Rebalancing of Currency Hedging and the Impact on Exchange Rates^{*}

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Abstract

We study the connection between currency-hedged investments of non-bank financial institutions (NBFIs), global return and exchange rates. A change in the value of foreign investments leads institutional investors to buy or sell domestic currency in order to align with the preferred hedge ratio. To identify this rebalancing mechanism, we use transaction-level data for Norwegian NBFIs. We find that lower portfolio return leads investors to sell domestic currency that in turn results in the depreciation of G10 currencies against USD. Our findings establish a relevant determinant of exchange rates in the economies with large currency-hedged foreign investments.

JEL Classification: E44, F31, F32, G11, G15, G22, G23 **Keywords:** Exchange Rates, Hedging, Non-Bank Financial Institutions, Order Flow

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1 Introduction

Non-bank financial institutions (NBFIs) have emerged as dominant players in global financial markets, managing trillions of dollars in securities globally. A substantial portion of these holdings are hedged against currency risk. In Norway alone, NBFIs maintain currency-hedged investments abroad, predominantly in USD, of approximately 600 billion Norwegian kroner (NOK), representing 10% of the country's GDP (see Figure 1a). This phenomenon extends beyond Norway. For instance, Australian NBFIs' foreign currency exposure has grown substantially from 25% of GDP in 2013 to 65% in 2022, with currency-hedged positions now making up 20% of GDP (Atkin and Harris, 2023). This growing influence stems from several factors, including changes in demographics, financial innovation, and a structural shift from pay-as-you-go to fully funded pension schemes. Despite NBFIs' increasing importance in foreign exchange (FX) markets, the mechanisms through which their behavior affects currency dynamics are still not well understood.

Our research aims to fill this gap by investigating how fluctuations in the market value of NBFIs' currency-hedged foreign investments generate systematic FX flows through rebalancing of their hedge ratio. When returns on currency-hedged foreign investments change, NBFIs must adjust their hedging positions to maintain predetermined hedge ratios, creating predictable patterns of currency flows. Specifically, rising portfolio returns trigger domestic currency purchases, while falling returns lead to sales, a dynamic that creates a link between asset returns, currency flows, and exchange rate fluctuations. Figure 1b illustrates the strong positive correlation between Norwegian NBFIs' cumulative net FX forward flow and the absolute return on the hedged assets of these institutions. As Figure 1b suggests, we find that NBFI's FX forward flows are largely driven by asset returns and that these flows have a material impact on the exchange rate. These findings help explain why USD tends to appreciate during periods of global market stress, as NBFIs across multiple economies sell their domestic currencies to maintain hedge ratios when foreign investments (largely denominated in USD) decline in value.



Figure 1: NBFIs' FX-Hedged Assets, FX Forward Flow and Asset Return



(b) FX Forward Flow and Asset Return

Figure 1a shows insurance (including pension) funds and mutual funds currency-hedged assets in billion NOK. Figure 1b shows the cumulative net forward purchase of NOK against USD for Norwegian NBFIs (measured in NOK) along with the cumulative return on USD-hedged assets measured as outstanding hedges multiplied with asset return, that is, the return on hedged investments in billion NOK. An increase in the cumulative forward flow means purchase of NOK and sale of USD forward. Both series are set to 0 at March 1, 2020 when our data starts.

Sample: March 2020 - August 2023.

Sources: European Market Infrastructure Regulation (EMIR), Bloomberg.

This rebalancing mechanism is rooted in NBFIs' institutional structure, particularly among mutual and pension funds. These institutions typically operate under strict investment mandates that require specific hedge ratios for foreign currency exposure. When foreign investment values fluctuate, initial hedging contracts become misaligned with the underlying portfolio value, forcing institutions to execute FX transactions to restore their target hedge ratios. To empirically validate this mechanism, we analyze a comprehensive dataset of Norwegian NBFIs' FX forward transactions from March 2020 to August 2023. Our data combine mandatory European Market Infrastructure Regulation (EMIR) reporting of derivative transactions with detailed fund-level information on flows and returns, covering mutual, insurance, and pension funds. This unique data set enables us to measure institutions' effective hedge ratios and quantify how portfolio returns drive subsequent FX market activity.

Our findings strongly support the proposed rebalancing mechanism. For fully FX-hedged portfolios and complete rebalancing, we would expect a one-to-one relationship between returns and hedging flows. Our empirical estimates closely match this prediction: monthly coefficients reach 0.9 for equity funds and 0.7 for fixed income funds. Even at daily frequencies, where the noise is higher, we find robust relationships of 0.56 and 0.75, respectively. The most important reason for the discrepancies between the theoretical prediction and our coefficients is that some funds may have a combination of foreign and domestic assets that make the total fund return less representative of its FX activity. Importantly, these relationships are almost equally strong if we replace individual fund returns with aggregate global market indices, confirming the systematic nature of these flows.

To substantiate that the flows indeed stem from rebalancing of NBFIs' currency hedge ratios, we exploit our proxy for the FX hedge ratio. First, we show that the NBFIs' activity in the FX forward market almost exclusively comes from institutions that have a positive hedge ratio, i.e., institutions without FX-hedged investments are not active in the FX forward market and do not show the same association between return and FX forward activity. Second, we show that the larger the hedge ratio, the stronger the association between portfolio return and FX forward activity. This is important, as institutions that are fully hedged (all assets in foreign currency and 100% hedge ratio) will most likely have a more pronounced association between the total portfolio return and FX forward activity than institutions with a lower share of FX-hedged assets.

After empirically validating the relationship between return and NBFI's FX flows, we analyze how these flows affect the exchange rate. Our analysis of price impacts proceeds through two complementary approaches. First, we conduct minute-by-minute event studies using EMIR data to capture the immediate exchange rate response to the forward flows of NBFIs. Second, we aggregate our transaction-level data to create daily net FX forward flow for NBFIs to examine sustained effects, employing a two-stage least squares (2SLS) framework that uses lagged global returns to predict NBFI flows.

Both approaches reveal substantial and persistent impacts on the USDNOK exchange rate. While the 2SLS methodology raises standard exclusion restriction concerns as lagged global returns could potentially affect exchange rates through other channels than flow, the highfrequency event study provides crucial corroborating evidence as it provides a well-identified lower bound of the immediate price impact of NBFI flows. The intraday results from the event study indicate a price impact on the USDNOK of about 0.2 percent per billion NOK, while the 2SLS estimate of the price impact is almost twice as large. The latter coefficient may contain effects that do not immediately follow the execution of the transaction with the NBFI (e.g., dealers that use longer time before hedging the FX forward transaction in the spot market). Together, these results strongly support our central thesis: portfolio returns trigger rebalancing flows that materially impact exchange rates. Furthermore, we employ local projections to assess the persistence of the impact on the exchange rate of these flows. We find no evidence of price reversal, that is, the price impact is not counteracted by opposite movements in the exchange rate in the future.

Drawing on the seminal work of Evans and Lyons (2002), we interpret the currency flows arising from the rebalancing mechanism as portfolio shifts in the FX market in which risk-averse participants need compensation to absorb. Since NBFIs in a wide range of currencies are exposed to global financial markets dominated by USD-denominated assets, these currency flows i) are coordinated across currency pairs, ii) can be large in times of significant changes in global return, and iii) particularly affect the USD. Aligned with this interpretation, we find that lagged global return (as a proxy for flows) is a statistically and economically significant factor of exchange rate fluctuations across a wide range of currency pairs against USD over the past four years.

Our research advances the literature in three distinct ways. First, we demonstrate that NBFI hedge rebalancing explains a significant portion of exchange rate dynamics. Using comprehensive transaction-level data, we extend recent work on currency hedging (e.g., Bräuer and Hau, 2022; Aldunate et al., 2025; Ben Zeev and Nathan, 2024; Liao and Zhang, 2025) by providing granular evidence of this mechanism's operation and implications for policy. Second, we deepen our understanding of the transmission between financial flows and exchange rates. Based on Evans and Lyons (2002), we show that NBFI flows have an immediate price impact, directly supporting the hypothesis of the rebalancing mechanism. Third, we illuminate the determinants of institutional hedging decisions by simultaneously analyzing fund asset composition and returns, contributing to fundamental questions in corporate risk

management (e.g., Stulz, 1984; Brown and Toft, 2002).

The remainder of the paper is organized as follows. Section 2 gives an overview of the related literature and how our work adds to it. Section 3 describes the rebalancing mechanism and develops two main hypotheses: 1) the relationship between the return and the NBFI rebalancing flow, and 2) the relationship between the NBFI rebalancing flow and the exchange rates. Section 4 discusses our empirical strategy and data sources. Section 5 zooms in on the tests for the first hypothesis and the respective empirical results. Section 6 presents the methodology for the second hypothesis and the respective empirical results. Section 7 concludes.

2 Related literature

The question why and how firms hedge is a long-standing question in finance. The seminal work is Stulz (1984); Froot et al. (1993) followed by Brown and Toft (2002); Purnanandam (2007), among others. Regarding currency hedging in particular, Alfaro et al. (2021) explores corporate hedging using granular data and Du and Huber (2023) zooms in on the hedging decisions of financial firms. Abbassi and Bräuning (2021) show that capital regulation affects currency hedging of non-US banks around quarter-ends. Sialm and Zhu (2024) document that currency hedging of US international fixed income funds can be driven by risk management, return enhancement and strategic motives. Our contribution here is to better understand the determinants of hedging decisions made by various types of institutional investors exploring their asset composition and returns at the same time.

The recent financial literature centers around the role of financial flows in explaining ex-

change rates. The portfolio shift model by Evans and Lyons (2002) shows that order flow can drive a significant proportion of exchange rate fluctuations. In the model, order flows contain information about (i) future cash flows (future interest rate differentials) and (ii) the discount factor that clears the market. The price effect comes from the fact that the market is not perfectly elastic and risk-averse agents require a compensation to absorb the order flows. These are key market frictions that we rely on in our empirical analysis. Froot and Ramadorai (2005) further argue that order flow is a significant determinant of short-term movements in exchange rates. Gabaix and Maggiori (2015) provide the theoretical foundation for the effect of intermediary constraints on the dynamics of exchange rates. Adrian et al. (2010) argue that funding liquidity and risk appetite of US financial intermediaries forecast USD exchange rates. Agarwal (2021) and Becker et al. (2023) support the bank lending channel in exchange rate determination via large foreign currency exposures of banks. Engel and Wu (2023) find that when the government bond rate in domestic currency goes down relative to the synthetic government bond rate, the domestic currency appreciates. Camanho et al. (2022) find that unhedged equity funds with higher relative equity returns rebalance their portfolios more affecting, therefore, exchange rates. Gabaix and Koijen (2022), Koijen and Y_{OOO} (2024) and Davis et al. (2022) argue that the price impact of financial flows on assets and exchange rates can be large due to inelastic demand.

Finally, our work relates to the emerging literature on currency hedging and exchange rates. Bräuer and Hau (2022) show that higher hedging pressure into USD through net sell USD forwards and swaps from investment funds is associated with USD depreciation. McGuire et al. (2021) discuss the connection between currency hedging of institutional investors in emerging Asian economies that have large USD investments and the local exchange rates. Melvin and Prins (2015) find evidence on the equity hedging channel in exchange rate determination using relative foreign equity fund returns at the end of the month around the London 4pm fix. Liao and Zhang (2025) also focus on pension funds but propose the debt hedging channel of exchange rate determination linking country-level measures of net external financial imbalances (without FX forward flows) to exchange rates. Faia et al. (2022) study the impact of investor demand for euro-denominated corporate bonds on hedged and unhedged euro-dollar differentials relying on a stronger preference for these bonds by European insurance and pension funds than by mutual funds. Aldunate et al. (2025) show that pension funds in Chile following the local financial advisor's recommendations induce flows that affect the exchange rate because of FX hedging done by local banks. Moreover, Steffensen et al. (2024) find that the hedging decisions of pension funds in Denmark affect exchange rates but the effect is only present for the exchange rate against USD and not EUR to which Danish krone is pegged. We extend this work by analyzing daily data for FX derivative transactions and all types of funds identifying the effects from rebalancing of currency hedging on exchange rates. Complementing existing studies, we cover the whole NBFI sector (mutual, insurance and pension funds) that allows for broader policy implications provided different institutional setups in different countries.

The paper closest to ours is Ben Zeev and Nathan (2024). However, our paper differs from Ben Zeev and Nathan (2024) in several important dimensions. While they document that USD depreciates against ILS when US stock market rises due to pension funds' hedging activities, we show that the rebalancing mechanism operates through both equity and fixed income portfolios. Their focus is on estimating the price impact of hedging flows, whereas our analysis reveals that the total effect on exchange rates is particularly pronounced when both equity and fixed income markets move in the same direction, as this creates concentrated rebalancing flows from NBFIs. This finding is especially relevant for understanding exchange rate dynamics during periods like 2022, when the traditional negative correlation between stocks and bonds broke down. The relationship has also evolved over time, becoming more pronounced after 2020 due to structural changes in financial markets - specifically, larger NBFIs, tighter bank risk limits, and more frequent rebalancing of currency hedging. Moreover, while they focus on establishing US equity returns as a driver of exchange rates through the hedging channel, we demonstrate how currency-hedged portfolio rebalancing needs systematically affect exchange rates across the G10 currency pairs. Finally, the detailed time stamps in our data allow us to employ a well-identified intraday analysis to estimate the price impact of the forward flow on the exchange rate. The evidence from high-frequency event studies and the cross-currency analysis suggests this mechanism has become an increasingly important determinant of exchange rate dynamics.

3 Hypotheses development

Our hypotheses build upon the influential work of Evans and Lyons (2002), which has established a microstructure approach to exchange rate determination. Their findings show that order flow, or the net balance of trades initiated by buyers and sellers, can explain a large portion of exchange rate fluctuations. These orders come from a variety of sources, such as demands for hedging, speculative activity, or unforeseen liquidity needs. Fundamentally, they represent portfolio shifts that risk-averse market participants must absorb, requiring compensation for doing so.

Building on the microstructure framework, we identify a structural mechanism that may affect FX flows and, in turn, FX market pricing. We hypothesize that the return on currencyhedged portfolios affects market participants' demand for foreign currency. Specifically, sudden changes in portfolio returns can trigger substantial portfolio shifts in the FX market as investors rebalance to maintain their preferred hedge ratios. Such portfolio shifts have a measurable impact on currency prices through flows. This mechanism establishes a novel link between global return, hedging demand and FX pricing, extending our understanding of how microstructure factors influence currency markets.

We illustrate the mechanism with a stylized example depicted in Figure 2. Consider an investor who invests 1000 NOK in a Norwegian fixed income fund that is 100%-hedged against exchange rate fluctuations, with an exchange rate of 10 NOK per USD.¹ To fully hedge against exchange rate risk, the fund buys 100 USD with 1000 NOK in the spot market for the equivalent value of USD-denominated bonds and sells 100 USD forward. These two transactions (buying USD spot and selling USD forward) are equivalent to an FX swap and cancel each other out, not affecting the FX spot price as a consequence. The hedge ratio of the FX-hedged exposure to the portfolio value is 1: 100 USD forward to 100 USD investment.

¹We choose a fully-hedged fixed income fund for the illustration, although the same mechanism applies to any type of fund that hedges against exchange rate risk. Figure 3 shows that Norwegian fixed income and equity funds both hedge a significant proportion of their investments against exchange rate risk. For a sample of US international fixed income funds, Sialm and Zhu (2024) document that these funds hedge, on average, 18% of their FX exposure.

Figure 2: Rebalancing Mechanism



This figure provides a stylized example of how fully-hedged fixed income funds' currency hedging can lead to foreign (e.g., USD) and domestic (e.g., NOK) currency flows.

The mark-to-market value of the fund's investment in USD-denominated bonds can change over time. For instance, if interest rates rise, the bond value may decrease. As illustrated in Figure 2, when the USD bond value decreases from 100 USD to 50 USD, the hedge ratio increases to 2 (100 USD forward to 50 USD investment). This overhedging exposes the fund to exchange rate risk.

To understand this, imagine an investor that requests to withdraw its money from the fund at the rebalancing date depicted in Figure 2. Since the fund is fully-hedged against exchange rate risk, the amount that the investor can withdraw is 500 NOK (50 USD×10 NOK per USD). The fund liquidates the USD-denominated asset at the current market price of 50 USD. However, the sale of 100 USD forward initiated prior to the drop in valuation requires the fund to deliver 100 USD (and receive 1000 NOK). This means that the fund has a USD shortfall equal to 50 USD. Since the liability is only 500 NOK and the fund receives 1000 NOK from the forward counterparty, the fund has 500 NOK left to cover the 50 USD shortfall stemming from the difference between the portfolio value and the USD value of the forward contract. Whether these 500 NOK are enough to acquire the necessary amount of 50 USD depends on the actual FX spot rate at the rebalancing date, implying that the fund is exposed to exchange rate risk.

To adjust the hedge ratio and reduce exchange rate risk, the fund must sell NOK (either forward or spot) equivalent to 50 USD immediately when the portfolio value drops. By doing so, the fund will restore the preferred hedge ratio of 1 and lock in the exchange rate on the rebalancing date. Thus, changes in the value of USD-denominated investments cause mechanical flows in the domestic spot market via selling NOK (forward or spot). This brings us to our first hypothesis which we test on granular Norwegian data:

Hypothesis 1: Domestic non-bank financial institutions (NBFIs) systematically adjust their currency hedges in response to changes in returns on currency-hedged investments, buying local currency when returns increase and selling local currency when returns decrease.

Our example emphasizes three main points. First, as Figure 2 demonstrates, the rebalancing mechanism applies regardless of the specific domestic and foreign currencies involved. The only two conditions guiding the choice of currencies are: 1) sizeable amounts of (FX-hedged) foreign investments, and 2) more FX-hedged domestic savings abroad than FX-hedged foreign savings invested in domestic currency. Consequently, a major currency (e.g., USD) is often a suitable choice for the foreign currency in many countries. Second, although mutual, insurance, and pension funds have different business models, the currency hedge rebalancing mechanism applies to any fund that hedges against exchange rate risk. Third, larger changes in foreign investment returns necessitate more fund rebalancing, potentially affecting the domestic spot rate more significantly.

It is worth spending some words on the counterparts occupying the other side of the currency hedges, emphasized in condition 2) in the previous paragraph. If the counterparts in the currency hedges apply mark-to-market on their investments and liabilities, they may also rebalance their hedge ratio, potentially neutralizing the flow in our example. This scenario occurs if foreign NBFIs have larger or equally large amounts of FX-hedged investments in the domestic currency as domestic NBFIs have abroad, and consequently take the other side of the domestic NBFIs' currency hedges. However, banks typically occupy the opposite side of currency hedges across most non-US advanced economies - especially when the foreign currency leg is a major currency like USD (Bräuer and Hau, 2022). Banks take advantage of deeper money markets in major currencies and use the FX swap market to convert these foreign liabilities into domestic currency with exchange rate risk fully hedged.

Unlike NBFIs, banks' balance sheets are characterized by assets that are often not markedto-market (or experience minimal price fluctuations, such as floating-rate loans). Moreover, banks' debt liabilities are not marked-to-market and are typically of short-term nature. This fundamental difference to NBFIs means that banks rarely need to adjust their hedge ratios. This distinction is crucial for two reasons. First, it demonstrates that the resulting flow is unidirectional, as there is no comparable hedging requirement in the opposite direction. Second, it underscores that the nature of assets and liabilities is the determining factor. NBFIs, particularly investment funds, have liabilities that are subject to immediate withdrawal and are directly linked to asset values. In contrast, banks' liabilities do not have the same immediate link to the mark-to-market value of the assets. Building on these insights and the portfolio shift model of Evans and Lyons (2002), our second hypothesis centers around the potential price impact of domestic NBFI flow stemming from rebalancing of currency hedges:

Hypothesis 2: The rebalancing flows from NBFIs have a significant impact on exchange rates due to the inelastic short-term supply of currency, leading to local currency appreciation when global returns increase and depreciation when global returns decrease.

In conclusion, it is important to emphasize the differences in FX spot market flows resulting from FX forward and FX swap transactions. In the FX market, market makers provide forward contracts to customers. Consequently, although these market makers automatically take the other side of the derivative contract, they strive not to sit on the exchange rate risk connected with this position. To eliminate exchange rate risk the market maker will typically conduct the exact same trade in the FX spot market, i.e., if the customer sells 100 USD against NOK forward, the market maker does the same in the spot market. To cancel the cross-currency liquidity need this spot transaction creates, the market maker will use an FX swap where it buys 100 USD spot and sells 100 USD forward. Together, this will eliminate exchange rate risk for the market maker without any need for liquidity. The immediate FX spot replication of the FX forward position creates a flow in the FX spot market.

In contrast, FX swap transactions have no impact on the net flows in the FX spot market. In an FX swap, the counterparts agree on exchanging currencies today and reverse the exchange at a predetermined date in the future. The counterparts take the prevailing spot rate as exogenous input and negotiate the forward premium. The easiest way to see that an FX swap does not have a direct impact on the FX spot flows is to separate two transactions underlying the FX swap into a spot transaction (e.g., sell 100 USD) and a corresponding forward transaction in the opposite direction (buy 100 USD forward). As described above, the FX forward transaction will trigger an immediate buy order in the FX spot market by the market maker and the two FX spot transactions will cancel out.

These basic insights on the implications of swap and forward transactions for FX spot flows provide useful guidance to understand why the initial hedging illustrated in Figure 2, i.e., when the fund receives inflow of domestic currency that must be converted and hedged through FX swaps, does not affect the exchange rate directly, while our proposed mechanism which leads to rebalancing of the hedge ratio does.

4 Data and institutional setting

To examine Hypothesis 1, we obtain granular data from the full universe of FX forward and swap transactions in NOK. We leverage the mandatory reporting of derivatives introduced by the European Market Infrastructure Regulation (EMIR). This is a post-crisis regulation that requires reporting of all derivative transactions to trade repositories available to supervisory authorities. Based on the EMIR reports, we obtain transaction-level data on all FX derivatives over the period from March 2020 to August 2023.²

We process the EMIR data in the following way. We select FX swap and forward transactions active in the period between March 1, 2020 and August 31, 2023, which involve a Norwegian

²Before March 2020, reporting volumes are questionably low in the EMIR reports. Norges Bank introduced its own money market transaction reporting in March 2020, which might have contributed to the increased reporting quality within the EMIR as well. We also observe that many FX derivative contracts are reported with the wrong currency denomination after August 2023.

NBFI, either a mutual fund ("Verdipapirfond") or insurance fund (either a life/pension or claims insurance fund, "Livsselskaper og pensjonskasser" or "Skadeforsikringsselskaper").³ As a rule, transactions are reported by both counterparties, therefore each transaction results in two reports: one report from the NBFI and another from the NBFI's counterparty, which is a bank for all transactions we observe. We keep the reports submitted by banks, as banks' reports appear to be of higher quality. Only keeping banks' reports reduces the number of reporting agents and potential reporting issues due to different reporting styles. To determine which counterparty is buying NOK and which is selling NOK, we follow the EMIR reporting guidelines.⁴

We use the EMIR data to create three main variables for our analysis. For each fund i and time t, we compute:

- 1. FX forward flow $f_{i,t}$, net domestic currency (NOK) to be received from forward contracts executed at time t.
- 2. Outstanding FX forwards $f_{i,t}^{Outs}$, net domestic currency to be received from forward contracts active at time t.
- 3. Outstanding FX swaps $s_{i,t}^{Outs}$, net domestic currency to be received from the second (forward) leg of swap contracts active at time t (equivalent to the net amount of foreign

³We map a LEI code for each entity to an organization number, entity and sector classification from the Brønnøysund Register (Norwegian public register).

⁴The EMIR reporting guidelines state that "in accordance with Article 3a of the Commission Implementing Regulation (EU) No 1247/2012 in case of cross-currency swaps and FX swaps and forwards, the counterparty receiving the currency which is first when sorted alphabetically by ISO 4217 standard shall be identified as the buyer" (ESMA, 2024). Therefore, we mark the counterparty as buying NOK if the counterparty is identified as the buyer in a contract where NOK is the first currency in the currency pair when two currencies are sorted alphabetically. For example, in a forward contract between NOK and USD, NOK precedes USD when sorted alphabetically, the buyer receives NOK (and pays USD), whereas in a forward contract between NOK and EUR, the buyer receives EUR (and pays NOK).

currency borrowed through swaps at time t).

To compute FX forward flow, we sum the notionals of contracts where the fund buys NOK and subtract the sum of the notionals of contracts where the fund sells NOK for each execution time. For outstanding volumes, we use the execution and maturity dates to determine when contracts are active, and sum the active contracts for each date in our sample.⁵

We merge our transaction-level data with fund-level data reported to Norges Bank by the Norwegian Fund and Asset Management Association (VFF) and fund-level return (as well as other market data) from Bloomberg. Two key measures we obtain from VFF are the net inflow and assets under management at the fund level.

Table 1 presents the summary statistics. Our panel consists of 222 unique NBFIs that do at least one FX swap or forward transaction according to the EMIR reports between March 2020 and August 2023. In the top panel, we report statistics by group, e.g., 232 billion NOK in outstanding swaps and forwards mean that mutual funds as a group have daily that amount on average. 222 NBFIs represent 171 mutual funds, out of which 138 are either fixed income or equity funds and 33 are other mutual funds which we further exclude. Among the remaining 138 mutual funds, we then distinguish between mutual funds with a median hedge ratio below and above 50%. We observe that despite the number of funds drops, the ones that remain cover most of mutual fund FX derivative flows and outstanding volumes. From Table 1, we see that the mean outstanding swap and forwards for the above 50%-hedged

mutual funds is almost 220 billion NOK, whereas the below 50%-hedged group approaches

⁵We consider a contract active starting two business days after its execution date (T+2 settlement date) and up to the day before its maturity date. We use this approach because the settlement and effective dates in the EMIR reports are often missing or are the same as the execution date.

just 13 billion NOK. The daily average forward flow from the above 50%-hedged group is also considerably larger (69 million NOK versus 5 million NOK). Thus, while the number of the above 50%-hedged mutual funds is low, the activity of this group appears to drive mutual fund FX forward (and swap) flows. Studying them allows us to cover the most of mutual funds' activity in the FX derivative market.

Norwegian NBFIs have about 600 billion NOK (400 billion NOK by insurance funds and 230 billion NOK by mutual funds) on average in outstanding forwards and swaps during the sample period as shown in Table 1 (also see Figure 1a). Assuming full rebalancing, 600 billion NOK in outstanding FX hedging contracts means that a negative return of 10% on the NBFIs' FX-hedged assets implies that the NBFIs would have to sell 60 billion NOK to keep their hedge ratio fixed. Reversely, a positive return of 10% would lead to buying 60 billion NOK.

In Figure 3, we look at the prevalence of currency hedging among different types of mutual funds.⁶ We see that equity funds appear to be fully-hedged if they are involved in hedging at all. Fixed income funds, on the other hand, appear as partially hedged. This is likely because they hold a mixture of foreign and domestic assets in their portfolios and not because of partial hedging of their foreign assets (we look up some of the largest funds in the 0.4-0.6 range in Bloomberg and see that they have a substantial share of domestic assets). We see that while volatile equity markets trigger large rebalancing flows, fixed income funds may be more eager to hedge, leading them to also generate substantial rebalancing flows.

In Figure 4, we combine FX-hedged and total assets for Norwegian mutual funds, and also

⁶The VFF provides fund-level information on assets of mutual funds. We therefore cannot illustrate hedge ratios of insurance and pension funds and the extent to which these types of funds hedge currency risk.

Group	Variable (million NOK)	Mean	SD	Min	50%	Max
Group-Level Statistics						
Mutual Funds $(N = 171)$	Forward net	72.68	661.27	-4667.71	40.28	3327.95
· · · · ·	Forward sell	-330.42	586.73	-4935.94	-111.46	-0.00
	Forward buy	383.99	569.33	0.13	169.38	3857.34
	Swap sell	-880.42	1323.40	-9233.80	-269.23	-0.47
	Swap buy	3233.61	2699.65	0.02	2683.10	14583.44
	Outstanding swaps and forwards	232128.66	18899.21	172879.32	230469.42	283940.41
	Outstanding swaps	166855.18	14659.03	138756.40	168711.40	204151.90
	Outstanding forwards	65273.48	16812.00	24433.24	62635.54	100142.79
Insurance Funds $(N = 51)$	Forward net	262.26	1026.38	-7798.53	185.16	5415.15
	Forward sell	-758.61	1118.74	-10767.67	-306.97	-0.01
	Forward buy	1002.78	1094.24	0.04	629.38	6421.44
	Swap sell	-1285.06	1676.47	-11852.06	-579.53	-0.17
	Swap buy	5105.58	3684.60	1.06	4581.31	25358.32
	Outstanding swaps and forwards	400161.80	31730.06	297019.45	408838.05	455841.13
	Outstanding swaps	334134.69	31738.58	264308.76	329044.20	391933.79
	Outstanding forwards	66027.11	15082.49	27172.99	64678.68	95372.46
Hedge Ratio $< 50\%$ ($N = 102$)	Forward net	4.64	43.59	-293.27	1.38	206.88
	Outstanding swaps and forwards	12675.34	2196.72	8215.92	12791.63	18615.67
	Outstanding swaps	8777.00	2060.44	5746.27	8138.66	16080.58
	Outstanding forwards	3898.34	1665.34	142.81	3377.41	8061.79
Hedge Ratio $> 50\%$ ($N = 36$)	Forward net	68.55	650.97	-4646.63	37.58	3223.64
	Outstanding swaps and forwards	216257.00	19464.90	157194.78	215358.29	271728.94
	Outstanding swaps	156410.18	15735.56	125427.07	157351.61	194300.63
	Outstanding forwards	59846.82	17741.87	16752.57	57333.86	94409.33
Fund-Level Statistics $(> 50\%)$						
Fixed Income Funds $(N = 23)$	Forward net	2.32	154.96	-2962.31	0.05	1994.71
	Outstanding swaps and forwards	6603.66	9494.16	-1073.54	2920.64	50432.09
	Outstanding swaps	6006.15	9656.82	-4112.48	2465.37	50049.23
	Outstanding forwards	1375.92	2606.55	-2277.18	207.26	14442.26
	Assets	7610.20	9772.14	398.11	3897.66	46622.34
	Monthly net inflow	14.92	1015.76	-27882.86	13.92	4227.67
	Day-to-day return (%)	0.00	0.31	-7.38	0.01	4.80
Equity Funds $(N = 13)$	Forward net	14.59	195.10	-2751.71	2.05	2062.61
	Outstanding swaps and forwards	5309.26	9348.09	-115.34	1179.16	60265.25
	Outstanding swaps	3336.90	7679.08	-12.18	777.87	37415.67
	Outstanding forwards	2472.74	6180.56	-6452.86	124.80	60265.25
	Assets	5388.81	9614.76	95.13	1162.00	38157.74
	Monthly net inflow	38.32	1593.67	-26084.23	3.82	21664.25
	Day-to-day return (%)	0.05	1.26	-13.07	0.07	12.60

Table 1: Summary Statistics

This table reports summary statistics for Norwegian non-bank financial institutions (NBFIs) based on the European Market Infrastructure Regulation (EMIR) reports over March 2020 - August 2023. In the top panel, the statistics are at the group level, and in the bottom panel, the statistics are at the fund level. We have 171 mutual funds and 51 insurance (incl. pension) funds. 138 out of 171 mutual funds are either fixed income or equity funds for which we report statistics separately for those with a hedge ratio below and above 50%.

Sources: European Market Infrastructure Regulation (EMIR), Norwegian Fund and Asset Management Association (VFF) and Bloomberg.

plot the ratio between the two, the hedge ratio, on top. The hedge ratio is quite flat and high on average approaching 90% and changes in the hedge ratio do not persist over time supporting our rebalancing mechanism and the adjustment done by funds to their preferred hedge ratio. In March 2020, the hedge ratio first increases as asset prices fall, before returning towards the mean as the funds sell domestic currency in the forward market.





This figure illustrates the exposures of the funds with a hedge ratio above 10% and splits them into four groups depending on the hedge ratio. The light gray area represents the exposures of low-hedged funds with the hedge ratio between 10% and 40%. The light blue and dark blue areas represent the exposures of medium-hedged funds with the hedge ratio of 40%–60% and 60%–80%, respectively. The dark gray area represents the exposures of highly-hedged funds with the hedge ratio above 80%. The hedge ratios are proxied by outstanding FX swaps and forwards as a share of assets under management.

Sample: March 2020 – August 2023.

Sources: European Market Infrastructure Regulation (EMIR), Norwegian Fund and Asset Management Association (VFF).



Figure 4: Mutual Funds' Hedge Ratios

This figure shows hedge ratios of Norwegian mutual funds. The black line depicts hedge ratios of Norwegian mutual funds with a positive hedge ratio proxied by outstanding FX swaps and forwards as a share of assets under management (AUM). The dark blue area represents the FX hedging exposures of Norwegian mutual funds (outstanding FX swaps and forwards). The light blue area represents the AUM of Norwegian mutual funds with positive hedge ratios.

Sample: March 2020 – August 2023.

Sources: European Market Infrastructure Regulation (EMIR), Norwegian Fund and Asset Management Association (VFF).

5 Rebalancing of hedge ratios and FX forward flows

In this section, we empirically investigate the relationship between NBFIs' portfolio return and FX forward flows (Hypothesis 1). We first present our methodology before we turn to the results.

5.1 Methodology

To test Hypothesis 1 we use our transaction-level FX forward data from EMIR in combination with fund-specific returns and our proxy for funds' hedge ratios. We specify the following regression:

$$\frac{f_{i,t}}{a_{i,t-1}} = \beta_1 r_{i,t-1} + \beta_2 \frac{inflow_{i,t}}{a_{i,t-1}} + \alpha_i + \varepsilon_{i,t}.$$
(1)

The dependent variable, $f_{i,t}/a_{i,t-1}$, is net purchases (buy minus sell) of NOK in the FX forward market scaled by total assets. This is our fund-level measure of FX forward flows. The main independent variable is the lagged return $r_{i,t-1}$, but we also report the results from similar specifications using monthly frequency where the return measure is the monthto-month returns (non-lagged) and the independent variable is the net forward purchase of NOK over the month. We add a control for inflows scaled by assets and fund fixed effects α_i . We also estimate (1) across funds with different hedge ratios to see whether the connection between returns and forward flows is stronger for funds with higher hedge ratios.

Following the literature on the equity versus debt hedging channel in exchange rate determination (Melvin and Prins, 2015; Ben Zeev and Nathan, 2024; Faia et al., 2022; Liao and Zhang, 2025), we also estimate a similar model where we replace the fund-specific returns with global equity and bond return indices and run the following model:

$$\frac{f_{i,t}}{a_{i,t-1}} = \beta_1 r_{t-1}^{Eq} + \beta_2 \frac{inflow_{i,t}}{a_{i,t-1}} + \varepsilon_{i,t}$$

$$\tag{2}$$

$$\frac{f_{i,t}}{a_{i,t-1}} = \beta_1 r_{t-1}^{FI} + \beta_2 \frac{inflow_{i,t}}{a_{i,t-1}} + \varepsilon_{i,t},\tag{3}$$

using the MSCI world index return (FX-hedged) as the index return for equity mutual funds r_t^{Eq} , and the global corporate bond index return (FX-hedged) as the index return for fixed income mutual funds r_t^{FI} .

As for insurance and pension funds we lack data on their assets from the VFF and fund-level return from Bloomberg, for these funds we use the NBFIs' outstanding FX contracts as a proxy for the asset value, and estimate

$$\frac{f_{i,t}}{s_{i,t-1}^{Outs} + f_{i,t-1}^{Outs}} = \beta_1 r_{t-1} + \varepsilon_{i,t}.$$
(4)

The dependent variable is FX forward flow as a share of net outstanding swap and forwards positions; we exchange $a_{i,t-1}$ for $(s_{i,t-1}^{Outs} + f_{i,t-1}^{Outs})$. As before, we see if this measure of rebalancing of currency hedging follows index returns, this time using the 50-50 weighted global return index r_t :

$$r_t = 0.5r_t^{Eq} + 0.5r_t^{FI}.$$
 (5)

5.2 Results

Table 2 presents the results from specifications (1) and (2) where we look at the relationship between the FX forward flows from mutual funds, their portfolio returns and index returns, considering equity and fixed income mutual funds separately. We include the funds that have a hedge ratio between 50% and 120%. We start by presenting results on a daily frequency, where we can make use of our granular data and use the previous day's return $r_{i,t-1}$ to predict the size of the forward flow $f_{i,t}$ the day after. Importantly, we exclude daily observations where the fund is not having any FX forward transactions.

		Equity	Funds			Fixed Inc	ome Funds	
	$rac{(1)}{rac{f_{i,t}}{a_{i,t-1}}}$	$\frac{(2)}{\frac{f_{i,t}}{a_{i,t-1}}}$	$\frac{(3)}{\frac{f_{i,t}}{a_{i,t-1}}}$	$\frac{(4)}{\frac{f_{i,t}}{a_{i,t-1}}}$	$\frac{(5)}{\frac{f_{i,t}}{a_{i,t-1}}}$	$rac{(6)}{rac{f_{i,t}}{a_{i,t-1}}}$	$\frac{(7)}{\frac{f_{i,t}}{a_{i,t-1}}}$	$\frac{(8)}{\frac{f_{i,t}}{a_{i,t-1}}}$
$\overline{r_{i,t-1}}$	0.561^{***} (0.087)	0.561^{***} (0.088)	0.560^{***} (0.030)		0.746^{***} (0.101)	0.741^{***} (0.103)	0.746^{***} (0.058)	
$inflow_{i,t}/a_{i,t-1}$	()	0.026^{**} (0.013)	0.029*** (0.006)		()	0.007 (0.005)	0.007^{**} (0.003)	
r_{t-1}^{Eq}		()	()	0.542^{***}		()	()	
r_{t-1}^{FI}				(0.002)				$\begin{array}{c} 0.844^{***} \\ (0.146) \end{array}$
Fund FE	No	No	Yes	No	No	No	Yes	No
Observations	2930	2930	2930	2930	1943	1943	1943	1943
Adjusted \mathbb{R}^2	0.107	0.112	0.131	0.104	0.078	0.079	0.083	0.037

Table 2: Determinants of NBFI Rebalancing Flows

This table reports the results for Norwegian mutual funds with the median hedge ratio above 50% and the 30% cap on returns and inflow. We exclude observations where a fund has in purchases more than 10% of AUM in a single day. Fund-level clustered standard errors are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Sample: March 2020 – August 2023, daily frequency, one-day lag on returns.

Sources: Norwegian Fund and Asset Management Association (VFF), European Market Infrastructure Regulation (EMIR) and Bloomberg.

We find a clear positive relationship between fund returns and FX forward flows meaning that higher return is associated with more (net) buying of domestic currency (NOK). The coefficients for both fund-specific and index returns are statistically and economically significant, also when controlling for inflows and fund fixed effects. Moreover, the relation between lagged return and FX forward flow is larger for fixed income funds who typically FX-hedge more than equity funds. The coefficient of 0.75 means that lower return by 1% leads fixed income funds to sell domestic currency equivalent to 0.75% of their assets (mean assets are around 7.6 billion NOK as appear in Table 1).

In Table 3, we estimate (1) for groups of mutual funds with different hedge ratios. In the first group "All", we include all funds regardless of estimated hedge ratio, "<10%" includes the funds with a hedge ratio less than 10 percent, "10-120%" the funds with a hedge ratio between 10 and 120 percent, and "80-120%" the funds with a hedge ratio between 80 and 120 percent. We see that portfolio return is significant as a predictor of FX forward flows at 1% for all groups except the funds with a hedge ratio "<10%". The relationship is stronger for the funds with the highest hedge ratios (the "80-120%" group). This indicates that returns influence mutual fund forward flows primarily through the rebalancing channel.

Whereas the daily frequency means lower explanatory power, we can still expect the coefficient for the impact of the previous day's return on rebalancing flows to be close to one. The return from the previous day is just added to the total return for the rebalancing period and thus pass through in an one-to-one way to the rebalancing volume. This seems to almost be the case for both fixed income funds with the coefficient of around 0.6 and equity funds with the coefficient of around 0.75 in Table 2. As we lag returns by more days (for example, two or three days instead of one), it becomes less likely that the effect from that day will last all the way until the rebalancing day.

Hedge Ratio	H < 10%	Equity Fund 10-120%	s 80-120%	Fix. < 10%	ed Income H 10-120%	Funds 80-120%
	$\frac{(1)}{\frac{f_{i,t}}{a_{i,t-1}}}$	$\frac{(2)}{\frac{f_{i,t}}{a_{i,t-1}}}$	${(3)\over {f_{i,t}\over a_{i,t-1}}}$	$\frac{(4)}{\frac{f_{i,t}}{a_{i,t-1}}}$	$\frac{(5)}{\frac{f_{i,t}}{a_{i,t-1}}}$	$rac{(6)}{rac{f_{i,t}}{a_{i,t-1}}}$
$r_{i,t-1}$ inflow _{i,t} /a _{i,t-1}	$\begin{array}{c} 0.001 \\ (0.011) \\ -0.019^{***} \\ (0.007) \end{array}$	$\begin{array}{c} 0.371^{***} \\ (0.082) \\ 0.009 \\ (0.010) \end{array}$	$\begin{array}{c} 0.552^{***} \\ (0.096) \\ 0.027^{**} \\ (0.013) \end{array}$	$\begin{array}{r} -0.338\\ (0.513)\\ -0.003\\ (0.053)\end{array}$	$\begin{array}{c} 0.677^{***} \\ (0.105) \\ 0.009 \\ (0.006) \end{array}$	$\begin{array}{c} 0.896^{***} \\ (0.090) \\ 0.006 \\ (0.005) \end{array}$
Observations Adjusted R^2	$2380 \\ 0.029$	$4295 \\ 0.066$	$2760 \\ 0.105$	254 -0.003	$2324 \\ 0.056$	$1243 \\ 0.090$

Table 3: Determinants of NBFI Rebalancing Flows by Hedge Ratio

This table shows the results of estimating (2) for Norwegian mutual funds whose median hedge ratio falls within different ranges. Under "All", we include all funds, "<10%" includes the funds with a hedge ratio less than 10% (not hedged funds), "10-120%" the funds with a hedge ratio between 10% and 120%, and "80-120%" the funds with a hedge ratio between 80% and 120% (fully-hedged funds). Fund-level clustered standard errors are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Sample: March 2020 – August 2023, daily frequency, one-day lag on returns. Sources: European Market Infrastructure Regulation (EMIR), Norwegian Fund and Asset Management Association (VFF) and Bloomberg.

There are various reasons for the less than one-for-one relationship between lagged daily return and FX forward activity. One is connected to funds not targeting an exact hedge ratio, but rather have a band they operate within. This means that large changes in return may push the fund outside its limits within which the fund does rebalancing.

Not surprisingly, running specification (1) on monthly frequency increases the explanatory of the model. In the Appendix Table 11, we consider monthly forward flows and month-tomonth returns. The coefficients for both fund-specific and index returns are statistically and economically significant, also when controlling for inflows and fund fixed effects. The point estimates for the coefficients are in the 0.70-0.93 range, indicating that there is close to a oneto-one relationship between monthly forward flows and returns on assets for mutual funds that currency hedge at least 50% of their assets. The frequency and extent of rebalancing likely vary from fund to fund, but our regression results indicate that within the span of a month, the returns of mutual funds have materialized almost fully into FX forward flows. The explanatory power increases further if we consider funds with a high swaps-to-assets hedge ratio (instead of the sum of FX forwards and swaps to assets) between 50% and 120% in the Appendix Table 14. This improves adjusted R^2 , especially for fixed income mutual funds. Inflows remain significant but do not affect the estimates for the return coefficients that become even closer to 1. Table 12 and Table 15 in Appendix show the results for funds with different hedge ratio on a monthly frequency. For the most hedged funds, there is almost one-to-one pass through from returns to forward flows.

Table 4 shows the regression results from also including insurance funds in our sample, using the specification (4), on a daily frequency (Table 13 in Appendix on a monthly frequency). We find that returns are statistically and economically significant for predicting FX forward flows of insurance funds, and the strength of the effect on different frequencies mimics what we find for mutual funds.

	All	Insurance Funds	Mutua	l Funds
	$\frac{(1)}{\frac{f_{i,t}}{f_{i,t}^{outs} + s_{i,t}^{outs}}}$	$\frac{(2)}{\frac{f_{i,t}}{f_{i,t}^{outs} + s_{i,t}^{outs}}}$	$(3) \\ \frac{f_{i,t}}{f_{i,t}^{outs} + s_{i,t}^{outs}}$	$\frac{(4)}{\frac{f_{i,t}}{f_{i,t}^{outs} + s_{i,t}^{outs}}}$
r_{t-1}	$\begin{array}{c} 0.403^{***} \\ (0.066) \end{array}$	$\begin{array}{c} 0.344^{***} \\ (0.087) \end{array}$	0.461^{***} (0.098)	
$r_{i,t-1}$				0.312^{***} (0.073)
Intercept	0.002^{***} (0.000)	0.002^{***} (0.000)	0.002^{***} (0.001)	0.002^{***} (0.001)
Frequency Observations Adjusted R^2	Day 13044 0.023	Day 6596 0.021	Day 6448 0.024	Day 6448 0.027

Table 4: Determinants of NBFI Rebalancing Flows (with Insurance Funds)

This table shows the results for Norwegian mutual and insurance funds for which we lack the data on their assets. As a dependent variable, we use the fund-level net forward purchases as a share of outstanding forwards and swaps (instead of assets). Fund-level clustered standard errors are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Sample: March 2020 – August 2023, daily frequency, one-day lag on returns.

Sources: European Market Infrastructure Regulation (EMIR), Norwegian Fund and Asset Management Association (VFF) and Bloomberg.

6 FX forward flows and the exchange rate

We now turn to the effects of NBFIs' FX forward flows on the exchange rate (Hypothesis 2). The importance of our rebalancing mechanism documented in Section 5 rests on a meaningful impact on exchange rates. Using two complementary approaches, we document substantial price impact. First, exploiting our granular transaction-level data, we conduct event studies that reveal the immediate price impact of NBFI forward flows on the USDNOK exchange rate (Section 6.1). Second, we corroborate these findings using a different methodology on daily data over a longer sample period (Section 6.2). Finally, we extend our analysis to other currencies. In reduced-form regressions, we show that lagged global returns significantly affect nearly all G10 currencies against USD, suggesting that the rebalancing mechanism we document based on Norwegian data operates broadly across currency markets (Section 6.3).

6.1 High-frequency price impact based on transaction-level data

To identify the price impact of NBFI-conducted FX forward flows, we leverage our transactionlevel data alongside intraday spot exchange rates for USDNOK obtained from LSEG Data & Analytics (previously Refinitiv). We obtain the exchange rate at one-minute intervals, using the mid-close price (the average of bid and ask close prices) and align the EMIR forward transactions with these exchange rate data by using the execution timestamps from EMIR contracts, which are recorded in milliseconds. To facilitate matching, we round these timestamps down to the nearest minute and standardize the time zone convention to match the LSEG Data & Analytics exchange rate data.

For the analysis, we aggregate the notionals of all NBFI-executed EMIR forward transactions

(including mutual, insurance and pension funds) within each minute to create a total flow variable f_t for minute t, where positive flow indicates NOK forward purchases by NBFIs. We then examine the minute-to-minute exchange rate changes to assess the immediate impact of these flows.

While the EMIR data is of high quality during the sample period, our quality assurance process - comparing EMIR FX forward data with transaction-level FX swap data reported directly to Norges Bank by a subset of banks - revealed that some transactions labeled as FX forwards in EMIR represent FX swaps. To address this, we implement two filtering criteria: we exclude identified FX swap transactions and retain only transactions within the standard Norwegian spot market clip size of 50 million NOK or less. This size-based filtering reflects our finding that transactions identified as FX swaps consistently exceed typical forward transaction sizes. However, since our reference FX swap data encompasses only a subset of total NOK FX swap transactions, we cannot definitively verify whether larger remaining transactions represent forwards or swaps. Including misclassified FX swaps could distort our price impact analysis, since these should not affect spot prices. After applying these filters, our dataset retains approximately 5,500 observations (after aggregation of FX forward transactions over the minute), representing about 75% of the reported transactions.⁷

⁷Including FX swap transactions will bias our estimate towards zero. This bias is particularly pronounced as FX swaps are typically larger than FX forward transactions. Moreover, even large FX forward transactions will be spread over a longer time period when the dealer hedge the transaction through the FX spot market. Consequently, including these transactions also bias our estimate towards zero. Given that all the reported FX forward transactions we have verified as FX swaps are above 50 million NOK and the clip size in the FX spot market is 50 million NOK, we believe 50 million NOK is a natural threshold ensuring that we only include relevant transactions.

We analyze the filtered EMIR dataset using the following regression specification:

$$\Delta \log e_t = \beta f_t + \varepsilon_t. \tag{6}$$

 $\Delta \log e_t$ represents the log change in the exchange rate from minute t to minute t + 1 and f_t the forward flow in minute t.

This event-study approach offers two key advantages: it minimizes the likelihood of confounding variables affecting our estimates within such short intervals, and it largely eliminates reverse causality concerns regarding the direction of influence between exchange rates and flows. However, the accuracy of this methodology depends on dealers immediately hedging their exposure in the FX spot market. The price impact may be underestimated if dealers accumulate inventory positions, encounter offsetting forward flows, or employ alternative hedging strategies. Consequently, we interpret our event-study price impact estimates as conservative lower bounds.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	$\Delta \log e_t$									
Time after:	1 min.	$2 \min$.	3 min.	$4 \min$.	5 min.	6 min.	7 min.	$8 \min$.	9 min.	$10~\mathrm{min}.$
f_t	-0.22***	0.01	0.01	0.01	-0.04	-0.01	-0.01	-0.01	0.06	-0.05
	(0.07)	(0.07)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.06)	(0.06)
Observations	5484	5484	5484	5484	5484	5484	5484	5484	5484	5484
R^2	0.0033	0.0000	0.0000	0.0000	0.0004	0.0000	0.0001	0.0000	0.0003	0.0002

Table 5: Intraday Exchange Rate Impact

The dependent variable $\Delta \log e_t$ is the log change in the exchange rate from minute t to minute t + 1 at various lags. The independent variable f_t is the forward flow in minute t. The standard errors are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Sample: March 2020 - August 2023.

Sources: European Market Infrastructure Regulation (EMIR) and LSEG Data & Analytics.

The column (1) in Table 5 represents the result of running the regression specification (6). Our analysis reveals that for each billion NOK purchased in the forward market, NOK appreciates by 0.22% against USD. To examine the persistence of this price impact, we employ local projection regressions. Specifically, we analyze the exchange rate dynamics over successive one-minute intervals following the execution, regressing the log exchange rate changes on the initial flow. We examine windows from 1-2 minutes post-execution (column 2), 2-3 minutes (column 3), etc. through column 10 in Table 5. As an example, in column 2, the regression specification is

$$\Delta \log e_{2min} = \beta f_t + \varepsilon_{2min},\tag{7}$$

where $\Delta \log e_{2min} = \log e_{t+2min} - \log e_{t+1min}$. This approach allows us to test for price reversal - if the initial price impact was temporary, we would observe statistically significant positive coefficients in the subsequent intervals, indicating a reversion towards the pre-trade price level. Table 5 reveals that this is not the case. Figure 5 illustrates this graphically. Figure 5: Local projections for high frequency forward flows on the USDNOK exchange rate



This figure shows the impact of 1 billion NOK FX forward flow on the minute-by-minute log change in the USDNOK exchange rate.

Sample: March 2020 – August 2023.

Sources: European Market Infrastructure Regulation (EMIR) and LSEG Data & Analytics.

As a robustness, we also exclude the COVID-19 outbreak. Figure 7 in the Appendix shows the local projection regressions starting the sample in June 2020. The price impact estimate falls to -0.12 percent per billion NOK, but remains significant without any evidence of price reversal. Higher price impact estimate during the COVID-19 period reflects the market stress and low market liquidity during March 2020 in the Norwegian spot market.

6.2 Daily exchange rate movements, forward flows and lagged global return

The event study's immediate price impact estimate provides a robust identification strategy that minimizes standard econometric issues like omitted variable bias and reverse causality. However, this approach has one key limitation: it cannot capture flow effects that may take some more time to materialize, for example when the dealer feeds the forward flow through to the FX spot market over time. To investigate sustained effects of the flows, we aggregate our transaction-level data for all NBFIs to a daily measure of net FX forward flow.

Moving to daily data introduces several identification issues. To address reverse causality concerns in the daily exchange rate-flow regression, we utilize our finding that lagged returns predict NBFI FX forward flows. Our two-stage least squares (2SLS) approach uses lagged global returns (from equal-weighted MSCI world and global corporate bond indices, both FX-hedged) as instruments in the first stage of the NBFI flow regression. Table 6 demonstrates this first stage relationship, showing results for the daily net NBFI flows from the EMIR data against contemporaneous (Column 1) and one-day lagged (Column 2) global returns.⁸ The

⁸Note that when we conduct the 2SLS regressions we also include all the control variables in the first stage.

results reveal strong correlation between NBFI FX forward flows and lagged global returns. The coefficient on lagged global return indicates that 1 percent increase in return is associated with 1.8 billion NOK purchase. Lagged global return explains 18 percent of the variation in NBFI flow and the F-statistic is around 200, indicating a highly valid instrument. For comparison, the corresponding numbers for contemporaneous return are several magnitudes smaller.

Table 6: FX Forward Flow and Global Return

	(1)	(2)	(3)	(4)	(5)
	f_t	f_t	Adj. R^2	F-stat	N
r_t	356^{***} (4.16)		0.02	24.00	910
r_{t-1}	(-)	1800^{***} (12.14)	0.18	204.51	910

This table shows the results from the regressions of rebalancing flow and FX forward flow of non-bank financial institutions (NBFIs) on (lagged) global return. r_t is daily equal-weighted FX-hedged return on MSCI world index and global corporate bond index. r_{t-1} is lagged daily global return. Frequency is daily. We use Newey-West standard errors. *** p<0.01, ** p<0.05, * p<0.1.

Sample: March 2020 – August 2023.

Sources: European Market Infrastructure Regulation (EMIR) and Bloomberg.

Global lagged returns serve as a relevant instrument given their strong correlation with Norwegian NBFI flows, as evidenced in Table 6. This aligns with our micro-level findings. Additionally, bilateral exchange rates are unlikely to influence global returns, minimizing reverse causality concerns.

However, the instrument's exogeneity requires careful consideration despite our micro and aggregate evidence supporting the mechanism. Global returns may affect exchange rates through channels beyond NBFI flows, potentially correlating with global uncertainty, relative stock performance, and interest rates. We address this through a comprehensive set of control variables capturing global uncertainty and other well-known channels affecting the exchange rate. Although we cannot exclude that the lagged global return affects the exchange rate through other channels than solely through rebalancing flow, corroborated by our transaction-level data we argue that this is the most plausible channel.

Leveraging our findings from Section 5.2 and Table 6, we estimate the following regression:

$$\Delta \log e_t = \beta \hat{f}_t + controls + \varepsilon_t, \tag{8}$$

where $\Delta \log e_t$ represents the log change in spot exchange rate and \hat{f}_t denotes Norwegian NBFI rebalancing flows predicted by one-day lagged global returns.

We control for the two-year swap interest rate differential Δi_t^R (domestic minus foreign), the VIX index $\Delta \log(VIX)$, the oil price $\Delta \log(Oil)$, commodity prices $\Delta \log(Com)$ and the differential in stock returns (contemporaneous and lagged) in the respective currencies Δs_t to account for exchange rate effects from mandate-driven portfolio rebalancing (Camanho et al., 2022). We also control for the lagged spot level $\log e_{t-1}$ to account for equilibrium effects.⁹ Moreover, we include the measure of government bond liquidity (liquidity yield) proposed by Engel and Wu (2023) $\Delta \hat{\eta}_t = \Delta i_t^R - \Delta i_t$, where Δi_t is the government bond interest rate differential. This effect is therefore subsumed by our interest rate differential using two-year swap rates. We also control for the lagged level of all control variables and the lagged dependent variable $\Delta \log e_{t-1}$. We use Newey-West standard errors in (8).

Table 7 presents the results of the specification outlined in (8) for three pairs of currencies:

 $^{^{9}}$ Engel and Wu (2023) show that it is quantitatively the same to control for the lagged spot level or the lagged real FX level.

USDNOK, EURNOK and SEKNOK. In the first three columns, we use the full sample from the beginning of March 2020 until the end of August 2023. Since this period includes the height of market turbulence connected to the outburst of the COVID-19 pandemic, we exclude the three first months of our sample in columns 4 to 6. Given USD's prominence in global returns, NBFI asset allocation, and the aggregate forward flow, we anticipate stronger effects for USDNOK.

There are three main takeaways from Table 7. First, the association between predicted forward flow and the USDNOK exchange rate is strong and statistically significant, both when the pandemic period is included and without it. The point estimates suggest that 1 billion NOK inflow is associated with an appreciation of NOK against USD of about 0.4 percent (0.37 percent if the COVID-19 period is included and 0.45 percent without this period). This price association is nearly twice as large as the immediate price impact estimate from the event study.

Second, there is no significant effect of these aggregated forward flows on EURNOK and SEKNOK exchange rates. The reason is that about 70 percent of the forward flow involves USD. Third, the other control variables have a correct sign and are roughly as expected. The interest rate differential is significant, but the magnitude is modest: 100 basis point increase in the interest rate differential (higher NOK rates) is associated with about 2 percent NOK appreciation. For NOK, the oil price is a significant driver of the exchange rate. However, also for this variable the magnitude is modest, indicating that 1 percent increase in the oil price is associated with about 0.05 percent NOK appreciation. The most significant economic control variable is the contemporaneous global return (r_t) . As expected, after removing the pandemic period, this variable has the strongest impact on the USDNOK pair and has no impact on SEKNOK.

	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \log e_t$	USDNOK	EURNOK	SEKNOK	USDNOK	EURNOK	SEKNOK
\widehat{forw}_t	-0.37***	-0.09	-0.10**	-0.45***	-0.13	-0.08
	(-3.21)	(-1.34)	(-2.02)	(-2.74)	(-1.60)	(-1.56)
Δi_t^R	-0.02***	-0.01***	-0.04***	-0.02***	-0.01***	-0.04***
	(-3.57)	(-2.95)	(-5.63)	(-3.57)	(-3.20)	(-6.47)
Δi_{t-1}^R	-0.00	0.00	0.00	0.00	0.00	0.00^{*}
	(-0.25)	(0.84)	(1.53)	(0.05)	(1.16)	(1.74)
$\Delta \log s_t$	-0.03	-0.07**	-0.09***	-0.03	-0.07***	-0.11***
	(-0.88)	(-2.44)	(-3.76)	(-0.97)	(-2.68)	(-5.33)
$\Delta \log s_{t-1}$	-0.02	-0.04	-0.06***	-0.04	-0.06**	-0.08***
	(-0.52)	(-1.21)	(-2.89)	(-1.22)	(-2.53)	(-4.58)
$\Delta \log(VIX)$	0.01	0.00	-0.00	0.02^{***}	0.01^{***}	0.00**
	(1.13)	(0.30)	(-0.41)	(3.72)	(4.63)	(2.47)
$\Delta \log(Oil)$	-0.05***	-0.07***	-0.05***	-0.06***	-0.07***	-0.07***
	(-2.75)	(-4.61)	(-4.25)	(-3.95)	(-7.33)	(-8.64)
$\Delta \log(Com)$	-0.21**	-0.08	-0.03	-0.31***	-0.13***	-0.07*
	(-2.01)	(-1.36)	(-0.62)	(-3.86)	(-2.68)	(-1.69)
r_t	-0.56***	-0.51***	-0.23***	-0.43***	-0.26***	-0.04
	(-4.60)	(-4.61)	(-2.90)	(-2.96)	(-4.09)	(-0.88)
$\Delta \hat{\eta}_t$	0.00	0.01	-0.00	0.00	0.00	0.00
	(0.87)	(1.64)	(0.83)	(0.60)	(0.61)	(1.37)
$\log e_{t-1}$	-0.02**	-0.03***	-0.03**	-0.02**	-0.02***	-0.03**
	(-2.12)	(-3.22)	(-2.56)	(-2.42)	(-3.63)	(-2.52)
Sample	full	full	full	excl covid	excl covid	excl covid
F-stat	26.00	41.15	21.56	20.40	26.52	18.69
N	742	771	738	690	718	685

Table 7: The Impact of Forward Flow on the USDNOK, EURNOK and SEKNOK Rates

This table shows the results from the regressions of exchange rates on foreign exchange (FX) hedge exposures of non-bank financial institutions (NBFIs): $\Delta \log e_t = \beta forw_t + controls + \varepsilon_t$. $\Delta \log e_t$ is the log spot rate change in Norwegian krone (NOK) against the US dollar (USD), Euro (EUR) and Swedish krone (SEK) in columns (1), (2) and (3), respectively. $\widehat{forw_t}$ is the aggregated daily FX forward flow for Norwegian NBFIs from the FX flow statistics (Norges Bank) instrumented with lagged daily global return r_{t-1} . Global return is equal-weighted FX-hedged return on MSCI world index and global corporate bond index. We control for the 2-year swap interest rate differential Δi_t^R , the VIX index $\Delta \log(VIX)$, the oil price $\Delta \log(Oil)$, commodity prices $\Delta \log(Com)$, contemporaneous global return r_t and the differential in log stock returns in the respective currencies $\Delta \log s_t$ (all against USD). We also control for the lagged spot level $\log e_{t-1}$ to account for equilibrium effects. Moreover, we control for the lagged level of all control variables (not reported) and the lagged dependent variable $\Delta \log e_{t-1}$ (not reported). We use Newey-West standard errors. *t*-statistics are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Sample: March 2020 – August 2023, daily frequency.

Sources: European Market Infrastructure Regulation (EMIR) and Bloomberg.

To analyze the persitence of the effects discovered above we run simple local projection regressions for the USDNOK exchange rate. This time we focus on the cumulative effect of the flow at time t on different horizions h. Figure 6 shows the effect for h up to 9 days ahead with a 95% confidence band around. This implies that observation 1 is the replication of column (1) in Table 7, while in observation 2 the dependent variable is now $loge_{t+1} - loge_{t-1}$. Figure 6: Local projections for daily FX forward flows on the USDNOK exchange rate



This figure shows the impact of 1 billion NOK FX forward flow on the daily cumulative log change in the USDNOK exchange rate.

Sample: March 2020 – August 2023. Sources: European Market Infrastructure Regulation (EMIR) and Bloomberg.

The figure illustrates that the point estimates actually become stronger over time before the exchange rate settles, but so do the standard errors. Taken together, there is no evidence of price reversal.

Despite our caution related to the exogeneity assumption, we believe that the event-study results together with 2SLS results provide valuable evidence that the flows stemming from the rebalancing mechanism have material impact on the exchange rate.

6.3 External validity: lagged global return and G10

The rebalancing mechanism we document for USDNOK raises the question: How general is this effect across currencies? While we lack detailed flow data for other markets, we can examine the broader relevance of this mechanism through reduced-form regressions using lagged global returns as the key explanatory variable.

Table 8 presents results for nine G10 currency pairs against USD, using the same specification as Section 6.2 but replacing predicted flows with lagged global returns. The sample period matches that of Table 7 to facilitate comparison. We find systematic and economically meaningful effects across advanced economy currencies. The coefficients on lagged global returns range from -0.16 to -0.33, indicating that a 1 percent increase in global returns is associated with a 0.16 to 0.33 percent appreciation of non-USD currencies the following day.

For USDNOK, comparing the reduced-form and 2SLS estimates provides additional insight into the mechanism. From the first stage of our 2SLS estimation, a 1 percent increase in global returns triggers 1.8 billion NOK of NBFI purchases (Table 6). Combined with our second-stage price impact estimate, this implies a 0.67 percent NOK appreciation (1.8 * 0.37) – about twice the magnitude of the reduced-form effect. While this comparison should be interpreted cautiously given potential offsetting flows not captured in our 2SLS framework, the pattern is consistent with global returns affecting exchange rates primarily through the rebalancing channel (i.e., support for the exclusion restriction).

The contemporaneous return coefficient is significantly negative for most currency pairs, except USDCHF and USDJPY. This aligns with its interpretation as a proxy for global uncertainty as both CHF and JPY has been regarded as currencies investors resort to during financial turmoil. Indeed, removing this variable leaves our main results unchanged but increases the magnitude and significance of the VIX coefficient across currency pairs.

Table 8: The Impact of Lagged Daily Return on Exchange Rates

-													
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
$\Delta \log e_t$	r_{t-1}	Δi_t^R	Δi_{t-1}^R	$\Delta \log s_t$	$\Delta \log s_{t-1}$	$\Delta \log(VIX)$	$\Delta \log(Oil)$	$\Delta \log(Com)$	$\Delta \hat{\eta}_t$	$\log e_{t-1}$	r_t	$AdjR^2$	N
USDAUD	-0.26***	-0.03***	-0.00	0.04	0.00	0.00^{**}	-0.01	-0.37***	0.00	-0.01***	-0.48^{***}	0.46	732
	(-3.63)	(-7.62)	(-1.06)	(1.65)	(0.48)	(2.08)	(-1.15)	(-6.11)	(0.23)	(-2.87)	(-7.43)		
USDCAD	-0.16^{***}	-0.02***	-0.00**	-0.00	-0.07***	0.01^{***}	-0.02***	-0.18^{***}	-0.01^{*}	-0.01**	-0.28^{***}	0.49	733
	(-3.02)	(-6.16)	(-2.37)	(-0.21)	(-2.70)	(4.29)	(-4.51)	(-4.61)	(-1.87)	(-2.27)	(-6.95)		
USDCHF	-0.27***	-0.05***	-0.00	0.10^{***}	-0.00	-0.00	0.01^{*}	-0.04	0.01	-0.02***	-0.03	0.28	412
	(-7.84)	(-4.15)	(-0.39)	(4.71)	(-0.13)	(-1.19)	(1.77)	(-0.99)	(1.34)	(-2.77)	(-0.74)		
USDEUR	-0.22***	-0.02***	-0.01**	0.02	-0.00	0.00	0.01^{**}	-0.19^{***}	0.00	-0.01**	-0.19***	0.25	766
	(-5.92)	(-5.87)	(-2.36)	(0.74)	(-0.45)	(1.22)	(2.01)	(-4.24)	(1.11)	(-2.18)	(-3.59)		
USDGBP	-0.30***	-0.06***	-0.01	0.03	-0.03	-0.00	-0.00	-0.16***	-0.01	-0.04***	-0.27***	0.32	414
	(-5.19)	(-3.44)	(-0.75)	(0.83)	(-1.34)	(-0.09)	(-1.00)	(-2.72)	(-0.89)	(-3.21)	(-2.87)		
USDJPY	-0.21***	-0.08***	0.00	0.03	-0.00	-0.00	0.03^{**}	-0.01	-0.02	-0.02*	0.03	0.42	368
	(-4.96)	(-5.74)	(0.78)	(1.40)	(-0.35)	(-0.43)	(2.60)	(-0.24)	(-0.83)	(-1.79)	(0.54)		
USDNOK	-0.33***	-0.02***	-0.00	-0.03	-0.06*	0.00	-0.06***	-0.27***	0.00	-0.01**	-0.73***	0.47	742
	(-4.67)	(-5.18)	(-1.41)	(-1.11)	(-1.87)	(0.65)	(-3.03)	(-3.26)	(0.71)	(-2.31)	(-7.67)		
USDNZD	-0.22***	-0.03***	-0.00	-0.02	-0.03	0.01^{***}	-0.00	-0.30***	-0.00	-0.01***	-0.48***	0.42	765
	(-4.41)	(-9.18)	(-1.55)	(-1.43)	(-1.50)	(3.60)	(-0.81)	(-4.62)	(-0.39)	(-2.78)	(-7.83)		
USDSEK	-0.22***	-0.02***	-0.01***	-0.07***	-0.02	0.01**	0.00	-0.25***	-0.00	-0.01**	-0.50***	0.34	722
	(-4.30)	(-4.79)	(-3.22)	(-2.78)	(-1.14)	(2.24)	(0.62)	(-3.95)	(-0.67)	(-1.59)	(-7.52)		

This table shows the results from the regressions of exchange rates on global lagged return: $\Delta \log e_t = \beta r_{t-1} + controls + \varepsilon_t$. $\Delta \log e_t$ is the log spot rate change across G10 currencies against USD. r_{t-1} is global lagged return on daily frequency. Global return is equal-weighted FX-hedged return on MSCI world index and global corporate bond index. We control for the 2-year swap interest rate differential Δi_t^R , the VIX index $\Delta \log(VIX)$, the oil price $\Delta \log(Oil)$, commodity prices $\Delta \log(Com)$, contemporaneous global return r_t and the differential in log stock returns in the respective currencies $\Delta \log s_t$ (all against USD). We also control for the lagged spot level $\log e_{t-1}$ to account for equilibrium effects. Moreover, we control for the lagged level of all control variables (not reported) and the lagged dependent variable $\Delta \log e_{t-1}$ (not reported). We use Newey-West standard errors. t-statistics are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Sample: March 2020 – August 2023, daily frequency.

To ensure our results are not driven by the extreme market conditions during the initial COVID-19 period, we re-estimate our specifications excluding March-May 2020. Table 9 presents results for the June 2020 to August 2023 sample. The relationship between lagged global returns and exchange rates remains robust. Apart from USDCAD, which loses statistical significance, the effects persist across G10 currencies. While the magnitude of some coefficients declines, they remain both economically and statistically significant, suggesting

that our findings reflect a broader mechanism rather than being driven by the pandemic market turmoil.

Table 9: The Impact of Lagged Daily Return on Exchange Rates (without COVID-19)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
$\Delta \log e_t$	r_{t-1}	Δi_t^R	Δi_{t-1}^R	$\Delta \log s_t$	$\Delta \log s_{t-1}$	$\Delta \log(VIX)$	$\Delta \log(Oil)$	$\Delta \log(Com)$	$\Delta \hat{\eta}_t$	$\log e_{t-1}$	r_t	$AdjR^2$	N
USDAUD	-0.16^{**}	-0.03***	-0.01	0.02	0.02	0.01^{*}	-0.04***	-0.38***	0.01	-0.02***	-0.57^{***}	0.47	674
	(-2.27)	(-7.55)	(-1.32)	(0.70)	(0.84)	(1.90)	(-3.66)	(-6.30)	(1.25)	(-2.91)	(-6.53)		
USDCAD	-0.03	-0.02***	-0.01^{**}	-0.04	-0.02	0.01^{***}	-0.04***	-0.18***	-0.00	-0.02***	-0.39***	0.52	677
	(-0.67)	(-6.30)	(-2.39)	(-1.07)	(-0.63)	(3.40)	(-5.23)	(-4.97)	(-0.61)	(-3.11)	(-7.77)		
USDCHF	-0.32***	-0.07***	-0.01	0.08^{***}	-0.06**	0.00	0.01	-0.12**	0.01	-0.04***	-0.00	0.20	359
	(-6.16)	(-5.26)	(-0.46)	(3.16)	(-2.51)	(0.05)	(0.67)	(-2.53)	(1.04)	(-2.78)	(-0.04)		
USDEUR	-0.16^{***}	-0.02***	-0.01^{**}	-0.00	-0.03	0.00	0.01	-0.20***	0.01^{**}	-0.02***	-0.32^{***}	0.28	708
	(-3.82)	(-5.98)	(-2.44)	(-0.11)	(-1.51)	(0.61)	(0.85)	(-4.48)	(2.05)	(-3.31)	(-4.47)		
USDGBP	-0.18^{***}	-0.03**	-0.01	0.09^{***}	0.01	0.01	-0.04***	-0.20***	-0.01	-0.05***	-0.11	0.25	359
	(-2.62)	(-2.16)	(-0.87)	(3.23)	(0.42)	(1.27)	(-2.98)	(-3.52)	(-0.86)	(-2.86)	(-1.43)		
USDJPY	-0.13***	-0.08***	0.01	0.03	-0.00	0.00	0.04^{***}	-0.04	0.02	-0.03*	0.04	0.15	320
	(-2.84)	(-5.17)	(0.56)	(1.29)	(-0.04)	(0.44)	(3.14)	(-0.77)	(1.40)	(-1.91)	(0.48)		
USDNOK	-0.34***	-0.02***	-0.01	-0.05*	-0.09***	0.02^{***}	-0.07***	-0.32***	0.01	-0.02**	-0.65^{***}	0.47	690
	(-4.46)	(-5.72)	(-1.39)	(-1.87)	(-3.67)	(3.57)	(-4.94)	(-4.67)	(1.20)	(-2.41)	(-7.45)		
USDNZD	-0.17***	-0.03***	-0.01	-0.05**	-0.05**	0.01^{***}	-0.02***	-0.34***	0.00	-0.01***	-0.58***	0.43	706
	(-2.59)	(-9.18)	(-1.55)	(-2.46)	(-2.51)	(3.07)	(-2.68)	(-5.82)	(0.85)	(-3.13)	(-7.40)		
USDSEK	-0.22***	-0.02***	-0.02***	-0.09***	-0.06**	0.01^{*}	0.01	-0.28***	-0.00	-0.01*	-0.63***	0.35	669
	(-3.67)	(-4.59)	(-3.18)	(-2.95)	(-2.37)	(1.87)	(0.38)	(-4.24)	(-0.51)	(-1.86)	(-7.28)		

This table shows the results from the regressions of exchange rates on global lagged return:

$$\Delta \log e_t = \beta r_{t-1} + controls + \varepsilon_t.$$

 $\Delta \log e_t$ is the log spot rate change across G10 currencies against USD. r_{t-1} is global lagged return on daily frequency. Global return is equal-weighted FX-hedged return on MSCI world index and global corporate bond index. We control for the 2-year swap interest rate differential Δi_t^R , the VIX index $\Delta \log(VIX)$, the oil price $\Delta \log(Oil)$, commodity prices $\Delta \log(Com)$, contemporaneous global return r_t and the differential in log stock returns in the respective currencies $\Delta \log s_t$ (all against USD). We also control for the lagged spot level $\log e_{t-1}$ to account for equilibrium effects. Moreover, we control for the liquidity yield proposed by Engel and Wu (2023) $\Delta \hat{\eta}_t$. Δ is a difference operator. We also control for the lagged level of all control variables (not reported) and the lagged dependent variable $\Delta \log e_{t-1}$ (not reported). We use Newey-West standard errors. *t*-statistics are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Sample: June 2020 – August 2023, daily frequency. Sources: Bloomberg.

Finally, the reduced form specification has the advantage that we can expand the sample substantially. When extending our sample back to 2002, we find that the relationship between lagged global returns and exchange rates only becomes consistently significant from 2020 onwards (see Table 10). This timing coincides with several structural changes in financial markets that have likely amplified the rebalancing mechanism. First, non-bank financial institutions have grown substantially in size and sophistication. The volume of currencyhedged foreign investments has increased markedly, particularly in fixed income markets. This growth means that currency hedge rebalancing needs now translate into larger currency flows than in previous periods.

Second, market-making capacity has evolved significantly. Following the market stress during COVID-19, banks face tighter Value-at-Risk based capital constraints, limiting their ability to warehouse risk. This reduced intermediation capacity means rebalancing flows may have more immediate price impact than in earlier periods when dealers could more easily absorb and distribute these flows over time.

Third, institutional investment practices have changed. Prior to 2020, many funds primarily rebalanced at quarter-end. The extreme market volatility during COVID-19 appears to have prompted a shift toward more frequent rebalancing. This change means portfolio return shocks now translate more quickly into currency market flows, strengthening the link between global returns and next-day exchange rate movements. The unprecedented market conditions of 2022, when both equity and fixed income markets experienced significant declines, provide particularly strong evidence of this mechanism. During such periods, the rebalancing needs of institutional investors become concentrated in the same direction, potentially amplifying their price impact in currency markets.

Table 10: The Impact of Lagged Daily Return on Exchange Rates (before March 2020)

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
r_{t-1}	Δi_t^R	Δi_{t-1}^R	$\Delta \log s_t$	$\Delta \log s_{t-1}$	$\Delta \log(VIX)$	$\Delta \log(Oil)$	$\Delta \log(Com)$	$\Delta \hat{\eta}_t$	$\log e_{t-1}$	r_t	$AdjR^2$	N
0.02	-0.03***	-0.01***	0.01	-0.01	-0.00	-0.06***	-0.27***	-0.01^{***}	-0.01***	-0.73***	0.40	3840
(0.49)	(-13.35)	(-4.21)	(0.33)	(-0.61)	(-0.16)	(-9.87)	(-7.42)	(-3.48)	(-2.75)	(-7.23)		
0.05	-0.03***	-0.01***	0.05^{***}	0.00	0.00	-0.07***	-0.16***	0.00	-0.00**	-0.42***	0.35	3772
(1.50)	(-10.35)	(-2.74)	(2.66)	(0.07)	(1.08)	(-13.94)	(-7.21)	(0.73)	(-2.25)	(-8.12)		
-0.05	-0.04***	-0.01***	0.17^{***}	0.07^{***}	-0.01***	-0.03***	-0.21***	0.01^{*}	-0.00**	0.10**	0.16	3951
(-1.51)	(-10.98)	(-3.04)	(3.94)	(3.80)	(-2.76)	(-4.68)	(-7.38)	(1.81)	(-2.20)	(2.54)		
-0.03	-0.04***	-0.01***	0.14^{***}	0.06***	-0.00*	-0.04***	-0.21***	0.00	-0.00**	-0.12***	0.19	4133
(-1.20)	(-13.44)	(-2.75)	(9.42)	(4.38)	(-1.88)	(-6.15)	(-8.40)	(1.23)	(-2.28)	(-2.78)		
-0.02	-0.04***	-0.01***	0.11^{***}	0.03**	-0.00	-0.04***	-0.18***	0.00^{*}	-0.00***	-0.15***	0.19	4028
(-1.09)	(-14.17)	(-2.91)	(8.31)	(2.31)	(-0.90)	(-7.84)	(-8.30)	(1.67)	(-3.96)	(-3.31)		
-0.20***	-0.05***	-0.01***	0.08^{***}	0.03^{***}	-0.01***	-0.00	-0.06**	-0.00	-0.00	0.39^{***}	0.27	3578
(-5.57)	(-14.83)	(-3.01)	(7.61)	(4.70)	(-3.13)	(-0.09)	(-2.47)	(-0.49)	(-1.52)	(5.94)		
0.04	-0.03***	-0.01***	0.01	0.01	0.00	-0.09***	-0.24***	-0.00	-0.00*	-0.31^{***}	0.24	3869
(0.86)	(-9.17)	(-3.87)	(0.70)	(1.13)	(1.23)	(-12.82)	(-7.99)	(-0.86)	(-1.87)	(-5.52)		
0.06	-0.04***	-0.01***	0.08^{***}	-0.02	-0.00	-0.04***	-0.21***	-0.01***	-0.01***	-0.62***	0.34	3877
(1.38)	(-14.90)	(-4.03)	(4.32)	(-1.31)	(-0.85)	(-5.75)	(-6.33)	(-3.15)	(-4.67)	(-9.17)		
0.05	-0.03***	-0.01***	0.06***	0.01	-0.00	-0.06***	-0.23***	-0.00	-0.00***	-0.42***	0.20	3850
(1.05)	(-9.13)	(-3.50)	(4.61)	(0.95)	(-1.01)	(-8.12)	(-7.23)	(-0.71)	(-2.64)	(-6.33)		
	$\begin{array}{c} (1) \\ r_{t-1} \\ 0.02 \\ (0.49) \\ 0.05 \\ (1.50) \\ -0.05 \\ (-1.51) \\ -0.03 \\ (-1.20) \\ -0.02 \\ (-1.09) \\ -0.02 \\ (-5.57) \\ 0.04 \\ (0.86) \\ 0.06 \\ (1.38) \\ 0.05 \\ (1.05) \end{array}$	$\begin{array}{c cccc} (1) & (2) \\ \hline r_{t-1} & \Delta i_t^R \\ \hline 0.02 & -0.03^{***} \\ (0.49) & (-13.35) \\ 0.05 & -0.03^{***} \\ (1.50) & (-10.35) \\ -0.05 & -0.04^{***} \\ (-1.51) & (-10.98) \\ -0.03 & -0.04^{***} \\ (-1.20) & (-13.44) \\ -0.02 & -0.04^{***} \\ (-1.09) & (-14.17) \\ -0.20^{***} & -0.05^{***} \\ (-5.57) & (-14.83) \\ 0.04 & -0.03^{***} \\ (0.86) & (-9.17) \\ 0.06 & -0.04^{***} \\ (1.38) & (-14.90) \\ 0.05 & -0.03^{***} \\ (1.05) & (-9.13) \end{array}$	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$

This table shows the results from the regressions of exchange rates on global lagged return:

 $\Delta \log e_t = \beta r_{t-1} + controls + \varepsilon_t.$

 $\Delta \log e_t$ is the log spot rate change across G10 currencies against USD. r_{t-1} is global lagged return on daily frequency. Global return is equal-weighted FX-hedged return on MSCI world index and global corporate bond index. We control for the 2-year swap interest rate differential Δi_t^R , the VIX index $\Delta \log(VIX)$, the oil price $\Delta \log(Oil)$, commodity prices $\Delta \log(Com)$, contemporaneous global return r_t and the differential in log stock returns in the respective currencies $\Delta \log s_t$ (all against USD). We also control for the lagged spot level $\log e_{t-1}$ to account for equilibrium effects. Moreover, we control for the lagged level of all control variables (not reported) and the lagged dependent variable $\Delta \log e_{t-1}$ (not reported). We use Newey-West standard errors. *t*-statistics are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Sample: January 2002 – February 2020, daily frequency. Sources: Bloomberg.

7 Conclusion

We study the connection between FX-hedged investments abroad, the return on these foreign investments and exchange rates. Building on the microstructure framework by Evans and Lyons (2002), we identify a rebalancing mechanism through which the return on NBFIs' FX-hedged portfolios affects their demand for foreign currency and, in turn, FX market pricing. Sudden changes in the mark-to-market value of the investments abroad leads NBFIs to rebalance their hedge ratio to ensure alignment with the preferred hedge ratio. That is, when the mark-to-market value of NBFI portfolio increases, the original hedge is too low and vice versa. To manage the hedge ratio, NBFIs must buy or sell domestic currency. When the hedge ratio on the foreign portfolio becomes too low, NBFIs have to buy local currency (spot or forward). In the opposite case, when the hedge ratio becomes too high, NBFIs have to sell local currency (spot or forward).

We find that lower portfolio return leads NBFIs to sell domestic currency (as a result of the adjustment of the hedge ratio) that results in the depreciation of most G10 currencies against USD.

Our results shed light on why USD appreciates in times of global uncertainty and poor financial market performance. Due the role of USD as major investment and funding currency, domestic investors in most countries have more FX-hedged savings in USD than foreign.

We believe our approach provides valuable insights into the relationship between NBFI flows and exchange rates, grounded in both theoretical mechanisms and empirical evidence. Our findings also give more scope for FX interventions given that the mechanism is mechanical. They support the policy reaction to sharp declines in foreign investment values and mitigate volatility in the FX market.

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Appendix

Figures

Figure 7: Local projections for high frequency forward flows on the USDNOK exchange rate (without COVID-19)



This figure shows the impact of 1 billion NOK FX forward flow on the minute-by-minute log change in the USDNOK exchange rate.

Sample: June 2020 – August 2023.

Sources: European Market Infrastructure Regulation (EMIR) and LSEG Data & Analytics.



Figure 8: NBFI FX Forward Flows

This figure shows Norwegian FX-hedged (hedge ratio > 50%) mutual funds' net FX forward flows as a share of their assets overlayed with the volume-weighted fund-level return on a monthly basis.

Sample: March 2020 – August 2023.

Sources: European Market Infrastructure Regulation (EMIR), Bloomberg.

Tables (EMIR, Monthly Frequency)

In Tables 11-13, we show the results for similar tests as in Tables 2-4, but on a monthly frequency.

		Equity	v Funds			Fixed Inc	ome Funds	
	$\frac{(1)}{\frac{f_{i,t}}{a_{i,t-1}}}$	$\frac{(2)}{\frac{f_{i,t}}{a_{i,t-1}}}$	$\frac{(3)}{\frac{f_{i,t}}{a_{i,t-1}}}$	$\frac{(4)}{\frac{f_{i,t}}{a_{i,t-1}}}$	$\frac{(5)}{\frac{f_{i,t}}{a_{i,t-1}}}$	$\frac{(6)}{\frac{f_{i,t}}{a_{i,t-1}}}$	$\frac{(7)}{\frac{f_{i,t}}{a_{i,t-1}}}$	$\frac{(8)}{\frac{f_{i,t}}{a_{i,t-1}}}$
r_t^{Eq}	0.832*** (0.108)				, i		,	
r_t^{FI}	~ /				0.814^{***} (0.125)			
$r_{i,t}$		0.908^{***} (0.100)	0.930^{***} (0.098)	0.930^{***} (0.054)	. ,	0.706^{***} (0.129)	0.698^{***} (0.132)	0.705^{***} (0.046)
$inflow_{i,t}/a_{i,t-1}$			0.280^{***} (0.078)	$\begin{array}{c} 0.261^{***} \\ (0.035) \end{array}$			0.049^{**} (0.023)	0.047^{***} (0.014)
Fund FE	No	No	No	Yes	No	No	No	Yes
Frequency	Month	Month	Month	Month	Month	Month	Month	Month
Observations	526	526	526	526	702	702	702	702
Adjusted R^2	0.266	0.300	0.372	0.438	0.094	0.241	0.253	0.279

Table 11: Determinants of NBFI Rebalancing Flows (Monthly)

This table reports the results for Norwegian mutual funds with a median hedge ratio above 50% and cap returns and inflow at 30%. We exclude observations where a fund has in purchases more than 10% of AUM in a single day. Fund-level clustered standard errors are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Sample: March 2020 – August 2023, monthly frequency.

Sources: Norwegian Fund and Asset Management Association (VFF), European Market Infrastructure Regulation (EMIR) and Bloomberg.

Table 12: Determinants of NBFI Rebalancing Flows by Hedge Ratio (Monthly)

Hedge Batio	H	Equity Fund 10-120%	s 80-120%	Fix < 10%	ed Income I 10-120%	Funds 80-120%
fieldge flattio	(1) $\frac{f_{i,t}}{a_{i,t-1}}$	(2) $\frac{f_{i,t}}{a_{i,t-1}}$	(3) $\frac{f_{i,t}}{a_{i,t-1}}$	$(4) \\ \frac{f_{i,t}}{a_{i,t-1}}$	(5) $\frac{f_{i,t}}{a_{i,t-1}}$	(6) $\frac{(6)}{\frac{f_{i,t}}{a_{i,t-1}}}$
$r_{i,t}$ $inflow_{i,t}/a_{i,t-1}$	-0.052 (0.032) -0.118^{***} (0.036)	$\begin{array}{c} 0.930^{***} \\ (0.098) \\ 0.280^{***} \\ (0.078) \end{array}$	$\begin{array}{c} 0.939^{***} \\ (0.107) \\ 0.281^{***} \\ (0.081) \end{array}$	-0.045 (0.123) -0.012 (0.045)	$\begin{array}{c} 0.523^{***} \\ (0.123) \\ 0.048^{**} \\ (0.021) \end{array}$	$\begin{array}{c} 0.916^{***} \\ (0.077) \\ 0.053 \\ (0.034) \end{array}$
Frequency Observations Adjusted R^2	Month 768 0.157	Month 526 0.372	Month 487 0.365	Month 86 -0.021	Month 814 0.180	Month 408 0.359

This table shows the results of estimating (2) for Norwegian mutual funds whose median hedge ratio falls within different ranges. Under "All", we include all funds, "<10%" includes the funds with a hedge ratio less than 10% (not hedged funds), "10-120%" the funds with a hedge ratio between 10% and 120%, and "80-120%" the funds with a hedge ratio between 80% and 120% (fully-hedged funds). Fund-level clustered standard errors are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Sample: March 2020 – August 2023, monthly frequency.

Sources: European Market Infrastructure Regulation (EMIR), Norwegian Fund and Asset Management Association (VFF) and Bloomberg.

	All	Insurance Funds	Mutual Funds		
	$\frac{(1)}{\frac{f_{i,t}}{f_{i,t}^{outs} + s_{i,t}^{outs}}}$	$\frac{(2)}{\frac{f_{i,t}}{f_{i,t}^{outs} + s_{i,t}^{outs}}}$	$\frac{(3)}{\frac{f_{i,t}}{f_{i,t}^{outs} + s_{i,t}^{outs}}}$	$\frac{(4)}{\frac{f_{i,t}}{f_{i,t}^{outs} + s_{i,t}^{outs}}}$	
r_t	0.712^{***} (0.073)	0.649^{***} (0.089)	0.761^{***} (0.109)		
$r_{i,t}$				0.884^{***} (0.077)	
Intercept	0.009^{***} (0.002)	0.009^{***} (0.003)	0.009^{***} (0.003)	0.008^{***} (0.003)	
Frequency Observations Adjusted R^2	Month 2294 0.141	Month 981 0.126	Month 1313 0.152	Month 1313 0.291	

Table 13: Determinants of NBFI Rebalancing Flows (with Insurance Funds, Monthly)

This table shows the results for Norwegian mutual and insurance funds for which we lack the data on their assets. As a dependent variable, we use the fund-level net forward purchases as a share of outstanding forwards and swaps (instead of assets). Fund-level clustered standard errors are reported in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.1.

Sample: March 2020 – August 2023, monthly frequency.

Sources: European Market Infrastructure Regulation (EMIR), Norwegian Fund and Asset Management Association (VFF) and Bloomberg.

Tables (Swap Hedge Ratio)

In Tables 14-15, we show the results for the same tests as in Tables 11-12, but defining the hedge ratio as a swaps-to-assets hedge ratio (instead of forwards and swaps to assets).

Table 14: Determinants of NBFI Rebalancing Flows (Monthly, Swap Hedge Ratio)

	Equity Funds				Fixed Income Funds			
	$\frac{(1)}{\frac{f_{i,t}}{a_{i,t-1}}}$	$\frac{(2)}{\frac{f_{i,t}}{a_{i,t-1}}}$	(3) $\frac{f_{i,t}}{a_{i,t-1}}$	(4) $\frac{f_{i,t}}{a_{i,t-1}}$	$\frac{(5)}{\frac{f_{i,t}}{a_{i,t-1}}}$	$\frac{(6)}{\frac{f_{i,t}}{a_{i,t-1}}}$	$\frac{(7)}{\frac{f_{i,t}}{a_{i,t-1}}}$	$\frac{(8)}{\frac{f_{i,t}}{a_{i,t-1}}}$
r_t^{Eq}	0.904^{***} (0.127)							
r_t^{FI}	· · ·				0.906^{***} (0.175)			
$r_{i,t}$		0.935^{***} (0.114)	0.960^{***} (0.112)	0.962^{***} (0.061)		0.645^{***} (0.141)	0.644^{***} (0.141)	0.655^{***} (0.033)
$inflow_{i,t}/a_{i,t-1}$. ,	0.307^{***} (0.083)	0.278^{***} (0.038)		. ,	0.003 (0.006)	0.006 (0.012)
Fund FE	No	No	No	Yes	No	No	No	Yes
Frequency	Month	Month	Month	Month	Month	Month	Month	Month
Observations	407	407	407	407	407	407	407	407
Adjusted R^2	0.283	0.315	0.405	0.458	0.216	0.478	0.477	0.489

This table reports the results for Norwegian mutual funds with a swaps-to-assets hedge ratio (instead of forwards and swaps to assets) between 50% and 120%. Fund-level clustered standard errors are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Sample: March 2020 – August 2023, monthly frequency.

Sources: Norwegian Fund and Asset Management Association (VFF), European Market Infrastructure Regulation (EMIR) and Bloomberg.

	Equity Funds				Fixed Income Funds			
Hedge Ratio	All	<10%	10-120%	80-120%	All	< 10%	10-120%	80-120%
	$\frac{(1)}{\frac{f_{i,t}}{a_{i,t-1}}}$	$\frac{(2)}{\frac{f_{i,t}}{a_{i,t-1}}}$	$\frac{(3)}{\frac{f_{i,t}}{a_{i,t-1}}}$	$\frac{(4)}{\frac{f_{i,t}}{a_{i,t-1}}}$	$\frac{(5)}{\frac{f_{i,t}}{a_{i,t-1}}}$	$\frac{(6)}{\frac{f_{i,t}}{a_{i,t-1}}}$	$\frac{(7)}{\frac{f_{i,t}}{a_{i,t-1}}}$	$\frac{(8)}{\frac{f_{i,t}}{a_{i,t-1}}}$
$r_{i,t}$	0.382^{***}	0.004	0.955^{***}	1.037^{***}	0.547^{***}	0.752^{**}	0.482^{***}	0.908***
$inflow_{i,t}/a_{i,t-1}$	(0.097) -0.002 (0.043)	$\begin{array}{c} (0.057) \\ -0.115^{***} \\ (0.036) \end{array}$	$\begin{array}{c} (0.105) \\ 0.275^{***} \\ (0.079) \end{array}$	$\begin{array}{c} (0.153) \\ 0.269^{***} \\ (0.094) \end{array}$	(0.115) 0.048^{**} (0.020)	$\begin{array}{c} (0.306) \\ 0.111^{**} \\ (0.048) \end{array}$	$\begin{array}{c} (0.121) \\ 0.015^* \\ (0.009) \end{array}$	$\begin{array}{c} (0.061) \\ 0.008 \\ (0.007) \end{array}$
Frequency Observations Adjusted R^2	Month 1336 0.080	Month 845 0.094	Month 449 0.379	Month 287 0.447	Month 991 0.172	Month 349 0.140	Month 583 0.239	Month 302 0.572

Table 15: Determinants of NBFI Rebalancing Flows by Swap Hedge Ratio (Monthly)

This table shows the results of estimating (2) for Norwegian mutual funds whose median swaps-to-assets (instead of forwards and swaps to assets) ratio falls within different ranges. Under "All", we include all funds, "<10%" includes the funds with a swaps-to-assets ratio less than 10% (not hedged funds), "10-120%" the funds with a swaps-to-assets ratio between 10% and 120%, and "80-120%" the funds with a swaps-to-assets ratio between 80% and 120% (fully-hedged funds). Fund-level clustered standard errors are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Sample: March 2020 – August 2023, monthly frequency.

Sources: European Market Infrastructure Regulation (EMIR), Norwegian Fund and Asset Management Association (VFF) and Bloomberg.