] These intermediaries collectively hold a total of $\$S_k$ in factor k at time $t = 0$ and absorb the trading demand shock q_k at time $t = 0^+$, which changes the factor-k price from $P_k(0)$ at time 0 to $P_k(q_k)$ at time 0^+. By market clearing, the intermediaries sell $\$q_k$ and retain $\$S_k - q_k$ of factor k after accommodating the trading demand shock. The equilibrium price $P_k(q_k)$ for factor k must therefore be set such that it is optimal for the intermediaries to sell $y_k = q_k$ dollars or $y_k/P_k(0)$ units of factor k at the new price $P_k(q_k)$,

$$\{q_1, \ldots, q_K\} = \arg \max_{\{y_1, \ldots, y_K\}} \mathbb{E}\left[-\exp\left(-\sum_{k=1}^{K} \gamma_k ((S_k - y_k)\mathbf{b}_k^\top \mathbf{R} + R_{F,N+1} P_k(q_k) y_k / P_k(0)) \right) \right]. \tag{5}$$

[11]In practice, not all intermediaries may be willing to provide liquidity for every factor. If some intermediaries choose not to provide liquidity for certain factors, this would manifest as a higher effective risk aversion, γ_k, in our model.

Here, $S_k - y_k$ multiplied by $\mathbf{b}_k^\top \mathbf{R}$ represents the time-1 payoff from holding $S_k - y_k$ dollars of factor k. Meanwhile, $R_{F,N+1}P_k(q_k)y_k/P_k(0)$ is the time-0^+ proceeds from selling y_k dollars of factor k, compounded to time 1 at the gross risk-free rate $R_{F,N+1}$. Applying the first-order condition to (5), Proposition 1 determines the equilibrium price impact for each factor.

PROPOSITION 1 (Intermediary elasticity). *Denoting $\lambda_k = \gamma_k/R_{F,N+1}$, the price impact of factor k satisfies*

$$\Delta p_k := \frac{P_k(q_k) - P_k(0)}{P_k(0)} = \lambda_k q_k \mathrm{var}(\mathbf{b}_k^\top \mathbf{R}). \tag{6}$$

The parameter λ_k is termed the "intermediary elasticity" of factor k. By equation (6), we can express λ_k as follows:

$$\lambda_k = \frac{\Delta p_k}{q_k \mathrm{var}(\mathbf{b}_k^\top \mathbf{R})}. \tag{7}$$

Here, Δp_k represents the price impact (percentage price change) of factor k from time 0 to 0^+. The denominator, $q_k \mathrm{var}(\mathbf{b}_k^\top \mathbf{R})$, measures the change in the quantity of risk due to the marginal trading demand shock into the factor. Consequently, λ_k captures the price compensation that intermediaries require for absorbing an additional unit of *traded* risk at the margin. This concept extends the canonical price of risk that measures price compensation required for taking on an extra unit of *unconditional* risk.

We highlight three features of the intermediary elasticity. First, because the traded risk factors have uncorrelated returns by construction, the equilibrium solution from (5) implies that demand shocks q_k for factor k affect only the price of factor k, without influencing any other factors. Appendix A.3 provides a proof. Second, λ_k is invariant to scaling or sign reversal of a factor. This underscores that, economically, λ_k reflects the per-capita risk aversion of intermediaries with respect to the factor.[12] Third, intermediary elasticity differs from the (inverse) elasticity $(\Delta P/P)/(\Delta Q/Q)$ used in IO in two respects. On the one hand, intermediary elasticity considers the quantity of risk in the denominator rather than the quantity of securities. On the other hand, intermediary elasticity focuses on the amount change in the quantity of risk rather than the percentage change, as the quantity of risk can be compared directly across factors without further normalization.

2.4 Cross-Elasticity

We now appeal to the law of one price and use factor-specific intermediary elasticity to determine the cross-elasticity between individual currencies. Consider the scenario where currency n experiences a \$1 trading demand shock, while customers' trading demand shocks for all other currencies remain constant. As explained in Section 2.2, this additional \$1 trading demand shock for currency n would increase the trading demand shock to factor k by an amount $\beta_{n,k}$, which are shocks that cannot be diversified away. To induce the intermediaries to bear these additional non-diversifiable factor risks, the price of these traded risk factors must change, as discussed in Section 2.3, which in turn affects the prices of all currencies that load on these risk factors.

Denoting the price impact of individual currency n as[13]

$$\Delta p_n := \frac{P_n(\mathbf{f}) - P_n}{P_n}. \tag{8}$$

Proposition 2 computes the model-implied cross-elasticity, which quantifies how a \$1 trading

[12] For example, suppose we double the portfolio weight $\mathbf{b}_k$, then by equation (2), the factor-level trading demand shock q_k halves. By the law of one price, the factor-level price impact Δp_k and the return variance $\text{var}(\mathbf{b}_k^\top \mathbf{R})$ double and quadruple, respectively, leaving λ_k unchanged.

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

demand shock into currency m impacts the price of currency n. Note that this formula also covers the case where m and n are the same, thereby calculating a currency's price elasticity to its own trading demand shock. Appendix A.4 provides a proof.

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

$$\frac{\partial \Delta p_n}{\partial f_m} = \sum_{k=1}^{K} \frac{\partial q_k}{\partial f_m} \times \frac{\partial \Delta p_k}{\partial q_k} \times \frac{\partial \Delta p_n}{\partial \Delta p_k} = \sum_{k=1}^{K} \beta_{m,k} \times \lambda_k \text{var}(\mathbf{b}_k^\top \mathbf{R}) \times \beta_{n,k}. \tag{9}$$

The intermediary cross-elasticity, $\partial \Delta p_n / \partial f_m$, calculates the price impact on currency-n, Δp_n, from currency-m's trading demand shock, f_m, as channeled through the traded risk factors and while holding customers' trading demand shocks into all other currencies constant. Proposition 2 shows that such cross-currency price impacts are channeled via three steps. First, the trading demand shock into currency m changes factor-k trading demand shock q_k, with the sensitivity given by the beta coefficient $\beta_{m,k}$, as shown in equation (2). Second, changes in factor-k trading demand shock impact its price Δp_k, where the price sensitivity is $\lambda_k \text{var}(\mathbf{b}_k^\top \mathbf{R})$ (Proposition 1). Finally, changes in factor-k price Δp_k impact currency-n price Δp_n through the law of one price, with the sensitivity being $\beta_{n,k}$.

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

$$\frac{\partial \Delta p_n}{\partial f_n} = \sum_{k=1}^{K} \beta_{n,k}^2 \times \lambda_k \text{var}(\mathbf{b}_k^\top \mathbf{R}) \tag{10}$$

is always positive as long as λ_k is positive. Positive λ_k indicates that intermediaries are averse to bearing trading-induced risks rather than risk-seeking. On the other hand, the cross-elasticity between two currencies could be negative, if the currencies have opposite signs of beta loading to a factor, which reflects complementarity. We return to this point empirically in Section 5.3.

Second, the model-implied cross-elasticity is symmetric between any two currencies n and m, as shown by

$$\frac{\partial \Delta p_n}{\partial f_m} = \frac{\partial \Delta p_m}{\partial f_n}. \tag{11}$$

This symmetry arises because

$$\frac{\partial q_k}{\partial f_n} = \beta_{n,k} = \frac{\partial \Delta p_n}{\partial \Delta p_k}. \tag{12}$$

The first equality, relating to the sensitivity of trading demand shock, follows from our portfolio theory (2), while the second equality, concerning price sensitivity, results from the law of one price. Both sensitivities equal the beta of currency n to factor k, which gives rise to the symmetry of the intermediary cross-elasticity.

2.5 Implementation Issues

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

With a slight abuse of notation, we use R_n to also denote the counterfactual currency return from time 0 to 0^+ in a scenario with no demand shock. The equilibrium return r_n from time 0 to 0^+ is then the sum of Δp_n and R_n. Accordingly, the equilibrium return of factor k from time 0 to 0^+ is also the sum of the price impact from Proposition 1 and the counterfactual return, $\mathbf{b}_k^\top \mathbf{R}$:

$$r_k = \lambda_k q_k \text{var}(\mathbf{b}_k^\top \mathbf{R}) + \mathbf{b}_k^\top \mathbf{R}. \tag{13}$$

Because Proposition 1 measures var($\mathbf{R}$) using $\mathbf{R}$ from time 0 to 1 and we are now using $\mathbf{R}$ from time 0 to 0^+, an assumption for equation (13) to hold is that var($\mathbf{R}$) is proportional across these time horizons. This assumption holds if, for example, $\mathbf{R}$ is i.i.d. over time.

Recall that the factors constructed in Section 2.2 have uncorrelated counterfactual returns, i.e., $\text{cov}(\mathbf{b}_k^\top \mathbf{R}, \mathbf{b}_l^\top \mathbf{R}) = 0$, and uncorrelated trading demand shocks, i.e., $\text{cov}(q_k, q_l) = 0$. Hence, equation (13) implies that the equilibrium returns of different factors are also uncorrelated, i.e., $\text{cov}(r_k, r_l) = 0$ for any $k \neq l$. Consequently, when we empirically use equilibrium return rather than counterfactual return, we recover the same set of factors (up to scaling) as those in Section 2.2.

Finally, as price impacts are not directly observable, we estimate λ_k by running a time-series regression of r_k on q_k, scaled by $\text{var}(\mathbf{b}_k^\top \mathbf{R})$. An unbiased estimate of λ_k requires that $\text{cov}(q_k, \mathbf{b}_k^\top \mathbf{R}) = 0$, or that q_k is truly a trading demand shock that is exogenous to the counterfactual factor return $\mathbf{b}_k^\top \mathbf{R}$. This condition is often violated in observed data, we thus adopt an instrumental variables (IV) strategy in Section 5 to estimate λ_k.

3 Data

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

3.1 Trading Data

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

We obtain FX order flow data from CLS. Specifically, we have the daily aggregate value of all buy orders and all sell orders done between Banks and their customers in 17 currencies between September 2012 and December 2023. The currencies in our sample include U.S. dollar (USD), Australian dollar (AUD), Canadian dollar (CAD), Swiss frank (CHF), Danish kroner (DKK), Euro (EUR), British pound (GBP), Hong Kong dollar (HKD), 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 of our data have Banks as one of the two counterparties in the trade. Trades by Banks encompass trades by dealers who are affiliated with banks and, by extension, trades by hedge funds who trade through their prime brokers. We interpret the trading by Banks as capturing the activities of the representative financial intermediary in our model. The customers in our data, who are Banks' counterparty, are from one of three groups: Funds, which include mutual funds, pension funds, and sovereign wealth funds; Non-bank Financials, which include insurance companies and clearing houses; and Corporate.

To capture the *total* amount of FX risk exposure facing intermediaries, we are the first to jointly analyze data on FX spot with data on FX forward and FX swap. The CLS data on spot flows have recently been used in papers that examine topics ranging from market microstructure to the impact of Fed policies (e.g. Ranaldo and Somogyi (2021), Roussanov and Wang (2023)). Yet as we detail in Appendix Section B, the pronounced negative correlation between flows into spot versus forward and swap means that any elasticity estimated from spot flows alone could underestimate the price impact of trading demand shocks. The CLS data for forward and swap order flows organize transactions by maturity buckets. We calculate the FX spot exposure inherent in future-settled forward and swap by discounting the notional using forward rates.[14] From the FX flow data in spot, forward, and swap, we construct the dollar-valued total daily net customer inflow into each currency. As discussed in Section 2.1, we measure all flows relative to USD.

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

Our final trading data is a panel, between 2012-09-06 and 2023-12-31, of weekly net inflow into 16 non-USD currencies, measured in USD across spot, forward, and swap transactions.

3.2 Return Data

We obtain most of the data needed to construct returns from Bloomberg. To calculate FX returns, we get forward and spot price data for the 16 non-USD currencies in our sample. All prices are at London closing, consistent with our trading flow measure.[15]

We define the weekly currency return as the outcome from borrowing USD at the US risk-free rate today, converting to one unit of foreign currency at the spot exchange rate and earning the foreign risk-free rate, then in a week, converting the foreign proceeds back

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

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

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

3.3 Other Data

We collect data on various sovereign bond auctions to instrument for FX trading demand shocks. Specifically, we obtain from government websites the auction announcement data for the U.S. Treasury auctions, the Australian Treasury bond auctions, the Canadian Treasury bond auctions, the U.K. Gilt auctions, the Japanese government bond auctions, the Italian government bond auctions, the French OAT auctions, and the German Bund auctions.

We also collect various data to construct excess returns in six other asset classes. 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. Returns to these CDS indices are defined from the perspective of the seller. For commodities, we obtain six Bloomberg commodity futures return indexes on energy, grains, industrial metals, livestock, precious metal, and softs. For corporate bonds, we obtain five Bloomberg indices on U.S. corporate bonds by credit rating (Aaa, Aa, A, Baa, high yield). For equities, we use the "Market" return from Ken French's website, which is the value-weighted returns from all publicly traded U.S. firms in CRSP. For options, we obtain call and put pricing data on S&P500 from OptionMetrics, and construct portfolios of leverage adjusted option returns following Constantinides, Jackwerth, and Savov (2013). For US Treasury bonds, we get yields of the six maturity-sorted "Fama Bond Portfolios" from CRSP. We exclude the portfolio of Treasury bills due to correlation with the risk-free rate. Finally, we use the 1-month U.S. Libor as a proxy for the risk-free rate. The Bloomberg CDS data are available from 2007 onward, and the OptionMetrics data are available until December 2022. All other pricing data start in January 2000 and end in December 2023.

4 Traded Risk Factors in FX

In this section, we identify traded FX factors from data. We first find that three risk factors account for most of the non-diversifiable risks induced by FX trading. We then show that these risk factors can be interpreted as the Dollar, the Carry, and the Euro-Yen, respectively. Finally, we highlight that these risk factors also capture the preponderance of the unconditional return and trading variations in individual currencies.

4.1 Baseline Traded FX Factors

Our objective is to find risk factors that can model FX trading's impacts on currency prices in the cross-section. We therefore need to find factors that maximally explain the risks induced by trading. Following the procedure outlined in Section 2.2, we identify the traded risk factors using weekly net flows ($\mathbf{f}$) and log returns ($\mathbf{r}$) of 16 non-USD currencies. The three factors that explain the most amount of trading-induced risk are reported in Table 1. Each column of Table 1 represents a factor, and the component values are the currency weights in this factor. For example, in Factor 1, for every \$1 bought, \$0.15-worth of Canadian dollars and \$0.5-worth of Euro are sold. As discussed in Section 2.3, we can freely scale each factor without affecting the intermediary elasticity, and we accordingly scale all factors to facilitate comparison.[16] Because the risk factors that we identify are traded, they logically place more weight on currencies that are more widely traded. In particular, six developed economy currencies have consistently high weights across the top 3 factors, these currencies are AUD, CAD, CHF, EUR, GBP, and JPY, and we highlight them in red. Of the total trading-induced non-diversifiable risks, given by $\sum_{l=1}^{K} \text{var}(q_l)\text{var}(\mathbf{b}_l^\top \mathbf{r})$, our three traded risk factors account for 65%, 16%, and 9%, respectively. In other words, these three factors explain approximately 90% of the risk that intermediaries bear when accommodating trading flows.

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

A tempting alternative approach to finding traded FX factors may be to perform a PCA directly on trading data. Portfolios from such an approach would simply place weight in one single major currency. For example, as Appendix Table A3 illustrates, the first such "traded FX factor" would place a portfolio weight of -1 on EUR and 0 on all other non-USD currencies, reflecting that EUR/USD is the most actively traded pair. This result arises because the standard PCA does not require the portfolios to also have uncorrelated

[16] Specifically, 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.

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

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

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

returns. In contrast, the portfolios identified in Table 1 have both uncorrelated returns and uncorrelated flows, endowing the portfolios with the interpretation of risk factors.

4.2 Interpretation of Traded FX Factors

To better understand the risks captured, we conjecture and verify that the top three traded FX factors represent the Dollar, the Carry, and the Euro-Yen, respectively. Examining Factor 1 in Table 1, we see that all non-USD currencies enter the portfolio with a negative

Table 2: **Correlation Between Traded FX Factors in Full Sample vs. Subsamples**

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

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

weight. This pattern is reminiscent of the proverbial Dollar portfolio, which shorts all non-USD currencies simultaneously and bets on the dollar exchange rate. We thus propose a traded Dollar factor that goes long in USD and shorts the six most traded currencies (AUD, CAD, CHF, EUR, GBP, and JPY) in equal weights. In contrast, Factor 2 in Table 1 has positive weights on high interest rate currencies, e.g., AUD, and negative weights on low interest rate currencies, e.g., JPY. This pattern coheres with the proverbial Carry portfolio, which bets on violations of the uncovered interest-rate parity (UIP). We accordingly propose a traded Carry factor that goes long in AUD, CAD, and GBP, and shorts CHF, EUR, and JPY. Finally, Factor 3 in Table 1 has a large positive weight on EUR and a large negative weight on JPY. We postulate a traded Euro-Yen factor that goes long in EUR and shorts JPY. This Euro-Yen factor reflects the active currency trading between two of the world's largest economies, the Euro area and Japan, even as the Dollar and Carry factors place both EUR and JPY on the same side of trading. In other words, long-short the Euro-Yen generates non-diversifiable risks even after hedging out the Dollar and Carry factors.

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

Table 3: **Correlation between Return and Flow to Baseline PC Factors versus to 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 displays the correlation between return and flow to baseline traded FX factors in Table 1 ("PC Factors") and return and flow to traded FX factors constructed from the proposed factor weights of the Dollar, the Carry, and the Euro-Yen ("Economic Factors").

Carry, and Euro-Yen factor weights, we construct factor returns and factor flows.[17] In Table 3, we show the correlation between the baseline traded FX factors in Table 1 ("PC Factors") and the traded FX factors constructed from the proposed factor weights ("Economic Factors"). The correlations are close to 1 in both returns and flows for all three factors. Together, the three Economic Factors can explain about 86% of all trading-induced non-diversifiable risks, close to the risks accounted for by the PC Factors. Given the striking similarity between the PC Factors and the Economic Factors, we focus on analyzing the more interpretable Economic Factors in the rest of the paper.

The construction of traded FX risk factors reveals two important results. First, that just three factors can explain almost all trading-induced risks validates our conceptual framework. Indeed, we postulate that non-diversifiable trading risks are what get priced by intermediaries; in such a world, FX trading flows would exhibit a strong factor structure. Second, the traded FX factors have clear economic interpretations, elevating the relevance of our

[17]Specifically, we perform the procedures outlined in Section 2.2 after projecting both returns and flows onto the space spanned by the proposed Dollar, Carry, and Euro-Yen factor weights. The resulting Dollar, Carry, and Euro-Yen factors have uncorrelated returns and uncorrelated flows with each other.

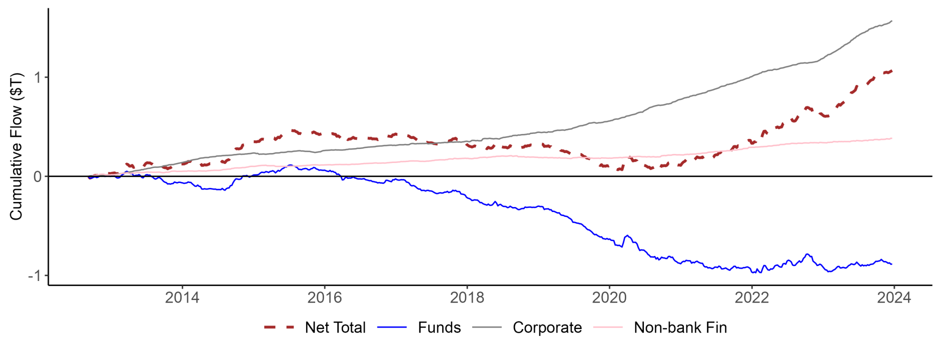
analysis on intermediaries' risk exposure and risk tolerance. For example, the Carry trade is a popular FX trading strategy and the Carry factor is a well-known risk factor in FX returns (e.g., Lustig, Roussanov, and Verdelhan (2011)). Yet it is not previously known how much Carry trades are done[18] or how much trading of Carry contributes to observed return. We answer the first question in this section by estimating intermediaries' cumulative exposure to the traded risk factors. We tackle the second question in Section 5.2 after we estimate the intermediary elasticity of different traded FX factors.

The economic exposure to, say, the Carry trade is challenging to assess from trading data alone: FX traders can simultaneously buy and sell multiple currencies, and exposures in one currency can be quickly hedged or diversified away by trading other currencies. Yet the traded FX risk factors represent precisely what is non-diversifiable. Cumulative flows into the risk factors thus show the cumulative exposure to the currency portfolios that define the risk factors.

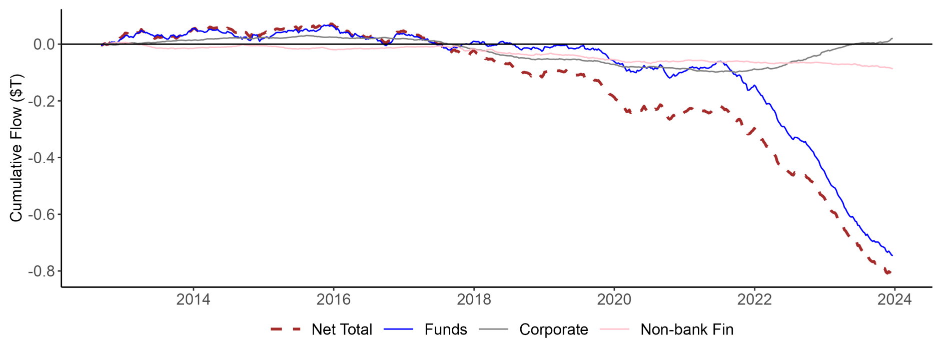
Figure 1 plots the cumulative flow to each of the three factors by customer type. As detailed in Section 3.1, there are three types of customers: Funds; Corporates; and Non-Bank Financials. We also plot in dashes the Net Total, which represents the net customer flows that Banks need to absorb. Then, by market clearing, the negative of the Net Total represents the intermediaries' cumulative flow. Panel (a) illustrates the flow to the Dollar factor. Over the sample period, Funds are persistently selling Dollars, whereas Corporates are persistently buying. In recent years, the buying pressure has been so strong that intermediaries have had to be net sellers of the Dollar factor. We note that intermediaries, especially dealers, may not be able to maintain a sustained inventory imbalance. The sustained provision of USD here likely reflects deposit or wholesale funding made available by banks to which the

[18] https://www.economist.com/leaders/2024/08/15/time-to-shine-a-light-on-the-shadowy-carry-trade

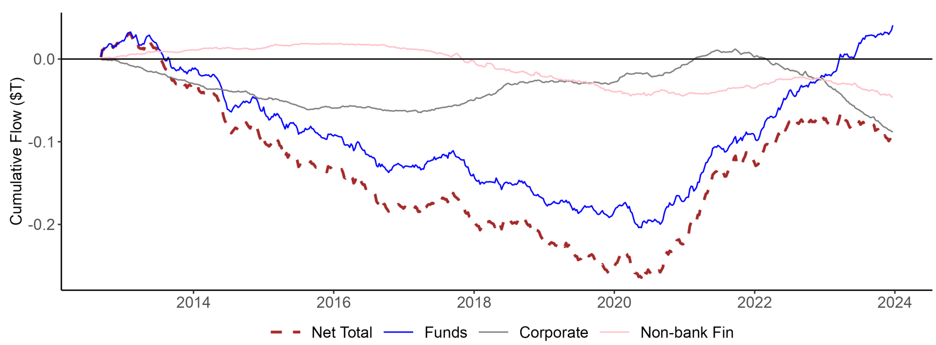
Figure 1: **Cumulative Flow by Investor Type to Top 3 Traded FX Factors**



(a) **Dollar Factor**



(b) **Carry Factor**



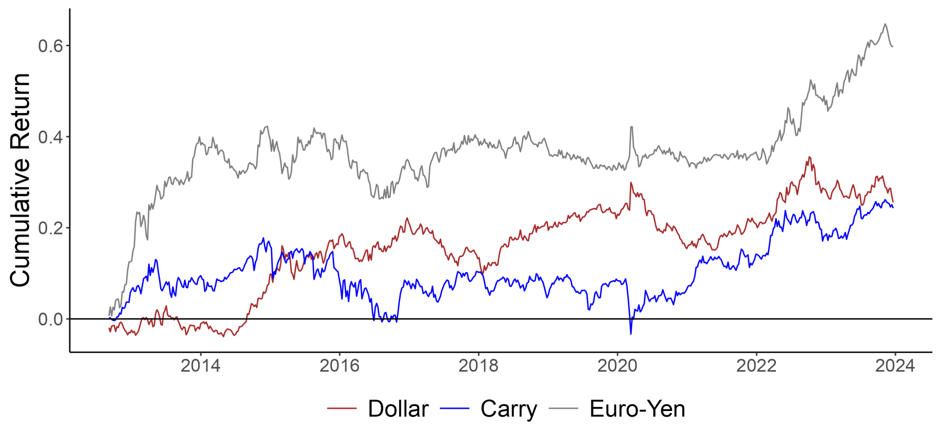
(c) **Euro-Yen Factor**

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

dealers are affiliated (Du and Huber (2024)). Moreover, intermediaries' cumulative flows represent their cumulative exposures from FX trading, but intermediaries could also offload risks associated with the traded FX factors in other asset markets, a point that we explore in Section 6. Panel (b) illustrates the flow to the Carry factor. We observe that customers had not taken large directional bets with the Carry factor until 2022, but since then, they have sold off the Carry factor, an action almost exclusively undertaken by Funds. As a result, the Carry trade exposure borne by Banks, or intermediaries including dealers and hedge funds, accumulated to $0.8 trillion between 2012 and 2023. Finally, from Panel (c), we see that the Euro-Yen factor was sold by both Corporate and Funds right up to around the Covid-19 Crisis in 2020. Since then, Funds have bought back all of their short position to approximately neutral, while Corporate continued to sell the Euro-Yen factor. Thus, intermediaries have also been accumulating exposures in the Euro-Yen. As JPY serves as a "funding currency" (negative weight in the portfolio) in both the Carry and the Euro-Yen, our analysis underscores that any unwinding of intermediaries' short JPY positions may not simply be a story about Carry trade.

In Figure 2, we plot the cumulative returns to the three traded FX factors. The Dollar return has been strong, as USD has appreciated against most currencies over the last decade. The Carry return had been around zero until 2022, but has since taken off. The uptick in the Carry return coincided with the accumulation of Carry exposures by the intermediaries. This suggests that FX trading may affect the pricing of these traded risk factors. We return to this in Section 5.

Figure 2: **Cumulative Return of Top 3 Traded FX Factors**



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

4.3 Factor Decomposition of Individual Currencies

Although the three factors are designed to maximally capture *trading-induced* risks, we show that these factors also explain a substantial amount of *unconditional* return and trading of individual currencies. Figure 3 illustrates the decomposition of individual currency's trading flow and return into the Dollar, the Carry, and the Euro-Yen factors. This decomposition is achieved by regressing currency-level flows or returns on the flows or returns of traded FX factors in the time series. Because the returns and flows of different factors are uncorrelated by construction, the R^2 from each regression is additive. Starting with flows in Panel (a), the three factors account for virtually all of the trading in EUR and JPY (91% and 98%), almost half of trading in CAD (48%), and a smaller fraction in AUD, CHF, and GBP. The unexplained flow represents customer trading that can be diversified by intermediaries or belong to other non-diversifiable risks that are, by construction, uncorrelated with the top three factors.

As Panel (b) illustrates, the Dollar, the Carry, and the Euro-Yen factors together account for between 69% and 94% of individual currency's unconditional return. The fact that these traded risk factors can explain a high fraction of individual currency's return variation is not a foregone conclusion: the traded FX factors are only designed to rationalize changes in FX risk that are induced by trading, not necessarily all the risks that are priced in the FX markets. Reassuringly, these trade factors are also able to explain a significant amount of the total risk in FX returns.

The large common variation with factors in both return and flow implies complex cross-elasticity between currencies. We map out these cross-elasticities in the next section.

5 Elasticity in FX Markets

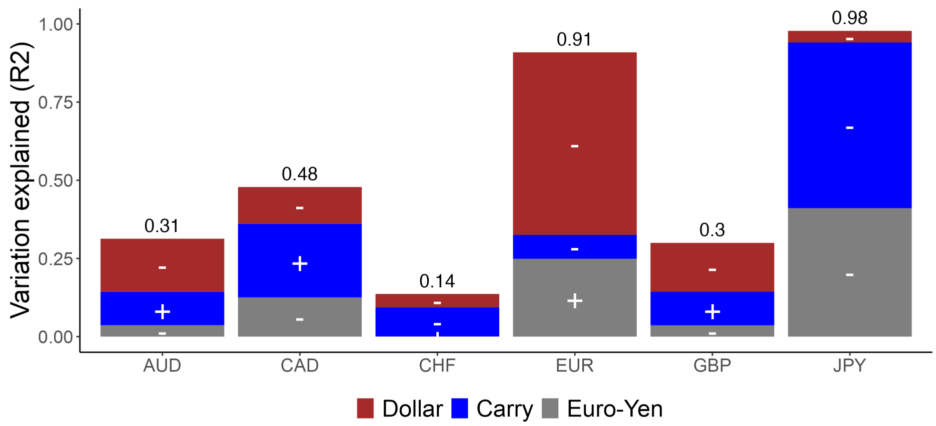
In this section, we estimate intermediary elasticity of the traded FX risk factors and apply the estimates to recover the own- and cross-elasticity of individual currencies.

5.1 Instrument Construction

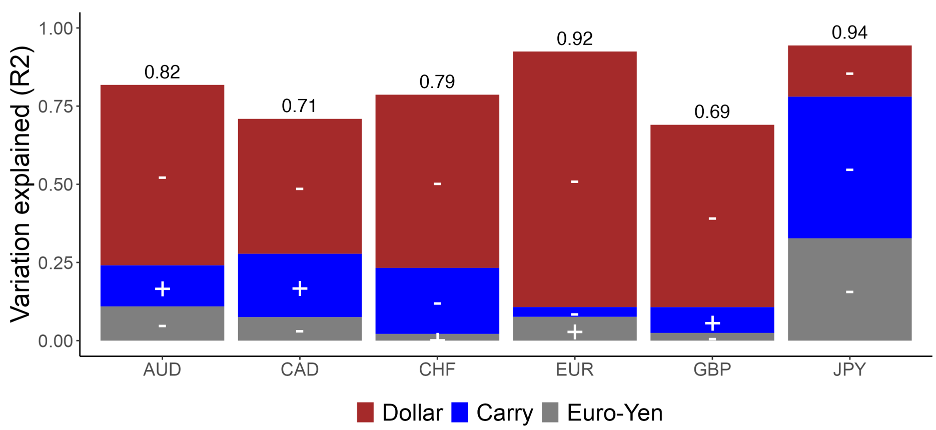
We are interested in estimating λ_k, the intermediary elasticity of traded FX factor k, in equation (6). However, as discussed in Section 2.5, we do not directly observe price responses induced by trading demand shocks (Δp_k); instead, we observe the equilibrium return (r_k) that reflects both Δp_k and the counterfactual return in the absence of demand shocks (R_k). Analogously, the factor flow that we construct, q_k, includes both the flow due to trading demand shocks and the flow due to fundamental changes, e.g., information. To isolate the impact of λ_k, we must instrument for the trading demand shocks in q_k.

As the traded FX factors are constructed to have uncorrelated returns, we apply Proposition 1 to estimate λ_k factor-by-factor without worrying about any cross-substitution. Specif-

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



(a) **Flow**



(b) **Return**

Notes: This figure decomposes the trading flows and returns of individual currencies into the Dollar, the Carry, and the Euro-Yen factors. The decomposition is achieved by regressing currency-level flows and returns against the flows and returns of the traded FX 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.

ically, for each factor $k = \text{Dollar}, \text{Carry}, \text{Euro-Yen}$, we run a time-series regression of the factor's weekly equilibrium return $r_{k,t}$ on its instrumented weekly flow $\hat{q}_{k,t}$:

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

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

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

The key is to find instruments (z_k) for observed factor flows (q_k) that are both relevant (equation (15)) and valid (equation (16)). We propose sovereign bond auction announcements as instruments. Government entities such as the US Treasury periodically auction off long-term debt obligations, e.g., US Treasury notes and bonds. Foreign investors participate in auctions of advanced economies, making these auctions relevant instruments. For example, foreign investors directly purchased on average 14% of US Treasury notes and bonds sold at auctions between September 2012 and December 2023.[19]

We moreover argue that these auctions, and in particular, the *announcements* of the *offered* amount at upcoming auctions are valid instruments because they are plausibly exogenous and satisfy the exclusion restriction. First, the amount of securities planned to be sold at auctions is likely not influenced by FX market conditions. This is in part because fiscal considerations such as tax receipt and expenditures are of paramount importance, and in part because the majority of the security buyers are domestic. In other words, the instrument is possibly exogenous. Second, our focus on the amount of securities *offered* to be auctioned limits the information content of investors' purchase. Foreign investors' actual purchase amount may be influenced by (expectations of future) exchange rates. Measures of auction demand such as the bid-to-cover ratio may therefore affect exchange rates through channels

[19]Foreign investors' actual purchase of auctioned Treasury securities could be much higher, as 14% excludes foreign purchases done indirectly via U.S. investment funds and dealers.

other than the trading volume that the purchase induces. We circumvent this concern by using *offers* rather than actual sales, lending credibility to the exclusion restriction.

Specifically, we use the US Treasury auction announcements as the instrument for the Dollar factor. We use the Australian, Canadian, British, and Japanese government bond auction announcements as the instrument for the Carry factor. We use the announcements of Euro-Area Government bond auctions, defined as the sum of German, French, and Italian government bond auctions, as the instrument for the Euro-Yen factor. For each auction, we aggregate the offered amount across all announcements in a week, as in FX trading flows.[20] To instrument for factor flows in week t, we use announcements in week t for the Dollar and the Carry, and announcements in weeks $t-1$ and t for the Euro-Yen. The longer window for European sovereign auctions allows for potential delays in auction-induced currency conversion, which is a relevant concern because sovereign auctions in Germany, France, and Italy do not allow direct bids from foreign investors. Finally, we remove any linear trend in the size of the auctions over time.

5.2 Factor-Level Elasticity

Table 4 presents the λ_k estimation results for the Dollar, Carry, and Euro-Yen factors. For all three factors, the estimated intermediary elasticity is positive and statistically significant, pointing to intermediaries having limited risk-bearing capacity. Both the OLS and the IV estimates show that the intermediary elasticity is the smallest for the Dollar and the largest for the Euro-Yen. Intermediaries are best able to bear marginal risks in the Dollar factor, yet the Dollar factor accounts for the most trading-induced risks (Table 1); these two facts together underscore that the Dollar factor is the most commonly traded FX risk factor.

[20] We focus on auctions for securities with maturity of one year or longer, as short-term securities are typically bought by domestic investors such as money market funds.

Table 4: **Estimated Intermediary Elasticity**

	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)
1st stage F-stat		24.8		6.5		3.8
Anderson-Rubin CI				(0.01, 2.39)		(0.09, 1.91)
Observations	590	386	590	228	590	560

Notes: This table presents the λ_k estimation results for the Dollar, Carry, and Euro-Yen factors, based on regression (14). The 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 from 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. *$p<.1$; **$p<.05$; ***$p<.01$.

We note that the OLS estimates are similar to the IV estimates but slightly smaller. In other words, the bias that the IV corrects is that FX customers often "buy the dip": when a currency depreciates, they buy, and vice versa. Such behaviors are plausible for mutual funds that buy foreign assets when exchange rates are favorable, and are consistent with evidence showing that corporations flexibly adjust the denomination of their bond issuance depending on exchange rates (Liao (2020)).

Table 5 quantifies the economic magnitude of the estimated intermediary elasticity λ_k. Using Proposition 1, we calculate the impact of a \$1 billion factor flow on factor price as $\lambda_k \sigma^2(r_{k,t})$, where $\sigma(r_{k,t})$ is the annualized volatility of the factor return. Our estimates imply that a \$1 billion flow into the Dollar, Carry, and Euro-Yen factors increases their price by 5, 9, and 29 basis points, respectively. In other words, intermediaries raise the factor price by

Table 5: **Economic Magnitude of Intermediary Elasticity**

	Int. elasticity (IV) λ_k	Return volatility $\sigma(r_{k,t})$	Price impact per \$B flow $\lambda_k \sigma^2(r_{k,t})$	Flow volatility $\sigma(q_{k,t})$	Return var due to flow $\lambda_k^2 \sigma^2(r_{k,t}) \sigma^2(q_{k,t})$
Dollar	0.11	6.9%	5.0 bps	84.5 \$B	38.6%
Carry	0.14	8.2%	9.3 bps	34.0 \$B	14.8%
Euro-Yen	0.34	9.4%	29.3 bps	22.0 \$B	47.6%

Notes: This table quantifies the economic magnitude of intermediary elasticity for the Dollar, Carry, and Euro-Yen factors. The columns report, from left to right, the elasticity estimates from the IV regression, the standard deviations of factor returns, the impact on factor prices per billion of factor flow, the standard deviations of factor flows, and the share of factor return variance explained by factor flow.

about 1% in response to a \$20 billion net trading demand shock to the Dollar factor, a \$11 billion net trading demand shock to the Carry factor, and a \$3.5 billion net trading demand shock to the Euro-Yen factor. These price impacts are large compared to the estimated (inverse) elasticity of US equities.[21] Viewed through the lens of our model, the higher FX intermediary elasticity reflects intermediaries' greater aversion to liquidity provision, which is especially pronounced for less well-known factors like Euro-Yen. The FX market is highly specialized, where only participants like bank dealers and hedge funds offer liquidity to absorb trading demand shocks. This specialization could result in a more limited supply of arbitrage capital, which in turn leads to a higher aversion to liquidity provision.

Using annualized factor flow volatility, we further quantify the share of each factor's total return variance that can be explained by its flows. The last column of the table shows that this fraction is 38%, 15%, and 48% for the Dollar, the Carry, and the Euro-Yen factors, respectively.[22] These numbers show that FX trading is an important driver of

[21] Gabaix and Koijen (2021) find that a 1% greater trading demand shock in the entire US stock market increases price by 5%. The average market capitalization between 2012 and 2022 is about \$31.7 trillion. To raise the stock market price by 1% over our sample period therefore requires about \$63 billion.

[22] Note that the Euro-Yen factor is constructed by orthogonalizing returns with respect to the Dollar and

observed factor returns because of intermediaries' limited risk-bearing capacity. We must note, however, that this share of return variance explained is likely an upper bound because it linearly extrapolates our IV estimates of the intermediary elasticity, which are based on local variation. In practice, the price impacts of trading demand shocks are likely to be concave in the size of the shocks, as larger price impacts could attract more intermediaries to provide liquidity.

Our estimation period excludes the first half of 2020, which corresponds to the onset of COVID. Markets experienced extreme price volatility and dislocation during this period, casting doubts over our instruments' validity and strength. Our estimates therefore reflect the average intermediary elasticity outside of crisis periods. To examine possible fluctuations in intermediaries' risk-bearing capacity during normal times, we interact the factor flow with measures that plausibly capture conditions that can affect the intermediaries.[23] We investigate the Dollar factor, as this is the most traded FX risk factor, and we present the results in Appendix Table A4. The two measures that we consider are the 3-month AUD-JPY cross-currency basis[24] and the usage of the Federal Reserve's (Fed's) central bank liquidity swap lines.[25] We are interested in the instrumented interaction term between factor flow and

Carry factors. Hence, we do not claim that the Euro-Yen factor flow explains 48% of the variance of the Euro-Yen currency pair exchange rate. Rather, the factor flow explains 48% of the variance of Euro-Yen factor return, which is the return of the Euro-Yen currency pair after removing the effects of the Dollar and Carry factors. Using Proposition 2, we find that Euro-Yen factor flow explains 29% of the return variance of the Euro-Yen currency pair.

[23] To implement in the context of instrumented flow, we run two first-stage regressions, one for factor flow, and one for factor flow interacted with the time-varying measure. Both regressions include the instrument, the time-varying measure, and the interaction between the instrument and the time-varying measure as explanatory variables. We demean and standardize the time-varying measure.

[24] Cross-currency basis measures deviations from covered interest-rate parity (CIP) and captures regulatory risks that affect asset prices (Du, Hébert, and Huber (2022)). The basis between AUD-JPY is the largest among developed country currency pairs. We use the average basis in week t with factor flow in the same week.

[25] Swap lines were set up during the financial crisis of 2007-09, and have been used throughout our estimation period to provide occasional dollar funding to foreign central banks who then pass the funding to local intermediaries. Given the friction in dispersing funding to local intermediaries, we use swap usage

the time-varying measure. The interaction term with CIP deviation has the intuitive, positive sign: our measure of CIP deviation increases when intermediaries are more constrained, and this likely increases intermediary elasticity. However, the interaction term is not statistically significant. The interaction term with swap line usage, on the other hand, is negative. This is also intuitive: swap line provides immediate dollar funding, relieving potential funding constraints, and should reduce the intermediary elasticity. This interaction is statistically significant and sizeable. A one standard deviation increase in swap line usage decreases intermediary elasticity by 5.6 bps. The fact that swap line usage increases intermediary's risk-bearing capacity for the Dollar factor suggests that the risk underlying the Dollar factor is indeed USD funding.

Finally, we note that the precision of an IV estimation depends on the strength of the instrument. The heteroscedasticity and autocorrelation consistent (HAC) effective F-statistics of the instruments are 24.8, 6.5, and 3.8, respectively, for flows to the Dollar, the Carry, and the Euro-Yen. The effective F-statistics for flows to the Carry and the Euro-Yen are below the rule-of-the-thumb threshold of 10. To better understand the implications of using potentially weak instruments on the IV inference, we compute the Anderson-Rubin confidence interval, which has the correct coverage regardless of the strength of the instrument (Andrews, Stock, and Sun (2019)). For both the Carry and the Euro-Yen, the Anderson-Rubin confidence interval is bounded away from zero, but is very wide in the other direction. In other words, we are reasonably confident that the instrumented intermediary elasticity is not zero; however, we are much less certain that the true value is not larger. A larger estimate would mean even greater price response for a given unit of risk, implying an even more limited risk-bearing capacity.

in week $t-1$ with factor flow in week t. The Fed often conducts small-value operations. We exclude them but the results are invariant to their inclusion.

5.3 Cross-Currency Elasticity

Based on the IV estimated intermediary elasticity λ_k, we apply Proposition 2 to compute the cross-currency elasticity and report the results in Table 6. 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. The rows represent price impacts, and the columns correspond to demand shocks. For instance, the entry of 7.9 in the first row and second column implies that a \$1 billion trading demand shock to the CAD increases the return of AUD by 7.9 bps, holding the trading demand shocks in all other currencies equal. As noted after Proposition 2, the model-implied cross-elasticity matrix is symmetric, meaning that the impact of a \$1 billion trading demand shock to CAD on AUD is the same as the impact of a \$1 billion trading demand shock to AUD on CAD.

Our panel of currency-level cross-elasticity is achieved by overcoming two key estimation challenges. First, trading demand shocks likely correlate across currencies. Finding cross-elasticity via regressions directly at the currency level would require instrumenting the trading demand shocks in every currency and will likely have low power due to multicollinearity. Second, currencies can have complex substitution patterns due to complementarity. A structured IO model such as nested logit generates cross-elasticity by imposing potentially counterfactual substitution restrictions. In contrast, our approach leverages the law of one price to reduce the cross-elasticity table to only three factor-level intermediary elasticities, λ_k, which we carefully estimate using instrumental variables. The subsequent mapping of λ_k to the cross-elasticity between a panel of currencies is a standard asset-pricing procedure that requires only returns.

Table 6 reveals several interesting patterns of cross-currency elasticity. First, all entries are positive. This is because all currencies load on the Dollar factor in the same direction,

Table 6: **Cross-Currency Elasticity**

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

Notes: This table uses Proposition 2, the estimated factor-level elasticity λ_k from Table 4, and the beta loadings of currencies to factors (signs illustrated in Figure 3) to compute cross-currency elasticity. Each entry represents the price movement in bps of a row-currency, as induced by a $1 billion trading demand shock into a column-currency. As noted after Proposition 2, the model-implied cross-elasticity matrix is symmetric, meaning that the impact of a $1 billion trading demand shock to AUD on CAD is the same as the impact of a $1 billion trading demand shock to CAD on AUD, so we report only the upper half.

which is the most important traded risk factor in the cross-section. Second, the cross-elasticity between currencies on the long leg of the Carry trade (e.g., AUD, CAD, GBP, MXN) and those on the short leg (e.g., CHF, EUR, JPY) is generally smaller. This modest cross-elasticity owes to opposing beta loadings with respect to the Carry factor, so that the currencies from these two groups hedge each other in risk exposures to the Carry factor. In IO, such phenomena are typically referred to as complementarity. Third, we note that although EUR and JPY are both low interest-rate currencies, the cross-elasticity between them is rather small. This is because the two currencies are on the opposite side of the Euro-Yen factor.

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

6 Intermediary Elasticity Across Asset Classes

In this section, we use the traded FX risk factors to inform cross-elasticity between asset classes. When intermediaries are able to hedge FX trading-induced non-diversifiable risks cross-market, the traded FX factors become common factors across markets. Accordingly, trading demand shocks in any one market could impact the prices in all markets by affecting the traded FX factors. We show that six non-FX assets load on the traded FX factors, and use the intermediary elasticity of the trade FX factors to compute between-asset cross-elasticity.

6.1 Traded FX Factors in Other Assets

We study six non-FX asset classes: credit default swap (CDS), commodities (Comm), corporate bonds (CorpBond), equities (Equity), equity options (Opt), and US Treasury bonds (UST).[26] We regress each asset class' monthly average excess return between 2000-02 and 2023-12 on returns from the Dollar, the Carry, and the Euro-Yen. We use the R^2 from these regressions to measure the amount of asset return variations explained by the three traded FX factors and illustrate the results in Figure 4.[27] Figure 4 also illustrates the sign of asset class m's return loading on each of the three traded FX factors ($\beta_{m,k}$ in Proposition 2).

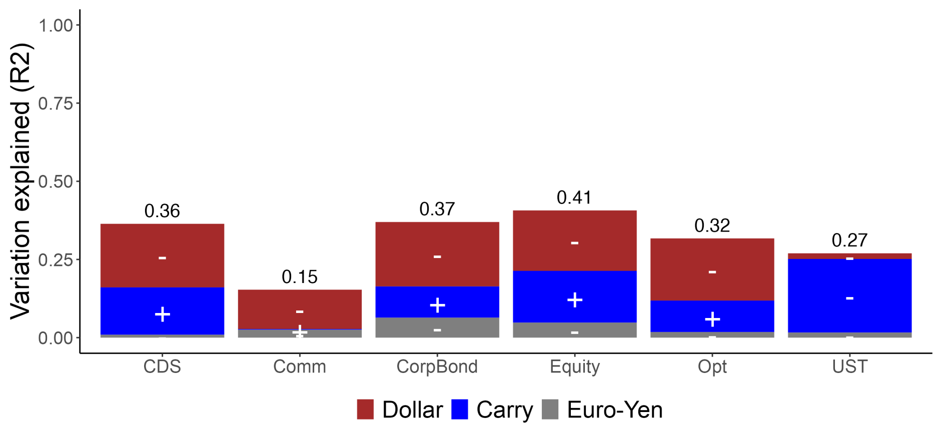
The three traded FX factors jointly explain between 15% (commodities) and 41% (equities) of the returns in the six non-FX asset classes we examine. In other words, markets are neither fully integrated, where only non-diversifiable risks that are systematic across all markets are priced by intermediaries (extending Sharpe (1964) to the representative intermediary in He and Krishnamurthy (2013)), nor completely segmented such that risks priced in each market are idiosyncratic to that market (possibly due to reasons in Siriwardane, Sundaram, and Wallen (2022)). We note that our analysis provides a lower bound on the degree of integration between markets, as there could be non-traded common risk factors priced across markets.[28]

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

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

[28]We also explore the explanatory power of traded FX factors for other assets' returns outside of crisis periods (e.g., GFC, Covid). As Appendix Figure A3 shows, the results are largely similar.

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



Notes: This figure decomposes the returns of individual assets into the Dollar, the Carry, and the Euro-Yen factors. The decomposition is achieved by regressing asset class monthly average excess return between 2000-02 and 2023-12 on returns from the three traded FX factors. The returns from CDS are available starting in 2007-04. The returns from Opt end in 2022-12. The figure 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.

Figure 4 shows that each asset market has its unique loading on the three traded FX factors, both in terms of strength and in terms of direction. To start, while the Dollar factor is statistically significantly present in the return of all six asset classes, it is least important in explaining the return of US Treasury bonds.[29] Moreover, while all other asset classes load positively on the Carry factor, the US Treasury bonds load negatively on it. This contrast suggests that large shocks to the Carry factor could be a reason for divergent price movements in US Treasury bonds versus other assets. Finally, the Euro-Yen factor is less prominent in non-FX asset classes but it does explain a non-negligible amount of return in corporate bonds and equities.

[29]Given that foreign investors hold nearly a quarter of Treasury bonds, and that their demand potentially affects both Treasury returns and exchange rate, it may be surprising that Treasury returns load so little on the Dollar factor. One possible reason for this attenuated connection is that foreign investors hedge a substantial amount of the USD FX risks associated with their security holdings, especially bonds (Du and Huber (2024)).

Table 7: **Asset Elasticity to Traded FX Factors**

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

Notes: This table uses Proposition 2, the estimated factor-level elasticity λ_k from Table 4, and the beta loadings of assets to factors (signs illustrated in Figure 4) to compute cross-elasticity between traded FX factors and six non-FX asset classes. Each entry represents the price movement in bps of a row-asset, as induced by a \$1 billion trading demand shock into a column-asset. As noted after Proposition 2, the model-implied cross-elasticity matrix is symmetric, so the table only presents traded FX factors in rows and the six asset classes in columns.

6.2 Intermediary Elasticity and Cross-Asset Elasticity

The presence of traded FX factors in other asset classes implies that, because of intermediaries' limited risk-bearing capacity, trading in FX could also affect risk premia in these markets. In Table 7, we report the price impact (bps) in non-FX markets due to a \$1 billion trading demand shock to each of the three traded FX factors. The magnitude of the price impact depends on two forces: the loading of an asset class m on traded FX factor k, and the intermediary elasticity of factor k. This is why although most asset classes load heavily on the Dollar factor, the price impact from a \$1 billion trading demand shock to the Dollar factor is rather modest. In contrast, the Carry factor and the Euro-Yen factor elicit much stronger price responses in other markets. We must bear in mind, however, that on average, shocks to the Carry and the Euro-Yen factors are much smaller in magnitude (Table 5, column Flow Volatility $\sigma(q_{k,t})$).

We can moreover consider cross-market elasticity as channeled through the traded FX factors. Trading demand shocks in any one market would alter the intermediary's exposure to the traded FX factors. As the intermediary hedges, or offloads, the altered risk exposure,

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

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

Notes: This table uses Proposition 2, the estimated factor-level elasticity λ_k from Table 4, and the beta loadings of assets to factors (signs illustrated in Figure 4) to compute cross-asset elasticity. Each entry represents the price movement in bps of a row-asset, as induced by a $1 billion trading demand shock into a column-asset. As noted after Proposition 2, the model-implied cross-elasticity matrix is symmetric, meaning that the impact of a $1 billion trading demand shock to Comm on CDS is the same as the impact of a $1 billion trading demand shock to CDS on Comm, so we report only the upper half.

prices of the traded FX factors change, which in turn affect the price of all other asset classes. Following Proposition 2, we combine the intermediary elasticity for traded FX factors with asset classes' return loadings on these factors to arrive at the own- and cross-elasticity between six asset classes (Table 8). Similar to Table 6, each number in Table 8 represents a row-asset's price movement in bps that is induced by a $1 billion trading demand shock into a column asset, as channeled through both assets' *exposure to the three traded FX factors*.

Consider a $1 billion trading demand shock in corporate bonds. This influx exposes the intermediary to more risk associated with the three traded FX factors. As these risks are non-diversifiable, the intermediary demands compensation, increasing the price on the three factors, which increases the price on corporate bonds by 4.8 bps. Moreover, because CDS returns depend on the same set of risk factors, the price of CDS also increases, by 3.2 bps. The same forces lead to price impact in the US Treasury bonds as well. However, because corporate bonds and US Treasury bonds load on the Carry factor with opposite signs, a trading demand shock that increases intermediaries' exposure to Carry actually lowers the price of US Treasury bonds. The net impact on Treasury price is a decrease of 0.2 bps.

Cross-elasticity between asset classes arises because intermediaries are simultaneously active across many markets and these intermediaries have limited risk-bearing capacity for commonly traded risk factors. The degree of cross-elasticity thus depends on loadings of traded common risk factors across asset classes. Our analysis provides the first estimates of cross-elasticity across asset classes. Yet we must underscore that our estimates capture only the intermediary elasticity due to exposure to traded FX factors. That is, our estimate should not be interpreted as the total price response to $1 of trading into an asset market, as these assets can load on other risk factors that we do not capture. Nevertheless, our approach advances the understanding of how asset markets are linked, addressing an important question that has been elusive due to the limited availability of trading data and reliable instruments across markets.

7 Conclusion

In conclusion, this paper studies the limited risk-bearing capacity of intermediaries and its implication for asset prices. We measure intermediaries' risk-bearing capacity with a new measure, "intermediary elasticity", defined as the price response to a marginal unit of risk induced by trading demand shocks. We apply our framework to the FX market and find that just three traded risk factors can jointly account for 90% of the non-diversifiable risks borne by intermediaries when accommodating FX trading flows. These three traded FX factors resemble the Dollar, the Carry, and the Euro-Yen, and reveal intermediaries' otherwise unobserved risk exposure. Through instrumental variable analysis, we show that intermediaries raise prices by 5 to 30 bps in response to \$1 billion net trading demand shock to these factors. In addition to pricing individual currencies, the three traded FX factors also price CDS, commodities, corporate bonds, equities, options, and US Treasury bonds. This allows us to use our estimated FX-factor elasticity to quantify the cross-elasticity of a panel of currencies and across 7 major asset classes.

A distinguishing feature of our paper is the use of factor-level intermediary elasticity to inform cross-elasticity at both the currency and asset-class levels. At the heart of this cross-asset and cross-market demand transmission are three elements: assets' exposure to the traded risk factors, the amount of non-diversifiable factor risks assumed by intermediaries when accommodating trading demand shocks, and the price intermediaries charge for absorbing these risks. Combining these three elements generates novel transmission patterns, where trading demand shocks in one market could affect prices in other markets by differential magnitudes and even directions. As intermediaries function at the juncture of financial markets and real sectors, how intermediaries transmit trading demand shocks to asset prices across different markets is essential to understanding intermediaries' role in the broader economy.

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A Proofs

This appendix provides proofs omitted in the main text.

A.1 Solution for Traded Risk Factors

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

We conduct Cholesky decomposition of $\text{var}(\mathbf{R})$ as $\mathbf{U}^\top\mathbf{U}$. Then, we define $\mathbf{g}_k = \mathbf{U}\mathbf{b}_k$ for each factor k. Equation (2) implies that the factor-level demand shock is

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

Moreover, the sequential optimization problem (4) becomes

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

This becomes a standard PCA problem that is solved by the eigenvalue decomposition of the matrix $\text{var}(\mathbf{U}\mathbf{f})$ (Jolliffe, 1986). The eigenvectors are $\mathbf{g}_k$ and the corresponding eigenvalues are proportional to the fraction of explained variance. Once we obtain $\mathbf{g}_k$, the portfolio weights are obtained by $\mathbf{b}_k = \mathbf{U}^{-1}\mathbf{g}_k$. Moreover, because q_k are the outcome of the PCA problem (A2), different q_k are uncorrelated with each other by construction.

A.2 Invariance of Factors under Alternative Numeraire Currency

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

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

$$\tilde{\mathbf{f}} = (\tilde{f}_1, \tilde{f}_2, \ldots, \tilde{f}_{N-1}, \tilde{f}_N)^\top = \left(f_1, f_2, \ldots, f_{N-1}, -\sum_{n=1}^{N} f_n\right)^\top = \mathbf{C}\mathbf{f}, \tag{A3}$$

where we define the matrix

$$\mathbf{C} := \begin{pmatrix} 1 & 0 & \ldots & 0 & 0 \\ 0 & 1 & \ldots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \ldots & 1 & 0 \\ -1 & -1 & \ldots & -1 & -1 \end{pmatrix}. \tag{A4}$$

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

$$\tilde{\mathbf{R}} = (\tilde{R}_1, \tilde{R}_2, \dots, \tilde{R}_{N-1}, \tilde{R}_N)^\top = (R_1 - R_N, R_2 - R_N, \dots, R_{N-1} - R_N, -R_N)^\top = \mathbf{C}^\top \mathbf{R}. \tag{A5}$$

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

$$\tilde{\mathbf{U}} \mathrm{var}(\tilde{\mathbf{f}}) \tilde{\mathbf{U}}^\top = \mathbf{U}\mathbf{C}\mathbf{C}\mathrm{var}(\mathbf{f})\mathbf{C}^\top \mathbf{C}^\top \mathbf{U}^\top = \mathbf{U}\mathrm{var}(\mathbf{f})\mathbf{U}^\top, \tag{A6}$$

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

A.3 Proof of Proposition 1

Simplifying equation (5), we have

$$\begin{aligned} &\mathbb{E}\left[-\exp\left(-\sum_{k=1}^{K} \gamma_k ((S_k - y_k)\mathbf{b}_k^\top \mathbf{R} + R_{F,N+1} P_k(q_k) y_k / P_k(0)) \right) \right] \\ &= -\exp\left[-\sum_{k=1}^{K} \left(\gamma_k (S_k - y_k)\mathbb{E}[\mathbf{b}_k^\top \mathbf{R}] + \gamma_k R_{F,N+1} P_k(q_k) y_k / P_k(0) - \gamma_k^2 (S_k - y_k)^2 \mathrm{var}(\mathbf{b}_k^\top \mathbf{R})/2 \right) \right], \end{aligned} \tag{A7}$$

where the last equality uses the fact that $\text{cov}(\mathbf{b}_k^\top \mathbf{R}, \mathbf{b}_j^\top \mathbf{R}) = 0$ for $k \neq j$. Taking the first-order condition against y_k, we obtain

$$0 = \gamma_k \mathbb{E}[\mathbf{b}_k^\top \mathbf{R}] - \gamma_k R_{F,N+1} P_k(q_k)/P_k(0) - \gamma_k^2 (S_k - y_k)\text{var}(\mathbf{b}_k^\top \mathbf{R}). \tag{A8}$$

Because the optimal $y_k = q_k$, we obtain

$$P_k(q_k)/P_k(0) = \frac{\gamma_k (q_k - S_k)\text{var}(\mathbf{b}_k^\top \mathbf{R}) + \mathbb{E}[\mathbf{b}_k^\top \mathbf{R}]}{R_{F,N+1}}, \tag{A9}$$

Specifically, when $q_k = 0$, we have

$$P_k(0)/P_k(0) = \frac{-\gamma_k S_k \text{var}(\mathbf{b}_k^\top \mathbf{R}) + \mathbb{E}[\mathbf{b}_k^\top \mathbf{R}]}{R_{F,N+1}}. \tag{A10}$$

Taking the difference, we obtain equation (6).

A.4 Proof of Proposition 2

Because factors have uncorrelated returns by equation (4), we can project the return of any currency n onto the factors and obtain

$$\mathbf{R}(n) = \sum_{k=1}^{K} \beta_{n,k} \mathbf{b}_k^\top \mathbf{R} + e_n, \tag{A11}$$

where e_n is the idiosyncratic return of currency n that is uncorrelated with any factor $\mathbf{b}_k^\top \mathbf{R}$. Hence, by the law of one price and equation (6), the price impact of currency n is

$$\Delta p_n = \sum_{k=1}^{K} \beta_{n,k} \Delta p_k = \sum_{k=1}^{K} \lambda_k q_k \text{var}(\mathbf{b}_k^\top \mathbf{R}) \beta_{n,k}. \tag{A12}$$

Therefore, we have

$$\frac{\partial \Delta p_n}{\partial q_k} = \frac{\partial \Delta p_k}{\partial q_k} \times \frac{\partial \Delta p_n}{\partial \Delta p_k} = \lambda_k \mathrm{var}(\mathbf{b}_k^\top \mathbf{R}) \times \beta_{n,k}. \tag{A13}$$

Next, equation (2) implies that $\partial q_k / \partial f_m = \beta_{m,k}$. Hence, we have

$$\frac{\partial \Delta p_n}{\partial f_m} = \sum_{k=1}^{K} \frac{\partial q_k}{\partial f_m} \times \frac{\partial \Delta p_n}{\partial q_k} = \sum_{k=1}^{K} \beta_{m,k} \times \lambda_k \mathrm{var}(\mathbf{b}_k^\top \mathbf{R}) \times \beta_{n,k}, \tag{A14}$$

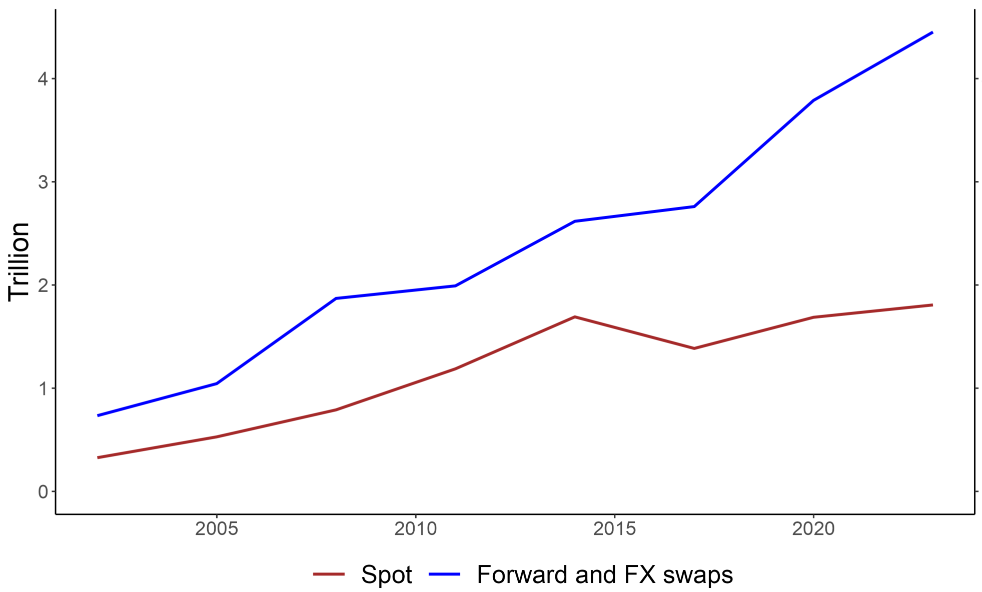
which is equation (9).

B Inclusion of Non-spot FX Derivatives Trading Flows

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

Because we are interested in measuring all the FX risks that intermediaries have to bear by accommodating customer trading flows, we consider trading flows in both the spot and

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 derivatives market.[30] 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.

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

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.

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 FX risk factors. At the same time, if there are strong comovements in trading flows to the traded FX factors, then relying on data from only one market risks introducing measurement error in the elasticity estimation.

In Appendix Table A2, we compare the traded FX factors recovered separately from the spot market and the non-spot derivatives market. The top row shows the correlation between *returns* of factors estimated using only one of the individual markets. For the first factor, the return correlation is close to 1, and this correlation is 77% for the second factor and 73% for the third factor. Such pronounced relationships underscore the robustness of the underlying factors and suggest that the same risk factors drive trades 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

Table A2: **Correlation between Returns to Factors Estimated in Different Samples**

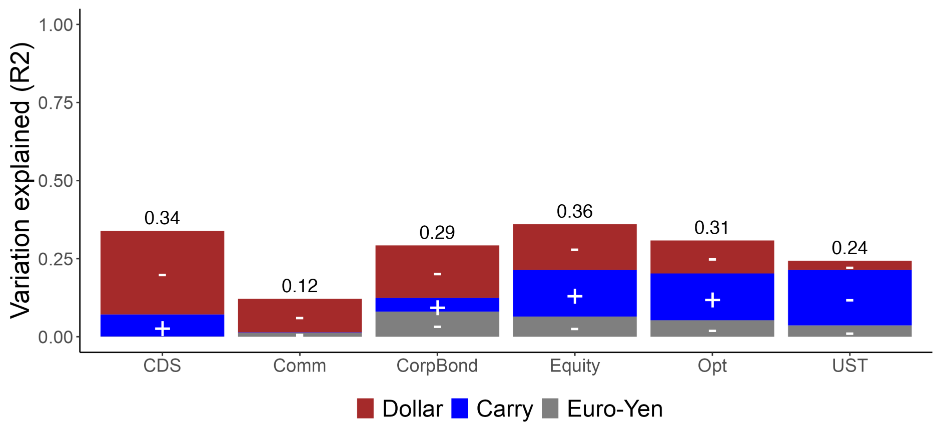
	Factor 1	Factor 2	Factor 3
Return	0.99	0.77	0.73
Flow	-0.51	-0.13	-0.35

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

trades in both the spot and derivatives markets. On the other hand, using only data from the spot market is likely insufficient for estimating elasticity to the risk factors because the spot market data alone may not provide an appropriate measure of the flow changes. Estimating elasticity requires instrumenting for the flow that induced 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 less price change per unit of additional risk.

C Additional Figures and Tables

Figure A3: **Cross-Asset Return Variation Outside of Crises**



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

Table A3: **Top 3 PCs from FX Trading Flows**

Currency	PC 1	PC 2	PC 3
AUD	-0.03	0.03	0.12
CAD	-0.04	1.00	-0.06
CHF	-0.01	-0.02	-0.06
DKK	-0.00	-0.00	0.01
EUR	-1.00	-0.03	0.03
GBP	-0.02	-0.01	0.26
HKD	-0.00	-0.02	-0.00
ILS	-0.00	-0.01	-0.00
JPY	-0.04	-0.06	-0.95
KRW	-0.00	0.01	-0.00
MXN	-0.01	0.01	-0.00
NOK	0.00	0.01	0.01
NZD	-0.01	0.01	0.01
SEK	0.01	0.00	0.00
SGD	-0.01	-0.01	0.01
ZAR	-0.01	0.00	0.01
USD	1.17	-0.92	0.62
Flow Var explained	46%	21%	12%

Notes: This table presents the portfolio weights of the top 3 traded FX factors, constructed using a standard PCA of FX trading flows. We use weekly flow data for 16 non-USD currencies from September 2012 to December 2023. The portfolio weight of USD is computed as the negative sum of the weights of all other currencies.

Table A4: **Time-varying λ for the Dollar factor**

	Baseline (1)	CIP deviation (2)	Swap line usage (3)
Factor flow	0.107^{***}	0.160^{*}	0.106^{***}
	(0.037)	(0.092)	(0.029)
Flow × CIP dev		0.063	
		(0.130)	
CIP deviation		0.172	
		(0.178)	
Flow × swap line			-0.056^{*}
			(0.034)
Swap line usage			-0.449^{**}
			(0.217)
Observations	386	386	385

Notes: This table reports the time-varying λ_k estimation results for the Dollar factor, as obtained using instrumental variables. "CIP deviation" is measured by the weekly average AUD-JPY 3-month IBOR cross-currency basis, demeaned and standardized. "Swap line usage" is the week $t-1$ average amount outstanding at the Federal Reserve's central bank liquidity swap line, demeaned and standardized. Newey-West standard errors are reported in parentheses, where the bandwidth is chosen by the Newey and West 1994 selection procedure. *$p < .1$; **$p < .05$; ***$p < .01$.