Price Discovery in the U.S. Dollar Index Market

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ABSTRACT

The U.S. dollar index (USDX) tracks the dollar value against a basket of six major currencies (i.e., EUR, JPY, GBP, CAD, SEK, and CHF). This study aims to analyze the dynamics of price discovery between the USDX and the synthetic USDX futures estimated from its underlying foreign exchange (FX) futures in the Chicago Mercantile Exchange (CME Group). We examine the dynamics of price discovery between the USDX and its derivative products, i.e., spots, futures, ETFs, and synthetic USDX futures. The empirical results show that the synthetic USDX Futures significantly leads the USDX spot and futures, reflecting the importance of the synthetic USDX Futures in the U.S. dollar price-discovery process. We also show that USDX futures are the dominant net transmitter of return spillovers to all other FX futures. Our results suggest that the spillover effects from index products strengthen the price-discovery process. The empirical results of this study provide regulators with a vital reference about the change in the value of the U.S. dollar arising from USDX products.

Keywords: U.S. dollar index, price discovery, foreign exchange, futures, ETFs, spillovers

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1. INTRODUCTION

The U.S. dollar is the principal reference for international trade and finance, and it has been popularly employed as the invoicing and settlement currency for international commodity markets, especially for its use in the international oil trade. The U.S. dollar exchange rate has played a crucial role in soaring commodity prices, influencing the economic actions in import-export trades for countries. Furthermore, Martin et al. (2017) summarize three important international roles of the U.S. dollar, including reserve currency, invoicing currency, and funding currency. The U.S. Federal Reserve developed a set of indexes of the foreign exchange value of the U.S. dollar.

The U.S. dollar index (USDX) provides the world with a comprehensive indicator of the value of the U.S. dollar, and it tracks the value of the dollar against a basket using a trade-weighted geometric average of six major world currencies, including the Euro, Japanese Yen, British Pound, Canadian Dollar, Swedish Krona, and Swiss France. Futures contracts based on the USDX are traded on the electronic trading platform of the Intercontinental Exchange (ICE), and its component foreign exchange (FX) futures are traded on the ICE and the Chicago Mercantile Exchange (CME Group). The USDX futures enable market participants to monitor moves in the value of the U.S. dollar relative to a basket of world currencies and hedge their portfolios against the risk of a move in the dollar.[1]

This study analyzes the dynamics of price discovery between the spot index, futures, exchange-traded funds (ETFs), and synthetic USDX futures. The lead-lag

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[1] In addition to the USDX futures contracts, the USDX options contracts also provide market participants with effective ways to design trading strategies and manage FX risk.

relationship and price discovery function in information-linked FX markets, such as futures, options, and spot markets, have been analyzed in numerous studies[2]; however, to date, there is no study within the literature considering more than three assets, including USDX products. In order to fill the gap, this study examines the price-discovery process of synthetic USDX futures and these USDX products, showing that synthetic USDX futures play an essential role in the price-discovery process.

As a result of the globalization process, trading volume and turnover of the global foreign exchange market have increased tremendously over the last two decades. The FX market is also the largest and deepest financial market.[3] Price discovery and volatility spillovers of the FX markets are essential for international trade, asset allocation, and risk management for multinational corporations and global investors. The spillover relationship between the USDX futures and its FX futures may be derived from speculating, hedging, or arbitrage trading activities. One perception is that index derivatives trading increases speculative trading activities that, in turn, create price pressures in the underlying assets and are responsible for higher volatility of their underlying assets. Therefore, index derivatives induce speculating and arbitrage trading activities in the underlying assets, further leading to an increase in price discovery and volatility of their underlying assets. Liu, Zhang, and Zhao (2014) show that speculative activities can be contagious across derivatives and their underlying asset markets, showing the existence of speculation spillover. This phenomenon of

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[2] For example, please see Covrig and Melvin (2002), Andersen et al. (2003), Tse et al. (2006), Rosenberg and Traub (2009), Cabrera et al. (2009), Chen and Gau (2010), Phylaktis and Chen (2010), Piccotti and Schreiber (2015), Chen et al. (2016), Gau and Wu (2017), Padungsaksawasdi and Parhizgari (2017), Piccotti and Schreiber (2020), and Li et al. (2021).

[3] As noted in the survey of the Bank of International Settlements (BIS) and the Chicago Mercantile Exchange (CME) Group, all FX transactions globally average 5.3 trillion dollars per day. OTC derivatives trade approximately $2.1 trillion daily, the U.S. bond market trades roughly $800 billion daily, and the most quoted market, U.S. stocks, trades about $200 billion daily. Due to the highly transparent and safe nature of exchange-traded products, the exchange-traded and cleared FX products are growing rapidly worldwide.

speculation spillover may be a virtual channel in the price discovery and spillover relationship between the USDX futures and its FX futures.

Furthermore, the role of ETF arbitrage in increased volatility of the underlying assets has been shown in the study of Ben-David et al. (2018). As Ben-David et al. (2018) mentioned, ETFs increase the non-fundamental volatility of their underlying securities because of arbitrage activity between ETFs and their underlying securities. Therefore, arbitrage activity between ETFs and their underlying securities is determined by the premium or discount of ETFs.[4] Accordingly, ETFs will increase the good volatility of their underlying securities in the case of an ETF premium, and ETFs will lead to an increase in the bad volatility of their underlying securities in the case of an ETF discount. When additional volatility of the underlying securities caused by ETFs can be separated into good and bad volatilities, two types of volatility should be related to ETFs' premium/discount situation. Following the concept of Ben-David et al. (2018), we conjecture that the magnitude of asymmetric price discovery among the USDX futures and its FX futures may be related to the basis of these FX derivatives. This study is motivated by relevant questions concerning piece discovery in the FX futures market, where the behavior of the USDX futures represents a concept of the FX portfolio.

It is an essential issue regarding the change in the value of the U.S. dollar. In this study, the purpose aims to investigate the price discovery among the spot index (USDX), futures (DX), ETFs (UUP), and synthetic USDX futures. Significantly, this study estimates a synthetic USDX spot and synthetic USDX futures, discussing which products will dominate the price-discovery process. Ben-David et al. (2018) show that the arbitrage

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[4] If the price of the ETF is above the NAV (i.e., in the case of ETF shares creation), authorized participants (APs) are incentivized to buy the underlying securities and create ETF shares in exchange. If the price of the ETF is below the NAV (i.e., in the case of ETF shares redemption), APs buy ETF units in the market and redeem them for the basket of underlying securities from the ETF sponsor.

mechanism between ETFs and their underlying securities can lead to higher volatility for the underlying securities. According to prior studies, ETFs can exacerbate herding (Bhattacharya & O'Hara, 2018), and the APs of ETFs create information asymmetry in ETF markets (Xu et al., 2018). This study conjectures that synthetic USDX futures significantly contribute to the price-discovery process. Overall, these analyses help explore that price discovery could propagate to the change in the information content of the USDX and its component FX products.

The remainder of this study is organized as follows. A review of the related literature is presented in the next section, followed by a discussion of the data and research methodology adopted for this study. Section 4 presents the empirical results of the price-discovery analysis. Finally, conclusions drawn from this study are presented in Section 5.

2. LITERATURE REVIEW

Price discovery analysis in the FX market has been analyzed in many studies (Covrig & Melvin, 2002; Andersen, Bollerslev, Diebold, & Vega, 2003; Tse, Xiang, & Fung, 2006; Rosenberg & Traub, 2009; Cabrera, Wang, & Yang, 2009; Chen & Gau, 2010; Phylaktis & Chen 2010; Piccotti & Schreiber, 2015; Chen, Gau, & Liao, 2016; Gau & Wu, 2017; Padungsaksawasdi & Parhizgari, 2017; Piccotti & Schreiber, 2020; Li, Chen, & Nguyen, 2021) For example, Covrig and Melvin (2002) identify a period with a high concentration of informed yen/dollar traders active in Tokyo. Andersen, Bollerslev, Diebold, and Vega (2003) characterize the conditional means of U.S. dollar spot exchange rates, indicating that announcement surprises produce conditional mean jumps; hence, high-frequency exchange-rate dynamics are linked to fundamentals.

In addition, Tse, Xiang, and Fung (2006) examine the relative contributions to price discovery of the floor and electronically traded euro FX and Japanese yen futures markets and the corresponding retail online foreign exchange spot markets, showing that electronic trading platforms facilitate price discovery more efficiently than floor trading. Rosenberg and Traub (2009) investigate shifts in foreign exchange price discovery between the spot and futures markets as these markets evolve, suggesting that the spot market has the dominant information share because of increased spot market transparency. Cabrera, Wang, and Yang (2009) investigate the contribution to the price discovery of Euro and Japanese Yen exchange rates in three foreign exchange markets based on electronic trading systems (i.e., the CME GLOBEX regular futures, E-mini futures, and the EBS interdealer spot market), showing that E-mini futures do not contribute more to the price discovery than the electronically traded regular futures.

Furthermore, Chen and Gau (2010) examine competition in price discovery between spot and futures rates for the EUR-USD and JPY-USD markets around scheduled macroeconomic announcements, showing that the spot rates provide more price discovery than the CME futures rates overall. However, the contribution of the futures rates to price discovery increases in the time surrounding macroeconomic announcement releases. Chen, Gau, and Liao (2016) investigate the relationship between trading activities and the price discovery efficacy of the futures markets for EUR-USD and JPY-USD, showing the association between price discovery and trading activities by trade types. Gau and Wu (2017) examine changes in information shares before and after the announcement, showing that the dominance of the overlapping trading hours of London and New York in the price discovery of the EUR/USD and

USD/JPY markets only applies on days with U.S. announcements.

Moreover, Phylaktis and Chen (2010) examine the information share of the banks in the Reuters EFX system using indicative GBP-$US data, suggesting the possibility of private information over public news in the foreign exchange market. Padungsaksawasdi and Parhizgari (2017) investigate the behaviors of six major currency ETFs and their respective spot and futures markets prior to and during the financial crisis of 2008, suggesting that the spot and the futures currency markets possess more dominant informational positions relative to their corresponding ETF markets under more stable conditions. Li, Chen, and Nguyen (2021) examine the relative contributions to the price discovery process of EUR/USD futures traded in the CME and the ICE, showing that the CME dominates the price discovery in most periods because of the CME with lower transaction costs, and higher volatility as compared to the ICE.

Finally, Piccotti and Schreiber (2015) examine how transparency and trading costs affect price discovery in currency options that are simultaneously traded in parallel options markets, showing that the OTC options market robustly has a higher information share than the TASE options market across several information share measures, options types, and trade types. Piccotti and Schreiber (2020) examine price discovery across the inter-dealer and dealer–customer market tiers in the currencies market, indicating the market where customers’ trades are the most informative.

Overall, these studies are helping to explain the price-discovery relationship among the FX spot, futures, and ETF over distinctively different periods, especially for the change in the price-discovery process before, during, and after the implementation of quantitative easing (QE).

3. DATA AND RESEARCH METHODOLOGY

3.1 Data Description

The sample is comprised of the U.S. dollar index (USDX), ETFs (UUP), futures (DX), and its underlying FX futures and ETFs. The USDX is a weighted geometric average of the foreign exchange rates of six major currencies, including the euro (EUR), Japanese yen (JPY), British pound (GBP), Canadian dollar (CAD), Swedish krona (SEK), and Swiss franc (CHF). The sample comprises the USDX futures and its six underlying FX futures, including EUR, JPY, GBP, CAD, SEK, and CHF. All these FX futures contracts are quoted against the U.S. dollar (i.e., $USD/one unit of currency).

<Table 1 Inserted about here>

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The USDX futures contract is a leading benchmark for the international value of the U.S. dollar and the most widely recognized traded currency index. As shown in Tables 1 and 2, the USDX futures are traded on the electronic trading platform of the ICE from 8:00 pm through 5:00 pm EST the next day, while the underlying FX futures are traded on the electronic trading platform of the CME Group from 5:00 pm through 4:00 pm CST the next day. In order to avoid the potential non-synchronicity problem, on each trading day, this study retains only those trades of the USDX futures that occurred during regular trading hours between 8:00 pm and 5:00 pm EST the next day, while the corresponding data on those trades of these underlying FX futures cover the trading hours from 7:00 pm to 4:00 pm CST the next day. Furthermore, Li et al. (2021)

examine the relative contributions to the price discovery process of EUR/USD futures traded in the CME and the ICE, showing that the CME dominates the price discovery in most periods because of the CME with lower transaction costs, and higher volatility as compared to the ICE. In addition to the FX futures, the data set includes the U.S. dollar index ETFs and six FX ETFs. The U.S. dollar index ETFs and six FX ETFs are summarized in Table 3.

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The data are composed of the USDX and its underlying FX products. The FX spot data is obtained from the Kibot database. The USDX futures and their underlying FX futures are obtained from the TickData database, including the tick-by-tick quote and trade prices, trading volume, and quoted prices. In addition, the tick-by-tick data on FX ETFs are obtained from the Kibot databases.

3.2 The U.S. Dollar Index (USDX)

The USDX measures the value of the U.S. dollar relative to the value of a basket of currencies of most of the U.S.'s most significant trading partners. It tracks the value of the dollar against a basket using a trade-weighted geometric average of six major world currencies, including the Euro (57.6%), Japanese Yen (13.6%), British Pound (11.9%), Canadian Dollar (9.1%), Swedish Krona (4.2%), and Swiss France (3.6%). The U.S. Dollar Index is calculated with this formula as follows:

$$\begin{aligned} USDX = {} & 50.14348112 \times EURUSD^{-0.576} \times USDJPY^{0.136} \times GBPUSD^{-0.119} \\ & \times USDCAD^{0.091} \times USDSEK^{0.042} \times USDCHF^{0.036} \qquad (1) \end{aligned}$$

The U.S. Dollar Index shows the correlation between the US dollar and the currencies of other major countries. The value is positive if the U.S. dollar is the base currency and negative if the U.S. dollar is the quote currency. The above value is compared against the U.S. dollar relative to March 1973, when the world's major trading nations allowed their currencies to float freely against each other.

Furthermore, this study also constructs the futures value of the U.S. dollar index (USDXF) by using Euro FX futures (EU), Japanese Yen futures (JY), British Pound futures (BP), Canadian Dollar futures (CD), Swedish Krona futures (SEK), and Swiss France futures (SF). The synthetic USDX futures is calculated with this formula as follows:

$$\begin{aligned} USDXF = 50.14348112 \times EU^{-0.576} \times JY^{-0.136} \times BP^{-0.119} \times CD^{-0.091} \\ \times SEK^{-0.042} \times SF^{-0.036} \end{aligned} \quad (2)$$

3.3 Measurements of Price Discovery

Within the prior literature on common factor models, two popular approaches have emerged within the investigation of the mechanics of price discovery: the 'permanent-transitory' (PT) model discussed by Gonzalo and Granger (1995), and the 'information shares' (IS) model developed by Hasbrouck (1995). Although both models are based on the 'vector error correction model' (VECM), each model adopts different price discovery definitions.

The PT and IS models have attracted considerable attention within the literature, where the relationships and differences between the two models have been discussed at length. The Gonzalo and Granger (1995) model focuses on the common factor components and the error correction process, whereas the Hasbrouck (1995) model considers the contribution of each market to the innovation variance to the common factor. For an overview of the various price-discovery issues, refer to Baillie et al. (2002), Hasbrouck (2002), de Jong (2002), Lehmann (2002), and Harris, McInish and Wood (2002a, 2002b).

These two models are directly related and provide similar results if the residuals are uncorrelated between markets; however, they typically provide mixed results in cases with substantive correlation. Numerous studies have adopted the two models to examine the price discovery contribution from closely related markets (see Booth et al., 1999; Chu et al., 1999; Hasbrouck, 2003; So & Tse, 2004; Chen & Chung, 2012). The analysis is based on the information share approach, which requires the estimation of the VECM. According to Engle and Granger (1987), the representation of the VECM can be shown as follows:

$$\Delta Y_t = \mu + \Pi Y_{t-1} + \sum_{i=1}^{k} A_i \Delta Y_{t-i} + \varepsilon_t \tag{3}$$

where $\Pi Y_{t-1} = \alpha\beta^T Y_{t-1} = \alpha z_{t-1}$; Y_t is an $n \times 1$ vector of cointegrated prices; A_i represent $n \times n$ matrices of autoregressive coefficients; k is the number of lags; $z_{t-1} = \beta^T Y_{t-1}$ is an $(n-1) \times 1$ vector of error correction terms; α is an $n \times (n-1)$ matrix of adjustment coefficients; and ε_t is an $n \times 1$ vector of price innovations.

The coefficient alphas of the error correction term measure the price reaction to the deviation from the long-run equilibrium relationship. The project follows Hasbrouck (2003) for the definition of z_t; if there are n securities, then there are $n-1$ linearly independent differences, and thus, z_t can be defined as:

$$z_t = [(Y_{1t} - Y_{2t})\ (Y_{1t} - Y_{3t})\ \cdots\ (Y_{1t} - Y_{nt})]^T \tag{4}$$

3.3.1 Permanent-Transitory (PT) Decomposition Model

Gonzalo and Granger (1995) focus on the error correction process, which involves only permanent (as opposed to transitory) shocks resulting in disequilibrium. The measure is based on the permanent-transitory (PT) decomposition, where the permanent component is assumed to be a linear function of the original series. The PT model measures the contribution to the common factor for each market, where the contribution is defined as a function of the error correction coefficients of the markets. Stock and Watson (1988) demonstrated that the price vector could be decomposed into permanent and transitory components. Accordingly, the common trend of the price series is as follows:

$$Y_t = f_t + G_t \tag{5}$$

where f_t is the common factor, and G_t is the transitory component that has no permanent impact on Y_t Gonzalo and Granger (1995) decompose the common factor f_t into a linear combination of the prices, in which $f_t = \Gamma^T Y_t = (\alpha_\perp^T \beta_\perp)^{-1} \alpha_\perp^T Y_t$, where Γ is the common factor coefficient vector, Γ are normalized so that their sum is equal to 1, and the coefficients of Γ_i can be interpreted as portfolio weights (de Jong, 2002). In this project, we follow the approach proposed by Gonzalo and Ng (2001) for the estimation of $\alpha_\perp$ and $\beta_\perp$.

The common factor framework provides an opportunity to examine the extent to which each market is involved in the price discovery process, with the advantage of the Gonzalo and Granger (1995) model being that the common factor estimates are identified exactly since they are not dependent on the ordering of the variables. However, the common factor weights may be negative for each estimated VECM.

3.3.2 Information Share (IS) Model

Hasbrouck (1995) transforms the VECM into a vector moving average (VMA) model, which is represented as follows:

$$\Delta Y_t = \Psi(L)\varepsilon_t \tag{6}$$

along with its integrated form:

$$Y_t = Y_0 + \Psi(1)\sum_{i=1}^{t}\varepsilon_i + \Psi^*(1)\varepsilon_t \tag{7}$$

where Y_t is the vector of the price series; ε_t is a zero-mean vector of serially uncorrelated innovations with covariance matrix Ω, such that σ_i^2 is the variance in ε_{it}, and ρ_{ij} is the correlation between ε_{it} and ε_{jt}. Furthermore, t is a column vector of ones, Ψ is a row vector, and $\Psi(L)$ and $\Psi^*(L)$ are matrix polynomials in the lag operator L.

Hasbrouck (1995) notes that the common factor of innovation in Equation (19) is the increment, ε_t, with the price change component permanently impounded into the price. He demonstrates that Equation (19) is closely related to Equation (17). In addition, he further decomposes the variance in the innovations in the common factor, $\mathrm{Var}(\psi\varepsilon_t) = \psi\Omega\psi^T$, and defines the information share of a trading center as the proportion of $\mathrm{Var}(\psi\varepsilon_t)$ attributable to the innovations in that market.

Hasbrouck (1995) uses the Cholesky factorization of $\Omega = FF^T$ to eliminate the contemporaneous relationship, where F is a lower triangular matrix. The information shares are then given as:

$$IS_j = \frac{\left([\psi F]_j\right)^2}{\psi\Omega\psi^T}, j = 1, 2, \dots, n \tag{8}$$

where $[\psi F]_j$ is the j^{th} element of the row of matrix ψF.[5] The contribution to price discovery in a particular market is measured as its relative contribution to the innovation variance in the common trend.

Baillie et al. (2002) demonstrate a simpler method of calculating information shares directly from the VECM results without obtaining the VMA representation, with the calculations of information share based on the VECM method. The upper and lower bounds of the information share of a market will, however, become apparent when the variables are given different orderings, with the largest (smallest) information share value occurring when the variable is first (last) in a sequence, assuming that the cross-correlation, ρ, is positive. This relationship also indicates that the higher the correlation, the greater (smaller) the upper (lower) bound. Baillie et al. (2002) propose using the mean of the bounds to resolve such interpretational ambiguity.

3.3.3 Modified Information Share (MIS) Model

The results of the information shares are typically dependent on the ordering of the variables in the Cholesky factorization of the innovation covariance matrix. The first (last) variable in the ordering tends to have a higher (lower) information share, with this discrepancy potentially being substantial if the series' innovations are highly and

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[5] It should be further noted that Baillie et al. (2002) present evidence of the existence of an important relationship between $\psi = (\psi_1, \psi_2, \dots, \psi_n)$ and $\Gamma = (\gamma_1, \gamma_2, \dots, \gamma_n)$, i.e., $\psi_i/\psi_j = \gamma_i/\gamma_j$. This relationship is substituted into Equation (20) to calculate the information share.

contemporaneously correlated.

Lien and Shrestha (2009) propose a modified information shares (MIS) approach that leads to a unique measure of price discovery, as opposed to upper and lower IS bounds. When adopting the MIS model, it is suggested that the factorization matrix (based on the correlation matrix) be used. Lien and Shrestha (2009) further define Φ as representing the innovation correlation matrix and Λ as representing the diagonal matrix, with the diagonal elements being the eigenvalues of the correlation matrix Φ, where the columns of matrix G give the corresponding eigenvectors. In addition, V is a diagonal matrix containing the innovation standard deviations on the diagonal—that is, $V = \mathrm{diag}\left(\sqrt{\Omega_{11}}, \sqrt{\Omega_{22}}, \dots, \sqrt{\Omega_{nn}}\right)$. Lien and Shrestha (2009) subsequently transform $F^* = \left[G\Lambda^{-1/2}G^T V^{-1}\right]^{-1}$ from $\Omega = F^*(F^*)^T$. Under this factor structure, the MIS is given by:

$$IS_j^M = \frac{\left(\psi_j^M\right)^2}{\psi\Omega\psi^T}, j = 1, 2, \dots, n \tag{9}$$

where $\psi^M = \psi(F^*)$ and ψ_j^M is the jth element of ψ^M. Under this new factor structure, Lien and Shrestha (2009) show that the resultant IS are independent of order, which leads to a measure of price discovery that orders are invariant but not unique. Based on their use of the square-root matrix, they indicate that this solves the problem of the lack of uniqueness. In addition, they also show that the MIS measure outperforms both the IS measure and the PT measure.

3.4 The Spillover Model

In this study, the spillover measures among the USDX and its underlying FX futures by adopting methods provided by Diebold and Yilmaz (2009, 2012). Diebold and Yilmaz (2009) develop a volatility spillover measure (spillover index) based on forecast error variance decompositions from the VAR model. The spillover index can be used to measure the spillovers in price efficiency or volatilities across individual assets, asset portfolio, asset markets, etc., both within and across countries, revealing spillover trends, cycle, bursts, etc. However, there are two limitations in the framework of Diebold and Yilmaz (2009). One is the variable ordering problem arising from the use of Cholesky decompositions, and another is a directional problem in spillovers. Diebold and Yilmaz (2012) propose measures of both the total and directional spillovers using the concept provided by Koop et al. (1996) and Pesaran and Shin (1998). Accordingly, Diebold and Yilmaz (2015) provide a concept of connectedness that quantifies the dynamic and directional characterization of spillovers among various assets or across markets. Krause and Lien (2014) use the model of Diebold and Yilmaz (2009, 2012) to generate implied volatility spillovers from the ETFs to their respective component stocks.

Suppose the N-variable vector x_t is return of FX futures, and x_t is represented as follows:

$$RET_t = \left[RET_{DX,t},\ RET_{EC,t},\ RET_{JY,t},\ RET_{BP,t},\ RET_{CD,t}, RET_{SEK,t},\ RET_{SF,t}\right]' \quad (10)$$

where RET is return of the FX futures, respectively. Let N denote the number of futures contracts analyzed in the study, and a stationary N-variable VAR(p) can be specified as follows:

$$x_t = \sum_{i=1}^{p} \Phi_i x_{t-1} + \varepsilon_t \qquad (11)$$

where $\varepsilon \sim (0, \Sigma)$ is a vector of independently and identically distributed disturbances.

The number of lags (p) in the above equations is determined on the basis of the Akaike information criterion (AIC) and Schwarz information criterion (SIC). By transforming the VAR into a vector moving average (VMA) model, it is represented as follows:

$$x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i} \tag{12}$$

where the $N \times N$ coefficient matrices A_i obey the recursion $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \cdots + \Phi_p A_{i-p}$, with A_0 being a $N \times N$ identity matrix and with $A_i = 0$ for $i < 0$. Diebold and Yilmaz (2009, 2012) define own variance shares as the fractions of the H-step-ahead error variances in forecasting x_i that is due to shocks to x_i, for $i = 1, 2, \ldots, N$, and cross variance shares (or spillovers) as the fractions of the H-step-ahead error variances in forecasting x_i that is due to shocks to x_j, for $i, j = 1, 2, \ldots, N$, such that $i \neq j$.

Diebold and Yilmaz (2012) denote the generalized H-step-ahead forecast error variance decompositions by θ_{ij}^{H}, for $H = 1, 2, \ldots$, as follows:

$$\theta_{ij}^{H} = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h \Sigma e_j \right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_h \Sigma A_h' e_i \right)} \tag{13}$$

where the Σ is the variance matrix for error vector ε, σ_{jj} is the standard derivation of the error term for jth equation, and e_i is the select vector, with one as the ith element and zeros otherwise. Since the sum of elements in each row of the variance decomposition table is not equal to 1, Diebold and Yilmaz (2012) normalize each entry of the variance decomposition matrix by the row sum as follows:

$$\tilde{\theta}_{ij}^{H} = \frac{\theta_{ij}^{H}}{\sum_{j=1}^{N} \theta_{ij}^{H}} \tag{14}$$

where $\sum_{j=1}^{N}\tilde{\theta}_{ij}^{H}=1$ and $\sum_{i,j=1}^{N}\tilde{\theta}_{ij}^{H}=N$.

Using the return contributions from the generalized H-step-ahead forecast error variance decompositions, Diebold and Yilmaz (2012) construct the total spillover index as follows:

$$S^{H}=\frac{\sum_{\substack{i,j=1\\ i\neq j}}^{N}\tilde{\theta}_{ij}^{H}}{\sum_{i,j=1}^{N}\tilde{\theta}_{ij}^{H}}\times 100=\frac{\sum_{\substack{i,j=1\\ i\neq j}}^{N}\tilde{\theta}_{ij}^{H}}{N}\times 100 \tag{15}$$

Diebold and Yilmaz (2012) indicate that this total spillover index measures the contribution of spillovers of shocks across the FX futures to the total forecast error variance. In addition, Diebold and Yilmaz (2012) calculate the directional spillovers using the normalized elements of the generalized variance decomposition matrix, showing the directional spillovers received by FX futures i from all other FX futures j as follows:

$$S_{i\leftarrow\blacksquare}^{H}=\frac{\sum_{\substack{j=1\\ j\neq i}}^{N}\tilde{\theta}_{ij}^{H}}{\sum_{i,j=1}^{N}\tilde{\theta}_{ij}^{H}}\times 100=\frac{\sum_{\substack{j=1\\ j\neq i}}^{N}\tilde{\theta}_{ij}^{H}}{N}\times 100 \tag{16}$$

Similarly, Diebold and Yilmaz (2012) measure the directional spillovers transmitted by FX futures i to all other FX futures j as follows:

$$S_{\blacksquare\leftarrow i}^{H}=\frac{\sum_{\substack{j=1\\ j\neq i}}^{N}\tilde{\theta}_{ji}^{H}}{\sum_{i,j=1}^{N}\tilde{\theta}_{ji}^{H}}\times 100=\frac{\sum_{\substack{j=1\\ j\neq i}}^{N}\tilde{\theta}_{ji}^{H}}{N}\times 100 \tag{17}$$

The net return spillovers are the difference between the gross shocks transmitted to and those received from all other FX futures. Therefore, the net spillovers from FX futures i to all other FX futures j can be defined as follows:

$$S_{i}^{H}=S_{\blacksquare\leftarrow i}^{H}-S_{i\leftarrow\blacksquare}^{H} \tag{18}$$

The total connectedness among the USDX futures and its underlying FX futures can be measured by the grand total of the off-diagonal entries in $\tilde{\theta}_{ij}^{H}$.

Furthermore, Diebold and Yilmaz (2012) define the net pairwise spillovers as follows:

$$S_{ij}^{H} = \left[\frac{\tilde{\theta}_{ji}^{H}}{\sum_{i,k=1}^{N}\tilde{\theta}_{ik}^{H}} - \frac{\tilde{\theta}_{ij}^{H}}{\sum_{j,k=1}^{N}\tilde{\theta}_{jk}^{H}}\right] \times 100 = \left[\frac{\tilde{\theta}_{ji}^{H} - \tilde{\theta}_{ij}^{H}}{N}\right] \times 100 \qquad (19)$$

The net pairwise spillover between FX futures i and j is simply the difference between the gross volatility shocks transmitted from FX futures i to FX futures j and those transmitted from j to i. Diebold and Yilmaz (2014) further propose several connectedness measures built from pieces of variance decomposition, providing natural and insightful measures of connectedness. Accordingly, this study estimates measures of both the total and directional spillovers by adopting the framework of Diebold and Yilmaz (2009; 2012; 2014).

4. EMPIRICAL RESULTS

4.1 Summary Statistics

The sample data comprises the FX currencies, futures, and ETFs. Figure 1 presents the daily price pattern for the U.S. dollar index (USDX) and the six FX currencies (i.e., EURUSD, USDJPY, GBPUSD, USDCAD, USDSEK, and USDCHF), showing the significant uptrend pattern in the USDX from 2021 to 2022. In addition, Figure 1 also explores the co-movement relationship among the six currencies. The U.S. dollar index and six FX currencies futures contracts are presented in Figure 2, and The U.S. dollar index and six FX currencies ETFs are presented in Figure 3. The FX futures and ETFs trend patterns are similar to that of FX currencies.

<Figure 1 Inserted about here>

<Figure 2 Inserted about here>

<Figure 3 Inserted about here>

Comprehensive details on the number of trades, trade size, daily return, range volatility, and realized volatility in the U.S. dollar index market are reported in Table 4. Panels A to C of Table 4 show the daily summary statistics of the return, range volatility, and realized volatility of the six FX currencies, futures contracts, and ETFs, respectively. In Panel A of Table 4, the empirical results show that the USDSEK had a higher average volatility during the research period. In Panel B of Table 4, the empirical results explore that the SF future contract has a higher average return during the research period. In Panel C of Table 4, the empirical results show that the FXC ETF had a higher average volatility during the research period. Overall, the U.S. dollar index, futures, and ETFs have higher volatile characteristics during the research period, indicating the impact of quantitative easing (QE) implementation on the financial market.

<Table 4 Inserted about here>

4.2 Liquidity Analyses

The liquidity analysis of the USDX and its underlying FX products is reported in Table 5. The liquidity proxies include the quoted spread, percentage quoted spread, effective spread, and percentage effective spread calculated from the tick bid-ask data.

<Table 5 Inserted about here>

In Panel A of Table 5, the empirical results show that the EURUSD has the lowest percentage spread in the research period, indicating that higher liquidity causes a lower market impact cost within the transaction costs as a whole. In Panel B of Table 5, similar results also occur in the futures contracts, showing that the EU has the lowest percentage spread in the research period. In Panel C of Table 5, the FXE shows the lowest percentage spread in the research period. The EURUSD shows a higher liquidity characteristic than other currencies in the spot, futures, and ETF markets. This study infers that the EURUSD will lead to the highest contribution to the overall process of price discovery in the USDX market owing to higher liquidity.

4.3 Price Discovery Analyses

This study aims to examine the dynamics of price discovery among the USDX, futures, ETFs, and its underlying FX futures (i.e., EUR, JPY, GBP, CAD, SEK, and CHF) to evaluate different hypotheses about price discovery and examine whether the existence of the associated derivatives helps promote the completeness and efficiency of the overall market. Price discovery is modeled in this study using one-minute resolution, with lagged terms of up to ten minutes. The trade price is the last sale price at the end of the minute. This study also follows the suggestion of Hasbrouck (2003) for the computation of the daily common factor weight, information share, and modified information share measures.

< Table 6 Inserted about here>

The price-discovery results for the spot index (USDX), futures (DX), and ETFs (UUP) using the PT, IS, and MIS models are reported in Table 6. The results of the PT, IS, and MIS models indicate that the spot index (USDX) is quite dominant relative to the other markets, with a significant contribution to the price-discovery process in the research period. The finding that the spot index (USDX) appears to significantly lead the futures (DX) and ETFs (UUP) reflects the importance of the spot currencies in the price-discovery process of the U.S. dollar index market. This result differs from the prior studies (Chu et al., 1999; Hasbrouck, 2003; Tse et al., 2006; Chen & Chung, 2012), which argue the E-mini futures playing a dominant role in the price-discovery process and reemphasize the significance of the spot currencies in contributing to price discovery. However, the USDX futures have more contributions to price discovery in the QE period than in the first period, reflecting that the contribution of spot currencies to price discovery is more damaged than that of futures from the QE implementation.

<Table 7 Inserted about here>

Furthermore, this study constructs the synthetic USDX futures using the EUR, JPY, GBP, CAD, SEK, and CHF futures. The price-discovery results on the spot index (USDX), futures (DX), ETFs (UUP), and synthetic USDX futures in Table 7; these results are provided in order to examine our argument and to facilitate a comparative analysis with that of the results obtained by the prior studies. In order to demonstrate the changes in contribution to price discovery made by the synthetic USDX futures relative to spot index, futures, and ETFs, this study further compares the synthetic USDX futures with the prices of spot index, futures, and ETFs. The results for the PT, IS, and MIS models for the comparison between the synthetic USDX futures, spot index, futures, and ETFs are reported in Table 7. Table 7 shows a significant contribution to the price-discovery process provided by the synthetic USDX futures. Overall, these results reveal that the synthetic USDX futures play an essential role in the contribution to the price-discovery process.

4.4 Spillover Analyses

Following Diebold and Yilmaz (2012), this study computes directional return and realized volatility spillovers, respectively, and shows how the return from a specific FX futures transmits to other FX futures (“contribution TO”). This study analyzes the total return connectedness over the rolling 200-day windows from January 2, 2015 to October 20, 2022.[6] Figure 4 exhibits the dynamic return connectedness among the USDX and its underlying FX futures, showing a dynamic pattern of return spillover index over time.

< Figure 4 inserted about here >

The return spillovers reveal that spillover effects across the USDX and its underlying FX futures were remarkable, fluctuating between about 57% and 70%, except in 2021, when it exceeded the 70% mark.

Table 2 displays the directional return connectedness measures for the USDX and its underlying forex futures based on the methodology of Diebold and Yilmaz (2009; 2012; 2015). This study computes directional spillovers and shows how to return from

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[6] All of the results are based on vector autoregressions (VARs) of lag order 4 and generalized variance decompositions of 10-day-ahead return/volatility forecast errors. Following the suggestion of Diebold and Yilmaz (2012), this study also calculate the spillover index for lag orders 2 to 6 and for forecast horizons varying from 4 to 10 days, respectively. The results do not materially change and are robust with respect to the selections of the lag orders and forecast horizon.

a specific FX future transmits to other FX futures in the sample ("contributions TO others"). Similarly, the opposite link of the extent of spillovers coming from other FX futures to a specific FX future ("contributions FROM others"). The ijth entry of the connectedness matrix is the estimated contribution to the forecast error variance of a FX future i coming from innovations to a FX future j. The off-diagonal column sums or row sums are the directional connectedness "contributions TO others" and "contributions FROM others", and the difference between the "contribution TO others" and "contribution FROM others" is the "NET" (i.e., "TO" minus "FROM") directional connectedness. The total connectedness index appears in the lower right corner of the connectedness tables, and it is approximately the grand off-diagonal column sum (or row sum) relative to the grand column sum including diagonal (or row sum including diagonals), expressed in percentage terms. The diagonal values of the connectedness matrix represent the extent to which the return of a specific future affects its subsequent return, and the off-diagonal values of the connectedness matrix show the return spillover impact between forex futures pairs. Diebold and Yılmaz (2012; 2015) noted that the connectedness table provides an approximate "input-output" decomposition of the total connectedness index.

<Table 7 inserted about here >

The information presented within Table 7 shows in aggregate form the difference in how specific FX futures transmit and receive return spillovers. The total return connectedness index of the USDX futures and its underlying FX futures, with a value of 65.18%, is higher than the return connectedness index among the global stock (52.2%) and bond (48.2%) markets reported in Diebold and Yilmaz (2015, p.89 and p.125). As expected, the most striking result of the total directional connectedness measures is that the USDX futures and EUR futures have high "TO" connectedness, 102.70% and 88.73%, respectively, and also have high “FROM” connectedness, 75.82% and 74.15%, respectively. Their net directional connectedness measures are all among the positive and highest in the connectedness value and show that shocks to returns of the USDX futures and EUR futures have a substantial indirect impact on returns in other FX futures. On the contrary, the JYP, CAD, and GBP futures are the least connected in returns among the USDX and its underlying FX futures. They stand out with their low “TO” connectedness, 31.99%, 36.39%, and 51.66%, respectively, and low “FROM” connectedness, 51.87%, 52.60%, and 62.32%, respectively, over the full sample on average. Their net directional connectedness measures are also among the negative in the connectedness value and show that they are net recipients of shocks from other FX futures.

<Table 8 inserted about here >

In Table 8, the net pairwise directional return connectedness result for the FX futures suggests that a negative/positive value means the FX futures is a receiver/transmitter of spillovers. The USDX futures are the dominant net transmitter of return spillovers to all other FX futures. These results confirm the findings of Table 7, in which the return connectedness matrix coefficient of USDX futures to all other FX futures displays a higher degree than those of other FX futures. Figure 5 also shows that the USDX futures are the dominant net transmitters of return spillovers.

<Figure 5 inserted about here >

5. CONCLUSIONS

This study analyzes the price discovery of USDX products. According to the study of Cespa and Foucault (2014), cross-asset learning of liquidity providers or market makers makes the liquidity of asset pairs interconnected. By constructing and using price discovery models for the USDX and its underlying FX products, this study compares the contributions of the USDX products to the price-discovery process. By constructing and using price discovery models for the USDX and its underlying FX products, this study compares the contributions of the USDX products to the price-discovery process.

The dynamics of price discovery between the spot index (USDX), futures (DX), and ETFs (UUP) show that the spot currencies play an important role in the price-discovery process in the U.S. dollar index market. By constructing the synthetic USDX futures from the EU, JY, BP, CD, SEK, and SF futures, the dynamics of price discovery between the spot index (USDX), futures, ETFs, and the synthetic USDX futures have been examined. The empirical results show that the synthetic USDX futures appear to lead the spot currencies significantly; DX futures and UUP ETFs reflect the importance of the synthetic USDX futures in the price-discovery process in the U.S. dollar index market. We also show that USDX futures are the dominant net transmitter of return spillovers to all other FX futures. Our results suggest that the spillover effects from index products strengthen the price-discovery process.

From the comparison analysis, this study will provide insight into how the USDX affects the price-discovery dynamics of the underlying FX products from the perspectives of arbitrageurs, speculators, and hedgers. Overall, these analyses help explore how the information content of fundamental trades at the USDX market could propagate to the underlying FX products. The U.S. dollar especially plays a critical role in the world.

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Table 1 Contract Specifications of ICE FX Futures

FX Futures	US Dollar Index Futures	Dollar Based Currency Pairs Euro/US Dollar Futures	Dollar Based Currency Pairs Japanese Yen/US Dollar Futures	Dollar Based Currency Pairs British Pound/US Dollar Futures	Dollar Based Currency pairs Canadian Dollar/US Dollar Futures	Dollar Based Currency Pairs US Dollar/Swedish Krona Futures	Dollar Based Currency Pairs Swiss Franc/US Dollar Futures
Symbol	DX	KEO	KSN	MP	KSV	KX	KMF
Contract Size	$1000 x Index value	125,000 Euro	12,500,000 Japanese yen	62,500 pounds	100,000 Canadian dollars	100,000 U.S. dollars	125,000 Swiss francs
Price Quotation	US Dollar Index points, calculated to three decimal places 0.010 = $10	U.S. dollars per euro to 5 decimal places	U.S. dollars per yen to 7 decimal places	U.S. dollars per pound to 4 decimal places	U.S. dollars per C. dollar to 5 decimal places	Krona per dollar to 5 decimal places	U.S. Dollars per franc to 5 decimal places
Tick Size	0.005 = $5	0.0001 or 6.25 U.S. dollars per contract	$0.0000005 per Japanese yen increment ($6.25 per contract)	0.0001 or 6.25 U.S. dollars per contract	$0.00005 per Canadian dollar increments ($5.00/contract)	0.00005 or 5 krona per contract	$0.00005 per Swiss Franc increments ($6.25/contract)
Final Settlement	Physical delivery on the third Wednesday of the expiring month						
Contract Series	Four months in the March/June/September/December quarterly expiration cycle						
Trading Hours	CITY (NEW YORK); Trading: 8:00 PM - 5:00 PM* (20:00 - 17:00); Pre-open: 7:55 PM (19:55)						

Source: ICE website (https://www.theice.com/products/Futures-Options/FX/).
Note: The US Dollar Index is physically settled on the third Wednesday of the expiration month against six component currencies (euro, Japanese yen, British pound, Canadian dollar, Swedish krona and Swiss franc) in their respective percentage weights in the Index. Settlement rates may be quoted to three decimal places. The volume-weighted average of all electronic trades transacted in the closing session (14:59 to 15:00 Eastern time). The DX contract has no position limits.

Table 2 Contract Specifications of CME FX Futures

FX Futures	Euro FX Futures (EUR/USD)	Japanese Yen Futures (JPY/USD)	British Pound Futures (GBP/USD)	Canadian Dollar Futures (CAD/USD)	Swedish Krona Futures (SEK/USD)	Swiss Franc Futures (CHF/USD)
Symbol	EU	JY	BP	CD	SEK	SF
Contract Size	125,000 euro	12,500,000 Japanese yen	62,5000 pounds	100,000 Canadian dollars	2,000,000 Swedish kronor	125,000 Swiss francs
Minimum Price Fluctuation	0.00005 per Euro increment = $6.25 $0.00005 per euro increments ($6.25)	0.0000005 per JPY increment = $6.25 $0.0000005 per yen increments ($112.50)	0.0001 USD per GBP increments ($6.25 USD). $0.0001 per pound increments ($6.25)	0.00005 USD per CAD ($5.00 USD). $0.0001 per CAD increments ($10.00)	$0.00001 per Swedish krona increments ($20.00/contract)	$0.0001 per Swiss Franc increments ($12.50/contract)
Termination of Trading	Trading terminates at 9:16 a.m. CT on the second business day prior to the third Wednesday of the contract month.					
Contract Series	Quarterly contracts (Mar, Jun, Sep, Dec) listed for 20 consecutive quarters and serial contracts listed for 3 consecutive months.					
Trading Hours	CME Globex: Sunday - Friday 6:00 p.m. - 5:00 p.m. (5:00 p.m. - 4:00 p.m. CT) with a 60-minute break each day beginning at 5:00 p.m. (4:00 p.m. CT) CME ClearPort: Sunday 5:00 p.m. - Friday 5:45 p.m. CT with no reporting Monday - Thursday from 5:45 p.m. – 6:00 p.m. CT					

Source: CME Group website (https://www.cmegroup.com/markets/fx.html)

Table 3 Summary of Major FX ETFs

	Invesco DB U.S. Dollar Index Bullish Fund	Invesco CurrencyShares Euro Trust	Invesco CurrencyShares Japanese Yen Trust	Invesco CurrencyShares British Pound Sterling Trust	Invesco CurrencyShares Canadian Dollar Trust	Invesco CurrencyShares Swedish Krona Trust	Invesco CurrencyShares Swiss Franc Trust
Ticker Symbol	UUP	FXE	FXY	FXB	FXC	FXS	FXF
Fund Description	UUP offers exposure to a basket of currencies relative to the U.S. dollar, decreasing in value when the trade weighted basket strengthens and increasing when the dollar appreciates.	FXE tracks the changes in value of the euro relative to the US dollar.	FXY tracks the changes in value of the Japanese yen relative to the US dollar.	FXB delivers exposure to changes in value of the British pound relative to the US dollar.	FXC tracks the changes in value of the Canadian dollar relative to the US dollar.	FXE tracks the changes in value of the Swedish krona relative to the US dollar. FXS ceased trading on 02/14/20.	FXF tracks the changes in value of the Swiss franc relative to the US dollar.
Inception Date	2007/02/20	2005/12/09	2007/02/12	2006/06/21	2006/06/21	2006/06/26	2006/06/21
Expense Ratio	0.79%	0.40%	0.40%	0.40%	0.40%	0.40%	0.40%

Source: https://www.etf.com/; https://etfdb.com/

Table 4 Summary Statistics

	Avg. Daily Number of Trades	Avg. Daily Volume (contract / 100 shares)	Avg. Daily Return (x100)	Avg. Daily Range Volatility (x100)	Avg. Daily Realized Volatility (x100)
Panel A: FX Currencies					
USDX	-----	-----	-0.7787	4.1325	6.0305
EURUSD	111,244	111,244	-0.3790	5.1742	5.5061
USDJPY	108,886	108,886	-0.9107	4.6967	4.9559
GBPUSD	141,972	141,972	-2.0068	5.6136	6.0375
USDCAD	124,930	124,930	-2.1572	5.5738	5.9478
USDSEK	91,361	91,361	-8.2142	6.6178	7.3423
USDCHF	85,242	85,242	-4.9108	5.1584	5.6475
Panel B: FX futures					
DX	9,165	15,994	-0.9705	4.4835	6.5457
EU	63,804	108,489	1.1882	5.2262	5.5193
JY	36,559	63,562	-0.8612	4.7705	4.9878
BP	29,670	55,015	0.7919	5.6608	6.0589
CD	26,773	47,066	0.3261	5.6294	5.9617
SEK	56	80	-0.8122	4.9286	6.9592
SF	9,424	13,285	1.2034	5.1741	5.6653
Panel C: FX ETFs					
UUP	1,814	13,759	-0.4922	3.8425	4.5550
FXE	835	3,063	1.0665	4.1141	4.6676
FXY	303	1,100	-0.1517	3.6877	4.3460
FXB	134	427	0.8391	4.0000	5.0091
FXC	122	481	1.0516	4.2529	5.0870
FXS	6	14	2.1054	2.2725	3.2660
FXF	63	236	0.5891	3.6576	4.7182

Table 5 Liquidity Analysis

	Avg. Quoted Spread	Avg. Percentage Quoted Spread	Avg. Effective Spread	Avg. Percentage Effective Spread
Panel A: FX Currencies (x1,000)				
EURUSD	0.4254	0.3809	0.2127	0.1904
USDJPY	45.2382	0.3888	22.6191	0.1944
GBPUSD	0.7073	0.5162	0.3537	0.2581
USDCAD	0.6560	0.5083	0.3280	0.2542
USDSEK	14.3365	1.6036	7.1683	0.8018
USDCHF	0.6899	0.7198	0.3450	0.3599
Panel B: FX futures (x1,000)				
EU	0.6058	0.5372	0.3315	0.2940
JY	0.0057	0.6415	0.0031	0.3457
BP	1.0654	0.7991	0.5706	0.4280
CD	0.6394	0.8314	0.3404	0.4426
SEK	1.2907	11.2255	0.6495	5.6489
SF	1.0870	1.0440	0.5764	0.5542
Panel C: FX ETFs (x100)				
UUP	1.0058	0.0395	0.3638	0.0143
FXE	1.3973	0.0131	0.6030	0.0056
FXY	1.8167	0.0217	0.7276	0.0087
FXB	3.2873	0.0255	1.2638	0.0098
FXC	2.3985	0.0316	0.8980	0.0118
FXS	22.4162	0.2060	7.0753	0.0649
FXF	4.5163	0.0469	1.5349	0.0159

Table 6 Price Discovery Analysis for the USDX, Futures, and ETFs

	USDX (Currency)	DX (Futures)	UUP (ETFs)
Panel A: January 2, 2015-October 20, 2022, 1946 trading days			
PT Model	**0.5520**	0.3529	0.0951
IS Model	**0.7324**	0.1430	0.1246
MIS Model	**0.7707**	0.1394	0.0899
Panel B: January 2, 2015-March 13, 2020, 1293 trading days			
PT Model	**0.5654**	0.3405	0.0941
IS Model	**0.7485**	0.1354	0.1162
MIS Model	**0.7854**	0.1306	0.0840
Panel C: March 16, 2020- October 20, 2022, 653 trading days			
PT Model	**0.5255**	0.3774	0.0971
IS Model	**0.7006**	0.1580	0.1414
MIS Model	**0.7416**	0.1568	0.1016

Note: The results of price discovery using common factor (PT), information share (IS), and modified information share (MIS) models are reported for the U.S. dollar index (USDX), futures (DX), and ETFs (UUP). The statistics are based on a VECM of prices for these variables estimated as one-second resolution data. The models are estimated for each day during our sample period (from January 2, 2015, to October 20, 2022). The daily estimates are calculated from the average price-discovery measures of all permutations of the order of variables in the estimation process. The figures throughout the table are the means of the daily measures of price discovery.

Table 6 Price Discovery Analysis for the USDX, Futures, ETFs, and Synthetic USDX Futures

	USDX (Currency)	DX (Futures)	UUP (ETFs)	Synthetic USDX Futures
Panel A: January 2, 2015-October 20, 2022, 1946 trading days				
PT Model	0.2973	0.2947	0.0650	**0.3430**
IS Model	0.3559	0.1492	0.0880	**0.4070**
MIS Model	0.3254	0.1491	0.0667	**0.4589**
Panel B: January 2, 2015-March 13, 2020, 1293 trading days				
PT Model	0.2863	0.2972	0.0633	**0.3532**
IS Model	0.3512	0.1510	0.0803	**0.4176**
MIS Model	0.3073	0.1508	0.0612	**0.4807**
Panel C: March 16, 2020- October 20, 2022, 653 trading days				
PT Model	0.3192	0.2897	0.0684	**0.3227**
IS Model	0.3650	0.1456	0.1033	**0.3861**
MIS Model	0.3613	0.1456	0.0775	**0.4156**

Note: The results of price discovery using common factor (PT), information share (IS), and modified information share (MIS) models are reported for the U.S. dollar index (USDX), futures (DX), ETFs (UUP), and synthetic USDX futures. The statistics are based on a VECM of prices for these variables estimated as one-second resolution data. The models are estimated for each day during our sample period (from January 2, 2015, to October 20, 2022). The daily estimates are calculated from the average price-discovery measures of all permutations of the order of variables in the estimation process. The figures throughout the table are the means of the daily measures of price discovery.

Table 7 Return spillover analysis for the USDX futures and its underlying futures

	DX	EU	JY	BP	CD	SEK	SF	FROM
DX	24.18	20.65	7.12	11.44	7.10	15.01	14.51	75.82
EU	22.28	25.85	5.49	8.71	5.22	16.34	16.11	74.15
JY	13.57	9.54	48.13	4.46	2.62	5.33	16.34	51.87
BP	17.55	12.46	3.21	37.68	9.19	11.45	8.45	62.32
CD	12.71	8.72	2.35	10.91	47.40	11.52	6.38	52.60
SEK	18.49	18.75	3.48	9.21	7.91	30.50	11.67	69.50
SF	18.10	18.62	10.33	6.94	4.34	11.66	30.01	69.99
TO	102.70	88.73	31.99	51.66	36.39	71.31	73.46	Spillover
OWN	126.88	114.59	80.12	89.34	83.79	101.81	103.47	Index
NET	26.88	14.59	-19.88	-10.66	-16.21	1.81	3.47	65.18

Note: This table presents the connectedness matrix among the returns of the USDX futures (DX) and its underlying FX futures (i.e., EU, JY, BP, CD, SEK, and SF). TO: directional spillovers from each futures to all other futures ("To others"). OWN: directional spillovers from each futures to all futures, including own ("To all"). FROM: directional spillovers from all other futures to each futures ("From others"). NET: spillover transmitted by each futures to all other futures, where positive (negative) values indicate that the futures in question is a net transmitter (receiver) of spillovers to all other futures ("TO minus FROM"). The lower right corner of the spillover table computes the total volatility spillover index. It is in the region the grand off-diagonal column sum (or row sum) relative to the grand column sum including diagonals (or row sum including diagonals), expressed as a percentage. The models are estimated for each day during our sample period (from January 2, 2015, to October 20, 2022). The figures throughout the table are the means of the daily spillover measures.

Table 8 Net pairwise directional return connectedness among the USDX futures and its underlying futures

FROM	DX	EU	JY	BP	CD	SEK
TO						
EU	1.63					
JY	6.45	4.05				
BP	6.11	3.76	-1.24			
CD	5.61	3.50	-0.27	1.72		
SEK	3.48	2.40	-1.84	-2.24	-3.62	
SF	3.59	2.51	-6.01	-1.51	-2.04	0.00

Note: This table presents the net pairwise directional connectedness among the returns of the USDX futures (DX) and its underlying FX futures (i.e., EU, JY, BP, CD, SEK, and SF). TO: directional spillovers from each futures to each other futures. FROM: directional spillovers from each other futures to each futures. NET: spillover transmitted by each futures to another futures, where positive (negative) values indicate that the futures in question is a net transmitter (receiver) of spillovers to another futures ("TO minus FROM"). The models are estimated for each day during our sample period (from January 2, 2015, to October 20, 2022). The figures throughout the table are the means of the daily spillover measures.

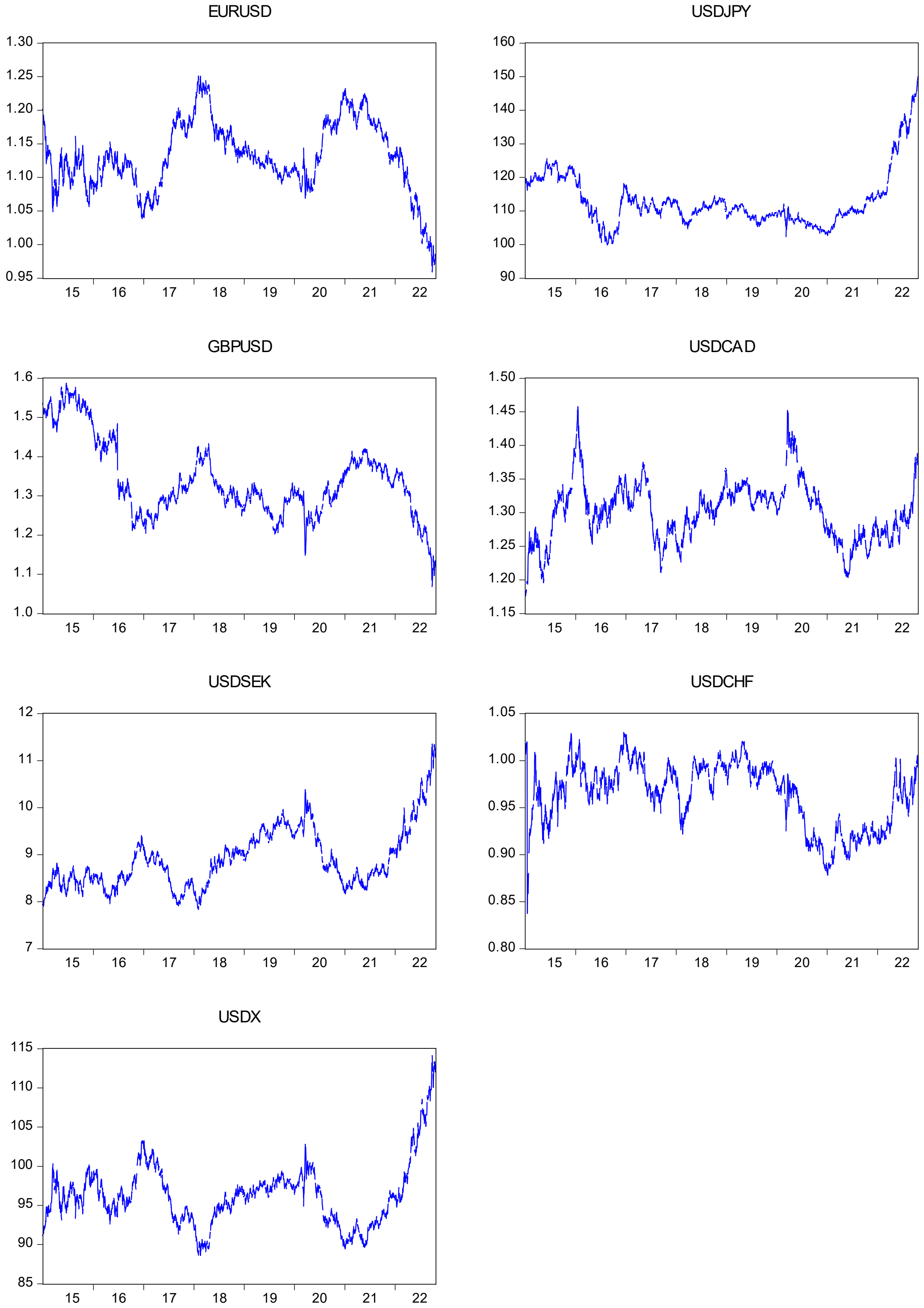

Figure 1 U.S. dollar index and the major FX currencies

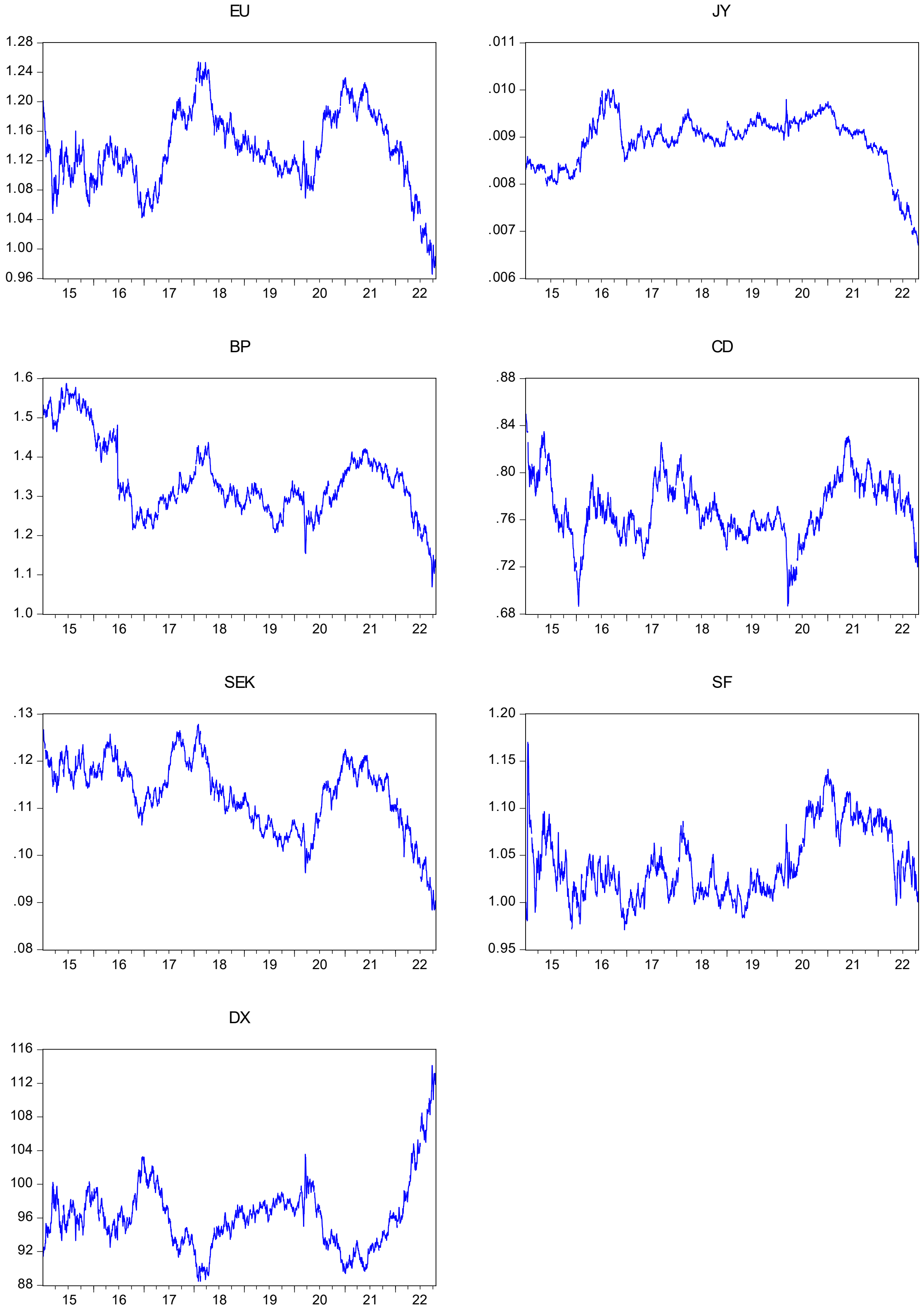

Figure 2 U.S. dollar index futures and the major FX currency futures

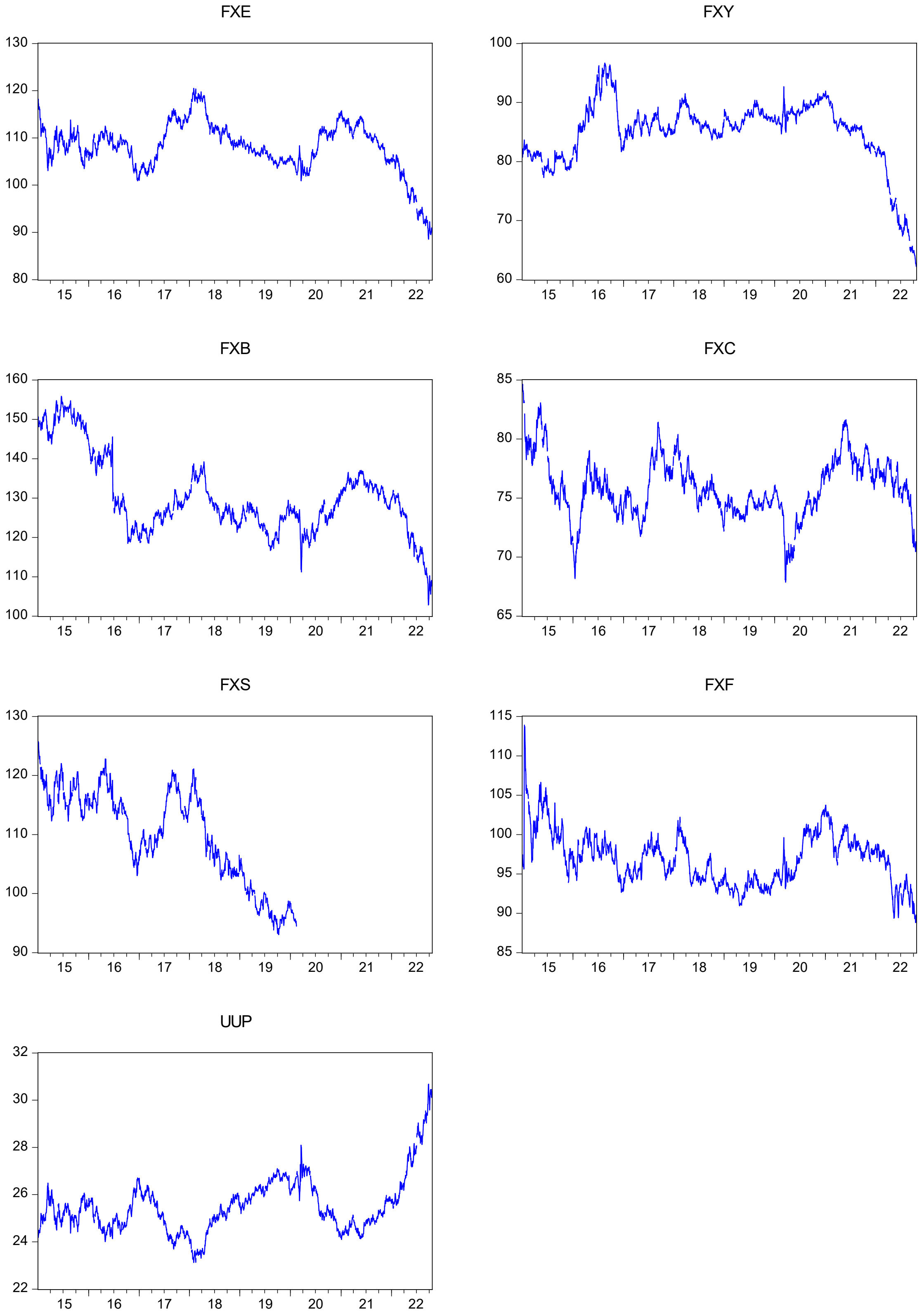

Figure 3 U.S. dollar index ETFs and the major FX currency ETFs

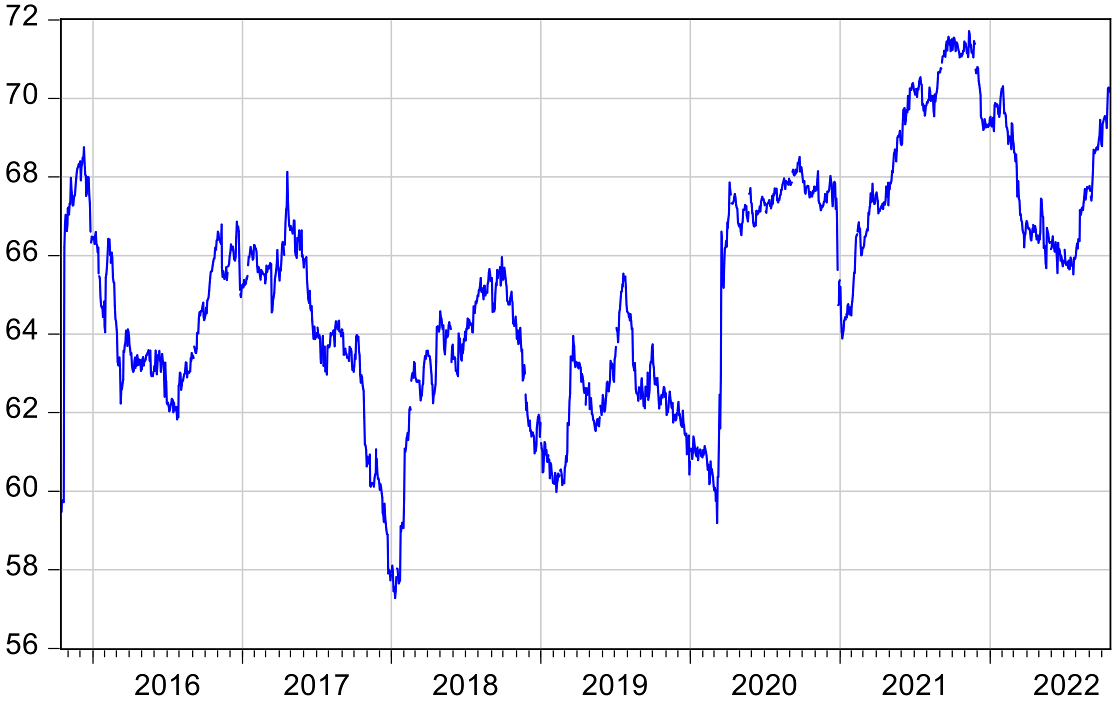

Figure 4 Return spillover index among the USDX futures and its underlying futures

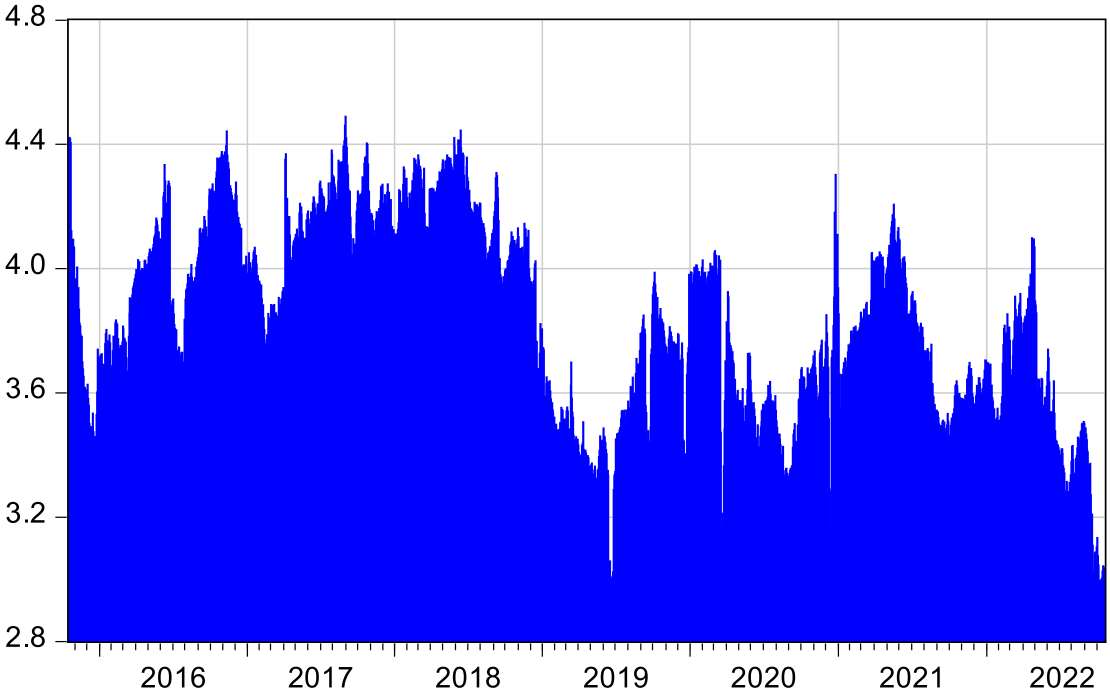

Figure 5 Net directional return spillovers of the USDX futures (DX)