

Topography of the FX Derivatives Market: A View from London*

Sinem Hacıoglu-Hoke[†]

Daniel Ostry[‡]

Hélène Rey[§]

Adrien Rousset Planat[¶]

Vania Stavrakeva^{||}

Jenny Tang^{**}

August 11, 2025

Abstract

We use 100 million transactions in the London FX derivatives market to provide the first high-frequency, granular topography of the world's largest hub for currency trading. Using daily firm-level net FX derivatives exposures, we analyze the motives behind financial and non-financial firms' derivatives use and trace the dynamic response of the entire market to macro news. Pension and investment funds, insurers, and non-financial corporations use FX derivatives primarily to hedge. Hedge funds, by contrast, trade speculatively, while dealer banks insulate themselves from changes in speculative demand by taking offsetting positions with hedgers. Hedge funds help transmit monetary policy shocks to exchange rates, while investment fund flows contribute to dollar appreciations when credit risk rises. Finally, all sectors' positions contain some information for exchange rate movements, but hedge funds and non-financial corporations are particularly important.

Keywords: FX Derivatives, Exchange Rates, Non-Bank Financial Institutions, Banks, Non-Financial Corporations, Hedging, Speculation, Macro News, Monetary Policy, Credit Risk.

JEL Codes: F30, F31, G15, G20

*The authors would like to thank the Bank of England for giving us access to the data. We are also grateful to Wenxin Du, Rohan Kekre, Christian Kubitz, Oleg Itskhoki, Jeremy Stein and seminar participants at the Bank of England, Harvard Business School, Federal Reserve Bank of Boston, the 2025 NBER Summer Institute (International Asset Pricing meeting) and 2025 CEBRA conferences for very useful comments. We thank Will Parry for his help with the UK OTC FX derivatives data. Sinem Hacioglu-Hoke was employed at the Bank of England when some of the analysis was done. The views expressed are those of the authors and do not necessarily reflect those of the Bank of England or any of its committees, nor those of the Federal Reserve Board of Governors, Federal Reserve Bank of Boston or the Federal Reserve System. All errors remain our own.

† Federal Reserve Board & CEPR. Email: sinem.haciogluhoke@frb.gov

‡ Bank of England & Centre for Macroeconomics. Email: daniel.ostry@bankofengland.co.uk

§ London Business School, CEPR & NBER. Email: hrey@london.edu

¶ London Business School. Email: adrienroussetplanat@gmail.com

|| London Business School & CEPR. Email: vstavrakeva@london.edu

** Federal Reserve Bank of Boston & CEPR. Email: Jenny.Tang@bos.frb.org

1 Introduction

Foreign exchange (FX) markets are at the center of trade and financial flows. They affect financial stability, economic activity and the transmission of monetary and fiscal policies. Over 70% of global FX turnover now takes place in derivatives, as opposed to spot markets.¹ Borio et al. (2022) highlight that US dollar debt from FX derivatives is huge, growing and “in a blind spot” since they are off balance-sheet—the \$80 trillion in outstanding obligations to pay USD via FX swaps, forwards, and currency swaps exceeds the combined stock of Treasury bills, repo, and commercial paper.

Yet the inner workings of FX derivatives markets remain largely unknown. Existing studies provide useful but partial views of these markets, focusing typically on one sector in a single country, on a small niche market (e.g., the CBOE currency futures market), or rely on infrequent company filings and reports that offer incomplete coverage across sectors, currencies and jurisdictions. As a result, the international finance literature has had to make modeling assumptions, based on a very limited empirical foundation, that are highly consequential for model predictions and policy implications.² A more comprehensive view of the structure of this market at the core of international finance—including its concentration, the balance between firms’ speculative, hedging and market-making activities, and how it adjusts to macro, financial and policy shocks—is key to understand exchange rates, and their role in global trade and finance.

This paper provides the first high-frequency, granular topography of the largest FX market in the world—in the UK, accounting for 38% of global FX turnover.³ It brings to bear the weight of more than 100 million FX derivative transactions to characterize currency risk taking and risk management by all major market participants—pension funds, investment

¹Average daily turnover is \$5.4 trillion in 2022, according to Bank of International Settlements (2024).

²For example, on hedging practices of financial and non-financial firms, Gopinath and Stein (2021) assume that firms are fully unhedged while Camanho et al. (2022) assume that investors are fully unhedged for equities and fully hedged for bonds.

³This is twice the share of the second largest FX market (New York). For details, see 2022 BIS Triennial Central Bank Survey of FX and OTC Derivatives Markets, henceforth “BIS Triennial Survey”.

funds, insurers, dealer and non-dealer banks, hedge funds, non-financial corporations and non-bank market makers.⁴ It does so, unlike the existing literature, at a daily frequency, at the firm level, and across currency pairs and geographies, highlighting important differences both across and within sectors. By studying the behavior of all market participants, this paper provides new insights on the underlying structure of the market, especially on how it adjusts as the macro environment shifts.

Our analysis is underpinned by the construction of a novel dataset comprising over 16 million *daily net* FX derivatives exposure observations at the firm–currency-cross level, covering more than 16,000 firms active in the UK FX derivatives market from January 1, 2015 to December 31, 2020. Our measure improves in two dimensions relative to the existing literature. First, we provide daily firm-level net FX derivatives exposures for all sectors and currency crosses. Second, we do so for a large and meaningful share of the global FX market, i.e., the near-universe of firms trading in the UK, making our analysis representative. In contrast, existing studies with wide coverage examine only sector-level exposures, either gross as in the BIS Triennial Survey, or net as in Du and Huber (2024). To our knowledge, no prior work documents *firm-level* net exposures for an entire market, let alone their high-frequency dynamics. The focus on net exposures is important because net, and not gross, exposures determine firms' profits and are therefore a key choice variable that can inform us about the incentives behind firms' FX derivatives use.

Our unique data allow us to uncover important new facts.

First, we measure firm-level *net* obligations in the London FX derivatives market to average \$3 trillion over our sample. This stands in stark contrast to gross exposures, valued at \$37 trillion by Borio et al. (2022).⁵ This gap arises since dealer banks and non-bank market makers largely net their gross exposures among each other in the inter-dealer market.

⁴Asset managers dominate the landscape, accounting for 70% of individual firms, followed by non-financial corporates (25%). Within asset managers, 89% are investment funds (at the fund-level), 8% pension funds, and 3% hedge funds.

⁵The latter value is calculated from the \$97 trillion gross size of the global FX market in 2022 quoted by Borio et al. (2022), times the 38% UK market share quoted by the 2022 BIS Triennial Survey.

Second, leveraging the firm-level detail in our data across all sectors, we document significant market concentration and within-sector heterogeneity in firms' net exposures. Dealer banks—on (at least) one side all transactions—are the most concentrated sector, with the 5 largest dealers accounting for about 90% of the entire sector's net exposures. Among client sectors, insurance companies and pension funds are the most concentrated, while investment funds are the least. Investment funds, non-financial corporations and non-dealer banks also exhibit the greatest within-sector heterogeneity in the direction of their exposures. These patterns are critical for systemic-risk assessment, since directional heterogeneity affects aggregate resilience to exchange-rate risk, while concentration raises the risk of idiosyncratic shocks spilling over to the broader market (see Bippus et al., 2023).

Third, using both the granularity and high frequency of our data, we develop a new methodology to identify which firms are primarily FX hedgers or speculators. We interpret the data through a partial equilibrium model in which clients trade FX derivatives to: (i) speculate, based on their exchange rate expectations, and (ii) hedge the currency risk associated with their non-derivatives profits. A key distinction emerges: hedging demand is often one-directional and persistent, reflecting persistence in firms' non-derivatives operations. For example, UK investment funds that are consistently long US fixed income assets would hedge currency risk by maintaining persistently net-short USD and net-long GBP FX derivatives exposures. In contrast, speculative demand is unlikely to be one-directional since exchange rate expectations move frequently with market developments.⁶

At one extreme, we find that over 60% of individual non-financial corporations maintain the same one-sided net exposures to the USD over at least 95% of our sample. At the other extreme, this statistic is over 30 percentage points lower for individual hedge funds. The other sectors' one-sided exposure shares lie in between, with individual insurers and pension funds tending to be more one-directional than individual investment funds and non-dealer

⁶This should be especially true for the currencies of advanced economies, for which it is rare to have persistent trends in nominal exchange rates.

banks. Through the lens of our model, this suggests that the non-financial sector is comprised of the greatest fraction of ‘pure’ hedgers, while the hedge fund sector is comprised of the greatest fraction of ‘pure’ speculators.

Fourth, we exploit our high frequency data to study how firms adjust their FX derivatives exposures alongside correlates of speculative demand, namely, the carry trade, momentum, and macroeconomic news investment strategies. Hedge funds robustly adjust their derivatives exposures in accordance with all three strategies, confirming their role as speculators.⁷ Their activity correlates with well-documented exchange rate phenomena, such as carry trade profitability (Fama, 1984) and how exchange rates respond to macro news (Stavrakeva and Tang, 2024), highlighting their important role for exchange-rate determination.

On the other side, non-financial corporations adjust their net exposures opposite to the investment strategies, and thereby appear to accommodate hedge funds’ speculative activity in FX derivatives markets.⁸ This behavior is embodied by “noise traders” in international macro models, but may reflect the correlation between non-financials’ hedging demand and the variables defining these investment strategies.⁹

In contrast, dealer banks—despite serving as counterparties to all clients—remain neutral with respect to these investment strategies. They effectively serve as “toll-takers” in the market (Duffie et al., 2005), with minimal net risk held (Lu and Wallen, 2024), by taking offsetting exposures with speculators and hedgers.

Fifth, we examine how hedging agents—namely, non-financials and pension and investment funds—adjust their net exposures to changes in hedging costs, proxied by CIP deviations (Du et al., 2018a;b). The sign of this reduced-form correlation can inform on the balance between shifts in hedging supply—by dealers—and shifts in hedging demand—by

⁷Some investment funds and non-dealer banks also appear to trade speculatively, although the results are less consistent across currency crosses and less statistically significant than for hedge funds.

⁸Some pension funds and insurance companies also move opposite to hedge funds, although the results are less robust than for non-financials.

⁹For example, US interest rates may rise in response to a stronger US economy in which non-financials earn greater USD sales revenue. They would hedge these profits by going more short the USD, opposite to the carry trade.

hedgers—in driving movements in hedging prices and quantities. We find that higher USD hedging costs vis-à-vis the EUR and GBP are associated with less USD hedging (fewer net-short exposures) in these sectors, suggesting that hedging supply shifts are dominant in the market and that hedgers have downward sloping (price-sensitive) hedging demand.

Finally, we analyze the conditional and unconditional co-movement between sectors' FX derivatives exposures and exchange rates. We first investigate which sectors help transmit two important types of aggregate shocks—monetary policy and credit risk (from macro news)—to exchange rates. Using IV local projections, we document that greater hedge fund exposure to a given currency m , in response to an exogenous monetary policy tightening in jurisdiction m , is associated with an appreciation of currency m . Investment funds, by contrast, play a key role in propagating flight-to-safety shocks to exchange rates: greater investment fund exposure to the USD, due to adverse macro news that raises US credit spreads, is associated with a USD appreciation.

Last but not least, we find that a reduced form regression of weekly exchange rate movements on changes in all client sectors' positions yields a correlation between actual and predicted exchange rate movements as high as 66%, with hedge funds and non-financial positions being the most informative.¹⁰

Related Literature

While the literature is growing rapidly, there are relatively few papers that study FX derivatives use in advanced economies with wide coverage. An important exception is Du and Huber (2024) who document stylized facts about foreign investors' USD securities and derivatives positions using sector-level data across various jurisdictions. They merge official data

¹⁰Stavrakeva and Tang (2020) and, more recently, Dao et al. (2025) perform a similar analysis using CFTC data on the CBOE currency futures market using dealer banks' positions and find similar R^2 's. Our finding that hedge funds' positions correlate most strongly with exchange rates is in line with their findings (since dealers positions in the CBOE market largely reflect the other side of trades with hedge funds), but the importance of non-financials, among hedgers—who cannot be disentangled in the CBOE market, is a new and promising avenue for future research.

sources and some company filings at monthly or lower frequencies to estimate sectoral hedge ratios and show their rise since 2008. Interestingly, they also find a strong correlation between the cross section of CIP deviations and hedging demand across currencies. Our work is highly complementary to theirs as we use daily firm-level data for an entire market, document its structure and adjustment to shocks, and explore speculative and hedging motives of all participants.

Our paper also relates to the vibrant literature that studies the link between hedging demand and asset prices, in particular exchange rates, both empirically and theoretically (see e.g., Liao and Zhang, 2024, Czech et al., 2021, Brauer and Hau, 2023, and Ben Zeev and Nathan, 2024a).¹¹¹² Several papers use derivatives data to study deviations from covered interest rate parity (CIP) (Avdjiev et al., 2019, Du et al., 2018b, Ben Zeev and Nathan, 2024b, Aldunate et al., 2023, Khetan, 2024, and Kloks et al., 2024). Bahaj and Reis (2022) show that central bank swap lines put a ceiling on CIP deviations. Abbassi and Bräuning (2021) use transaction-level FX derivatives data in Germany to show that German banks' FX risk management is an important driver of spikes in CIP deviations around quarter ends.¹³ Hau et al. (2021) use contract-level data to document price discrimination in OTC FX derivatives markets that is consistent with the failure of CIP since the financial crisis. Cenedese et al. (2021) use UK transaction-level FX derivatives data to relate the breakdown of CIP to the dealer balance-sheet constraints resulting from post-crisis financial regulations. Ferrara et al. (2022) draws on the same data to examine how dealer banks that drew on swap lines adjusted their FX exposures during the COVID-19 recession. Kubitza et al. (2024) exploits euro-area transaction-level data to show that EU investors sell USD bonds when they want to roll over their existing FX derivatives positions and EUR/USD CIP deviations widen.

¹¹This literature builds on models of spot exchange rate determination in imperfect financial markets, e.g., Jeanne and Rose 2002, Hau and Rey 2006, Gabaix and Maggiori 2015, Ivashina et al. 2015, Stavrakeva and Tang 2021, Gourinchas et al. 2022, Greenwood et al. 2023.

¹²For a theoretical treatment of optimal currency hedging, see Campbell et al. (2010).

¹³Abbassi and Bräuning (2023) argues, based on the same data, that the Brexit shock affected local credit supply by impacting banks' profits via their currency derivatives positions.

There is also a literature on the speculative use of FX derivatives. Based on quarterly SEC filings, Sialm and Zhu (2021) study US international fixed income mutual funds' use of currency derivatives, finding some evidence for carry and momentum trading strategies, although a large fraction of positions are for risk management purposes.¹⁴ Kremens (2020) uses aggregate CFTC currency futures data to show that leveraged funds unwind futures positions when there are negative equity market shocks, leading to currency-equity comovement. Brunnermeier et al. (2009) uses the CFTC currency futures data to examine non-commercial traders' (speculators') unwinding of carry trades during risk-off episodes while Ostry (2023) uses the same data to document a flight-to-USD by commercial traders (hedgers) during such episodes and studies hedgers' interactions with speculators in crises.

Much of the earlier literature on FX derivatives has focused on non-financial corporations in emerging markets, where data has been more readily available.¹⁵ Alfaro et al. (2021) show that Chilean firms supplement their limited operational hedging with significant financial hedging via FX forwards. Kuzmina and Kuznetsova (2018) hand-collects data to show that German corporates tend to use FX derivatives if they are net exporters or importers and when exchange rate movements are larger, while Lyonnet et al. (2022), relying on survey data, finds that large EU corporates are more likely to hedge if they price in foreign currency.

Relative to these other branches of the literature, we provide the first detailed assessment of firm-level currency derivatives usage by all types of financial and non-financial firms in the largest FX market, at a daily frequency, drawing on more than 100 million FX derivative transactions. Within this ecosystem, we uncover a series of important new facts that reshape our understanding of the structure of FX markets. First, we highlight significant within-sector heterogeneity and concentration in firms' net FX derivatives exposures, features that were obscured from earlier studies that used aggregate data and which are first order for

¹⁴Using similar data, Opie and Riddiough 2024 find that US international equity funds' FX derivatives use does not affect their portfolio returns on average, which they attribute to sub-optimal use.

¹⁵Alfaro et al. (2024) provides an excellent survey of non-financial firms' currency hedging with an emphasis on emerging markets.

shock transmission and market resilience. Second, we provide first evidence on how the net exposures of the entire market equilibrate as interest rates, exchange rates and macro news move. In particular, we show that dealer banks remain neutral with respect to changes in these variables by taking offsetting exposures with speculative (e.g., hedge funds) and hedging (e.g., non-financials) agents, suggesting they act as toll-takers in the market. This helps clarify how real-world sectors map to distinct agents in international macro models. Third, we provide a novel method to classify clients into speculators or hedgers based on the direction and persistence of their net FX exposures, which helps map sectors into the agents in international macro models. Fourth, we show that shifts in hedging supply are the main driver of movements in hedging costs and positions in the market. And finally, we show that hedge funds play a key role in transmitting monetary policy shocks to exchange rates, while investment funds' flight-to-safety contributes to dollar appreciations when US credit risk rises. By studying the whole market, our analysis thus goes a step further to inform the design of theoretical models of exchange rate determination, which sit at the heart of international finance.

The remainder of the paper is structured as follows. In Section 2, we introduce notation, define our key variables of interest and provide a theoretical framework for decomposing firms' FX derivatives holdings into speculative and hedging components. Section 3 then discusses the UK FX derivatives data we use throughout the paper. Leveraging insights from these previous sections, Sections 4 and 5 provide an overview of the participants in the UK FX derivatives market, focusing on the market's structure and firms' net FX derivatives exposures, respectively. Section 6 examines how firms' adjust their net FX derivatives exposures with respect to well-known FX investment strategies and changes in hedging costs. Lastly, Section 7 studies the conditional (on aggregate shocks) and unconditional co-movement between sector-level exposures and exchange rates. Section 8 concludes.

2 Notation and Theoretical Framework

Before turning to the data, we first introduce notations and define the two key variables we study in the paper: firms' *net* currency-cross and currency derivatives exposures. We then present a theoretical framework that decomposes these net FX derivative exposures into speculative and hedging components, which we will use to interpret our empirical results.

Each FX derivatives contract refers to a currency pair, denoted by $\{k, m\}$, with k and m indexing the two different currencies. The contract reports two notional values linked to these two currencies. For example, if firm i is long currency k and short currency m via an n -period $\{k, m\}$ FX forward contract entered into at time t , the contract specifies that the firm will receive the notional amount $N_{t,t+n}^{i,\{k,m\}} > 0$ in currency k and will pay the notional amount $-\tilde{N}_{t,t+n}^{i,\{k,m\}} > 0$ in currency m in n periods.¹⁶ The transaction-and-firm specific n -period FX forward rate is then defined as $F_{t,n}^{i,m/k} = -\frac{\tilde{N}_{t,t+n}^{i,\{k,m\}}}{N_{t,t+n}^{i,\{k,m\}}}$, such that an increase implies a forward appreciation of currency k against currency m .¹⁷

Let c^i denote the currency of operation of firm i . Firm i 's profits in units of currency c^i from this derivatives transaction, realized in $t + n$, are:

$$\pi_{t,t+n}^{i,\{k,m\}, deriv} = N_{t,t+n}^{i,\{k,m\}} S_{t+n}^{c^i/k} + \tilde{N}_{t,t+n}^{i,\{k,m\}} S_{t+n}^{c^i/m} = S_{t+n}^{c^i/m} \left(S_{t+n}^{m/k} - F_{t,n}^{i,m/k} \right) N_{t,t+n}^{i,\{k,m\}}, \quad (1)$$

where $S_{t+n}^{m/k}$ is the bilateral m/k spot exchange rate that prevails at $t + n$, with units of currency m per one unit of currency k . So long as firm i is long currency k and short currency m ($N_{t,t+n}^{i,\{k,m\}} > 0$), the transaction is profitable if $S_{t+n}^{m/k} > F_{t,n}^{i,m/k}$. That is, the transaction is profitable if the relative value of currency k to currency m in the spot market at $t + n$ is greater than the relative value implied by the n -day forward rate. We refer to $N_{t,t+n}^{i,\{k,m\}}$, our first key variable, as *firm i's net currency-cross exposure* with respect to the

¹⁶If firm i is short currency k and long currency m via a $\{k, m\}$ contract, then it pays the notional amount $-N_{t,t+n}^{i,\{k,m\}} > 0$ in currency k and receives the notional amount $\tilde{N}_{t,t+n}^{i,\{k,m\}} > 0$ in currency m in n periods.

¹⁷A client i chooses the notional for only one leg of the contract, $N_{t,t+n}^{i,\{k,m\}}$, and is quoted the forward rate by a market maker or dealer bank. Together, these determine the notional of the second leg of the contract.

$\{k, m\}$ cross at horizon n from this contract.¹⁸

In practice, firm i may enter into multiple n -period derivatives contracts across a range of currency crosses. Firm i 's total profits in units of currency c^i from all time- t n -period FX derivatives transactions can be expressed as:

$$\begin{aligned}\pi_{t,t+n}^{i,FX,deriv} &= \sum_{\{k,m\} \in \Omega_n} \pi_{t+n}^{i,\{k,m\},deriv} = \sum_{\{k,m\} \in \Omega_n} \left(N_{t,t+n}^{i,\{k,m\}} S_{t+n}^{c^i/k} + \tilde{N}_{t,t+n}^{i,\{k,m\}} S_{t+n}^{c^i/m} \right) \\ &= \underbrace{\sum_l S_{t+n}^{c^i/l} \left(\sum_m N_{t,t+n}^{i,\{l,m\}} + \sum_k \tilde{N}_{t,t+n}^{i,\{k,l\}} \right)}_{N_{t,t+n}^{i,l}},\end{aligned}\quad (2)$$

where Ω_n is the set of all derivatives contracts issued at t of horizon n , indexed by their currency pair $\{k, m\}$. We refer to $N_{t,t+n}^{i,l}$, our second key variable, as *firm i's net currency exposure* with respect to currency l at horizon n . $N_{t,t+n}^{i,l}$ captures the net amount of currency l that firm i will receive (or pay if negative) at $t+n$, which is constructed by netting out all bilateral net currency-cross exposures in which firm i receives or pays currency l .¹⁹

In summary, from equation (2), we see that firm i 's profits from trading FX derivatives are a function of their net currency exposures, which in turn, via equation (1), depend on their net currency-cross exposures. This is why these two net FX derivative exposure measures are the two key variables we study in this paper.

There are advantages to studying *both* variables. On the one hand, it is very common for firms to transact “through the USD” due to the liquidity of crosses involving the USD in FX derivatives markets. For example, if a firm wants to short the *MXN* and long the *EUR*, it will often short the *MXN* and long the *USD* and, simultaneously in a second transaction, short the *USD* and long the *EUR*. These two contracts together are neutral with respect

¹⁸We use this terminology since $N_{t,t+n}^{i,\{k,m\}}$ reflects firm i 's net exposure to the bilateral exchange rate $S_{t+n}^{m/k}$ from this FX derivatives contract. When we move to the data, we will account for the fact that firm i may enter into multiple contracts in the same currency cross $\{k, m\}$ (and $\{m, k\}$) by netting the exposures from each contract, as we detail below.

¹⁹ $N_{t,t+n}^{i,l}$ captures firm i 's net exposure to the $S_{t+n}^{c^i/l}$ exchange rate from all n -period FX derivatives contracts entered into at t .

to the *USD*, a feature that would be ignored if we examine firms' net exposures at the currency-cross level; this highlights the benefit of focusing on *firms'* currency exposures. On the other hand, investment strategies that use FX derivatives, such as the carry trade, are typically defined with respect to a currency cross, i.e., to go net-long a 'higher-interest-rate' country's currency and net-short a 'lower-interest-rate' country's currency. Thus, in order to investigate whether firms adjust derivatives positions in line with these FX investment strategies, we also consider firms' net currency-cross exposures.

Building on these definitions, we introduce a framework for decomposing firms' FX derivatives holdings into hedging and speculative components. Consider, for simplicity, a UK-based firm, whose currency of operation is the *GBP*, that trades only the $\{\text{USD}, \text{GBP}\}$ cross using one-period FX derivatives. The firm solves a two-period optimization problem, $t = \{0, 1\}$, in which the total profits of firm i in *GBP* are given by $\pi_1^i = \pi_{0,1}^{i,\text{FX,deriv}} + X_1^{i,H}$, with $X_1^{i,H}$ denoting the non-FX derivatives profits of firm i , which are potentially exposed to the *USD/GBP* exchange rate. If firm i is a financial institution, $X_1^{i,H}$ reflects profits from the rest of the investment portfolio. If, instead, firm i is a non-financial corporation, $X_1^{i,H}$ reflects its operating profit. Assuming that firm i has mean-variance preferences and takes $X_1^{i,H}$ as given (e.g., because FX derivatives decisions are operationally disjoint from the rest of the firm), then firm i solves the following optimization problem:

$$\max_{N_{0,1}^{i,\{\text{USD}, \text{GBP}\}}} \tilde{E}_0^i \left(\pi_{0,1}^{i,\text{FX,deriv}} + X_1^{i,H} \right) - \frac{\rho}{2} \text{Var} \left(\pi_{0,1}^{i,\text{FX,deriv}} + X_1^{i,H} \right),$$

where $\pi_{0,1}^{i,\text{FX,deriv}} = \left(S_1^{\text{GBP/USD}} - F_{0,1}^{i,\text{GBP/USD}} \right) N_{0,1}^{i,\{\text{USD}, \text{GBP}\}}$ and \tilde{E}_0^i denotes firm i 's expectations, which can be subjective or objective. Firm i 's optimal net $\{\text{USD}, \text{GBP}\}$ derivatives exposure is:

$$N_{0,1}^{i,\{\text{USD}, \text{GBP}\}} = \underbrace{\frac{\tilde{E}_0^i \left(S_1^{\text{GBP/USD}} - F_{0,1}^{i,\text{GBP/USD}} \right)}{\rho \text{Var}_0 \left(S_1^{\text{GBP/USD}} \right)}}_{\text{Spec}_{0,1}^{i,\{\text{USD}, \text{GBP}\}}} - \underbrace{\frac{\text{Cov}_0 \left(S_1^{\text{GBP/USD}}, X_1^{i,H} \right)}{\text{Var}_0 \left(S_1^{\text{GBP/USD}} \right)}}_{\text{Hedge}_{0,1}^{i,\{\text{USD}, \text{GBP}\}}}, \quad (3)$$

where we define $Spec_{0,1}^{i,\{USD,GBP\}}$ as the speculative component of firm i 's net FX derivatives exposure and $Hedge_{0,1}^{i,\{USD,GBP\}}$ as the hedging component.²⁰ The sign of $Spec_{0,1}^{i,\{USD,GBP\}}$ is governed by firm i 's expectations about how the future spot exchange rate will compare to their contract-specific forward rate. Intuitively, the speculative component does not depend on firm i 's profits from their non-derivatives investments. Instead, these non-derivatives profits determine the sign of $Hedge_{0,1}^{i,\{USD,GBP\}}$ via their covariance with the future spot exchange rate. The relative magnitude of these two components is a function of firm i 's risk aversion ρ , where lower risk aversion increases the relative size of the speculative component compared to the hedging component.

To gain further intuition, consider the following concrete examples. First, assume firm i is a UK investment fund that holds the US stock market in its non-derivatives portfolio. In this case, $X_1^{i,H}$ increases if the USD appreciates against the GBP, *ceteris paribus*, i.e., $\frac{Cov_0(S_1^{GBP/USD}, X_1^{i,H})}{Var_0(S_1^{GBP/USD})} > 0$. This covariance results in a hedging component of FX derivatives holdings in which firm i is net-short the USD. Such a position is profitable when the USD depreciates against the GBP, providing a hedge against the FX risk from firm i 's non-derivatives portfolio. If firm i 's position in the US stock market is persistent and its hedging demand for FX derivatives dominates its speculative demand, then we would expect firm i to be net-short the USD ($N_0^{i,\{USD,GBP\}} < 0$) over the whole sample.

Take now the example of a firm i , which is a non-financial corporation that operates in the UK (i.e., produces and pays wages primarily in the UK) and also, on net, exports to the US. As was the case for the UK investment fund, we would expect that $Hedge_{0,1}^{i,\{USD,GBP\}} > 0$, i.e., net-short the USD, if firm i 's USD exports are priced in USD. This is because the firm's operating profits $X_1^{i,H}$, which depend on its USD sales revenue and its GBP input costs, increase as the USD appreciates against the GBP. The opposite is true if firm i is a net importer from the US, with imports priced in USD. Since the speculative component of non-

²⁰Since firm i trades only the $\{USD, GBP\}$ cross and its currency of operation is the GBP , its net $\{USD, GBP\}$ currency-cross exposure $N_{0,1}^{i,\{USD,GBP\}}$ is equivalent to a net USD currency exposure $N_{0,1}^{i,USD}$.

financial corporations' FX derivatives positions are likely small (due to high risk aversion), and their net importer/exporter statuses and currencies of invoicing are relatively persistent, we would also expect non-financial corporates to have one-directional net currency exposures over the whole sample.²¹

In contrast, if firm i 's speculative demand, $Spec_{0,1}^{i,\{USD,GBP\}}$, dominates its hedging demand for FX derivatives, which might be the case if firm i is a financial firm with low risk aversion such as a hedge fund, we are unlikely to observe one-directional net currency derivatives exposures over the *whole* sample. This should be especially true for the currencies of advanced economies, for which it is rare to have persistent trends in nominal exchange rates that would show up in firms' exchange rate expectations and lead to persistent one-directional exposures for speculative reasons. Instead, we would expect that firms' overall currency exposure should fluctuate and change sign in response to changes in firms' expectations, reflecting classic FX investment strategies. We investigate this hypothesis in detail in Section 6.²²

3 Data

Turning to the data, this paper uses the UK segment of the European Market Infrastructure Regulation (EMIR) Trade Repository (TR) dataset of FX derivatives transactions, which we access via the Bank of England.²³ This data contains all FX derivatives (e.g., swaps, forwards and futures) transactions that have either a UK entity as a counterparty or that have an EU entity as a counterparty, provided that the transactions take place on a UK

²¹Interestingly, Garofalo et al. (2024) document a significant decrease (increase) in the extent to which UK non-financial firms invoice in GBP (USD) following the Brexit referendum. Our data will allow us to see whether this was accompanied by a similarly dramatic change in UK firms' USD/GBP exposures.

²²Online Appendix A.1 presents derivations for the general optimization problem with a firm that trades a range of currency crosses. The main difference is that the hedging component of the firm's FX derivatives holdings also include an "across" FX derivatives hedging term. This additional term takes into account that the firm might trade the $\{USD, GBP\}$ currency cross, for example, to hedge FX risk that arose from the trading of different currency crosses.

²³This data was collected under EU EMIR.

trading venue or include the GBP.²⁴ We retrieve these transactions from the two largest trade repositories for FX derivatives in the UK, Depository Trust & Clearing Corporation (DTCC) and UnaVista.²⁵

Our analysis is conducted at a daily frequency and at the firm-level. To construct our final dataset from the raw second-by-second transaction-level data, we use two types of TR files: (i) daily activity files, which record the flow of new transactions that occurred on a given date; and (ii) end-of-month state files, which contain all open transactions, i.e., transactions that have not yet matured, as of that date. Using these two types of files, we construct a list of cleaned transactions, as described in Online Appendix B.²⁶ We then aggregate each firms' transactions on a given day to construct a series of end-of-day firm-level variables. We discuss how we construct these firm-level variables throughout the paper.

Our daily firm-level analysis begins on January 1, 2015, except for banks, where it begins on July 1, 2016. Although EMIR commenced in early 2014, the data quality is not adequate for our analysis in the beginning of the sample due to the transition to EMIR reporting.²⁷ We also end our analysis on December 31, 2020. Due to the regulatory and reporting changes after the UK's exit from the EU, the data after December 31, 2020 ceases to include reporting by EU-based entities, affecting data coverage.

Finally, to facilitate our analysis, we manually classify individual firms into broad sectors and sub-sectors. The five broad sectors we consider are: (i) asset managers; (ii) non-financial corporates; (iii) insurance companies; (iv) (non-bank) market makers;²⁸ and (v)

²⁴As only one of the counterparties needs to be a UK or EU firm—and because the UK is the world's largest centre for currency trading—we also observe transactions involving non-UK and EU firms.

²⁵Having examined other TRs, we are confident our sample covers the vast majority of UK FX derivatives trading over our sample. Of note, UnaVista is now known as LSEG Regulatory Reporting Limited.

²⁶We have carefully cleaned the data and addressed the various data issues we detected, of which there were many, while still keeping as many transactions as possible. Figures B.1 and B.2 in the Online Appendix underscore the critical importance of data cleaning.

²⁷We detected data issues for banks in 2015 and the first half of 2016, which were not present for other types of firms, and so begin analyzing banks on July 1, 2016.

²⁸Within non-bank market makers are all agents that plausibly play a market-making role in FX derivatives market, namely, FCA-authorized market makers, FX brokers, FX services firms, clearinghouses and financial market administrators.

banks. Within the asset management sector, we consider three sub-sectors: hedge funds, investment funds and pension funds. Within the banking sector, we consider two sub-sectors: dealer and non-dealer banks. In addition, we also sort firms based on their country of residence. Online Appendix B.4 provides further details on our sector classifications.

4 Overview of the London FX Derivatives Market

To introduce the OTC FX derivatives market in the UK, we provide summary statistics on the market's participants, their transactions, and the market's average size over our sample.

4.1 Firms and Transactions

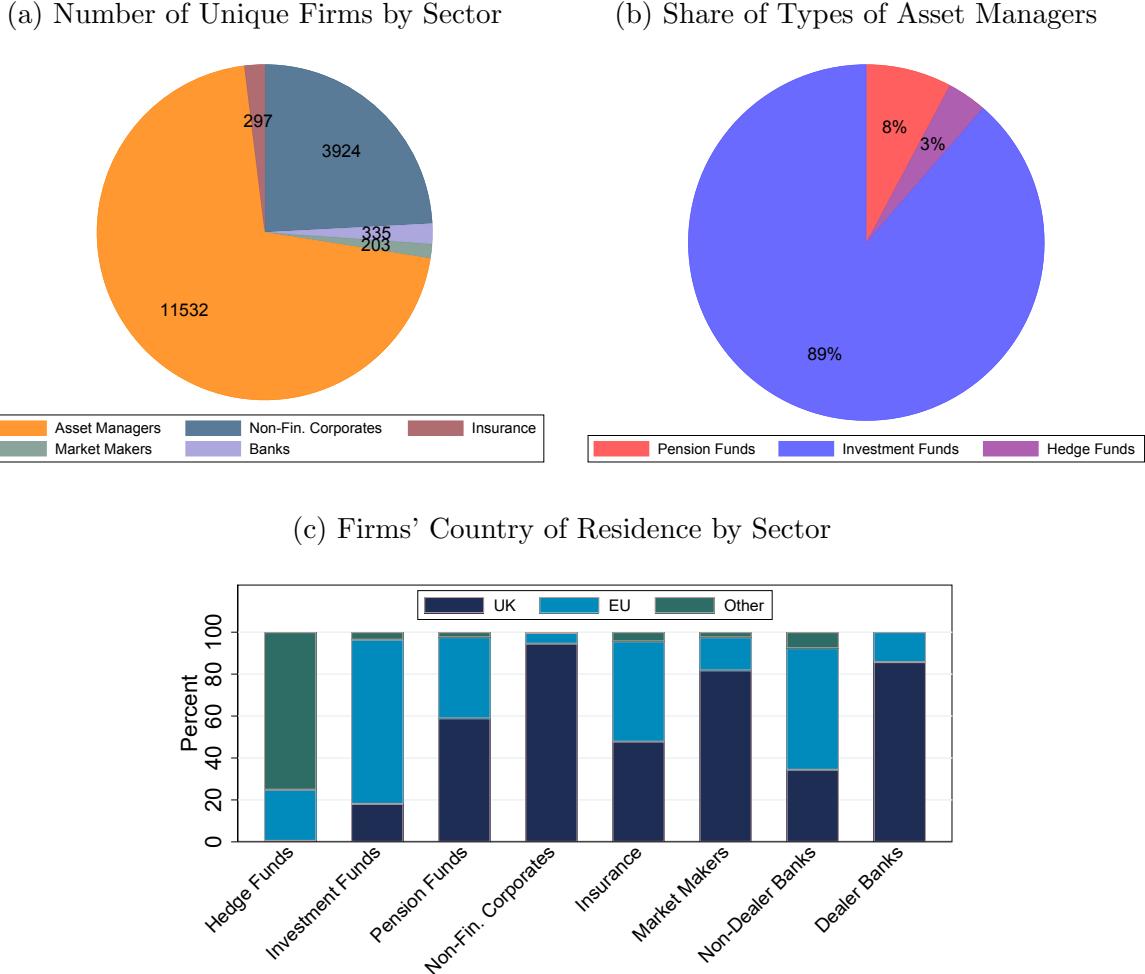
We begin by tabulating the number of firms in each sector that transact in the UK OTC FX derivatives market at least once over our six-year sample. Figure 1a summarizes the statistics, which highlight that asset managers make up roughly 70% of the over 16,000 individual firms that we observe.²⁹ The next largest segment are non-financial corporations, which make up close to 25% of all firms. The remaining 5% of firms are split roughly evenly between banks, insurance companies, and market makers. Within banks, we identify 21 dealers, with the remainder classified as non-dealer banks.

Investment funds are by far the most common type of asset manager trading FX derivatives (see Figure 1b), making up 89% of the 11,500 asset managers in our sample. Pension funds' share sits significantly lower at 8% while hedge funds' share is even lower at 3%. Overall, since the vast majority of FX derivatives transactions have a dealer bank or market maker on (at least) one side of the contract, these statistics showcase the significant asymmetry between the number of clients and dealers/market makers in the OTC FX derivatives market.³⁰

²⁹The entity of observation is at the fund-level, e.g., “Blackrock US Small Cap”, which is the level at which currency risk is managed, and -not at the institution-level, e.g., “Blackrock”.

³⁰Figure A.1 in the Online Appendix presents the number of firms in each sector trading FX derivatives in 4 “major” crosses. Figure A.2 presents the same for types of asset managers.

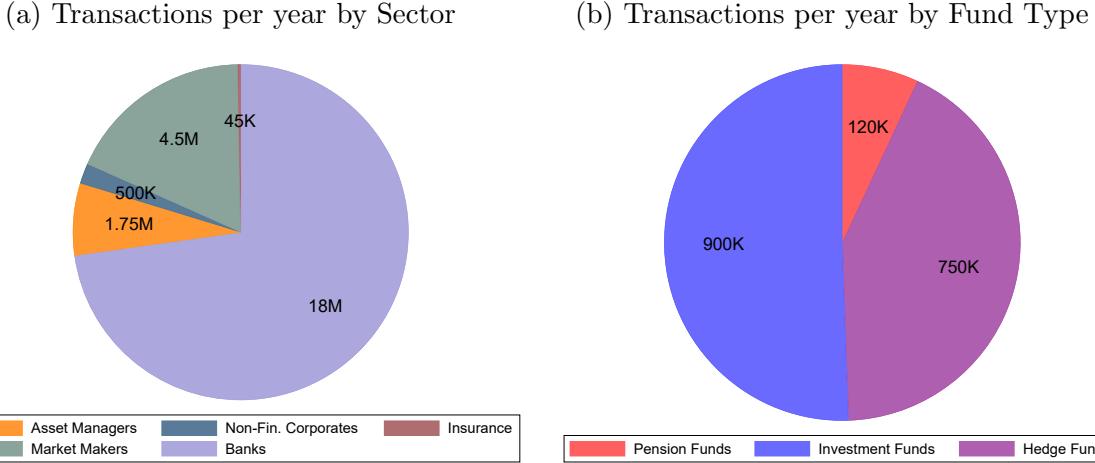
Figure 1: Firms in the UK FX Derivatives Market



Note. Number of unique firms in the UK FX derivatives market, by sector and type of Asset Manager, and their countries of residence. Firms included are those reporting under EMIR to the DTCC and UnaVista trade repositories between January 1 2015 (July 1 2016 for Banks) and December 31 2020.

Figure 1c sorts firms according to their country of residence. At one extreme, the vast majority of individual non-financial corporates, dealer banks and market makers in the UK FX derivatives market over our sample are UK-resident entities. At the other, over 2/3 of the individual investment funds and non-dealer banks in the UK market are resident in Europe. Lying in between are pension funds and insurance companies, whose countries of residence are split roughly evenly between the UK and EU. Interestingly, nearly 80% of the hedge funds in our sample are resident outside the UK and EU, with many in offshore tax havens. The significant share of non-UK entities in our sample highlights London's role as a

Figure 2: FX Derivative Transactions by Sector



Note. Average number of transactions per year across all currency-crosses and maturities, by sector and type of Asset Manager (i.e., type of fund). Firms included are those reporting under EMIR to the DTCC and UnaVista trade repositories between January 1 2015 (July 1 2016 for Banks) and December 31 2020.

global center for currency trading.

Moving from firms to their transactions, Figure 2a presents the yearly average number of FX derivatives transactions taken by all firms in each sector. The banking sector, as a whole, transacts 18 million times per year, on average, across all maturities and currency crosses, by far the most of any sector. This transaction volume is dominated by dealer banks (17 million per year). Market makers transact the second most, at about 4.5 million per year. Among clients, the asset management sector transacts the most, at nearly 2 million per year, followed by non-dealer banks (1 million per year), non-financial corporates (500 thousand per year) and insurance companies (50 thousand per year). Within the asset management sector, as shown in Figure 2b, the investment fund sector (900 thousand per year) and hedge fund sector (750 thousand per year) transact significantly more than the pension fund sector (120 thousand per year). On a per fund basis, however, individual investment funds and pension funds transact in similar amounts, whereas individual hedge funds transact over 20 times more frequently. That dealers transact significantly more than their clients showcases that the vast majority of transactions in the UK FX derivatives market occur between dealers.³¹

³¹In the Online Appendix, we break down each sector's and sub-sector's transactions by maturity (Figures A.3, A.4 and A.5) and currency-cross (Figures A.6, A.7 and A.8). We find that 80% of market makers'

4.2 Market Size

From firms and transactions, we next move to a notion of market size based on the *stock* of firms' net currency-cross derivatives exposures.³²

To calculate firm i 's net currency-cross stock exposure for the $\{k, m\}$ currency cross at time (end-of-day) t , we net-out, across all maturities, all of firm i 's transaction-level $\{k, m\}$ cross exposures from all non-expired FX derivatives contracts, indexed by μ , as of t :

$$Stock_t^{i,\{k,m\}} = \sum_{\mu: \tau_{start}^\mu \leq t < \tau_{end}^\mu} N_{\tau_{start}^\mu, \tau_{end}^\mu}^{\mu, i, \{k, m\}} + \sum_{\mu: \tau_{start}^\mu \leq t < \tau_{end}^\mu} \tilde{N}_{\tau_{start}^\mu, \tau_{end}^\mu}^{\mu, i, \{m, k\}}, \quad (4)$$

where $N_{\tau_{start}^\mu, \tau_{end}^\mu}^{\mu, i, \{k, m\}}$ and $\tilde{N}_{\tau_{start}^\mu, \tau_{end}^\mu}^{\mu, i, \{m, k\}}$ are defined in Section 2.³³ The start and end timestamps for a contract μ are τ_{start}^μ and τ_{end}^μ and are measured in seconds while the time index t is at a daily frequency and is measured end of day. Therefore, $Stock_t^{i,\{k,m\}}$ reflects the net amount of currency k that firm i will receive (or pay if negative) in the future from all non-expired FX derivatives contracts in the $\{k, m\}$ cross as of the end of day t .³⁴

To measure the size of the UK FX derivatives market, we examine the sum of firms' *absolute* net currency-cross stock exposures, in USD and averaged over time, for each sector S , which is given by $|\overline{Stock}|^{S,\{k,m\}} = \frac{1}{T} \sum_t S_t^{USD/k} \sum_{i \in S} |Stock_t^{i,\{k,m\}}|$. This variable represents a measure of sector S 's daily footprint in the market for $\{k, m\}$ FX derivatives in the UK based on how exposed firms in sector S are, on average, to the m/k bilateral exchange rate. The more firms there are in sector S , and the larger are these

transactions have a maturity of under 1 week, consistent with their use of high-frequency trading to limit the currency risk on their balance sheets. At the other extreme, non-financial corporations tend to have much longer investment horizons, with over a third of their FX derivatives transactions having maturities of longer than 3 months. The majority of asset managers', banks' and insurers' derivatives transactions have maturities between 1 week and 2 months. Although the EUR/USD, EUR/GBP and USD/GBP crosses have the highest transaction volumes, there is significant heterogeneity across sectors, with the share accounted for by these three crosses ranging from as high as 58% (non-financials) to as low as 16% (hedge funds).

³²Our measure of 'net market size' is constructed at the currency-cross level in order to compare with the 'gross market size' measure used by the BIS Triennial Survey.

³³In Section 2, we omitted the contract index μ since firm i traded only one contract in the $\{k, m\}$ cross.

³⁴To give a concrete example, to construct the net stock exposure on the 5th of January 2020, we consider all contracts that were entered into *prior* to the end of the day on the 5th of January 2020 and that are still open as of the end of the day on the 5th of January 2020.

firms' net stock exposures, the greater is sector S 's footprint. Summing across all currency crosses yields sector S 's average daily footprint in the UK FX derivatives market $|\overline{Stock}|^{S,FX,deriv} = \sum_{\{k,m\} \in \Omega^{cross}} |\overline{Stock}|^{S,\{k,m\}}$, where Ω^{cross} is the set of all currency crosses.³⁵ We refer to this quantity as sector S 's "Market Size" in Figure 3. Finally, summing over all sectors gives the average daily size of the entire UK FX derivatives market $|\overline{Stock}|^{FX,deriv} = \sum_S |\overline{Stock}|^{S,FX,deriv}$ based on firms' net currency-cross stock exposures.

Figure 3 showcases that, across all sectors and crosses, the average (absolute) size of the UK FX derivatives market in net terms, $|\overline{Stock}|^{FX,deriv}$, is about 3 trillion USD, far less than the 37 trillion USD gross figure quoted in Borio et al. (2022).³⁶ The large discrepancy between measures of the gross and net size of the UK FX derivatives market points to a substantial amount of long and short derivatives positions in the same currency cross at the same time for the same firm, most likely by dealer banks in the inter-dealer market.

In terms of the market sizes of individual sectors, $|\overline{Stock}|^{S,FX,deriv}$, the banking sector averages 2 trillion USD in absolute net stock exposure over our sample, the largest of any sector in the UK FX derivatives market. These stock exposures are taken predominantly by dealer banks (1.6 trillion USD see Figure A.10). This stands in marked contrast to market makers, who, despite their significant transaction volume, average only 10 billion USD in stock exposures over our sample. This highlights an important distinction between the behaviour of dealer banks and market makers in UK FX derivatives markets.³⁷

In terms of clients, asset managers have the largest footprint in FX derivatives markets, with absolute currency-cross net stock exposures averaging 600 billion USD, followed by non-

³⁵We ensure there is no double counting since if $\{k, m\} \in \Omega^{cross}$ then $\{m, k\} \notin \Omega^{cross}$ as the definition in equation (4) ensures that we consider both orderings when constructing our net stock exposure variable.

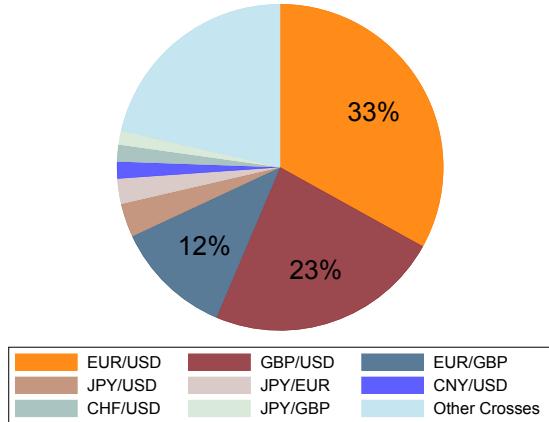
³⁶The latter value corresponds to the 97 trillion USD gross size of the global FX market in 2022 quoted by Borio et al. (2022), times the 38% UK market share quoted by the 2022 BIS Triennial Survey of FX Markets. The gross size is constructed by adding up the notional of all outstanding contracts across all firms, rather than netting contracts at the firm-level.

³⁷Note that we do not observe the FX derivatives positions of UK dealer banks in other jurisdictions, such as the US, and, as a result, do not observe dealer banks' global net exposure across all jurisdictions. In contrast, the non-bank market makers in our dataset are unlikely to have significant FX derivatives positions elsewhere, which explains their limited net exposures from contracts reported in the UK.

Figure 3: Average Absolute Value of Firms' Net Currency-Cross Stock Exposures by Sector

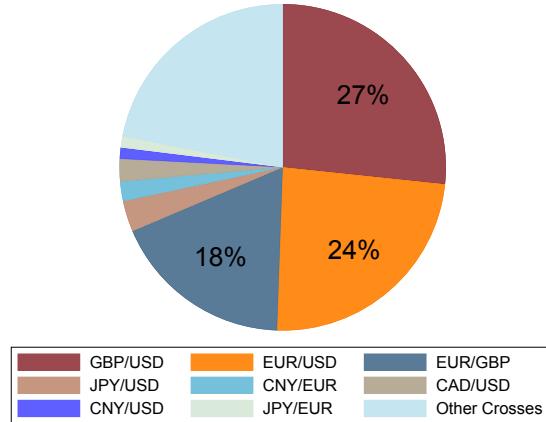
(a) Asset Managers

Market Size: 600 Billion USD



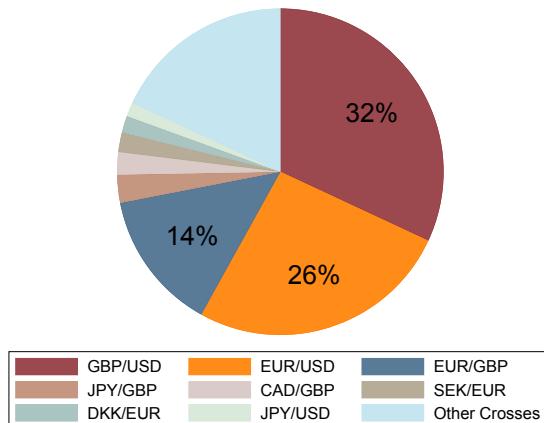
(b) Non-Financial Corporates

Market Size: 250 Billion USD



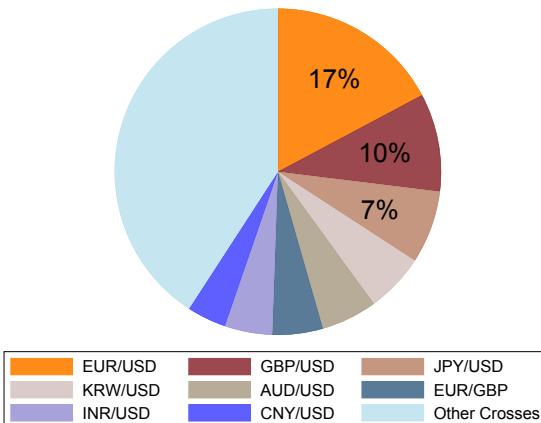
(c) Insurers

Market Size: 70 Billion USD



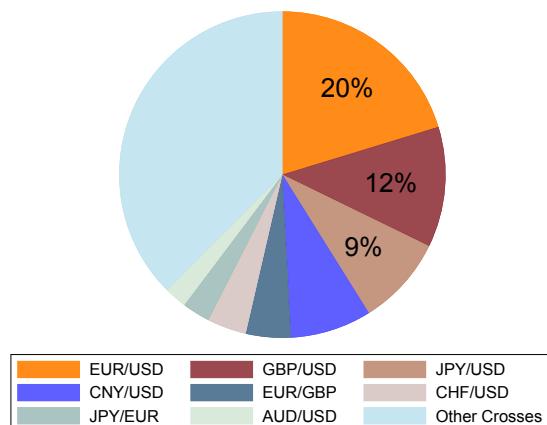
(d) Market Makers

Market Size: 10 Billion USD



(e) Banks

Market Size: 2 Trillion USD



Note. Average absolute value of firms' *net* currency-cross stock exposures in USD across all firms in a sector $|\overline{Stock}|^{S,\{k,m\}}$ and across all currency crosses $|\overline{Stock}|^{S,FX,deriv}$. Firms included are those reporting under EMIR to the DTCC and UnaVista trade repositories between January 1 2015 (July 1 2016 for Banks) and December 31 2020.

dealer banks (450 billion USD), non-financial corporates (250 billion USD), and insurance companies (70 billion USD). Within asset managers, as shown in Figure A.9, hedge funds have limited net stock exposure, averaging only 40 billion USD, despite their significant transaction volume. Investment funds, by contrast, have significant net stock exposures averaging nearly 350 billion USD, with pension funds lying in between at 200 billion USD.³⁸

Turning to the composition of sectors' FX market footprint, $|\overline{Stock}|^{S,\{k,m\}}$, the EUR/USD and GBP/USD crosses represent the two largest currency-cross markets, as measured by firms' net stock exposures, for all sectors. For asset managers, namely pension funds and investment funds, as well as non-financial corporates and insurers, the EUR/USD and GBP/USD crosses capture a majority of their sectors' overall net stock exposures, with shares ranging from 51% to 70%. By contrast, for banks, market makers and hedge funds, the share of sector-wide stock exposures accounted for by these two "major" crosses are smaller, ranging from only 27% to 34%, since these sectors take positions in a much wider array of currency crosses. Aside from these two major crosses, the EUR/GBP and JPY/USD crosses also represent a significant share of each sectors' overall net cross stock exposure. More generally, sectors' net cross stock exposures are dominated by crosses involving G7 currencies. In terms of emerging market currency crosses, the CNY/USD cross is the most prevalent, especially for banks and hedge funds, although these average figures are skewed by the large exposures that these sectors built up during the US-China trade war. Overall, differences in the currency-crosses traded across sectors may reflect differences in the size and currency denomination of their assets/liabilities as well as differences in the degree to which they use derivatives to hedge versus speculate.

³⁸Of note, the average absolute net cross exposures of dealers (1.6 trillion USD) and clients (1.3 trillion USD) need not be equal for two reasons: 1. dealers take cross exposures with other dealers; and 2. dealers take cross exposures with foreign entities, especially through intra-group transactions.

5 Currency Positions

This section documents a series of novel facts related to firms’ and sectors’ net *currency* stock exposures from FX derivatives. We focus on net currency exposures since firms’ profits and losses when trading FX derivatives depend on the net amount of, e.g., USD, they are set to receive or pay in the future, regardless of the underlying composition of trades across different currency crosses (see Section 2). This makes firms’ net currency stock exposures central in theoretical models.

Based on equation (2), firm i ’s net currency- l stock exposure is constructed by netting all of firm i ’s transaction-level currency-cross exposures from all non-expired contracts in which it receives or pays currency l :

$$Stock_t^{i,l} = \sum_{m \neq l} \left\{ \sum_{\mu: \tau_{start}^\mu \leq t < \tau_{end}^\mu} N_{\tau_{start}^\mu, \tau_{end}^\mu}^{\mu, i, \{l, m\}} + \sum_{\mu: \tau_{start}^\mu \leq t < \tau_{end}^\mu} \tilde{N}_{\tau_{start}^\mu, \tau_{end}^\mu}^{\mu, i, \{m, l\}} \right\}. \quad (5)$$

$Stock_t^{i,l}$ therefore measures firm i ’s net exchange-rate exposure to currency l from all FX derivatives contracts that remain open as of time t . To help interpret $Stock_t^{i,l}$ in the data, we leverage insights from our theoretical framework in Section 2, which showed that firms’ net currency exposures are comprised of a hedging component—which is often one-directional due to persistence in firms’ non-derivatives operations—and a speculative component—whose direction is likely to fluctuate over time due to changes in exchange-rate expectations.

5.1 Net Currency Stock Exposures

We begin by presenting sector-level net currency stock exposures, constructed by summing the positive and negative net stock exposures of firms in a given sector S , i.e., we report $Stock_t^{S,l} = \sum_{i \in S} Stock_t^{i,l}$. This variable captures how exposed sector-level aggregate profits from FX derivatives are to movements in the currency- l exchange rate (vis-à-vis the firms’ currencies of operation). Figures 4 and 5 display sector-level net currency stock exposures for the three major currencies traded in the UK: the USD, EUR, and GBP. We further break

down these sector-level net exposures into the net exposures taken by UK- and EU-resident firms, which are presented in Figures A.11 and A.12 in the Online Appendix.³⁹ Together, these figures reveal a number of noteworthy facts.

I. Direction

The first set of facts relate to the direction of firms' net currency stock exposures. The asset management sector—namely pension funds and investment funds—along with the insurance sector, always maintain a stock of net-long exposures to both the EUR and GBP and net-short exposures to the USD. Strikingly, these positions are highly stratified according to firms' country of residence: EU-based firms in these financial sectors carry net-long EUR and net-short USD exposures while UK-based firms hold net-long GBP and net-short USD exposures. Notably, EU- (UK-) based firms in these sectors retain minimal net exposure to the GBP (EUR)⁴⁰. Through the lens of our framework in Section 2, these one-directional net currency exposures are consistent with a strong hedging demand for FX derivatives. Specifically, these positions are consistent with the UK- and EU-based financial firms in these sectors holding persistent long positions in USD-denominated securities, with obligations indexed in either GBP or EUR, which they seek to hedge via FX derivatives.⁴¹

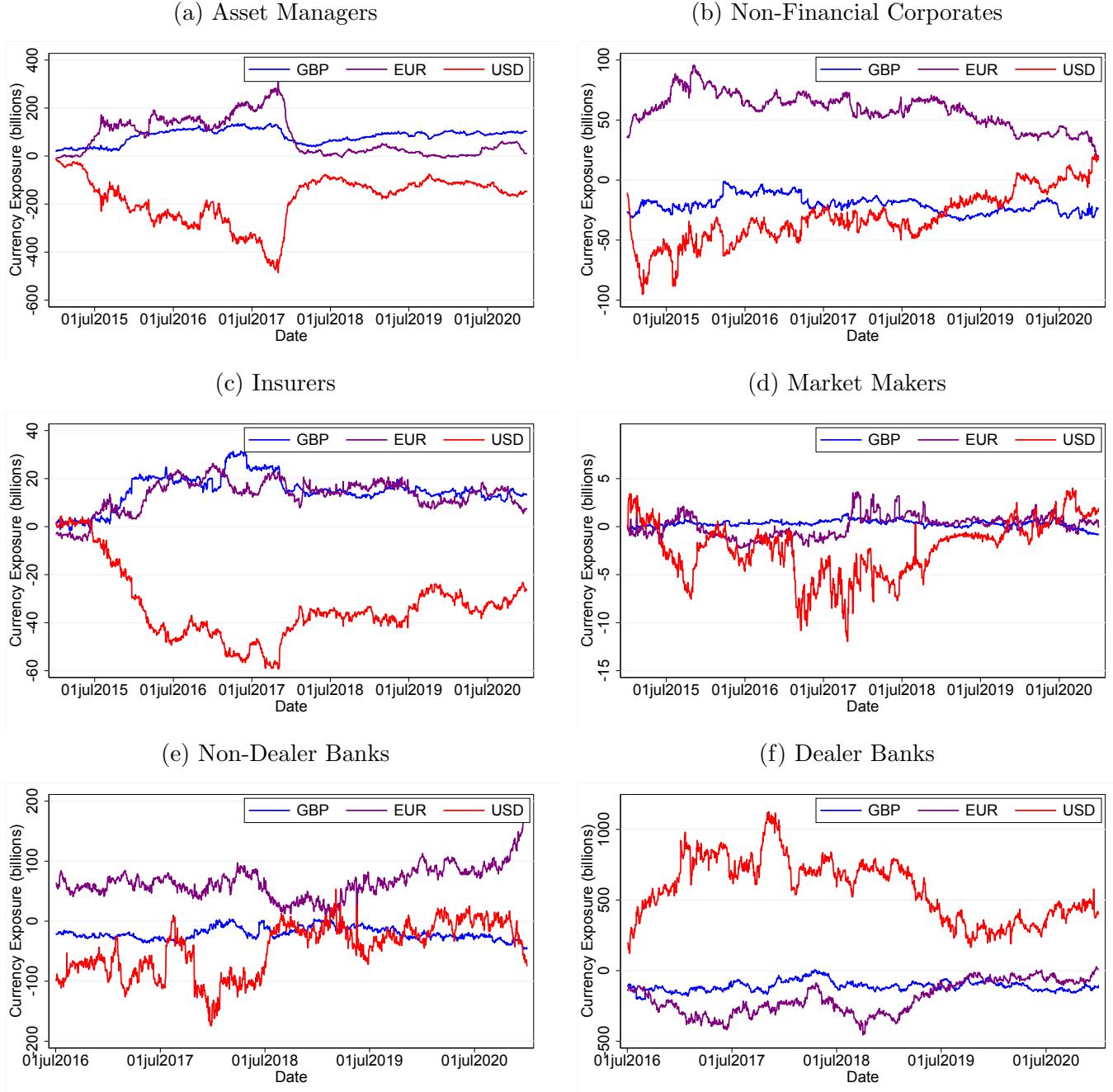
Turning to non-financial corporations, the sector is net-short the USD for most of the sample, net-long the EUR and, different to financial firms, net-short the GBP. Most of the non-financial sector's net-short USD exposure is held by EU-resident corporates, who are also commensurately net-long the EUR. These positions may once again be driven by hedging demand. Specifically, if EU corporates are net-exporters to the US and invoice US sales in USD, then they would hedge future profits from US sales by maintaining a stock of net-short

³⁹We present this decomposition by country of residence only for the client sectors, since there are too few market makers and dealer banks in some cases to preserve anonymity. Similarly, since there are very few UK hedge funds in our sample, we decompose the hedge fund sector's net exposures into the exposures by EU and non-EU hedge funds.

⁴⁰Maggiori et al. (2020) show that mutual funds are biased towards holding securities denominated in home currencies and in dollars, which is consistent with these findings.

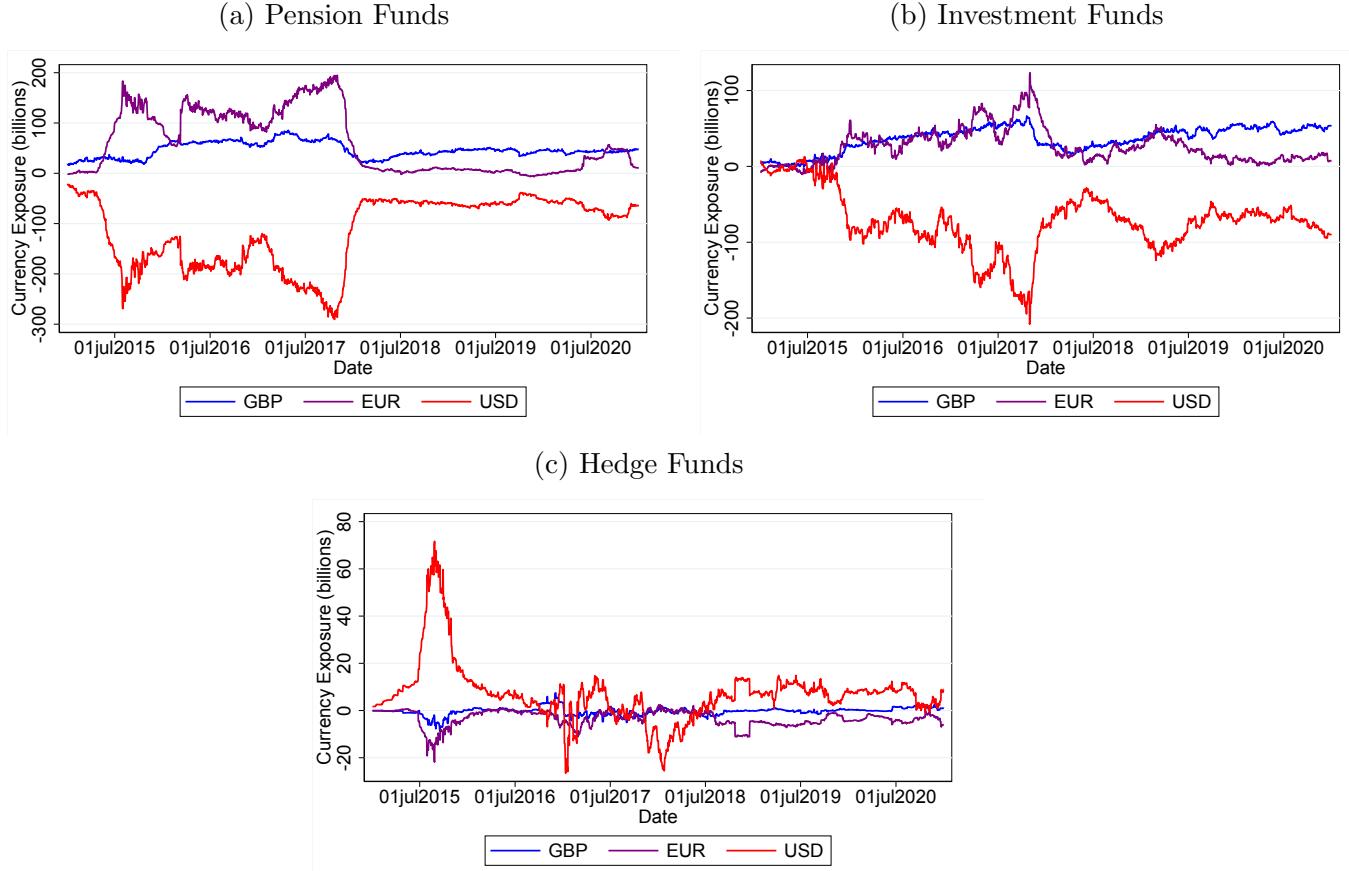
⁴¹Although the magnitudes are small, the UK asset management and insurance sectors are persistently net-short the EUR while their EU counterparts are persistently net-short the GBP. These one-directional exposures are also consistent with a hedge by these UK (EU) firms of their EUR (GBP) denominated assets.

Figure 4: Sector-Level Net Currency Stock Exposures to Major 3 Currencies



Note. Sector-level net currency stock exposures, calculated as the net currency stock exposure (see equation (5)) of firms in a particular currency vis-à-vis all other currencies and then aggregated across firms in a particular sector, for the major three currencies—USD, EUR, GBP. Currency exposures are measured in units of local currency (i.e., in GBP for GBP exposures). Firms included are those reporting under EMIR to the DTCC and UnaVista trade repositories between January 1 2015 (July 1 2016 for Banks) and December 31 2020.

Figure 5: Asset Manager Types' Net Currency Stock Exposures to Major 3 Currencies



Note. Types of asset managers' net currency stock exposures, calculated as the net currency stock exposure (see equation (5)) of firms in a particular currency vis-à-vis all other currencies and then aggregated across firms in a particular sector, for the major three currencies—USD, EUR, GBP. Currency exposures are measured in units of local currency (i.e., in GBP for GBP exposures). Firms included are those reporting under EMIR to the DTCC and UnaVista trade repositories between January 1 2015 and December 31 2020.

USD derivatives exposures. In terms of the other currencies, the corporate sector's net-short GBP exposure, as well as much of their net-long EUR exposure, can be rationalized by the hedging demand of both UK- and EU-resident non-financials. Specifically, UK-based corporates may be net-short the GBP and net-long the EUR to hedge the cost of future intermediate inputs imported from the Eurozone. Relatedly, EU-based non-financial firms may be net-exporters to the UK and choose to hedge their UK sales revenue, priced in GBP, by taking net-short GBP and net-long EUR derivatives exposures.

We next move to the currency positions of hedge funds and non-dealer banks. Different

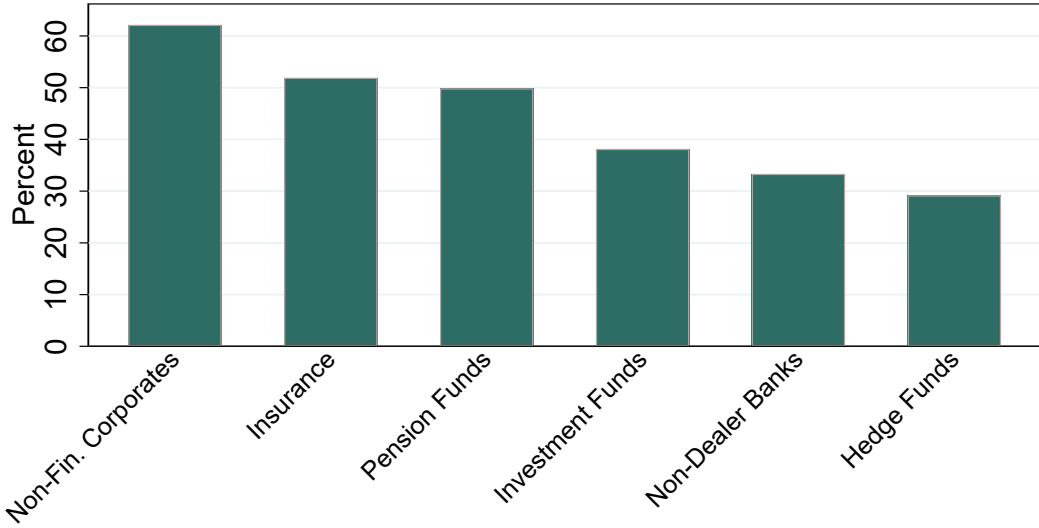
to the other sectors, hedge funds' net currency stock exposure to all three major currencies changes signs repeatedly over time. This may be due to frequent FX derivatives rebalancing in response to market developments, indicative of a stronger speculative demand for FX derivatives, as compared to hedging demand. For instance, hedge funds move to being net-long the USD at the start of the Fed hiking cycle in 2015, a period in which the USD appreciated. Similarly, non-dealer banks' USD exposure is also volatile and changes sign over our sample, which suggests that speculative demand may play a role for their overall FX derivatives positions as well. Interestingly, the direction of the net stock exposures taken by EU and non-UK hedge funds over time are similar. Conversely, the positions taken by UK and EU non-dealer banks are distinct, with EU-based entities' net exposures being more stable and one directional compared to those of UK-based entities. This suggests that hedging demand may be more prominent for EU-resident non-dealer banks than for UK-resident ones.

In the case of market makers, we would expect that if we observe all of their transactions, their net exposure should be very close to zero. This is precisely the case for the GBP. The net exposure with respect to the EUR is close to zero as well. However, their USD exposure sometimes deviate from zero, most likely due to us not observing some of their USD transactions, reported elsewhere. Having said that, the value of the market making sectors' net USD stock exposure is generally below 10 billion USD, despite the tens of thousands of daily transactions we document for market makers.

In contrast to these other sectors, the 21 large dealer banks in our sample are net-long the USD and net-short the EUR and GBP. Dealer banks therefore appear to be the primary sector accommodating clients' FX derivatives demand in the UK market by taking the complementary net currency stock exposures.

Importantly, due to potential within-sector heterogeneity in firms' FX derivatives use, sector-level net exposures may obscure whether individual firms' net exposures are one-directional or change signs frequently over time. To address this, Figure 6 presents the

Figure 6: Share of Firms with Persistent ($> 95\%$ of sample) One-Directional USD Exposures



Note. Figure 6 presents the share of firms in each sector that maintain the same one-directional (either net-long or net-short) USD stock exposures over at least 95% of the sample, for the six client sectors. Firms included are those reporting under EMIR to the DTCC and UnaVista trade repositories between January 1, 2015 (July 1 2016 for Banks) and December 31, 2020.

fraction of individual firms in each client sector that maintain the same one-sided (either net-long or net-short) USD stock exposures over the vast majority (at least 95% of the days) of our sample.

We find that over 60% of individual non-financial corporates and over 50% of individual insurers and pension funds maintain the same one-sided exposures to the USD over at least 95% of our sample. This is consistent with strong one-directional hedging demand by the majority of individual firms in these sectors. On the other hand, fewer than 30% of individual hedge funds and about one third of individual non-dealer banks maintain the same one-directional USD net exposures over our 95% of our sample. This suggests that speculative demand may play a larger role in these sectors' FX derivatives use. Lying in between are individual investment funds, with a share of just short of 40%, suggestive of more heterogeneity in the motives behind firms in this sectors use. Overall, these firm-level findings are in line with the conclusions from our sector-level analysis. Moreover, they suggest, through

the lens of our model, that the non-financial sector is comprised of the greatest fraction of ‘pure’ hedgers, while the hedge fund sector is comprised of the greatest fraction of ‘pure’ speculators.

II. Magnitude

The second set of facts relate to the magnitude of sectors’ net currency stock exposures. Over our sample, the asset management sector’s net currency stock exposure is significantly larger than those of the other client sectors. At its peak in 2017Q3, asset managers as a whole had a net-short position in the USD of just under 450 billion USD—reflecting the roughly 250 and 200 billion USD net-short positions by pension funds and investment funds, respectively. They were, in this period, also net-long the EUR and GBP to the tune of 300 billion EUR and 110 billion GBP, respectively. By comparison, non-financial corporates’, non-dealer banks’ and insurers’ net currency exposures are smaller. In the case of corporates and non-dealer banks, as we document in the next sub-section, the sector’s relatively small net currency exposure, as compared to their absolute exposures displayed in Figure 3, reflects significant within-sector heterogeneity in the direction of firms’ currency derivatives use.

While dealer banks absorb UK clients’ net currency demand, the two groups’ currency exposures are not equal and opposite to one another, pointing to substantial cross-border leakage from the UK FX derivatives market. For example, in 2017Q3, dealer banks have a net-long USD exposure of over 1 trillion USD, whereas all other sectors combined have a net-short USD position of less than 700 billion USD. This discrepancy is due to dealer banks’ transactions with foreign entities, in particular, with their foreign headquarters and/or subsidiaries. These intra-group transactions allow dealer banks to manage their currency exposures while continuing to meet USD hedges demanded by other sectors.

III. Patterns and Trends

The third set of facts relate to patterns in sectors’ net currency stock exposures over time. The asset management sector’s net USD and EUR stock exposures decrease dramatically

from 2017Q3 to 2018Q1, shrinking from -450 billion to -100 billion USD and from 300 billion to 30 billion EUR, respectively. While their net USD exposures partially rebound to near -200 billion USD, their net EUR exposures do not. The sector's net GBP exposure declines as well, although more mildly, before fully rebounding. As can be seen in Figure 5, about 70% of the initial decline comes from a reduction in pension funds' net exposures, with the remainder due to a fall in investment funds' net exposures. Beginning a year later, we also observe a significant but more gradual decline in the net USD and EUR exposures of non-financial corporates and dealer banks, although these are not accompanied by movements in their GBP exposures.

To interpret these trends, we decompose these sectors' net currency exposures by firms' country of residence, as well as by firms' size, in order to help distinguish between the intensive and extensive margins of adjustment. Beginning with pension funds, we observe that about 70% of the decline in this sector's USD net exposures can be attributed to the departure of a handful of very large European pension funds from our sample over this period (see Figures A.12 and A.20).⁴² This extensive margin adjustment cuts the European pension fund sector's net EUR exposure in the UK derivatives market to near zero in early-2018.

The remaining 30% of the decline in pension funds' USD net exposures, as well as most the decline in the sector's GBP net exposures, comes from UK pension funds along the intensive margin (see once again Figures A.12 and A.20). UK pension funds may have had an incentive to build up larger net exposures in 2016 and 2017 as a hedge against greater economic uncertainty in the UK—tied to the Brexit referendum—and in the US—tied to the presidential election—which they then unwound from 2017Q3 to 2018Q1.

A similar pattern is present for the investment fund sector: about 70% of the decline in the sector's net USD exposure reflects reduced exposures by EU investment funds—including by the largest funds—with the remaining 30% due to reduced exposures by UK

⁴²To assess the contribution of the departure of large funds, Figure A.20 separately aggregates the exposures of funds that are net-long and net-short as well as highlights the net exposures taken by the largest funds, as outlined in the next Section 5.2.

investment funds, mostly along the intensive margin (see Figures A.12 and A.21). The intensive-margin adjustment may once again reflect the unwinding of net exposures built up during the period of heightened geopolitical risk in 2016-2017. Interestingly, UK investment funds' net exposures, especially with respect to the GBP, rebound following their trough in 2018Q1.

Turning to non-financial corporates, we observe that the erosion of their USD and EUR net exposures can be almost entirely attributed to a reduction in exposures by EU-based entities (see Figures A.11 and A.18). In terms of dealer banks, the decline in their USD and EUR net exposures occurs predominantly via the EUR/USD currency cross.⁴³ In both cases, while these sectors' USD and EUR net exposures decline considerably, we do not observe any changes in their net GBP exposures.

In all, these patterns are consistent with the reduction of EUR trading and the departure of EU-based entities from the UK FX derivatives market in anticipation of Brexit-related regulatory changes, which eventually came into effect at the end of 2020.

5.2 Heterogeneity and Concentration

Next, we leverage our firm-level data to examine within-sector heterogeneity and concentration in firms' currency derivatives net stock exposures. Relative to the previous section, rather than netting out the positive and negative currency stock exposures across firms in a sector, we separately aggregate the exposures of firms who are net-long and net-short particular currencies to generate sector-level net-long and net-short currency stock exposures. Specifically, we construct $Stock_t^{S_t^+, l} = \sum_{i \in S_t^+} Stock_t^{i, l}$ and $Stock_t^{S_t^-, l} = \sum_{i \in S_t^-} Stock_t^{i, l}$, where S_t^+ and S_t^- correspond to the set of firms in sector S that are net-long and net-short currency l at time t , respectively. This enables us to explore within-sector heterogeneity in the direction and magnitude of firms' currency exposure.

⁴³Figures A.24 and A.25 in the Online Appendix present sector-level net *currency-cross* stock exposures for the major crosses. Figures A.26 and A.27 do the same broken down by firms' country of residence.

Furthermore, to investigate within-sector concentration in firms' currency derivatives positions, we also distinguish the positions taken by the largest firms in each sector—those with the largest sample-average absolute net stock exposures—from those taken by smaller players. Specifically, we decompose, e.g., $Stock_t^{S_t^+, l}$ into the exposures of three mutually exclusive groups denoted by $Stock_t^{S_t^{+,m}, l}$, where $m \in \{5 \text{ Largest Players}, \text{Next } 10 \text{ Largest Players}, \text{Smaller Players}\}$, with $Stock_t^{S_t^-, l}$ decomposed analogously.⁴⁴

Sectoral net-long and net-short USD stock exposures, broken down by firm size, are displayed in Figures 7 and 8. The corresponding figures for the EUR and GBP are shown in Figures A.13 – A.16 in the Online Appendix. Figures A.17 — A.23 in the Online Appendix further break down the sectoral net-long/short exposures by firms' countries of residence.⁴⁵

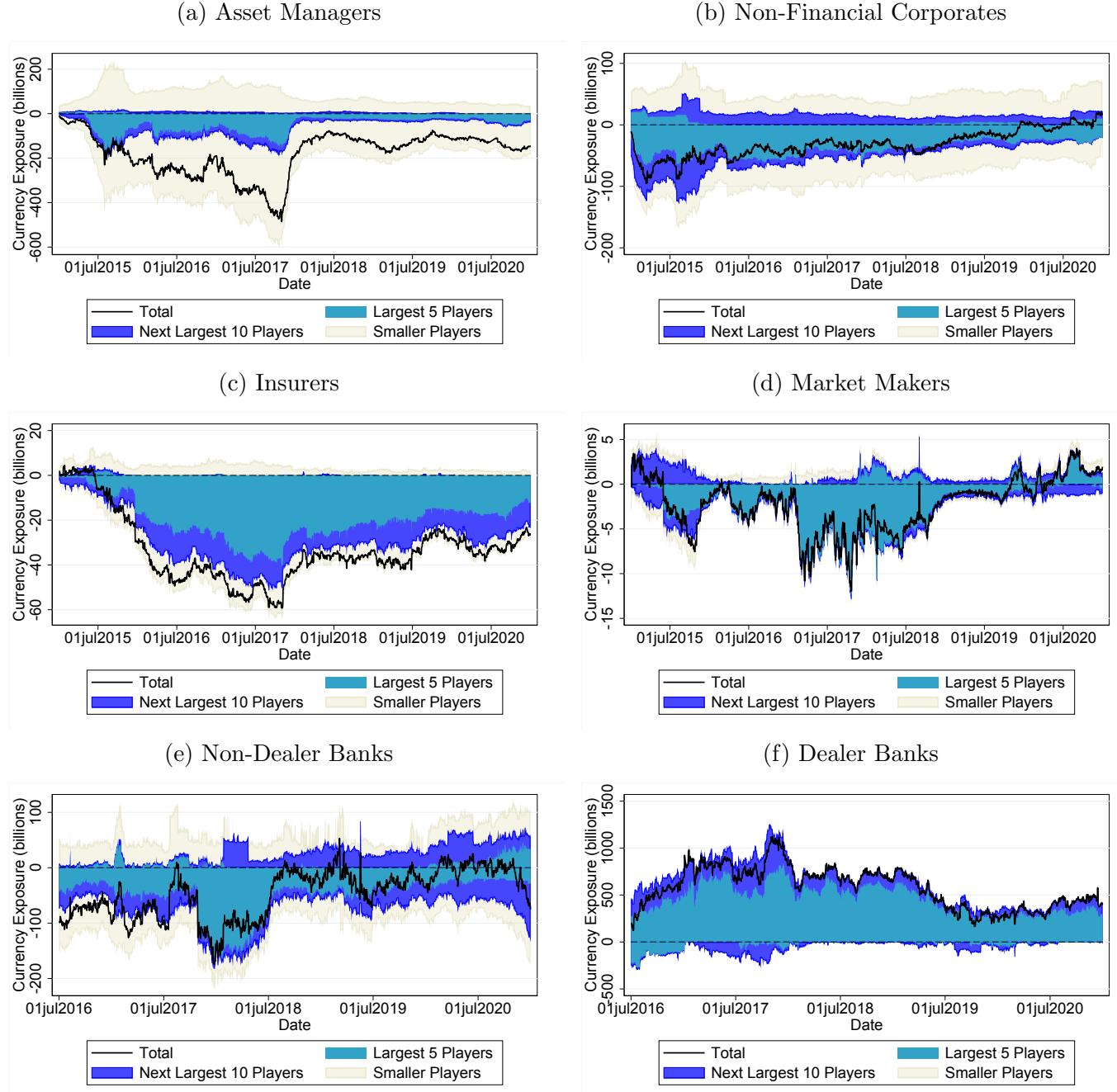
I. Concentration

We document significant levels of concentrations for most sectors. In particular, the dealer bank, market maker and insurance sectors are all highly concentrated, both as a whole as well as broken down by firms' countries of residence. At the most extreme in terms of concentration is the dealer bank sector, which also holds the largest net exposure. In absolute value, the five largest dealer banks (light blue) hold on-average about 90% of the sector's entire USD net stock exposure. In contrast, the investment fund industry is significantly less concentrated than other sectors, as seen by the relatively small share of the sector's overall USD, EUR and GBP net stock exposures maintained by the largest 5 (and next largest 10) players, which are shaded in light (dark) blue. This result holds for both UK and EU investment funds. The corporate sector's net stock exposures are also distributed relatively evenly across firms, although this result is driven entirely by UK-based non-financials. Similarly, while the net stock exposures taken by the UK pension fund sector

⁴⁴For example, $S_t^{+,5 \text{ Largest Players}}$ is the aggregated net-long currency- l stock exposure at time t of firms in sector S that are among the 5 Largest Players in sector S in terms of sample-average absolute net stock exposure in currency l .

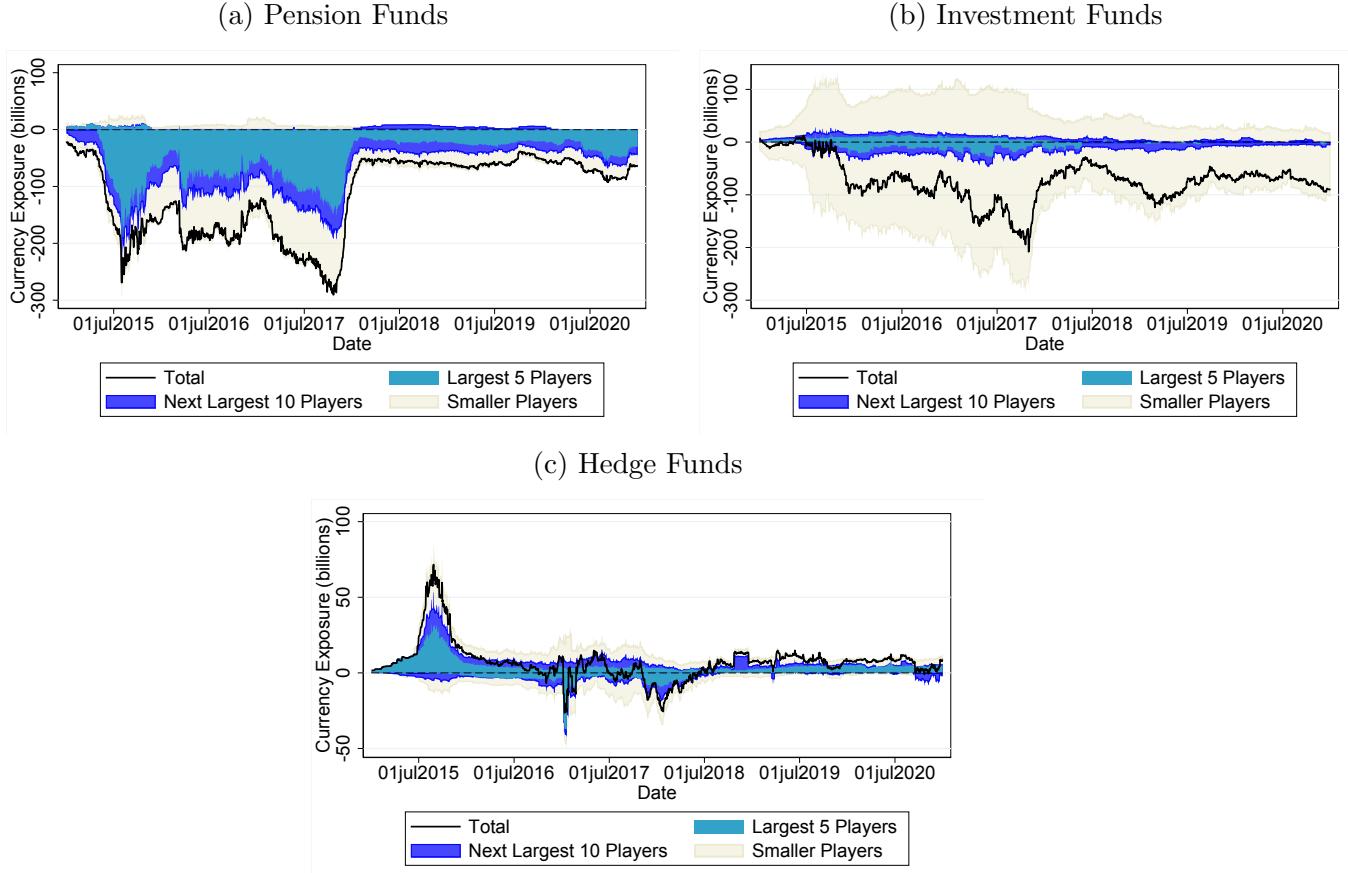
⁴⁵Figures A.28–A.36 in the Online Appendix present sectoral net-long/short *currency-crosses* stock exposures for the major crosses, again distinguishing between large and small players. Figures A.37-A.43 do the same broken down by firms' country of residence.

Figure 7: Firms' Net-Long and Net-Short USD Stock Exposures Across Sectors



Note. Sectoral net-long and net-short USD stock exposures, highlighted in blue and beige, are calculated by separately aggregating the net stock exposures of firms in a sector that are net-long and net-short the USD vis-à-vis all other currencies. The black line refers to the sum of the net-long and net-short USD stock exposures, which is shown in Figure 4. Shaded in light and dark blue are the net-long and net-short positions of the largest 5 and next largest 10 firms (players) in the sector in terms of average net USD stock exposure over the sample. In beige are the exposures of the smaller firms. USD stock exposures are measured in units of USD. Firms included are those reporting under EMIR to the DTCC and UnaVista trade repositories between January 1, 2015 (July 1 2016 for Banks) and December 31, 2020.

Figure 8: Firms' Net-Long and Net-Short USD Stock Exposures Across Fund Types



Note. Types of asset managers' (funds') net-long and net-short USD stock exposures, highlighted in blue and beige, are calculated by separately aggregating the net stock exposures of firms in a sector who are net-long and net-short the USD vis-à-vis all other currencies. The black line refers to the sum of the net-long and net-short USD stock exposures, which is shown in Figure 5. Shaded in light and dark blue are the net-long and net-short positions of the largest 5 and next largest 10 firms in the sector in terms of average net USD stock exposure over the sample. In beige are the exposures of the smaller players. USD stock exposures are measured in units of USD. Firms included are those reporting under EMIR to the DTCC and UnaVista trade repositories between January 1, 2015 and December 31, 2020.

are less concentrated, the EU pension fund sector's net positions are attributable to only a handful of large firms. The opposite is the case for non-dealer banks, where UK-based firms' exposures are more concentrated than those of their EU-resident counterparts. This pattern of high concentration suggests that counterparty and operational risks are likely sizable in the market, which raises important issues for financial stability.

II. Heterogeneity

We observe considerable heterogeneity in the direction of individual asset managers',

corporates' and non-dealer banks' net stock exposures. The heterogeneity in asset managers' net exposures is primarily due to investment funds. As a result, while the net USD stock exposure of the asset management industry peaks at around -450 billion USD, the sum of the absolute value of individual funds' net-short and net-long stock is nearly 750 billion USD, reflecting short positions of 600 billion USD and long positions of 150 billion USD. This cross-sectional heterogeneity in the direction of asset managers'—namely, UK and EU investment funds'—USD positions may reflect differences across funds in the currency denomination of their assets/liabilities or the extent to which they use derivatives to hedge vs. speculate. A similar pattern is present for non-dealer banks. Non financial corporations are likely to have different hedging needs depending on whether they are EU or UK firms, importers or exporters.

In contrast, there is limited within-sector heterogeneity in the direction of UK and EU pension funds' and insurance companies' net exposures. This may reflect within-sector similarities in firms' non-derivatives portfolios alongside strong hedging demand.

6 FX Market Adjustment

6.1 Speculative Demand and Investment Strategies

The previous section studied patterns in the cross-section and time series of firms' net currency stock exposures, which primarily shed light on the hedging component of firms' FX derivatives use by sector and country of residence. In this section, we shift focus to the speculative component of firms' FX derivatives demand by examining how firms adjust their exposures "on the margin" with respect to three well-known FX investment strategies: the carry trade, momentum and a strategy based on the arrival of exchange-rate-relevant macroeconomic news.⁴⁶ Our unique dataset allows us to focus on the behaviour of *all market participants*, so that our findings also shed light on how the market equilibrates as speculative

⁴⁶See e.g. Burnside et al. (2011), Lustig et al. (2011) and Stavrakeva and Tang (2024).

demand changes.

Our empirical analysis is once again motivated by the theoretical framework outlined in Section 2, which showed that firms' FX derivatives demand is comprised of a hedging component and a speculative component. In particular, equation (3) expressed the speculative component of firms' FX derivatives demand as a function of their expected excess return. These expectations, and hence firms' net exposures, may load on classic FX investment strategies.

To evaluate this, we use firms' net *currency-cross* stock exposures, defined in equation (4), since FX investment strategies are defined with respect to a currency cross. We focus on the net exposures of the most-traded currency crosses in our dataset, namely, the EUR/USD, GBP/USD, EUR/GBP and JPY/USD. For a given currency cross $\{m, k\}$ and a series of horizons (days) $h = [0, 90]$, we estimate three sets of firm-level panel regressions, by sector, to assess the extent to which the net cross exposures of firms in a given sector adjust in ways consistent with the three FX investment strategies. Each set of regressions estimates:

$$\frac{Stock_{t+h}^{i,\{m,k\}} - Stock_{t-1}^{i,\{m,k\}}}{|Stock_t^{i,\{m,k\}}|} = \alpha_i^h + \beta^h Z_{t+h}^{m,k} + u_{i,t}^h, \quad (6)$$

where, as before, $Stock_t^{i,\{m,k\}}$ is firm i 's net currency-cross stock exposure in cross $\{m, k\}$ defined such that an increase corresponds to a greater net-long (short) stock exposure to currency m (k). The change in exposure is scaled by the sample-average absolute firm-level net exposure, $\overline{|Stock_t^{i,\{m,k\}}|} = (1/T) \sum_t |Stock_t^{i,\{m,k\}}|$. We winsorize the dependent variable at the 1% and 99% levels to remove outliers. α_i^h is a firm fixed effect and we examine horizons $h = [0, 90]$ (days) to capture the fact that firms may re-balance over different horizons. In each set of regressions, $Z_{t+h}^{m,k}$ is a variable that defines the FX investment strategy in terms of country m and k observables, as outlined below.

It is important to point out that the hedging component of firms' FX derivatives holdings are subsumed in the residual $u_{i,t}^h$. This implies that estimates of β^h will capture both

speculative trading in line with the given FX investment strategy and co-movement between firms' hedging demand and the variable $Z_{t+h}^{m,k}$.

I. Carry Trade

Given the well-known forward premium puzzle, firm i may expect to earn a positive excess return from an investment strategy in which they go net-long a 'higher-interest-rate' country's currency and net-short a 'lower-interest-rate' country's currency. In other words, firm i may believe that $\tilde{E}_t^i \left(S_{t+h}^{k/m} - F_{t,h}^{i,k/m} \right)$ is increasing in the country m versus k interest rate differential, $r_t^m - r_t^k$. This implies the following specification:

$$Z_{t+h}^{m,k} = (r_{t+h}^m - r_{t+h}^k) - (r_{t-1}^m - r_{t-1}^k)$$

We use 10-year nominal government bond yields to measure interest rate differentials in our baseline, but find similar results when using 1-year nominal government bond yields.

As a concrete example, consider the EUR/USD cross where $m = USD$ and $k = EUR$. Firms speculating based on the carry trade strategy on the margin would increase their net-long (net-short) stock exposure to the USD (EUR), through the EUR/USD cross, as US interest rates rise relative to German yields. This will result in a positive β^h . A negative β^h would imply the accommodation of speculative demand, which may reflect a reflect a covariance between interest differentials and the hedging component of firms' FX derivatives demand.

II. Momentum

Another well-known FX investment strategy is momentum, where firm i may expect that if one currency has appreciated against another over the past month, it will continue appreciating in the future in excess of the forward rate, i.e., $\tilde{E}_t^i \left(S_{t+h}^{k/m} - F_{t,h}^{i,k/m} \right)$ may be increasing in the log exchange rate change, $s_t^{k/m} - s_{t-30}^{k/m}$. This implies a specification with:

$$Z_{t+h}^{m,k} = (s_{t+h}^{k/m} - s_{t-30+h}^{k/m}) - (s_{t-1}^{k/m} - s_{t-30-1}^{k/m})$$

Considering an example with $m = USD$ and $k = EUR$, firms that trade on a momentum FX strategy will increase their net-long derivatives positions in the USD and their net-short positions in the EUR as the 30-day USD appreciation against the EUR grows. This results in a positive β^h . Conversely, if firms take a “reversal” investment strategy of decreasing their net-long (net-short) USD (EUR) derivatives exposure as the USD’s appreciation against the EUR grows, we would see a more negative β^h . Again, however, a negative β^h would imply the accommodation of speculative demand, which is more likely tied to firms’ hedging demand.

III. FX Macro News

Lastly, we consider how firms adjust their FX derivatives exposures based on the arrival of macroeconomic news that move exchange rates. Specifically, firm i ’s expectation for future exchange rate movements, $\tilde{E}_t^i \left(S_{t+h}^{k/m} - F_{t,h}^{i,k/m} \right)$, may be related to contemporaneous and lagged macro news surprises, with each surprise defined as the difference between the actual value released for a macroeconomic variable, such as GDP, unemployment or inflation in country k or m , and the consensus expectation for that variable from survey responses. To examine how firms adjust their net FX derivatives exposures in response to macro news relevant for exchange rates, we adopt the following specification:

$$Z_{t+h}^{m,k} = \mathbf{FXMacroNews}_{t-1,t+h}^{m,k}$$

where $\mathbf{FXMacroNews}_{t-1,t+h}^{m,k}$ is an aggregate between dates t and $t + h$ of a daily FX macroeconomic news index. Similar to Stavrakeva and Tang (2024), this FX macroeconomic news index is the fitted value from the following daily regression:

$$\Delta s_t^{k/m} = \alpha + \gamma \mathbf{MacroSurp}_t + \varepsilon_t,$$

where $\mathbf{MacroSurp}_t$ contains contemporaneous and lagged macroeconomic surprises.⁴⁷ As this FX macroeconomic news index explains 50-60% of monthly and quarterly exchange

⁴⁷We use the lag structure $\{0, 1, 2, 30, 60, 90, 120, 150, 180\}$ for the macro surprises in the estimation, where if a macroeconomic surprise is not present on a given date, we use the latest available surprise. For the full list of macro surprises, see section B.5 in the Online Appendix.

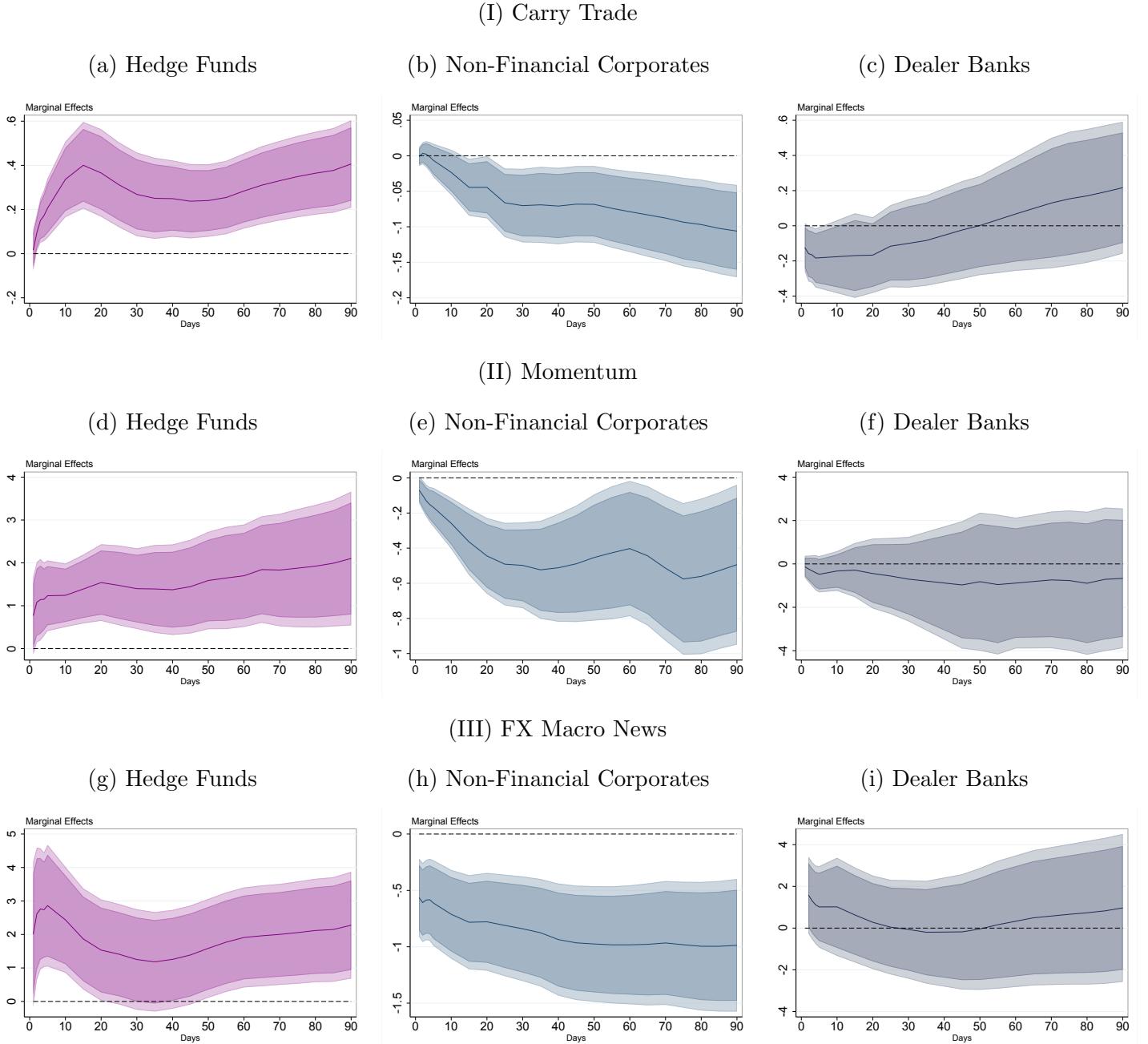
rate movements (Stavrakeva and Tang, 2024), it may correlate with firms’ exchange-rate expectations.

Taking the $m = USD$ and $k = EUR$ example, firms may adjust their FX derivatives demand in a way that propagates macro news to exchange rates by increasing their net-long stock exposure to the *USD* vis-à-vis the *EUR* over the same period in which US and Euro-area macro news appreciates the *USD* against the *EUR*. Such behavior would result in a positive β^h . Conversely, if firms adjust FX derivatives exposure in a manner contrary to the transmission of macro news to exchange rates, then this would push β^h to be negative—thereby accommodating speculative trading—which may be due to firms’ hedging demand.

Adjusting Net FX Derivatives Exposures “On the Margin” Figure 9 presents results by sector from estimating regression (6) in the EUR/USD cross for each of the three FX investment strategies. In particular, Figure 9 displays results for three sectors—hedge funds, non-financial corporates and dealer banks—since, as we discuss below, these three sectors define three distinct patterns of “on-the-margin” adjustment, with the other sectors’ behavior aligning—albeit less consistently across the different strategies and currencies—into one (or more) of these patterns. The results for the other sectors and other crosses, which we discuss in this section as well, are displayed in the Online Appendix A.4. By studying the adjustment of all sectors, we can shed light for the first time on how net exposures equilibrate across the entire FX derivatives market in response to moves in interest rates, exchange rates and macro news.

First, we find clear and robust evidence that hedge funds adjust their net derivatives exposures in line with the carry trade, momentum and macro-news FX investment strategies, with their positive rebalancing coefficients evident across almost all adjustment horizons up to 1 quarter. Furthermore, these FX adjustments hold not only for the EUR/USD cross but also for the GBP/USD, JPY/USD and EUR/GBP crosses as well (see Figures A.44 –A.46). Given that FX derivatives hedging demand is likely second order for hedge funds, these

Figure 9: Investment Strategies and Changes in Firms' EUR-USD Derivatives Exposure



Note. Figure 9 presents the β^h 's for $h \in [0, 90]$ from estimating firm-level panel regressions (6) for three FX investment strategies—Carry Trade (Row I), Momentum (Row II) and FX Macro News (Row III)—for 3 sectors—hedge funds, non-financial corporates and dealer banks—in the EUR/USD currency cross. Results for the remaining sectors and crosses are in Appendix A.4. Inner and outer shaded areas correspond to 90% and 95% confidence intervals constructed using two-way clustered standard errors by firm and time.

estimated coefficients predominantly reflect changes in hedge funds' speculative demand for FX derivatives in response to changes in interest differentials, exchange rates and macro

news. Importantly, by adjusting their exposures in a manner consistent with exchange rate anomalies—i.e., the forward premium puzzle à la Fama (1984)—and with the strong relationship between exchange rates and macro news (see Stavrakeva and Tang, 2024), hedge funds appear to play an important role in price formation in FX derivatives markets.

Speculative demand also seems to play a role in investment funds' and non-dealer banks' on-the-margin FX rebalancing (see Figures A.47–A.50). In particular, investment funds' behaviour is consistent with their performing the carry trade in the EUR/USD, JPY/USD and EUR/GBP crosses, but not in the USD/GBP. The magnitude of these associations is smaller than for hedge funds and is present only for horizons of about 20 days or less. However, there is little consistent evidence that investment funds trade speculatively on momentum and macro news. Similarly, non-dealer banks appear to carry trade in the EUR/USD, GBP/USD and JPY/USD crosses and trade speculatively on macro news in the EUR/USD and GBP/USD crosses, although the results are much weaker than for hedge funds. Overall, the lower β^h s and wider error bands for investment funds and non-dealer banks compared to hedge funds likely reflect the significant within-sector heterogeneity in firms' FX derivatives use. In particular, many firms in these sectors likely have strong hedging demand for FX derivatives, which may be associated with negative β^h s, muddying the results.

Turning to the behavior of non-financial corporations, Figure 9 highlights that firms in this sector robustly move in the opposite direction to hedge funds across all three investment strategies, decreasing their exposures on the margin to higher-interest-rate and appreciating currencies. As for hedge funds, these negative β^h s hold across all horizons and for the GBP/USD and EUR/GBP crosses as well (see Figures A.44–A.46).⁴⁸ These negative coefficients imply that non-financials are the primary sector accomodating hedge funds' speculative activity, which may reflect a co-movement between corporations' hedging demand and the variables defining these investment strategies. Taking the EUR/USD cross as an example, higher U.S. interest rates that appreciate the dollar, potentially due to positive U.S. macro

⁴⁸The results are not present for the JPY/USD cross, where non-financial corporates are much less active.

news, may be associated with greater USD-denominated sales revenues for non-financials (due to the stronger US economy), which they may choose to hedge by going more net-short the USD in derivatives markets. This hedging demand can thus appear as a contrarian trade, pushing the exchange rate towards mean-reversion. This may make non-financial companies appear to behave like the “noise traders” of some international macro models.

In addition to non-financials, there is some evidence that pension funds and insurance companies also move in the opposite direction to hedge funds with respect to these investment strategies (see Figures A.51–A.54). The results are clearest for pension funds in the USD/GBP currency cross and for insurance companies in the EUR/USD cross. For these sectors, however, the direction of their rebalancing depends on the currency cross, suggesting the presence of cross-specific correlations between pension funds’ and insurers’ hedging demand and the variables defining these investment strategies.⁴⁹

Finally, dealer banks appear largely insulated from exposure to these three investment strategies, as shown in Figure 9 as well as in Figures A.44–A.46 for the other crosses. Since dealer banks are on (at least) one side of almost all transactions in the FX derivatives market, this suggests that they take offsetting exposures with speculative players—like hedge funds—and hedging noise traders—like non-financials. Despite being net-neutral on the margin, banks presumably still earn profits from their positions by discriminating between the forward rates charged to speculators and “noise” traders, suggestive of a toll-taking role (e.g., Duffie et al., 2005).

Market-makers, who overall have a very small net exposure, are less able at the margin to remain neutral with respect to most investment strategies (see Figures A.51–A.54). They sometimes appear to accommodate speculators’ demand, although the magnitudes are usually small, suggestive of a desire to offset these exposures.

⁴⁹To fully understand how the observed FX derivatives rebalancing co-moves with the firms’ hedging demand, we would require additional information on the rest of these firms’ portfolios/balance sheets, which are not readily available for the wide-range of sectors we consider here. We leave these explorations for future work.

6.2 Hedging Costs and Hedging Exposures

While the previous section documented how correlates of speculative demand move in tandem with the net exposures of certain sectors like hedge funds, this section examines how different sectors' currency stock exposures move with a correlate of hedging demand, namely changes in hedging costs—as measured by CIP deviations (Du et al., 2018a). To do so, we re-estimate regression (6) with $Z_{t+h}^{m,k} = CIP_{t+h}^{\{m,k\}} - CIP_{t-1}^{\{m,k\}}$:

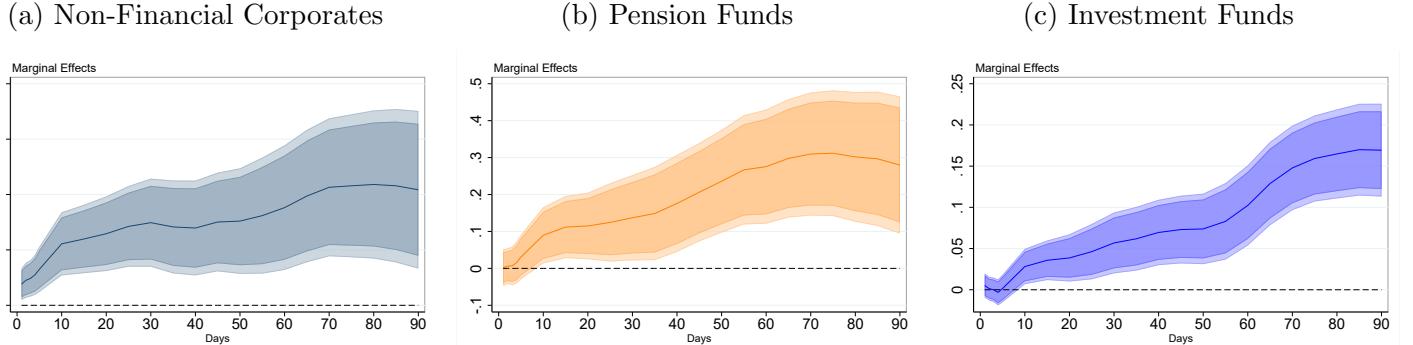
$$\frac{Stock_{t+h}^{i,\{m,k\}} - Stock_{t-1}^{i,\{m,k\}}}{|Stock^{i,\{m,k\}}|} = \alpha^h + \beta^h [CIP_{t+h}^{\{m,k\}} - CIP_{t-1}^{\{m,k\}}] + u_{i,t}^h, \quad (7)$$

where $CIP_t^{\{m,k\}} = f_t^{m/k} - s_t^{m/k} + r_t^k - r_t^m$ is the difference between the cost of synthetic currency- m borrowing via FX derivatives ($f_t^{m/k} - s_t^{m/k} + r_{t,h}^k$) and direct currency- m borrowing $r_{t,h}^m$.⁵⁰ If $CIP_{t,h}^{\{m,k\}} > 0$, then synthetic borrowing in currency m is costlier than direct borrowing. Hence it is more expensive for firms, on average, to take short positions selling currency m in the future. If firms are net-short currency m vis-à-vis currency k via FX derivatives to hedge their on-balance sheet positions in currency m , then this corresponds to a *hedging cost*.

Figure 10 presents results from estimating regression (7) in the EUR/USD currency cross (with $m = USD$ and $k = EUR$) for three sectors: non-financial corporates, pension funds and investment funds. Across these three sectors, the positive coefficients indicate that as the hedging costs to net-short positions in the USD vis-à-vis the EUR increase, firms in these sectors decrease their net-short USD positions against the EUR. Since, as we have documented previously, these sectors appear to maintain persistent net-short USD positions to hedge the currency risk on their balance sheets, these results suggest that non-financials and pension and investment funds hedge less as hedging costs increase. This pattern holds across investment horizons and in the USD/GBP currency cross as well (see Appendix A.5)

⁵⁰Synthetic currency- m borrowing involves borrowing in currency k , converting to currency m in spot markets, and taking a net-short currency- m position with an $\{m,k\}$ FX forward. This could also be done in a single transaction with an FX swap.

Figure 10: Changes in CIP Deviations and Firms' EUR-USD Derivatives Exposure



Note. Figure 10 presents the β^h s for $h \in [0, 90]$ from estimating firm-level panel regressions (7) for 3 sectors—non-financial corporates, pension funds and investment funds—in the EUR/USD currency cross. Results for the remaining sectors and the USD/GBP cross are in Appendix A.5. Inner and outer shaded areas correspond to 90% and 95% confidence intervals constructed using two-way clustered standard errors by firm and time.

This negative correlation between hedging costs and USD hedging positions by non-financials and pension and investment funds suggests that movements in CIP deviations (hedging costs) may be driven predominantly by changes in hedging supply, likely by dealer banks, whose net-long USD positions are negatively associated with CIP deviations (see Appendix A.5). Further, it suggests that these sectors have downward sloping and price-sensitive demand for hedging.

7 FX Derivatives Exposures and Exchange Rates

In this section, we move from a firm-level analysis that examines how typical firms in particular sectors change their net currency exposures with correlates of speculative and hedging demand to a sector-level analysis that investigates the transmission of aggregate shocks to exchange rates through changes in sectors' FX derivatives positions. We then show that the sectors' FX derivatives exposures can explain a significant fraction of weekly exchange rate changes—correlations between actual and predicted exchange rate changes reach up to 0.66—with hedge funds' and non-financials' positions being particularly informative.

7.1 Shock Transmission via Derivatives Positions to Exchange Rates

We begin by exploring which sectors mediate the transmission of aggregate shocks to exchange rates. To do so, we run panel IV local projections, across four crosses $\{m, k\}$, of the form:

$$s_{t+h}^{k/m} - s_{t-1}^{k/m} = \alpha + \beta^s \frac{\Delta \mathbf{S}_t^{s,\{m,k\}}}{|\mathbf{S}^{s,\{m,k\}}|} + \boldsymbol{\gamma}' \mathbf{X}_{t-1} + u_t \quad (8)$$

where $\frac{\Delta \mathbf{S}_t^{s,\{m,k\}}}{|\mathbf{S}^{s,\{m,k\}}|} = \frac{1}{N} \sum_{i=1}^N \frac{\Delta Stock_t^{i,\{m,k\}}}{|Stock^{i,\{m,k\}}|}$ is the average of the scaled changes in derivatives exposures across all firms i in sector s (assuming there are N such firms) and $\mathbf{X}_{t-1} = \{\Delta CIP_{t-1}^{\{m,k\}}, \Delta \log VIX_{t-1}, \Delta(r_{t-1}^m - r_{t-1}^k), \Delta s_{t-1}^{k/m}\}$ are macro-financial controls, namely, lagged changes in CIP deviations, the VIX index, interest differentials and exchange rates. We use equal-weighted averages, rather than size-weighted, to extract the maximum variation in positions across all players in a sector while limiting noise.⁵¹

To understand which agents systematically adjust their exposures in a manner consistent with transmitting shocks to exchange rates, we instrument $\frac{\Delta \mathbf{S}_t^{s,\{m,k\}}}{|\mathbf{S}^{s,\{m,k\}}|}$ with two types of aggregate shocks: monetary policy surprises and surprise movements in a US credit spread macro news index. We discuss each of these surprises in turn below.

Hedge Funds and Monetary Policy Surprises

As has been shown in many studies (e.g., Rogers et al., 2014), surprise monetary policy tightenings in a given country appreciate the country's currency on-impact. In this section, we are interested in understanding which agents adjust their FX derivatives positions to facilitate this transmission. To do so, we run a first-stage regression instrumenting sector-

⁵¹Rey et al. (2024) studies common components of changes in equity holdings similarly estimated with equal-weighted averages of observed holdings within groups of asset managers. They compute a market-clearing-based decomposition of equity price movements by extrapolating these “representative” common components to unobserved investors. While we observe a large fraction of the currency derivatives market, we do not observe the entire market, as in Rey et al. (2024), and so we similarly use sector-level common components of changes in net exposures to “represent” behavior of each sector, including the behavior of firms in other markets.

level average positions with monetary policy surprises:

$$\frac{\Delta \mathbf{S}_t^{s,\{m,k\}}}{|\mathbf{S}^{s,\{m,k\}}|} = \sigma_0 + \sigma^{s,m} \varepsilon_t^m + \sigma^{s,k} \varepsilon_t^k + \boldsymbol{\delta}' \mathbf{X}_{t-1} + u_t, \quad (9)$$

where ε_t^m and ε_t^k denote the monetary policy shock in the base m and quote k currency, respectively. If a sector s plays a role in transmitting monetary policy shocks to exchange rates, we would expect that a tightening of monetary policy in jurisdiction m (k) leads sector s to go more long currency m (k), i.e., we should expect $\sigma^{s,m} > 0$ and $\sigma^{s,k} < 0$.

We use Fed, ECB, BoE and BoJ monetary policy shocks in our panel specification (9).⁵² Our baseline Fed and ECB shocks are the pure monetary policy shocks of Jarociński and Karadi (2020) purged of the “central bank information effect”, although our results are robust to using the shocks of Bauer and Swanson (2023) and Altavilla et al. (2019), respectively.⁵³ For the BoE, we use the monetary policy shocks of Braun et al. (2025) and for the BoJ, we use the shocks of Kubota and Shintani (2022).

While we estimate regression (9) for each sector, we focus on the sector for which monetary policy shocks are a strong instrument and of the expected sign, which corresponds to the hedge fund sector. As shown in Table A.1 in Appendix A.6, the first-stage F-stat for hedge funds is 13.67, with the coefficients $\sigma^{s,m} > 0$ and $\sigma^{s,k} < 0$ and significant.

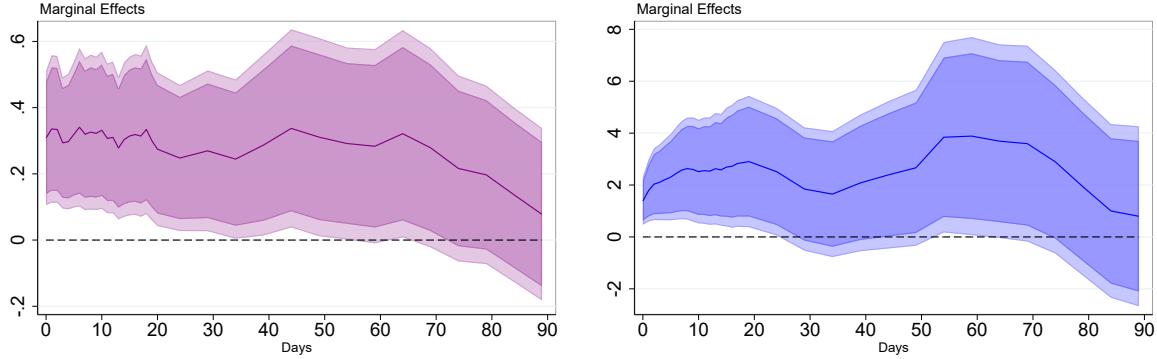
The second-stage impulse response function from estimating (8) using changes in exposures of the hedge fund sector by 2SLS is shown in Panel (a) of Figure 11. It highlights that as hedge funds go long currency m vis-à-vis currency k via FX derivatives, induced by a tightening (loosening) monetary policy surprise in jurisdiction m (k), currency m appreciates against currency k . Quantitatively, a 1pp increase in hedge funds’ net FX derivatives position in currency m vis-à-vis k (relative to their average net exposure) appreciates currency m by over 0.3% against k . This highlights that hedge funds appear to play a key role in mediating monetary shocks to exchange rates via FX derivatives.

⁵²For example, in the EUR/USD cross, we use Fed (m) and ECB (k) monetary policy surprises.

⁵³We use a 2-day change of the dependent variable, from $t - 1$ to $t + 1$, since FOMC announcements on day t occur after UK markets have closed.

Figure 11: Aggregate Shocks, FX Derivatives Exposure and Exchange Rates

(a) Hedge Funds & Monetary Policy Shocks (b) Investment Funds & Credit Risk Shocks



Note. Figure 11 presents impulse responses from estimating cross-level panel regressions (8) by 2sls. In Panel (a), hedge funds' average positions are instrumented using monetary policy shocks according to first-stage regression (9). In Panel (b), investment funds' average positions are instrumented using daily changes in a credit spread macro news index via first-stage regression (10). For Panel (a), we use 4 crosses: EUR/USD, USD/GBP, JPY/USD and EUR/GBP, while in Panel (b) we use only the first two crosses. First stage regressions are shown in Table A.1. Inner and outer shaded areas correspond to 90% and 95% confidence intervals constructed using HAC standard errors.

Investment Funds and Credit Risk Surprises Next, we investigate the transmission of surprise movements in US credit spreads, which have been shown to appreciate the USD (see e.g., Cesa-Bianchi and Sokol, 2022). To identify surprise movements in US credit spreads, we construct a credit-spread macro news index, akin to the macro news indices constructed for exchange rates (Stavrakeva and Tang, 2024), equities (Boehm and Kroner, 2025) and Treasuries (Altavilla et al., 2017). To investigate which sectors' currency adjustments may be facilitating a USD appreciation when US credit spreads rise, we estimate the following first-stage regression:

$$\frac{\Delta \mathbf{S}_t^{s,\{\text{USD},k\}}}{|\mathbf{S}^{s,\{\text{USD},k\}}|} = \sigma_0 + \sigma^{s,Cs} \mathbf{CSMacroNews}_t^{Us} + \delta' \mathbf{X}_{t-1} + u_t, \quad (10)$$

for $k = \{\text{EUR}, \text{GBP}\}$, where $\mathbf{CSMacroNews}_t^{Us}$ is the fitted value from the following daily regression:⁵⁴

$$\Delta CS_t^{Us} = \alpha + \gamma MacroSurp_t^{Us} + \varepsilon_t,$$

⁵⁴We exclude the JPY/USD and EUR/GBP since these exchange rates do not always move in a consistent direction when US credit spreads rise.

with CS_t^{US} denoting the ICE BoA US high-yield credit spread index and where $MacroSurrp_t^{US}$ contains contemporaneous and lagged US macroeconomic surprises used by Boehm and Kroner (2025). Note, importantly, that this spread-relevant macro news index is a combination of macro news that traders are most attentive to in determining the value of corporate bonds relative to Treasuries—likely capturing news relevant to the economic health of US corporations. The index bears little resemblance, with a correlation of only 6%, to the FX macro news index used in Section 6.1.

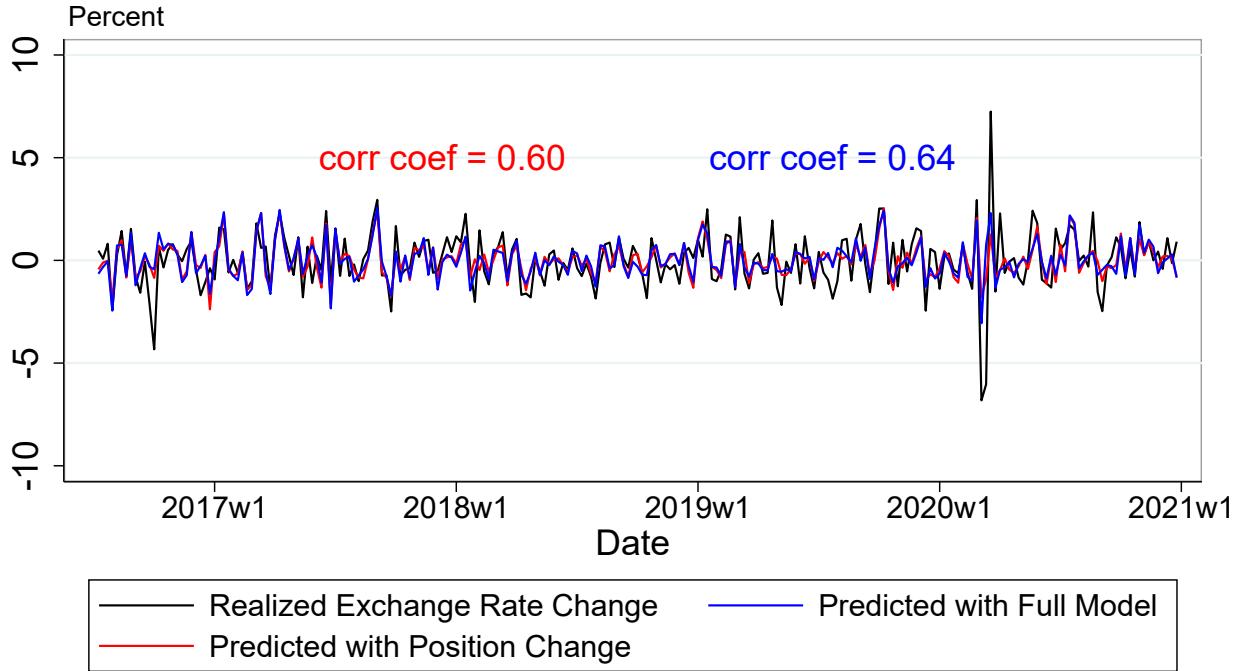
Again, while we estimate the first stage (10) for all sectors, we focus on the sector for which the credit risk shock is a strong instrument and for which its coefficient has the expected sign, which we find to be the investment fund sector. As shown in Table A.1 in Appendix A.6, the first-stage F-stat for investment funds is 26.66, with the coefficients on $\sigma^{s,CS}$ positive and significant, indicating that investment funds go more long the USD against the EUR and the GBP when US credit spreads rise due to (adverse) US macro news. This may reflect a purely speculative motive, as well as an unwinding of USD hedging positions.

Turning to the second stage impulse response function shown in Panel (b) of Figure 11, which is estimated by 2SLS using equation (8), we see that as investment funds go more long the USD, induced by the surprise increase in US credit spreads due to macro news, the USD appreciates against the EUR and GBP. Quantitatively, a 1pp increase in investment funds’ net FX derivatives position in the USD vis-à-vis the GBP or EUR (relative to their average net exposure) appreciates the USD by about 1.5% on impact. This highlights that investment funds’ flight to the USD via FX derivatives appears to mediate the transmission of credit risk surprises to exchange rates.

7.2 Fitting Exchange Rate Movements

Finally, we turn to how much information FX derivatives positions encode of contemporaneous exchange rate dynamics. Motivated by the previous section, which showed that different sectors appear to play a role in transmitting distinct shocks to exchange rates, we

Figure 12: Fitting Weekly USD/GBP Movements with Derivatives Positions



Note. Figure 12 plots weekly non-overlapping USD/GBP exchange rate log changes in percent (in black) along with fitted values from regression (11), which regresses exchange rates changes on changes in sectors’ FX derivatives positions, with (in blue, full model) and without (in red) macro-financial controls. “corr coeff” refers to the correlation coefficient between realized changes and model fit. Table A.2 in Appendix A.6 provides full regression results.

include positions changes (and 1 lag) of *all* sectors, aside from dealer banks, together to try to “explain” weekly moves in exchange rate.⁵⁵ Specifically, we run the following time-series regression at a weekly frequency (non-overlapping) for a currency cross $\{m, k\}$.

$$\Delta s_t^{k/m} = \alpha + \sum_{s \in S} \sum_{l=0}^1 \beta^s \frac{\Delta \mathbf{S}_{t-l}^{s, \{m, k\}}}{|\mathbf{S}^{s, \{m, k\}}|} + \boldsymbol{\gamma}' \mathbf{X}_t + u_t. \quad (11)$$

The fitted values from this regression for the USD/GBP currency cross, along with the model’s correlation coefficient with realized exchange rate changes, are displayed in Figure 12, with the remaining crosses shown in Figures A.57–A.59 in Appendix A.6. The fit is incredibly strong, with a correlation coefficient of 0.6 between actual and fitted exchange

⁵⁵As dealer banks can take positions outside the UK market, their positions may be less informative in this market than in closed markets. Including individual demands of each of the other sectors also allows us to understand which sectors positions are particularly informative for exchange rates.

rate changes from a regression with only sector-level changes in positions. The coefficient rises to 0.64 when macro-financial controls are included. We find similar patterns for the other crosses, although the fit is strongest for crosses involving the GBP, likely because the London market hosts the vast majority of global GBP trading. Of note, the fit is less strong when including each sector individually, which suggests that the positions of each sector contain unique information for exchange rates, potentially because different sectors transmit different shocks to exchange rate markets.

While all sectors' positions contain some information for exchange rate movements, two sectors stand out. First, hedge funds positions correlate strongly and positively with exchange rates changes in all USD crosses. And second, non-financial corporates positions correlate strongly, but negatively, with exchange rates in all crosses not involving the JPY. That hedge funds positions correlate positively, again, suggests their speculative activity plays a key role in driving exchange rate dynamics.

8 Conclusion

This paper uses 100 million FX derivative contracts to document important new facts about the use of FX derivatives by firms, both financial and non-financial, in the biggest center for currency trading, London. We construct daily *net* FX derivatives exposure at the *firm-level* for the near-universe of firms trading FX in the UK over the period 2015-2020. This measure, which contrasts with the sector-level net or gross exposures used in many existing studies, enables us to better capture within- and across-sector heterogeneity in the degree to which firms' profits are exposed to exchange rate fluctuations from FX derivatives. It enables us to describe the structure of the market and how the different market participants adjust their derivative portfolios following a number of shocks. Leveraging our firm-level net FX derivatives exposures, we show that individual pension funds, insurance companies, non-financial corporates and, to a lesser degree, investment funds, maintain persistent one-

directional net-short exposures to the USD and net-long exposures to their currencies of operation over our sample, consistent with their use of FX derivatives for hedging purposes “on average”. Dealer banks accommodate these firms’ hedging needs by maintaining persistent net-long USD exposures. We find interesting heterogeneity in net exposures depending on the geography of firms’ countries of residence. Importantly, we also document significant within-sector concentration in firms’ net exposures, with the largest 5 players accounting for a considerable share of sector-wide exposures. This puts to the fore issues of resilience and financial stability, as the distress of a limited number of big players could carry systemic implications.

We turn to the issue, very important for regulators, of whether FX derivatives are used for speculative or hedging motives. To do so, we examine how firms adjust their net FX derivatives exposures “on the margin” with respect to three well-known FX investment strategies: the carry trade, momentum and macro news-based FX trading. Our findings show that hedge funds speculate using FX derivatives, whereas non-financials adjust their exposures in the opposite direction, accomodating speculative demand, which may reflect hedging. In line with this, non-financials, as well as pension funds and investment funds, decrease their USD hedging positions as the cost of hedging rises. Owing to this heterogeneity, dealer banks are able to remain neutral “on the margin” with respect to these investment strategies. Hence our work also sheds light on the adjustment dynamics of the largest FX derivatives market in the world.

Finally, we document that hedge funds play a primary role in transmitting monetary policy shocks to exchange rates by adjusting their FX derivatives exposures. On the other hand, investment funds’ flight to the dollar in FX derivatives markets in response to US credit risk shocks appears to contribute to USD appreciations in risk-off episodes. Overall, our findings suggest that an array of heterogeneous sectors, each guided by distinct objectives, each transmit macroeconomic surprises and interact to collectively determine exchange rates.

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A Appendix

A.1 Derivations

Here we derive the general optimization problem of firm i with currency of operation c^i .

Firm i solves the following optimization problem:

$$\begin{aligned}
& \max_{N_{0,1}^{i,\{k,m\}}} \tilde{E}_0^i [\pi_1^i] - \frac{\rho}{2} Var_0 (\pi_1^i) \\
&= \tilde{E}_0^i [\pi_1^{i,FX,deriv} + X_1^{i,H}] - \frac{\rho}{2} [Var_0 (\pi_1^{i,FX,deriv}) + Var_0 (X_1^{i,H}) + 2Cov_0 (\pi_1^{i,FX,deriv}, X_1^{i,H})] \\
&= \tilde{E}_0^i \left[\sum_{\{k,m\}} \left[S_1^{c^i/k} - (F_{0,1}^{i,m/k}) S_1^{c^i/m} \right] N_{0,1}^{i,\{k,m\}} + X_1^{i,H} \right] \\
&- \frac{\rho}{2} \left[\begin{array}{l} \sum_{\{k,m\}} Var_0 (S_1^{c^i/k} - (F_{0,1}^{i,m/k}) S_1^{c^i/m}) (N_{0,1}^{i,\{k,m\}})^2 + \\ 2 \sum_{\{l,n\}: \{l,n\} \neq \{k,m\}} Cov_0 (S_1^{c^i/k} - (F_{0,1}^{i,m/k}) S_1^{c^i/m}, S_1^{c^i/l} - (F_{0,1}^{i,n/l}) S_1^{c^i/n}) N_{0,1}^{i,\{k,m\}} N_{0,1}^{i,\{l,n\}} \\ + Var_0 (X_1^{i,H}) + 2 \sum_{\{k,m\}} Cov_0 (S_1^{c^i/k} - (F_{0,1}^{i,m/k}) S_1^{c^i/m}, X_1^{i,H}) N_{0,1}^{i,\{k,m\}} \end{array} \right], \\
N_{0,1}^{i,\{k,m\}} &= \frac{\tilde{E}_0^i [S_1^{c^i/k} - (F_{0,1}^{i,m/k}) S_1^{c^i/m}]}{\rho Var_0 (S_1^{c^i/k} - (F_{0,1}^{i,m/k}) S_1^{c^i/m})} \\
&- \frac{\sum_{\{l,n\}: \{l,n\} \neq \{k,m\}} Cov_0 (S_1^{c^i/k} - (F_{0,1}^{i,m/k}) S_1^{c^i/m}, S_1^{c^i/l} - (F_{0,1}^{i,n/l}) S_1^{c^i/n}) N_{0,1}^{i,\{l,n\}}}{Var_0 (S_1^{c^i/k} - (F_{0,1}^{i,m/k}) S_1^{c^i/m})} \\
&- \frac{Cov_0 (S_1^{c^i/k} - (F_{0,1}^{i,m/k}) S_1^{c^i/m}, X_1^{i,H})}{Var_0 (S_1^{c^i/k} - (F_{0,1}^{i,m/k}) S_1^{c^i/m})}
\end{aligned}$$

Consider the case where one of the legs of all derivative transactions has the same currency as the currency of operation of the investor, i.e. $m = c^i$. Then the expression above simplifies to:

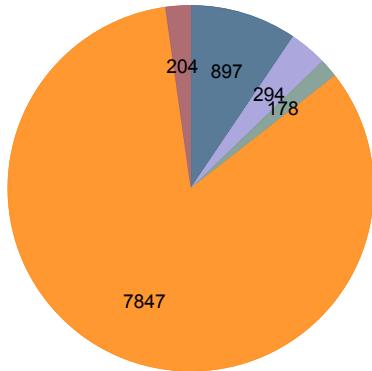
$$N_{0,1}^{i,\{k,m\}} = \frac{\tilde{E}_0^i [S_1^{m/k} - F_{0,1}^{i,m/k}]}{\rho Var_0 (S_1^{m/k})} - \frac{\sum_{\{l,m\}: \{l,m\} \neq \{k,m\}} Cov_0 (S_1^{m/k}, S_1^{m/l}) N_{0,1}^{i,\{l,m\}} + Cov_0 (S_1^{m/k}, X_1^{i,H})}{Var_0 (S_1^{m/k})}$$

A.2 Supplement to Overview of Market

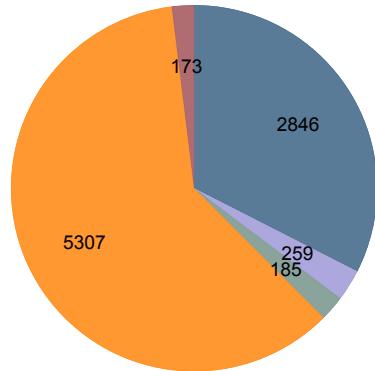
A.2.1 Firms

Figure A.1: Number of Unique Firms Trading Derivatives by Currency Cross

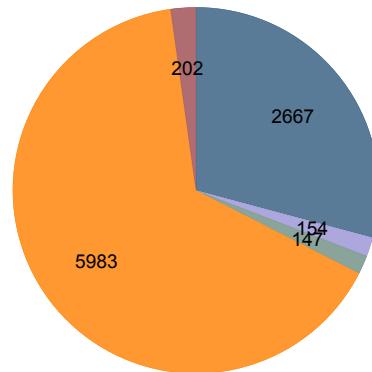
(a) EUR/USD Derivatives



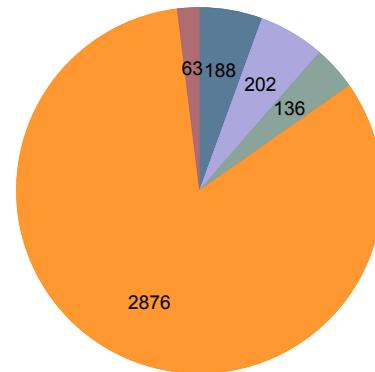
(b) USD/GBP Derivatives



(c) EUR/GBP Derivatives



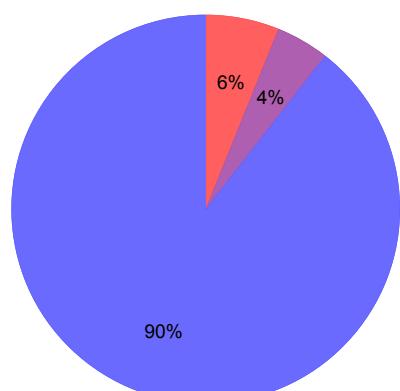
(d) JPY/USD Derivatives



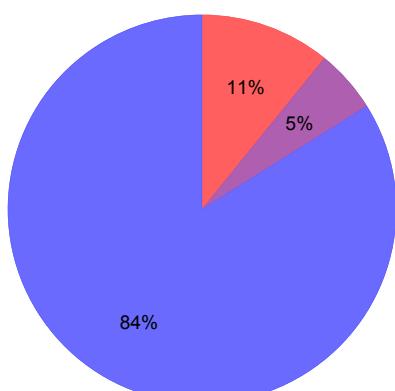
Note. Number of unique firms trading FX derivatives in major currency crosses, by sector. Firms included are those reporting under EMIR to the DTCC and UnaVista trade repositories between January 1, 2015 (July 1 2016 for Banks) and December 31, 2020.

Figure A.2: Breakdown of Asset Managers Derivatives Trading by Currency Cross

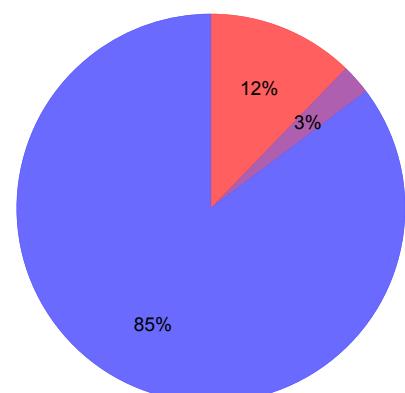
(a) EUR/USD Derivatives



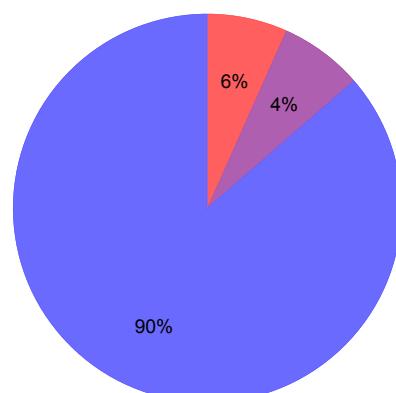
(b) USD/GBP Derivatives



(c) EUR/GBP Derivatives



(d) JPY/USD Derivatives

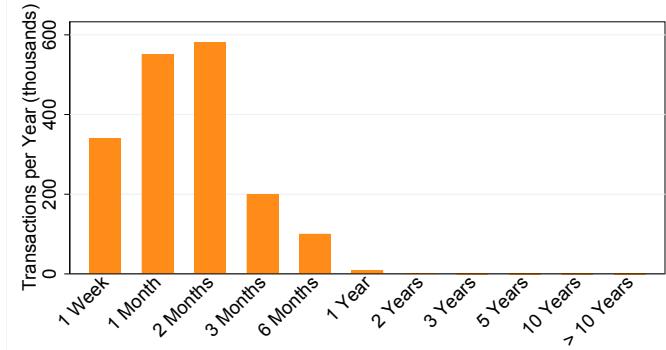


Note. Share of types of asset managers trading FX derivatives in major currency crosses, by sector. Firms included are those reporting under EMIR to the DTCC and UnaVista trade repositories between January 1, 2015 and December 31, 2020.

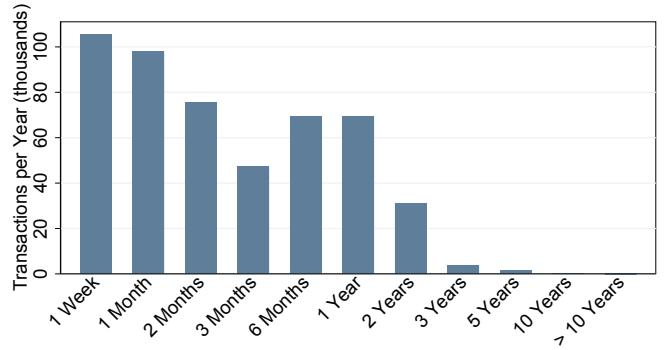
A.2.2 Transaction

Figure A.3: Maturity Profile of FX Derivatives Transactions by Sector

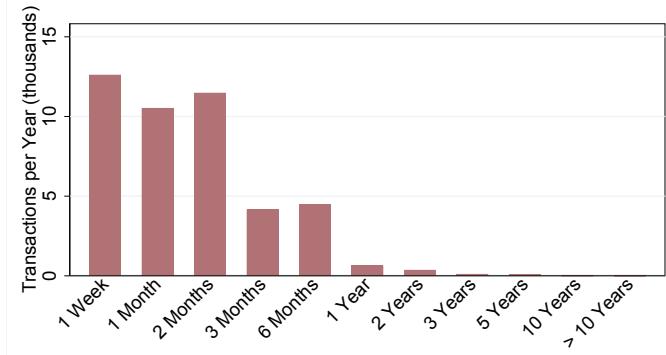
(a) Asset Managers



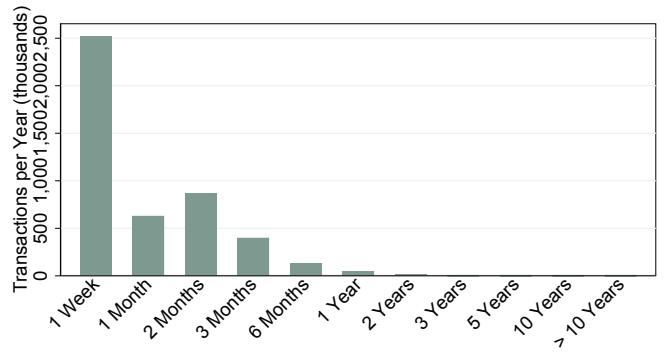
(b) Non-Financial Corporates



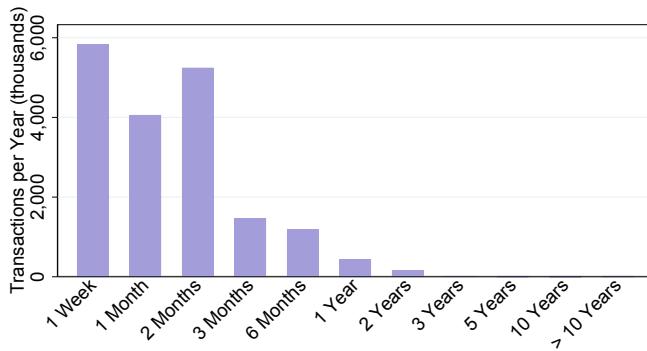
(c) Insurers



(d) Market Makers



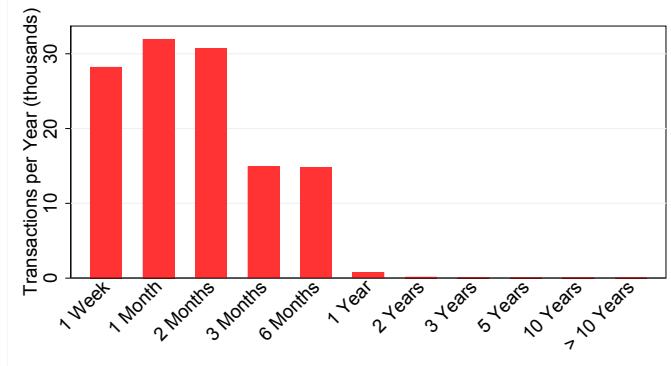
(e) Banks



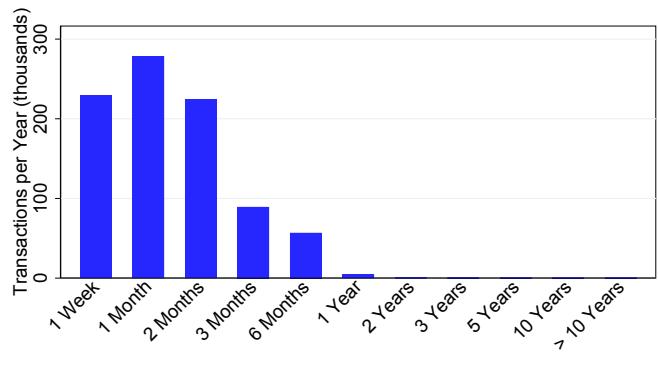
Note. Number of FX derivatives transactions per year, by sector and maturity, taken by firms reporting under EMIR to the DTCC and UnaVista trade repositories from January 1 2015 (July 1 2016 for Banks) to December 31 2020. To construct this chart, we sort transactions into bins based on their maturity. The x-axis labels denote the upper bound of each bin, e.g., “1 week” refers to transactions with a maturity $\in (1 \text{ day}, 1 \text{ day}]$, “1 month” refers to transactions with a maturity $\in (1 \text{ week}, 1 \text{ month}]$ and so on. Since our analysis is conducted daily, we do not consider intraday transactions.

Figure A.4: Maturity Profile of FX Derivatives Transactions by Type of Asset Managers

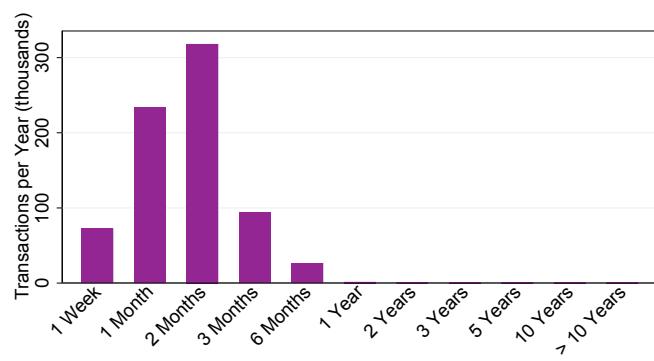
(a) Pension Funds



(b) Investment Funds



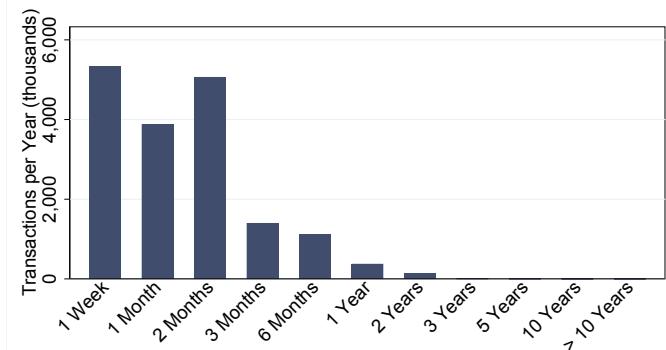
(c) Hedge Funds



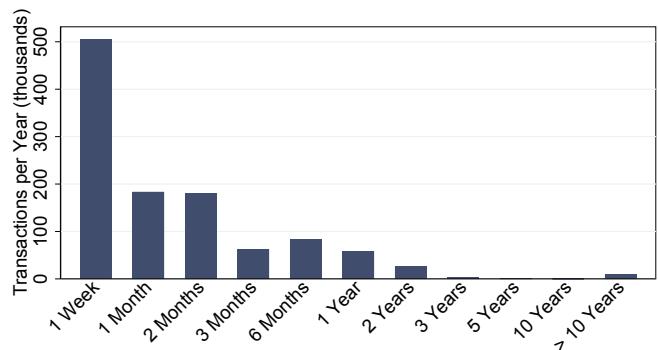
Note. Number of FX derivatives transactions per year, by type of Asset Manager and maturity, taken by firms reporting under EMIR to the DTCC and UnaVista trade repositories from January 1 2015 to December 31 2020. The remaining notes from Figure A.3 apply here.

Figure A.5: Maturity Profile of FX Derivatives Transactions by Bank Type

(a) Dealer Banks



(b) Non-Dealer Banks

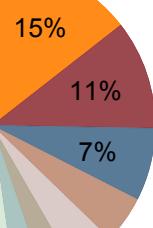


Note. Number of FX derivatives transactions per year, by bank type and maturity, taken by banks reporting under EMIR to the DTCC and UnaVista trade repositories from July 1, 2016 to December 31, 2020. The remaining notes from Figure A.3 apply here.

Figure A.6: Volume of FX Derivatives Transactions by Currency Cross and Sector

(a) Asset Managers

Transactions per Year: 1.75 Million



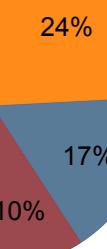
(b) Non-Financial Corporates

Transactions per Year: 500 Thousand



(c) Insurers

Transactions per Year: 45 Thousand



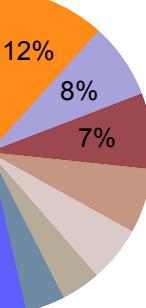
(d) Market Makers

Transactions per Year: 4.5 Million



(e) Banks

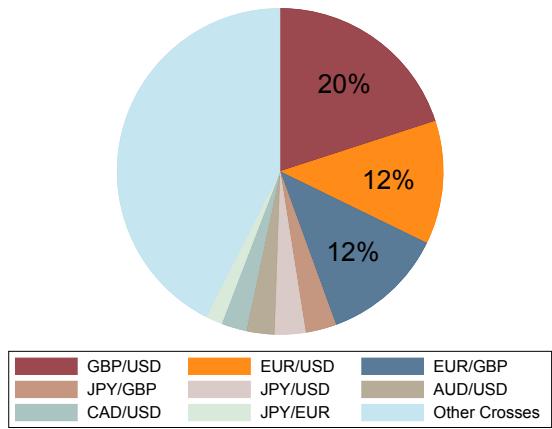
Transactions per Year: 18 Million



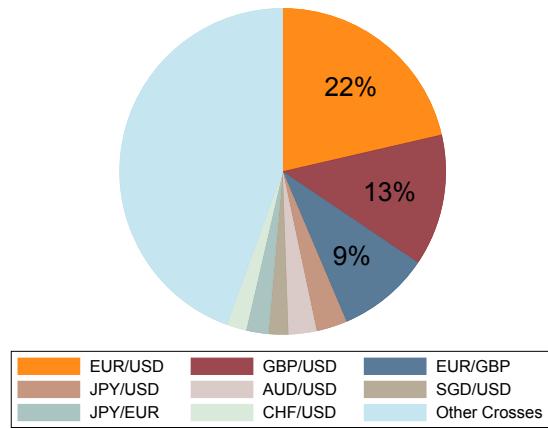
Note. Number of FX derivatives transactions per year, by sector and currency-cross, taken by firms reporting under EMIR to the DTCC and UnaVista trade repositories from January 1, 2015 (July 1, 2016 for banks) to December 31, 2020.

Figure A.7: Derivatives Transactions by Types of Asset Managers and Currency Cross

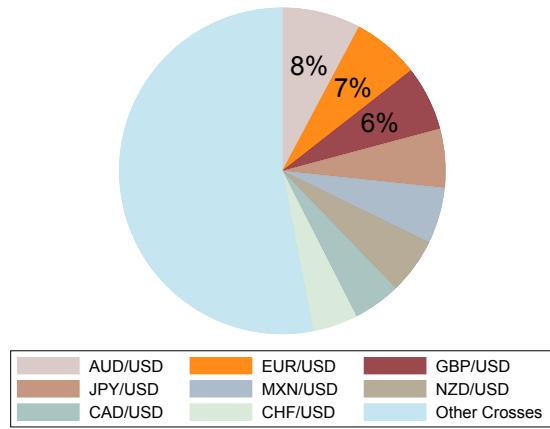
(a) Pension Funds
Transactions per Year: 120 Thousand



(b) Investment Funds
Transactions per Year: 900 Thousand



(c) Hedge Funds
Transactions per Year: 750 Thousand

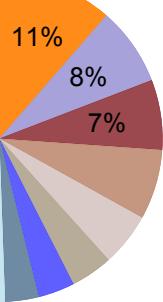


Note. Number of FX derivatives transactions per year, by type of Asset Manager and currency-cross, taken by firms reporting under EMIR to the DTCC and UnaVista trade repositories from January 1, 2015 to December 31, 2020.

Figure A.8: Derivatives Transactions by Types of Bank and Currency Cross

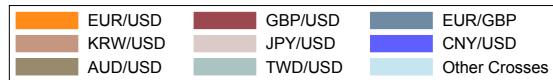
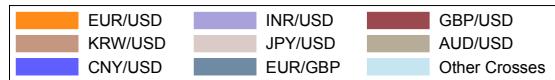
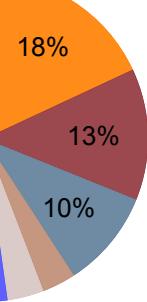
(a) Dealer Banks

Transactions per Year: 17 Million



(b) Non-Dealer Banks

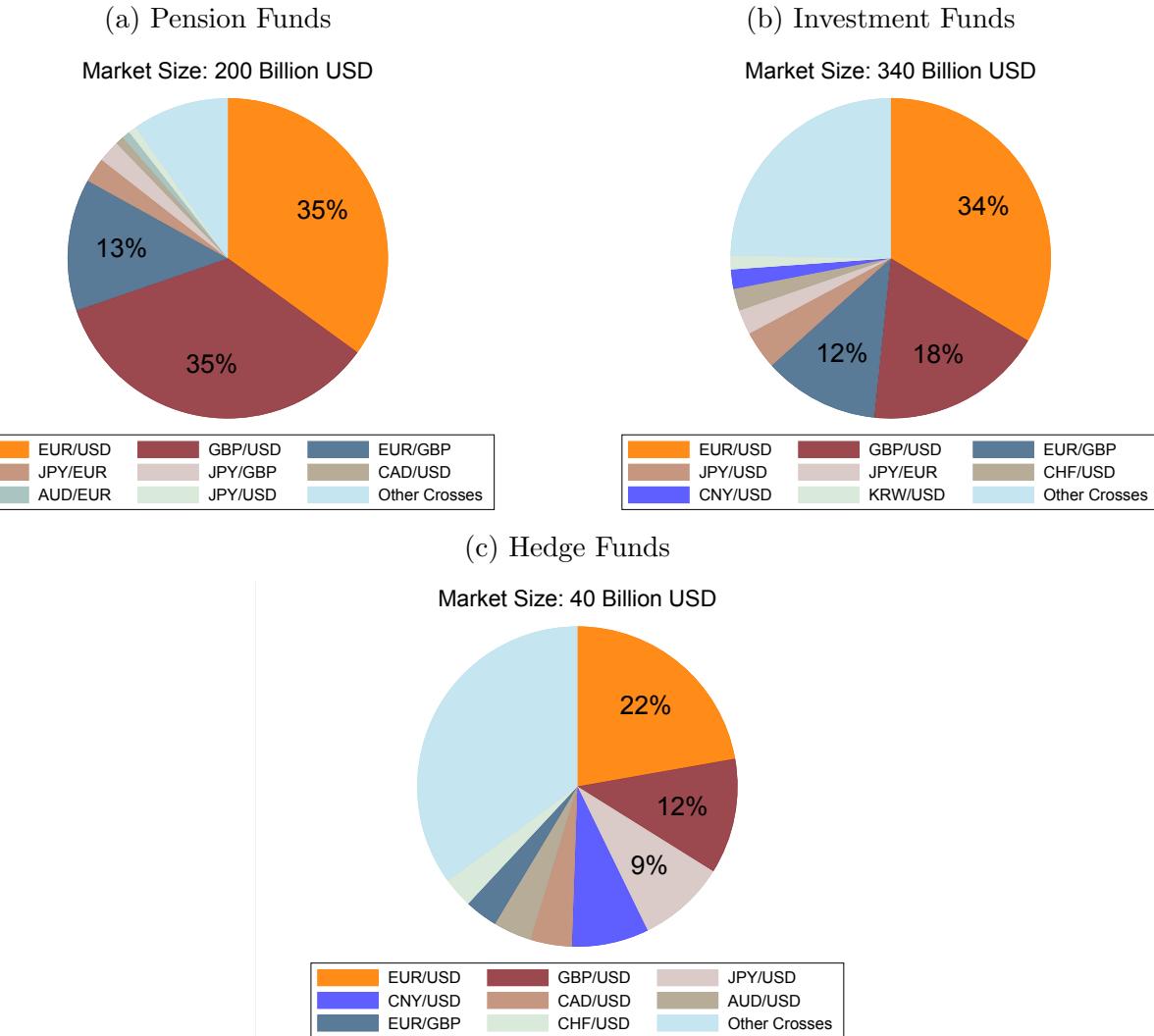
Transactions per Year: 1 Million



Note. Number of FX derivatives transactions per year, by type of bank and currency-cross, taken by banks reporting under EMIR to the DTCC and UnaVista trade repositories from July 1, 2016 to December 31, 2020.

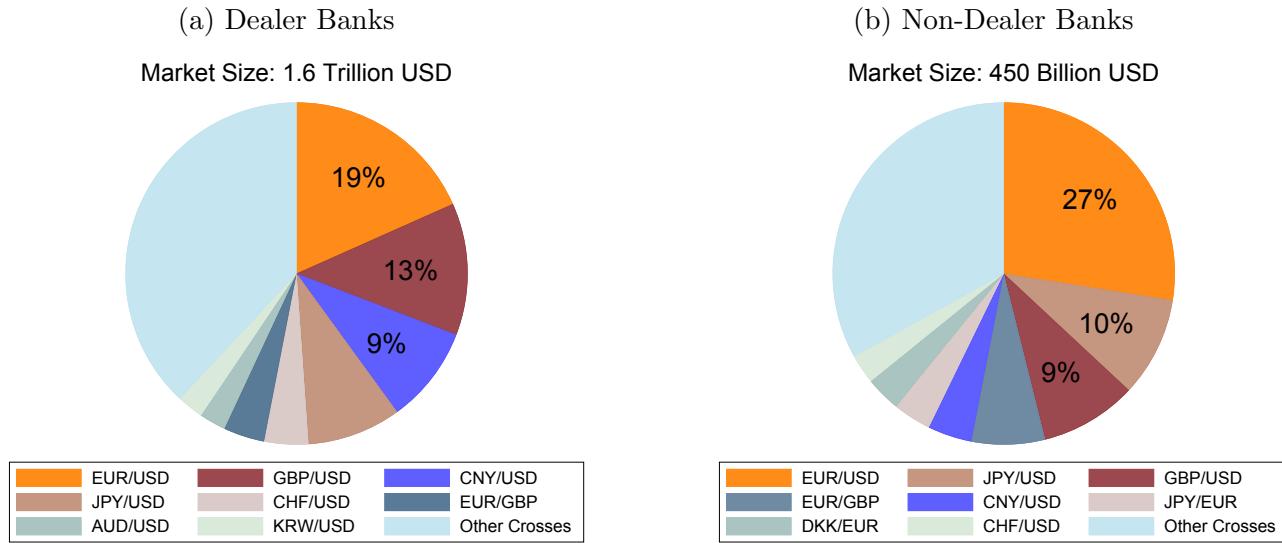
A.2.3 Market Size

Figure A.9: Average Absolute Value of the Stock of Firms' Net Cross Exposures by Fund Type



Note. The average absolute value of firms' *net* outstanding stock of FX derivatives contracts across all currency-crosses, maturities and fund-types over our sample period, measured in USD, by type of asset manager. Firms included are those reporting under EMIR to the DTCC and UnaVista trade repositories between January 1 2015 and December 31 2020.

Figure A.10: Average Absolute Value of Firms' Net Currency-Cross Exposures by Bank Type

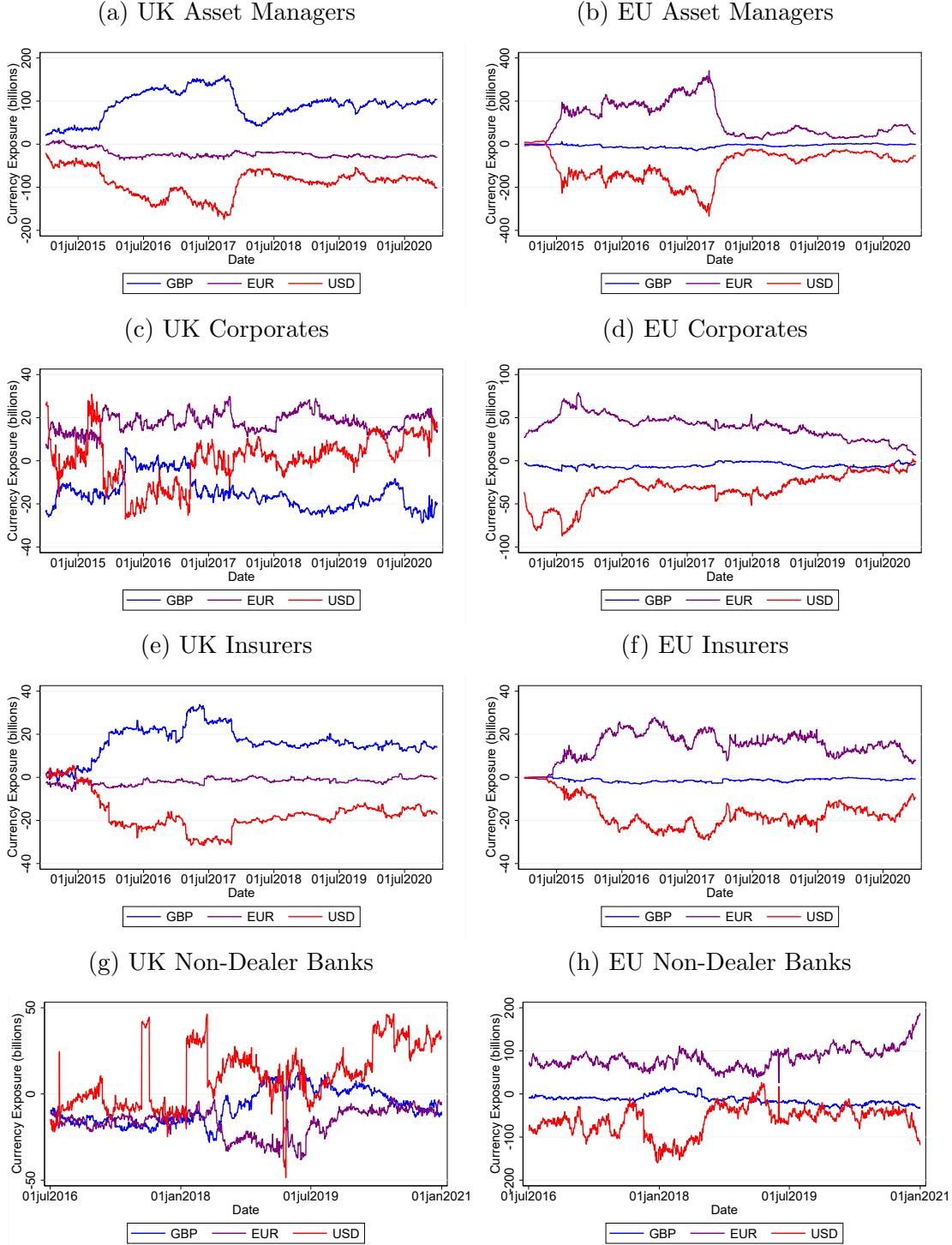


Note. The average absolute value of firms' *net* outstanding stock of FX derivatives contracts across all currency-crosses, maturities and bank-types over our sample period, measured in USD, by type of bank. Banks included are those reporting under EMIR to the DTCC and UnaVista trade repositories between July 1 2016 and December 31 2020.

A.3 Supplement to Currency Positions

A.3.1 Net Currency Stock Exposures by Sector and Country of Residence

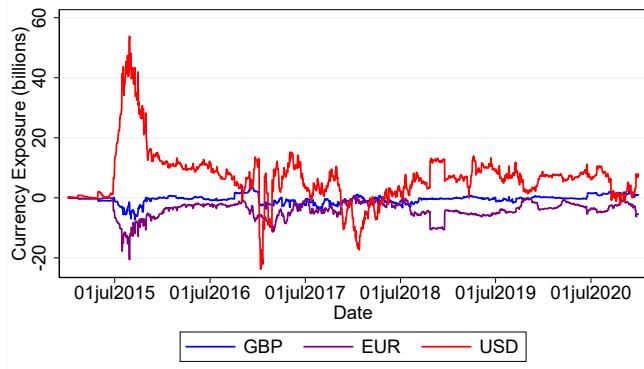
Figure A.11: UK & EU Sector-Level Currency Exposures to Major 3 Currencies



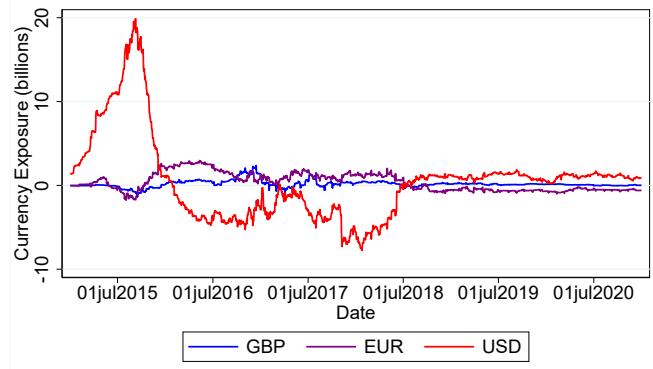
Note. UK and EU Sector-level currency exposures, calculated as the net currency exposure of firms in a particular currency vis-à-vis all other currencies and then separately aggregated across firms in a particular sector that are UK- and EU-resident, for the major three currencies—USD, EUR, GBP. Currency exposures are measured in units of local currency (i.e., in GBP for GBP exposures). Firms included are those reporting under EMIR to the DTCC and UnaVista trade repositories between January 1 2015 (July 1 2016 for Banks) and December 31 2020.

Figure A.12: UK & EU Fund-Level Currency Exposures to Major Three Currencies

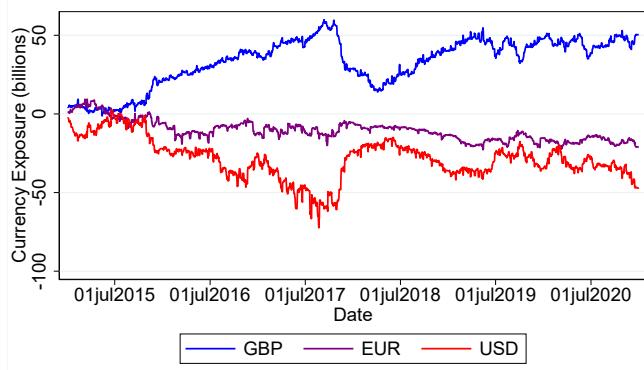
(a) Non-EU Hedge Funds



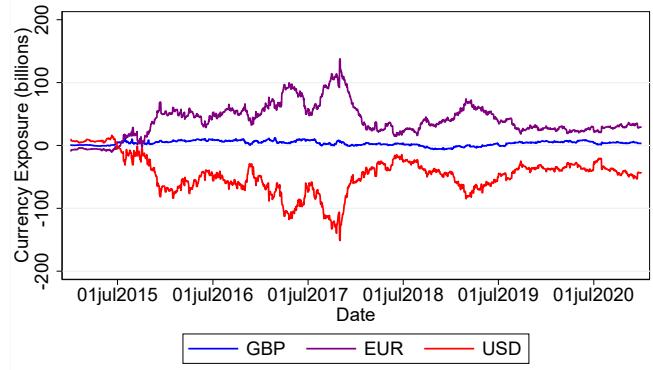
(b) EU Hedge Funds



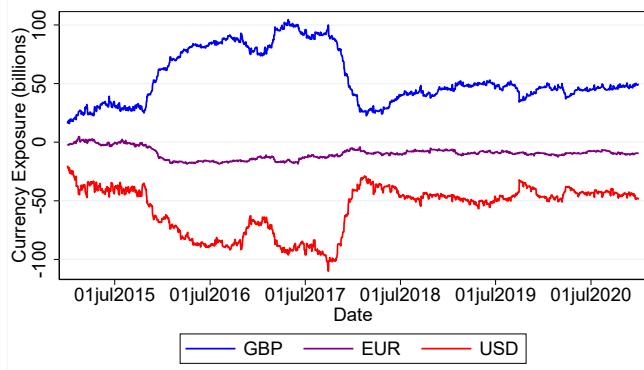
(c) UK Investment Funds



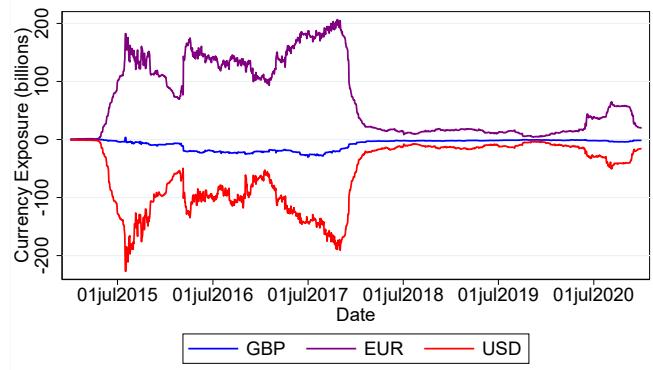
(d) EU Investment Funds



(e) UK Pension Funds



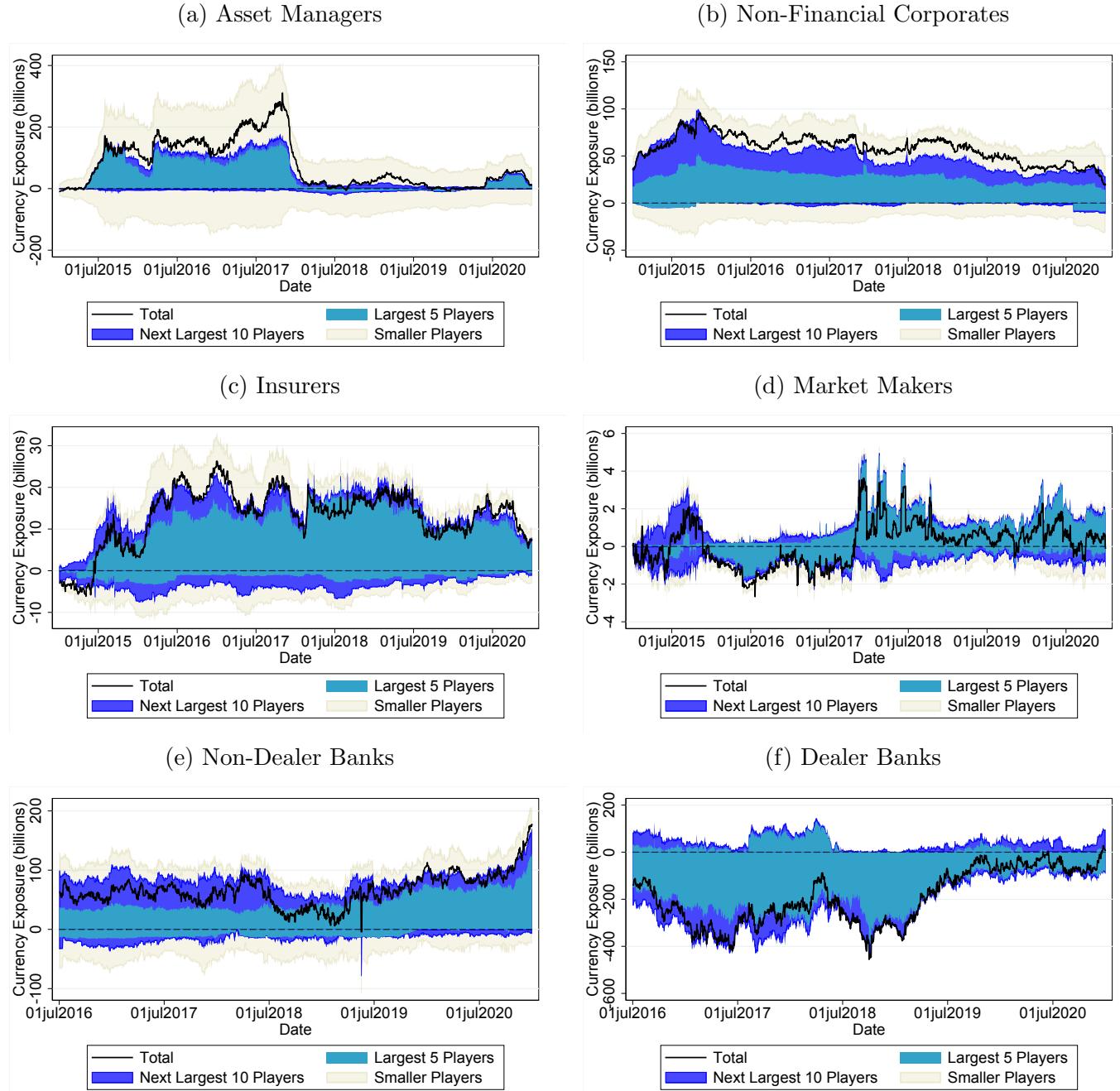
(f) EU Pension Funds



Note. EU and UK Sector-level currency exposures, calculated as the net currency exposure of firms in a particular currency vis-à-vis all other currencies and then separately aggregated across firms in a particular sector that are EU- and UK-resident (non-EU-resident for hedge funds), for the major three currencies—USD, EUR, GBP. Currency exposures are measured in units of local currency (i.e., in GBP for GBP exposures). Firms included are those reporting under EMIR to the DTCC and UnaVista trade repositories between January 1 2015 and December 31 2020.

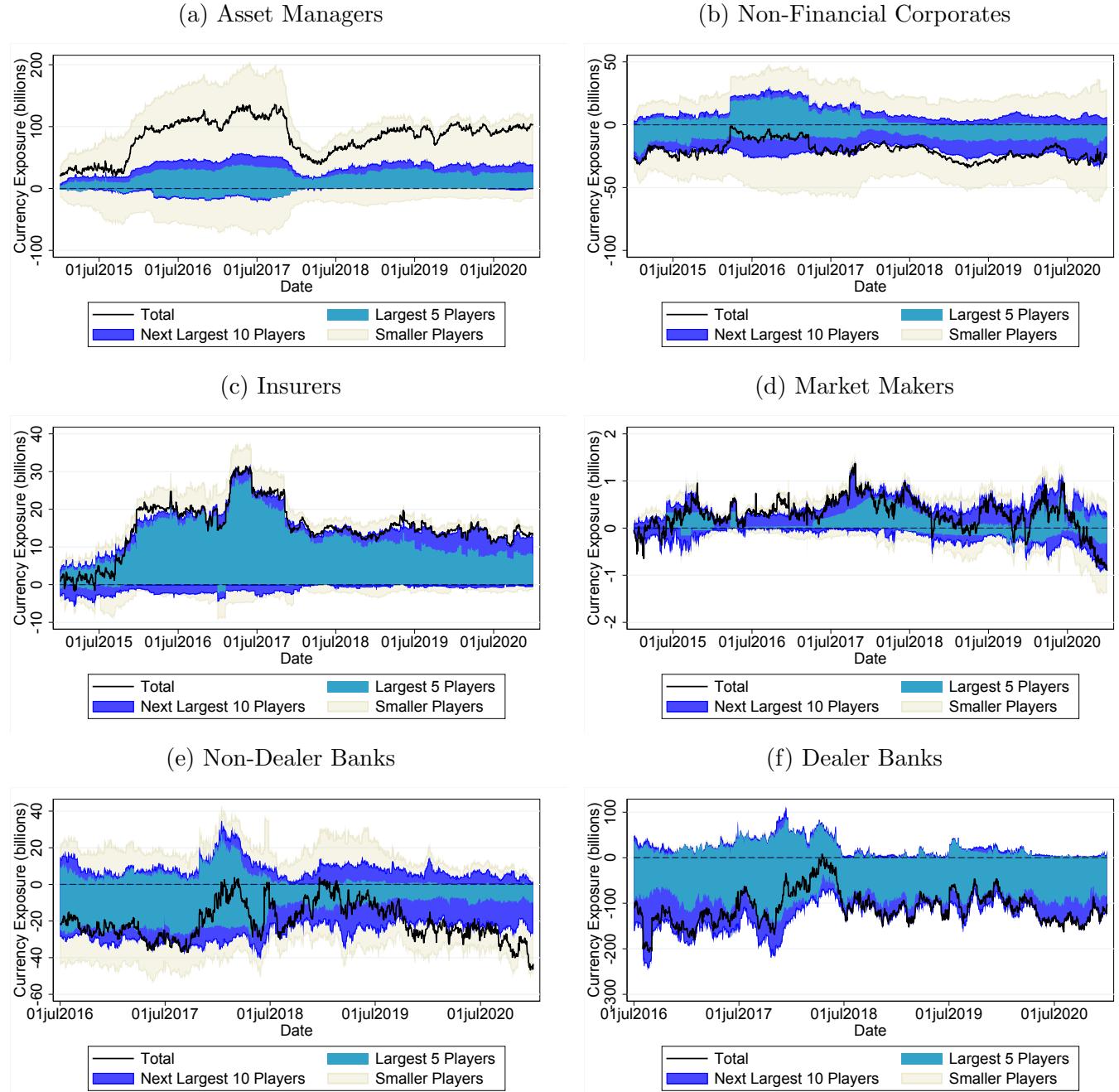
A.3.2 Net Currency Stock Exposures by Sector: Heterogeneity & Concentration

Figure A.13: Heterogeneous and Concentrated EUR Exposure Across Sectors



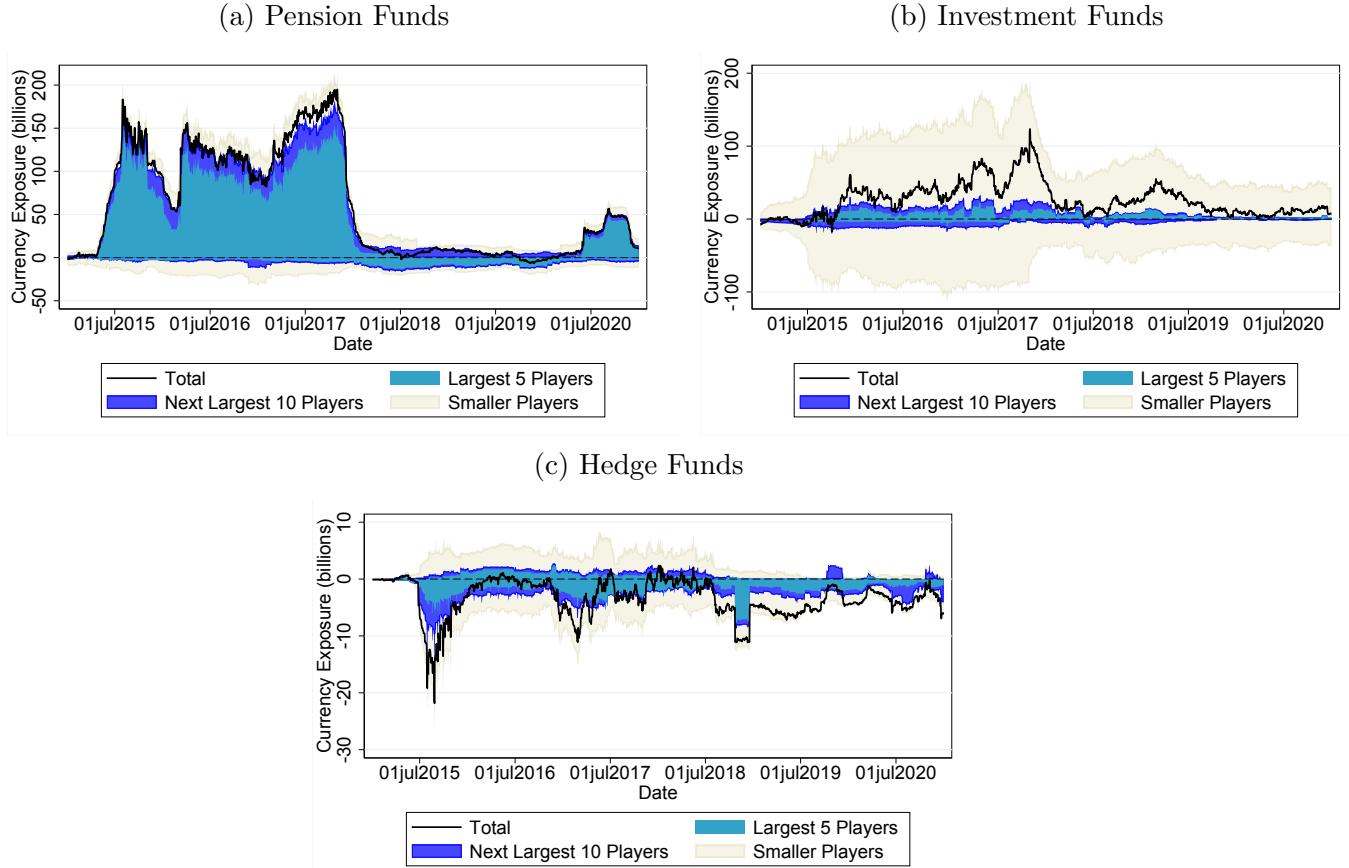
Note. Sectoral net-long and net-short EUR exposures, highlighted in blue and beige, are calculated by separately aggregating the exposures of firms in a sector that are net-long and net-short the EUR vis-à-vis all other currencies. The black line refers to the sum of the net-long and net-short EUR exposures, which is shown in Figure 4. Shaded in light and dark blue are the net-long and net-short positions of the largest 5 and next largest 10 firms in the sector in terms of average currency exposure over the sample. In beige are the exposures of the smaller players. EUR exposures are measured in units of EUR. Firms included are those reporting under EMIR to the DTCC and UnaVista trade repositories between January 1, 2015 (July 1 2016 for Banks) and December 31, 2020.

Figure A.14: Heterogeneous and Concentrated GBP Exposure Across Sectors



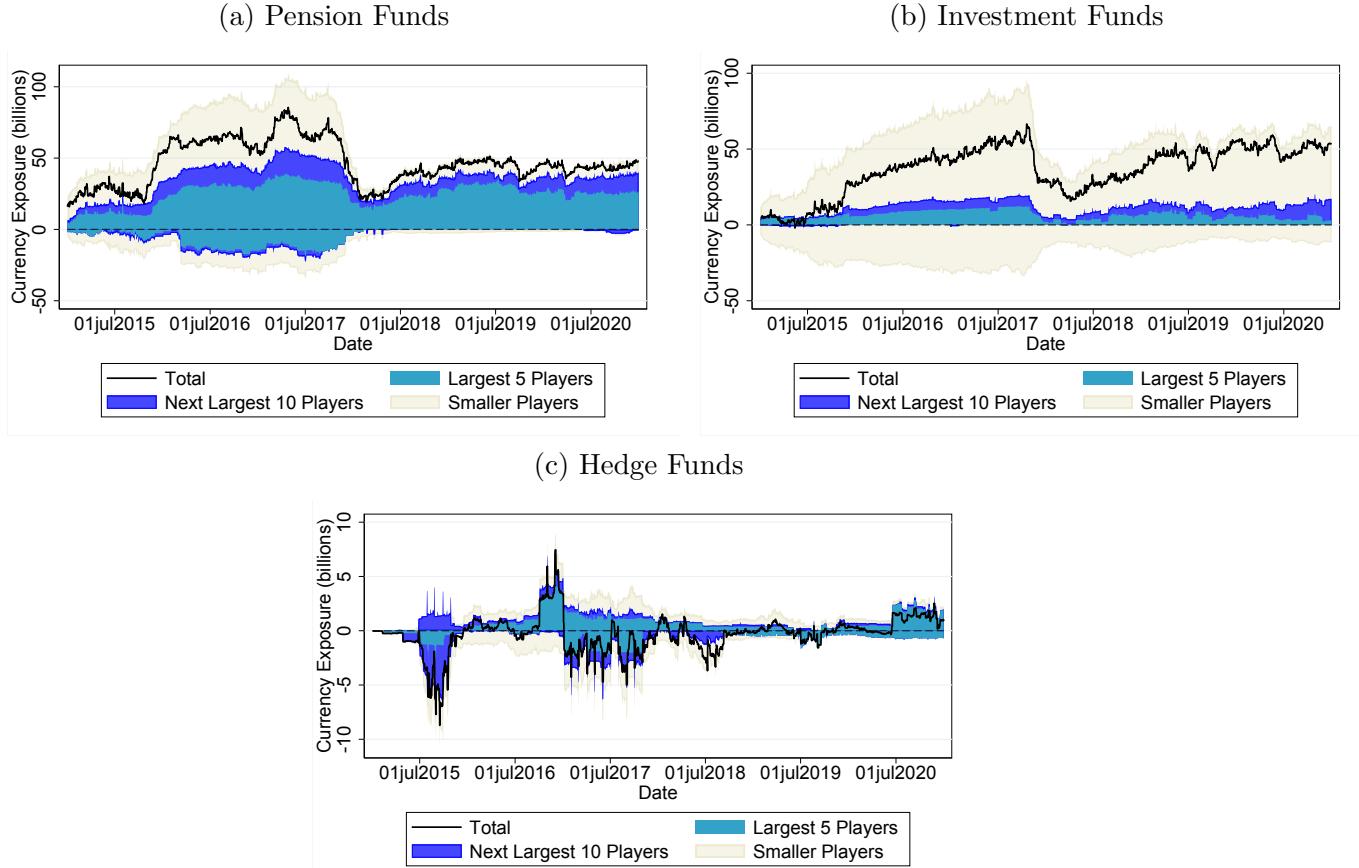
Note. Sectoral net-long and net-short GBP exposures, highlighted in blue and beige, are calculated by separately aggregating the exposures of firms in a sector that are net-long and net-short the GBP vis-à-vis all other currencies. The black line refers to the sum of the net-long and net-short GBP exposures, which is shown in Figure 4. Shaded in light and dark blue are the net-long and net-short positions of the largest 5 and next largest 10 firms in the sector in terms of average currency exposure over the sample. In beige are the exposures of the smaller players. GBP exposures are measured in units of GBP. Firms included are those reporting under EMIR to the DTCC and UnaVista trade repositories between January 1, 2015 (July 1 2016 for Banks) and December 31, 2020.

Figure A.15: Heterogeneous and Concentrated EUR Exposure Across Asset Management Types



Note. Types of asset managers' net-long and net-short EUR exposures, highlighted in blue and beige, are calculated by separately aggregating the exposures of firms in a sector who are net-long and net-short the EUR vis-à-vis all other currencies. The black line refers to the sum of the net-long and net-short EUR exposures, which is shown in Figure 5. Shaded in light and dark blue are the net-long and net-short positions of the largest 5 and next largest 10 firms in the sector in terms of average currency exposure over the sample. In beige are the exposures of the smaller players. EUR exposures are measured in units of EUR. Firms included are those reporting under EMIR to the DTCC and UnaVista trade repositories between January 1, 2015 and December 31, 2020.

Figure A.16: Heterogeneous and Concentrated GBP Exposure Across Asset Management Types

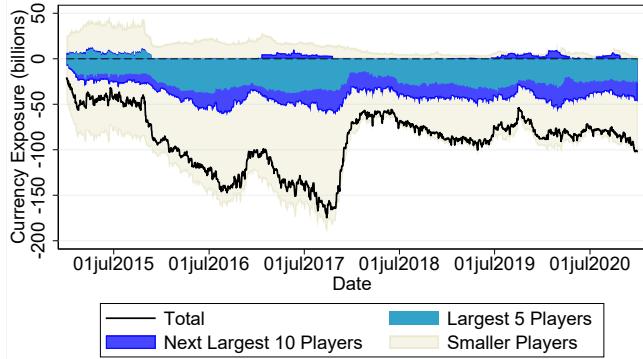


Note. Types of asset managers' net-long and net-short GBP exposures, highlighted in blue and beige, are calculated by separately aggregating the exposures of firms in a sector who are net-long and net-short the GBP vis-à-vis all other currencies. The black line refers to the sum of the net-long and net-short GBP exposures, which is shown in Figure 5. Shaded in light and dark blue are the net-long and net-short positions of the largest 5 and next largest 10 firms in the sector in terms of average currency exposure over the sample. In beige are the exposures of the smaller players. GBP exposures are measured in units of GBP. Firms included are those reporting under EMIR to the DTCC and UnaVista trade repositories between January 1, 2015 and December 31, 2020.

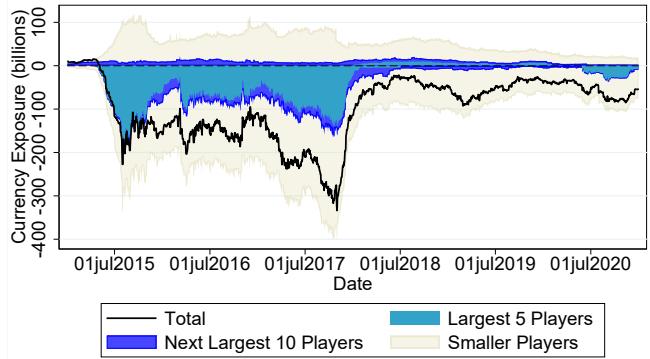
A.3.3 Net Currency Stock Exposures by Sector & Country of Residence: Heterogeneity & Concentration

Figure A.17: UK and EU Asset Managers' Exposure to the Major 3 Currencies

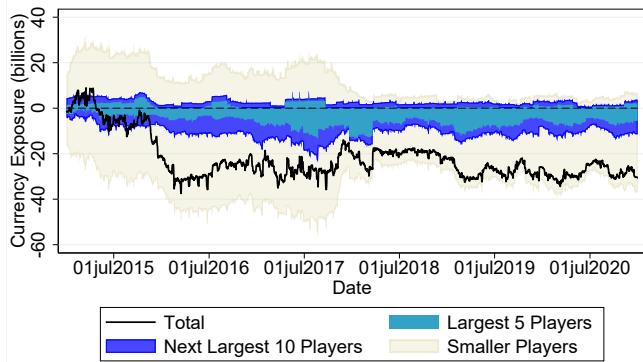
(a) UK Asset Managers' USD Exposures



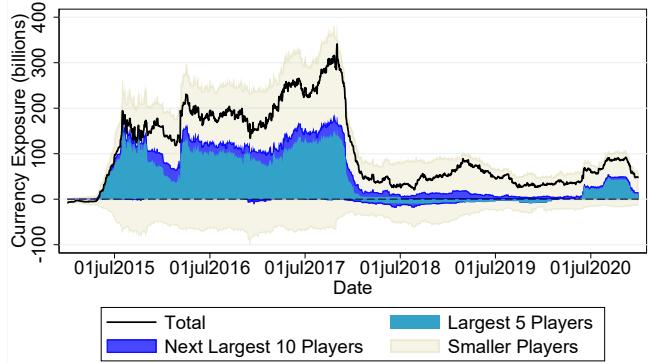
(b) EU Asset Managers' USD Exposures



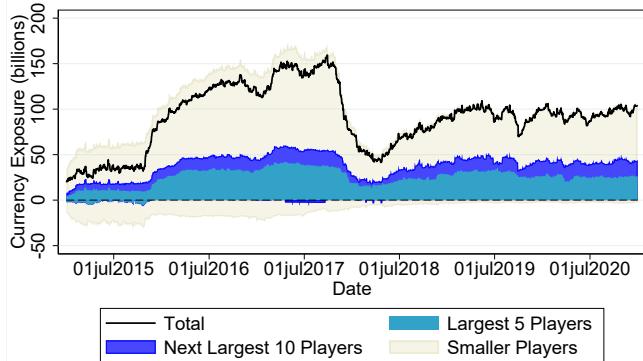
(c) UK Asset Managers' EUR Exposures



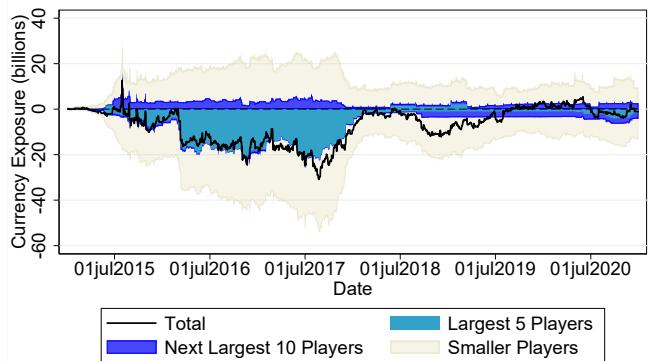
(d) EU Asset Managers' EUR Exposures



(e) UK Asset Managers' GBP Exposures



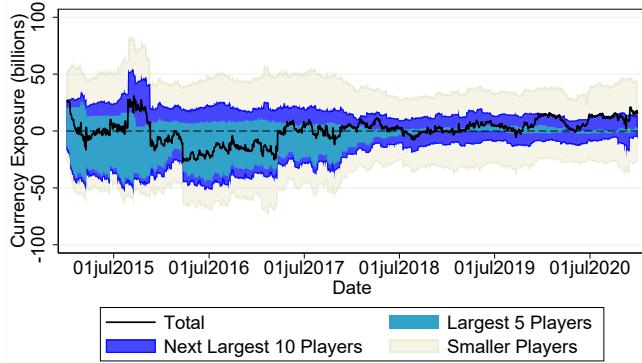
(f) EU Asset Managers' GBP Exposures



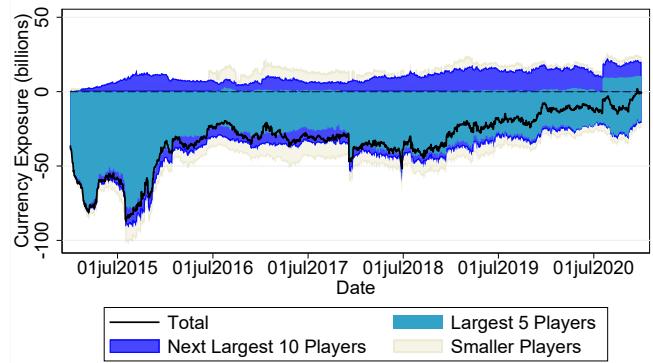
Note. UK and EU Asset Managers' net-long and net-short currency exposures, highlighted in blue and beige, for the major 3 currencies are calculated by separately aggregating the currency exposures of UK and EU asset managers that are net-long and net-short each currency. The black line refers to the sum of the net-long and net-short currency exposures in each panel. Shaded in light and dark blue are the net-long and net-short positions of the largest 5 and next largest 10 firms in the sector in terms of average currency exposure over the sample. In beige are the currency exposures of the smaller players. Currency exposures are measured in units of local currency (i.e., in GBP for GBP exposures). Positive (negative) values refer to firms being net-long (net-short) the base currency. Firms included are those reporting under EMIR to the DTCC and UnaVista trade repositories between January 1, 2015 and December 31, 2020.

Figure A.18: UK and EU Non-Financial Corporates' Exposure to the Major 3 Currencies

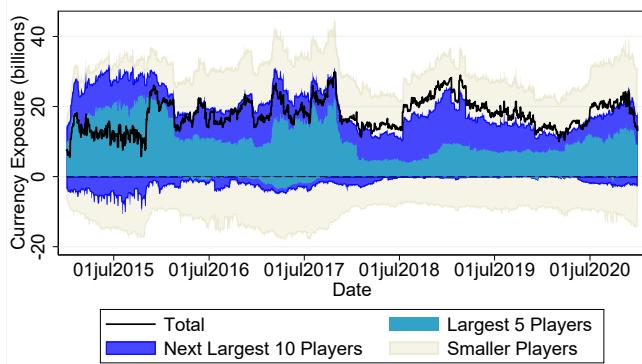
(a) UK Corporates' USD Exposures



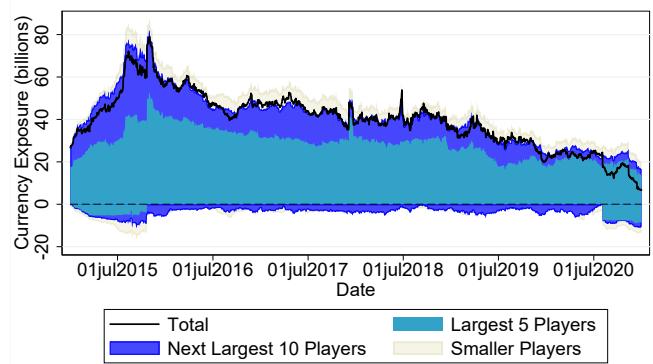
(b) EU Corporates' USD Exposures



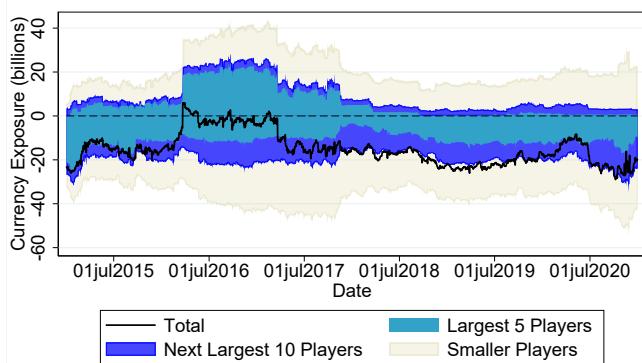
(c) UK Corporates' EUR Exposures



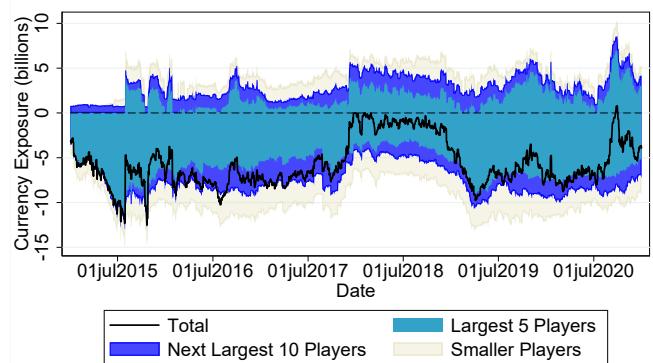
(d) EU Corporates' EUR Exposures



(e) UK Corporates' GBP Exposures

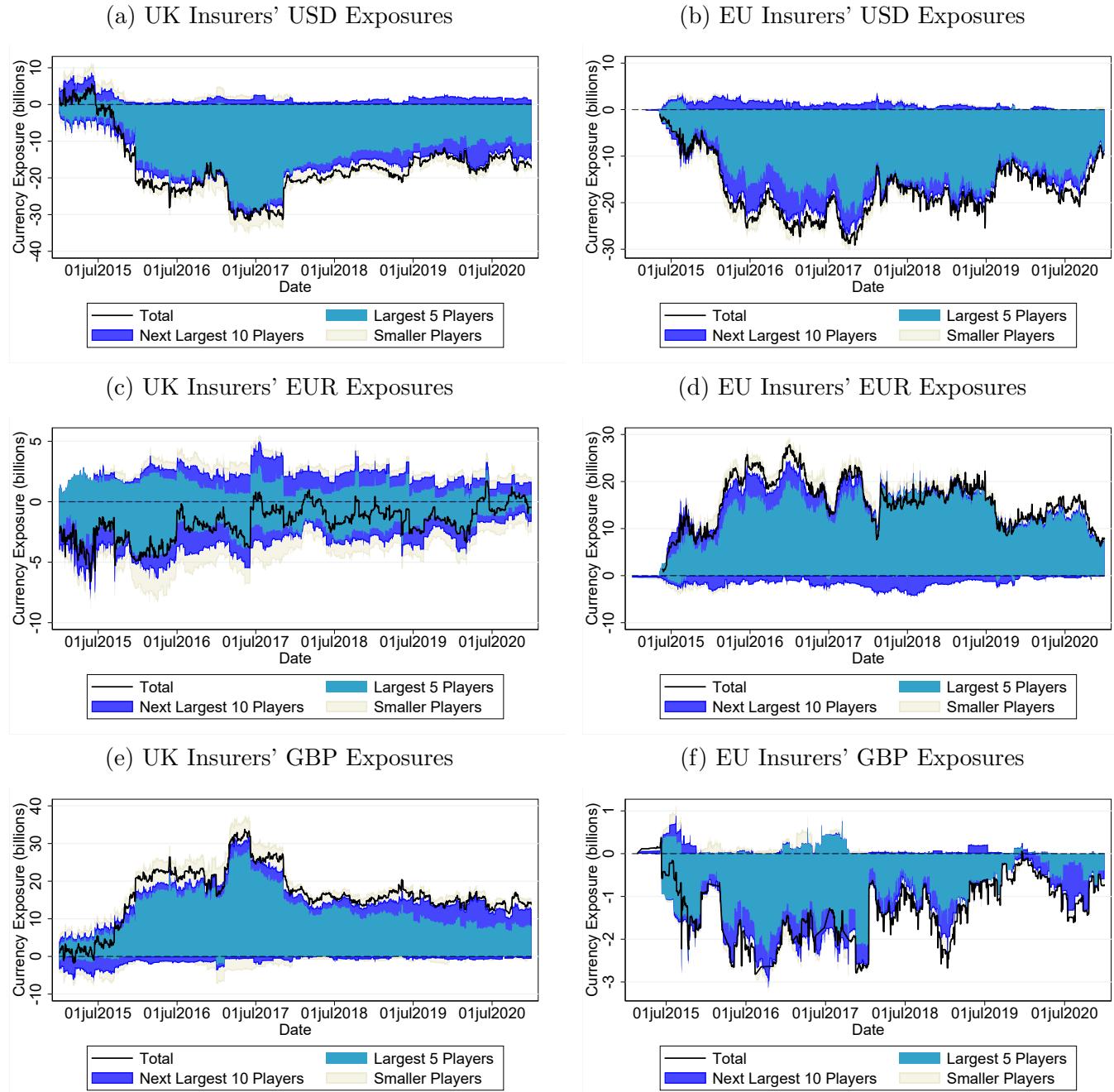


(f) EU Corporates' GBP Exposures



Note. UK and EU Corporates' net-long and net-short currency exposures, highlighted in blue and beige, for the major 3 currencies are calculated by separately aggregating the currency exposures of UK and EU corporates that are net-long and net-short each currency. The black line refers to the sum of the net-long and net-short currency exposures in each panel. Shaded in light and dark blue are the net-long and net-short positions of the largest 5 and next largest 10 firms in the sector in terms of average currency exposure over the sample. In beige are the currency exposures of the smaller players. Currency exposures are measured in units of local currency (i.e., in GBP for GBP exposures). Positive (negative) values refer to firms being net-long (net-short) the base currency. Firms included are those reporting under EMIR to the DTCC and UnaVista trade repositories between January 1, 2015 and December 31, 2020.

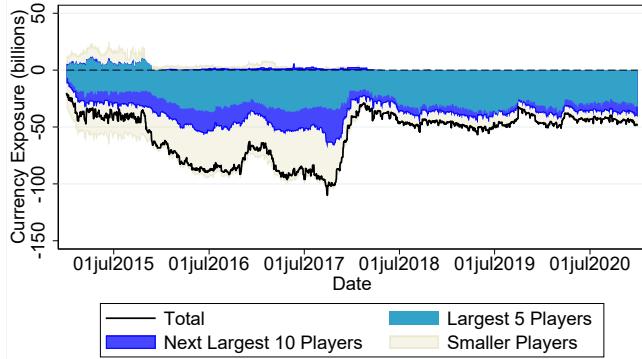
Figure A.19: UK and EU Insurers' Exposure to the Major 3 Currencies



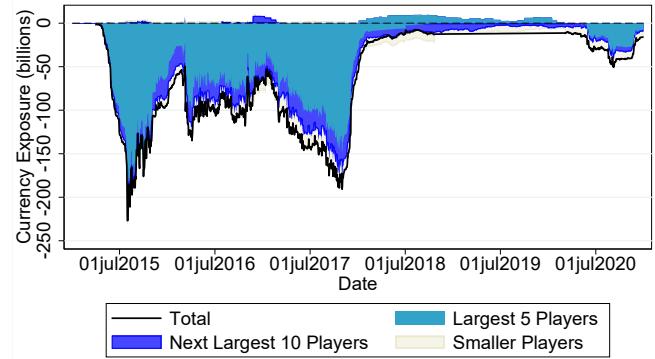
Note. UK and EU Insurers' net-long and net-short currency exposures, highlighted in blue and beige, for the major 3 currencies are calculated by separately aggregating the currency exposures of UK and EU insurers that are net-long and net-short each currency. The black line refers to the sum of the net-long and net-short currency exposures in each panel. Shaded in light and dark blue are the net-long and net-short positions of the largest 5 and next largest 10 firms in the sector in terms of average currency exposure over the sample. In beige are the currency exposures of the smaller players. Currency exposures are measured in units of local currency (i.e., in GBP for GBP exposures). Positive (negative) values refer to firms being net-long (net-short) the base currency. Firms included are those reporting under EMIR to the DTCC and UnaVista trade repositories between January 1, 2015 and December 31, 2020.

Figure A.20: UK and EU Pension Funds' Exposure to the Major 3 Currencies

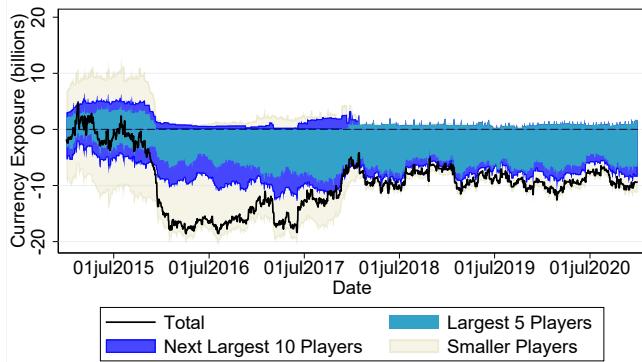
(a) UK Pension Funds' USD Exposures



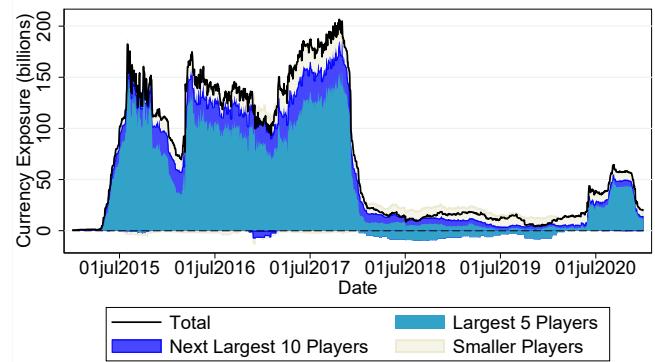
(b) EU Pension Funds' USD Exposures



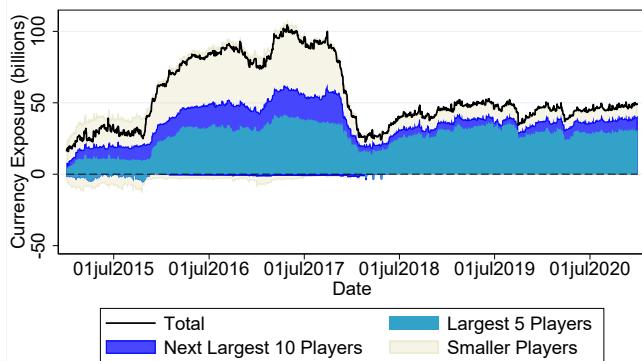
(c) UK Pension Funds' EUR Exposures



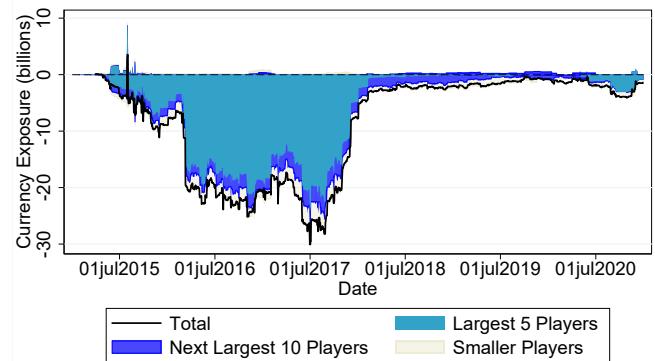
(d) EU Pension Funds' EUR Exposures



(e) UK Pension Funds' GBP Exposures

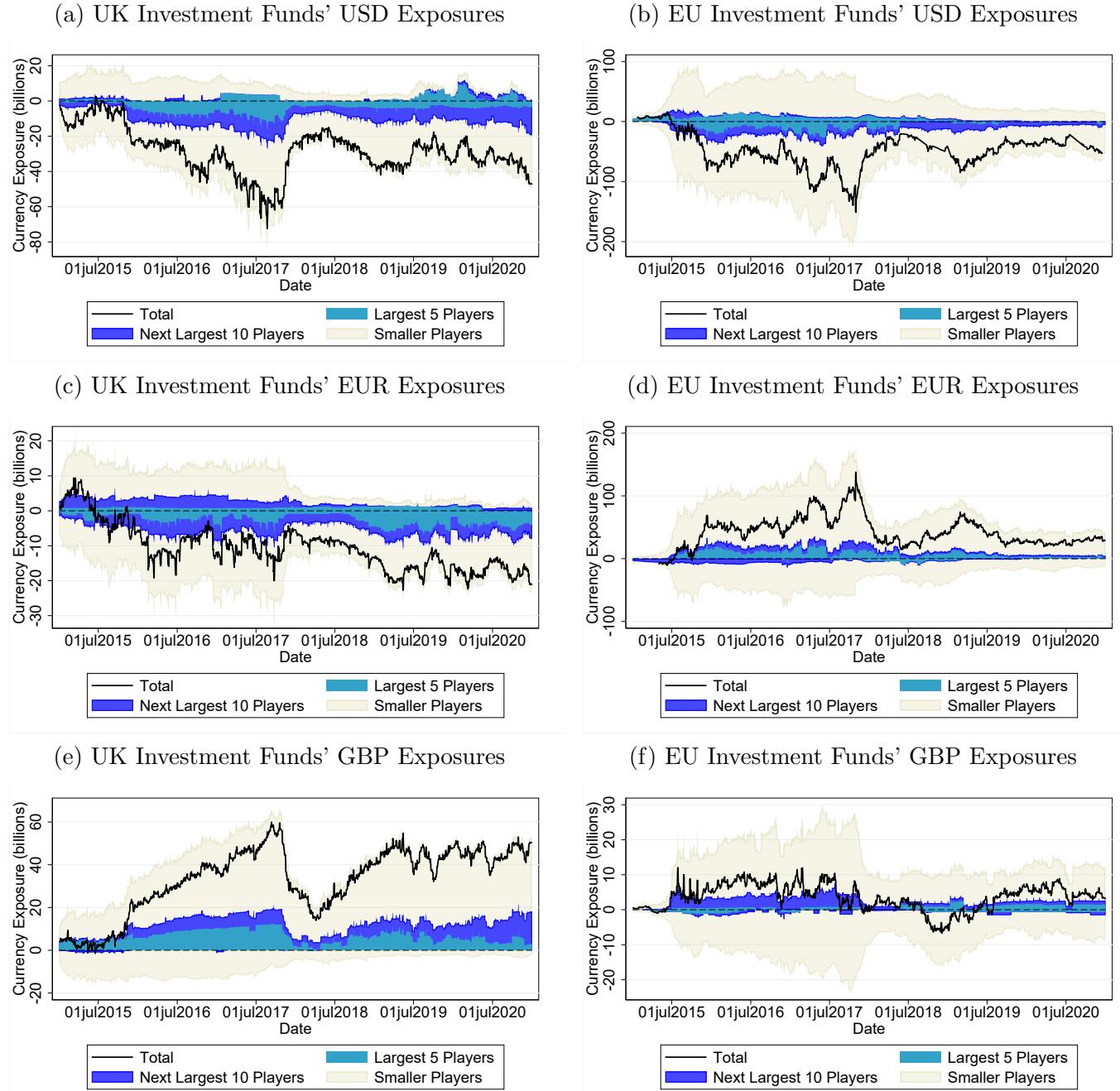


(f) EU Pension Funds' GBP Exposures



Note. UK and EU Pension Funds' net-long and net-short currency exposures, highlighted in blue and beige, for the major 3 currencies are calculated by separately aggregating the currency exposures of UK and EU pension funds that are net-long and net-short each currency. The black line refers to the sum of the net-long and net-short currency exposures in each panel. Shaded in light and dark blue are the net-long and net-short positions of the largest 5 and next largest 10 firms in the sector in terms of average currency exposure over the sample. In beige are the currency exposures of the smaller players. Currency exposures are measured in units of local currency (i.e., in GBP for GBP exposures). Positive (negative) values refer to firms being net-long (net-short) the base currency. Firms included are those reporting under EMIR to the DTCC and UnaVista trade repositories between January 1, 2015 and December 31, 2020.

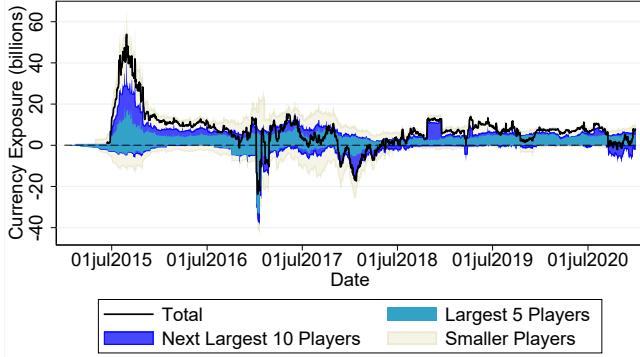
Figure A.21: UK and EU Investment Funds' Exposure to the Major 3 Currencies



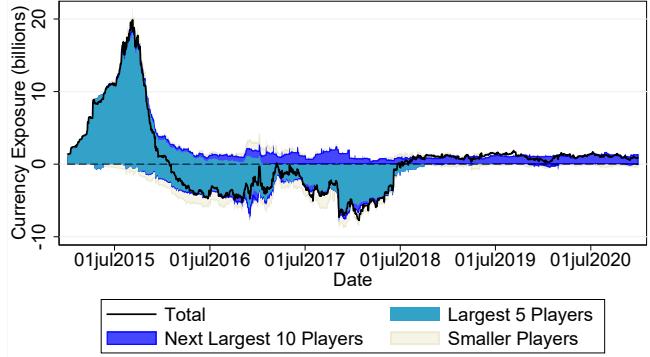
Note. UK and EU Investment Funds' net-long and net-short currency exposures, highlighted in blue and beige, for the major 3 currencies are calculated by separately aggregating the currency exposures of UK and EU investment funds that are net-long and net-short each currency. The black line refers to the sum of the net-long and net-short currency exposures in each panel. Shaded in light and dark blue are the net-long and net-short positions of the largest 5 and next largest 10 firms in the sector in terms of average currency exposure over the sample. In beige are the currency exposures of the smaller players. Currency exposures are measured in units of local currency (i.e., in GBP for GBP exposures). Positive (negative) values refer to firms being net-long (net-short) the base currency. Firms included are those reporting under EMIR to the DTCC and UnaVista trade repositories between January 1, 2015 and December 31, 2020.

Figure A.22: Non-EU and EU Hedge Funds' Exposure to the Major 3 Currencies

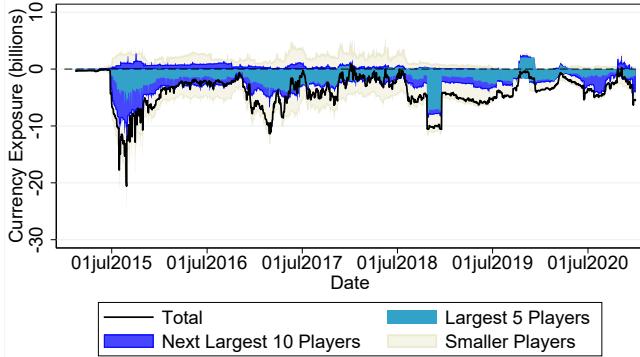
(a) Non-EU Hedge Funds' USD Exposures



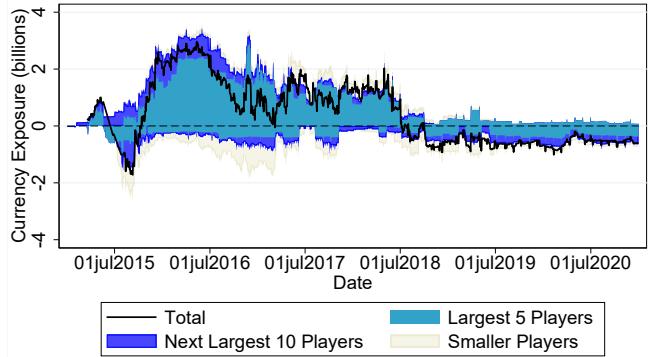
(b) EU Hedge Funds' USD Exposures



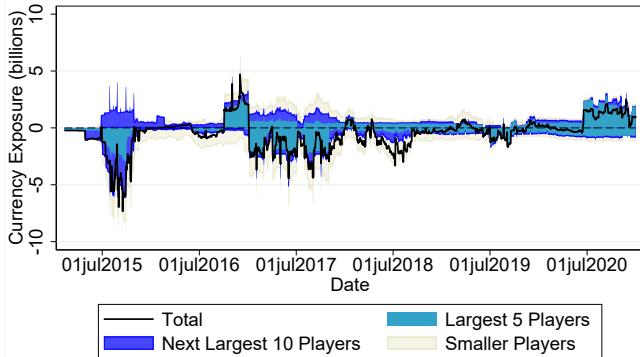
(c) Non-EU Hedge Funds' EUR Exposures



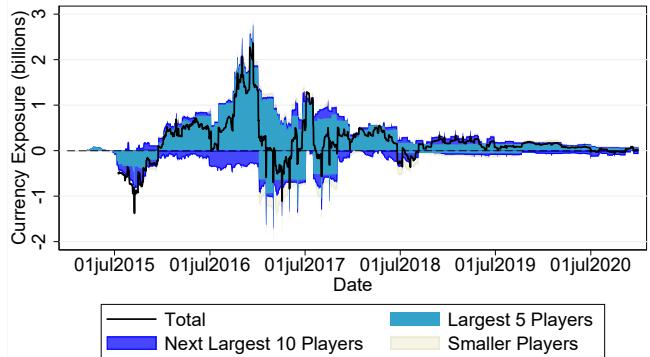
(d) EU Hedge Funds' EUR Exposures



(e) Non-EU Hedge Funds' GBP Exposures

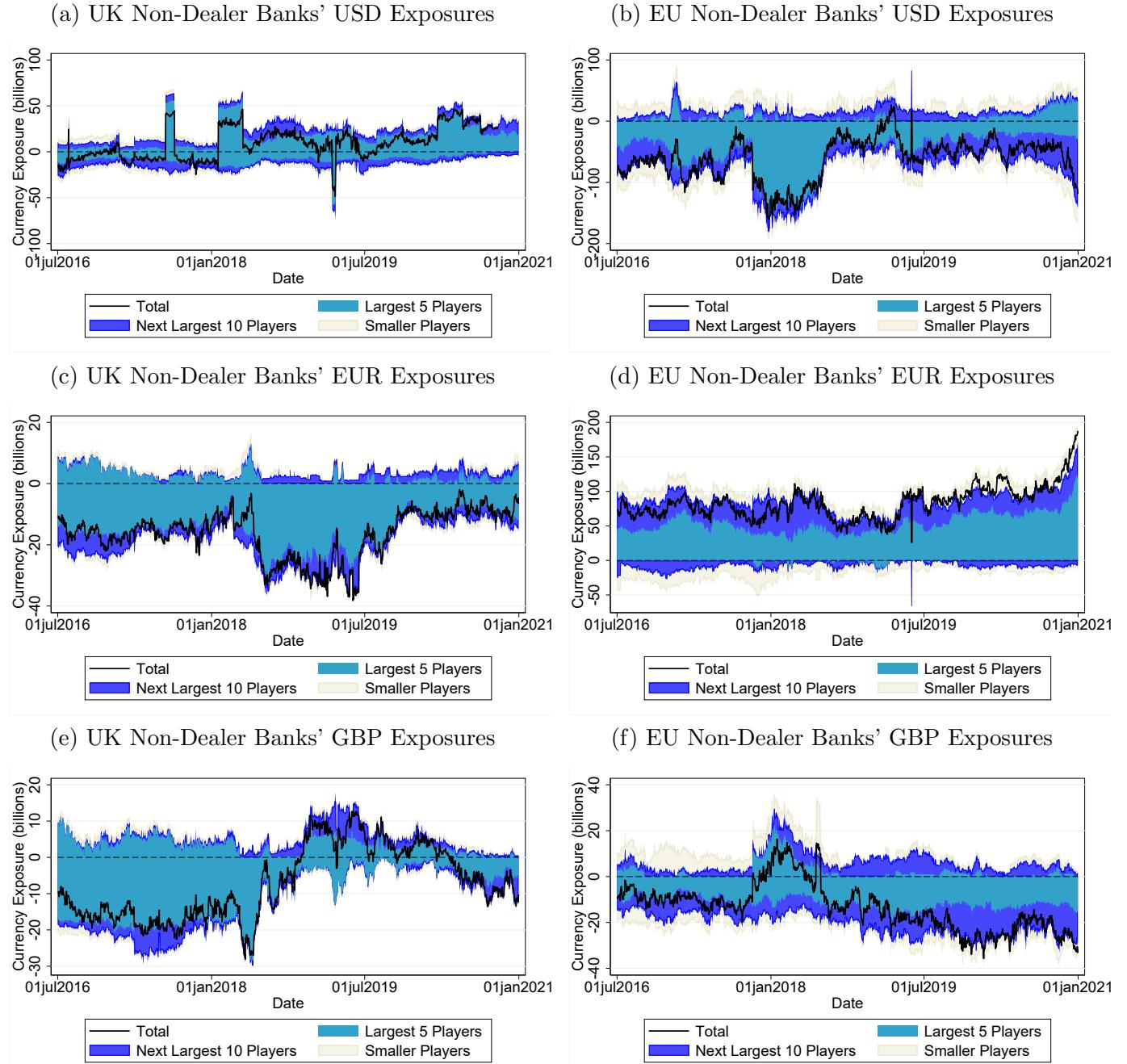


(f) EU Hedge Funds' GBP Exposures



Note. Non-EU and EU Hedge Funds' net-long and net-short currency exposures, highlighted in blue and beige, for the major 3 currencies are calculated by separately aggregating the currency exposures of Non-EU and EU hedge funds that are net-long and net-short each currency. The black line refers to the sum of the net-long and net-short currency exposures in each panel. Shaded in light and dark blue are the net-long and net-short positions of the largest 5 and next largest 10 firms in the sector in terms of average currency exposure over the sample. In beige are the currency exposures of the smaller players. Currency exposures are measured in units of local currency (i.e., in GBP for GBP exposures). Positive (negative) values refer to firms being net-long (net-short) the base currency. Firms included are those reporting under EMIR to the DTCC and UnaVista trade repositories between January 1, 2015 and December 31, 2020.

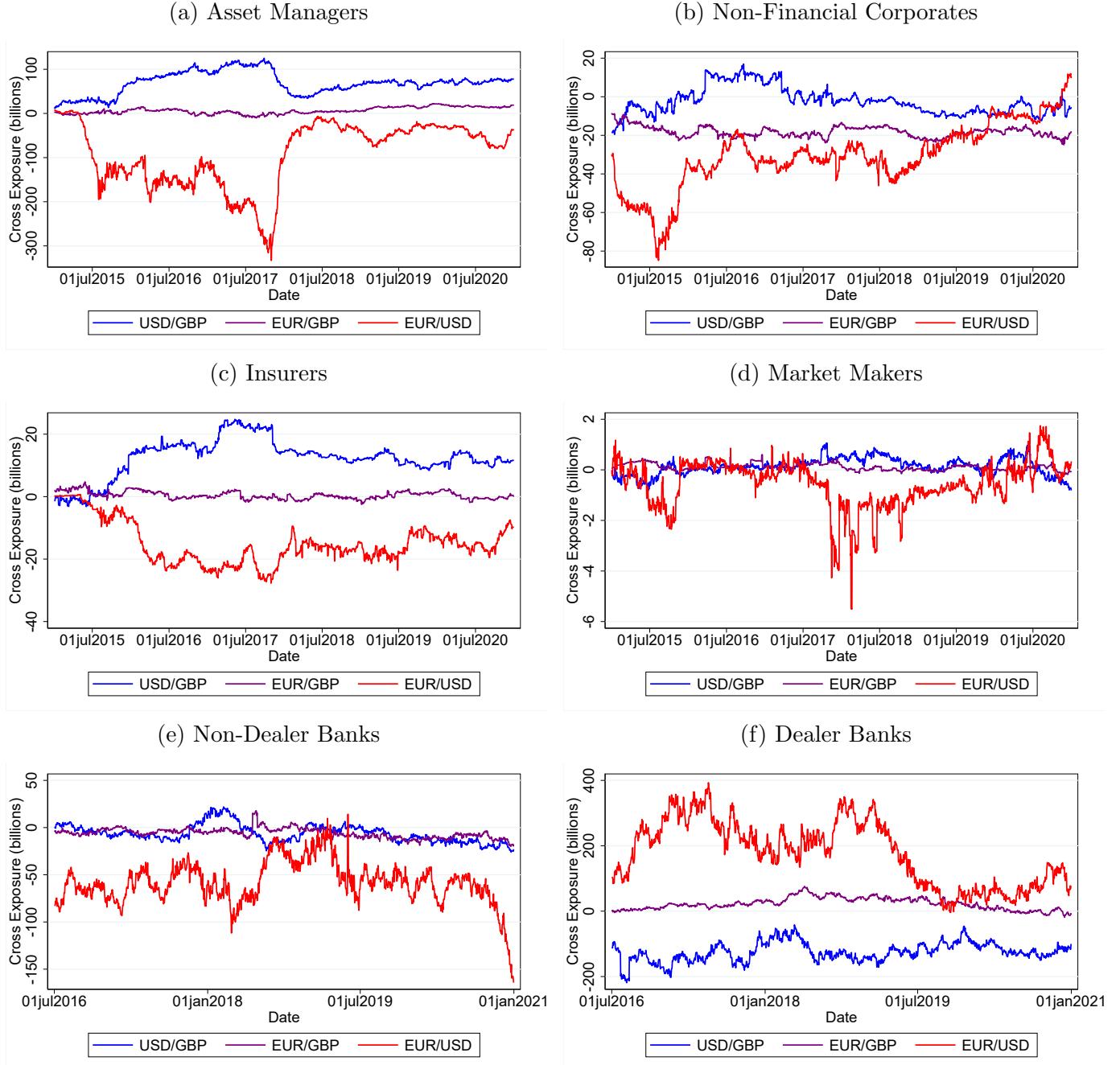
Figure A.23: UK and EU Non-Dealer Banks' Exposure to the Major 3 Currencies



Note. UK and EU Non-Dealer Banks' net-long and net-short currency exposures, highlighted in blue and beige, for the major 3 currencies are calculated by separately aggregating the currency exposures of UK and EU non-dealer banks that are net-long and net-short each currency. The black line refers to the sum of the net-long and net-short currency exposures in each panel. Shaded in light and dark blue are the net-long and net-short positions of the largest 5 and next largest 10 firms in the sector in terms of average currency exposure over the sample. In beige are the currency exposures of the smaller players. Currency exposures are measured in units of local currency (i.e., in GBP for GBP exposures). Positive (negative) values refer to firms being net-long (net-short) the base currency. Firms included are those reporting under EMIR to the DTCC and UnaVista trade repositories between January 1, 2015 and December 31, 2020.

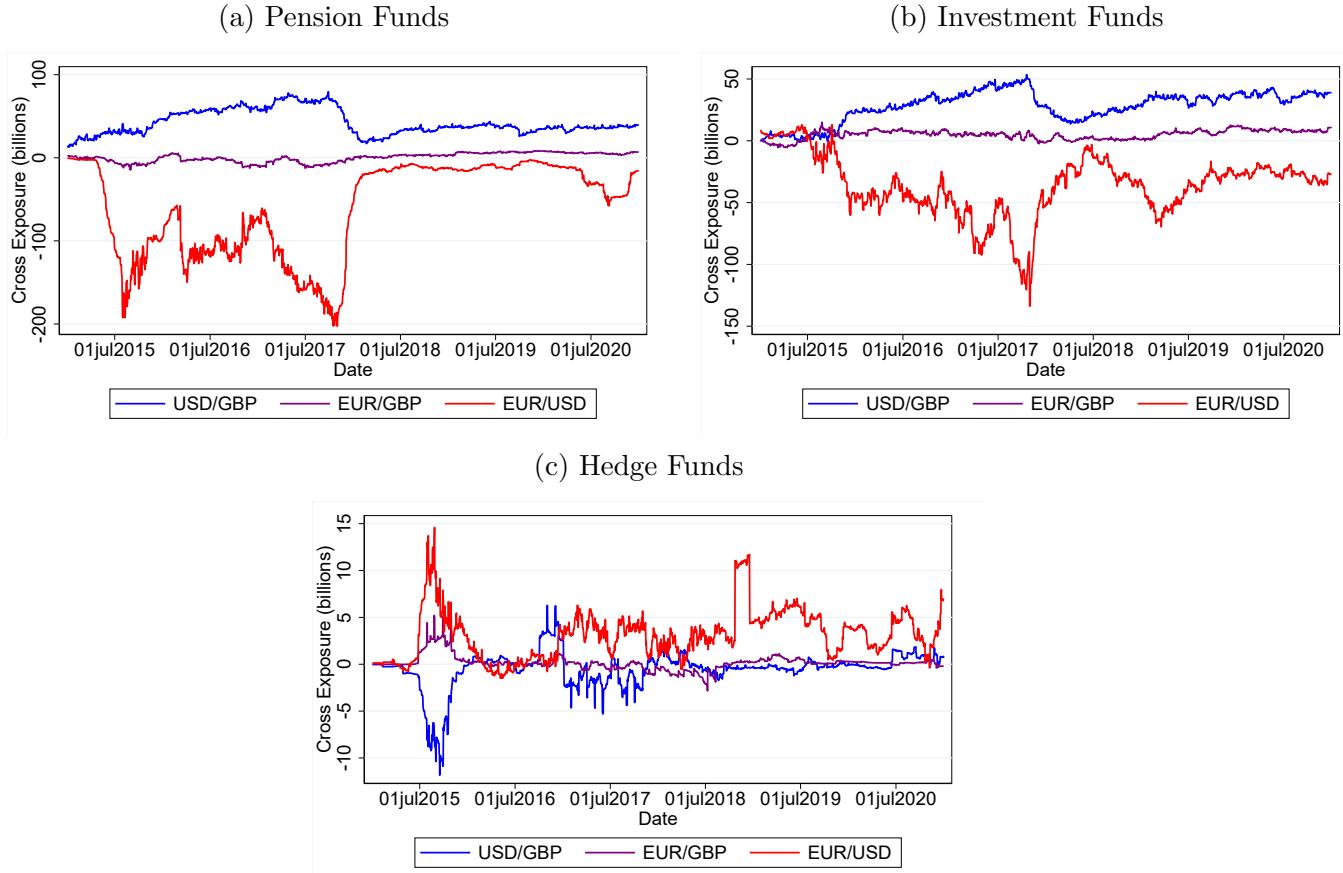
A.3.4 Net Currency-Cross Stock Exposures by Sector

Figure A.24: Sectoral Currency-Cross Exposures for Major Three Crosses



Note. Sector-level currency-cross exposures, calculated as the sum over net currency-cross exposure of firms in a particular sector, for the major three crosses—USD/GBP, EUR/GBP, EUR/USD. Currency-cross exposures are measured in units of the base currency (with curr/base shown in each panel). Positive (negative) values refer to firms being net-long (net-short) the base currency. Firms included are those reporting under EMIR to the DTCC and UnaVista trade repositories between January 1 2015 (July 1 2016 for Banks) and December 31 2020.

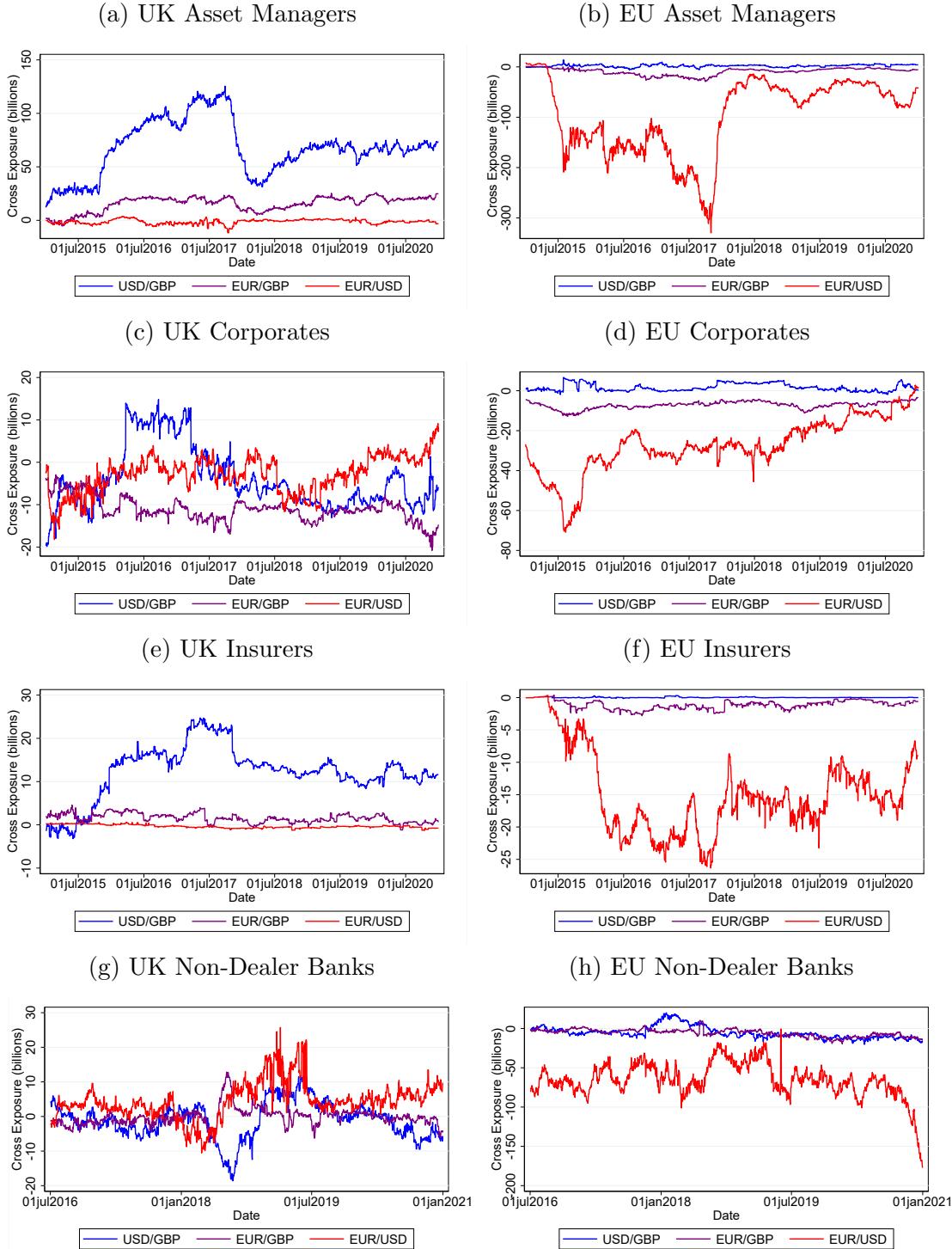
Figure A.25: Asset Manager Types' Cross Exposures to Major Three Crosses



Note. Types of asset managers' currency-cross exposures, calculated as the sum over net currency-cross exposure of firms in a particular sector, for the major three crosses—USD/GBP, EUR/GBP, EUR/USD. Currency-cross exposures are measured in units of the base currency (with curr/base shown in each panel). Positive (negative) values refer to firms being net-long (net-short) the base currency. Firms included are those reporting under EMIR to the DTCC and UnaVista trade repositories between January 1 2015 (July 1 2016 for Banks) and December 31 2020.

A.3.5 Net Currency-Cross Stock Exposures by Country of Residence

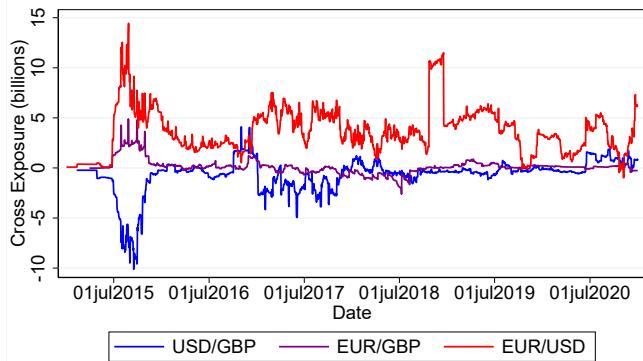
Figure A.26: UK & EU Sector-Level Cross Exposures to Major 3 Crosses



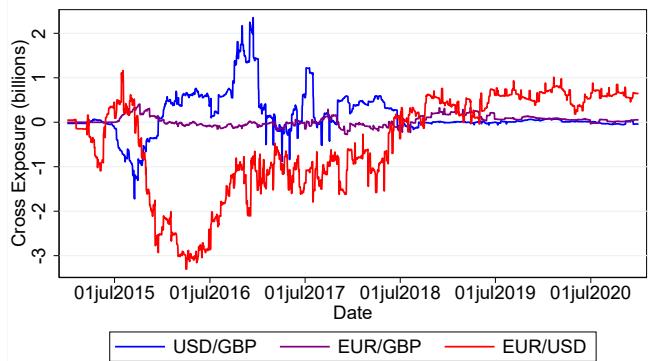
Note. UK and EU Sector-level currency-cross exposures, calculated by separately summing over the net currency-cross exposures of UK and EU firms in a particular sector, for the major three crosses—USD/GBP, EUR/GBP, EUR/USD. Currency-cross exposures are measured in units of the base currency (with curr/base shown in each panel). Positive (negative) values refer to firms being net-long (net-short) the base currency. Firms included are those reporting under EMIR to the DTCC and UnaVista trade repositories between January 1 2015 (July 1 2016 for Banks) and December 31 2020.

Figure A.27: UK & EU Fund-Level Cross Exposures to Major Three Crosses

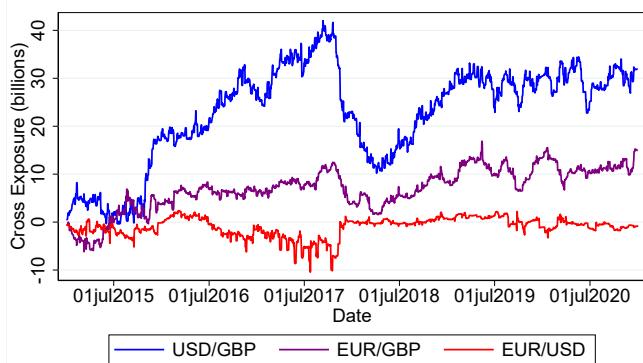
(a) Non-EU Hedge Funds



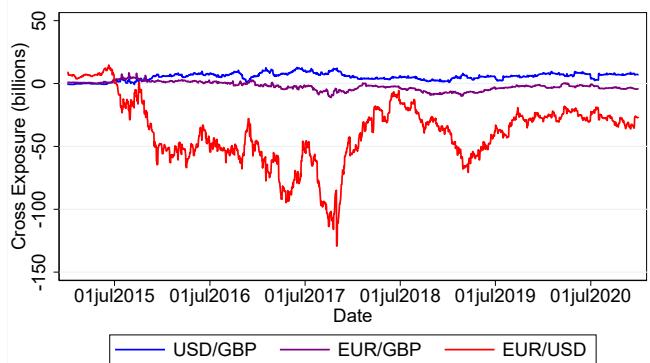
(b) EU Hedge Funds



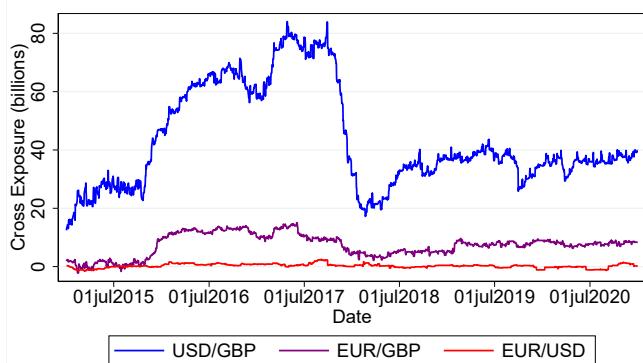
(c) UK Investment Funds



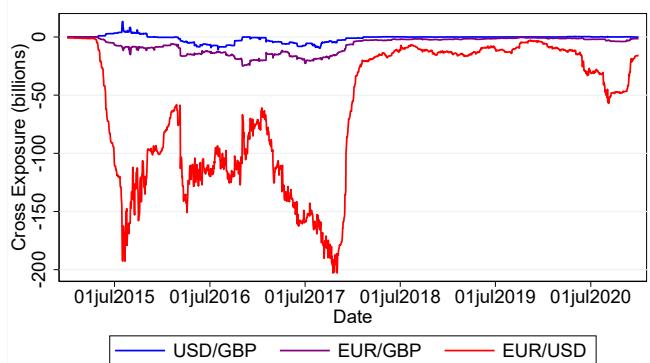
(d) EU Investment Funds



(e) UK Pension Funds



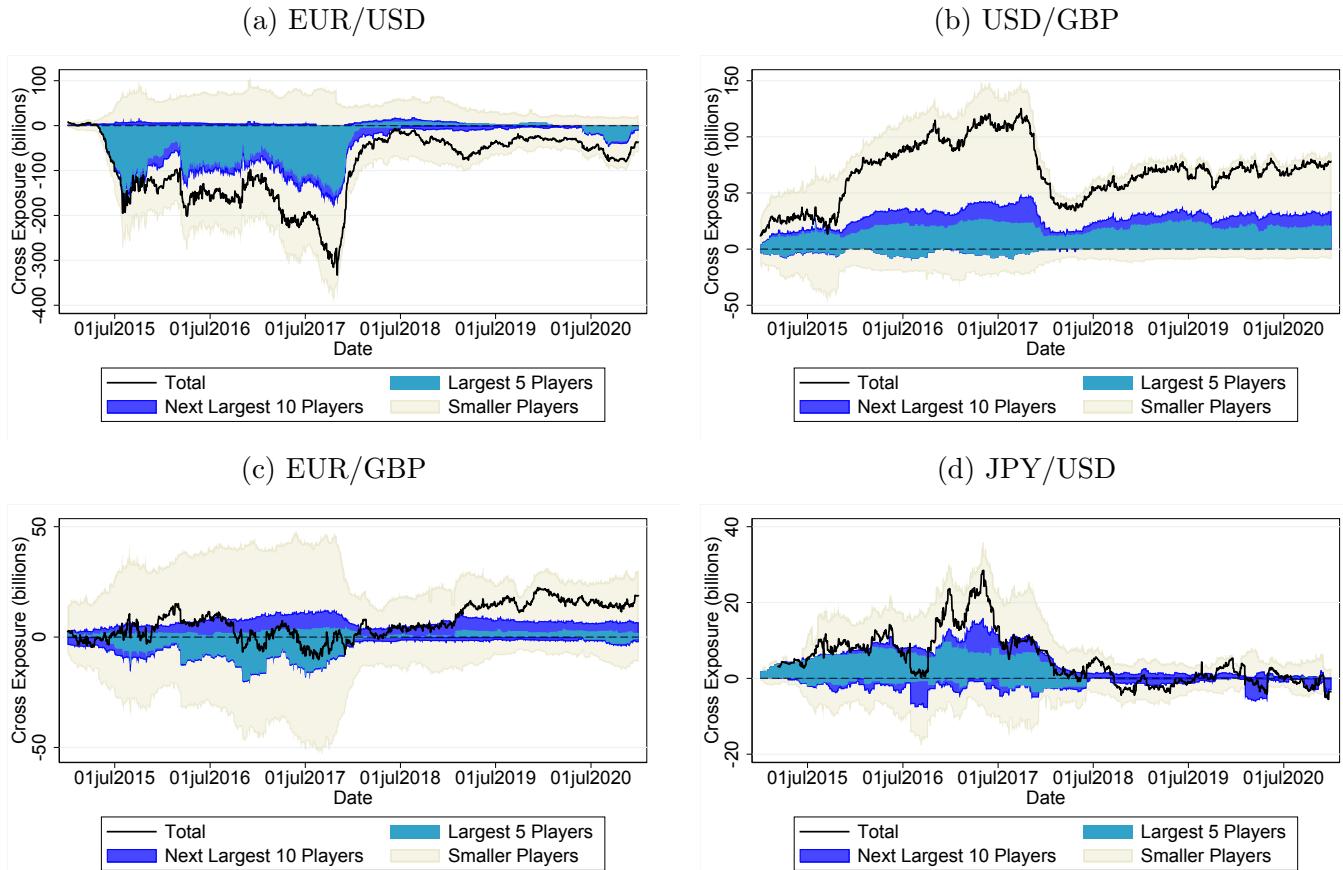
(f) EU Pension Funds



Note. UK and EU Sector-level currency-cross exposures, calculated by separately summing over the net currency-cross exposures of UK (non-EU for hedge funds) and EU firms in a particular sector, for the major three crosses—USD/GBP, EUR/GBP, EUR/USD. Currency-cross exposures are measured in units of the base currency (with curr/base shown in each panel). Positive (negative) values refer to firms being net-long (net-short) the base currency. Firms included are those reporting under EMIR to the DTCC and UnaVista trade repositories between January 1 2015 and December 31 2020.

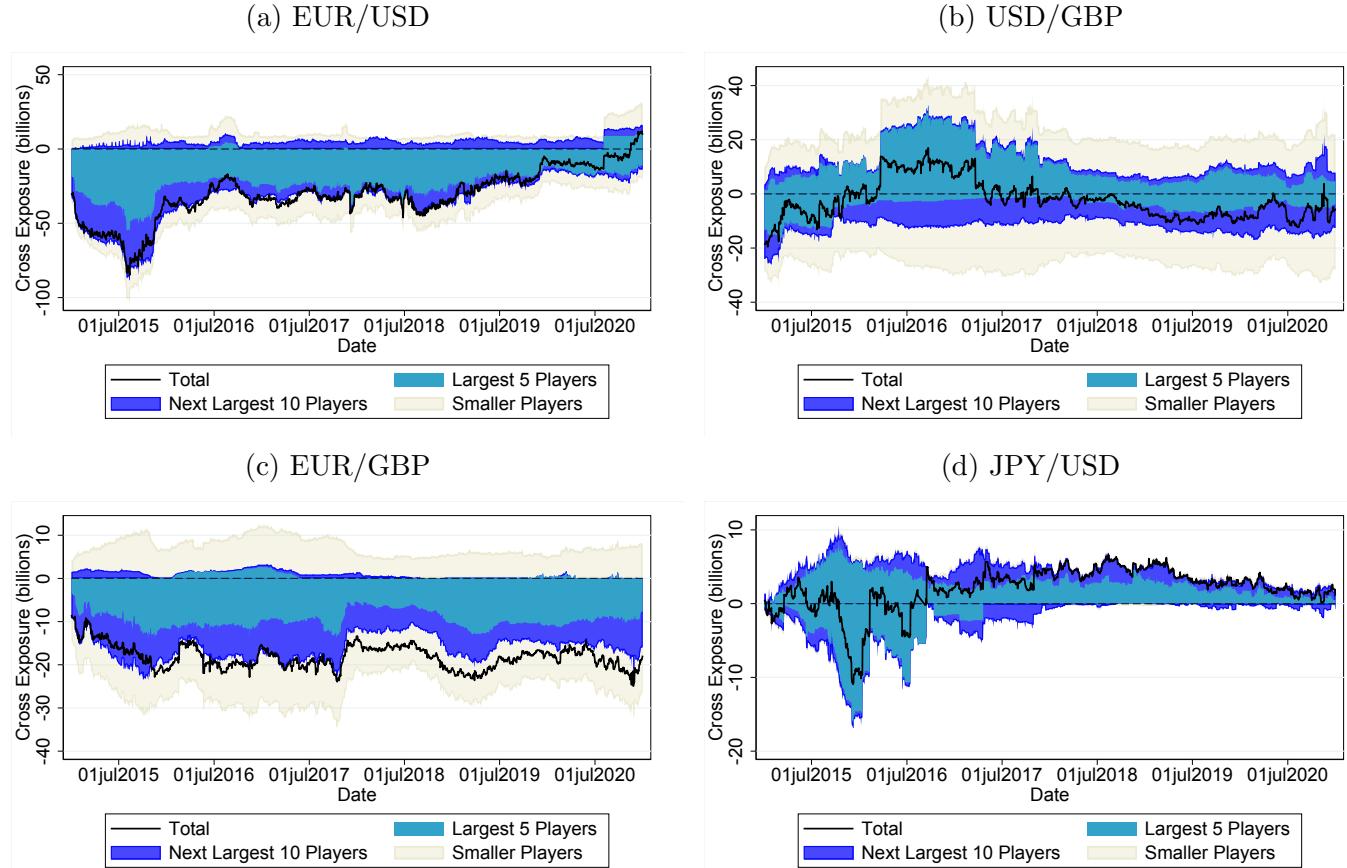
A.3.6 Net Currency-Cross Stock Exposures by Sector: Heterogeneity and Concentration

Figure A.28: Asset Managers' Exposure to the Major 4 Currency Crosses



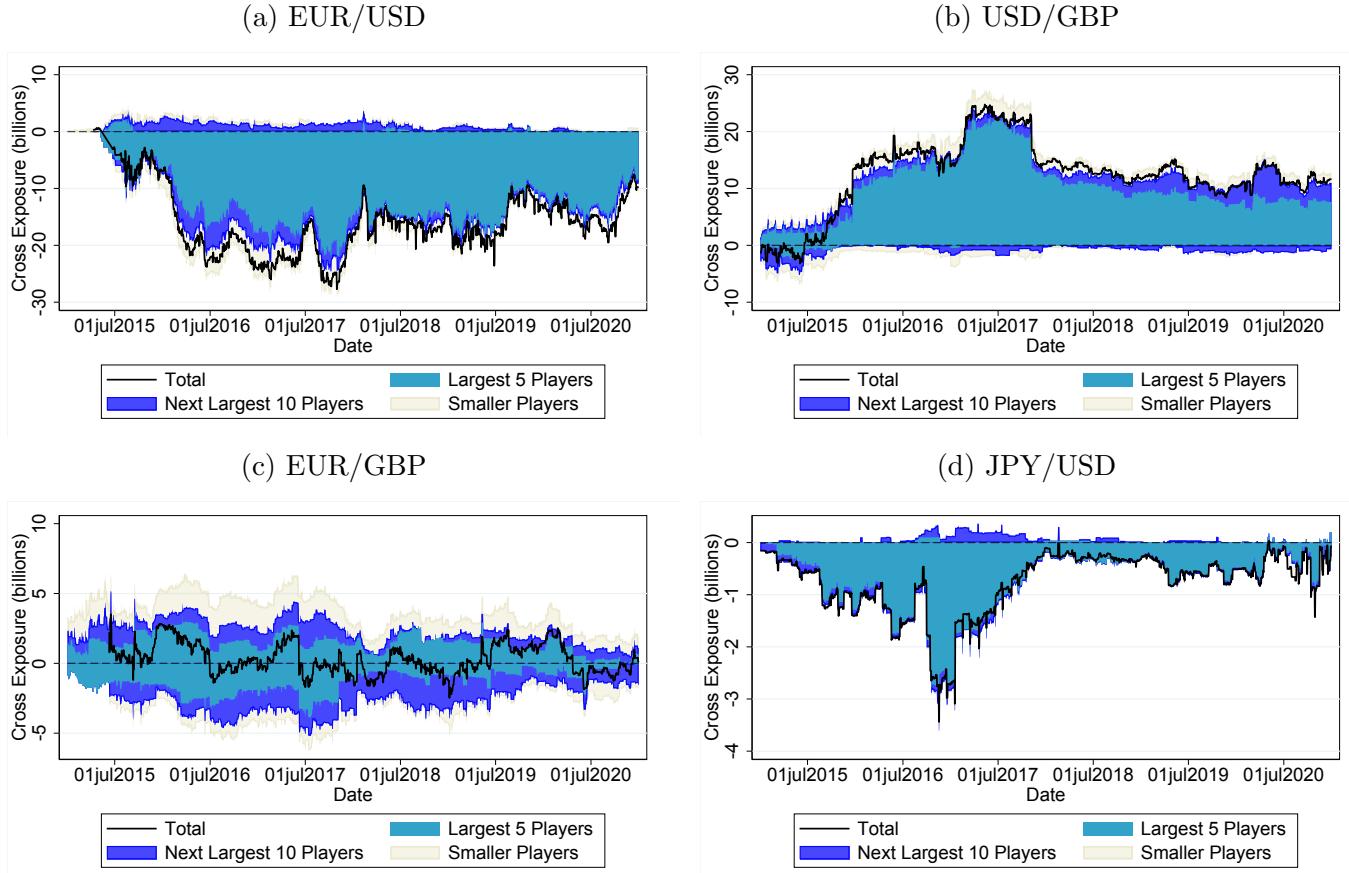
Note. Asset Managers' net-long and net-short currency-cross exposures, highlighted in blue and beige, for the major 4 crosses are calculated by separately aggregating the currency-cross exposures of asset managers that are net-long and net-short each currency cross. The black line refers to the sum of the net-long and net-short currency-cross exposures in each panel. Shaded in light and dark blue are the net-long and net-short positions of the largest 5 and next largest 10 firms in the sector in terms of average currency-cross exposure over the sample. In beige are the cross exposures of the smaller players. Currency-cross exposures are measured in units of the base currency (with curr/base shown above each panel). Positive (negative) values refer to firms being net-long (net-short) the base currency. Firms included are those reporting under EMIR to the DTCC and UnaVista trade repositories between January 1, 2015 and December 31, 2020.

Figure A.29: Non-Financial Corporates' Exposure to the Major 4 Currency Crosses



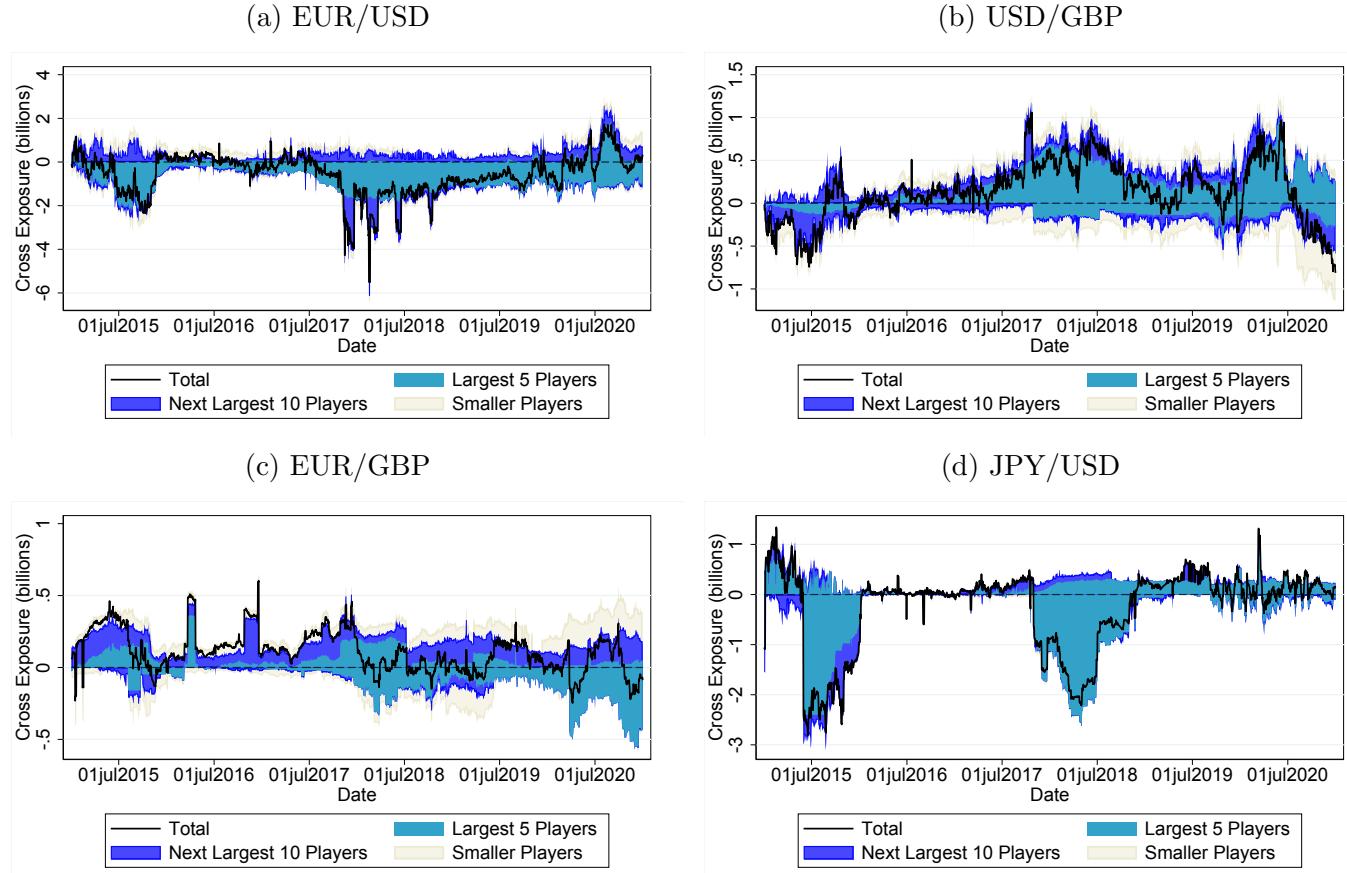
Note. Non-Financial Corporates' net-long and net-short currency-cross exposures, highlighted in blue and beige, for the major 4 crosses are calculated by separately aggregating the currency-cross exposures of asset managers that are net-long and net-short each currency cross. The black line refers to the sum of the net-long and net-short currency-cross exposures in each panel. Shaded in light and dark blue are the net-long and net-short positions of the largest 5 and next largest 10 firms in the sector in terms of average currency-cross exposure over the sample. In beige are the cross exposures of the smaller players. Currency-cross exposures are measured in units of the base currency (with curr/base shown above each panel). Positive (negative) values refer to firms being net-long (net-short) the base currency. Firms included are those reporting under EMIR to the DTCC and UnaVista trade repositories between January 1, 2015 and December 31, 2020.

Figure A.30: Insurers' Exposure to the Major 4 Currency Crosses



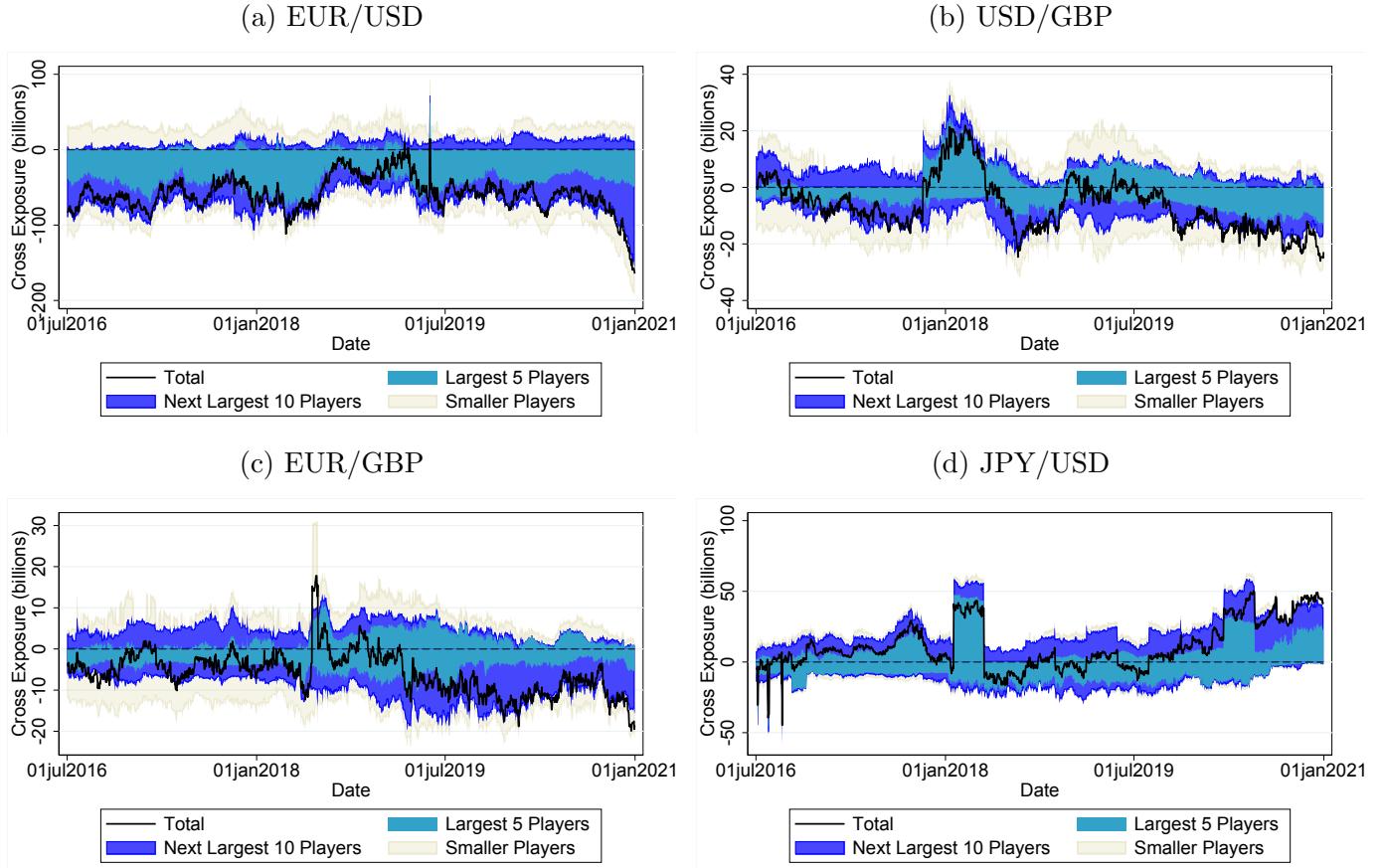
Note. Insurers' net-long and net-short currency-cross exposures, highlighted in blue and beige, for the major 4 crosses are calculated by separately aggregating the currency-cross exposures of asset managers that are net-long and net-short each currency cross. The black line refers to the sum of the net-long and net-short currency-cross exposures in each panel. Shaded in light and dark blue are the net-long and net-short positions of the largest 5 and next largest 10 firms in the sector in terms of average currency-cross exposure over the sample. In beige are the cross exposures of the smaller players. Currency-cross exposures are measured in units of the base currency (with curr/base shown above each panel). Positive (negative) values refer to firms being net-long (net-short) the base currency. Firms included are those reporting under EMIR to the DTCC and UnaVista trade repositories between January 1, 2015 and December 31, 2020.

Figure A.31: Market Makers' Exposure to the Major 4 Currency Crosses



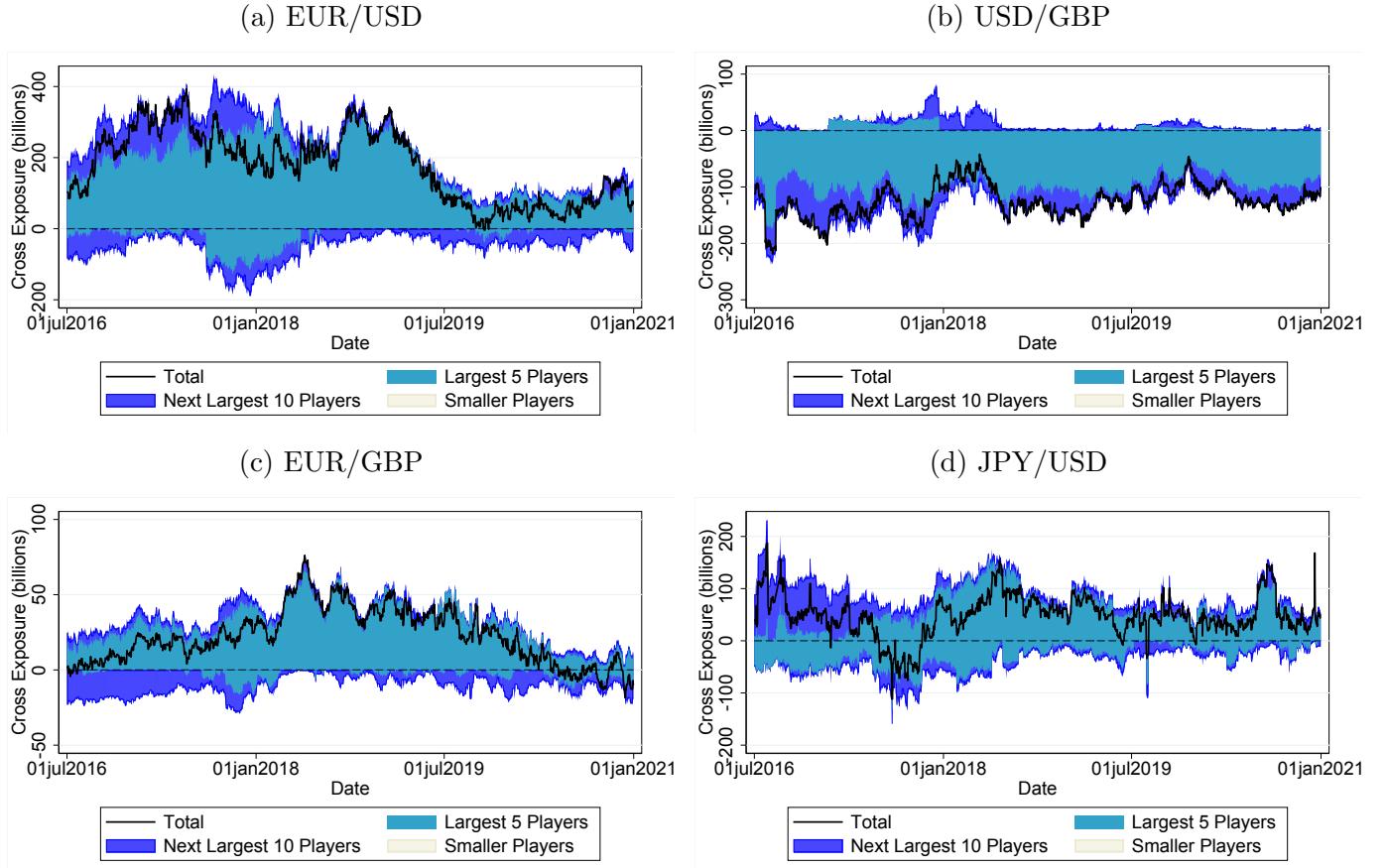
Note. Market Makers' net-long and net-short currency-cross exposures, highlighted in blue and beige, for the major 4 crosses are calculated by separately aggregating the currency-cross exposures of asset managers that are net-long and net-short each currency cross. The black line refers to the sum of the net-long and net-short currency-cross exposures in each panel. Shaded in light and dark blue are the net-long and net-short positions of the largest 5 and next largest 10 firms in the sector in terms of average currency-cross exposure over the sample. In beige are the cross exposures of the smaller players. Currency-cross exposures are measured in units of the base currency (with curr/base shown above each panel). Positive (negative) values refer to firms being net-long (net-short) the base currency. Firms included are those reporting under EMIR to the DTCC and UnaVista trade repositories between January 1, 2015 and December 31, 2020.

Figure A.32: Non-Dealer Banks' Exposure to the Major 4 Currency Crosses



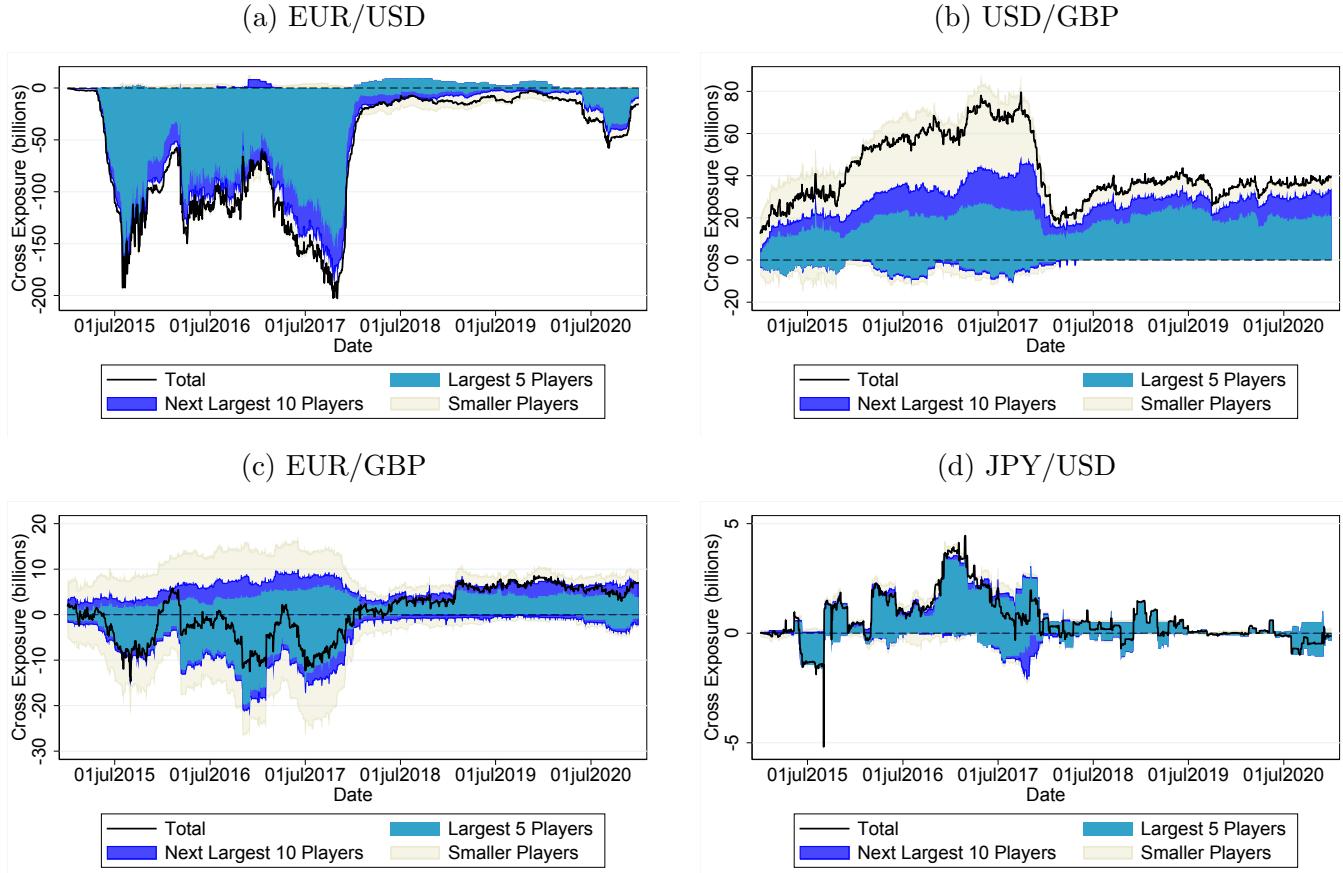
Note. Non Dealer Banks' net-long and net-short currency-cross exposures, highlighted in blue and beige, for the major 4 crosses are calculated by separately aggregating the currency-cross exposures of asset managers that are net-long and net-short each currency cross. The black line refers to the sum of the net-long and net-short currency-cross exposures in each panel. Shaded in light and dark blue are the net-long and net-short positions of the largest 5 and next largest 10 firms in the sector in terms of average currency-cross exposure over the sample. In beige are the cross exposures of the smaller players. Currency-cross exposures are measured in units of the base currency (with curr/base shown above each panel). Positive (negative) values refer to firms being net-long (net-short) the base currency. Firms included are those reporting under EMIR to the DTCC and UnaVista trade repositories between July 1, 2016 and December 31, 2020.

Figure A.33: Dealer Banks' Exposure to the Major 4 Currency Crosses



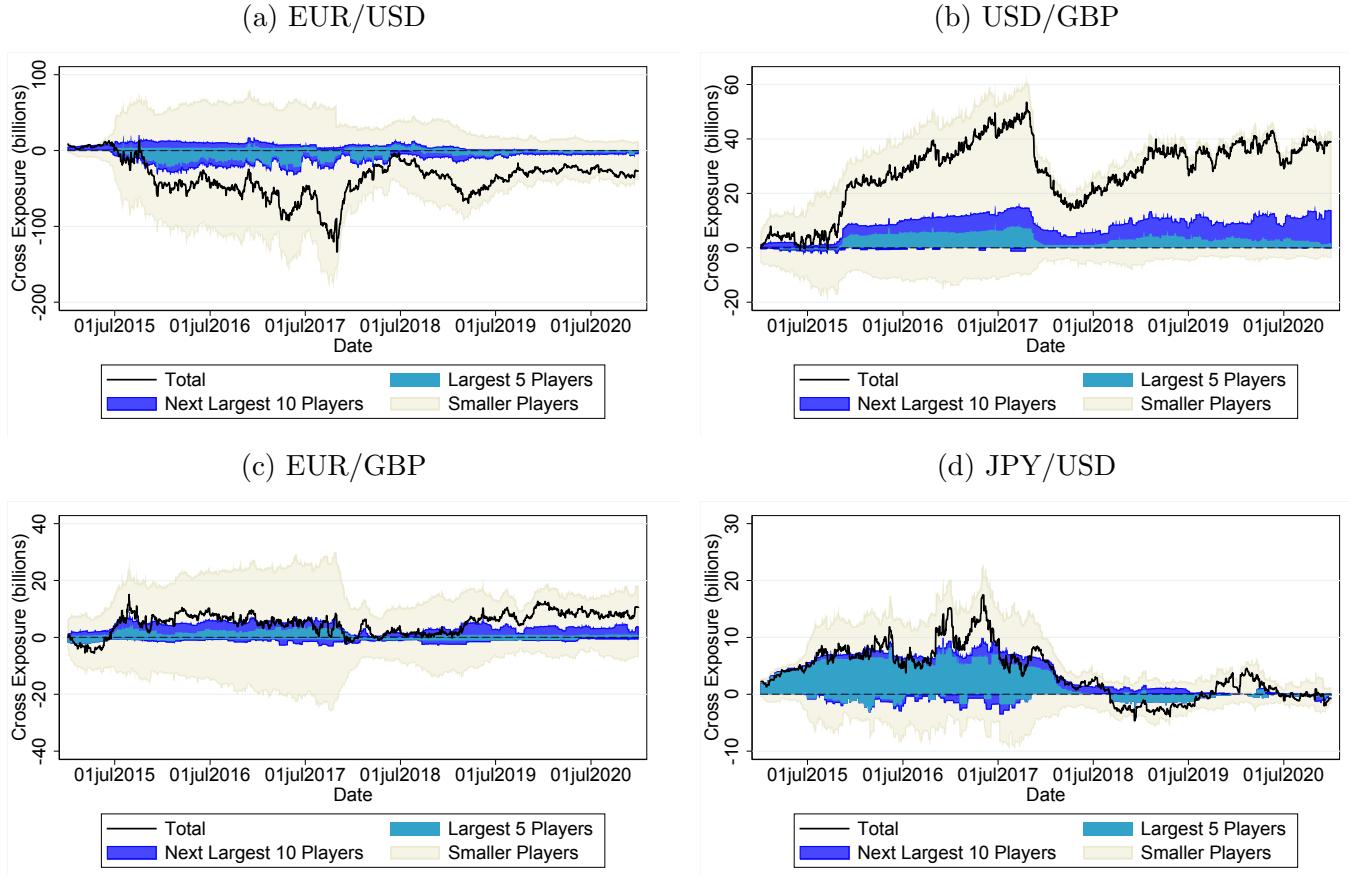
Note. Dealer Banks' net-long and net-short currency-cross exposures, highlighted in blue and beige, for the major 4 crosses are calculated by separately aggregating the currency-cross exposures of asset managers that are net-long and net-short each currency cross. The black line refers to the sum of the net-long and net-short currency-cross exposures in each panel. Shaded in light and dark blue are the net-long and net-short positions of the largest 5 and next largest 10 firms in the sector in terms of average currency-cross exposure over the sample. In beige are the cross exposures of the smaller players. Currency-cross exposures are measured in units of the base currency (with curr/base shown above each panel). Positive (negative) values refer to firms being net-long (net-short) the base currency. Firms included are those reporting under EMIR to the DTCC and UnaVista trade repositories between July 1, 2016 and December 31, 2020.

Figure A.34: Pension Funds' Exposure to the Major 4 Currency Crosses



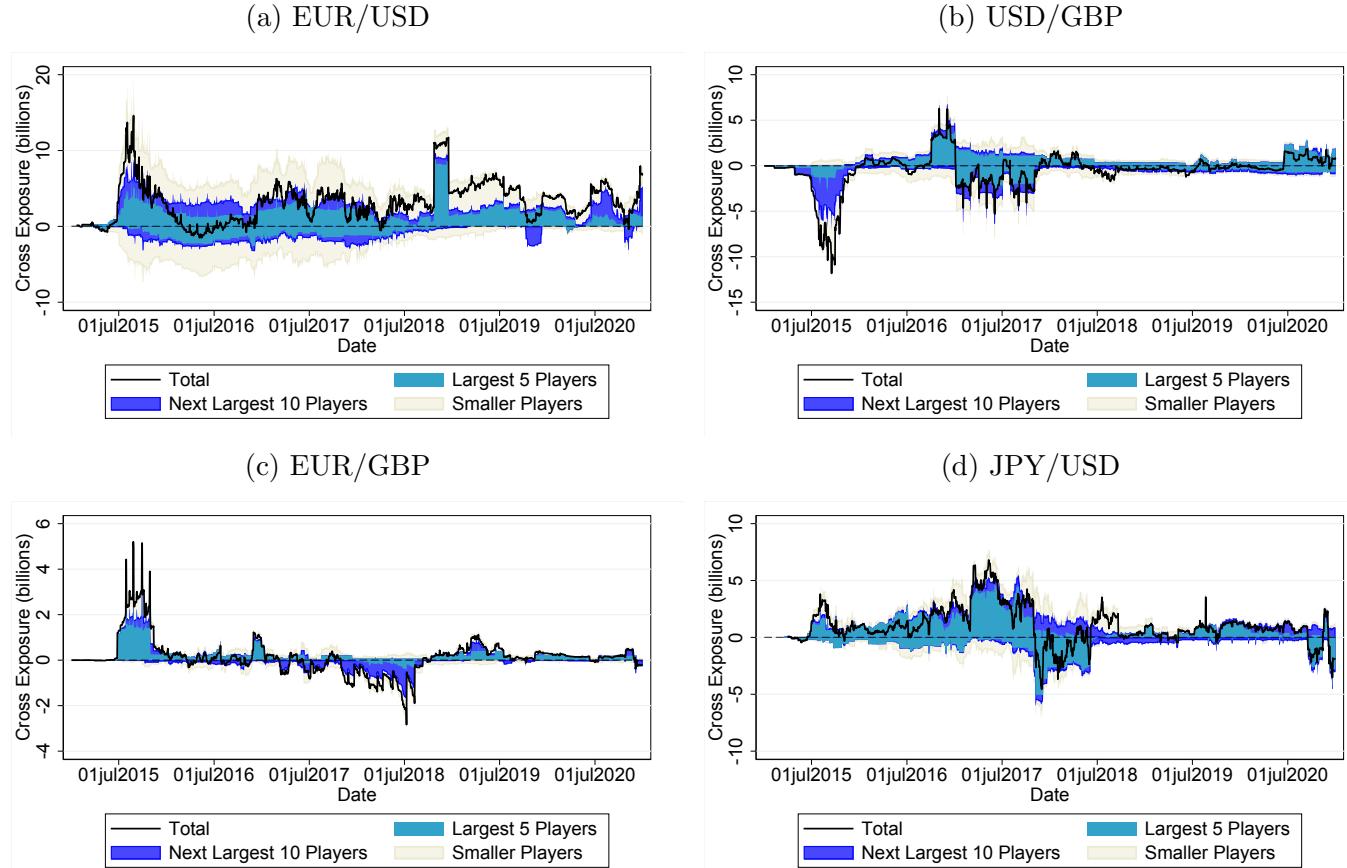
Note. Pension Funds' net-long and net-short currency-cross exposures, highlighted in blue and beige, for the major 4 crosses are calculated by separately aggregating the currency-cross exposures of asset managers that are net-long and net-short each currency cross. The black line refers to the sum of the net-long and net-short currency-cross exposures in each panel. Shaded in light and dark blue are the net-long and net-short positions of the largest 5 and next largest 10 firms in the sector in terms of average currency-cross exposure over the sample. In beige are the cross exposures of the smaller players. Currency-cross exposures are measured in units of the base currency (with curr/base shown above each panel). Positive (negative) values refer to firms being net-long (net-short) the base currency. Firms included are those reporting under EMIR to the DTCC and UnaVista trade repositories between January 1, 2015 and December 31, 2020.

Figure A.35: Investment Funds' Exposure to the Major 4 Currency Crosses



Note. Investment Funds' net-long and net-short currency-cross exposures, highlighted in blue and beige, for the major 4 crosses are calculated by separately aggregating the currency-cross exposures of asset managers that are net-long and net-short each currency cross. The black line refers to the sum of the net-long and net-short currency-cross exposures in each panel. Shaded in light and dark blue are the net-long and net-short positions of the largest 5 and next largest 10 firms in the sector in terms of average currency-cross exposure over the sample. In beige are the cross exposures of the smaller players. Currency-cross exposures are measured in units of the base currency (with curr/base shown above each panel). Positive (negative) values refer to firms being net-long (net-short) the base currency. Firms included are those reporting under EMIR to the DTCC and UnaVista trade repositories between January 1, 2015 and December 31, 2020.

Figure A.36: Hedge Funds' Exposure to the Major 4 Currency Crosses

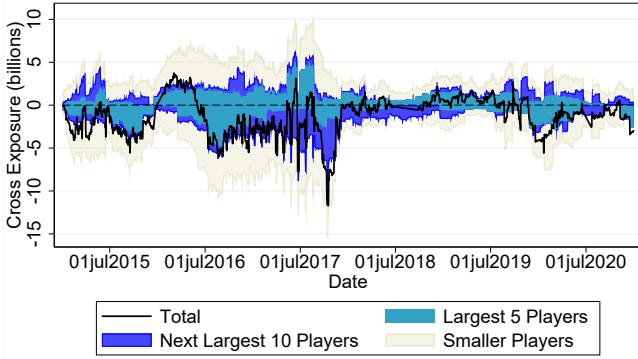


Note. Hedge Funds' net-long and net-short currency-cross exposures, highlighted in blue and beige, for the major 4 crosses are calculated by separately aggregating the currency-cross exposures of asset managers that are net-long and net-short each currency cross. The black line refers to the sum of the net-long and net-short currency-cross exposures in each panel. Shaded in light and dark blue are the net-long and net-short positions of the largest 5 and next largest 10 firms in the sector in terms of average currency-cross exposure over the sample. In beige are the cross exposures of the smaller players. Currency-cross exposures are measured in units of the base currency (with curr/base shown above each panel). Positive (negative) values refer to firms being net-long (net-short) the base currency. Firms included are those reporting under EMIR to the DTCC and UnaVista trade repositories between January 1, 2015 and December 31, 2020.

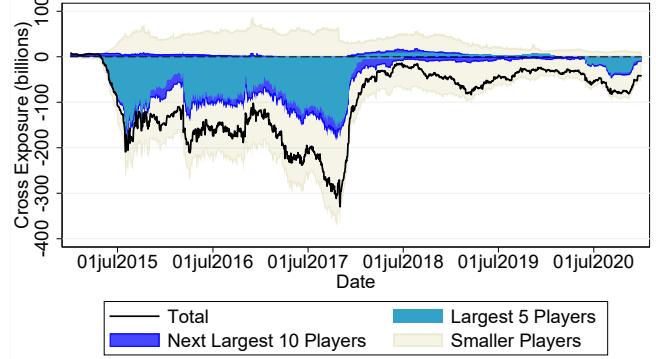
A.3.7 Net Currency-Cross Stock Exposures by Sector and Country of Residence: Heterogeneity and Concentration

Figure A.37: UK and EU Asset Managers' Exposure to the Major 3 Crosses

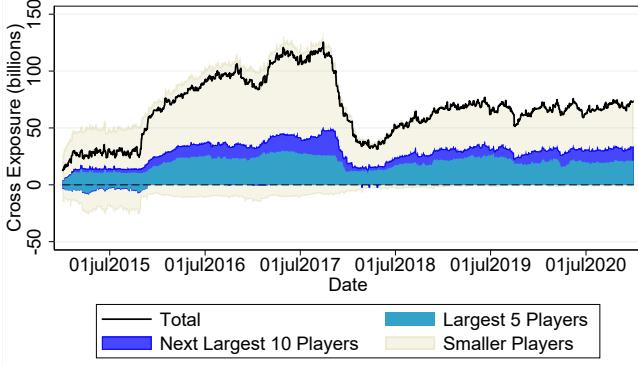
(a) UK Asset Managers' EUR/USD Exposures



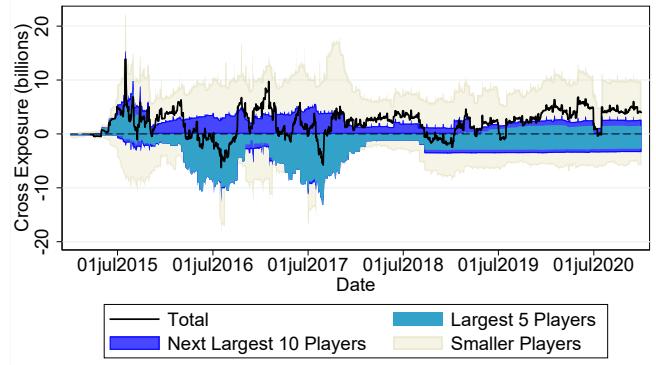
(b) EU Asset Managers' EUR/USD Exposures



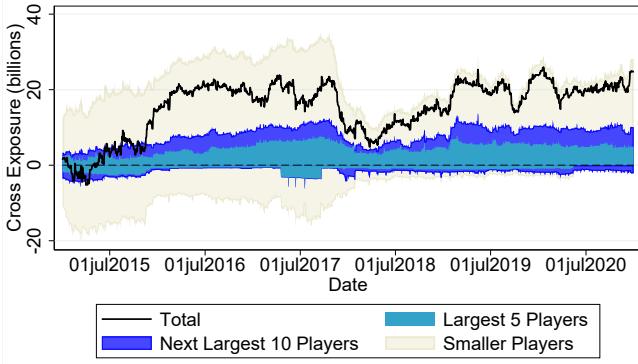
(c) UK Asset Managers' USD/GBP Exposures



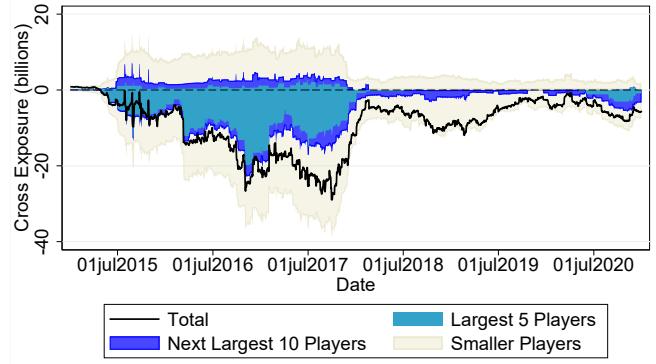
(d) EU Asset Managers' USD/GBP Exposures



(e) UK Asset Managers' EUR/GBP Exposures

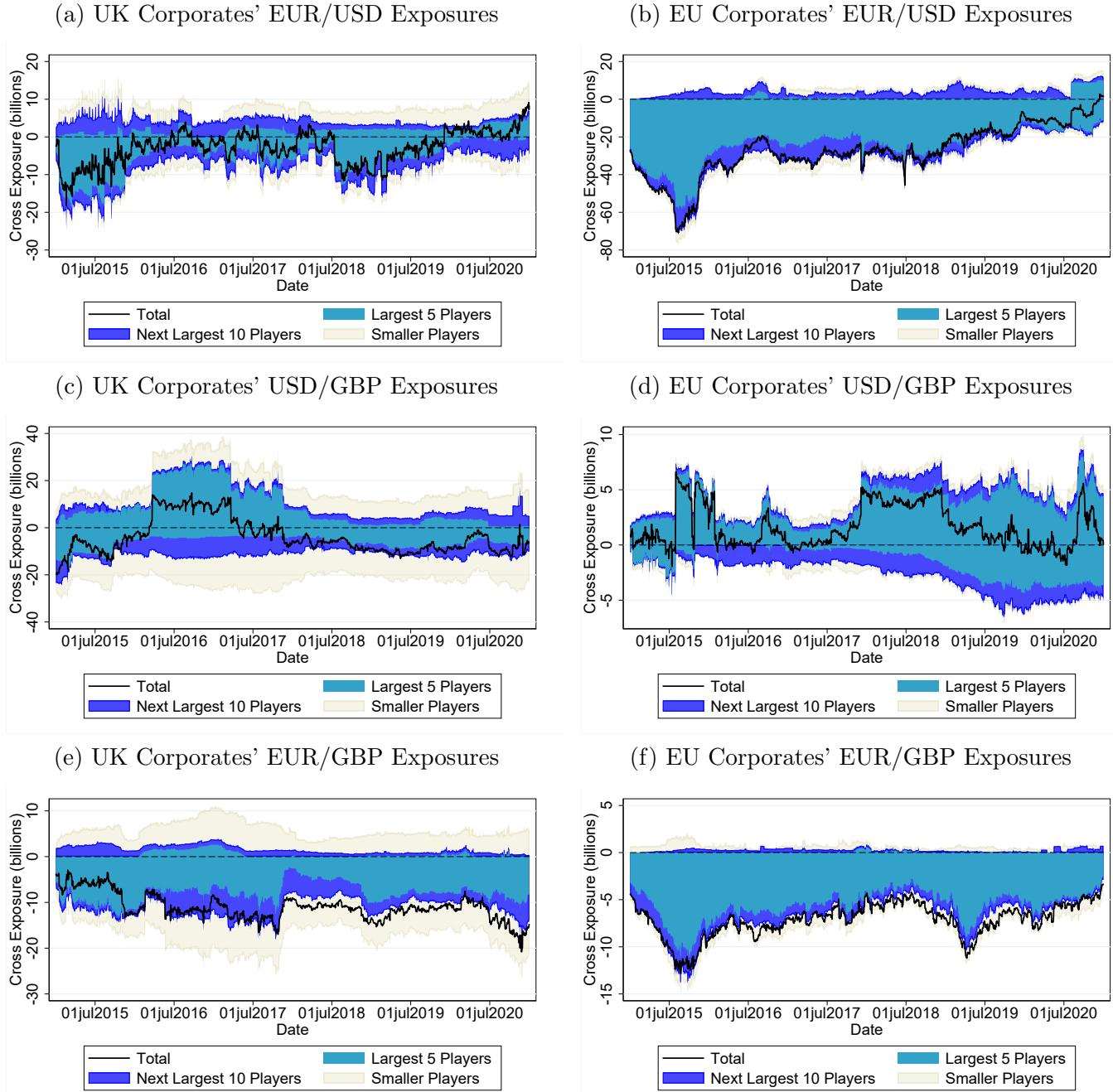


(f) EU Asset Managers' EUR/GBP Exposures



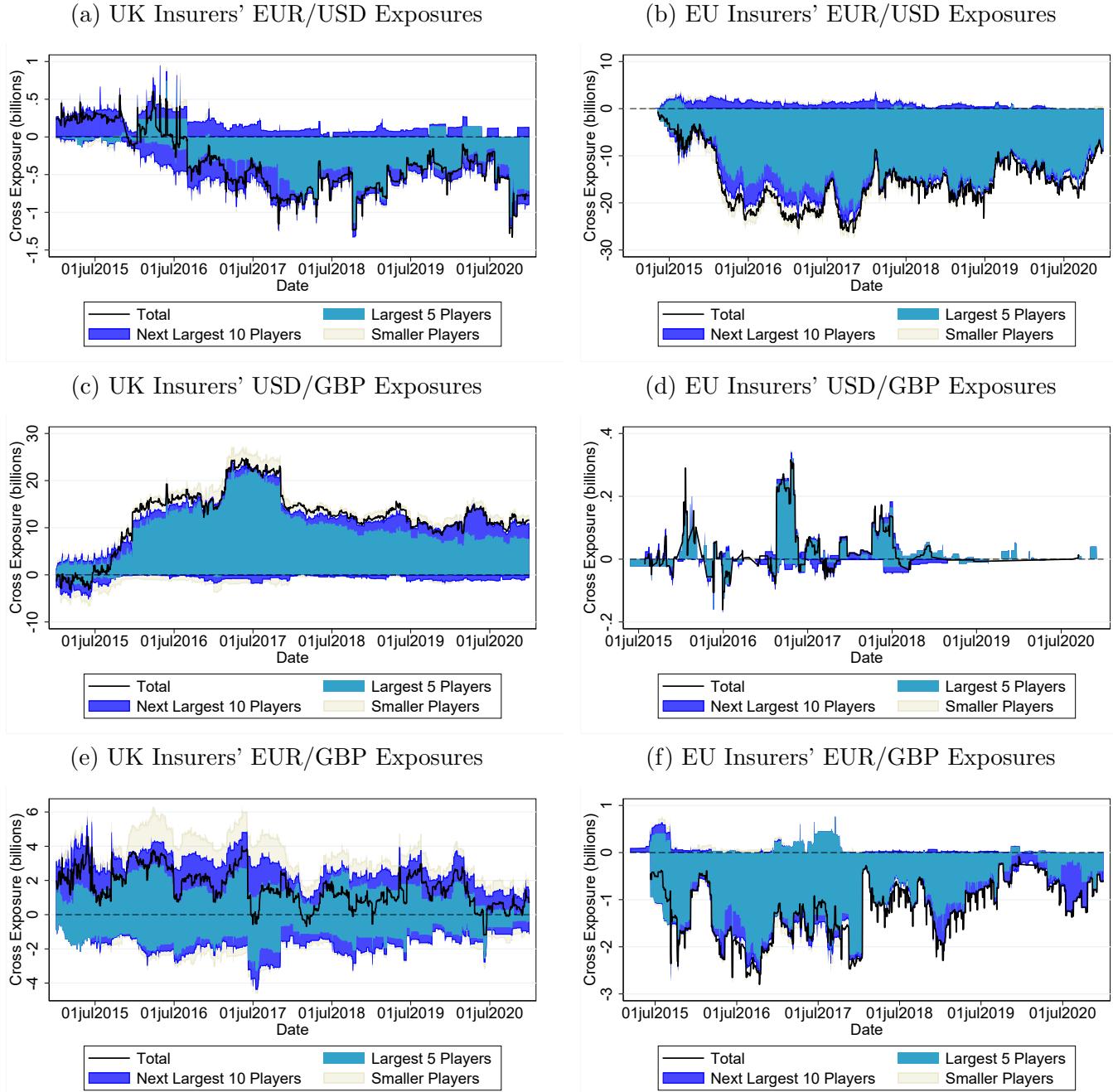
Note. UK and EU Asset Managers' net-long and net-short cross exposures, highlighted in blue and beige, for the major 3 currency crosses are calculated by separately aggregating the cross exposures of UK and EU asset managers that are net-long and net-short each cross. The black line refers to the sum of the net-long and net-short cross exposures in each panel. Shaded in light and dark blue are the net-long and net-short positions of the largest 5 and next largest 10 firms in the sector in terms of average cross exposure over the sample. In beige are the cross exposures of the smaller players. Currency-cross exposures are measured in units of the base currency (with curr/base shown above each panel). Positive (negative) values refer to firms being net-long (net-short) the base currency. Firms included are those reporting under EMIR to the DTCC and UnaVista trade repositories between January 1, 2015 and December 31, 2020.

Figure A.38: UK and EU Non-Financial Corporates' Exposure to the Major 3 Crosses



Note. UK and EU Non-Financial Corporates' net-long and net-short cross exposures, highlighted in blue and beige, for the major 3 currency crosses are calculated by separately aggregating the cross exposures of UK and EU corporates that are net-long and net-short each cross. The black line refers to the sum of the net-long and net-short cross exposures in each panel. Shaded in light and dark blue are the net-long and net-short positions of the largest 5 and next largest 10 firms in the sector in terms of average cross exposure over the sample. In beige are the cross exposures of the smaller players. Currency-cross exposures are measured in units of the base currency (with curr/base shown above each panel). Positive (negative) values refer to firms being net-long (net-short) the base currency. Firms included are those reporting under EMIR to the DTCC and UnaVista trade repositories between January 1, 2015 and December 31, 2020.

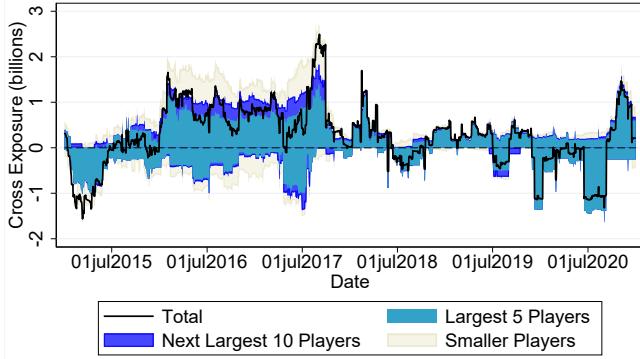
Figure A.39: UK and EU Insurers' Exposure to the Major 3 Crosses



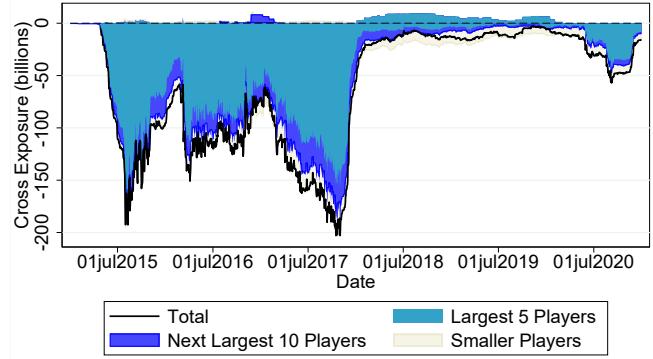
Note. UK and EU Insurers' net-long and net-short cross exposures, highlighted in blue and beige, for the major 3 currency crosses are calculated by separately aggregating the cross exposures of UK and EU insurers that are net-long and net-short each cross. The black line refers to the sum of the net-long and net-short cross exposures in each panel. Shaded in light and dark blue are the net-long and net-short positions of the largest 5 and next largest 10 firms in the sector in terms of average cross exposure over the sample. In beige are the cross exposures of the smaller players. Currency-cross exposures are measured in units of the base currency (with curr/base shown above each panel). Positive (negative) values refer to firms being net-long (net-short) the base currency. Firms included are those reporting under EMIR to the DTCC and UnaVista trade repositories between January 1, 2015 and December 31, 2020.

Figure A.40: UK and EU Pension Funds' Exposure to the Major 3 Crosses

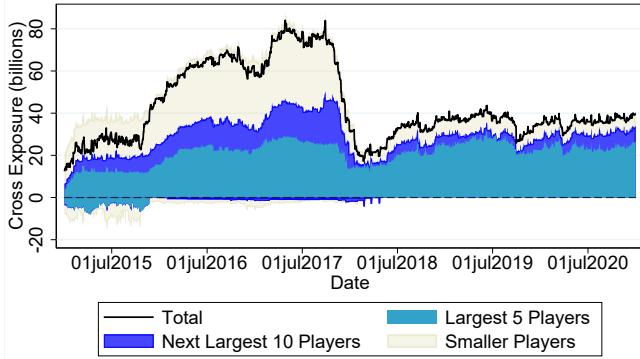
(a) UK Pension Funds' EUR/USD Exposures



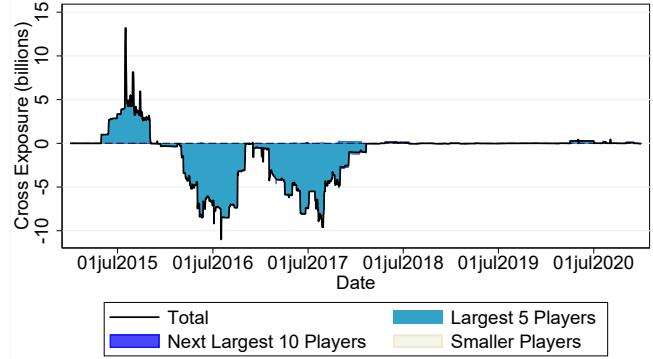
(b) EU Pension Funds' EUR/USD Exposures



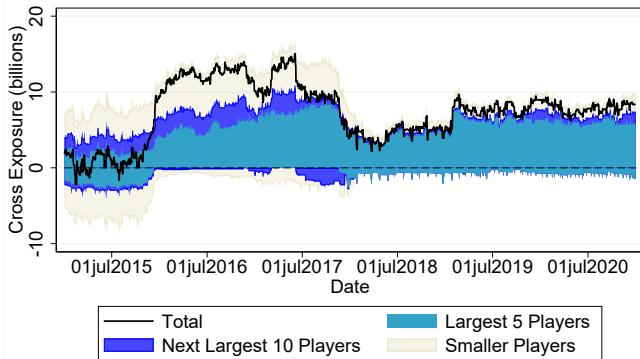
(c) UK Pension Funds' USD/GBP Exposures



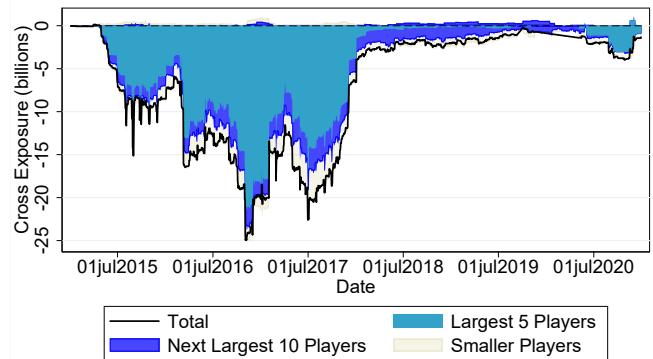
(d) EU Pension Funds' USD/GBP Exposures



(e) UK Pension Funds' EUR/GBP Exposures



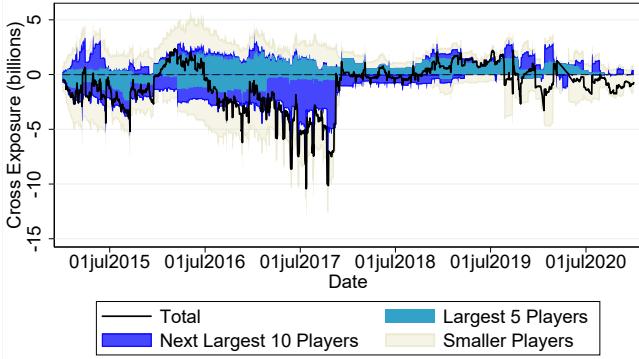
(f) EU Pension Funds' EUR/GBP Exposures



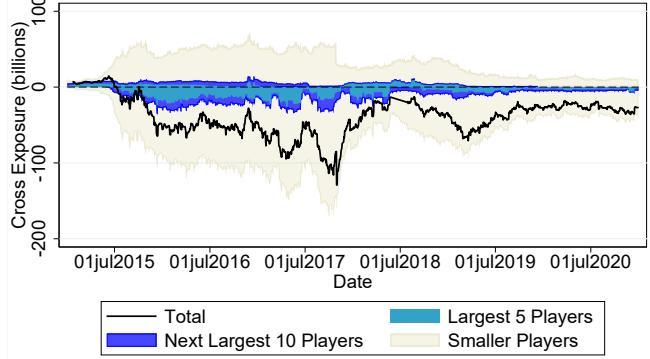
Note. UK and EU Pension Funds' net-long and net-short cross exposures, highlighted in blue and beige, for the major 3 currency crosses are calculated by separately aggregating the cross exposures of UK and EU pension funds that are net-long and net-short each cross. The black line refers to the sum of the net-long and net-short cross exposures in each panel. Shaded in light and dark blue are the net-long and net-short positions of the largest 5 and next largest 10 firms in the sector in terms of average cross exposure over the sample. In beige are the cross exposures of the smaller players. Currency-cross exposures are measured in units of the base currency (with curr/base shown above each panel). Positive (negative) values refer to firms being net-long (net-short) the base currency. Firms included are those reporting under EMIR to the DTCC and UnaVista trade repositories between January 1, 2015 and December 31, 2020.

Figure A.41: UK and EU Investment Funds' Exposure to the Major 3 Crosses

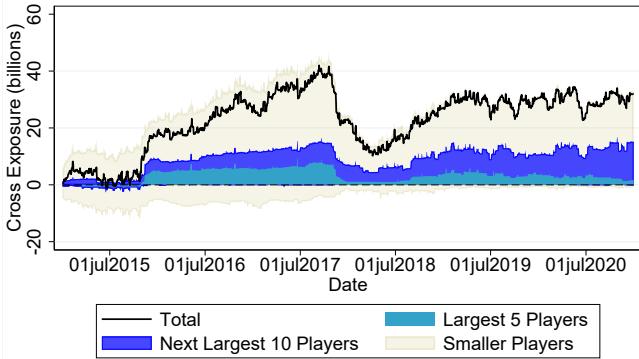
(a) UK Investment Funds' EUR/USD Exposures



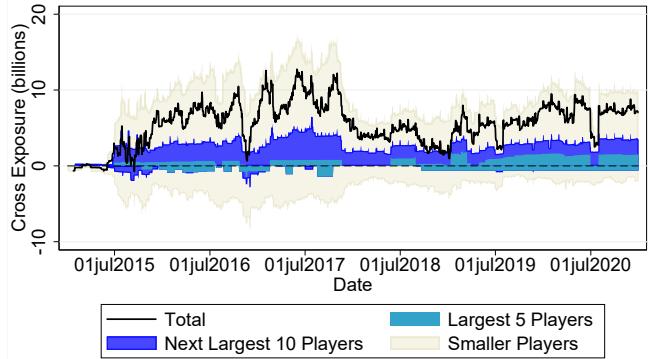
(b) EU Investment Funds' EUR/USD Exposures



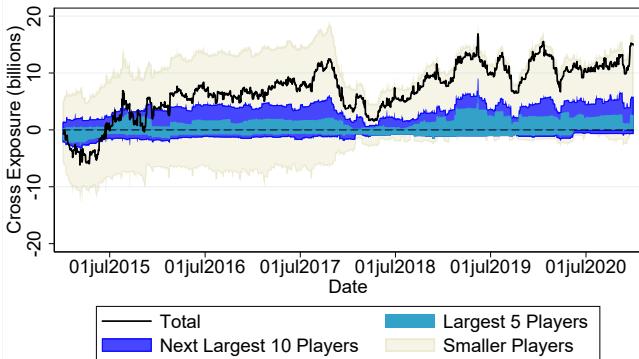
(c) UK Investment Funds' USD/GBP Exposures



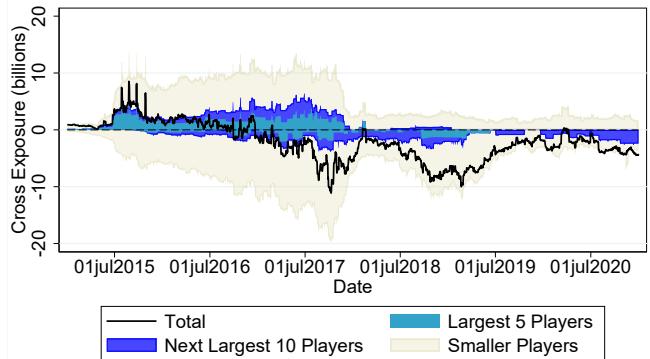
(d) EU Investment Funds' USD/GBP Exposures



(e) UK Investment Funds' EUR/GBP Exposures

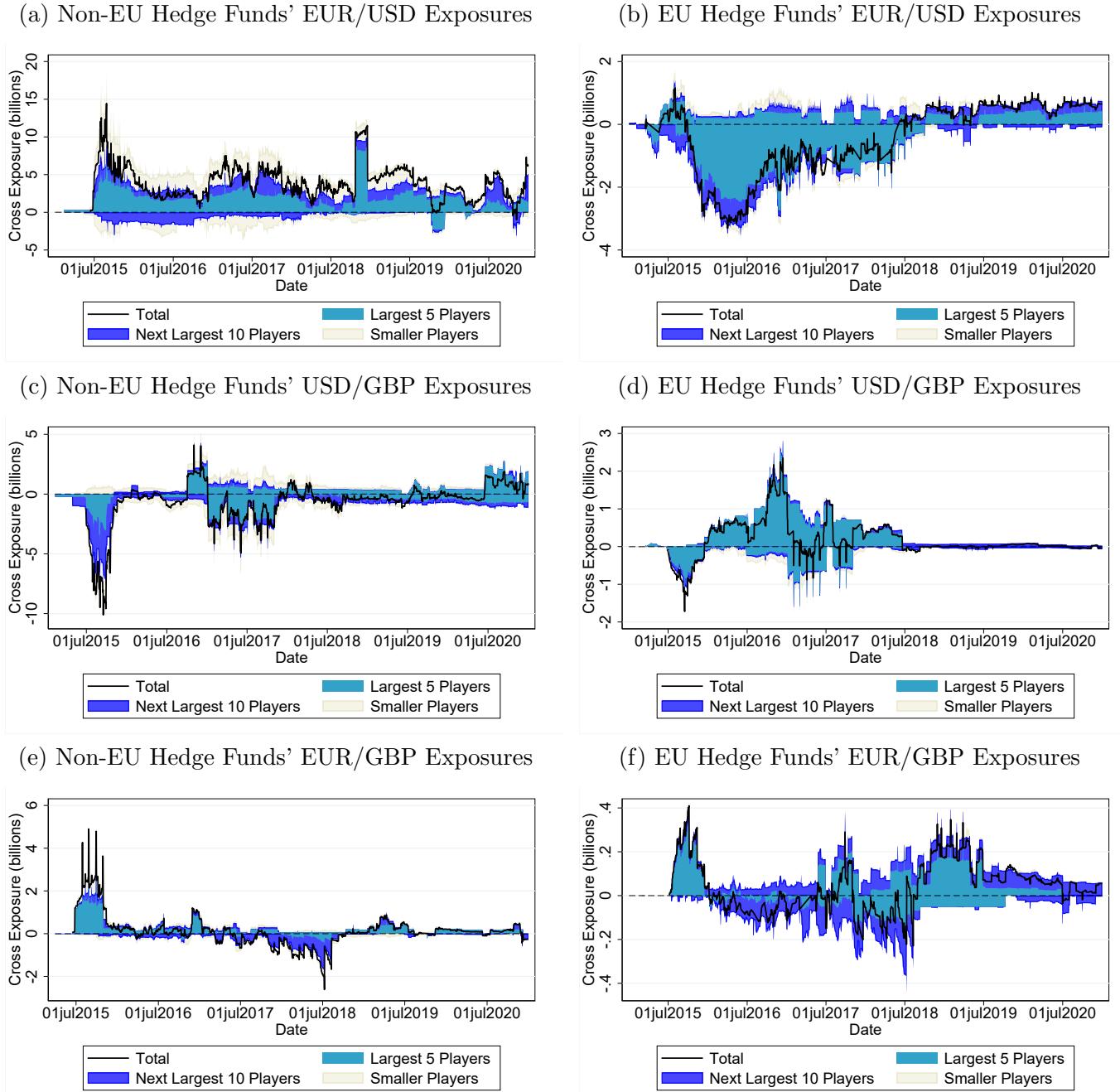


(f) EU Investment Funds' EUR/GBP Exposures



Note. UK and EU Investment Funds' net-long and net-short cross exposures, highlighted in blue and beige, for the major 3 currency crosses are calculated by separately aggregating the cross exposures of UK and EU investment funds that are net-long and net-short each cross. The black line refers to the sum of the net-long and net-short cross exposures in each panel. Shaded in light and dark blue are the net-long and net-short positions of the largest 5 and next largest 10 firms in the sector in terms of average cross exposure over the sample. In beige are the cross exposures of the smaller players. Currency-cross exposures are measured in units of the base currency (with curr/base shown above each panel). Positive (negative) values refer to firms being net-long (net-short) the base currency. Firms included are those reporting under EMIR to the DTCC and UnaVista trade repositories between January 1, 2015 and December 31, 2020.

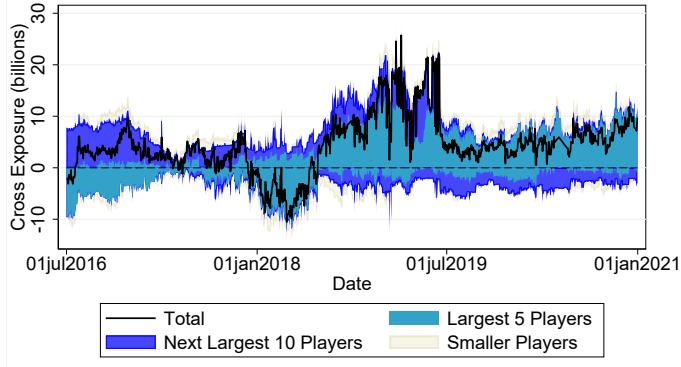
Figure A.42: Non-EU and EU Hedge Funds' Exposure to the Major 3 Crosses



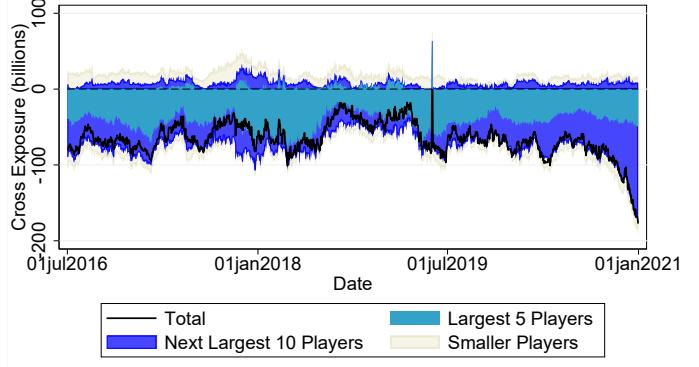
Note. Non-EU and EU Hedge Funds' net-long and net-short cross exposures, highlighted in blue and beige, for the major 3 currency crosses are calculated by separately aggregating the cross exposures of Non-EU and EU hedge funds that are net-long and net-short each cross. The black line refers to the sum of the net-long and net-short cross exposures in each panel. Shaded in light and dark blue are the net-long and net-short positions of the largest 5 and next largest 10 firms in the sector in terms of average cross exposure over the sample. In beige are the cross exposures of the smaller players. Currency-cross exposures are measured in units of the base currency (with curr/base shown above each panel). Positive (negative) values refer to firms being net-long (net-short) the base currency. Firms included are those reporting under EMIR to the DTCC and UnaVista trade repositories between January 1, 2015 and December 31, 2020.

Figure A.43: UK and EU Non-Dealer Banks' Exposure to the Major 3 Crosses

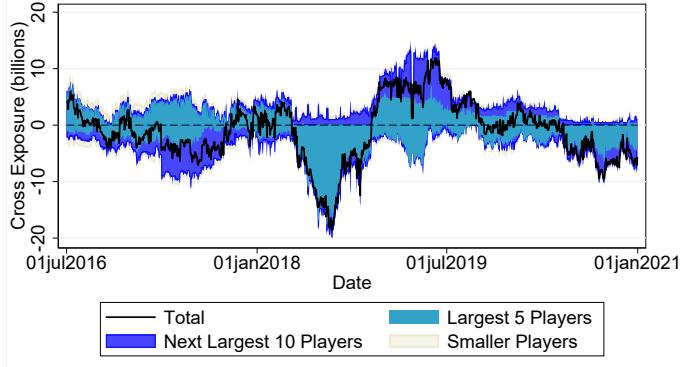
(a) UK Non-Dealers' EUR/USD Exposures



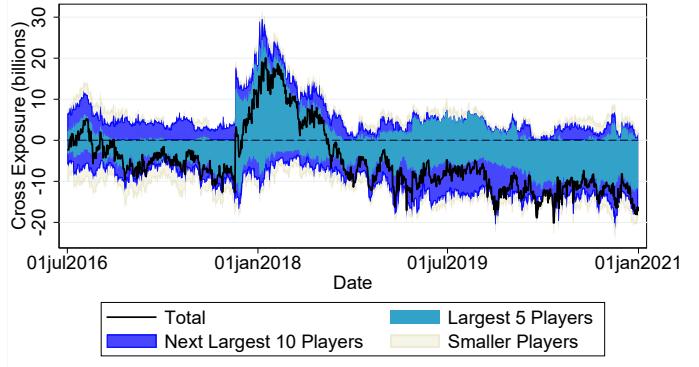
(b) EU Non-Dealers' EUR/USD Exposures



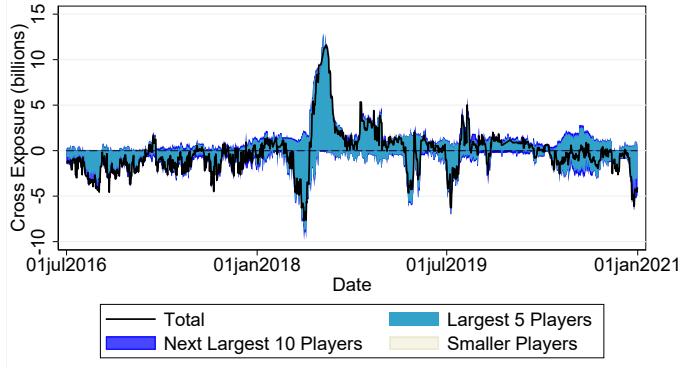
(c) UK Non-Dealers' USD/GBP Exposures



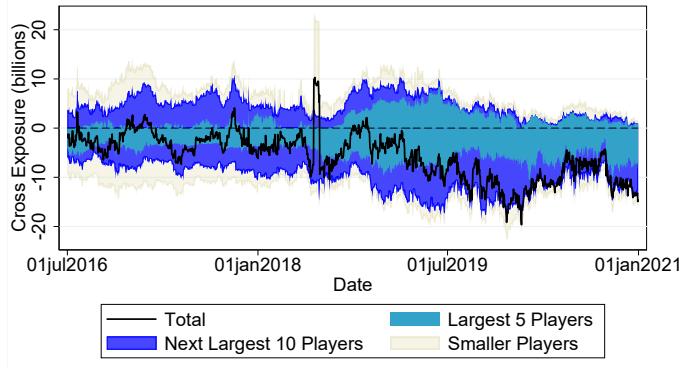
(d) EU Non-Dealers' USD/GBP Exposures



(e) UK Non-Dealers' EUR/GBP Exposures



(f) EU Non-Dealers' EUR/GBP Exposures



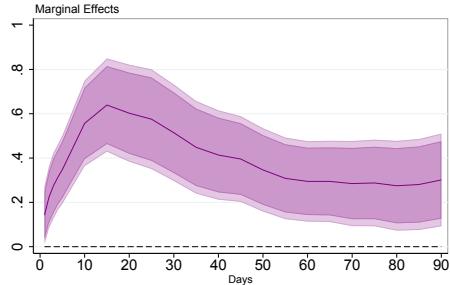
Note. UK and EU Non-Dealer Banks' net-long and net-short cross exposures, highlighted in blue and beige, for the major 3 currency crosses are calculated by separately aggregating the cross exposures of UK and EU non-dealer banks that are net-long and net-short each cross. The black line refers to the sum of the net-long and net-short cross exposures in each panel. Shaded in light and dark blue are the net-long and net-short positions of the largest 5 and next largest 10 firms in the sector in terms of average cross exposure over the sample. In beige are the cross exposures of the smaller players. Currency-cross exposures are measured in units of the base currency (with curr/base shown above each panel). Positive (negative) values refer to firms being net-long (net-short) the base currency. Firms included are those reporting under EMIR to the DTCC and UnaVista trade repositories between January 1, 2015 and December 31, 2020.

A.4 Supplement to FX Investment Strategies

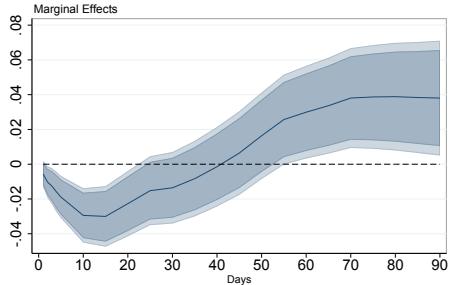
Figure A.44: Investment Strategies and Changes in Firms' USD-GBP Derivatives Exposure

(I) Carry Trade

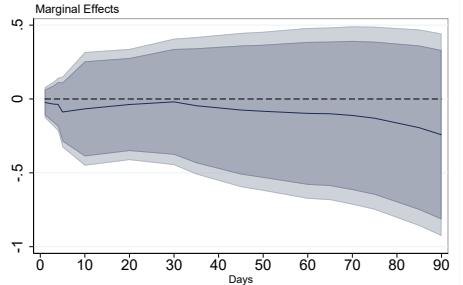
(a) Hedge Funds



(b) Non-Financial Corporates

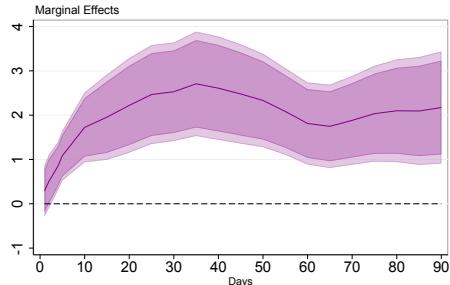


(c) Dealer Banks

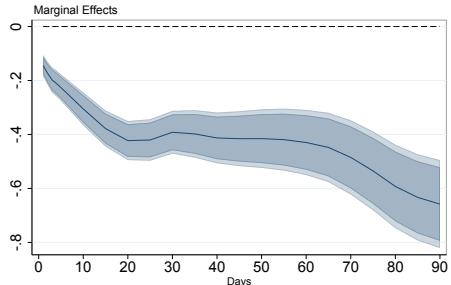


(II) Momentum

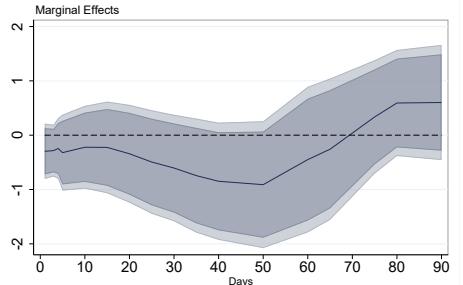
(d) Hedge Funds



(e) Non-Financial Corporates

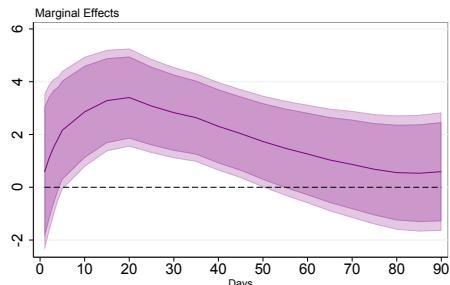


(f) Dealer Banks

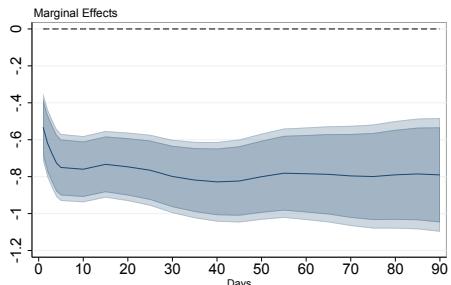


(III) FX Macro News

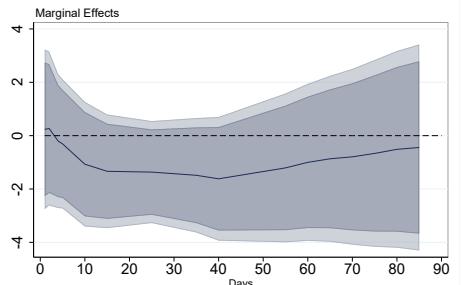
(g) Hedge Funds



(h) Non-Financial Corporates



(i) Dealer Banks

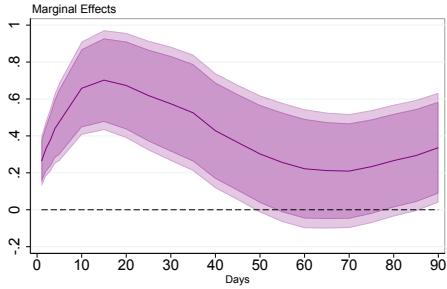


Note. Figure A.44 presents the β^h 's for $h \in [0, 90]$ from estimating firm-level panel regressions (6) for three FX investment strategies—Carry Trade (Row I), Momentum (Row II) and FX Macro News (Row III)—for 3 sectors—hedge funds, non-financial corporates and dealer banks—in the GBP/USD currency cross. Results for the remaining sectors and crosses are in Appendix A.4. Inner and outer shaded areas correspond to 90% and 95% confidence intervals constructed using two-way clustered standard errors by firm and time.

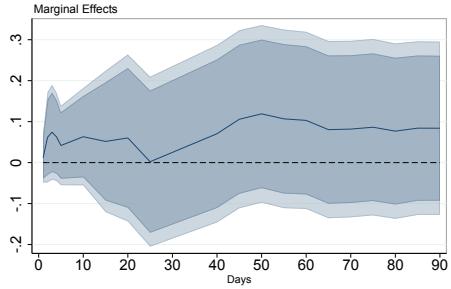
Figure A.45: Investment Strategies and Changes in Firms' JPY-USD Derivatives Exposure

(I) Carry Trade

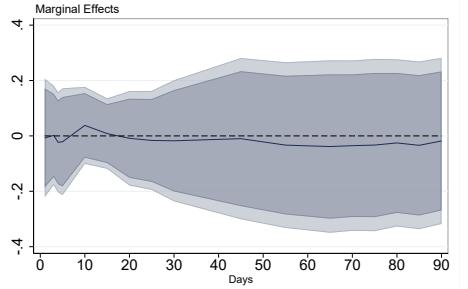
(a) Hedge Funds



(b) Non-Financial Corporates

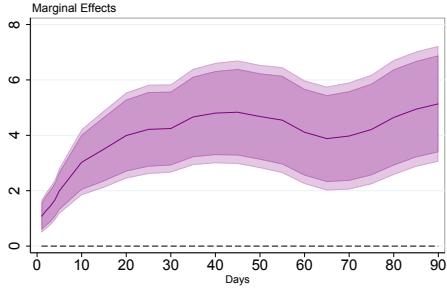


(c) Dealer Banks

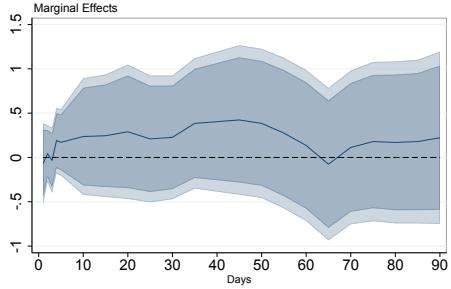


(II) Momentum

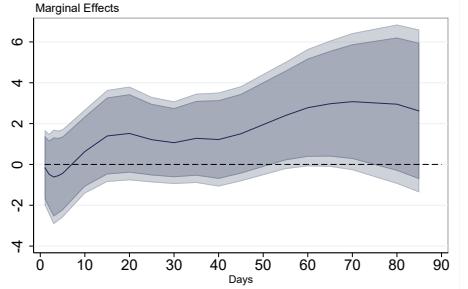
(d) Hedge Funds



(e) Non-Financial Corporates

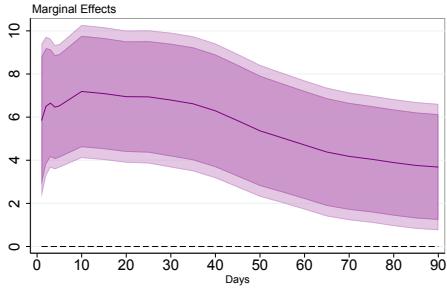


(f) Dealer Banks

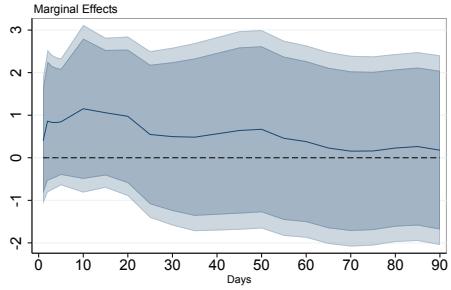


(III) FX Macro News

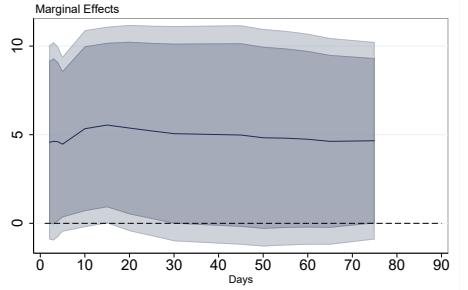
(g) Hedge Funds



(h) Non-Financial Corporates



(i) Dealer Banks

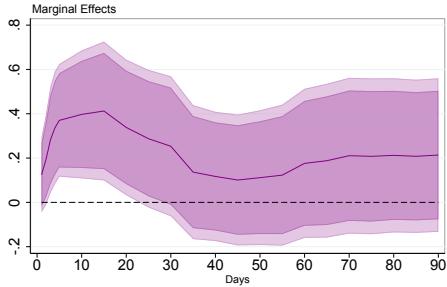


Note. Figure A.45 presents the β^h 's for $h \in [0, 90]$ from estimating firm-level panel regressions (6) for three FX investment strategies—Carry Trade (Row I), Momentum (Row II) and FX Macro News (Row III)—for 3 sectors—hedge funds, non-financial corporates and dealer banks—in the JPY/USD currency cross. Results for the remaining sectors and crosses are in Appendix A.4. Inner and outer shaded areas correspond to 90% and 95% confidence intervals constructed using two-way clustered standard errors by firm and time.

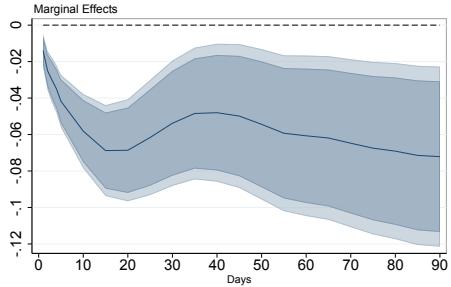
Figure A.46: Investment Strategies and Changes in Firms' EUR-GBP Derivatives Exposure

(I) Carry Trade

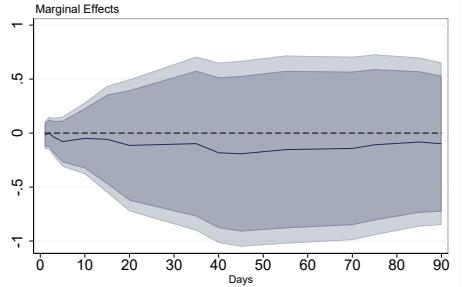
(a) Hedge Funds



(b) Non-Financial Corporates

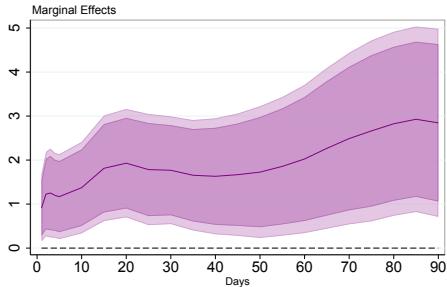


(c) Dealer Banks

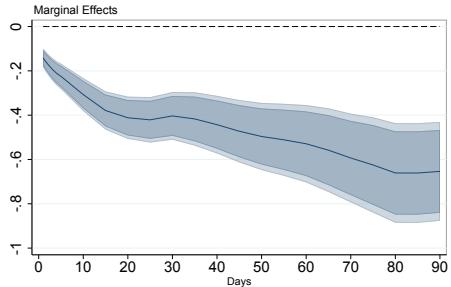


(II) Momentum

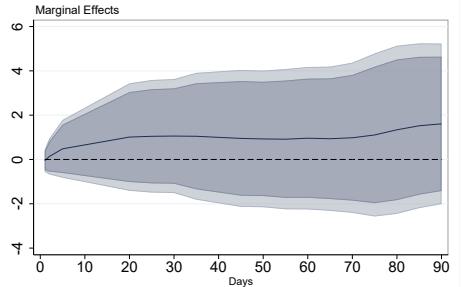
(d) Hedge Funds



(e) Non-Financial Corporates

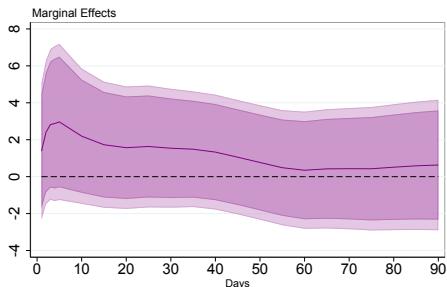


(f) Dealer Banks

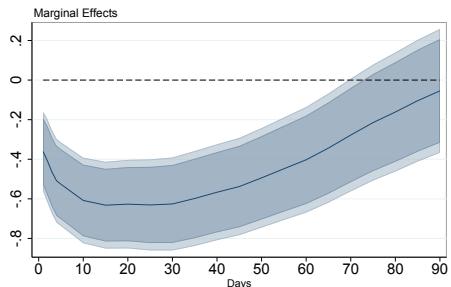


(III) FX Macro News

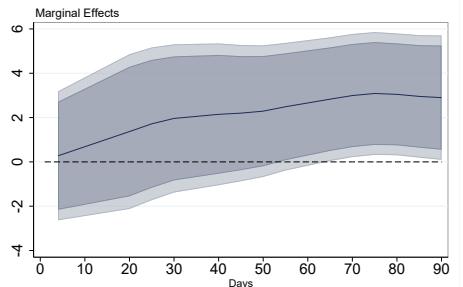
(g) Hedge Funds



(h) Non-Financial Corporates

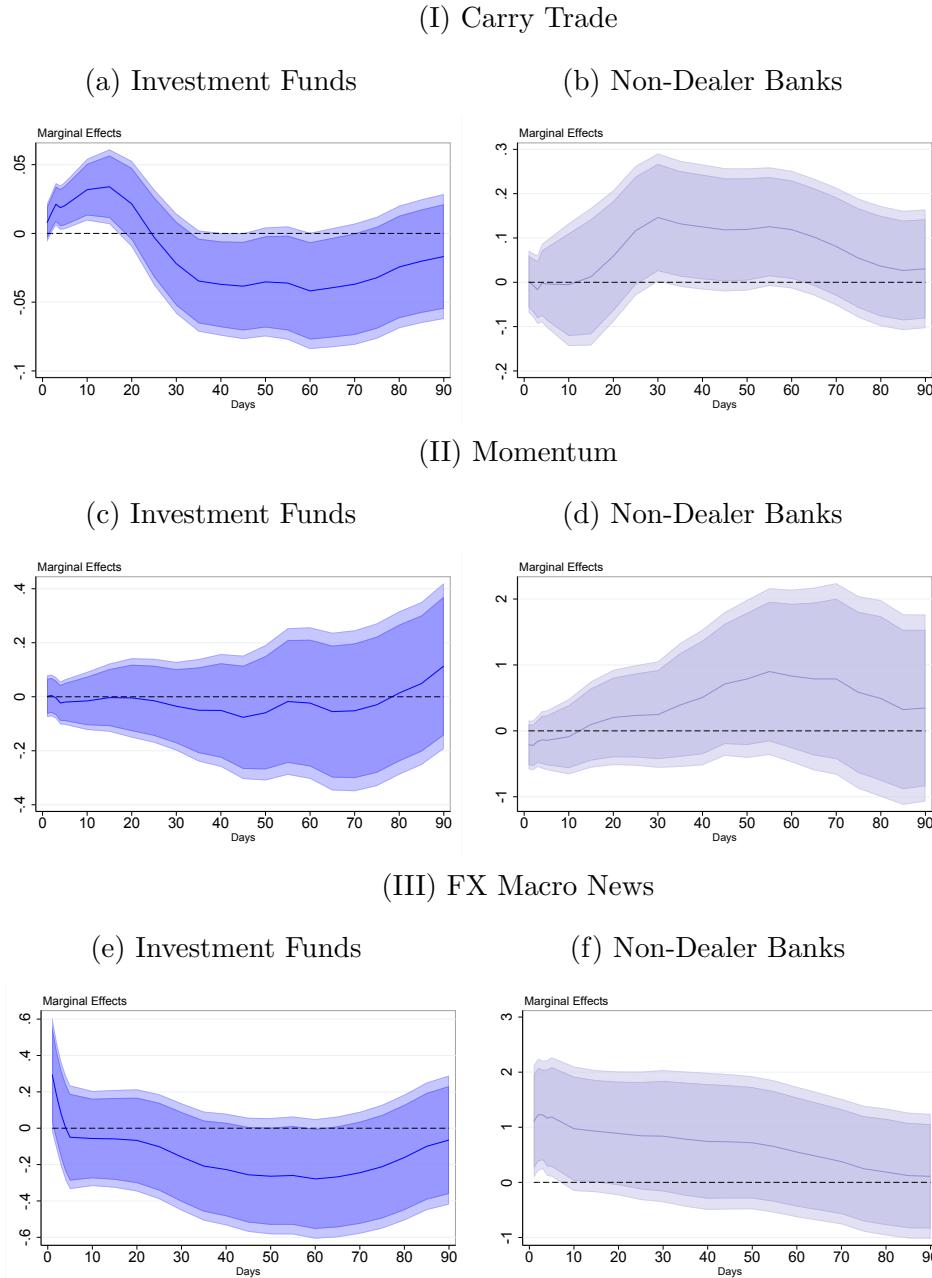


(i) Dealer Banks



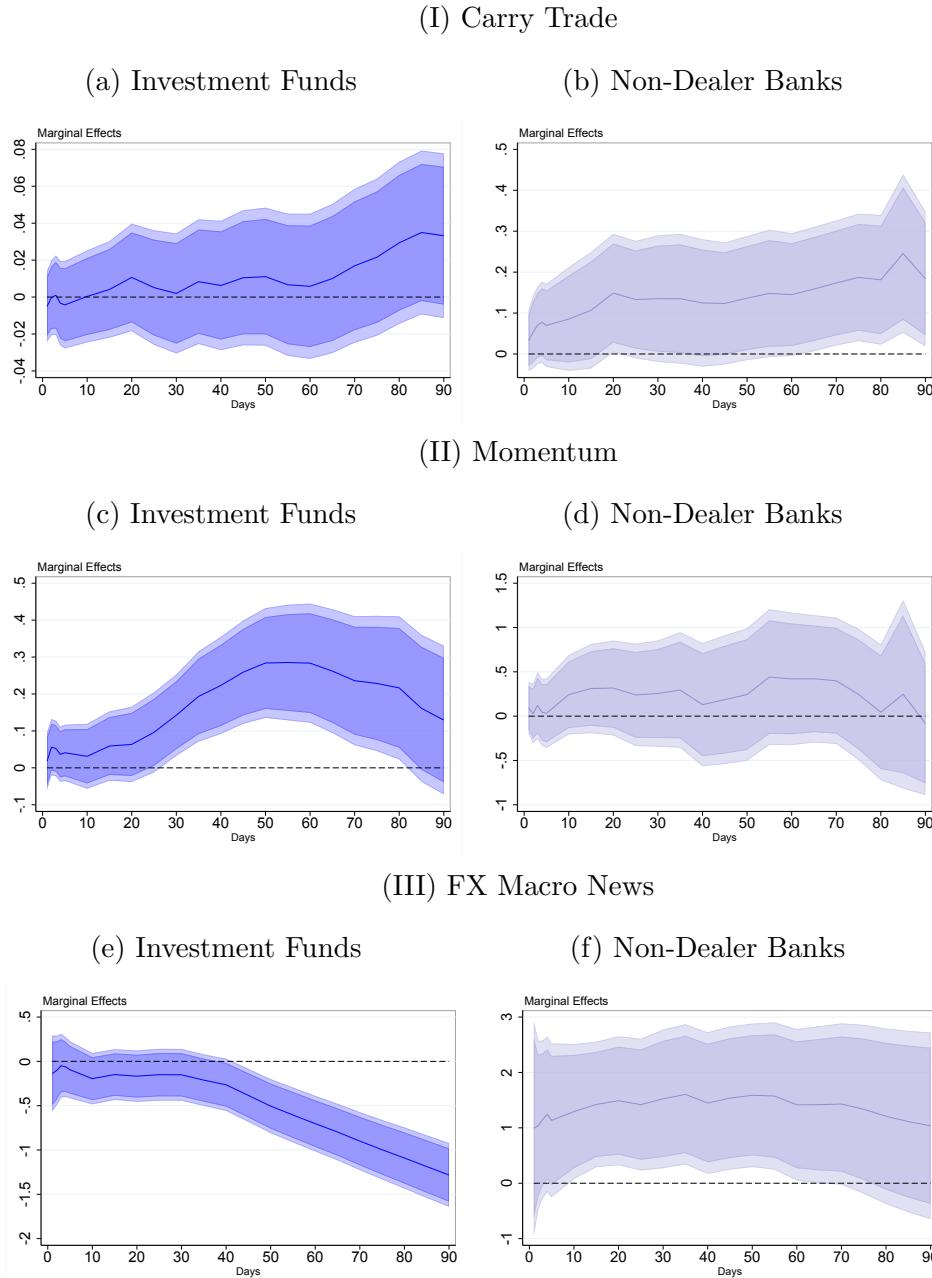
Note. Figure A.46 presents the β^h 's for $h \in [0, 90]$ from estimating firm-level panel regressions (6) for three FX investment strategies—Carry Trade (Row I), Momentum (Row II) and FX Macro News (Row III)—for 3 sectors—hedge funds, non-financial corporates and dealer banks—in the EUR/GBP currency cross. Results for the remaining sectors and crosses are in Appendix A.4. Inner and outer shaded areas correspond to 90% and 95% confidence intervals constructed using two-way clustered standard errors by firm and time.

Figure A.47: Investment Strategies and Changes in Firms' EUR-USD Derivatives Exposure



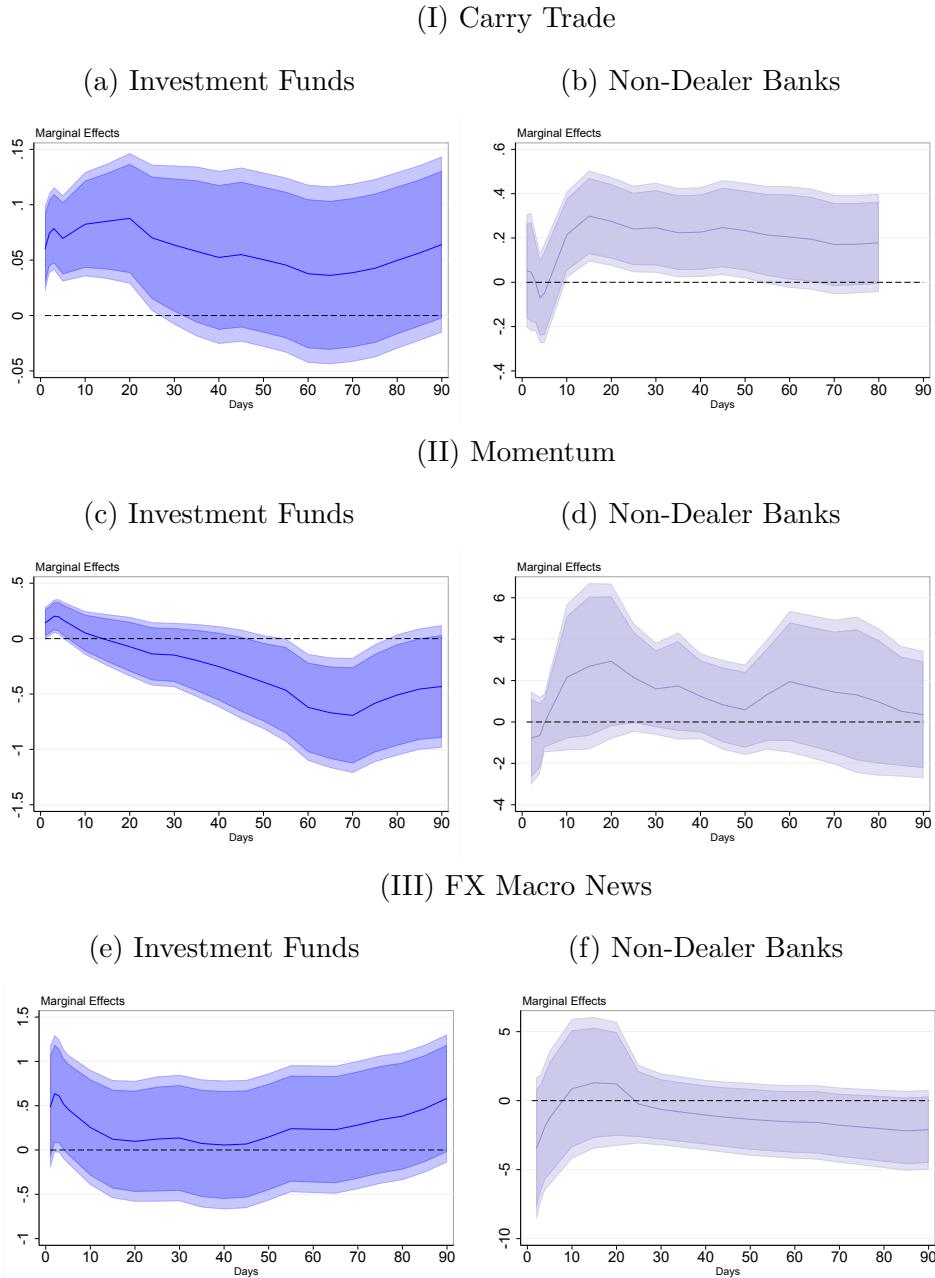
Note. Figure A.47 presents the β^h 's for $h \in [0, 90]$ from estimating firm-level panel regressions (6) for three FX investment strategies—Carry Trade (Row I), Momentum (Row II) and FX Macro News (Row III)—for 2 sectors—investment funds and non-dealer banks—in the EUR/USD currency cross. Results for the remaining sectors and crosses are in Appendix A.4. Inner and outer shaded areas correspond to 90% and 95% confidence intervals constructed using two-way clustered standard errors by firm and time.

Figure A.48: Investment Strategies and Changes in Firms' USD-GBP Derivatives Exposure



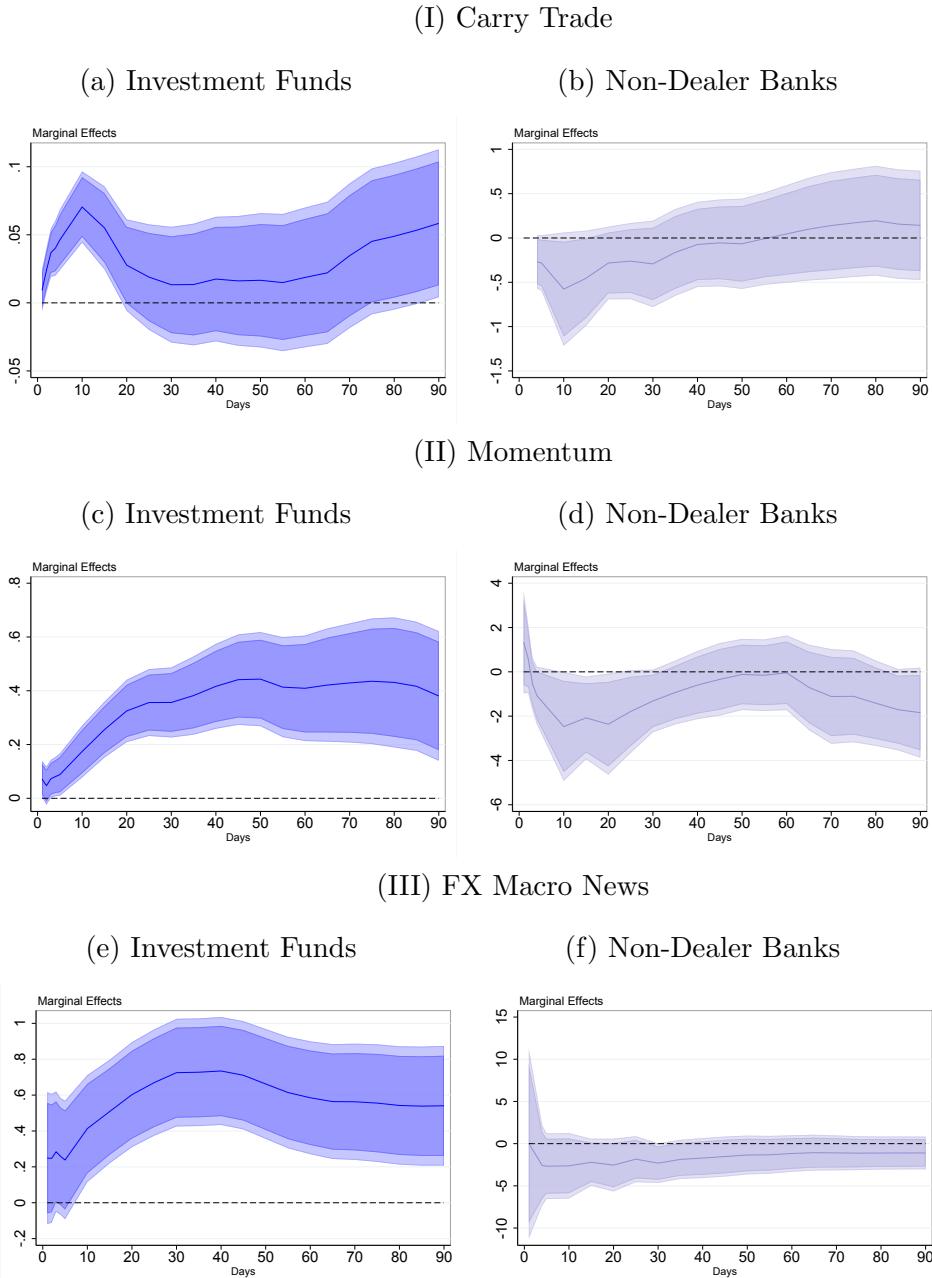
Note. Figure A.48 presents the β^h 's for $h \in [0, 90]$ from estimating firm-level panel regressions (6) for three FX investment strategies—Carry Trade (Row I), Momentum (Row II) and FX Macro News (Row III)—for 2 sectors—investment funds and non-dealer banks—in the USD/GBP currency cross. Results for the remaining sectors and crosses are in Appendix A.4. Inner and outer shaded areas correspond to 90% and 95% confidence intervals constructed using two-way clustered standard errors by firm and time.

Figure A.49: Investment Strategies and Changes in Firms' JPY-USD Derivatives Exposure



Note. Figure A.49 presents the β^h 's for $h \in [0, 90]$ from estimating firm-level panel regressions (6) for three FX investment strategies—Carry Trade (Row I), Momentum (Row II) and FX Macro News (Row III)—for 2 sectors—investment funds and non-dealer banks—in the JPY/USD currency cross. Results for the remaining sectors and crosses are in Appendix A.4. Inner and outer shaded areas correspond to 90% and 95% confidence intervals constructed using two-way clustered standard errors by firm and time.

Figure A.50: Investment Strategies and Changes in Firms' GBP-EUR Derivatives Exposure

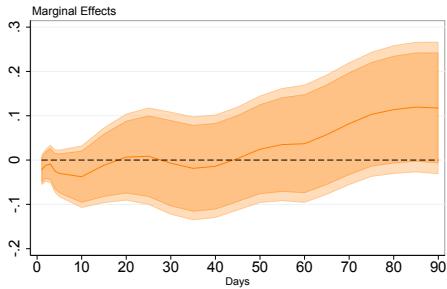


Note. Figure A.50 presents the β^h 's for $h \in [0, 90]$ from estimating firm-level panel regressions (6) for three FX investment strategies—Carry Trade (Row I), Momentum (Row II) and FX Macro News (Row III)—for 2 sectors—investment funds and non-dealer banks—in the EUR/GBP currency cross. Results for the remaining sectors and crosses are in Appendix A.4. Inner and outer shaded areas correspond to 90% and 95% confidence intervals constructed using two-way clustered standard errors by firm and time.

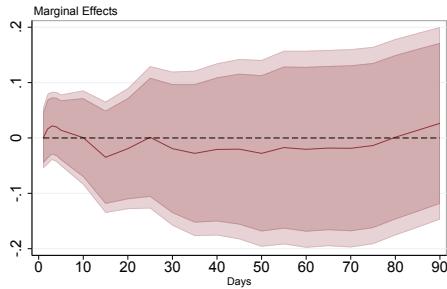
Figure A.51: Investment Strategies and Changes in Firms' EUR-USD Derivatives Exposure

(I) Carry Trade

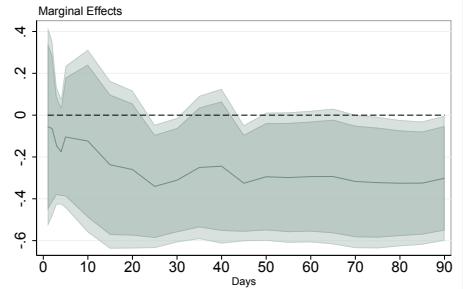
(a) Pension Funds



(b) Insurers

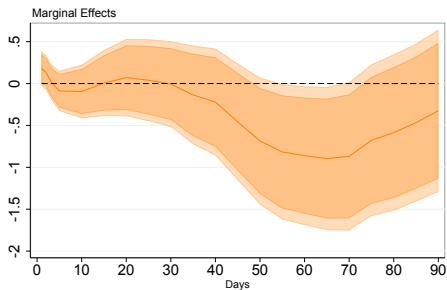


(c) Market Makers

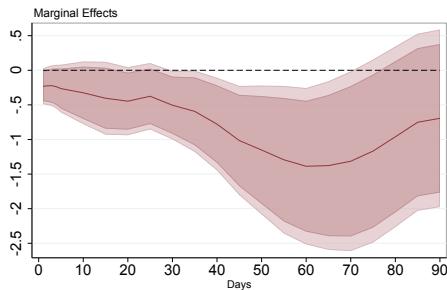


(II) Momentum

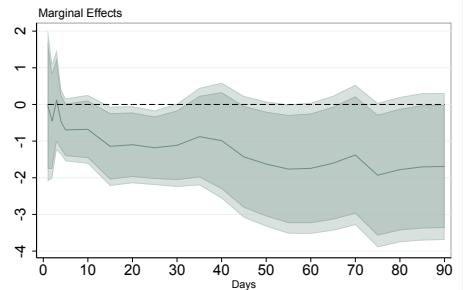
(d) Pension Funds



(e) Insurers

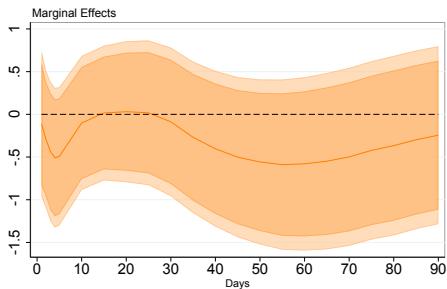


(f) Market Makers

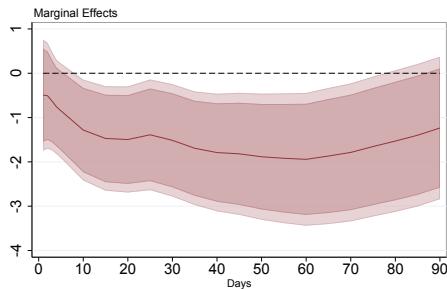


(III) FX Macro News

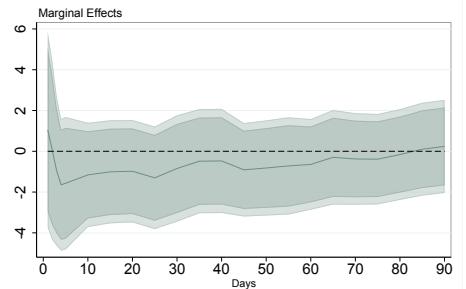
(g) Pension Funds



(h) Insurers



(i) Market Makers

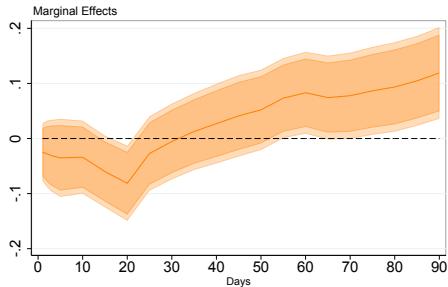


Note. Figure A.51 presents the β^h s for $h \in [0, 90]$ from estimating firm-level panel regressions (6) for three FX investment strategies—Carry Trade (Row I), Momentum (Row II) and FX Macro News (Row III)—for 3 sectors—pension funds, insurance companies, and market makers—in the EUR/USD currency cross. Results for the remaining sectors and crosses are in Appendix A.4. Inner and outer shaded areas correspond to 90% and 95% confidence intervals constructed using two-way clustered standard errors by firm and time.

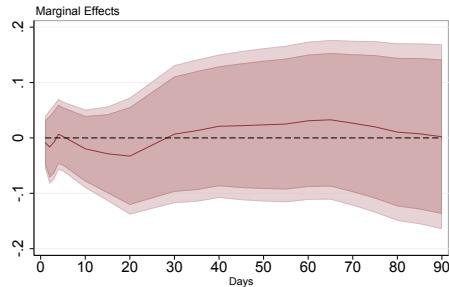
Figure A.52: Investment Strategies and Changes in Firms' USD-GBP Derivatives Exposure

(I) Carry Trade

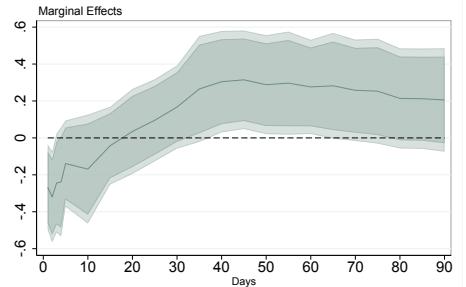
(a) Pension Funds



(b) Insurers

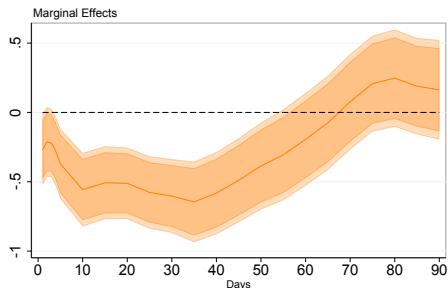


(c) Market Makers

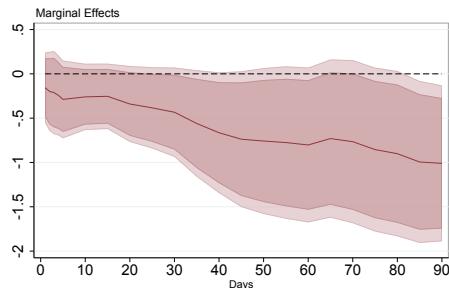


(II) Momentum

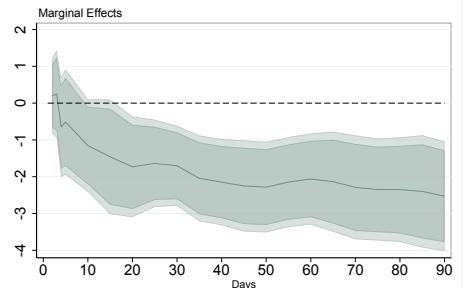
(d) Pension Funds



(e) Insurers

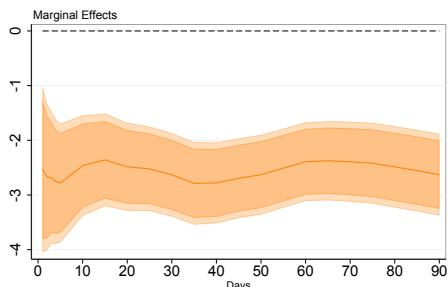


(f) Market Makers

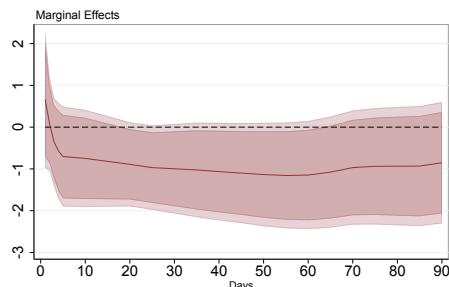


(III) FX Macro News

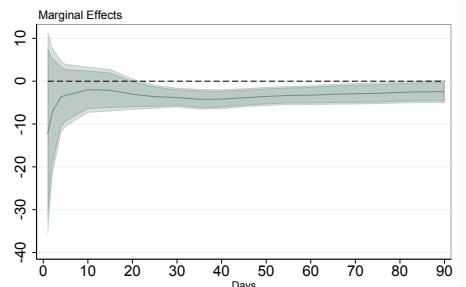
(g) Pension Funds



(h) Insurers



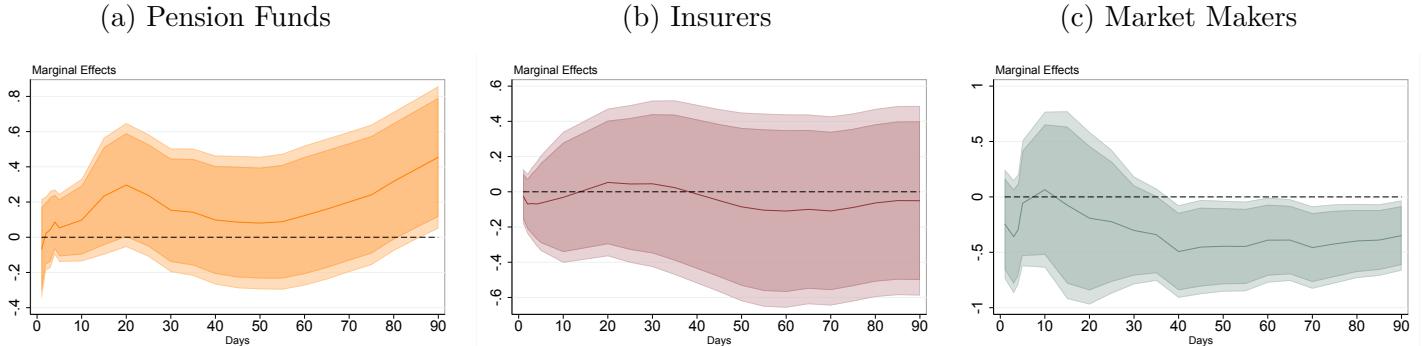
(i) Market Makers



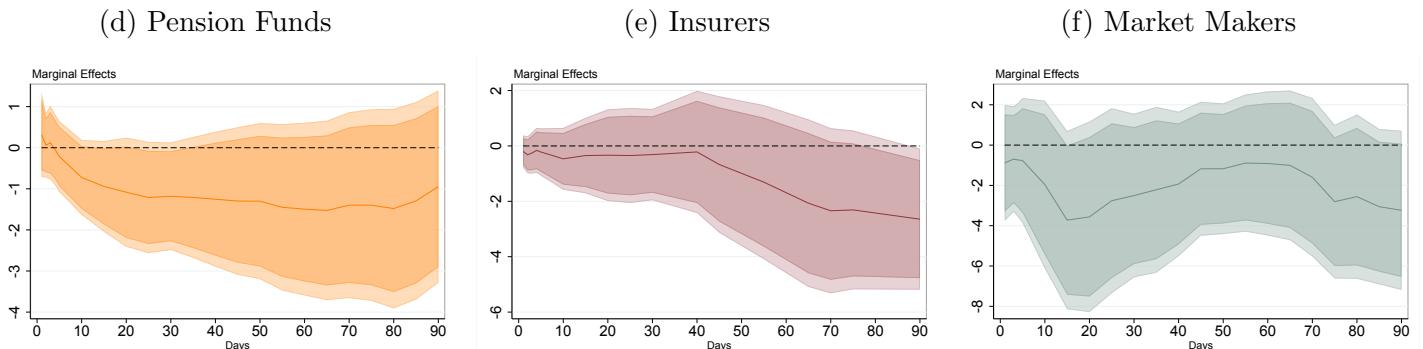
Note. Figure A.52 resents the β^h s for $h \in [0, 90]$ from estimating firm-level panel regressions (6) for three FX investment strategies—Carry Trade (Row I), Momentum (Row II) and FX Macro News (Row III)—for 3 sectors—pension funds, insurance companies, and market makers—in the GBP/USD currency cross. Results for the remaining sectors and crosses are in Appendix A.4. Inner and outer shaded areas correspond to 90% and 95% confidence intervals constructed using two-way clustered standard errors by firm and time.

Figure A.53: Investment Strategies and Changes in Firms' JPY-USD Derivatives Exposure

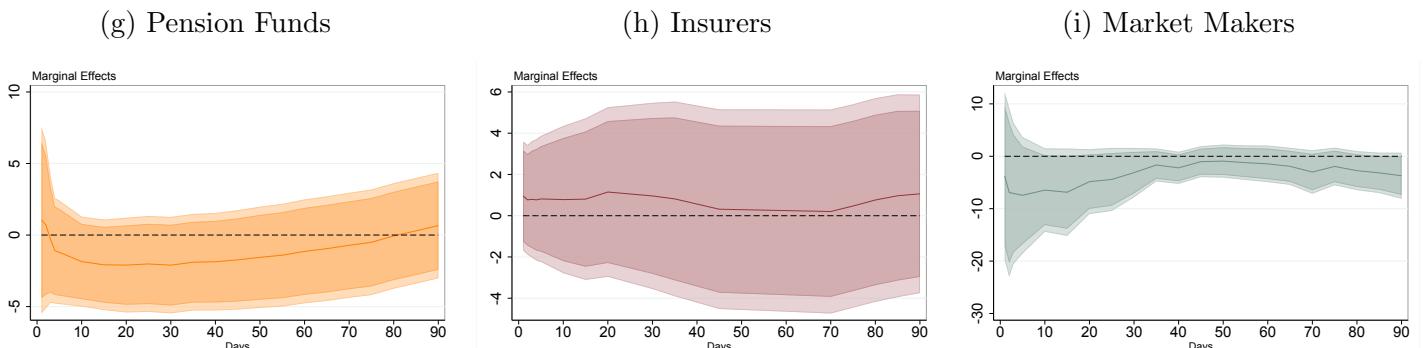
(I) Carry Trade



(II) Momentum

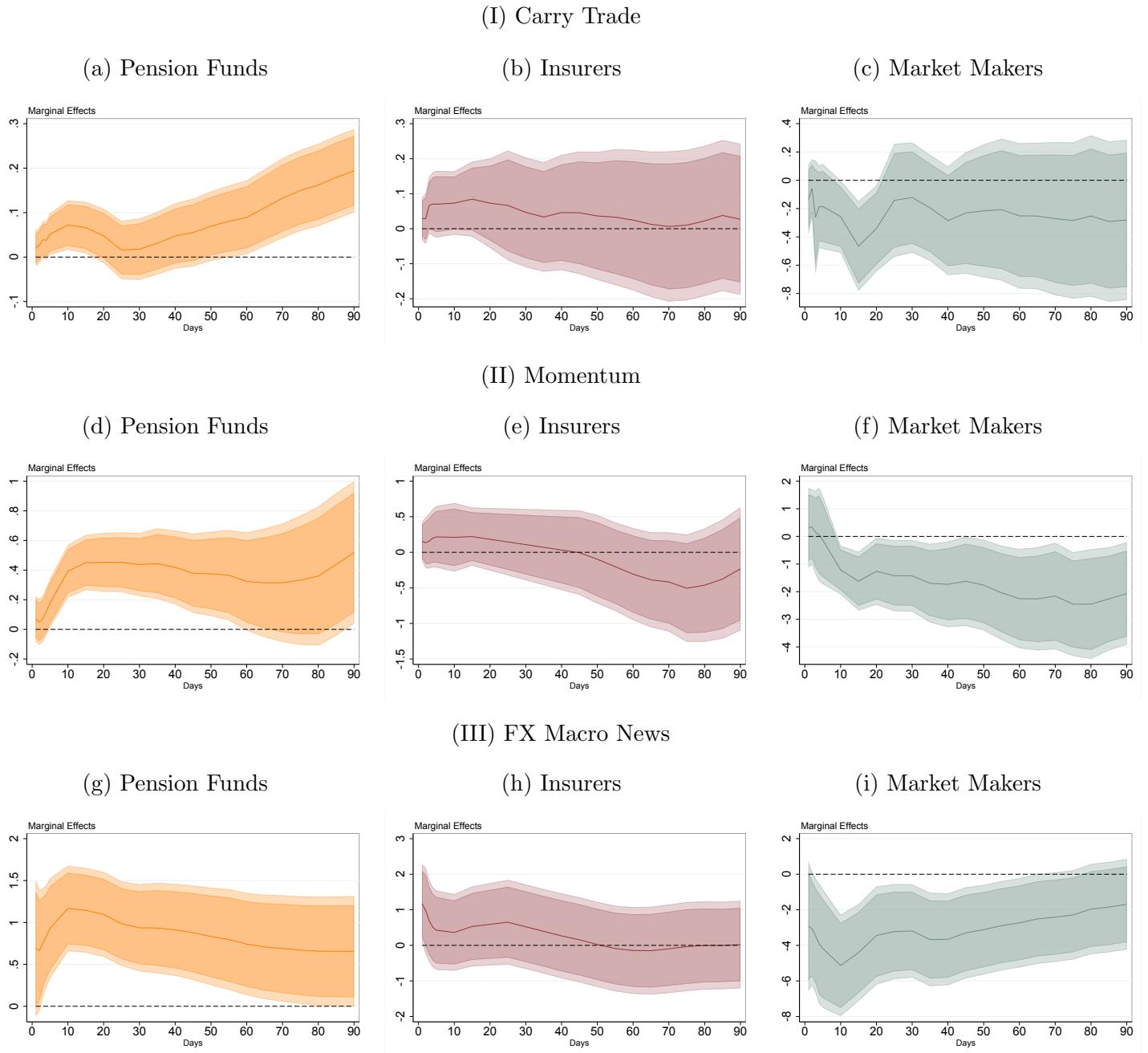


(III) FX Macro News



Note. Figure A.53 resents the β^h s for $h \in [0, 90]$ from estimating firm-level panel regressions (6) for three FX investment strategies—Carry Trade (Row I), Momentum (Row II) and FX Macro News (Row III)—for 3 sectors—pension funds, insurance companies, and market makers—in the JPY/USD currency cross. Results for the remaining sectors and crosses are in Appendix A.4. Inner and outer shaded areas correspond to 90% and 95% confidence intervals constructed using two-way clustered standard errors by firm and time.

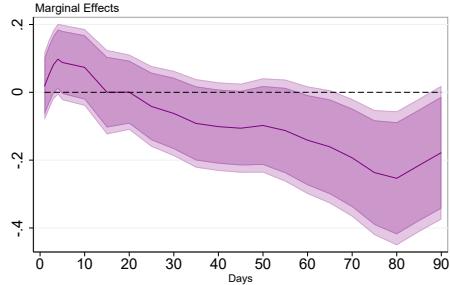
Figure A.54: Investment Strategies and Changes in Firms' EUR-GBP Derivatives Exposure



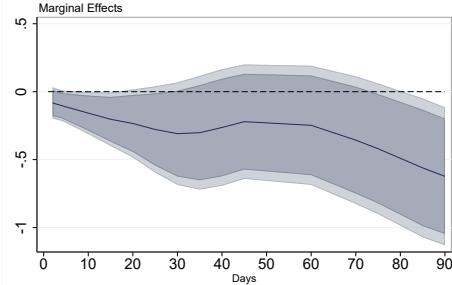
Note. Figure A.54 resents the β^h s for $h \in [0, 90]$ from estimating firm-level panel regressions (6) for three FX investment strategies—Carry Trade (Row I), Momentum (Row II) and FX Macro News (Row III)—for 3 sectors—pension funds, insurance companies, and market makers—in the EUR/GBP currency cross. Results for the remaining sectors and crosses are in Appendix A.4. Inner and outer shaded areas correspond to 90% and 95% confidence intervals constructed using two-way clustered standard errors by firm and time.

Figure A.55: Changes in CIP Deviations and Firms' EUR-USD Derivatives Exposure

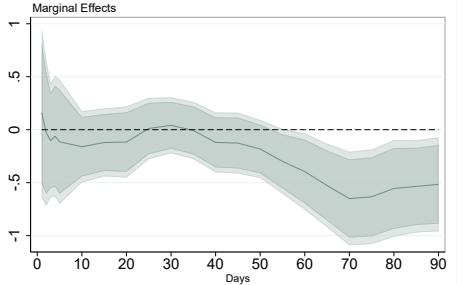
(a) Hedge Funds



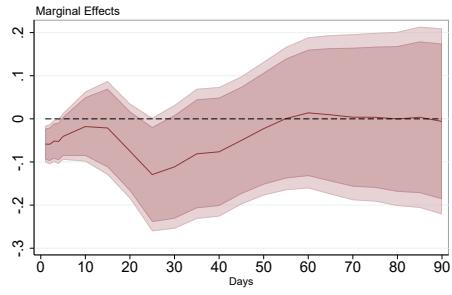
(b) Dealer Banks



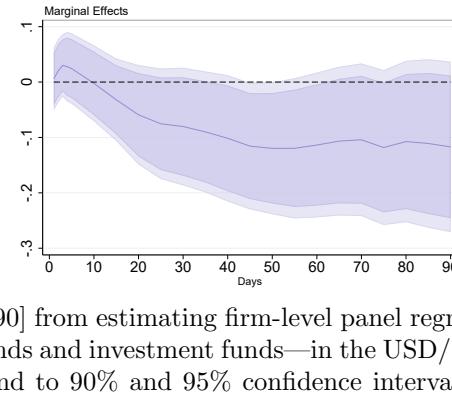
(c) Market Makers



(d) Insurance



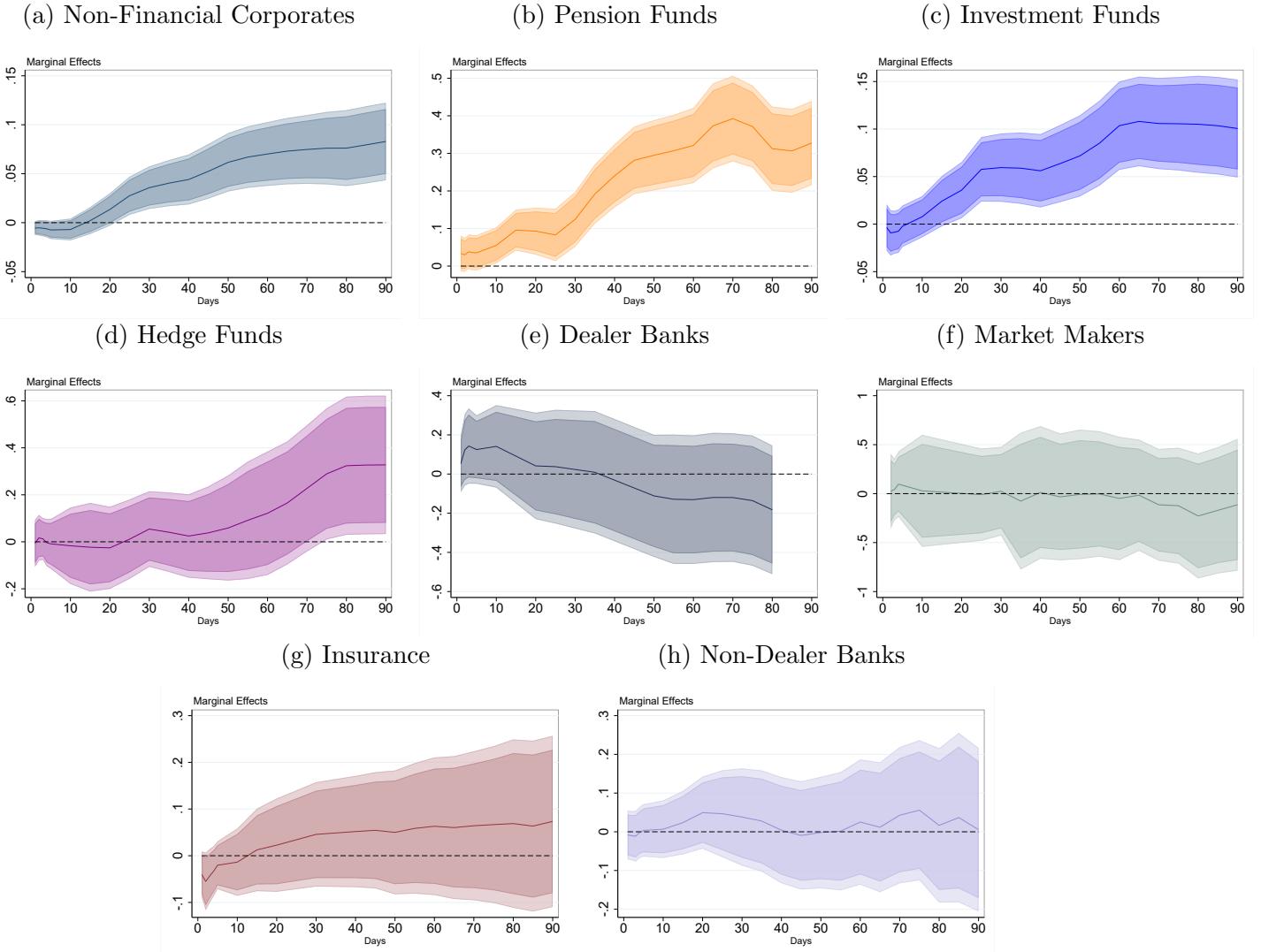
(e) Non-Dealer Banks



Note. Figure A.55 presents the β^h 's for $h \in [0, 90]$ from estimating firm-level panel regressions (7) for 3 sectors—non-financial corporates, pension funds and investment funds—in the USD/GBP currency cross. Inner and outer shaded areas correspond to 90% and 95% confidence intervals constructed using two-way clustered standard errors by firm and time.

A.5 Supplement to Hedging Costs and Hedging Exposures

Figure A.56: Changes in CIP Deviations and Firms' USD-GBP Derivatives Exposure



Note. Figure 10 presents the β^h 's for $h \in [0, 90]$ from estimating firm-level panel regressions (7) for 3 sectors—non-financial corporates, pension funds and investment funds—in the USD/GBP currency cross. Inner and outer shaded areas correspond to 90% and 95% confidence intervals constructed using two-way clustered standard errors by firm and time.

A.6 Supplement to Exchange Rates and Derivatives Exposures

A.6.1 Shock Transmission via Derivatives Positions to Exchange Rates

Table A.1: Monetary Policy, Financial Shocks and Positions: First-Stage Regressions

	$\Delta \mathbf{S}_t^{s,\{m,k\}} / \mathbf{S}^{s,\{m,k\}} $	
	Hedge Funds	Investment Funds
ε_t^m	.424** (.181)	
ε_t^k	-.461* (.247)	
$CSMacroNews_t^{m=US}$.016*** (.005)
Controls	Yes	Yes
F-Stat	13.67	26.66
# Panels	4	2
N	342	4022

Notes: First stage regression results for IV local projections in Figure 11. For hedge funds and monetary policy shocks, we use 4 crosses: EUR/USD, USD/GBP, JPY/USD and EUR/GBP. For investment funds and financial shocks, we use the first two crosses. *** denotes $p < 0.01$, ** $p < 0.05$ and * $p < 0.10$ based on HAC standard errors.

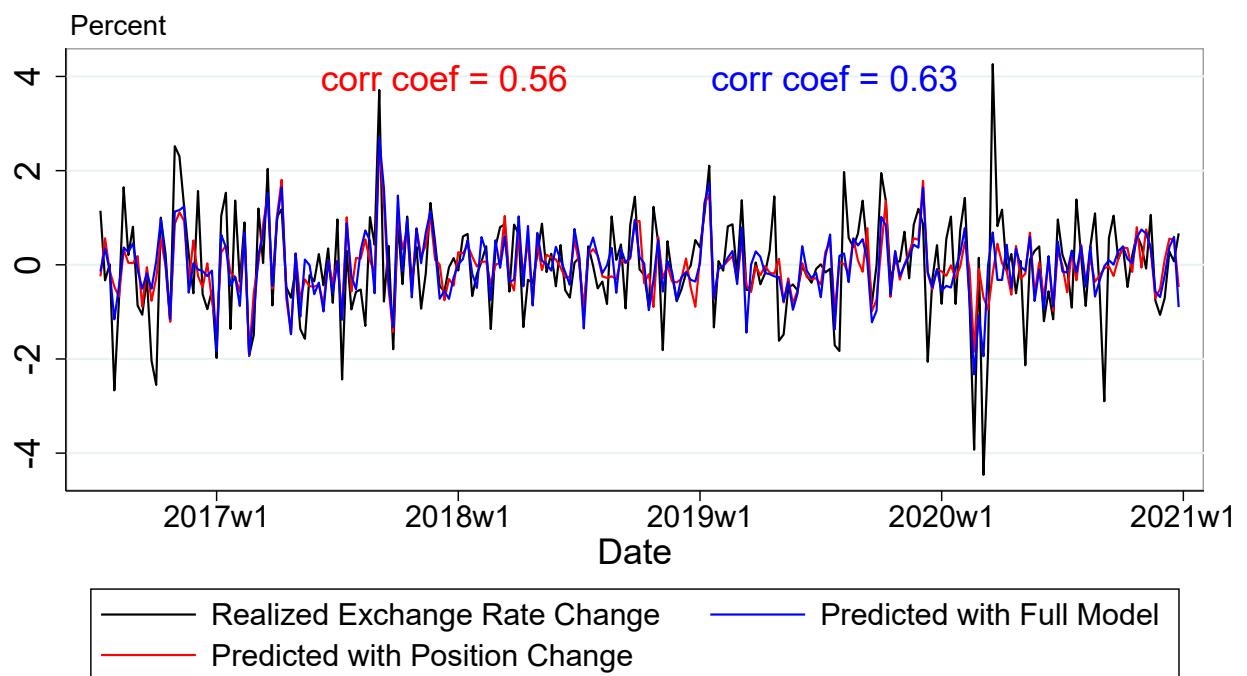
A.6.2 Fitting Exchange Rate Movements

Table A.2: Weekly Exchange Rate Changes and Sectors' FX Derivatives Positions

	$\Delta s_t^{k/m}$			
	USD/GBP	EUR/USD	JPY/USD	EUR/GBP
$\Delta \mathbf{S}_t^{s,\{m,k\}} / \mathbf{S}^{s,\{m,k\}} $				
<i>Hedge Funds</i>	1.20*** (.44)	1.36*** (.52)	1.55*** (.58)	-.11 (.30)
<i>Investment Funds</i>	3.13 (6.06)	6.03*** (2.25)	1.54 (1.16)	6.29 (3.94)
<i>Pension Funds</i>	-1.63 (1.63)	3.04 (2.05)	-.42** (.20)	.49 (1.63)
<i>Non-Fin. Corporates</i>	-44.90*** (5.80)	-8.58*** (2.70)	-.51 (1.31)	-23.84*** (3.17)
<i>Insurers</i>	-1.66 (2.49)	-.02 (.92)	.14 (.14)	2.38*** (.85)
<i>Non-Dealer Banks</i>	-.23 (0.86)	-.37 (0.71)	.50 (.34)	-.38* (.21)
<i>Market Makers</i>	.33** (.15)	-.57** (.27)	-.08 (.09)	.02 (.19)
Controls				
$\Delta \log VIX_t$	-1.19*** (.32)	-.15 (.42)	-.90* (.46)	-1.27*** (.36)
$\Delta(r_t^m - r_t^k)$	2.24** (1.07)	2.62** (1.18)	6.44*** (1.40)	4.04*** (1.10)
$\Delta s_{t-1}^{k/m}$	-.16** (.07)	-.16** (.07)	-.10* (.05)	-.10** (.05)
$\Delta CIP_t^{\{m,k\}}$.01 (.01)	.01** (.01)	.01** (.01)	.00 (.01)
R^2	.41	.25	.44	.40
N	233	233	233	233

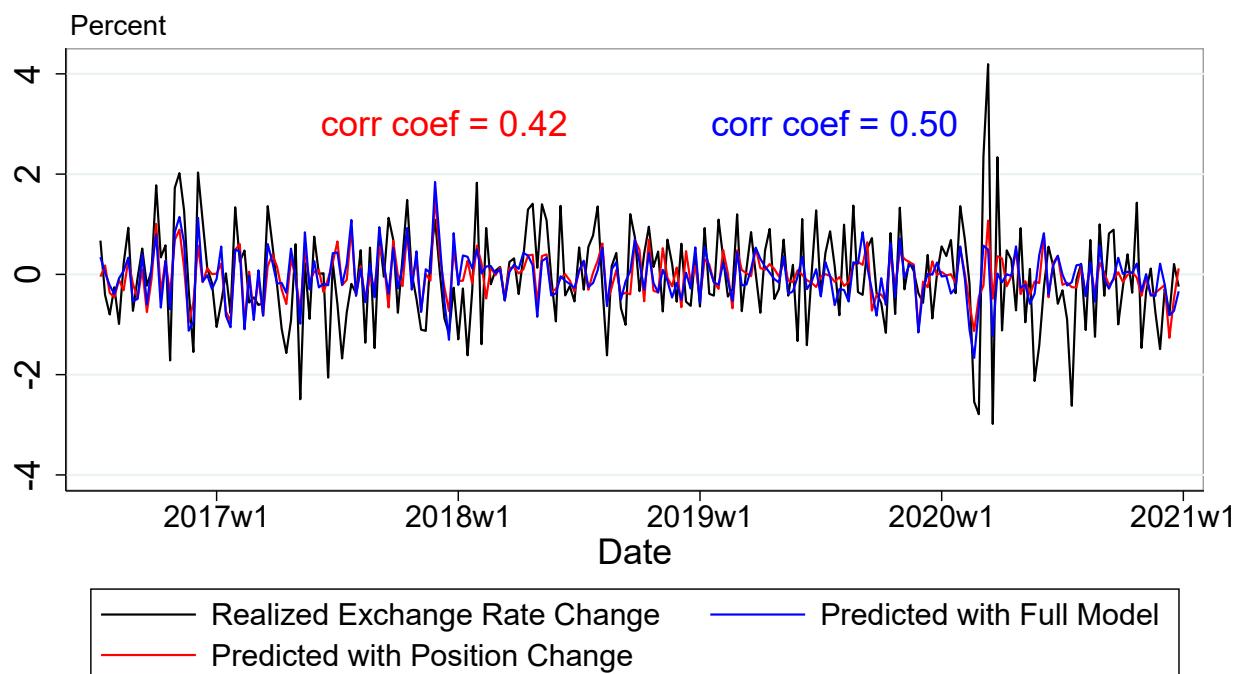
Notes: Table A.2 reports regression coefficients, and standard errors in parentheses, from regression (11) for four crosses. Lags of derivatives positions are suppressed for compactness. *** denotes $p < 0.01$, ** $p < 0.05$ and * $p < 0.10$ based on newey-west standard errors with 12 lags.

Figure A.57: Fitting Weekly EUR/GBP Movements with Derivatives Positions



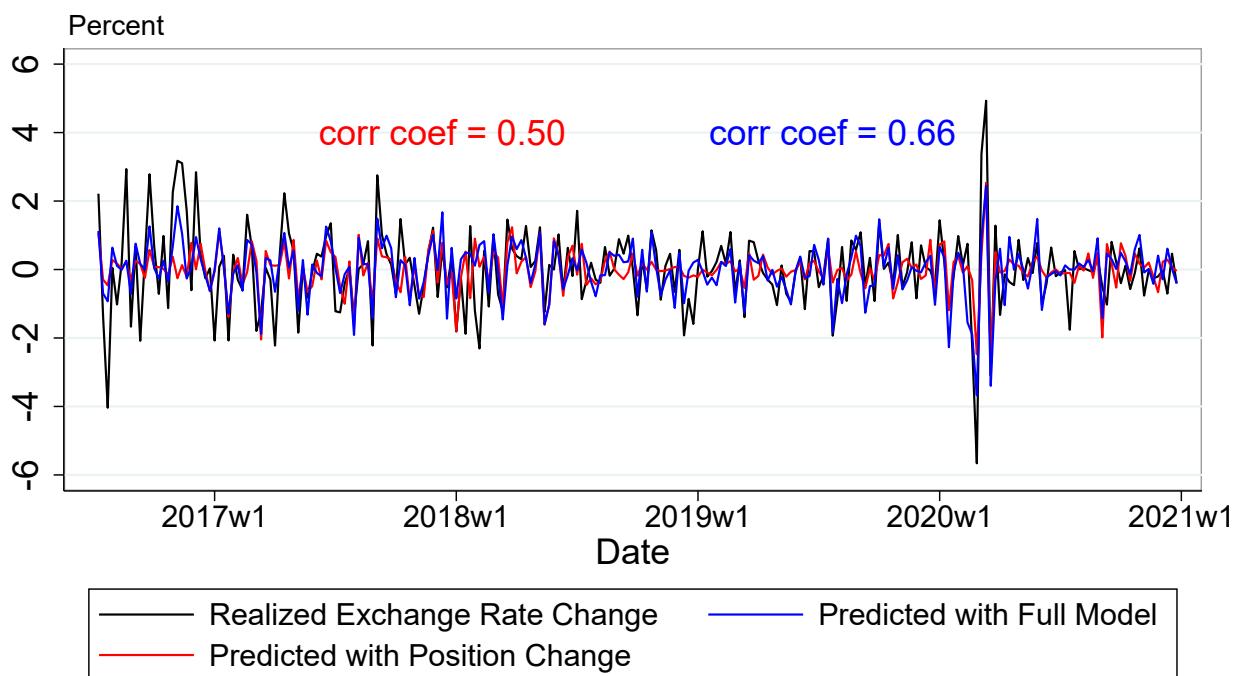
Note. Figure A.57 plots weekly non-overlapping EUR/GBP exchange rate changes in percent (in black) along with fitted values from regression (11), which regresses exchange rates changes on changes in sectors' FX derivatives positions, with (in blue, full model) and without (in red) macro-financial controls. "corr coeff" refers to the correlation coefficient between realized changes and model fit. Table A.2 in Appendix A.6 provides the full regression results.

Figure A.58: Fitting Weekly EUR/USD Movements with Derivatives Positions



Note. Figure A.58 plots weekly non-overlapping EUR/USD exchange rate changes in percent (in black) along with fitted values from regression (11), which regresses exchange rates changes on changes in sectors' FX derivatives positions, with (in blue, full model) and without (in red) macro-financial controls. "corr coeff" refers to the correlation coefficient between realized changes and model fit. Table A.2 in Appendix A.6 provides the full regression results.

Figure A.59: Fitting Weekly JPY/USD Movements with Derivatives Positions



Note. Figure A.59 plots weekly non-overlapping JPY/USD exchange rate changes in percent (in black) along with fitted values from regression (11), which regresses exchange rates changes on changes in sectors' FX derivatives positions, with (in blue, full model) and without (in red) macro-financial controls. "corr coeff" refers to the correlation coefficient between realized changes and model fit. Table A.2 in Appendix A.6 provides the full regression results.

B Data Appendix

B.1 EMIR Trade Repository Data

UK-reporting entities meet their EMIR reporting obligations by submitting their derivatives transactions to trade repositories (TRs). We use the two largest TRs in the UK to which UK-reporting entities report: Depository Trust & Clearing Corporation (DTCC) and Unisys. Although EMIR reporting is highly standardized by the European Securities and Markets Authority (ESMA)⁵⁶, there are differences in reporting between the two repositories regarding coverage and variable names. For each TR, there are two file types per trading day: state and activity files. The state file of a particular date contains the stock of open transactions, which have not matured, as of that day. The activity file contains the flow of transactions that take place on that day.

We use daily activity and end-of-the-month state files to construct a definitive list of clean transactions, as outlined below. A transaction, defined by the two counterparties involved and its unique trade ID, can appear multiple times in the data. First, both counterparties can report the transaction. Second, an intermediary can report it on the counterparties' behalf. Third, for both cases, there are different types of ‘actions’ a particular transaction can be labelled as. These are new (N), modification (M), corrections (R), error (E), cancellation/termination (C).⁵⁷ After a new transaction appears in the data, its modification (e.g. a change in its maturity or notional) or correction can appear at any time before the maturity date. Similarly, a transaction can be terminated early, before its maturity. Fourth and last, if a position is open for a long while, the same transaction would appear multiple times in the end-of-the-month state files. We need to address all such cases carefully to ensure we retain all the relevant information and discard the duplicates.

⁵⁶Extensive explanations of the EMIR reporting standards can be found in Regulatory Technical Documents (<https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A32013R0148>) and Implementing Technical Standards (<https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A32012R1247>).

⁵⁷We do not take into account valuation (V) or position (P), given these actions do not constitute any importance for our analysis.

There are also several other issues related to reporting mistakes, which we attempt to fix to the best of our abilities as we outline below.

B.2 Basic Cleaning Steps

Below we outline the steps we take to clean the data. We go through the data cleaning steps for each TR separately first. Note that there is a reporting change in 2017Q4 that leads to changes in variable names and the number of variables that is collected for each transaction. Before following the cleaning steps listed below, we reconcile all the daily TR files by going over all the files manually to make sure the variable names are synchronized. Amongst the extensive list of variables reported under EMIR for each transaction, we keep the following variables in our sample: asset class, reporting time stamp, trade ID, reporting counterparty ID, ID of the other counterparty, report submitting entity ID, counterparty side, product ID 1, product ID 2, notional currency 1, notional currency 2, deliverable currency 1, deliverable currency 2, currency of price, notional, notional amount leg 2 (if it exists), execution timestamp, maturity date, termination date, exchange rate 1, forward exchange rate, exchange rate basis, contract type, action type.

Once we keep the relevant variables and clean the data in both repositories, we merge them to construct our time series data. The cleaning steps involved are listed below.

1. Once we obtain state and activity files separately from both TRs, we drop if counterparty IDs, i.e. LEI codes of either counterparty, are not 20 characters.
2. We only keep asset classes of Forwards (FW), Futures (FU) and Swaps (SW).
3. For each currency cross, we group transactions by unique transaction identifier: reporting counterparty, other counterparty, trade ID.
4. We drop the transaction if the notional value is zero, missing, 1, or negative.
5. We drop the transaction if trade ID is missing or zero.
6. We drop the transaction where the execution date is listed after the maturity date.

Note that we keep the observations if the execution date and the maturity date are the same.

7. We drop the transaction if counterparty side, which indicates if the counterparty is the buyer or seller, is missing.
8. We delete the transaction if one of the records of action type indicates an error (E).
9. If any of the action types of a particular transaction is correction (R), we backward fill what is corrected at a later date, such that we reflect the correction in the previous records of it.
10. If cancellation/termination (C) appears within the group, we carry backwards the termination date to earlier records of the transaction as the maturity date.
11. If a transaction is modified (M), counterparties do not have to report all the variables they reported in the previous transactions but only the mandatory ones. We forward-fill all the missing entries if there are any modifications.
12. After eliminating duplicates, for a given date, we keep the closest reporting date prior to this of a non-expired transaction, which allows us to use the correct modified transaction to calculate our variables of interest for a particular date. As discussed, modifications occur a lot in the data.
13. Unavista reporting includes notional 2, i.e. notional that the counterparty would receive at the end of the maturity of the contract. DTCC, however, only reports notional 1 and forward rates. We explain below in detail how we handle the issues around forward rates. At this stage, for DTCC, we treat notional 2 as missing. For Unavista, we drop the transaction if notional one and two are the same.
14. We keep the transaction only if its execution date is after 1990.
15. We retain only transactions involving one of the following major currencies: GBP, USD, EUR, JPY, CHF.
16. We merge DTCC and UnaVista activity and state files of the same file dates.

17. Although rare, merging DTCC and Unavista might introduce duplicates. For a given counterparty, currency cross, notional, same execution date and maturity date, forward rate and buyer/seller, we sort all the transactions by reporting date and drop duplicated transactions. We keep the record of the transaction with the earliest reporting date.
18. We then merge all daily files to construct our time series data.

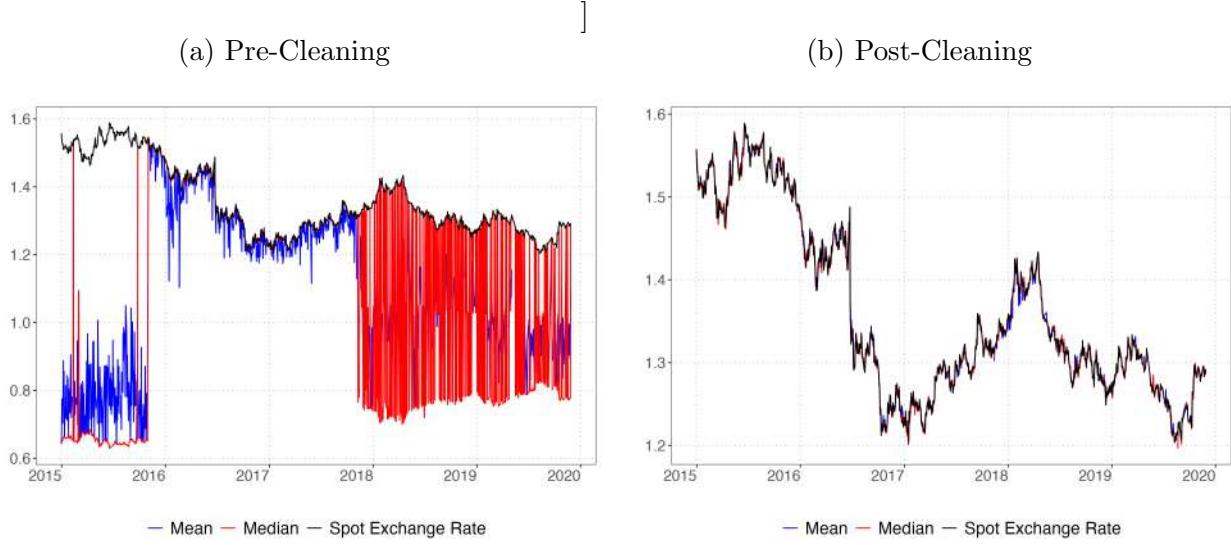
Note that, based on a manual mapping of external data sources, including Company House and the Global Legal Entity Identifier Foundation (GLEIF), we consolidate corporate firms that belong to the same holding company. This ensures that transactions are not potentially double-counted, as we remove duplicate transactions at the group level. For example, BP p.l.c. initially reported under seven different entities, which we have grouped into a single entity. This grouping does not apply to other players as they manage their currency exposures separately. For instance, the BlackRock UK Equity Fund manages its currency exposure independently from the BlackRock Japan Equity Fund, and therefore they are treated as separate entities. Additionally, asset manager holding entities are excluded from the analysis.

B.3 Constructing new variables

After the cleaning steps, we construct the new variables that we need for our analysis. While we do not study all these variables in this paper, we describe how we construct them for completeness.

Forward Rates There are multiple records of which currencies are involved in the transaction, such as notional currency 1 and 2, deliverable currency 1 and 2, currency of price. Accompanying these, there are different exchange rates reported in the data, such as exchange rate 1, forward exchange rate and exchange rate basis. All of these variables collectively identify which currency is being sold and bought, what the spot and forward exchange rates are. However, there are many errors in the data. Often we observe that the currencies involved are flipped during reporting, i.e. that the exchange rate basis variable has been

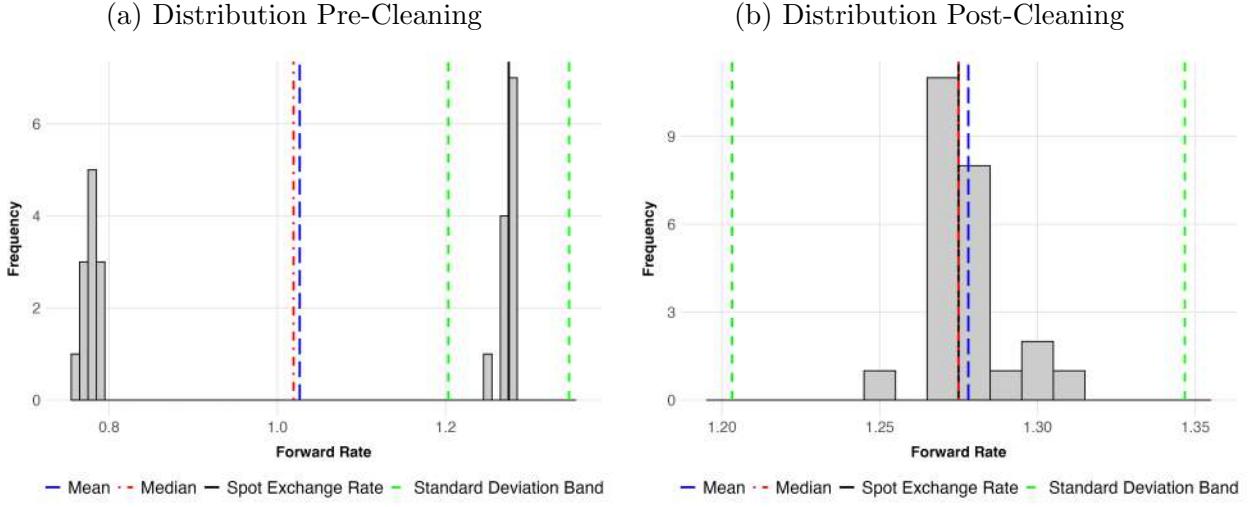
Figure B.1: USD/GBP Forward Rates of Non-Financial Corporates (Maturity \leq 1 Month): Pre- and Post-Cleaning



Note. Figure B.1 compares the mean and median USD/GBP forward rates for non-financial corporates (transactions with a maturity of 1 month or less) against the spot exchange rate, both before and after data cleaning.

misinterpreted by the reporters. This is clear when we consider e.g. JPY/USD where an erroneous flipping of the currency cross would lead to large swings in the exchange rate from e.g. below 0.01 to over 100. However, errors in currency-cross reporting become more subtle when we study currencies where the exchange rate between two currencies is close to 1, e.g. EUR/GBP. In this case, we detect the issue either by using the two notional, when available, where this mistake is not present, to construct the forward rate or by plotting the forward rate distributions. In some cases, some values of the forward rate are multiplied by numbers such as 10^5 or 0.00001 either due to mistakes or due to differences in reporting conventions. These issues collectively affect a significant share of the data. Therefore, we construct multiple versions of forward rates to account for all sorts of wrongful reporting in the data and design robust cleaning algorithms which allow us to retain as much information as possible. The algorithm for detecting and correcting mistakes leverages the bi-modality of the reported forward rate distribution, supplemented by external information from spot rates. Using the raw data without correction would be inaccurate, given the numerous errors detected, as illustrated in Figures B.1 and B.2.

Figure B.2: USD/GBP Forward Rates of Non-Financial Corporates (Maturity \leq 1 Month, Transaction on 27th November 2018): Pre- and Post-Cleaning



Note. Figure B.2 shows the distribution of USD/GBP forward rate transactions for non-financial corporates with a maturity of 1 month or less on November 27th, 2018, before and after data cleaning.

More specifically, when constructing forward rates, the first step is to determine the base currency. According to EMIR reporting standards, exchange rates are quoted as the price of the base currency in terms of the quote currency. The first currency in the pair represents the base currency, and the second represents the quote currency. For example, in the JPY/USD currency pair, USD is the base currency, and JPY is the quote currency. We expect the forward rate for this pair to be in three digits, as 1 US dollar is approximately 145 Japanese yen at the time of writing.

Our remediation process to clean the forward rate includes the following steps:

- 1. Correcting decimal point errors in the forward rate:**

- We calculate a variable called the *transform index* by dividing the spot exchange rate by the forward exchange rate. This result is rounded to the nearest power of 10. If the *transform index* falls within the range [0.2, 5], we set it to 1, indicating no major discrepancy.
- We define the *adjusted forward rate* as the reported forward rate multiplied by the *transform index*.

(c) Finally, we calculate the absolute differences between the spot exchange rate and both the *adjusted forward rate* and the *reported forward rate*. We keep the forward rate with the smallest difference.

2. Correcting flipped forward rates:

- (a) We classify forward rate values as outliers if they fall outside the range of the spot exchange rate plus or minus eight times the one-month standard deviation of the spot exchange rate.
- (b) For the identified outliers, we calculate the *flipped forward rate* as $\frac{1}{\text{forward exchange rate}}$.
- (c) We then apply the same process used in step 1 to the *flipped forward rate* to address cases where both the decimal point and the forward rate are inverted.
- (d) If the *flipped forward rate* remains an outlier after this correction, we replace it with a missing value.

For forward rates derived from reported notional values, we only correct for flipped values, as it is not possible to identify which leg of the transaction has the decimal point error.

3. Handling missing forward rate values:

In many cases, the reported spot exchange rate corresponds to either the reported forward rate or the forward rate derived from notional values. When the reported forward rate is missing, we replace it with the reported spot exchange rate—this occurs because reporters often mistakenly enter the forward rate in the spot exchange rate field. However, this substitution is made only if the reported spot exchange rate significantly deviates from the true spot rate, i.e., it falls outside a band of the spot exchange rate plus or minus 0.1 times the one-month spot exchange rate standard deviation.

Net Currency-Cross Stock Exposures We compute the daily stock, intraday flow, non-intraday flow, and expiring positions at the firm level, where the change in stock is equivalent

to non-intraday flow minus expiring positions. This involves aggregating the notional value of each transaction and using buyer/seller information to determine if the firm is short or long. This computation is done for each currency cross and various maturities. Reporting issues in the notional values are corrected by cross-referencing with our cleaned forward rate series.

Profits Profits are computed in two ways: based on notionals, trade direction, and either the realized exchange rate at maturity or the exchange rate at the execution date.

Net Currency Stock Exposures We have constructed net currency exposure by summing both legs of each transaction for a given currency. For instance, USD exposure is obtained by summing leg 1 and leg 2 of all transactions involving USD. This currency exposure is computed daily at the firm level.

Returns Returns are calculated as profits divided by the absolute value of the notional, representing the average return per transaction for each currency cross and maturity for each firm.

Mean and Median Maturity We have calculated the mean and median maturity of transactions for each firm and currency cross on a daily basis by determining the number of days from the contract initiation to its expiration.

Number of Transactions Similar to positions, we have constructed variables indicating the stock of outstanding contracts, opening intraday flow transactions, opening non-intraday flow transactions, and expiring transactions.

Counter-parties We have a variable that measures the number of unique counter-parties for each reporting entities to capture the network dimension.

B.4 Firm Classifications

Below, we describe the sources we use to manually classify firms into broad sectors and sub-sectors. The five broad sectors we consider are: (i) asset managers; (ii) non-financial

corporates; (iii) insurance companies; (iv) (non-bank) market makers; and (v) banks. Within the asset management sector, we consider three sub-sectors: hedge funds, investment funds and pension funds. Within the banking sector, we consider two sub-sectors: dealer and non-dealer banks. Using GLEIF, we also sort firms based on their legal jurisdiction: UK, EU and other. Other sectors such as charities and universities, which make up a small share of firms in the data, are not included in our analysis.

- Hedge funds: Manuel mapping with the help of AUM 13F - AUM Metrics Analysis (<https://aum13f.com>), Section 4 of SEC Form D (Industry Group: Pooled Investment Fund - Hedge Fund) and website of the funds.
- Investment funds: Sourced from various databases, including ECB investment funds (https://www.ecb.europa.eu/stats/financial_corporations/list_of_financial_institutions/html/index.en.html#if), the subcategory Money Market Fund of Monetary financial institutions dataset (MFIs), and ESMA Money Market Funds (<https://www.esma.europa.eu/publications-and-data/databases-and-registers>). Additionally, we referenced the GLEIF file for entity legal forms (e.g., “FUND”, “ICVC”, “POOL”, “UNIT TRUST”) and employed manual classification.
- Pension funds: Classified as pension funding, plans, and schemes using EIOPA Institutions for Occupational Retirement Provision, along with string matching (e.g., ”FONDO PENSIONE”, ”PENSION FUND”, ”PENSION SCHEME”, ”Pensioenfonds”), and manual classification.
- Non-Financial Corporations: Use the 2021 Global Industry Classification Standard (GICS) key as a guideline incorporating four levels of classification: Type, sector, industry, and sub-industry. Type is the broadest classification while sub-industry is the narrowest. We extend upon the GICS to accommodate for a wider range of types of businesses than what already exists within the GICS framework. Within each level of classification, our aim is to be as consistent as we can regarding the types of businesses that fit within each sub-category of the classification. The subset of firms we consider

are majority companies incorporated within the UK and also appear on Companies House. This provides us with a way to obtain the NAICS UK SIC 2007 classification standard per company.

- Insurance Companies: Classified as insurance, life insurance, reinsurance entities, and insurance brokerages using data from the ECB Insurance Corporations (ICB: https://www.ecb.europa.eu/stats/financial_corporations/list_of_financial_institutions/html/index.en.html#ic), EIOPA Insurance Corporations, and supplemented by manual classification.
- Non-bank Market Makers: Classified, through manual classification, as FCA-authorized market makers, FX brokers, FX services firms, clearinghouses and financial market administrators, as well as some payment services firms, electronic money institutions (identified from <https://thebanks.eu/emis>) and trade finance institutions, who all plausibly play a market-making role in FX markets.
- Banks: Classified as credit institutions (identified by the ECB or EBA), investment banks, and private banks. This includes credit institutions from the ECB Monetary Financial Institutions database, credit institutions registered with the EBA (<https://www.eba.europa.eu/risk-and-data-analysis/data/registers/credit-institutions-register>), and supplemented by manual classification. Dealer Banks are FCA-authorized primary dealers (<https://www.fca.org.uk/publication/documents/market-makers-authorised-primary-dealers.pdf>).

B.5 Macroeconomic Announcement Surprises

When constructing the FX macro news index we include both the US and the other country surprises in the daily regressions. We use surprises for the following indicators for each country. When both Bloomberg and Informa Global Markets (IGM) publish expectations for the same indicator, we choose the source based on data availability. In a few rare cases in which indicators are discontinued, we splice the surprise series with a close substitute.

- Euro area:
 - Germany: (Activity) ifo Business Climate Index, industrial production, total manufacturing new orders, manufacturing PMI, ZEW Indicator of Economic Sentiment
 - Euro area: (Inflation) CPI; (Activity) GDP, manufacturing PMI; (External) current account balance, (Monetary) ECB main refinancing operations announcement rate, 3-month and 10-year interest rate futures
- Japan: (Inflation) Tokyo core CPI, PPI; (Activity) unemployment rate, industrial production, GDP, core machinery orders, tertiary industry activity, manufacturing PMI, (External) current account balance; (Monetary) M2 money supply, 10-year interest rate futures
- United Kingdom: (Inflation) CPI; (Activity) claimant count rate, GDP, industrial production; (External) trade balance; (Monetary) Bank of England official bank rate, 3-month and 10-year interest rate futures
- US: (Inflation) CPI, core CPI, core PPI; (Activity) capacity utilization, Conference Board consumer confidence, University of Michigan consumer sentiment, new home sales, initial jobless claims, industrial production, leading indicators index, nonfarm payrolls, ISM manufacturing index, unemployment rate, GDP, retail sales; (External) trade balance, oil surprises from Käenzig (2021); (Monetary) Fed funds target rate, 3-month Fed funds rate futures, 4-quarter eurodollar futures, and 10-year Treasury yields