

Firms' Foreign Exchange Hedging^{*}

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Abstract

This paper combines evidence from 1.5 million foreign exchange derivatives contracts with a dynamic corporate finance model to propose a new view of currency hedging by Eurozone firms. We find that (i) a few firms bear most cash-flow currency risk and hedge 30–80% of it with derivatives, (ii) hedging is inexpensive because firms rarely post cash collateral and trading costs are small, and (iii) firms with large cash balances do not hedge less, even after controlling for risk. These facts are inconsistent with standard models in which firms hedge to manage cash needs but are constrained by collateralization. Guided by this evidence, we build and estimate a dynamic corporate finance model. Our estimation implies that earnings smoothing explains most of hedging demand, while hedge adjustment costs limit hedging.

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1 Introduction

Currency risk is a major concern for global nonfinancial firms. To insure this risk, they trade an average of \$283 billion per day in foreign exchange (FX) derivatives ([BIS, 2022](#)). Despite this staggering activity, there is accumulating evidence that exchange rates impact cash-flows and stock prices, even after hedging.¹ Why do firms trade so much on derivatives markets, yet do not hedge all of their risk?

The standard answer is that firms trade derivatives to finance their operations during unfavorable exchange rate episodes, when profits are low ([Froot et al., 1993](#)). In that view, hedging demand is limited by collateral requirements ([Rampini and Viswanathan, 2010](#); [Bolton et al., 2011](#)). However, due to the lack of data on derivatives holdings and collateral posting, there is no empirical consensus on whether collateralization constrains hedging, or even on how much risk firms actually hedge.

This paper proposes new answers based on a novel dataset built from contract-level regulatory filings by Eurozone firms. We document three sets of facts. First, currency risk is large and concentrated in a few firms. Firms hedge 30–80% of that risk with derivatives, confirming that most but not all risk is hedged. Second, collateralization and trading costs do not limit hedging. Fewer than one in five contracts are collateralized and trading costs are small. Third, financing plays a limited role in explaining hedging, as even cash-rich firms trade a lot on derivatives markets, despite being arguably unconstrained. These facts are inconsistent with standard models emphasizing a trade-off between managing liquidity and posting collateral.

To understand what financial frictions explain currency hedging, we build a dynamic model of risk management. We add two frictions to the standard framework: (i) firms hedge to smooth earnings, even when they have cash, and (ii) hedging is limited by adjustment frictions, even when other hedging costs are small. To identify these frictions, we use the fact that firms facing more FX risk hedge a larger fraction of that risk. Our estimation implies that firms' willingness-to-pay for derivatives is large at 1.6% of firm value. Earnings smoothing explains most of hedging value (1.2%) while liquidity management contributes less (0.4%). Furthermore, internal adjustment costs, such as sticky hedging ratios or hedge accounting frictions, explain why firms do not hedge fully.

¹The finding that exchange rates predict economically significant variation in cash-flows and stock prices holds across countries and time, as documented by [Barbiero \(2021\)](#); [Efing et al. \(2022\)](#); [Adams and Verdelhan \(2023\)](#); [Welch and Zhou \(2024\)](#).

Our work uses a novel contract-level dataset covering the portfolios of Eurozone public firms from 2017 to 2023. We exploit detailed reports collected under the European Market Infrastructure Regulation (EMIR). These reports allow us to observe granular information on derivatives contracts across European countries and industries.

The European Union (EU) offers an ideal empirical setting. It is the world's largest exporter, with over €2.8 trillion in exports in 2024. Despite the importance of the euro, the common currency is used in only 40% of imports and 52% of exports.² This generates considerable FX risk, which European firms hedge on financial markets. At the same time, the EU has well-developed financial markets, with ample hedging supply to meet demand.

We first quantify how much firms use derivatives relative to the risk they face, which requires measuring FX risk before and after hedging. This is difficult because firms usually report cash-flows after hedging, which creates an observability problem: if a firm's cash-flows are uncorrelated with exchange rates, then either it hedges or it faces no FX risk (Bartram et al., 2010). To solve this challenge, we first estimate FX risk after hedging using a multi-currency factor model. We then directly measure the cash-flow impact of hedging using contract-level information on derivatives portfolios. This allows us to back out FX risk before hedging. We find that FX risk is large and concentrated in a few firms. For the most exposed firms, exchange rates account for 7–31% of cash-flow variance. Firms hedge 30–80% of this risk with derivatives. Furthermore, we find that long-term hedging predicts more currency risk in the cross-section.

To understand why firms do not hedge all of their risk, we assess the importance of collateral requirements and trading costs in limiting hedging. Fewer than one in five contracts are collateralized. Moreover, trading costs are small when measured as markups over interdealer forward prices, or as deviations from covered interest parity (CIP). Our analysis suggests that the cost of fully hedging a large FX exposure is on the order of 0.1–1% of annual profits. We conclude that hedging is inexpensive. This suggests that frictions other than collateralization and trading costs limit hedging.

We then explore how financing frictions shape hedging demand. To do this, we draw on modern dynamic risk management models (Rampini and Viswanathan, 2010; Bolton et al., 2011). We derive analytically two testable predictions for hedging demand. First, in the absence of disaster risk, hedging demand eventually vanishes as firms accumulate liquidity and financial constraints are relaxed. Second, allowing for disaster risk, firms

²See Eurostat tet00066 and ext_lt_invcur respectively.

with high liquidity holdings value hedging tail risk the most, since only large shocks tighten their financial constraints. We find that hedging demand does not decline with liquidity, nor do firms trade out-of-the-money options to hedge tail risk. This suggests that hedging demand cannot be fully explained by external financing costs.

To understand what financial frictions can explain hedging demand, we build a dynamic quantitative corporate finance model. We add two mechanisms to the standard risk management model: firms value smooth earnings but face hedge adjustment costs. Earnings smoothing explains why firms hedge even when they do not need financing. Adjustment costs in hedge portfolios explain why firms do not hedge all of their risk. We estimate these parameters to match the fact that firms facing more FX risk hedge a larger fraction of that risk. Our estimates imply that firms' willingness-to-pay for hedging is 1.6% of firms value, an order of magnitude more than the 0.1% cost. Our estimation implies that dividends smoothing accounts for 1.2% of the value gain, while liquidity management accounts for the remaining 0.4%. Indeed, in the model, cash instruments allow firms to efficiently manage liquidity. Derivatives add value by helping firms smooth dividends efficiently.

We design the model with two key features that match our application, and use these features to validate the model. First, exchange rate shocks have a persistent impact on profits that can last for several quarters. Firms can match the duration of exchange rate risk using long-dated forwards without posting cash collateral. The model correctly replicates the fact that more persistent exchange rate shocks increase both currency risk and portfolio maturity. Second, we introduce deviations from covered interest parity (CIP) to generate hedging costs. Simulating responses to a one-time unexpected increase in CIP deviations, we find that the model can match short-run hedging demand responses observed in the data.

Our main contribution is to use hedging as a laboratory to study the nature of currency risk and financial frictions. As Friedman (1949) noted, demand for insurance has no place in a world of certainty. Likewise, firms have no incentives to trade derivatives without financial frictions (Modigliani and Miller, 1958; DeMarzo, 1988). Hedging provides a minimal deviation from these benchmarks: it only impact cash-flows, and this impact depends only on exchange rates. How much firms hedge thus informs us on how much currency risk they face. Portfolio maturity helps characterize currency risk duration. Option strategies reveal the relative value of insuring small fluctuations relative to disasters. The elasticity of hedging demand to trading costs quantifies the

value of insuring cash-flows. Our results therefore have broader implications for the understanding of currency risk in international economics and financial frictions in corporate finance.

Related literature

This paper brings new evidence on the determinants and limits of currency hedging. Starting with [Froot et al. \(1993\)](#), a rich theoretical literature links hedging demand to external financing costs. To rationalize the fact that large firms hedge more despite being arguably less constrained, this literature models risk management as the result of a dynamic trade-off between avoiding financing costs and posting collateral ([Rampini and Viswanathan, 2010](#); [Bolton et al., 2011](#)). Firms with more cash benefit less from hedging at the margin but also face much smaller perceived costs because they can easily post collateral. Our evidence shows that these forces are not sufficient to explain hedging demand empirically: collateralization is rare, and firms hedge more than what financing costs would imply. This points to alternative frameworks in which smoothing firm performance is valuable due to information or learning frictions, rather than cash management (e.g., [DeMarzo and Duffie, 1995](#); [DeMarzo and Sannikov, 2016](#)). It also highlights the importance of capital structure adjustment costs for hedging demand ([Myers, 1984](#); [Leary and Roberts, 2005](#); [Strebulaev, 2007](#)).

We also relate to the literature on collateral and commitment reviewed by [DeMarzo \(2019\)](#). Firms trade FX derivatives over-the-counter (OTC) and negotiate collateralization covenants bilaterally with dealer banks. Our results imply that there exist stable equilibria in which firms do not post collateral. This illustrates the empirical relevance of “alternative commitment mechanisms,” in the language of this literature, in disciplining corporate financing decisions. More broadly, our finding that firms rarely collateralize FX derivatives complements recent work showing that cash-flow borrowing constraints are more common than collateral constraints in U.S. corporate debt ([Lian and Ma, 2020](#)).

A separate literature examines rare disasters ([Farhi and Gabaix, 2015](#)) and the related “peso problem” ([Lewis, 2008](#)) in FX markets. Rare disasters can rationalize seemingly puzzling facts about FX markets, including the fact that unconstrained firms hedge ([Rochet and Villeneuve, 2011](#)). To analyze this possibility, we import insights from the catastrophe insurance pioneered by [Froot \(2001\)](#). Froot found that, while theory suggests that tail-risk insurance is most valuable when external financing is costly, insurance companies rarely purchase these products. We use options data to test these predictions and find limited demand for out-of-the-money options in our data.

We revisit the vast empirical literature that studies the impact (or lack thereof) of exchange rates on firm stock returns and cash-flow volatility (Jorion, 1990; He and Ng, 1998; Guay, 1999; Bodnar et al., 2002; Adams and Verdelhan, 2023; Welch and Zhou, 2024). As noted by Bartram et al. (2010), small risk exposures are observationally equivalent to hedging. We contribute to this literature in two ways. First, we exploit new data to solve this longstanding observability challenge. Second, we show that hedging maturity is connected to both currency risk and price flexibility, bridging the international corporate finance literature and the international economics literature that studies pricing with nominal rigidities and exchange rate risk (e.g., Gopinath et al., 2010).

Finally, our paper is connected to a long tradition in empirical corporate of studying corporate FX hedging using survey evidence or publicly available gross portfolio size (Mian, 1996; Géczy et al., 1997; Allayannis and Weston, 2001; Guay and Kothari, 2003; Giambona et al., 2018; Lyonnet et al., 2022). We add to this literature by leveraging novel contract-level evidence to measure the impact of derivatives and quantify what financial frictions generate hedging demand. Doing so, we contribute to a vibrant international finance literature that exploits granular data on derivatives contracts to explore portfolio hedging decisions (Hacıoglu-Hoke et al., 2024) and asset prices (Kubitsza et al., 2025). Closest to us is recent work by Alfaro et al. (2023b), who study the complementarity between natural hedging by matching imports and exports, which is limited, and financial hedging. Our work is complementary, as we focus on financial hedging. We combine empirical evidence with a quantitative corporate finance model to understand what determines cash-flow currency risk, and which financial frictions quantitatively explain currency hedging.

2 Framework

This section sets up a simple risk management framework to guide our empirical analysis. We show how the trade-off between managing financing constraints and hedging costs emerges endogenously in standard dynamic risk management models. The main result of this section is Equation (2), which characterizes optimal hedging demand as a function of risk, effective risk-aversion, and hedging costs. In Section 7, we extend and modify this stylized framework to build a quantitative model of hedging demand.

The model is a stylized version of Rampini and Viswanathan (2010) and Bolton et al. (2011). Time is discrete and indexed by t . The firm maximizes the discounted value

of its future dividends. It finances itself using net liquid assets L_t , one period risk-free bonds B_t , and equity. Net liquid assets consist of operating cash-flows $\Pi(\Delta E_{t+1})$ plus hedging gains minus debt repayments. Operating cash-flows are exposed to exchange rate risk $\Delta E_{t+1} = E_{t+1}/E_t - 1$, where one unit of foreign currency buys E_t units of domestic currency. The firm can hedge this risk by selling forward H_t units of foreign currency at constant cost $\kappa > 0$ per unit. Hedging requires putting a fraction $\chi \geq 0$ of the gross notional in a margin account.

The firm problem writes

$$\begin{aligned} V(L_t) &= \sup_{H,B} \sum_{k \geq 0} \frac{\Phi(D_{t+k})}{(1+r)^k}, \\ \text{s.t. } D_t &= L_t + B_{t+1} - \kappa |H_{t+1}|, \\ L_{t+1} &= \Pi(\Delta E_{t+1}) + H_{t+1}\Delta E_{t+1} - (1+r)B_{t+1}, \\ B_{\min} &\leq B_{t+1} \leq B_{\max}, \quad \chi |H_{t+1}| \leq \max(L_t, 0). \end{aligned}$$

Financial constraints arise from borrowing constraints and costly equity issuance, captured in Φ which we assume is increasing, concave, and smooth. The forward price equals the spot E_t , implying no carry or frictions. We also assume that ΔE_{t+1} is independent and identically distributed with mean zero, ruling out speculation.

A necessary condition for hedging is that future financial constraints $V'(L_{t+1})/V'(L_t)$ covary with exchange rates ΔE_{t+1} . The first order condition for an interior solution is:

$$\underbrace{\text{sgn } H_{t+1} \times \mathbf{E}_t \left[\frac{V'(L_{t+1})}{(1+r)V'(L_t)} \Delta E_{t+1} \right]}_{\text{Marginal value of forward purchase}} = \underbrace{\kappa + \lambda_t}_{\text{Marginal cost}}, \quad \lambda_t = \frac{\mu_t (\chi - \kappa \mathbf{1}\{L_t > 0\})}{V'(L_t)}. \quad (1)$$

Here, μ_t is the collateralization constraint multiplier and $\lambda_t \propto \mu_t$ is a rescaled multiplier. At the margin, the firm trades off hedging future liquidity needs against trading costs κ and collateralization costs λ_t . All derivations are relegated to Appendix B.1.

To gain intuition, we use a second order approximation of the value function around zero exchange rate shock, so $\Delta E_{t+1} = 0$ and next period's liquid assets are $\bar{L}_{t+1} = \Pi(0) - (1+r)B_{t+1}$, hedging reduces to the mean-variance program

$$\min_{H_{t+1}} \text{Var}_t (\Pi_{t+1} + H_{t+1}\Delta E_{t+1}) + 2(\kappa + \lambda_t) |H_t| \times \frac{(1+r)V'(L_t)}{V''(\bar{L}_{t+1})}.$$

Solving this program shows that the firm optimally follows a threshold rule:

$$H_{t+1} = \begin{cases} -\beta_t + c_t & \text{if } \beta_t > c_t \\ 0 & \text{if } |\beta_t| \leq c_t \\ -\beta_t - c_t & \text{if } \beta_t < -c_t \end{cases}, \quad (2)$$

where we define the exchange rate exposure β_t and the risk-adjusted cost c_t as

$$\beta_t = \frac{\text{Cov}_t(\Pi_{t+1}, \Delta E_{t+1})}{\text{Var}_t \Delta E_{t+1}} \quad \text{and} \quad c_t = \frac{\kappa + \lambda_t}{\gamma_t} \times \frac{(1+r)\bar{L}_{t+1}}{\text{Var}_t \Delta E_{t+1}}, \quad (3)$$

where $\gamma_t = -\bar{L}_{t+1}V''(\bar{L}_{t+1})/V'(L_t)$ measures the firm's effective risk-aversion. The exchange rate exposure is the covariance between profits and exchange rates. Hedging costs are trading costs κ plus collateralization costs λ_t . The perceived costs of hedging are higher when the firm's effective risk-aversion γ_t is low.

Hedging demand (2) summarizes the risk management trade-off. In the extreme where firms are effectively risk-averse and hedging is free ($\gamma_t > 0$ and $\kappa + \lambda_t = 0$ so $c_t = 0$), firms fully hedge their exposure ($H_t = -\beta_t$). In the other extreme where firms are risk-neutral but hedging is costly ($\gamma_t = 0$ and $\kappa + \lambda_t > 0$ so $c_t = +\infty$), they do not hedge at all because the perceived costs are infinite ($H_t = 0$).

Equation (2) is at the center of our empirical analysis. Ultimately, our goal is to estimate the increase in firm value V_t from financial hedging. To do so, we first measure how much risk firms face β_t , how much of that risk they hedge H_t , and how costly hedging is $\kappa + \lambda_t$. We then assess the importance of effective risk-aversion γ_t in determining H_t . Finally, we build a quantitative dynamic model to match our empirical estimates and quantify the increase in firm value from financial hedging.

3 Data

3.1 Background

Market structure and regulation

Foreign exchange derivatives are predominantly traded over-the-counter (OTC). The main feature of OTC markets is that firms negotiate contracts bilaterally with dealer banks. OTC derivatives can be customized, allowing firms to hedge longer maturities or less liquid currencies. The alternative is to buy exchange-traded derivatives (ETD), but these are anecdotal in corporate currency hedging because they cannot be customized.

Furthermore, while posting cash collateral is mandatory for ETD, it is not required for nonfinancial firms using OTC derivatives to hedge. Instead, collateralization is negotiated bilaterally between the firm and its dealer.

Derivatives markets have been increasingly regulated in the aftermath of the global financial crisis. The relevant regulation for European Union (EU) counterparties is the European Market Infrastructure Regulation (EMIR) EU No 648/2012. We exploit contract-level reporting, which became mandatory under EMIR. Specifically, EU counterparties to a derivatives transaction must report detailed information to trade repositories, which then transmit reports to EU regulators. The next section describes these reports in more details. While EMIR also imposes central clearing and margin posting requirements, it includes explicit exemptions for nonfinancial hedging.³ Such exemptions for nonfinancial counterparties are not specific to the EU, and are also included in the Dodd–Frank Act.

Hedge accounting

One of the main difficulties in measuring firms' currency exposure is that they use hedge accounting rules to report financial items after hedging. To qualify for hedge accounting, a derivatives contract must be designated as hedging a specific forecast or an item at initiation. The most common types of hedges are cash-flow hedges that insure future cash-flows, and fair value hedges that insure the value of an asset or a liability, such as debt or acquisitions. Hedge accounting allows firms to move the mark-to-market fluctuations of their hedging portfolios outside of the main income statement. When an item is realized, the value of the hedge is reclassified from reserves and cancels out the impact of exchange rates. Since most firms use hedge accounting, most Compustat items are observed after hedging.⁴

Beyond impacting its implications for measurement, hedge accounting is economically important because it constrains how firms trade and adjust their portfolios. Indeed,

³Nonfinancial counterparties are subject to clearing and collateral requirements if they exceed a threshold value. However, hedging transactions do not contribute to this threshold. See Article 10(3) of Regulation (EU) No 648/2012 (EMIR): “In calculating the positions [...] the non-financial counterparty shall include all the OTC derivatives contracts [...] which are not objectively measurable as reducing risks directly relating to the commercial activity or treasury financing activity of the nonfinancial counterparty or of that group.”

⁴If a firm applies cash-flow hedge accounting, gains and losses from derivatives are recognized in “Other comprehensive income” and later reclassified at the time the hedged item is realized. Reported sales, costs, and operating income then include derivatives hedging. If a firm does not apply hedge accounting, gains and losses on derivatives appear in financial income directly, and are not accounted for in reported EBIT.

hedge accounting rules require strict documentation and hedge effectiveness from firms, as laid out in IFRS 9. For example, an option trade in which the firm receives a net premium cannot qualify for hedge accounting. Hedge accounting documentation is audited and certified with financial statements. Failure to pass audits can result in hedges being reclassified in financial gains and losses after the EBIT, which generates volatility in earnings.

3.2 Derivatives and the European Market Infrastructure Regulation (EMIR)

Our main source of information comes from contract-level EMIR reports. The sample comprises all contracts where at least one counterparty is domiciled in the Eurozone. We now give an overview of how we build our dataset, with details in Appendix C. We access these reports through the European Central Bank's Virtual Lab. Uniquely, reports include granular information on counterparties' identities, contract type (such as forward, future, swap, and option), underlying currency pair, notional amount, the maturity date, execution timestamp, as well as contract characteristics (forward price or strike price, etc.), and collateralization status.

Cleaning

Data cleaning is especially important given reporting quality concerns raised by the European Securities and Markets Authority (ESMA).⁵ We focus on state files, which list active contracts at a daily frequency. We systematically process reports day-by-day and impose a number of validity checks on the main variables used in the analysis, as explained in Appendix C. When we observe both sides' reports for a given contract, we require that the notional, underlying asset, and maturity of the two reports agree. We then combine information from both reports to build the main variables.

Consolidation

EMIR reports are filed at the Legal Entity Identifier (LEI) level but a firm typically consolidates several LEIs. Matching derivatives portfolios to financials from Compustat Global therefore requires consolidating LEIs at the ultimate reporting level. To do this, we first use publicly available consolidation from GLEIF linking LEI to their heads for each year. We then manually check and improve upon this consolidation using LEI names. After these two steps, we are able to link LEIs in each year to a Compustat entity, identified by its gvkey. Finally, we further consolidate Compustat heads. For example,

⁵See the yearly data quality reports published by ESMA (2020, 2021, 2022, 2023).

Christian Dior is publicly listed but would be consolidated inside LVMH.

3.3 Financial statements

We take financial statements from Compustat Global Quarterly. We refer to Appendix D.1 for cleaning details. We restrict the sample to firms located in the Euro Area, Denmark, Sweden, Switzerland, and Norway. This is because we observe all transactions within the Euro Area, and we expect our coverage to be good for these additional countries.⁶ Furthermore, we remove financials, insurers, real-estate, and holding company sectors (SIC 60 to 67).

Our main measure of profits is earnings before interests and taxes (EBIT) normalized total assets ($oiadpq$ divided by atq). As a robustness, we use pretax income (piq divided by atq). We use cash and equivalents to measure cash positions ($cheq$ divided by atq). Book leverage is the sum of short-term debt plus long-term debt ($d1cq$ plus $dlttq$ divided by atq). Quarterly dividends and equity issuances are not well reported, so we take them from Compustat Global Annual instead.

3.4 Gross holdings and net holdings

Gross holdings

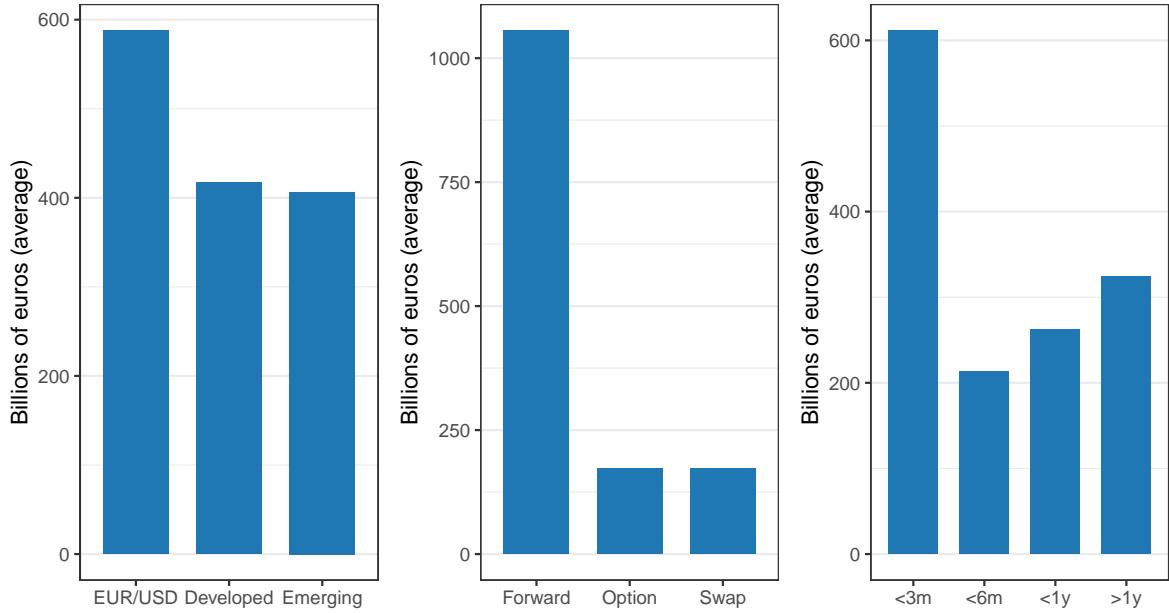
Figure 1 shows average gross holdings of derivatives in our sample. EUR/USD contracts are by far the most common, with almost €600 billion in gross notional, or about 40% of the total. Firms mainly use forwards, which make up about 70% of gross holdings, while options and swap each represent about 15% of the total. Finally, while about 40% of positions have a time-to-maturity under 3 months, positions with a time-to-maturity over 6 months are just as large. In fact, time-to-maturity exceeds 1 year for 20% of holdings.

Net holdings

While gross holdings are informative for trade volumes, they do not measure how much insurance derivatives provide. To measure net positions, we follow Tufano (1996) and compute delta-weighted notionals. The delta of a derivatives contract measures the sensitivity of its value to the underlying exchange rate. For forward contracts and swaps, we use a delta of ± 1 depending on counterparty side. For options, deltas depend

⁶By contrast, we expect our coverage to be poorer for the United Kingdom. An earlier version of this paper included these firms, without major impact on our main results.

Figure 1: Gross holdings by currency, contract type, and maturity



Note. This figure shows gross holdings outstanding. We sum gross notional by category for each date and then average results over time. *Left panel.* By currency, where “Developed” means G10 (USD, EUR, JPY, GBP, CHF, CAD, NZD, NOK, SEK) plus DKK; “Emerging” means other currencies. *Middle panel.* By contract type. *Right panel.* By maturity.

on volatility, time-to-maturity, and moneyness. Due to data limitations, we cannot accurately price exotic options. Therefore, we approximate option deltas using the Black–Scholes model for vanilla options calibrated with historical volatilities.⁷

Aggregating net notional is straightforward because deltas are linear. The net notional for a given contract c is $x_{ck\tau} = \delta_{ck\tau} n_{ck\tau}$, where n is the gross notional, k is the underlying, and τ is a week. Given a set of contracts $\mathcal{C}_{ik\tau}$ for firm i , the firm’s net position is obtained by summing net notional across contracts

$$X_{ik\tau} = \sum_{c \in \mathcal{C}_{ik\tau}} x_{ck\tau}.$$

Figure G.2 shows the aggregate net notional for the EUR/USD. The left panel shows that in the aggregate, firms in our sample buy EUR forward and sell USD, which is consistent with the fact that European exporters tend to have sales in dollars and costs in euros. Aggregate net holdings are on the order of €100 billion, which is large: this is comparable to the aggregate net position of Eurozone insurers and pension

⁷We compute historical exchange rate volatilities using daily log returns from the previous 252 days, requiring that at least 63 days of data be available.

funds (Kubitz et al., 2025, Figure 1). The right panel shows that the net notional of firms' portfolios can be large as a fraction of total assets, sometimes in excess of 10%.

4 Risk

Given that nonfinancial firms trade large volumes of FX derivatives, it is natural to ask how much insurance these contracts provide. In this section, we measure how much FX risk firms face, and how much of that risk they hedge with derivatives.

4.1 Factor model strategy

Factor model

We can measure currency risk with minimal assumptions because we observe hedging portfolios directly. We proceed in three steps: (i) we estimate the firm's FX exposure *after hedging* using a multi-currency factor model, (ii) we use notional-weighted deltas to measure the impact of financial hedging, and (iii) we undo this impact to compute the firm's FX exposure *before hedging*.

We assume that changes in yearly cash-flows $\Delta\pi_{it}^*$ follow a factor model in currency returns f_t and other systematic factors g_t , so that

$$\Delta\pi_{it}^* = \lambda_i^\top f_t + \theta_i^\top g_t + w_i^\top f_t + v_{it}, \quad (4)$$

Here, i denotes a firm and t a quarter. We use an asterisk to emphasize that cash-flows are measured *after hedging*. The model is in difference because economic theory predicts that changes in exchange rates impact profits due to nominal rigidities. As in Section 2, we model hedging as a loading w_i on currency factors. The main assumption in (4) is that risk loadings are constant. Importantly, currency and non-currency factors can be correlated. For example, a trade war between the European Union and the United States may move exchange rates. Both tariffs and rates impact cash-flows, but only currencies have deep derivatives markets.⁸

To isolate currency risk, we project all factors on currencies

$$\Delta\pi_{it}^* = \underbrace{(b_i + w_i)^\top}_{b_i^{*\top}} f_t + u_{it}. \quad (5)$$

⁸Strictly speaking, systematic factors like commodity and rates can also be hedged with derivatives. We assume hedges for other tradable factors are already incorporated in the baseline cash-flows.

Here, b_i is the firm's exposure to currency risk *before* financial hedging, and b_i^* is the exposure *after* hedging. The loading b_i captures both direct exposure to currency factors and indirect exposure through non-traded factors.⁹ It is the empirical counterpart of Equation (3) from our stylized framework. Our goal is to measure and compare currency risk before and after hedging.

4.2 Estimation

Step 1. Foreign exchange risk after hedging

We first estimate currency risk after hedging b_i^* in Equation (5). We work with differences over one year given that firms hedge over long horizons (Figure 1), rolling over quarters to maximize the number of observations. For annual changes in yearly cash-flows $\Delta\pi_{it}^*$, we compute the sum Π_{it}^* of the past four quarterly EBITs (oiadpq in Compustat). We then compute the one year difference $\Delta\pi_{it}^* = (\Pi_{it}^* - \Pi_{it-4}^*)/A_{it-7}$ normalized by total assets A_{it-7} , taken at the date of the oldest quarterly cash-flow used (atq in Compustat). Currency returns f_t are log yearly exchange rate returns relative to the euro for the USD, GBP, JPY, and CHF.

The main empirical challenge is that we only have 60 quarters of data per firm on average. Estimating the model firm-by-firm using OLS would lead to severe overfitting, inflating the importance of currency risk. To address this concern, we implement a two-step estimation strategy that exploits the natural clustering of firms within sectors. First, we estimate Equation (5) at the sector level using ridge regression in the pooled panel. Then, we run firm-level ridge regressions, shrinking estimates toward the previously obtained sector loadings. Ridge penalty parameters are selected through blocked cross-validation.¹⁰ Our assumption is that firms within a sector have similar currency risk exposures. Shrinkage is commonly applied to estimate factor models in asset pricing, motivated by the hierarchical structure of returns (e.g., [Vasicek, 1973](#)).

The pooled sector regressions weight firms by inverse cash-flow variance. Weighting improves efficiency given that smaller firms are more volatile ([Stanley et al., 1996](#)), which generates heteroskedasticity. It also avoids giving undue influence to economi-

⁹The risk loading is the projection $b_i = \lambda_i + \Omega_F^{-1}\Omega_{FG}\theta_i$, where Ω is the variance-covariance matrix of (f, g) with obvious block notations. The idiosyncratic cash-flow is $u_{it} = v_{it} + (I - \Omega_F^{-1}\Omega_{FG})\theta_i g_t$.

¹⁰Specifically, for the pooled sector regressions, we partition firms into three distinct groups, and consecutive quarters into three other groups, resulting in a total of nine groups. We then select the optimal penalty parameter using 9-fold cross-validation. For firm-level regressions, we partition consecutive quarters into three groups and select penalty parameters using 3-fold cross-validation.

cally negligible cash-flow swings from smaller firms. We winsorize cash-flow variance estimates at the 0.5 and 100 basis point levels to limit the influence of extreme outliers.

Step 2. Hedging

To measure the derivatives loadings w_i , we average the net notional computed in Section 3.4. For each firm i , underlying k , and week τ in quarter t , we identify the set of active contracts that expire or are unwound in the following 360 days. We first compute the net notional for this position, $X_{ik\tau}$. We then compute the quarterly average $X_{ikt} = \sum_\tau X_{ik\tau}/12$, which measures how the value of firm i 's derivatives portfolio changes with the exchange rate on currency k .¹¹

The quarterly derivatives loadings are the ratio of the net notional to total assets

$$w_{ikt} = \frac{X_{ikt}}{\text{Total assets}_{it}}.$$

Dividing by total assets puts the derivatives portfolio on the same basis as our cash-flow measure. To derive time-invariant derivatives loadings, we average across all quarters:

$$w_{ik} = \frac{1}{T_{ik}} \sum_t w_{ikt}, \quad (6)$$

where T_{ik} is the number of observed quarters. We then view $w_i = (w_{ik})_k$ as a vector.

Since our regression does not include all possible currency pairs, the derivatives loading vector w_i typically has a dimension $K \geq F$, with F being the dimension of factor returns f . To ensure compatibility, we project the K -dimensional vector onto the F -dimensional subspace of included currency pairs using daily returns data from 2003–2024. This projection is exact for omitted currency pairs spanned by included pairs (e.g., USD/JPY spanned by EUR/USD and EUR/JPY). Otherwise, it provides the best linear approximation of omitted pairs by included ones. For notational simplicity, we continue to denote projected derivatives loadings by w_i .

¹¹Profits and losses from derivatives portfolios depend on the full path of prices when positions change over time. To be precise, given a time interval $[0, T]$, a differentiable price path P , and continuous net notionals X , terminal profits and losses are $\Pi(T) = \int_0^T X(t)P'(t)dt$. Fixing $P(0)$ and $P(T)$, terminal profits and losses $\Pi(T)$ are independent of the full path of prices for any P only when the net notional X is constant. When X varies, the average net notional $\int_0^T X(t)/Tdt$ is the best path-independent approximation in L^2 norm.

Step 3. Financial risk before hedging

Having estimated currency exposure after hedging b_i^* and hedging w_i , we can back out currency exposure before hedging $b_i = b_i^* - w_i$. To transform these exposures into risk, we express them in variance shares by defining

$$\text{Currency risk before hedging} = \frac{b_i^\top \Omega_F b_i}{\text{Var}_i \Delta\pi_{it}^*}, \quad (7)$$

$$\text{Currency risk after hedging} = \frac{b_i^{*\top} \Omega_F b_i}{\text{Var}_i \Delta\pi_{it}^*}, \quad (8)$$

$$\text{Hedged currency risk} = \frac{b_i^\top \Omega_F b_i}{\text{Var}_i \Delta\pi_{it}^*} - \frac{b_i^{*\top} \Omega_F b_i^*}{\text{Var} \Delta\pi_{it}^*} = \frac{w_i^\top \Omega_F (-2b - w_i)}{\text{Var}_i \Delta\pi_{it}^*}. \quad (9)$$

We normalize risk by the observed variance of cash-flows to obtain estimates that are comparable across firms. We winsorize b_i and b_i^* component-wise at the 3rd and 97th percentiles, and we winsorize the resulting risk shares to limit extreme values from firms with very low cash-flow variance. By construction, risk before hedging equals risk after hedging plus hedged risk. This naturally maps to the factor model (5) since

$$\text{Var}_i \Delta\pi_{it}^* = \underbrace{b_i^\top \Omega_F b_i}_{\text{Currency risk before hedging}} - \underbrace{w_i^\top \Omega_F (-2b - w_i)}_{\text{Hedged currency risk}} + \underbrace{\text{Var}_i u_{it}}_{\text{Non-currency risk}}.$$

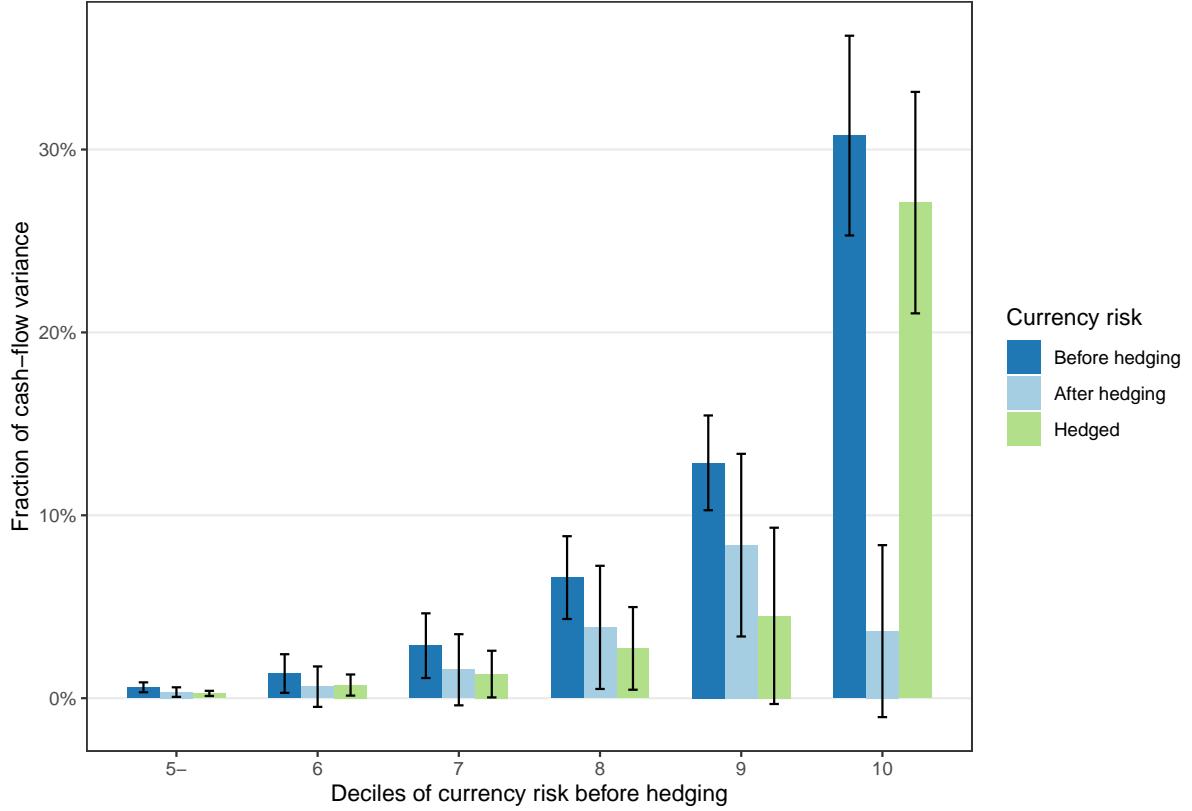
Note that this variance decomposition may not hold exactly due to bias from ridge shrinkage and winsorization. We attribute any deviation to non-currency risk.

4.3 Results

Currency risk is concentrated in a few firms

Figure 2 shows the results from the variance decomposition. We sort firms into deciles of currency risk before hedging, and show the asset-weighted average of each component. Focusing on currency risk before hedging (dark blue bars), we find that it is concentrated in a few firms. For the most exposed firms, foreign exchange factors explain between 13% (ninth decile) and 31% (tenth decile) of cash-flow variance. The importance of currency risk drops rapidly as exposure decreases. At the median and below, exchange rate is negligible, consistent with survey evidence showing that only 59% of nonfinancial firms face material currency risk (Giambona et al., 2018, Figure 4b).

Figure 2: Cash-flow currency risk by level of exposure



Note. This figure shows measures of currency risk across currency risk deciles. We sort firms into 10 deciles according to currency risk before hedging. We then compute the asset-weighted average for three risk measures: (1) currency risk before hedging (sorting variable), (2) currency risk after hedging, and (3) currency risk hedged. The five lower deciles are binned together for clarity. Cash-flows $\Delta\pi_{it}^*$ are the change in yearly EBIT normalized by total assets. Currency risk measures are obtained by estimating a factor model as described in the main text. Standard errors are computed using the Bayesian bootstrap blocked by firm.

Firms hedge most but not all currency risk

Turning to currency risk hedged (green bars), we find that firms hedge most, but not all currency risk. For the most exposed firms, hedging reduces cash-flow variance by 5% (ninth decile) to 27% (tenth decile). To interpret these numbers, Appendix F.1 translates this variance reduction into existing frameworks from the literature. Ultimately, we will quantify the value of this reduction in variance to firms using a quantitative model.

Turning to currency risk after hedging (light blue bars), Figure 2 shows that we reject the hypothesis that firms in the largest deciles have no remaining risk at the 95% confidence level. This is in line with recent work by [Adams and Verdelhan \(2023\)](#) and [Welch and Zhou \(2024\)](#), who show that exchange rates do predict firm profits, once they are appropriately weighted by measures of exposure. Our estimates imply that firms

hedge about 30% to 80% of currency risk on average. The large confidence bands reflect the fact that we compute asset-weighted averages, that there is substantial heterogeneity across firms, and the inherent difficulty in estimating firm-specific risk loadings using a limited time series.

Long-term hedging predicts more currency risk and less flexible prices

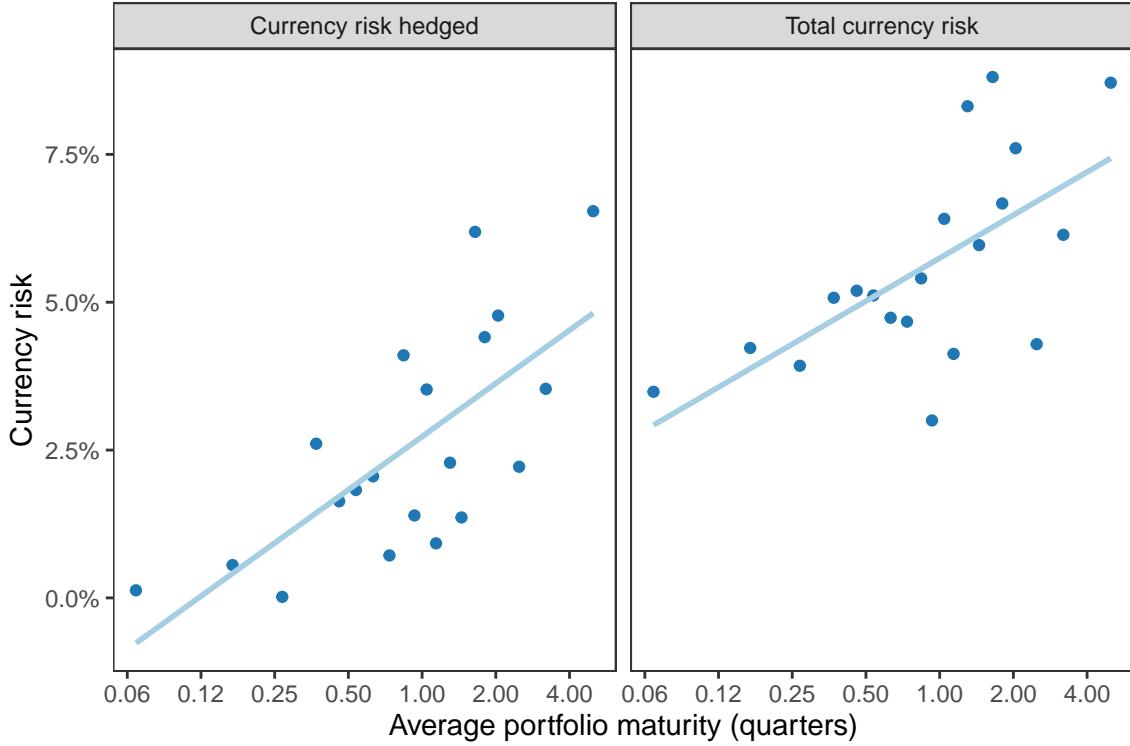
We now show that long-term hedging predicts more currency risk in the cross-section. We measure portfolio maturity as the average time-to-maturity for a portfolio, weighting contracts by gross volume. We compute this quantity for each firm and date and then average it over time. Appendix Figure G.6 plots the average portfolio maturity across sectors. The average portfolio duration is between one and two quarters in most industries. It reaches, and may even exceed one year for airlines and the transportation equipment sector (auto industry and aerospace industry). Appendix F.2 provides additional details on the construction and interpretation of this variable.

In Figure 3, we sort firms into bins according to their portfolio maturity, then plot the average maturity against average currency risk. Each dot is a bin. We find that firms which trade at longer maturities face more currency risk before hedging, and hedge more risk. Appendix Table G.2 explores several alternative specifications, including sector fixed effects.

One interpretation for this positive correlation is that some firms sign long-dated export contracts with prices fixed in a foreign currency. If contract prices cannot be renegotiated, firms that sign longer contracts face more currency risk because their profits are exposed to the cumulative impact of consecutive exchange rate shocks. At the same time, these firms will also use long-term derivatives to match the duration of forecasted cash-flow. The mechanism through which less flexible prices increase cash-flow currency risk is implicit in dynamic international pricing models, such as [Gopinath et al. \(2010\)](#). It aligns with microeconomic evidence that goods prices can take a year or more to adjust to exchange rates, with substantial heterogeneity across products (e.g., [Gopinath and Rigobon, 2008](#); [Auer et al., 2021](#); [Amiti et al., 2022](#)).

An additional piece of evidence supporting this mechanism is the correlation between portfolio maturity and price flexibility. To measure price flexibility, we use microdata underlying the French Producer Price Index (PPI). These data have been widely used (see [Lafrogne-Joussier et al., 2023](#), and references therein), and we refer to Appendix D.2 for details. We define price flexibility as the average quarterly price change for a firm across

Figure 3: Currency risk and portfolio maturity



Note. This figure shows a binned scatterplot of currency risk against maturity. Portfolio maturity is the average time-to-expiry of contracts in a firm's portfolio, weighted by gross volume. Portfolio maturity is in logarithmic scale. Currency risk measures are obtained by estimating a factor model as described in the main text.

products and time periods. A price change is the absolute log difference in prices.

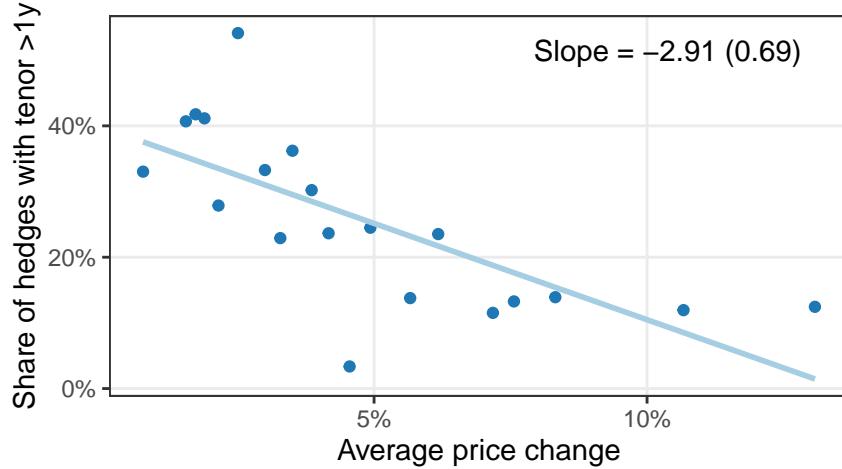
Figure 4 plots price portfolio maturity against average price changes. We sort firms into bins according to their average price change, and compute the average maturity and price change within each bin. Each dot is a bin. We find that more flexible prices, measured as larger average price changes, predict shorter portfolio maturities. This observational evidence supports a mechanism through which the inability to adjust contracted prices generates larger currency risk. The results in Figure 4 are subject to one caveat. we are only able to match 95 firms to the French PPI data. We therefore interpret these results as suggestive only.

4.4 Discussion and additional results

Financial income

There are three concerns with Figure 2. First, firms may use foreign currency borrowing to hedge cash-flows. Second, firms can use financial derivatives as fair value hedges, not

Figure 4: Hedging by maturity



Note. This figure plots hedging demand by maturity and its determinants. *Left panel*. This panel shows the breakdown of derivatives maturity for EUR/GBP and EUR/USD contracts across time. *Right panel*. This panel shows a binned scatterplot of the share of long-term contracts against receivables-to-sales.

cash-flow hedges. In both cases, the economically relevant impact happens in financial income, which is not included in EBIT. Third, although most firms use hedge accounting, for those do not, reported EBIT does not include financial derivatives. To address these concerns, we replicate our factor estimation using pretax income to measure cash-flows instead of EBIT. Appendix Figure G.4 shows the results, which are quantitatively and qualitatively similar, although risk measures are estimated more imprecisely. This shows that our main insights do not hinge on the precise measure of cash-flow used.

5 Hedging costs

The previous section shows that firms face significant foreign exchange risk but only hedge a fraction of it with derivatives. To understand whether hedging costs can explain this fact, this section quantifies the importance of collateralization and trading costs, in line with the framework presented in Section 2.

5.1 Few firms post cash collateral

Collateralization has been extensively studied theoretically, and it is the main limitation to hedging in modern corporate finance models (Rampini and Viswanathan, 2010; Bolton et al., 2011). The standard way to collateralize derivatives in practice is to post cash in a margin account. When the exchange rate moves and the firm loses on its derivatives, it adds cash to the margin account. This insures the bank against the risk

that its counterparty defaults. Collateralization is costly for firms because it ties up cash that could otherwise be invested. The opportunity cost is especially high for financially constrained firms and may cause them to abstain from hedging entirely.

We are able to directly measure the importance of collateralization because counterparties in our data report for each contract whether they post cash collateral or not. When the nonfinancial counterparty reports that it does not post cash margins, we flag the contract as *uncollateralized*. Otherwise, contracts with any type of cash margin are *collateralized*.¹² We exclude observations for which the collateralization field is missing, and we restrict the sample to the period 2020–2023 because collateralization reporting improves over time. For completeness, we tabulate the full distribution of collateralization status across years in Appendix F, Table G.5. To keep the analysis consistent with the next section, we focus on EUR/USD forward contracts. This does not impact our results, which hold for other major pairs such as EUR/GBP and EUR/JPY.

Figure 5 shows that 83% of firms collateralize less than 10% of their portfolio, while many firms do not post cash collateral at all. This suggests that cash collateral does not limit hedging. Furthermore, since contracts are negotiated bilaterally, our results imply that dealer banks let firms bypass margin posting entirely.

The fact that few firms post collateral may be surprising given the importance of collateralization in finance models and the recent regulatory push to require clearing and margin posting in over-the-counter markets. However, the European Commission has explicitly exempted hedging by nonfinancial firms from these requirements (see Section 3.1). Similar end-user exemptions exist in the United States under the Dodd–Frank Act. The absence of collateralization in nonfinancial hedging thus appears to be a direct consequence of modern macroprudential regulation.

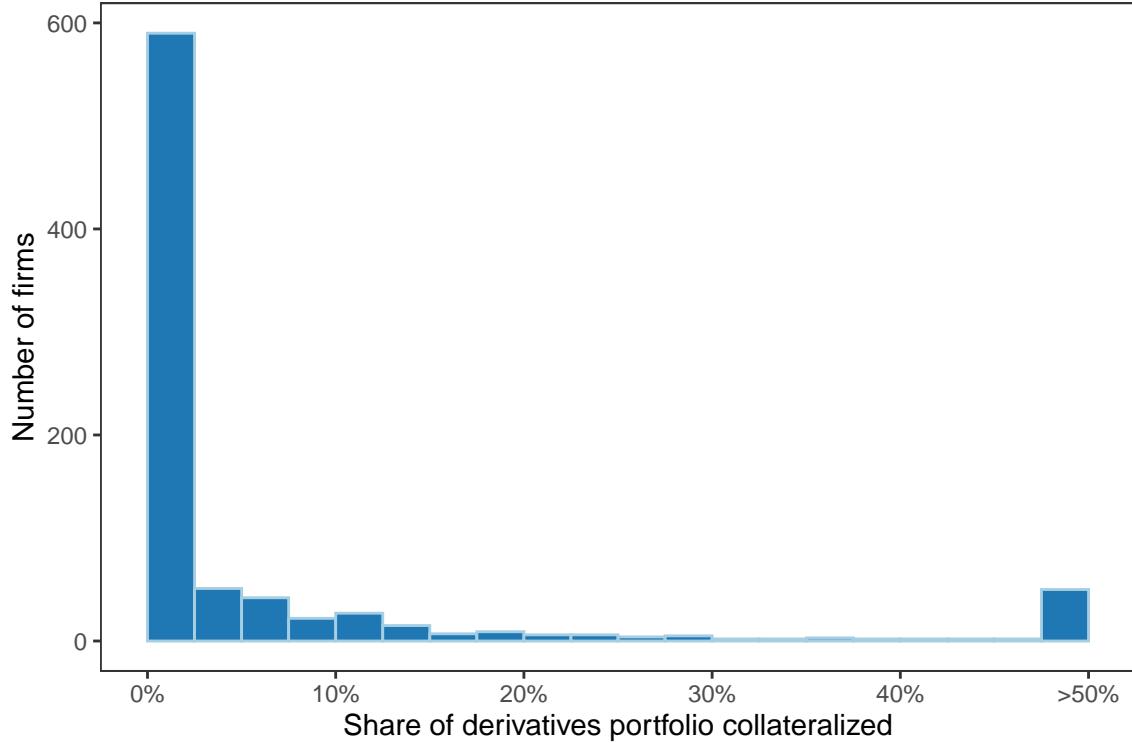
To interpret the economic risk associated with observed collateralization rates, we compute the value-at-risk (VaR), defined as

$$\text{Normalized VaR}_i(q) = \frac{\text{Portfolio size}_i \times \text{Collateralization rate}_i}{\text{Cash}_i} \times \Lambda(q), \quad (10)$$

where $\Lambda(q)$ denotes the q th quantile of quarterly adverse exchange rates returns for

¹²We observe the following values: “uncollateralized” indicates that the reporting counterparty does not post initial nor variation margins; “fully collateralized” indicates that both counterparties post both initial and variation margins; “partially collateralized” indicates that the reporting counterparty only posts variation margins; “one-way collateralized” indicate that the reporting counterparty posts initial and variation margins, but the other counterparty does not. See Article 3(b) of the Commission Implementing Regulation (EU) No 1247/2012.

Figure 5: Share of derivatives portfolio collateralized across firms



Note. This figure shows the distribution of collateralization shares across firms. For each firm and each week, we compute the collateralization share as the total gross volume of collateralized contracts divided by the total gross volume of the portfolio. For each firm, we then average this share across weeks. We only classify as uncollateralized those contracts for which the firm explicitly reports not posting cash collateral. All other contracts are thus classified as collateralized. We exclude contracts for which the collateralization field is missing.

the firm. We compute portfolio size as the average absolute net notional. We assume that the firm faces an adverse shock on the EUR/USD. We simulate shocks under a t distribution to allow for fat tails, assuming that the quarterly volatility is 5%. Figure G.8 shows the results under a 1 in 100 quarters adverse shock. Calibrating to observed collateralization rates, 98% of firms have a VaR under 5% of liquid assets. By contrast, if all portfolios were fully collateralized, 15% of firms would exceed this threshold. For the most 5% exposed firms, a 1 in 100 shock on the EUR/USD only would require posting over 10% of liquid assets to cover margins.

5.2 Forward prices are close to interdealer prices and covered interest parity

We now show that trading costs are small. This is important because high trading costs could limit hedging even if firms do not have to post collateral.

Deviations from interdealer prices

Our first measure of trading costs is the spread between the prices that banks charge to firms for EUR/USD forwards and the corresponding interdealer forward price, following Hau et al. (2021). We use high frequency interdealer quotes from LSEG Tick History. The markup $m_{ct}(T)$ embedded in the forward price $F_{ct}(T)$ of contract c at time t with maturity T is

$$m_{ct}(T) = \begin{cases} \log F_{ct}(T) - \log B_t(T) & \text{if the nonfinancial counterparty is long} \\ \log A_t(T) - \log F_{ct}(T) & \text{otherwise} \end{cases}. \quad (11)$$

Here, $B_t(T)$ is the bid for the same contract on the interdealer market, and $A_t(T)$ the ask. We match forward prices to the most recent interdealer quote using the contract's execution timestamp, and interpolate linearly between tenors. We also remove observations for which the markup (11) exceeds 100 basis points in absolute value (2.7% of observations). Appendix Figure G.10 shows that EMIR forward prices track interdealer quotes remarkably well. This validates our use of EMIR prices and suggests that contract-level markups are small. Figure G.11 plots the distribution of markups across contracts, confirming that markups are small. We refer to Appendix D.3 for additional details regarding measurement and cleaning.

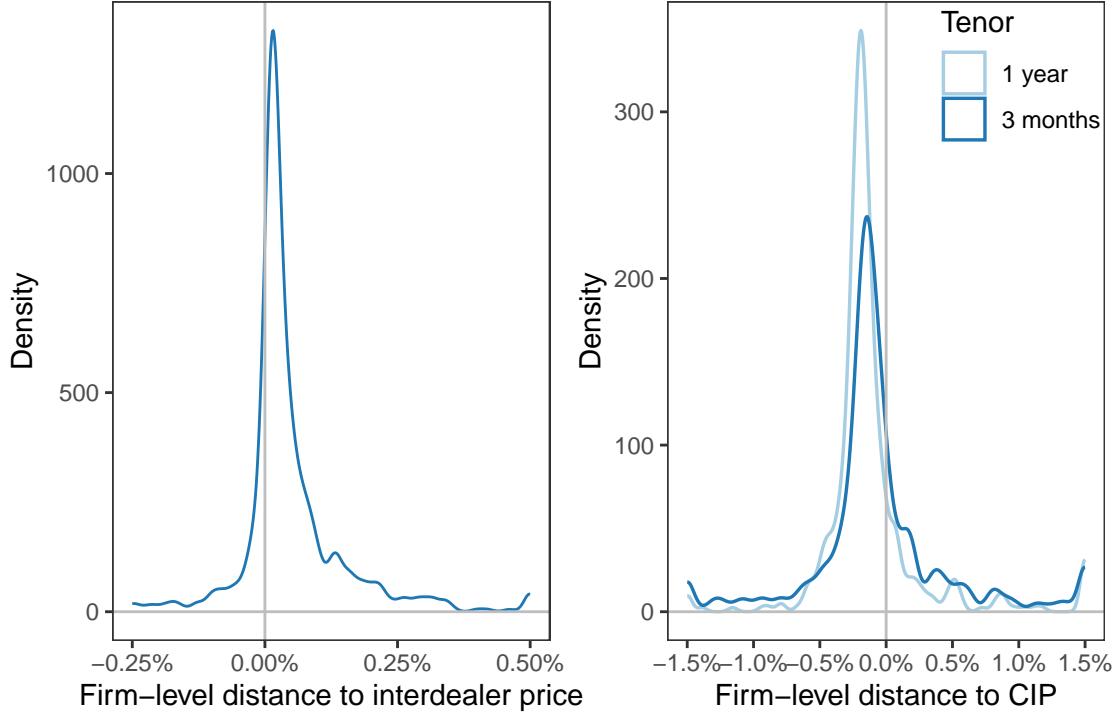
We compute the average markup paid by a firm as the average across contracts weighted by volume. Figure 6, left panel, shows that the average markup is small. Unlike most studies of trading costs in over-the-counter markets since Edwards et al. (2007) we do not include granular fixed effects. This is because our goal is to assess the magnitude of trading costs paid by firms, not variation in trading costs across contracts sold by a given dealer on a given day.

Deviations from covered interest parity

Our second measure of trading costs, the deviation from covered interest parity (CIP), also implies small trading costs. In foreign exchange markets, CIP pins down the fair forward price by no-arbitrage. Since 2008, there have been persistent deviations from CIP across currencies on the order of 10–30 basis points (Du et al., 2018). We compute CIP deviations for contract c with maturity T at time t as

$$z_{ct} = \frac{1}{T} \log \frac{F_t^*}{F_{ct}} \quad \text{with} \quad F_t^* = S_t e^{T(r_t^x(T) - r_t^y(T))}, \quad (12)$$

Figure 6: Distribution of trading costs across firms



Note. This figure shows trading costs on EUR/USD forwards. We define trading costs as the difference between forward prices and a benchmark. *Left panel.* Interdealer prices. *Right panel.* Covered interest parity (CIP). We follow standard sign conventions for CIP deviations: negative deviations are a cost for firms that buy euros forward against dollars.

where F_t^* is the CIP price. We then compute the average CIP deviation for a given firm by averaging across its contracts, weighting them by gross volume.

Figure 6, right panel, shows that over 80% of firms trade within 50 basis points of CIP. The median deviation is 12 basis points, squarely in line with the literature. Overall, this confirms that trading costs are small.

Hedging demand responds to deviations from CIP

To support our interpretation that trading costs are economically small, we study how hedging demand responds to a widening in aggregate EUR/USD CIP deviations in Appendix F.4. We measure portfolios in net position divided by total assets. We exploit the fact that firms that are long (i.e., buy euros forward against dollars) *pay* CIP deviations, while firms that are short *earn* them. We therefore expect long positions to decrease following shocks and short positions to increase. Figure G.2 shows that there is significant variation in the cross-section of exposures, with large flows on both sides. This is because net exporters tend to hedge dollar sales and go long, while net importers

take the opposite side.

Following a 10 basis points increase in EUR/USD CIP deviations, we find that long firms increase their position by 3 basis points while short firms decrease it by about 2 basis points over 12 weeks (Figure G.12). Given that CIP shocks on the order of 10 basis points are common in the time-series, this indicates that trading costs do not constrain hedging. Of course, these are short-run responses and responses to a large and permanent CIP shock could be more important. We will use our structural model to give a precise interpretation to the magnitude of those adjustments.

5.3 Additional results and discussion

Counterparty risk

If firms do not post collateral, then dealer banks bear counterparty risk. We now show evidence consistent with firms and banks diversifying away this risk. To measure diversification, we compute the number of dealers a firm trades with and how concentrated those trades are. We define concentration as the Herfindahl–Hirschman Index (HHI) of trades across dealers. Appendix Figure G.7 shows that a 10% increase in trading volume predicts a 3% increase in the number of dealers and a 3% decrease in HHI. Trading volume explains a large share of cross-sectional variation in both diversification measures (Table G.3). It also has predictive power for diversification measures in the time-series, after including firm fixed effects (Table G.4).

These findings are correlational. Qualitative evidence suggests that this correlation is the consequence of firms actively diversifying counterparty risk. For example, Volkswagen writes in its 2022 financial statements that “counterparty risk management imposes internal limits on the volume of business allowed per counterparty when financial transactions are entered into.” Such statements are frequent¹³ and support the interpretation that diversification limits counterparty risk in FX derivatives markets.

6 Financial frictions

This section studies the empirical determinants of corporate hedging demand. We use the results to inform us on what financial frictions cause firms to value derivatives hedging.

¹³See Airbus (2022, p.60), Sanofi (2022, p.163), Safran (2022, p.242).

6.1 Liquidity management theory

Liquidity management theory predicts that firms purchase insurance to relax financial frictions following adverse exchange rate shocks. This restricts the shape of hedging demand as a function of liquidity. To make this point precise, we start from the remark by [Rampini and Viswanathan \(2013\)](#) that the firm's stochastic discount factor depends on the marginal value of liquidity. This appears clearly in Equation (1), which we reproduce for clarity

$$\underbrace{\text{sgn } H_t \times \mathbf{E}_t \left[\frac{V'(L_{t+1})}{(1+r)V'(L_t)} \Delta E_{t+1} \right]}_{\text{Marginal value of forward purchase}} = \underbrace{\kappa + \lambda_t}_{\text{Marginal cost}} .$$

Here V denotes firm value, L_t denotes liquid assets holdings, and E_t is the exchange rate. The firm's stochastic discount factor is $V'(L_{t+1})/(1+r)V'(L_t)$.

The left-hand side of the equation quantifies the risk-management benefits of forwards. It implies that discount factor is a function of present and future liquid asset holdings. Furthermore, the appropriate discount factor is firm-specific. Its covariance with exchange rates depends on the firm's characteristics and risk exposure, both directly through state variables and indirectly through the value function. This departs from general equilibrium models in which firm cash-flows are discounted using the consumer's stochastic discount factor (e.g., [Gomes et al., 2003, 2009](#)).

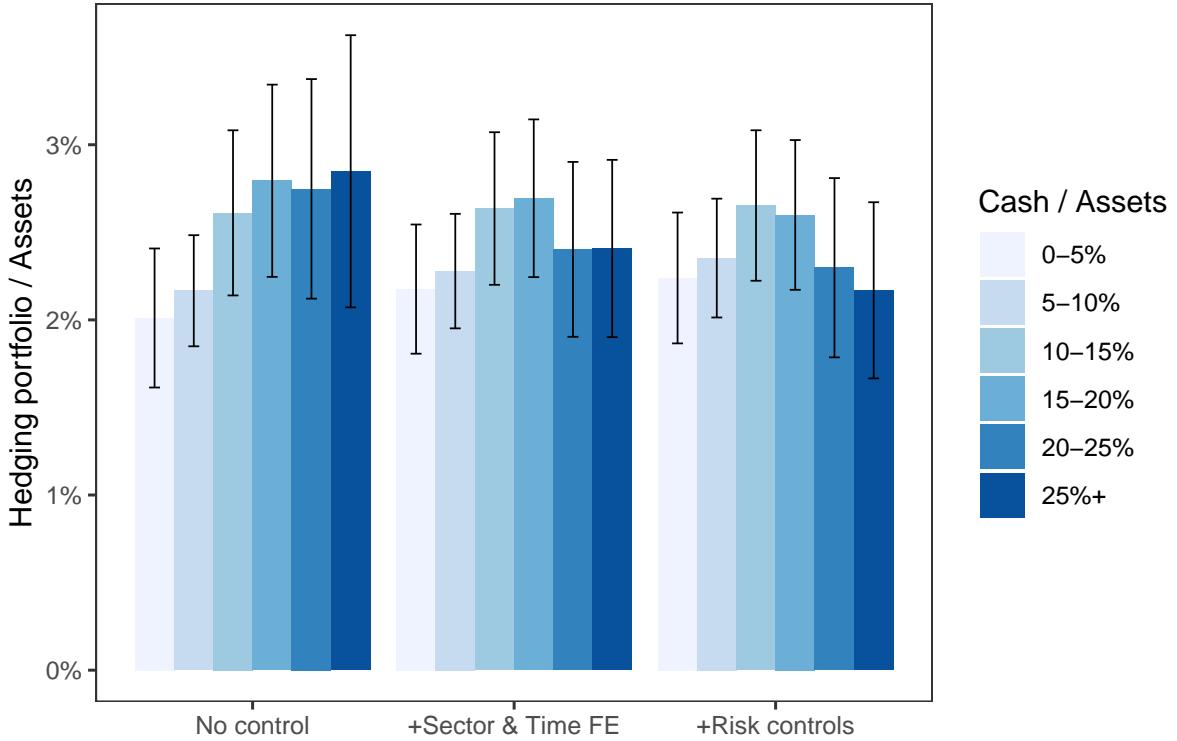
Equation (1) places sharp restrictions on how corporate discount factors covary with exchange rates. In fact, two robust and testable predictions can be derived analytically in the continuous-time limit of the model, as we show [Appendix B.2](#). These predictions are robust in the sense that they hold in a large class of models in which many of the simplifying assumptions made in [Section 2](#) are relaxed.

Prediction 1. *Hedging benefits go to zero as firms accumulate liquidity, assuming no tail risk.*

The intuition is that costly external financing is the only friction generating corporate risk-aversion. It creates a wedge between the marginal value of a dollar inside the firm and outside the firm $V'(L_{t+1}) - 1 \geq 0$. As the firm accumulates liquid assets, this friction is relaxed, the firm becomes risk-neutral, and the wedge goes to zero. This implies that the value of risk management products vanishes.

Prediction 2. *Firms with high liquid assets holdings benefit from hedging disaster risk first.*

Figure 7: Variation in hedging portfolio size by cash holdings

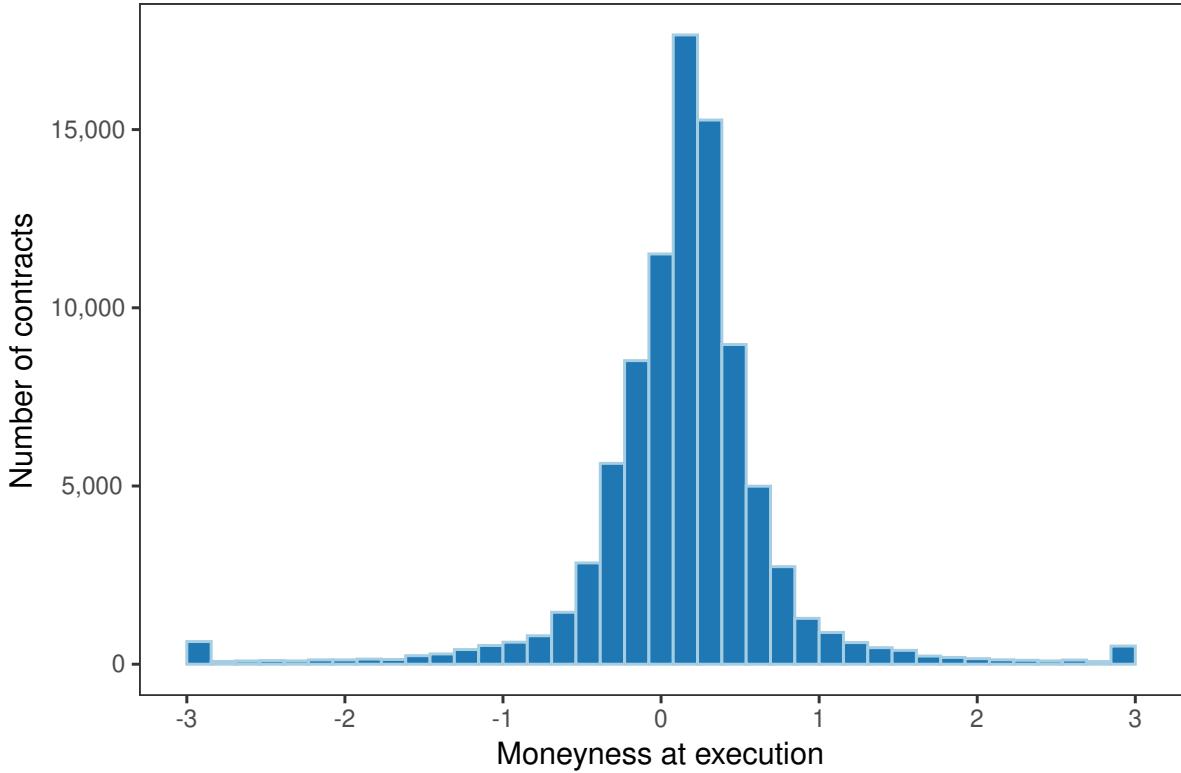


Note. This figure shows the average size of firms' hedging portfolios across the cash distribution. Both portfolio size and cash are measured at the firm-year-quarter level. Hedging portfolios are measured using EUR/USD derivatives outstanding only. The leftmost panel shows the raw average of portfolio size across cash-to-assets bins. The middle panel controls for sector and year-quarter fixed effects. The rightmost panel controls for a measure of risk, the volatility of EBIT-to-assets. Standard errors are computed using the Bayesian bootstrap blocked by firm.

The intuition is that because the firm discounts cash-flows at $\beta V'(L_{t+1})/V'(L_t)$, it assigns a high value to hedges that pay off in future states of the world where liquidity L_{t+1} is low. This includes states where the firm is constrained due to disaster exchange rate realizations. Therefore, even a firm that is unconstrained today may find it profitable to hedge those states. This prediction builds on the results of [Froot \(2001\)](#) in the context of catastrophe insurance and [Rochet and Villeneuve \(2011\)](#) in the context of corporations.¹⁴

¹⁴The same mechanism underlies Proposition 8 in [Rampini and Viswanathan \(2010\)](#) and its numerical counterpart in [Alfaro et al. \(2023a\)](#). In both cases, the gap between future productivity and today's productivity is large enough that high net worth firms always hedge. This is a form of jump risk, which is why it generates hedging from high net worth firms.

Figure 8: Option moneyness



Note. This figure shows the moneyness for all traded EUR/USD options in our sample. Moneyness is calculated as $\pm T^{-1} \log K/S$, where K is the strike, S the spot, and T the tenor, with premultiplying sign +1 for firms that buy EUR and -1 for firms that sell EUR. Values far from zero indicate out-of-the-money options. We winsorize the distribution of moneyness at ± 3 .

6.2 Empirical tests

Firms with larger cash positions do not have smaller derivatives portfolios

We directly test these predictions in the data. To test prediction 1, we use cash-to-assets as proxy for liquidity and assess whether, correlationally, firms eventually hedge less as they accumulate cash. Figure 7, shows the results. We find no evidence that firms with more cash holdings hedge less. The fact that firms with little cash hedge less is known and aligns with the findings of [Rampini et al. \(2014\)](#). What is surprising is that this correlation never turns negative, despite firms not having to post collateral.

An obvious concern with these results is that firms holding more cash are riskier, leading them to simultaneously hold more cash and hedge more. To address this concern, we include sector and year-quarter fixed effects, absorbing aggregate risk and sector-specific risk. The middle panel shows that cash-rich firms hold large hedging

portfolios, even after including these fixed effects. To further address the concern that risk exposures may be firm-specific, we control for firms cash-flow volatility (defined as the standard deviation of EBIT-to-asset). We argue that if firms face large amounts of uninsured risk that leads them to hedge and hold more cash, this risk should manifest in cash-flows. The rightmost panel shows that, again, variation in hedging portfolios remains limited across the cash distribution, with all confidence intervals overlapping.

Another important concern with Figure 7 is that firms across the cash distribution could hedge for different reasons. In the lines of Prediction 2, cash-poor firms could hedge small exchange rate shocks while cash-rich firms could hedge disaster risk. We examine this possibility next.

Firms rarely trade out-of-the-money options

To test prediction 2, we use data on options portfolios. If firms with high liquidity holdings wish to hedge tail risk, they should trade out-of-the-money options. We compute the moneyness of EUR/USD traded in our sample, which we show in Figure 8. We find that firms overwhelmingly trade in-of-the-money options. These findings echo those of [Froot \(2001\)](#) for the insurance market.

7 Model

The empirical analysis from the previous sections shows which firms use derivatives, how much, and at what cost. This section answers three remaining questions. What financial frictions explain hedging demand? How large are these frictions? How much do firms value financial insurance against exchange rate risk? To answer these questions, we build a dynamic corporate finance model with currency risk management. We add two mechanisms to the standard model: earnings smoothing and internal adjustment costs to hedging portfolios. Earnings smoothing generates hedging demand even when firms are unconstrained, and adjustment costs limit hedging even when trading costs are small.

7.1 Setup

Time is discrete and indexed by t . The firm maximizes its value by issuing dividends. It has four sources of funds: internal cash-flows, equity, debt, and derivatives. Three financial frictions explain why financing matters: external equity issuance is costly, borrowing is limited, and firms prefer smooth earnings.

Currency notations

The model is general but we think of the firm as a European exporter facing dollar risk. The exchange rate is E_t , expressed in euro per dollar. Any dollar amount $v_t^{\$}$ therefore has euro value $v_t = E_t v_t^{\$}$. Unless stated otherwise, all monetary variables are in euros.

Cash-flows

Operating cash-flows are exogenous and given by

$$\pi_t = q_t m_t, \quad (13)$$

where $q_t = e^{y_t}$ captures the firm's scale and m_t the profit margin. We think of q_t as the ratio of sales to assets and of π_t as cash-flows normalized by assets, as in Section 4. Firm scale evolves as

$$y_{t+1} = \alpha_y + \rho_y y_t + \nu_{t+1}, \quad (14)$$

where ν is an exogenous shock to the scale of operations. Exchange rates impact profit margins, which evolve as

$$m_{t+1} = \alpha_m + \rho_m(m_t - \alpha_m) + \beta_m \Delta e_{t+1} + \eta_{t+1}, \quad (15)$$

where $\Delta e_{t+1} = \log E_{t+1} - \log E_t$ is the exchange rate shock and η_{t+1} is an exogenous profitability shock. All shocks are independent and normally distributed

$$\nu_t \sim \mathcal{N}(0, \sigma_{\nu}^2), \quad \eta_{t+1} \sim \mathcal{N}(0, \sigma_{\eta}^2), \quad \text{and} \quad \Delta e_{t+1} \sim \mathcal{N}\left(-\frac{\sigma_e^2}{2}, \sigma_e^2\right). \quad (16)$$

Profit margin exposure (15) is the only source of exchange rate risk for firms. It captures in reduced form the fact that exchange rates have a persistent impact on firms' costs and prices, and therefore on profits. Indeed, prices of internationally traded goods frequently take up to a year or more to adjust to exchange rate shocks (Gopinath and Rigobon, 2008; Auer et al., 2021; Amiti et al., 2022). Modeling persistent exchange rate risk is essential to capture the fact that firms use contracts with long maturities (Figure 1).

Beyond the cost of goods sold embedded in (13), the firm also pays fixed operating costs c_f proportional to firm scale q_t . These costs capture the difference between EBIT and dividends that is not due to debt or hedging.

Hedging

Firms can use forward contracts to hedge. We use a tractable geometric model to capture long-term hedging, inspired by the long-term debt literature (e.g., [Cochrane, 2001](#)). A constant fraction δ of outstanding dollar notional $n_t^{\$}$ expires every period. Given forward purchases $h_t^{\$}$, this implies the following dynamics:

$$n_{t+1}^{\$} = (1 - \delta)n_t^{\$} + h_t^{\$}. \quad (17)$$

The firm is hedged at a blended forward rate, which is the average forward rate (in euro per dollar) of outstanding contracts. The blended forward rate evolves as

$$F_{t+1} = \begin{cases} \left(1 - \frac{h_t^{\$}}{n_{t+1}^{\$}}\right) F_t + \frac{h_t^{\$}}{n_{t+1}^{\$}} \times \tilde{F}_t & \text{if } h_t^{\$} \geq 0 \\ F_t & \text{otherwise} \end{cases},$$

where \tilde{F}_t is the forward price of new contracts at t . It is simpler to work with euro variables. Rewriting (17), the dynamics of the euro notional stock n_t are

$$n_{t+1} = [(1 - \delta_n)n_t + h_t] \times \exp(\Delta e_{t+1}). \quad (18)$$

The firm's gains or losses from hedging are

$$g_t = \delta n_t^{\$} (F_t - E_t) = \delta n_t (z_t - 1), \quad (19)$$

where we define the normalized blended forward rate $z_t = F_t/E_t$. Its dynamics are

$$z_{t+1} \times \exp(\Delta e_{t+1}) = \begin{cases} \left(1 - \frac{h_t}{n_{t+1}}\right) z_t + \frac{h_t}{n_{t+1}} \times \tilde{z}_t & \text{if } h_t \geq 0 \\ z_t & \text{otherwise} \end{cases}, \quad (20)$$

with $\tilde{z}_t = \tilde{F}_t/E_t$.

Positive positions indicate that the firm buys euro forward against dollars. This is typically the relevant case for exporters that hedge dollar sales. We therefore focus on positive positions and impose

$$n_t \geq 0 \quad \text{and} \quad \max(-h_t, 0) \leq n_t \quad (21)$$

This specification captures the main features of our setting: firms can hedge long-term, without posting collateral, and without incurring mark-to-market volatility from their book. We do not model any cash collateral constraint, in line with the evidence

shown in Section 5.1. Importantly, firms cannot dynamically replicate any derivative by trading the spot and bonds. This greatly simplifies the hedging decision and remains realistic, since such replication strategies conflict with hedge accounting rules, require large amounts of borrowing, and may generate substantial volatility.

Hedging frictions

Hedging is costly due to persistent deviations from covered interest parity (CIP), as documented in Section 5.2. We model these deviations as a constant wedge κ_0 between the forward price and the spot, so that $\tilde{F}_t = \kappa_0 E_t$. Note that we assume away any carry costs in this specification.

To rationalize the fact that firms do not hedge all of their risk despite the fact that hedging is inexpensive, as shown in Section 4, we introduce adjustment costs to hedging. Adjustment costs are standard in corporate finance (e.g., Myers, 1984) and are an important mechanism through which models generate realistic financing dynamics (Leary and Roberts, 2005).

Deviating from the current hedge portfolio requires paying a menu cost¹⁵

$$\psi(h_t, n_t) = \kappa_1 \mathbf{1} \{h_t \neq \delta n_t\}. \quad (22)$$

Equation (22) captures several frictions in reduced form. First, the hedging strategy is often decided by the board and re-examined periodically. This makes it difficult to adjust the strategy quickly in response to changes in product markets or in financial conditions, which in our model would be captured by shocks to firm scale q_t . Second, hedge accounting constrains the possible strategies and can make it difficult for firms to downsize their positions.

Debt

The firm issues one-period risk-free bonds with face value b_t , with $b_t > 0$ indicating that the firm is borrowing and $b_t < 0$ that it is holding cash. We let the bonds interest rates differ from cash interest rates, so that

$$r(b) = \begin{cases} r_b & \text{if } b \geq 0 \\ r_\ell & \text{if } b < 0 \end{cases}, \quad (23)$$

¹⁵The fact that firms facing more currency risk hedge a larger fraction of that risk rules out time-dependent adjustment à la Calvo.

with $r_\ell \leq 1/\beta - 1 \leq r_b$, where β is the discount rate. Borrowing is constrained:

$$-b_{\min} \leq b_t \leq b_{\max}. \quad (24)$$

Dividends and equity

The firm issues dividends to shareholders d_t given by

$$d_t = (1 - \tau) [\pi_t + g_t - r(b_t)b_t] - \psi(n_t, h_t) - c_f q_t + \Delta b_{t+1}. \quad (25)$$

Here, $\Delta b_{t+1} = b_{t+1} - b_t$ is the net debt issuance. Negative dividends indicate equity issuance.

Equity issuance and smoothing

The first financing friction comes from external financing costs, which we model as a proportional cost λ on equity issuance:

$$\iota(d) = \begin{cases} d & \text{if } d \geq 0 \\ (1 + \lambda)d & \text{if } d < 0 \end{cases}. \quad (26)$$

The firm pays no cost when it issues dividends ($d \geq 0$) but it incurs an extra cost λd if it issues equity ($d < 0$). Equity issuance costs capture costly external financing and distress costs. Capital structure becomes a dynamic problem where firms optimally trade-off debt and equity (Hennessy and Whited, 2005), as well as derivatives hedging (Froot et al., 1993; Rampini and Viswanathan, 2010; Bolton et al., 2011).

The second financial frictions comes from earnings smoothing. We specify

$$\varphi(\iota) = \begin{cases} (1 - e^{-\gamma})/\gamma & \text{if } \gamma > 0 \\ \iota & \text{if } \gamma = 0 \end{cases}. \quad (27)$$

Because there is no distinction between earnings and dividends in the model, we interpret (27) as earnings smoothing. The parameter $\gamma \geq 0$ controls in reduced form how strong smoothing is. The closer γ is to zero, the weaker is earnings smoothing, with $\gamma = 0$ nesting the standard model. Penalizing dividends volatility is common in macro-finance following Jermann and Quadrini (2012), who interpret it as a cost to adjusting the firm's capital structure. We use an exponential specification instead of their quadratic penalty for convenience, though this does not change our results.

Smoothing is mainly generated by two types of frictions. First, shareholders may

wish managers to bear some of the firm's risk to align interests. If a significant fraction of managers' human and financial capital is tied to the firm, they may wish to smooth the firm's performance (Jensen and Meckling, 1976). In that case, γ captures the curvature of managers' utility. Second, hedging removes cash-flow variation due to exchange rates, which is outside of managers' control (DeMarzo and Duffie, 1995). This helps investors and analysts learn about the quality of the firm and its management. In that case, γ captures in reduced form how much firms smooth cash-flows to improve earnings informativeness.

Exit

Firms exit exogenously with probability ϵ . To avoid distorting borrowing decisions, we assume that the firm repays its debt in full upon exit. Equityholders receive what is left of firm total assets, which are normalized to one

$$R_t = 1 - (1 + r(b_t))b_t. \quad (28)$$

Exit serves two purposes. First, it is a parsimonious way to introduce turnover in the model and generate more realistic firm dynamics. Second, it effectively increases the discount rate, which makes numerical resolution easier and faster. In our simulations, we assume that upon exiting, the firm is replaced by an identical copy.

Recursive formulation

There are five state variables $s_t = (y_t, m_t, b_t, n_t, z_t)$, where y is the firm's operating scale, m the profit margin, b the one-period debt, n_t the notional amount hedged, and z the normalized blended forward rate. There are two controls $a_t = (h_t, b_{t+1})$, where h_t denotes new hedges. In recursive form, the problem of the firm writes

$$v(s_t) = \sup_{a_t} \varphi \circ \iota(d_t) + \beta(1 - \epsilon)\mathbf{E}[v(s_{t+1}) | s_t, a_t] + \beta\epsilon R_t \quad (29)$$

subject to (13), (14), (15), (18), (20), (21), (24), (25), (26), (27), (28).

We assume that shareholders are risk-neutral and have a constant discount rate β , as is standard in structural corporate finance.

7.2 Estimation

The model is quarterly. It has 21 parameters. We calibrate 17 of those parameters externally. The remaining 4 parameters are estimated to match 4 empirical moments.

Table 1: Calibrated model parameters

| Parameter | Symbol | Value | Target/Source |
|-------------------------------------|---------------|--------------------|---|
| Financials | | | |
| Discount rate | β | $1.030^{-1/4}$ | Risk-free rate |
| Interest rate on cash | r_L | $1.030^{-1/4} - 1$ | Risk-free rate |
| Interest rate on debt | r_B | $1.045^{-1/4} - 1$ | Corporate bond spread |
| Tax rate | τ | 0.21 | Statutory tax rate |
| Cash limit | b_{\min} | 0.10 | Net debt 10% quantile |
| Debt limit | b_{\max} | 0.40 | Net debt 90% quantile |
| Exit probability | ϵ | 0.02 | Catherine et al. (2022) |
| Foreign exchange | | | |
| CIP deviations (bps) | κ_0 | 3×10^{-4} | Observed CIP deviations |
| Exchange rate volatility | σ_E | 0.05 | Observed volatility |
| Hedging duration | δ | 1.00 | Quarterly hedges |
| Cash-flows | | | |
| Scale drift (%) | α_y | -0.86 | Normalization |
| Scale autocorrelation | ρ_y | 0.88 | Sales-to-assets autocorrelation |
| Scale volatility | σ_ν | 0.18 | Sales-to-assets volatility |
| Margin drift (%) | α_m | 1.85 | EBIT average |
| Margin autocorrelation | ρ_m | 0.55 | EBIT autocorrelation |
| Margin exchange rate exposure | β_m | 0.26 | EBIT currency risk |
| Margin idiosyncratic volatility (%) | σ_η | 1.06 | EBIT standard deviation |

Note. This table summarizes the parameters of our models that are calibrated externally.

Externally calibrated parameters

The discount rate is $\beta = 1.03^{-1/4}$, corresponding to a risk-free rate of 3% annualized. The firm borrows at a spread of 1% annualized over the risk-free rate, so $r_B = 1.04^{1/4} - 1$. It receives $r_L = 1.02^{1/4} - 1$ on cash balances, corresponding to an annualized spread around 1%. The tax rate is $\tau = 21\%$, roughly the statutory tax rate in the Eurozone. We set deviations from CIP $1 - \kappa_0$ to 3 basis points in line with our median estimates of 12 basis points annualized. We take an annualized yearly exchange rate volatility of 10%, which implies $\sigma_e = 5\%$. For the borrowing constraints, we assume that model variables are scaled by total assets and we set $b_{\max} = 0.40$ and $b_{\min} = 0.10$. This roughly corresponds to the 10% and 90% quantiles of net debt in our sample (dlcq plus dlttq minus cheq divided by atq in Compustat). We calibrate the exit probability to $\epsilon = 2\%$ to match the 8% annualized exit rate from [Catherine et al. \(2022\)](#).

We now give an overview of our calibration of the cash-flow process (13, 15). We provide additional details in Appendix E.2. We calibrate y to match the autocorrelation (0.88) and idiosyncratic volatility (18%) of the logged ratio of sales to total assets (saleq divided by atq in Compustat). We calibrate the margin process m to match key

moments of cash-flows, measured as EBIT divided by total assets (*oiadpq* divided by *atq* in Compustat). Specifically, we target the average (1.78%), volatility (2.28%), and autocorelation of cash-flows (0.57). To calibrate the exchange rate exposure, we use the currency risk quantification from Section 4. Specifically, in our baseline, we target a correlation between yearly changes in cash-flows and yearly exchange rate returns of $0.57 = \sqrt{0.32}$, corresponding to the top decile in Figure 2.¹⁶ We also use an alternative target with lower risk by taking $0.39 = \sqrt{0.15}$, corresponding to the ninth decile.¹⁷ In this alternative calibration, we adjust the margin process to match the same targets as before, as shown in Appendix Table G.8.

Estimated parameters

We choose the remaining parameters $\theta = (\lambda, c_f, \kappa_1, \gamma)$ to match empirical moments \hat{m} . We look for parameters θ that minimize the distance between those moments \hat{m} and moments obtained from simulating the model $m(\theta)$. The distance is defined using a weighting matrix $\Omega(\theta)$. The estimation problem thus writes

$$\min_{\theta} (\hat{m} - m(\theta))^{\top} \Omega(\theta) (\hat{m} - m(\theta))$$

In principle, all targeted moments jointly identify all parameters. Nonetheless, we think that some moments are particularly informative for some model parameters. We now describe our rationale for choosing those moments.

Equity issuance cost λ and fixed operating cost c_f . We identify fixed operating costs c_f from dividends issuance because they capture the wedge between operating cash-flows and payouts. For equity issuance costs λ , we use equity issuance, as in [Hennessy and Whited \(2007\)](#). We measure equity and dividends from Compustat Annual following [Catherine et al. \(2022\)](#). Specifically, we compute dividends as sales of common and preferred stock (*sstk*) minus cash dividends (*dv*) and buybacks (*prstkc*). We fill missing observations with zeros and focus on fiscal years 2017 to 2023. Equity issuances are the negative part of dividends, $\max(-d, 0)$. We divide both by total assets (*atq*). After winsorizing at the 1st and 99th percentiles, average dividends are 1.03% of assets and average equity issuances are 0.84% of assets. We divide these annual values by 4 to get quarterly moments of 0.26% and 0.21% respectively.

¹⁶Since our model only has one exchange rate, cash-flow currency risk as defined in Section 4 simplifies to the squared correlation between yearly changes in cash-flows and yearly exchange rate returns.

¹⁷The slight difference with the values reported in Figure 2 reflects the fact that our calibration targets the average of the bootstrap draws instead of the point estimates in the full sample.

Adjustment costs κ_1 and smoothing γ . Adjustment costs limit hedging, while smoothing push firms to hedge more. We jointly identify these parameters by leveraging the fact that firms facing more FX risk hedge a larger fraction of that risk. Intuitively, the level and the slope of the fraction of risk hedged as a function of the underlying exposure can identify both parameters. For the baseline calibration in which FX explains 33% of cash-flow variance (higher risk), we target a fraction of risk hedged of 84%. For the alternative calibration in which FX explains 15% (lower risk), we target 37%.¹⁸ We do this by solving the model twice, once under each calibration.

7.3 Results

We solve the model using standard numerical dynamic programming, as described in Appendix E.1. We first estimate a standard model in which we shut down smoothing ($\gamma = 0$) and adjustment costs ($\kappa_1 = 0$). Table 2, Model 1, shows the results. Our equity issuance costs estimate are closely in line with the literature. Yet, that financing costs alone generate insufficient hedging demand, even without any adjustment costs. This is because freely trading one-period risk-free bonds gives the firm enough flexibility to face currency volatility. As a consequence, even small CIP deviations limit hedging.

We then estimate the full model, allowing for both smoothing ($\gamma > 0$) and adjustment costs ($\kappa_1 > 0$). The results in Table 2, Model 2, point to large enough smoothing that CIP deviations do not limit hedging, paired with large adjustment costs that explain why firms do not hedge all of their risk. Multiplied by the dividends issuance target (0.26%), smoothing γ maps to a moderate coefficient of relative risk-aversion around 0.04.

7.4 Model validation

Before using the model for counterfactuals, we check that it can replicate two empirical facts. The first fact is the correlation between hedge portfolio maturity and currency risk. The second fact is that the short-run response of hedging demand to CIP shocks is small.

Portfolio maturity

In Section 4, we document a correlation between long-term hedging and currency risk. We interpret this correlation as reflecting unobserved heterogeneity in currency risk

¹⁸We target moments obtained by first computing average currency risk before and after hedging and then taking the ratio. The order makes no big difference: taking the ratio first and computing the asset-weighted average would lead to targets of 80% and 41% respectively. As explained in Footnote 17, we target the average of the bootstrap draws.

Table 2: Estimated model parameters and moments

| Parameter | Symbol | Model 1 | Model 2 | Data/Target |
|--|------------|------------------------|------------------------|----------------------------------|
| | | $\gamma, \kappa_1 = 0$ | $\gamma, \kappa_1 > 0$ | |
| <i>Panel A. Estimated parameters</i> | | | | |
| Equity issuance cost | λ | 0.12 | 0.13 | Average equity issuance |
| Fixed operating cost (%) | c_f | 1.02 | 1.03 | Average dividends issuance |
| Smoothing | γ | – | 16.3 | Fraction of currency risk hedged |
| Hedge adjustment cost (bps) | κ_1 | – | 74 | Fraction of currency risk hedged |
| <i>Panel B. Simulated and targeted moments</i> | | | | |
| Average equity issuance | – | 0.25% | 0.36% | 0.21% |
| Average dividends issuance | – | 0.26% | 0.27% | 0.26% |
| Fraction hedged (high risk) | – | 43.6% [†] | 81.7% | 83.7% |
| Fraction hedged (low risk) | – | – | 37.8% | 37.3% |

Note. This table reports estimated model parameters (Panel A) and selected simulated moments versus targets (Panel B). A dagger (\dagger) superscript indicates an untargeted moment.

duration. We now show that the model can replicate this correlation with the same interpretation. Since both portfolio maturity and currency risk duration are fixed in the model, we conduct a comparative static.

The relevant model parameters are the autocorrelation of profit margins ρ_m and the portfolio maturity δ . Currency risk duration is controlled by ρ_m . Given an autocorrelation ρ_m , we solve numerically for the maturity δ that maximizes expected firm value. Figure G.14 plots firm value across values of δ relative to $\delta = 1.0$. We find that the optimal portfolio maturity for our baseline calibration of $\rho_m = 0.55$ is close to 2 quarters (δ around 0.5). This is remarkably similar to the sectoral averages shown in Figure G.6. Furthermore, the optimal maturity increases slightly with persistence. Finally, the gains from having access to long-term product are large, on the order of 1% of firm value.

Response to CIP shocks

In Section 5.3, we argue that trading costs are small on the grounds that the short-run slope of hedging demand with respect to trading costs is identified but small. By contrast, our empirical strategy does not identify the long-run slope. The model allows us to compute both slopes structurally. We use the short-run slope to validate the model and the long-run slope to inform us on the economic cost of CIP violations.

To compute these slopes, we draw firms from the steady state distribution of the model. This is $t = 0$. From $t = 1$ onward, we fix annualized CIP deviations to 22 basis points, an 83% increase from our baseline of 12 basis points. The slope of hedging

demand to trading costs is defined as

$$s(t) = \frac{1}{N} \sum_{i=1}^N \frac{n_{it} - n_{i0}}{10}.$$

8 Counterfactuals

We use the model to compare firm value under the baseline calibration (θ^*) and under infinite hedging costs (θ^∞). We define the value gains from hedging Δv as

$$\Delta v = v(\theta^*) - v(\theta^\infty). \quad (30)$$

Here, we let $v(\theta) = \mathbf{E}_\theta v(s \mid \theta)$ denote the average firm value under the stationary distribution. To attribute value gains from hedging to different financial frictions, we use the present value formula $v(\theta) = (\mathbf{E}\varphi \circ \iota(d) + \beta\epsilon\mathbf{E}R)/(1 - \beta(1 - \epsilon))$. Therefore

$$v(\theta) = \underbrace{\frac{\mathbf{E}\iota(d) - \mathbf{E}d}{1 - \beta(1 - \epsilon)}}_{\text{Financing costs } v_F(\theta)} + \underbrace{\frac{\mathbf{E}\varphi \circ \iota(d) - \mathbf{E}\iota(d)}{1 - \beta(1 - \epsilon)}}_{\text{Smoothing penalty } v_S(\theta)} + \underbrace{\frac{\mathbf{E}d}{1 - \beta(1 - \epsilon)}}_{\text{Risk-neutral } v_R(\theta)} + \underbrace{\frac{\beta\epsilon\mathbf{E}R}{1 - \beta(1 - \epsilon)}}_{\text{Exit shock } V_E(\theta)}.$$

The first term is the value of a dividends stream discounted at the risk-neutral rate, without any equity issuance or smoothing frictions. The second term captures financing costs. The third term isolates volatility costs generated by the smoothing motive. Both the second and last term are negative because our functional forms for equity issuance ι and smoothing φ are concave. Applying this decomposition to value gains (30) gives, in relative terms:

$$\underbrace{\frac{\Delta v}{v}}_{\text{Total hedging gains}} = \underbrace{\frac{\Delta v_F}{v}}_{\text{Financing gains}} + \underbrace{\frac{\Delta v_S}{v}}_{\text{Smoothing gains}} + \underbrace{\frac{\Delta v_R}{v}}_{\text{Risk-neutral}} + \underbrace{\frac{\Delta v_E}{v}}_{\text{Exit shock}}. \quad (31)$$

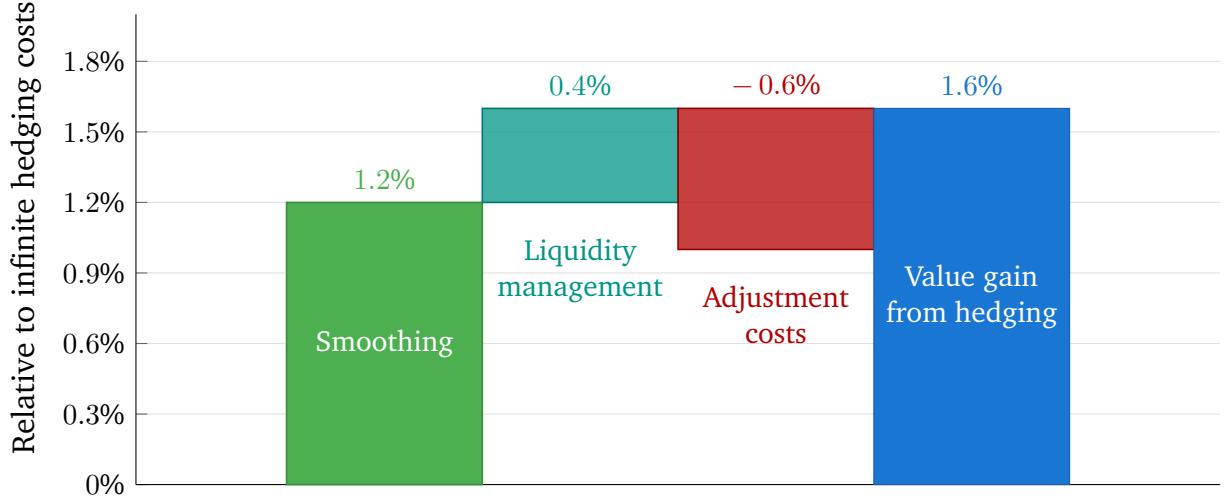
The risk-neutral comparison mainly captures hedging adjustment costs.

Figure 9 plots the value gains from hedging and its decomposition. In our baseline model, hedging increases firm value by 1.6%. The main channel for this increase comes from dividends smoothing. The gain from liquidity management, while not negligible, is an order of magnitude smaller and comparable with the cost of hedging.

9 Conclusion

This paper combines novel granular data on financial hedging with a structural corporate finance model to quantify the value of financial insurance against foreign exchange risk.

Figure 9: Value gains from FX hedging



Note. The figure decomposes the value effect of FX hedging relative to a counterfactual with infinite hedging costs. “Dividends smoothing” is the gain from smoothing alone. “Liquidity management” is the additional gain computed by discounting cash flows with $\gamma = 0$. “Adjustment costs” are the negative impact from trading and adjustment frictions. The final bar reports the net value gain from hedging.

Our findings imply four main lessons. First, currency risk is concentrated in a few global firms. These firms hedge most, but not all, of that risk using financial derivatives. Second, hedging is inexpensive because firms do not collateralize their contracts. This implies that dealer banks bear counterparty risk. Banks charge firms a risk premium embedded in the forward price. This premium and frictions create a wedge over the no-arbitrage forward price to which hedging demand responds. However, these deviations remain small in magnitude and cannot distort hedging given our estimates. Third, determinants of currency risk predict the level and maturity of hedging demand but liquidity does not. Fourth, our estimated model reveals that liquidity management plays a limited role because access to cash and debt instruments allow firms to hedge this risk well. Instead, most of the benefits are derived from smoothing earnings.

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Appendix

A Case studies and survey evidence

A.1 Survey literature

A.2 Case studies

B Theoretical appendix

B.1 Framework

Hedging Euler equation

The derivation of the first order condition for hedging is standard. Write the Bellman equation:

$$\begin{aligned} V(L_t) &= \sup_{H_{t+1}, B_{t+1}} \Phi(D_t) + \frac{\mathbf{E}_t V(L_{t+1})}{1+r}, \\ \text{s.t. } & D_t = L_t + B_{t+1} - \kappa |H_{t+1}|, \\ & L_{t+1} = \Pi(\Delta E_{t+1}) + H_{t+1} \Delta E_{t+1} - (1+r)B_{t+1}, \\ & B_{\min} \leq B_{t+1} \leq B_{\max}, \\ & \chi |H_{t+1}| \leq \max(L_t, 0). \end{aligned}$$

Let $\mu_t \geq 0$ be the Lagrange multiplier on the collateralization constraint. Clearly, either $H_{t+1} = 0$ or the following first order condition holds

$$\mathbf{E}_t \left[\frac{\Delta E_{t+1}}{1+r} V'(L_{t+1}) \right] - [\kappa \times \Phi'(D_t) + \chi \mu_t] \times \text{sgn } H_{t+1} = 0.$$

By the envelope theorem, $V'(L_t) = \Phi'(D_t) + \mu_t \mathbf{1}\{L_t > 0\}$ so the term in brackets writes:

$$\kappa \Phi'(D_t) + \chi \mu_t = V'(L_t) \left(\kappa + \frac{\mu_t (\chi - \kappa \mathbf{1}\{L_t > 0\})}{V'(L_t)} \right) = V'(L_t) (\kappa + \lambda_t).$$

Rearranging gives Equation (1), which holds at any interior solution

$$\text{sgn } H_{t+1} \times \mathbf{E}_t \left[\frac{V'(L_{t+1})}{(1+r)V'(L_t)} \Delta E_{t+1} \right] = \kappa + \lambda_t.$$

Optimal hedging formula

We now derive the mean-variance minimization objective and the optimal hedging formula. We approximate the value function around $\Delta E_{t+1} = 0$, implying $\bar{L}_{t+1} = \Pi(0) - (1+r)B_{t+1}$:

$$V(L_{t+1}) = V(\bar{L}_{t+1}) + (\Delta \Pi_{t+1} + H_{t+1} \Delta E_{t+1}) V'(\bar{L}_{t+1}) + \frac{(\Delta \Pi_{t+1} + H_{t+1} \Delta E_{t+1})^2}{2} V''(\bar{L}_{t+1}),$$

where $\Delta\Pi_{t+1} = \Pi(\Delta E_{t+1}) - \Pi(0)$ and omitting $O(\Delta\bar{L}_{t+1}^3)$ errors. Recall that $\mathbf{E}_t H_{t+1} \Delta E_{t+1} = 0$. Combining the approximation with the Bellman equation and collecting terms in H_{t+1} :

$$\max_{H_{t+1}} \frac{V''(\bar{L}_{t+1})}{2(1+r)} \text{Var}_t (\Delta\Pi_{t+1} + H_{t+1}\Delta E_{t+1}) + \Phi(D_t) - \mu_t \chi |H_{t+1}|.$$

The next step substitutes $\Phi(D_t) - \mu_t \chi |H_{t+1}|$ with $V'(L_t)(\kappa + \lambda_t) |H_{t+1}|$ in the objective. Formally, this is replacing Φ with its supporting hyperplane at the optimum and using the envelope theorem. This substitution simply turns out to make the problem more interpretable economically. After rearranging, we get the mean-variance program

$$\min_{H_{t+1}} \text{Var}_t (\Delta\Pi_{t+1} + H_{t+1}\Delta E_{t+1}) + 2(\kappa + \lambda_t) |H_{t+1}| \times \frac{V'(L_t)(1+r)}{V''(\bar{L}_{t+1})} \quad (\text{B.1})$$

To see that the two programs agree, one can simply check that they have the same first order conditions—which are also sufficient given convexity. This argument assumes that the envelope theorem still holds despite the error introduced by our approximation of V . It is then straightforward to derive the optimal hedging policy.

B.2 Robust risk management predictions

In this section, we derive two analytical predictions of liquidity management models for hedging demand. We use liquidity management to refer to settings in which financial frictions generate demand for liquid assets. The main friction we consider here is external financing costs, following Froot et al. (1993). We derive results in a general continuous-time model, which nests our stylized framework.

Setup

The firm has capital K and idiosyncratic productivity A . Productivity A evolves exogenously

$$dA_t = \mu_A(A_t)dt + \sigma_A(A_t)dZ_t,$$

where Z is a standard Brownian motion. Production generates a profit flow

$$d\Pi_t = \mu_\Pi(A_t, K_t)dt + \sigma_\Pi(A_t, K_t)dA_t + \underbrace{\beta(A_t, K_t)dE_t}_{\text{Exchange rate risk}},$$

which is exposed to exchange rates shocks. Exchange rate shocks follow a Lévy process

$$dE_t = \underbrace{\sigma_E dB_t}_{\text{Frequent and small shocks}} + \underbrace{\int_{\mathbf{R}} \ell N(dt, d\ell)}_{\text{Rare disasters}}$$

which has two components: a standard Brownian component B and a Poisson component N that captures rare disasters. We assume that disasters arrive at constant intensity ν and law μ (so the Lévy measure is $\Lambda(d\ell) = \nu\mu(d\ell)$). We further assume that $\int_{\mathbf{R}} \ell \Lambda(d\ell) = 0$.

Capital accumulation is standard

$$dK_t = (\iota_t - \delta)K_t dt,$$

where investment is $I = \iota K$, subject to adjustment costs $\Psi(I, K)$. The firm can also trade a forward contract on exchange rates with price F_t , evolving as

$$dF_t = F_t dE_t.$$

We let q be the quantity of such contracts the firm trades, and we let be $H = qF$ the corresponding notional, so $q_t dF_t = H_t dE_t$. Liquid assets, which can also be interpreted as net worth, evolve as

$$dL_t = d\Pi_t + rL_t dt - \Psi(I_t, K_t) dt - dD_t + H_t dE_t - \kappa_1 |H_t| dt.$$

We assume that all sources of risk (Z , B , and N) are independent.

Financial frictions

The firm faces three financial frictions. First, if liquid asset holdings L reach zero, the firm must default or raise equity, which is costly. Specifically, we assume that issuing e dollars of equity generates costs $\Phi(e, K)$. Second, liquid assets earn interests r which are smaller than the discount rate ρ of shareholders. Third, there is no long-term debt or borrowing. This is not important for our results, so long as borrowing is constrained.

Recursive problem

Let $S = (A, K, L)$ denote the state vector. The controls are investment I , hedging H , and dividends payout D . This is a standard impulse-control problem. The value function solves the Hamilton–Jacobi–Bellman variational inequality (e.g., [Øksendal and Sulem, 2019](#))

$$\max \left(\underbrace{\sup_{H, \iota} \mathcal{L}V - \rho V}_{\text{Continuation problem}}, \underbrace{1 - V_L}_{\text{Dividends issuance}}, \underbrace{KV - V}_{\text{Equity issuance}}, \underbrace{-V}_{\text{Default}} \right) = 0.$$

The continuation problem is the standard investment and hedging problem of the firm. The other three pieces of this equation each define a region for corporate finance decisions. The continuation problem is defined by the operator

$$\begin{aligned} \mathcal{L}V &= \mu_A V_A + \frac{\sigma_A^2}{2} V_{AA} + (\iota - \delta) K V_K + (\mu_\Pi + \sigma_\Pi \mu_A + r L - \Psi(\iota K, K) - \kappa_1 |H|) V_L \\ &\quad + \frac{(\sigma_\Pi \sigma_A)^2}{2} V_{LL} + \sigma_A^2 \sigma_\Pi V_{AL} \\ &\quad + \frac{1}{2} (\beta + H)^2 \sigma_E^2 V_{LL} + \int_{\mathbf{R}} \left[V(A, K, L + (\beta + H)\ell) - V(A, K, L) \right] \Lambda(d\ell). \end{aligned}$$

The equity issuance operator is $\mathcal{K}V(A, K, L) = \sup_e V(A, K, L + e) - \Phi(e, K)$.

We make the following assumptions: (i) the HJB-VI has a unique solution, (ii) this solution is concave in L and V_L is continuous, (iii) and for any point $S = (A, K, L)$ in the state space, there

exists L' such that $V_L(A, K, L') \geq 1$.

Assumption (i) is purely technical, with existence being the only substantive requirement, as uniqueness follows generically in the viscosity sense. Assumption (ii) reflects a standard economic outcome of corporate finance models. It can be enforced by letting the firm trade additional financial products (see [Reppen et al., 2020](#)). Assumption (iii) is purely economic and is substantive. It implies that regardless of its current productivity and capital, the firm will eventually issue dividends if it accumulates enough cash. All of these properties hold in usual models, such as [Bolton et al. \(2011\)](#).

Together, assumptions (ii) and (iii) have an intuitive implication: as the firm accumulates cash, financing frictions are relaxed, and the firm becomes risk-neutral. To see why this is true, note that there exists a smallest value $L^*(A, K)$ for any point S such that $V_L(A, K, L^*(A, K)) = 1$. The mapping $(A, K) \mapsto L^*(A, K)$ traces the dividends issuance boundary. Since $V_L(A, K, L) = 1$ for all $L \geq L^*(A, K)$, we also have $V_{LL}(A, K, L) = 0$.

Two predictions for hedging

The hedging problem is obtained by isolating the terms in H . It is

$$\sup_H -\kappa_1 |H| V_L + \frac{1}{2} \sigma_E^2 (\beta + H)^2 V_{LL} + \int_{\mathbf{R}} [V(A, K, L + (\beta + H)\ell) - V(A, K, L)] \Lambda(d\ell).$$

Let us assume that the optimal hedging policy verifies $H < 0$. The first order condition writes

$$0 \in - \underbrace{\kappa_1 V_L \partial |H|}_{\text{Marginal cost of hedging}} + \underbrace{\sigma_E^2 (\beta + H) V_{LL}}_{\text{Marginal value of hedging Brownian shocks}} + \underbrace{\int_{\mathbf{R}} V_L(A, K, L + (\beta + H)\ell) \Lambda(d\ell)}_{\text{Marginal value of hedging disasters}}, \quad (\text{B.2})$$

where $\partial |H|$ denotes the subgradient, that is 1 if $H > 0$, -1 if $H < 0$, and $[-1, 1]$ if $H = 0$.

Consider first the case in which there is no disaster risk (so $\Lambda = 0$). The optimal hedging policy simplifies to

$$H = \begin{cases} -\beta + \kappa_1/\gamma & \text{if } \beta > \kappa_1/\sigma_E^2 \gamma \\ 0 & \text{if } |\beta| \leq \kappa_1/\sigma_E^2 \gamma \\ \beta - \kappa_1/\gamma & \text{if } \beta < -\kappa_1/\sigma_E^2 \gamma \end{cases}.$$

where $\gamma = -V_L/V_{LL}$ is the firm's absolute risk-aversion. Notice the similarity with Equation (2). The mean-variance approximation we considered in our stylized framework is exact in continuous-time and holds much more generally. Now, as the firm accumulates cash, it becomes risk-neutral. This implies that $\kappa_1/\sigma_E^2 \gamma$ becomes infinite, so we always get $H = 0$.

Prediction 3. *Hedging benefits go to zero as firms accumulate liquidity, assuming no tail risk.*

Now, consider the general case. As the firm accumulates liquidity, V_{LL} goes to zero. If the margin value of hedging disasters is large enough, even cash-rich firms will hedge. Even more, disasters are the only reason why they hedge, and their policy will be to hedge as if there were

no Brownian shocks. Formally, at $L^*(A, K)$, the first order condition writes

$$0 \in -\kappa_1 V_L \partial |H| + \int_{\mathbf{R}} V_L(A, K, L^*(A, K) + (\beta + H)\ell) \Lambda(d\ell).$$

If disaster risk is large enough, it can push the firm into the constrained region $L + \beta\ell \ll L^*$ for $\ell \ll 0$, making it valuable to hedge.

Prediction 4. *Firms with high liquid assets holdings benefit from hedging disaster risk first.*

This prediction is new in a production framework, but the key insights are not. To our knowledge, [Froot \(2001\)](#) was the first to notice that standard risk management theory implies that disasters risk is the most valuable to hedge for unconstrained firms. In subsequent work, [Rochet and Villeneuve \(2011\)](#) use jump risk to generalize these insights to dynamic corporate finance settings.

C EMIR Appendix

We access EMIR reports through the ECB's Virtual Lab. We use only state files, which list open transactions that have not yet matured. Throughout, we refer to each observation as a transaction. Table C.1 summarizes the main variables used in our analysis.

Table C.1: Main variables from the EMIR dataset

| Variable | Obs. | Type | Description | Section |
|----------------------|--------|--------|---|---------|
| Contract type | Yes | Categ. | Forward, Future, Swap, Option, Other. | C.1 |
| Underlying | Yes | Categ. | EUR/USD, GBP/JPY, ... | C.1 |
| Reporting timestamp | Yes | Date | | C.1 |
| Execution timestamp | Yes | Date | | C.1 |
| Maturity date | Yes | Date | | C.1 |
| Strike/Forward price | Partly | Cont. | Observed variables need cleaning | C.1 |
| Gross notional | Partly | Cont. | Reported value converted to EUR | C.3 |
| Delta | No | Cont. | Computed from contract characteristics | 3.4 |
| Net notional | No | Cont. | $\text{Delta} \times \text{Gross notional}$ | 3.4 |

Note. This table summarizes the main variables from EMIR used in our analysis and how they are constructed. Obs. stands for “Observed,” “Cont.” stands for continuous and “Categ.” for categorical.

C.1 Preliminary cleaning

Identifying transactions by nonfinancial firms. We focus on currency and commodity derivatives. In our initial request, we remove transactions where both counterparties can be clearly identified as financial firms. Using ESA sector codes, we remove any deal where *at least one* counterparty is a money-market fund (S123), an investment fund (S124), an insurance company (S128), or a pension fund (S129).¹⁹ These transactions almost never involve nonfinancial firms, as they are typically intermediated by dealers. We also remove transactions where *both* entities

¹⁹Firms frequently use a financial subsidiary to hedge, usually registered in the category S125 (other financial intermediary).

are deposit-taking corporations (S122), a sector that includes most dealers. Because ESA codes are not always consistently maintained (especially early in our sample), we also keep a list of financial institutions which includes G16 dealers, CCPs, and G-SIBs. We remove any transaction where both parties appear on that list.

Preliminary cleaning.

- The EMIR Trade ID alone is not unique, so we concatenate each counterparty's LEI with the Trade ID to form a single unique transaction identifier.
- We discard deals whose termination date is before the reference period. If a maturity date is missing, we fill it using the termination date.
- We remove any observation lacking side (buyer/seller) information. Before deduplicating, we populate relevant variables where possible to minimize data loss.

Contract characteristics.

- We use ANNA DSB public reports to match product IDs. If available, we replace EMIR fields (product classification, option exercise style, option type, contract type, notional currency 1, delivery type, maturity date, price multiplier) with those from ANNA DSB.
- When the variable option type is PUTO, CALL, or OTHR, we set the contract type to option.
- foreign exchange steps
 - impute currency
 - impose alphabetical order in exchange rates
 - contract price for forwards, futures, and swaps

Deduplication. When we observe both legs of a trade, we impose a consistency filter. Specifically, we impose that there be a buyer and a seller, that both counterparties agree on the notional amount and [x]. For other fields, we systematically keep the dealer's report whenever possible. We also fill missing fields using both observations.

Additional cleaning steps.

- currency conversions
- strike price

C.2 Consolidation

EMIR reports are identified by a Legal Entity Identifier (LEI) while Compustat uses a gvkey. There can be many, sometimes hundreds, of LEIs associated with one gvkey. During the accounting consolidation process, intragroup derivatives are cancelled, and non-intragroup derivatives are

consolidated in the head. We therefore need to match individual LEIs to their respective heads. We proceed in four steps, which are summarized in Figure G.1.

We now describe each step in more details.

1. Using GLEIF’s ISIN-to-LEI dataset, we match Compustat-listed firms to their LEIs.²⁰ For firms not found in the dataset, we verify LEIs manually.
2. We then apply GLEIF’s publicly available annual consolidation to group together LEIs that appear in EMIR. This consolidation is annual.
3. Name consolidation. We review potential mismatches by comparing entity parent-subsidiary relationships from publicly available sources and corporate disclosures. Where we identify clear errors, we remove or correct the links in our master file. We then attempt to match all remaining unmatched LEIs to a head based on name similarity and additional verification with corporate websites or databases.
4. Compustat consolidation. We further consolidate Compustat groups to account for public subsidiaries of another public group. A notable example is Christian Dior, listed publicly but consolidated inside LVMH since 2017.

C.3 Correcting misreported currencies

Notionals on FX derivatives may be reported in either currency of the pair. However, the reporting currency is sometimes mislabelled. For pairs with large exchange rates, mislabelling can inflate reported notionals by factors as high as 100 for USD/JPY and 10,000 for EUR/IDR.

We do so using a simple statistical of mislabeling at random. The idea behind our procedure is that contracts with abnormally large notionals relative to firm size are likely misreported. Figure G.3 illustrates this by comparing the distribution of gross notionals scaled by firm total assets for EUR/GBP and EUR/JPY contracts. There is a visible spurious mass in the EUR/JPY distribution corresponding to notionals inflated by a factor 100. As shown, our procedure removes this spurious mass.

D Data appendix

D.1 Financial statements (Compustat)

Financial statements are from WRDS Compustat Global Fundamentals Quarterly. We apply standard filters to select consolidated financial statements (`consol` equals “C”) industrial firms (`indfmt` equals “INDL”) with standardized formats (`datafmt` equals “HIST_STD”). We observations where either the incorporation country (`fic`) or its location (`loc`) is in our country set (Euro Area, Denmark, Sweden, Switzerland, and Norway). We prefer quarterly reporting (`rp` equals “Q”) over semi-annual frequency when both are available, and we limit the panel to true quarter-length reports (`pqd` equals 3).

²⁰See <https://www.gleif.org/en/lei-data/lei-mapping/download-isin-to-lei-relationship-files>.

All accounting variables are converted to euros using WRD's daily exchange rate table (`comp_global_daily.wrds_g_exrate`) at the date of reporting (`datadate`) based on the currency of reporting (`curcdq`). We keep observations from January 2000 onward to align with the euro era and remove firms with non-positive total assets. All key ratios are winsorized at the 1st and 99th percentiles.

To construct annualized cash-flows at the quarterly frequency, we compute the cumulative sum of EBIT (operating income after depreciation, `oiadp`) and pretax income (`piq`), normalized by total assets. We also compute their year-over-year changes, as explained in the main text. We remove financials, insurers, real-estate, and holding company sectors (SIC 60–67) from the estimation universe.

D.2 French PPI microdata (OPISE)

We obtain microdata underlying the French Producer Price Index (PPI). These data are from the Observation of Prices in Industry and Services (OPISE), which is a representative survey. Firms are selected based on their sales within 4-digit industries to cover at least 40% of each product market. Firms then select their core products and report prices for these products at the monthly frequency. We refer to [Lafrogne-Joussier et al. \(2023\)](#), and the references therein, for a thorough description of the data.

We focus on manufacturing. For each year, the data come in two files: one with prices and one with product codes and sales weights. We prepare the data as follows. First, we focus on output prices (`indicateur` equals “C”, “E1”, or “E9”) and drop products names and weights for which no prices are available for that year. We define a price change as the log price difference at the product level (`idse`). We experiment with several lengths of time for price differences, although our baseline is quarterly (3 months). To aggregate log price differences at the firm level, our baseline is to weight all price changes equally. As a robustness, we also weight prices by sales (ponderation of `idperi` by `gvkey`).

Firms in OPISE are uniquely identified by an identifier (`idfour`). We first map this identifier to the main French statistical identifier for firms (`siren`). We then map those to Compustat firms (`gvkey`) by matching firms by on names. Note that one Compustat firm may consolidate many French legal entities.

D.3 Markups and high-frequency interdealer quotes (LSEG Tick History)

Measurement

We obtain high-frequency interdealer quotes from LSEG Tick History data. We use quotes of the EUR/USD spot and forward premium at the 1 month, 2 months, 3 months, 6 months, and 1 year tenor. We then construct bids and asks from these data, and compute the markup as defined in Equation (11). We use the most recent intedealer quote at the time of execution and interpolate linearly across tenors following [Hau et al. \(2021\)](#).

We implement the following cleaning steps:

1. During COVID, many EUR/USD forward prices are mistakenly quoted in EUR per USD instead of the market convention of USD per EUR, despite our preliminary cleaning steps. This appears very clearly in Figure D.1: some points line up on the hyperbola defined by $x \mapsto 1/x$ instead of the 45-degree line. We flag a contract as misreported if its markup is larger under the reported forward price than under its inverse. When that is the case, we replace the forward price with its inverse.
2. We drop observations for which the most recent interdealer spot price quote is more than 30 seconds old.
3. We drop observations for which the absolute markup is larger than 100 basis points (2.7% of observations).
4. We also restrict the sample to contracts executed in 2020 or after to be consistent with collateral measurement.

Markups

Figure G.10 shows that forward prices on EUR/USD contracts in EMIR track interdealer prices extremely closely, with an R^2 above 99%. This shows that forward prices reported in EMIR are precise after implementing the cleaning steps described above. To ensure that this is not an artifact of cleaning or variable definition, Table G.6 shows that EMIR prices still track interdealer prices well if we measured markups in levels, used a more lenient threshold for outliers, or did not drop outliers at all.

Figure G.11 shows the distribution of markups. As expected given the previous results, markups are small. For the overwhelming majority of contracts, markups are slightly positive, on the order of a few basis points. Our findings are in line with Figure 2 in Hau et al. (2021), which shows the same measure in levels. We find a tighter distribution of markups, which reflects the fact that firms in our sample are large, sophisticated, and publicly listed firms. The median markup is on the order of a few basis points.

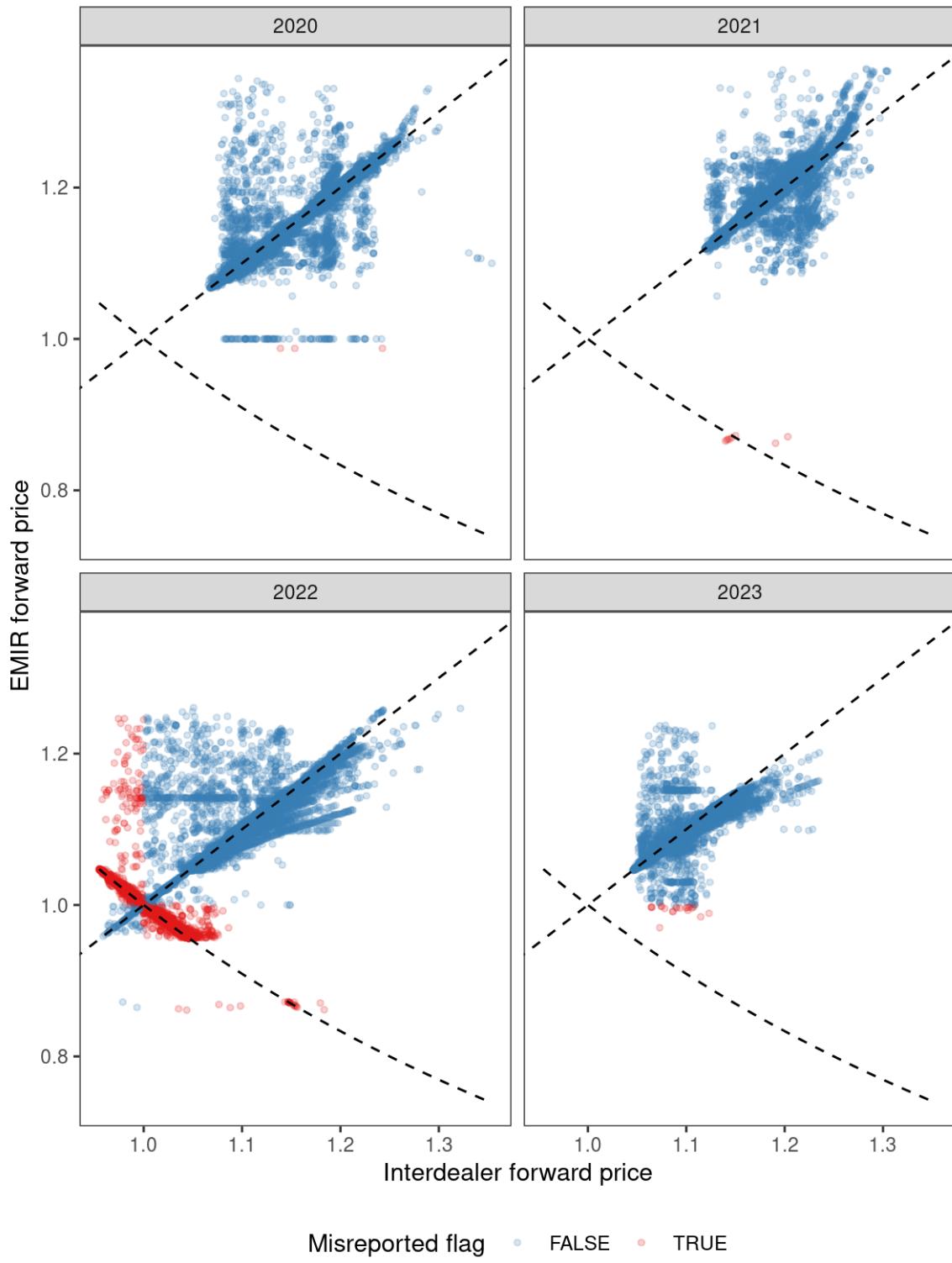
E Model appendix

E.1 Numerical resolution

Value function iteration

We solve the model numerically using standard discrete dynamic programming techniques. We discretize the states collected in $s_t = (y_t, m_t, b_t, n_t, z_t)$, controls $a_t = (h_t, b_{t+1})$, and shocks $u_t = (\nu_t, \eta_t, \Delta e_t)$. We use uniform grids for all variables. For the cash-flow process, the grids for logged scale y_t and margins m_t are centered using unconditional standard deviations. The grid for debt b_t runs from $-b_{\min}$ to b_{\max} , with 31 points. Turning to hedging, the grid for n_t runs from 0 to $[x]$ with 11 points and that for z is centered around κ_0 with width $3.5\sigma_e$ and 11 points. We use a change of variable $u = h - \delta n$ for the hedging control. The grid for u runs from $[x]$ to $[x]$ with 31 points. We discretize normally distributed shocks ν (5 points), Δe (7 points), and η (5 points), using Gauss–Hermite quadrature weights (FastGaussQuadrature in Julia).

Figure D.1: Markup cleaning step 1 – Detecting misreported observations for 2022



Note. This figure illustrates that some EUR/USD forward contracts are quoted in EUR per USD instead of USD per EUR in 2022. We plot EMIR forward prices against interdealer quotes from LSEG before any markup cleaning. Graphically, misreported contracts line up on the hyperbola defined by $x \mapsto 1/x$. Red dots show contracts that we flag as misreported, and blue dots show other contracts.

We use value function iteration to solve the Bellman equation numerically. We initialize $V_n(s) = 1$ for every s on the grid. We find the optimal control using grid search and update the value function

$$V_{n+1}(s) = \max_a \varphi \circ \iota(d(s, a)) + \beta \sum_u \omega_u V_n(s'(s, a, u)) + \beta \epsilon x(s'(s, a, x)). \quad (\text{E.1})$$

To integrate out the shocks x in the continuation value, we use Gauss–Hermite quadrature. Numerical integration requires evaluating the function between grid points, which we do using linear interpolation. If the evaluation point falls outside the grid, we use linear extrapolation. We stop iterating when the distance between two consecutive value functions $\Delta = \|V_{n+1} - V_n\|_\infty$ reaches a predetermined threshold. Since iterating on (E.1) alone can be slow, we add a policy iteration step in which we skip the grid search. We perform 30 iterations in each step until we reach $\Delta \leq 10^{-2}$, and then increase this number to 50 until we reach $\Delta \leq 10^{-4}$.

Simulated method of moments

Having solved for the value and policy functions for a set of parameters θ , we simulate the model for N firms over T time periods, after discarding an initial burn-in period to ensure that we have reached the stationary distribution. We then compute moments from the simulated model $m(\theta)$.

To find parameters that minimize the distance between simulated moments and empirical targets, we look to approximate numerically the map $F : \theta \mapsto m(\theta)$ numerically, in the spirit of Catherine et al. (2024). We proceed in four steps:

1. Draw K parameter vectors using Halton sequences, solve the model at each draw, and compute the simulated moments.
2. Use a neural network to find a surrogate \hat{F}_K for F based on Step 1 draws.
3. Find parameters $\hat{\theta}_K$ that minimize the distance between approximated moments $\hat{F}_K(\theta)$ and target moments \hat{m} using Nelder–Mead starting from the best candidate.
4. Verify that the candidate solution is optimal for the true map F using Nelder–Mead initialized at $\hat{\theta}_k$.

E.2 Cash-flow process calibration

This section describes our calibration for the cash-flow process defined in Equations (13), (14), and (15). There are 7 parameters to calibrate: 3 for the scale process $(\alpha_y, \rho_y, \sigma_\nu)$, and 4 for the profit margin process $(\alpha_m, \rho_m, \beta_m, \sigma_\eta)$. Without loss of generality, we set $\alpha_y = -\sigma_\nu^2/2(1 + \rho_y)$ so that $\mu_q = 1$.²¹ This leaves us with 6 parameters. Table G.8 summarizes the targets and results.

We calibrate ρ_y and σ_ν directly from the data, interpreting the firm’s scale q as sales divided by total assets (saleq divided by atq in Compustat). After taking logs, we winsorize this ratio at the 1st and 99th percentiles. We then regress this ratio on its lagged value with firm-calendar-quarter

²¹We use μ_X , σ_X^2 , and ρ_X for the mean, variance, and autocorrelation of a stationary process X .

fixed effects to find the autocorrelation ρ_y and the standard deviation of residuals σ_ν . Fixed effects control for firm-specific drift and seasonality, since we work with quarterly data.

The remaining parameters to calibrate are margins level α_m , persistence ρ_m , idiosyncratic volatility σ_η , and exchange rate exposure β_m . We set these parameters to match the average, standard deviation, and autocorrelation of cash-flows, as well as currency risk before hedging. To do this, we start with $\mu_\pi = \mu_q \mu_m = \mu_m$. Furthermore, we have

$$\sigma_\pi^2 = \sigma_m^2 + \mu_m^2 \sigma_q^2 + \sigma_m^2 \sigma_q^2 \quad \text{and} \quad \rho_\pi = \frac{\mu_m^2 \rho_q \sigma_q^2 + (1 + \rho_q \sigma_q^2) \rho_m \sigma_m^2}{\sigma_\pi^2}.$$

Solving for the profit margin autocorrelation ρ_m , we find

$$\rho_m = \frac{\rho_\pi \sigma_\pi^2 - \rho_q \sigma_q^2 \mu_m^2}{(1 + \rho_q \sigma_q^2) \sigma_m^2} \quad \text{with} \quad \sigma_m^2 = \frac{\sigma_\pi^2 - \mu_m^2 \sigma_q^2}{1 + \sigma_q^2},$$

We now only need to solve for β_m . Indeed, given β_m , we immediately have the two remaining parameters since $\alpha_m = \mu_m + \sigma_e^2 \beta_m / 2(1 - \rho_m)$ and $\sigma_\eta^2 = (1 - \rho_m^2) \sigma_m^2 - \beta_m^2 \sigma_e^2$. To solve for β_m , recall that we measure $\text{Corr}(\Delta\pi_{it}^{(y)}, \Delta e_t^{(y)})^2$ in Section 4, where

$$\Delta e_t^{(y)} = \sum_{k=0}^3 \Delta e_{t-k} \quad \text{and} \quad \Delta\pi_t^{(y)} = \sum_{k=0}^3 \pi_{t-k} - \sum_{k=0}^3 \pi_{t-4-k}.$$

It is easy to see that $\text{Cov}(\Delta e_t^{(y)}, \Delta\pi_{it}^{(y)}) = \beta_m \sigma_e^2 (\rho_m^3 + 2\rho_m^2 + 3\rho_m + 4)$. Therefore

$$\beta_m = \text{Corr} \left(\Delta e_t^{(y)}, \Delta\pi_{it}^{(y)} \right) \times \frac{2 \sqrt{\text{Var} \Delta\pi_t^{(y)}}}{\sigma_e (\rho_m^3 + 2\rho_m^2 + 3\rho_m + 4)}. \quad (\text{E.2})$$

A straightforward calculation shows that

$$\text{Var} \Delta\pi_t^{(y)} = 2 (4\gamma_\pi(0) + 5\gamma_\pi(1) + 2\gamma_\pi(2) - \gamma_\pi(3) - 4\gamma_\pi(4) - 3\gamma_\pi(5) - 2\gamma_\pi(6) - \gamma_\pi(7)),$$

where $\gamma_\pi(h) = \text{Cov}(\pi, \pi_{t-h})$ is the autocovariance function of π . It is given by

$$\gamma_\pi(h) = \mu_m^2 \left(e^{\sigma_y^2 \rho_y^h} - 1 \right) + \sigma_m^2 \rho_m^h e^{\sigma_y^2 \rho_y^h},$$

for $\sigma_y^2 = \sigma_\nu^2 / (1 - \rho_y^2)$. This completes the calibration of the cash-flow process.

In the data, we map cash-flows π_{it} to earnings before interests and taxes (EBIT) divided by assets (oiadpq divided by atq in Compustat), as in our baseline empirical analysis. We winsorize this ratio at the 1st and 99th percentiles. We then compute its average ($\mu_\pi = 1.78\%$) and standard deviation ($\sigma_\pi = 2.28\%$) in the pooled panel. We compute the autocorrelation ρ_π by regressing EBIT on its lag with firm-calendar-quarter fixed effects. In principle, we are measuring cash-flows after hedging. Given that currency risk is concentrated in a few firms, we view the moments μ_π , σ_π , and ρ_π as good approximations for their hedge-free analogues. Finally, we calibrate $\text{Corr}(\pi, \Delta e) = \sqrt{0.33}$ for high-risk firms and $\sqrt{0.15}$ for low-risk firms.

One issue is that we estimate autocorrelations ρ_y and ρ_π by regressing a variable on its lag

with unit fixed effects. It is well-known that the resulting estimator $\hat{\rho}$ is biased downward in finite samples. This also biases downward σ_ν , the standard deviation of residuals. To account for this, we implement a simple procedure proposed by [Dhaene and Jochmans \(2015\)](#) which exploits the fact that the bias scales as $1/T$. We split the sample in two halves and run two separate regressions, yielding $\hat{\rho}_1$ and $\hat{\rho}_2$. We then compute $\tilde{\rho} = 2\hat{\rho} - (\hat{\rho}_1 + \hat{\rho}_2)/2$, which is free of bias to the first order.

Table [G.7](#) shows the results from estimating the autocorrelation of cash-flows π_{it} and scale y_{it} in the full sample and in two half-samples of roughly equal size. First, the coefficients are comparable in the two half-samples. This suggests that the processes are stable across time. Second, the bias-corrected estimates are $\rho_\pi = 0.57$ and $\rho_y = 0.88$, as well as $\sigma_y = 0.18$. While not negligible, the implied biases are small given that we have over 60 quarter per firm on average.

F Additional empirical results

F.1 Interpreting cash-flow variance reduction

To interpret variance reductions, Table [G.1](#) translates the impact of a 20% reduction in cash-flow variance into three existing frameworks.

1. First, [Graham and Smith \(1999\)](#) show that cash-flow variance impacts the tax base when the tax schedule is convex. Their estimates imply that firms most exposed to FX risk reduce their tax base by 6% by hedging.
2. Second, firm volatility is a key input in computing distance-to-default, a robust creditor for credit spreads [Merton \(1974\)](#). Assuming that enterprise value volatility scales as cash-flow volatility, our estimates translate into a 10% reduction in distance-to-default.
3. Third, [Stanley et al. \(1996\)](#) show that the variance of firms' growth rates scales with size. Doubling firm size predicts a 20% reduction in the variance of sales growth. Assuming that cash-flow volatility scales as sales growth volatility, our estimates translate into a large effect. This suggests that risk management could play a role in explaining the smaller volatility of larger firms.

F.2 Hedge portfolio maturity

Our key measure of maturity is the time-to-maturity T_c of a contract c measured at time t , expressed in quarters. For a given firm i with active contracts \mathcal{C}_{it} , we define the portfolio maturity as

$$T_i = \sum_{c \in \mathcal{C}_{it}} \frac{n_c}{\sum_{c'} n_{c'}} \times T_c, \quad (\text{F.1})$$

where n_c is the gross notional of contract c , expressed in euros.

We can also view the average portfolio maturity defined in Equation [\(F.1\)](#) as a sufficient statistic for the full maturity profile in a simple constant hazard model. Indeed, natural way

to capture the full maturity profile is to compute the share of contracts with maturity above a threshold τ , that is

$$S_{it}(\tau) = \frac{\sum_c n_c \mathbf{1}\{T_c \geq \tau\}}{\sum_{c'} n_{c'}}. \quad (\text{F.2})$$

By construction, the maturity profile $S_{it}(\tau)$ is decreasing in τ . The standard way to analyze this object is to study the hazard rate $h_{it}(\tau) = -S'_{it}(\tau)/S_{it}(\tau)$. The hazard rate quantifies how fast the hedge portfolio shrinks when maturity increases. Constant hazards correspond to the functional form $S_{it}(\tau) \propto e^{-\lambda\tau}$ for some $\lambda > 0$. This amounts to assuming that the hedge portfolio notionals are exponentially distributed across maturities. Under this assumption, the maximum likelihood estimator for λ is given by $\lambda = 1/T_i$.

F.3 Collateralization and counterparty risk

As an additional consequence of counterparty risk, banks may require compensation in the form of markups embedded in forward prices. We expect long-term uncollateralized contracts to be riskier and therefore have higher markups. To compare the distribution of markups for contracts with and without margin accounts, we first compute markup quantiles separately by collateralization status and maturity bin. Then, we compute the difference in markups (uncollateralized minus collateralized) for a given quantile by maturity bin. This allows us to measure the premium associated with uncollateralized contracts for the full markup distribution. For this exercise, we classify as collateralized contracts for which the firm posts variation margins only (as opposed to initial margins *and* variation margins) because different types of collateralizations could lead to different markups. Given that very few contracts have initial margins, this choice has almost no impact on our results.

Figure G.9 shows the difference in quantiles. The difference is economically significant only at higher quantiles. At those higher quantiles, the difference is larger for long-term contracts (tenor over six months) as opposed to short-term contracts (tenor under six months). While the quantile differences are small in absolute values, they are sizable relative to the median markup of 2bps. These findings are consistent with the hypothesis that counterparty risk is associated with a risk premium embedded in forward prices.

F.4 Hedging demand and CIP costs

We now assess whether the cross-currency basis, which captures market-wide deviations from CIP, impacts firms' hedging demand. To do so, we first measure this basis directly using our data. We then exploit firms' heterogeneous exposure to quantify how hedging demands responds to widening in the cross-currency basis.

Measurement

We define the cross-currency basis (CCB) for a given currency pair x/y as above

$$x_t(T) = \text{median} \left(\frac{1}{T} \log \frac{F_{ict}(T)}{F_t^*(T)} \right) = \text{median} \left(\frac{1}{T} \log \frac{F_{ict}(T)}{S_t} - (r_t^y(T) - r_t^x(T)) \right), \quad (\text{F.3})$$

where i is a firm, c a contract, t a day, and T the time-to-maturity measured in years. We compute the cross-currency basis at the contract level and then bin contracts by maturity to compute the median over all contracts executed in day t . We use a rolling average over five days as our main measure of CIP deviations.

We focus on the 1-year tenor because corporates tend to hedge over longer horizons than financial firms, which mainly use 1 week to 3 months tenors. There is a persistent basis x_t between the two, however, as the right figure shows.

Strategy

Firms that buy euros forward against dollars will the cross-currency basis if it is negative but firms that sell euros forward receive it. Our empirical strategy exploits this fact. We estimate the following model:

$$\frac{\text{Net notional}_{ijt+h}}{\text{Book value}_{ijt}} = \beta_h^+ \times x_t \times \mathbf{1}\{\text{Net notional}_{ijt} > 0\} + \beta_h^- \times x_t \times \mathbf{1}\{\text{Net notional}_{ijt} < 0\} + \alpha_{jyq(t)h} + \theta_h^\top W_{ijt} + u_{ith} \quad (\text{F.4})$$

We expect $\beta_h^+ < 0$ and $\beta_h^- > 0$. We control for Net notional $_{ijt}$ /Book value $_{ijt}$, the spot exchange rate at time t , and lags of all variables.

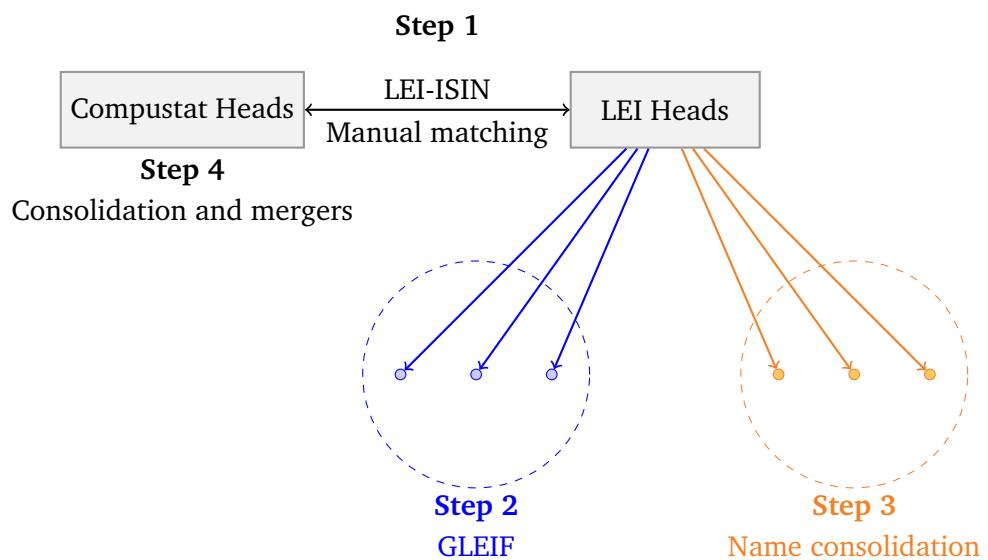
Results

Figure G.12 shows the cumulative impulse response of an increase in the CCB on hedging demand. For firms long EUR, a +10bps increase in the CCB is associated with a decrease in hedging demand of 2–3bps starting 1 to 2 months after the shock. For firms short EUR, the same shock is associated with an increase in hedging demand of 3bps. Shocks to the CCB dissipate in about three months, which explains our estimation horizon.

A key concern is that deviations from CIP could be correlated with shocks to hedging demand given that they correlate with dealers' financial constraints (Du et al., 2018; Kubitza et al., 2025). To address this concern, we re-estimate Equation (F.4), only this time looking at the *difference* between firms buying and selling the euro forward. This allows us to include time fixed effects, absorbing time-specific confounding factors that would impact hedging demand. The implied cumulative response qualitatively similar, though slightly smaller: a +10bps CCB shocks is associated with a reduction in hedging demand by 3bps for firms long EUR relative to firms short EUR.

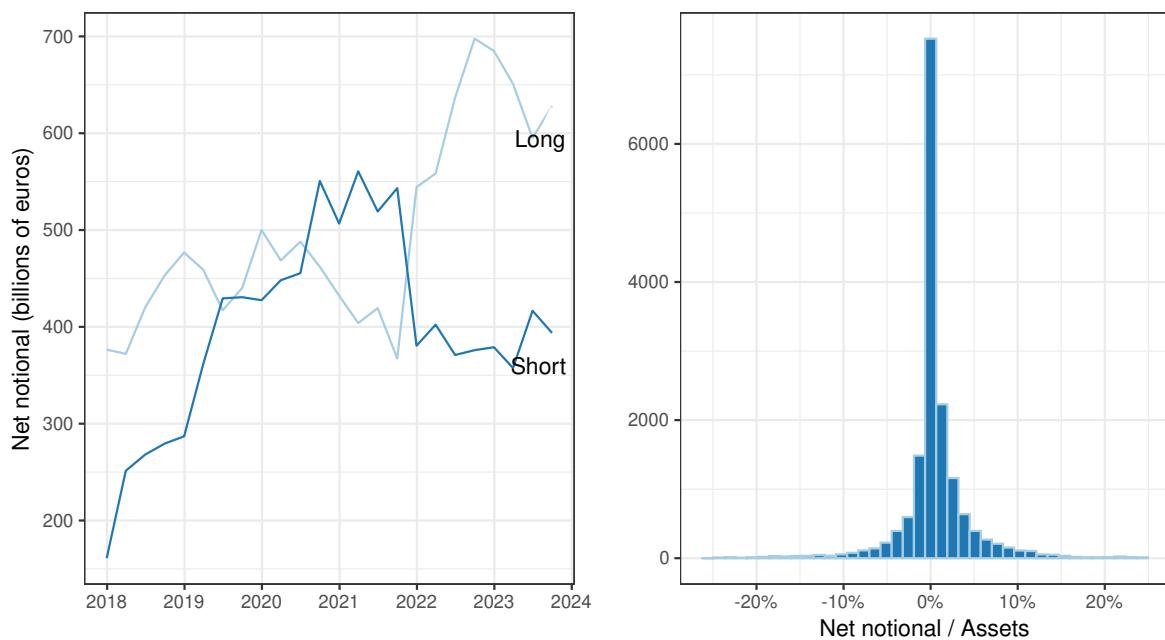
G Additional figures and tables

Figure G.1: Summary of the consolidation process



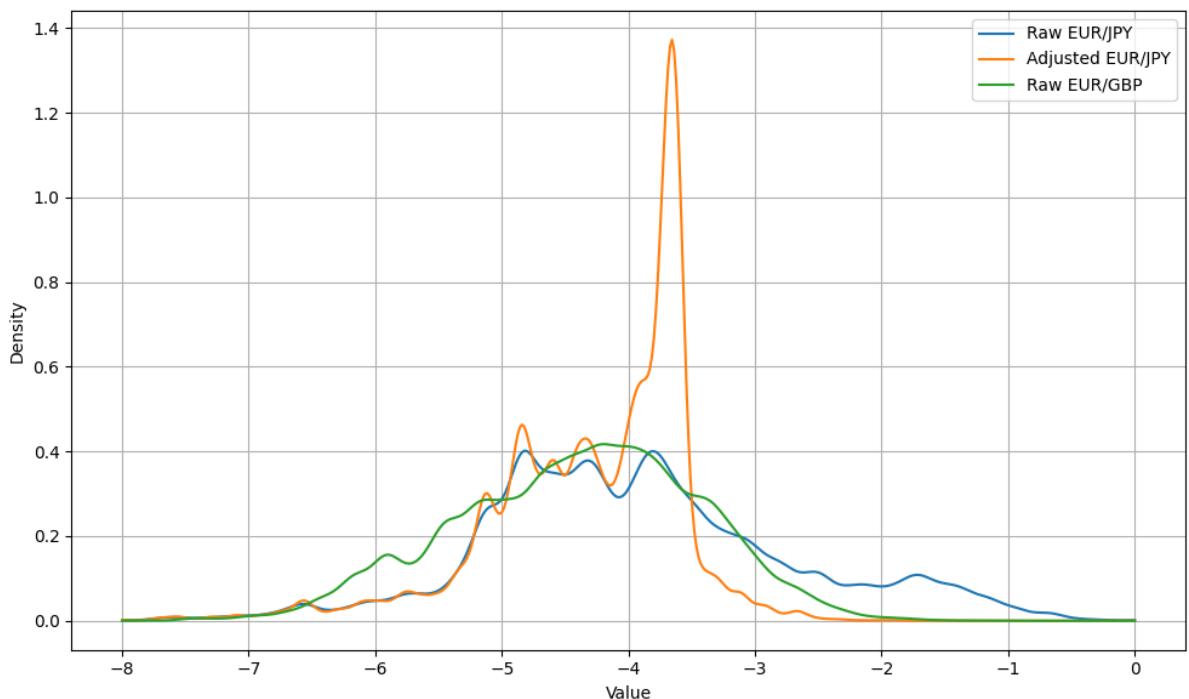
Note. This figure summarizes the consolidation process described in Section 3.2.

Figure G.2: Time-series and cross-section of EUR/USD net notentials



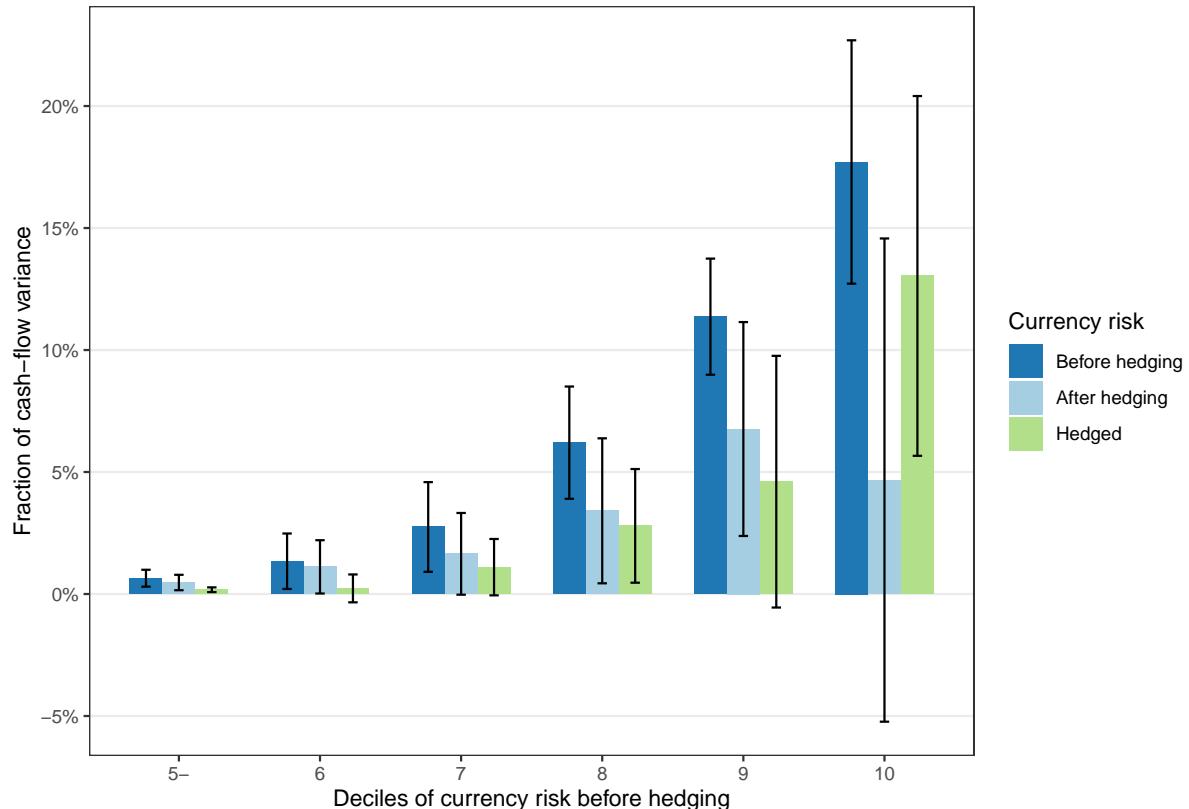
Left panel. For each firm and week, we compute the net notional of its total portfolio and average it over the quarter. We sum these for “long” firms (buy EUR and sell USD) and “short” firms (sell EUR and buy USD). *Right panel.* for each firm and week, we compute the net notional of its portfolio and divide it by total assets and average it over the quarter.

Figure G.3: Comparison of EUR/JPY log-scaled notional to EUR/GBP



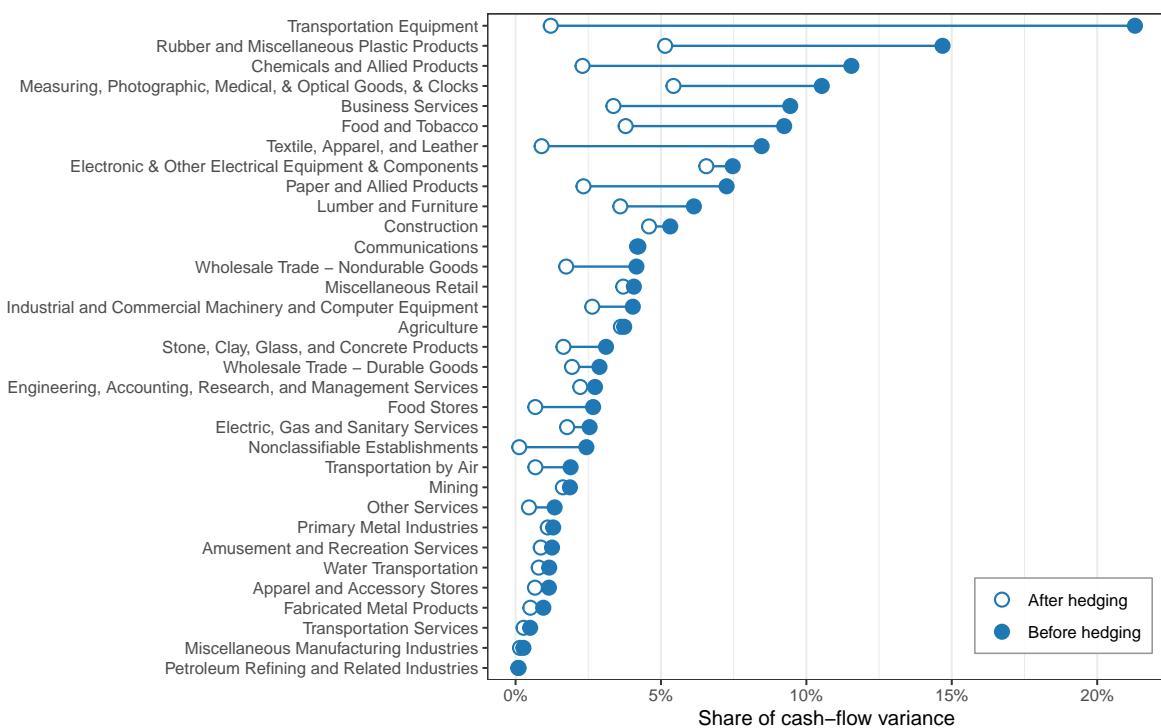
Note. We show the log-scaled notional for the EUR/JPY (blue) using the EUR/GBP (green) as a benchmark. Misreporting of EUR/JPY contracts as EUR instead of JPY generates a visible second mode relative to the benchmark. After correction (yellow), the second mode disappears.

Figure G.4: Cash-flow currency risk by level of exposure (using pretax income)



Note. This figure shows average measures of currency risk across currency risk deciles. We sort firms into 10 deciles according to currency risk before hedging ($b_i^\top \Omega_F b_i / \text{Var}_i \Delta\pi_{it}^*$). We then compute the asset-weighted average for three risk measures: (1) currency risk before hedging (sorting variable), (2) currency risk after hedging, and (3) currency risk hedged. The five lower deciles are binned together for clarity. Cash-flows $\Delta\pi_{it}^*$ are the change in yearly pretax income normalized by total assets. Currency risk measures are obtained by estimating a factor model as described in the main text. Standard errors are computed using the Bayesian bootstrap blocked by firm.

Figure G.5: Average currency risk before and after hedging by sector



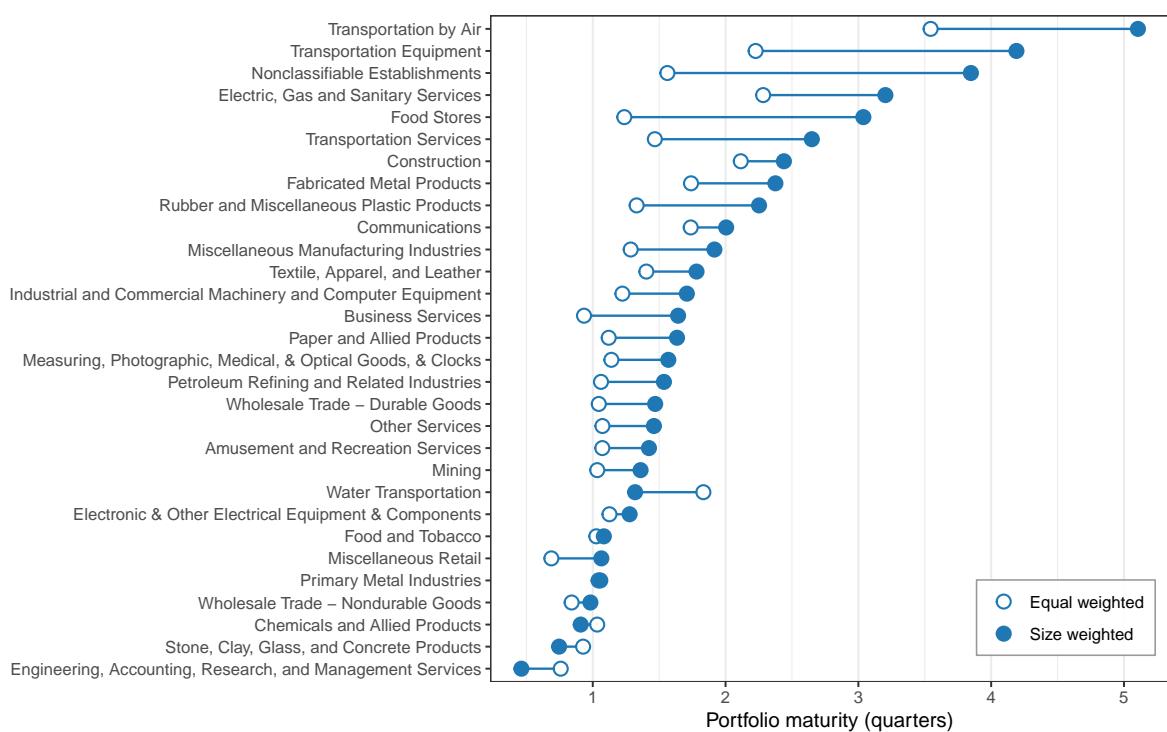
Note. This figure shows average measures of currency risk across sectors. We compute the asset-weighted average cash-flow currency risk before and after hedging. Cash-flows $\Delta\pi_{it}^*$ are the change in yearly EBIT normalized by total assets. Currency risk measures are obtained by estimating a factor model as described in the main text.

Table G.1: Interpreting a 20% reduction in cash-flow variance

| Paper | Variable | Effect | Assumption |
|-------------------------|---------------------|------------|-------------------------------|
| Graham and Smith (1999) | Tax base | -6% | |
| Merton (1974) | Distance-to-default | -10% | $\sigma_\pi \propto \sigma_v$ |
| Stanley et al. (1996) | Size | $\times 2$ | $\sigma_\pi \propto \sigma_s$ |

Note. This table translates the impact of a 20% reduction in cash-flow variance using several frameworks proposed by the literature. The translation corresponds to our estimates of the impact of hedging for the most exposed firms. Mapping cash-flow volatility to existing frameworks requires assumptions linking cash-flow volatility σ_π to enterprise value growth volatility σ_v , and sales growth volatility σ_s .

Figure G.6: Average portfolio maturity by sector



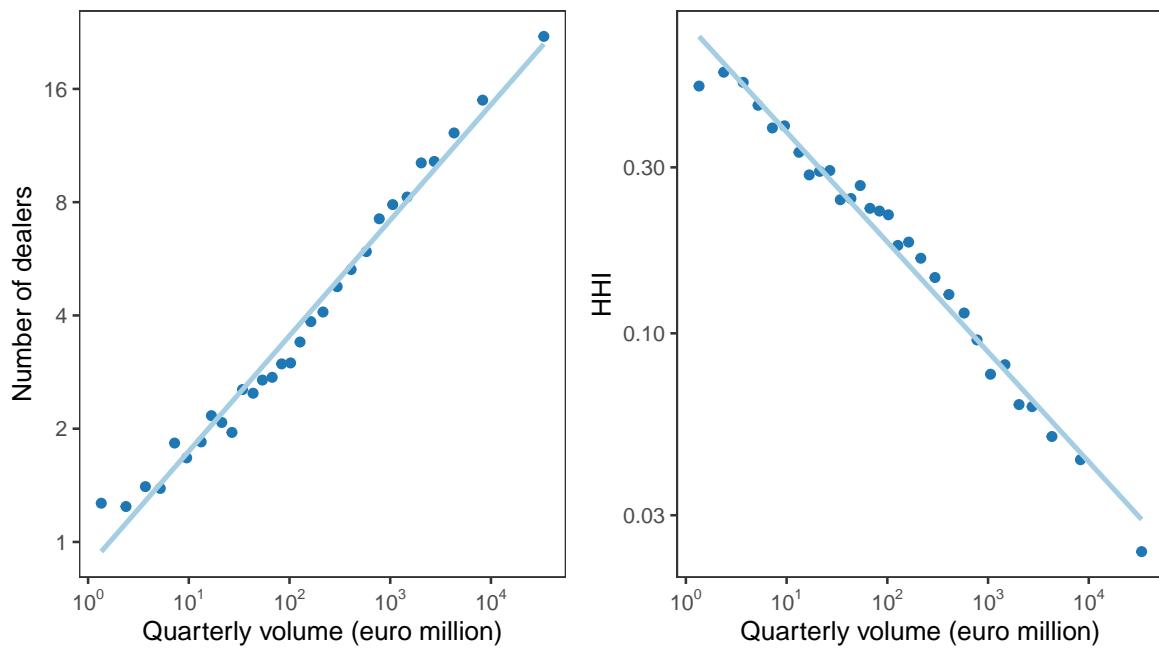
Note. This figure shows the average portfolio maturity for firms by sector. Empty dots show the equal-weighted average and full dots show the average weighted by gross portfolio size, measured as gross notional.

Table G.2: Currency risk and portfolio maturity

| | Currency risk before hedging (1) | Hedged currency risk (2) | Currency risk before hedging (3) | Hedged currency risk (4) | Currency risk before hedging (5) | Hedged currency risk (6) | Hedged currency risk (7) | Hedged currency risk (8) |
|-----------------------|-------------------------------------|-----------------------------|-------------------------------------|-----------------------------|-------------------------------------|-----------------------------|-----------------------------|-----------------------------|
| Constant | 5.8 (0.59) | | 2.7 (0.57) | | 7.3 (1.8) | | 5.0 (1.8) | |
| Log maturity | 1.2 (0.45) | 1.0 (0.34) | 1.4 (0.50) | 1.2 (0.33) | 3.8 (2.6) | 2.9 (1.6) | 4.7 (2.8) | 3.6 (1.8) |
| R ² | 0.02 | 0.10 | 0.04 | 0.15 | 0.11 | 0.43 | 0.18 | 0.52 |
| Within R ² | | 0.01 | | 0.03 | | 0.07 | | 0.12 |
| Observations | 752 | 752 | 752 | 752 | 752 | 752 | 752 | 752 |
| Weights | Equal | Equal | Equal | Equal | Assets | Assets | Assets | Assets |
| Sector fixed effects | | ✓ | | ✓ | | ✓ | | ✓ |

Note.

Figure G.7: High-volume firms use more dealers and spread trades across dealers more



Note. This figure shows a log-log binned scatterplot of measures of diversification against trading volume. For the calendar year 2020, we sort firms-time observations into bins according to quarterly trading volumes. For each bin, we compute the harmonic mean of the quarterly volume and diversification measures. Tables G.3 and G.4 explore the same relationship in the cross-section and the time-series by including fixed effects.

Table G.3: Link between volume and diversification in the cross-section

| | #Dealers (1) | HHI index (2) | Log(#Dealers) (3) | log(HHI index) (4) |
|-----------------------|-----------------|------------------|----------------------|-----------------------|
| log(Notional) | 1.1 (0.09) | -0.09 (0.003) | 0.28 (0.010) | -0.17 (0.007) |
| R ² | 0.46 | 0.35 | 0.50 | 0.40 |
| Within R ² | 0.44 | 0.34 | 0.49 | 0.38 |
| Observations | 14,941 | 14,941 | 14,941 | 14,941 |
| Firms | 650 | 650 | 650 | 650 |
| Time fixed effects | ✓ | ✓ | ✓ | ✓ |

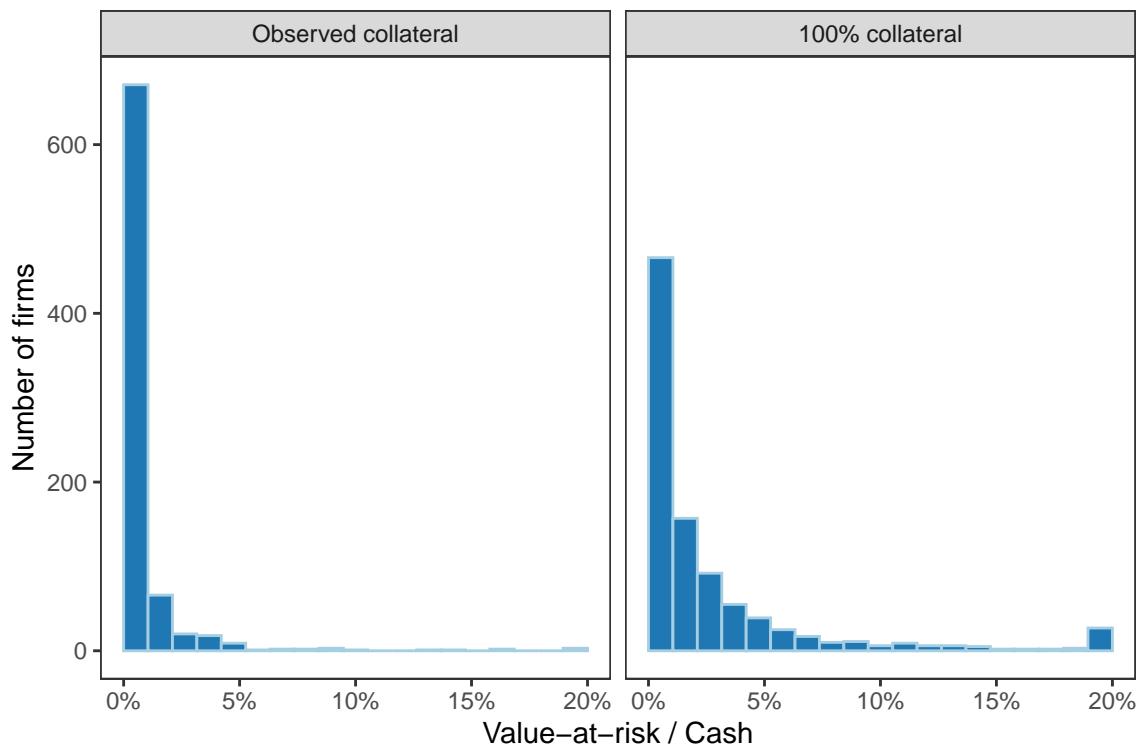
Note. This table shows regressions of diversification measures on trading volume for 2020. For each firm and quarter, we compute the gross volume traded (defined as the sum of gross notentials), the number of dealers, and the HHI across dealers. Standard errors are clustered by firm.

Table G.4: Link between volume and diversification in the time-series

| | #Dealers (1) | HHI index (2) | Log(#Dealers) (3) | log(HHI index) (4) |
|-----------------------|-----------------|------------------|----------------------|-----------------------|
| log(Notional) | 0.91 (0.17) | -0.07 (0.008) | 0.23 (0.02) | -0.15 (0.02) |
| R ² | 0.77 | 0.60 | 0.79 | 0.63 |
| Within R ² | 0.25 | 0.15 | 0.31 | 0.17 |
| Observations | 14,941 | 14,941 | 14,941 | 14,941 |
| Firms | 650 | 650 | 650 | 650 |
| Firm fixed effects | ✓ | ✓ | ✓ | ✓ |

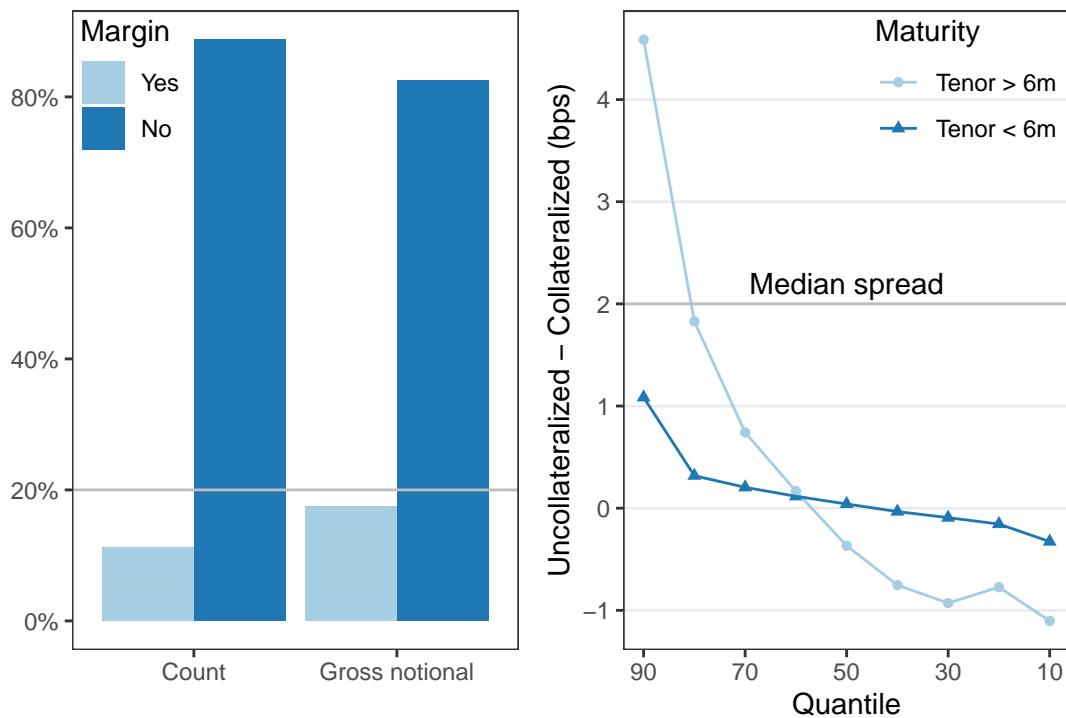
Note. This table shows regressions of diversification measures on trading volume for 2020. For each firm and quarter, we compute the gross volume traded (defined as the sum of gross notentials), the number of dealers, and the HHI across dealers. Standard errors are clustered by year-quarter-firm.

Figure G.8: Value-at-risk relative to cash positions given observed collateral



Note. This figure plots the distribution of quarterly value-at-risk on EUR/USD contracts, as defined in Equation (10). The shock is the 99th quantile of a t distribution with 7 degrees of freedom, rescaled to have standard deviation 5%. We winsorize the normalized VaR at 20%. *Left panel.* Observed collateralization rate. *Right panel.* Counterfactual 100% collateralization rate.

Figure G.9: Collateralization status and markups for EUR/USD forwards



Note. This figure shows descriptive statistics on whether EUR/USD forward contracts are tied to margin accounts between 2020 and 2023. *Left panel.* We show the share of collateralized contracts (i.e., have a margin account) in the pooled panel, weighted by count and gross notional. *Right panel.* We show the difference in markups across collateralization status at different quantiles. In the pooled panel, for each maturity group and collateralization status, we compute markup quantiles. We then compute the difference of the uncollateralized quantile minus the collateralized quantile by maturity group.

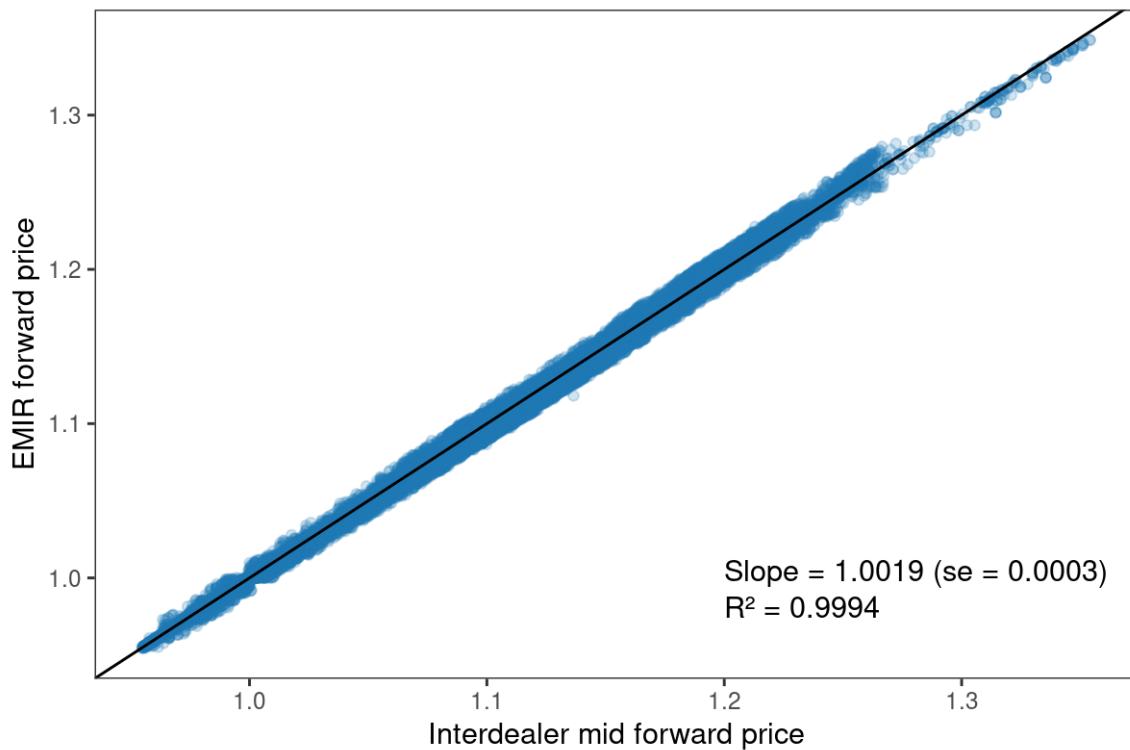
Table G.5: Collateralization status by year

| <i>Panel A. Share of gross volume</i> | | | | | | | |
|---------------------------------------|-------|-------|-------|-------|-------|-------|-------|
| Collateralization | 2017 | 2018 | 2019 | 2020 | 2021 | 2022 | 2023 |
| Missing | 77.7% | 66.5% | 55.5% | 39.6% | 26.1% | 24.1% | 27.8% |
| None | 16.5% | 25.0% | 35.5% | 48.5% | 61.7% | 61.1% | 59.4% |
| VM | 4.2% | 8.2% | 8.3% | 11.4% | 11.4% | 13.9% | 11.4% |
| IM and VM | 1.6% | 0.3% | 0.7% | 0.5% | 0.8% | 0.9% | 1.4% |
| <i>Panel B. Share of contracts</i> | | | | | | | |
| Collateralization | 2017 | 2018 | 2019 | 2020 | 2021 | 2022 | 2023 |
| Missing | 84.3% | 61.8% | 47.2% | 35.0% | 22.0% | 21.1% | 24.1% |
| None | 12.7% | 30.2% | 42.9% | 55.9% | 68.8% | 70.9% | 68.9% |
| VM | 2.0% | 7.7% | 9.2% | 8.6% | 8.9% | 7.6% | 6.3% |
| IM and VM | 1.0% | 0.4% | 0.7% | 0.5% | 0.4% | 0.5% | 0.7% |

Note. This table shows the breakdown of collateralization status for the nonfinancial counterparty by year. Collateralization status captures the use of a margin account and takes one of following values:

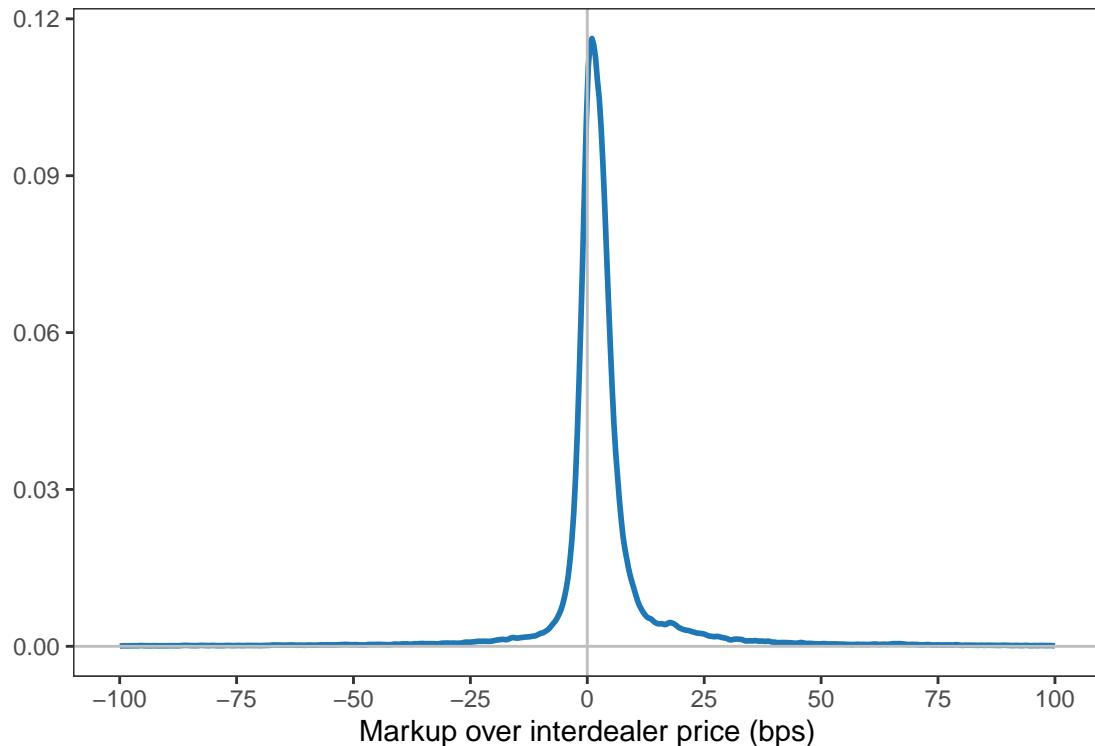
1. Missing: nonfinancial counterparty's report is not observed or does not provide collateralization information.
2. None: does not post any margin (UNCL in EMIR).
3. VM: posts variation margins (PRCL in EMIR).
4. IM and VM: posts initial and variation margins (FLCL or OWCL in EMIR).

Figure G.10: EMIR prices versus interdealer prices for EUR/USD forwards



Note. This figure plots forward prices observed in EMIR against interdealer prices, along with the 45-degree line. We drop observations which are more than 1% away from the interdealer price (2.7% of the sample). Table G.6 shows that the R^2 remains above 99% if we use a 5% threshold. See details in Section D.3.

Figure G.11: Distribution of markups charged by dealers on EUR/USD forwards



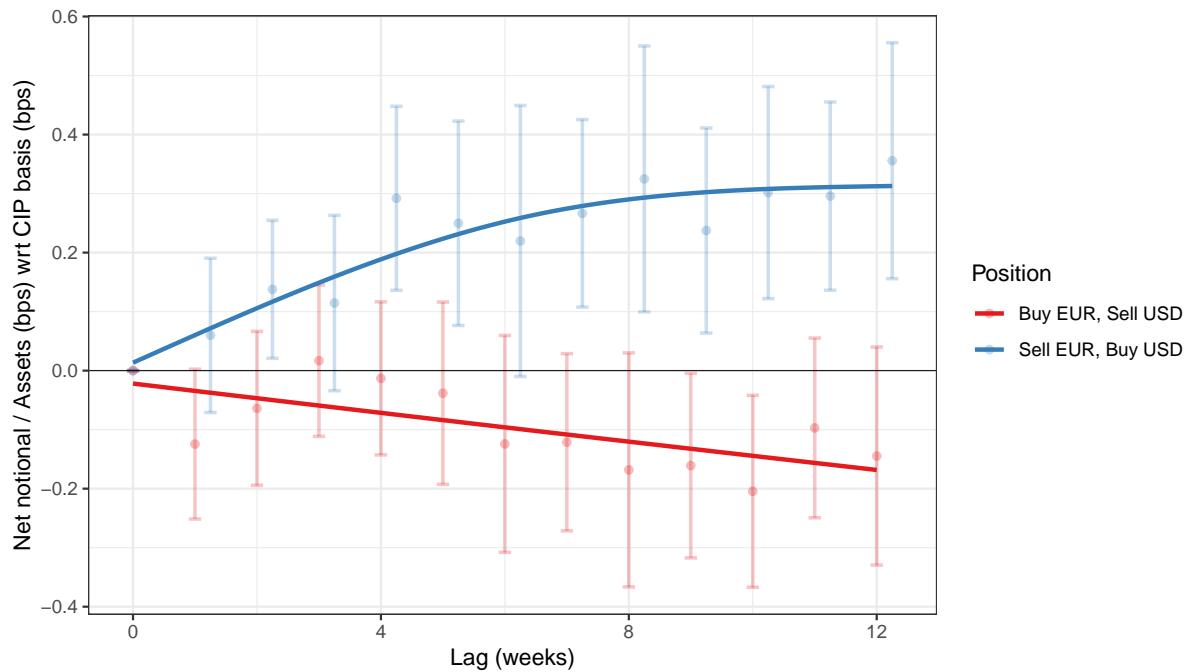
Note. This figure shows the distribution of the markup charged by dealer banks in EUR/USD forwards, as defined in Equation (11). We drop observations which are more than 1% away from the interdealer price (2.7% of the sample). See details in Section D.3.

Table G.6: Predictive power of interdealer prices for EMIR prices on EUR/USD forwards

| | EMIR price | | | log(EMIR price) | | |
|-------------------|--------------------|---------------------|---------------------|--------------------|--------------------------------------|--------------------------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Constant | 0.0062 (0.0020) | -0.0013 (0.0008) | -0.0025 (0.0003) | 0.0003 (0.0002) | -0.0005 (7.05×10^{-5}) | -0.0005 (3.66×10^{-5}) |
| Interdealer price | 0.9942 (0.0018) | 1.001 (0.0007) | 1.002 (0.0003) | | | |
| log(EMIR price) | | | | 0.9948 (0.0016) | 1.001 (0.0006) | 1.002 (0.0003) |
| R ² | 0.9756 | 0.9956 | 0.9994 | 0.9761 | 0.9958 | 0.9994 |
| Observations | 334,873 | 332,465 | 325,865 | 334,873 | 332,465 | 325,865 |
| Outliers filter | None | m < 500 | m < 100 | None | m < 500 | m < 100 |

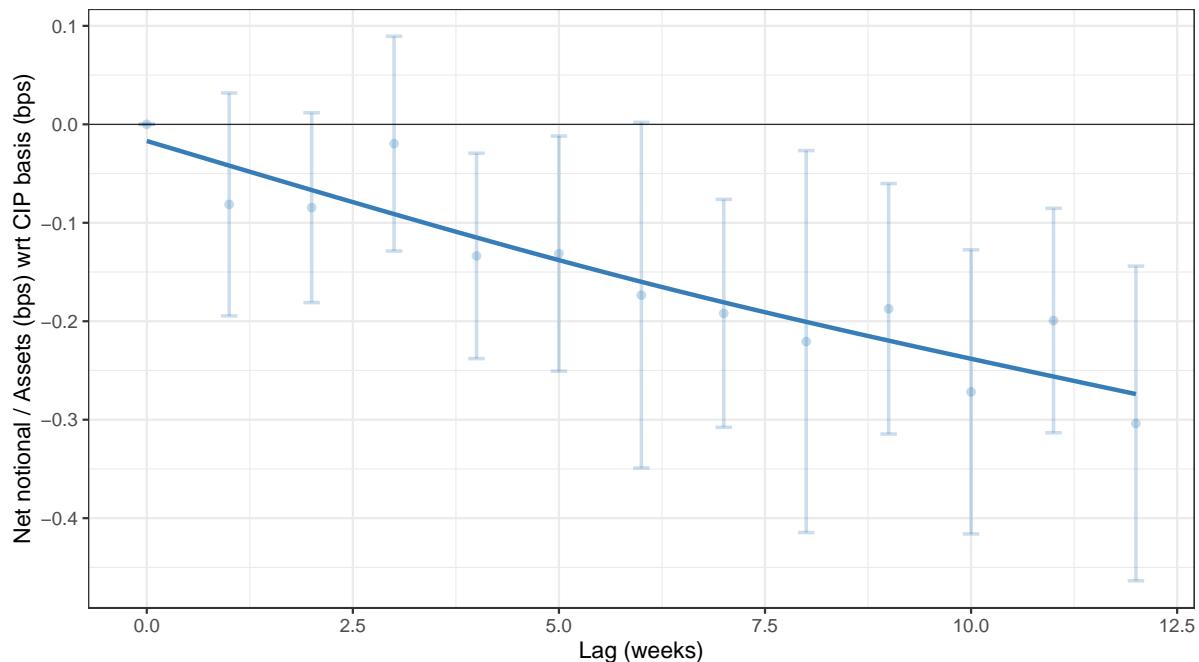
Note. This table shows the fit quality from regressing EMIR forward prices on interdealer quotes for EUR/USD forwards. Column (6) shows our baseline specification that uses logs and keeps only observations for which the log markup m is below 100 in absolute value. Column (3) shows the same results with markups in levels. Columns (1), (2), (4), and (5) show that the fit remains good even if we use a more lenient threshold or do not drop outliers at all. Standard errors are clustered by firm and execution day.

Figure G.12: Response of hedging demand to CIP shocks according to side



Note. This figure shows the cumulative response of the net notional divided by total assets (in basis points) to a 1 basis point shock to the EUR/USD cross-currency basis (CCB), which measures deviations from covered interest parity (CIP). We estimate the local projection model (F.4), splitting firms by position at the time of the shock. Confidence intervals are at the 95%, clustering standard errors by day.

Figure G.13: Relative response of hedging demand to CIP shocks across sides



Note. x

Table G.7: Autocorrelation estimation for EBIT and scale

| Sample period | EBIT | | | Scale | | |
|----------------------------|--------------------|-------------------|--------------------|--------------------|-------------------|--------------------|
| | Full sample (1) | After 2015 (2) | Before 2015 (3) | Full sample (4) | After 2015 (5) | Before 2015 (6) |
| Lagged EBIT | 0.529 (0.019) | 0.499 (0.026) | 0.486 (0.023) | | | |
| Lagged scale | | | | 0.814 (0.011) | 0.764 (0.011) | 0.731 (0.020) |
| R ² | 0.61 | 0.66 | 0.66 | 0.93 | 0.95 | 0.94 |
| Within R ² | 0.29 | 0.26 | 0.24 | 0.67 | 0.60 | 0.55 |
| Observations | 74,906 | 37,494 | 37,412 | 77,325 | 38,466 | 38,859 |
| Quarters per firm | 66 | 33 | 38 | 68 | 33 | 39 |
| Residual std.dev. (%) | 1.36 | 1.23 | 1.30 | 16.7 | 15.1 | 15.4 |
| Firm-Quarter fixed effects | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

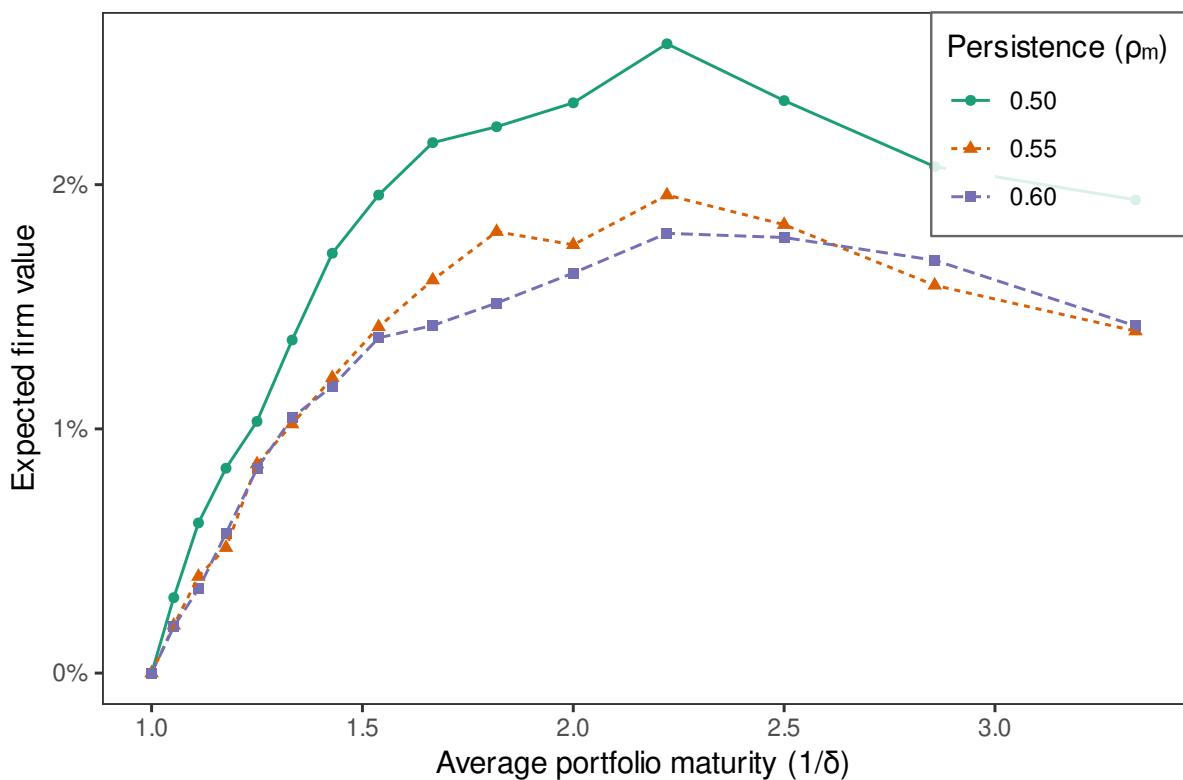
Note. This table shows the results from estimation the autocorrelation of EBIT divided by total assets and scale (sales divided by total assets) in the full sample and in two half-samples. We use these results to correct for estimating autocorrelations with unit fixed effects in finite panels. See details in Appendix E.2.

Table G.8: Summary of cash-flow process calibration

| Description | Symbol | Lower risk | Higher risk |
|---|--|------------|-------------|
| Empirical targets | | | |
| Scale idiosyncratic volatility (%) | σ_ν | 0.18 | 0.18 |
| Scale autocorrelation | ρ_y | 0.88 | 0.88 |
| EBIT average (%) | μ_π | 1.78 | 1.78 |
| EBIT idiosyncratic volatility (%) | σ_π | 2.28 | 2.28 |
| EBIT autocorrelation | ρ_π | 0.57 | 0.57 |
| EBIT currency risk | $\text{Corr}(\Delta\pi^{(y)}, \Delta e^{(y)})$ | 0.39 | 0.57 |
| Scale process: Equation (14) | | | |
| Persistence | ρ_y | 0.88 | 0.88 |
| Idiosyncratic volatility | σ_ν | 0.18 | 0.18 |
| Drift (%) | α_y | -0.86 | -0.86 |
| Profit margin process: Equation (15) | | | |
| Persistence | ρ_m | 0.55 | 0.55 |
| FX exposure | β_m | 0.20 | 0.29 |
| Idiosyncratic volatility (%) | σ_η | 1.37 | 0.88 |
| Drift (%) | α_m | 1.83 | 1.86 |

Note. This table summarizes our cash-flow process calibration. We first show the empirical targets we use to calibrate the process, and then the calibration outputs. The only difference between the low risk and high risk columns is the target currency risk. Scale is measured empirically as the logarithm of sales divided by total assets (*saleq* divided by *atq* in Compustat). EBIT is also normalized by total assets (*oiadpq* divided by *atq* in Compustat). See Section E.2 for details on cash-flow calibration, and Table 1 for an overview of the entire model calibration.

Figure G.14: Optimal hedging maturity



Note. This figure plots the expected firm value under the stationary distribution for portfolio maturity, measured in quarters. Portfolio maturity is inversely related to the hazard rate δ in the model. We show values in deviations relative to the value at $\delta = 1$, which corresponds to an average portfolio maturity of 1 quarter.