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Essays in International Finance and Monetary Economics

Essais de Finance Internationale et d'Économie Monètaire

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by
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Under the direction of
Prof. Harald HAU, Supervisor
in fulfillment of the requirements for the degree of

Docteur en économie et management
mention *Finance*

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La Faculté d'économie et de management, sur préavis du jury, a autorisé l'impression de la présente thèse, sans entendre, par-là, émettre aucune opinion sur les propositions qui s'y trouvent énoncées et qui n'engagent que la responsabilité de leur auteur.

Genève, le 21 juillet 2023

Dean
Markus MENZ

Impression d'après le manuscrit de l'auteur

To my family and loved ones, who always believed in me even when I did not myself.

UNIVERSITY OF GENEVA AND SWISS FINANCE INSTITUTE

Abstract

Geneva Finance Research Institute

Doctor of Philosophy

Essays in International Finance and Monetary Economics

by Tammaro TERRACCIANO

This dissertation encompasses an ample examination of various facets of pressing research questions in financial economics, providing critical insights into the real effects of foreign-exchange derivatives markets as well as exploring the implications and interlinkages of new monetary ventures. Specifically, this work focuses on the dynamics of currency hedging, crypto markets, and the interactions between the issuance of a central bank digital currency (CBDC) with quantitative easing.

In the first chapter, we investigate the link between FX hedging and firms' currency choice. When exporters price their goods in a foreign currency, they are exposed to exchange-rate risk. However, they can hedge this risk by underwriting a foreign exchange (FX) forward contract, which means selling forward the currency in which they price their goods. In this paper, we study how the cost of FX hedging influences the currency choice of French exporters. Our identification strategy exploits an exogenous increase in the trading costs of FX forward contracts, that was triggered by a spike in the Greek default risk. First, we find that higher FX trading costs lower the probability of pricing in dollars and in local (i.e., buyer's) currency for hedging firms. Second, we show that hedging firms price more their goods in dollars than in local currency. Third, we document that FX hedging affects the transmission of exchange-rate shocks to prices and find that FX hedging is associated with lower levels of exchange-rate pass-through. We conclude that FX hedging contributes to dollar dominance and to the exchange-rate disconnect puzzle.

In the second chapter, we examine fluctuations in crypto markets and their relationships to global equity markets and US monetary policy. We identify

a single price component—which we label the “crypto factor”—that explains 80% of variation in crypto prices, and show that its increasing correlation with equity markets coincided with the entry of institutional investors into crypto markets. We also document that, as for equities, US Fed tightening reduces the crypto factor through the risk-taking channel—in contrast to claims that crypto assets provide a hedge against market risk. Finally, we show that a stylized heterogeneous-agent model with time-varying aggregate risk aversion can explain our empirical findings, and highlights possible spillovers from crypto to equity markets if the participation of institutional investors ever became large.

In the third chapter, we study how issuing a CBDC interacts with monetary policy. We consider conventional monetary policy and quantitative easing, and we find that a CBDC has a different impact on the equilibrium allocations depending on the ongoing monetary policy. Under quantitative easing, we show that commercial banks optimally liquidate their excess reserves to accommodate households’ demand for CBDC. Without limitations, this process could negatively affect lending and render quantitative tightening problematic. However, it is always possible to find specific conditions for which issuing a CBDC is neutral to the economy.

Resumé

Cette thèse comprend un examen approfondi de diverses facettes de questions de recherche urgentes en économie financière, fournissant des aperçus critiques sur les effets réels des marchés de dérivés de change ainsi que l'exploration des implications et des interrelations des nouvelles entreprises monétaires. Plus précisément, ce travail se concentre sur la dynamique de la couverture des devises, les marchés cryptographiques et les interactions entre l'émission d'une monnaie numérique de banque centrale (MNBC) et l'assouplissement quantitatif.

Dans le premier chapitre, nous étudions le lien entre la couverture du risque de change et le choix de la devise par les entreprises. Lorsque les exportateurs fixent le prix de leurs marchandises dans une devise étrangère, ils sont exposés au risque de change. Toutefois, ils peuvent couvrir ce risque en souscrivant un contrat de change à terme, c'est-à-dire en vendant à terme la devise dans laquelle ils fixent le prix de leurs marchandises. Dans cet article, nous étudions comment le coût de la couverture du risque de change influence le choix de la devise des exportateurs français. Notre stratégie d'identification exploite une augmentation exogène des coûts de négociation des contrats de change à terme, déclenchée par un pic du risque de défaillance de la Grèce. Tout d'abord, nous constatons que l'augmentation des coûts de négociation des contrats de change réduit la probabilité de fixer les prix en dollars et en monnaie locale (c'est-à-dire dans la monnaie de l'acheteur) pour les entreprises qui se couvrent. Deuxièmement, nous montrons que les entreprises qui se couvrent fixent davantage le prix de leurs produits en dollars qu'en monnaie locale. Troisièmement, nous montrons que la couverture du risque de change affecte la transmission des chocs de taux de change aux prix et nous constatons que la couverture du risque de change est associée à des niveaux plus faibles de transmission du risque de change. Nous concluons que la couverture du risque de change contribue à la prédominance du dollar et à l'énigme de la déconnexion des taux de change.

Dans le deuxième chapitre, nous examinons les fluctuations des marchés des crypto-monnaies et leurs relations avec les marchés boursiers mondiaux et la politique monétaire américaine. Nous identifions une composante de prix unique - que nous appelons le "facteur crypto" - qui explique 80% de la variation des prix des crypto-monnaies, et nous montrons que sa corrélation croissante avec les marchés boursiers a coïncidé avec l'entrée des investisseurs institutionnels sur les marchés des crypto-monnaies. Nous montrons également que, comme pour

les actions, le resserrement de la politique monétaire de la Fed réduit le facteur crypto par le biais de la prise de risque, ce qui va à l'encontre des affirmations selon lesquelles les crypto-actifs constituent une couverture contre le risque de marché. Enfin, nous montrons qu'un modèle stylisé d'agents hétérogènes avec une aversion globale au risque variable dans le temps peut expliquer nos résultats empiriques et met en évidence les retombées possibles des crypto-monnaies sur les marchés d'actions si la participation des investisseurs institutionnels devenait importante.

Dans le troisième chapitre, nous étudions l'interaction entre l'émission d'une MNBC et la politique monétaire. Nous considérons la politique monétaire conventionnelle et l'assouplissement quantitatif, et nous constatons qu'une MNBC a un impact différent sur les allocations d'équilibre en fonction de la politique monétaire en cours. Dans le cadre d'un assouplissement quantitatif, nous montrons que les banques commerciales liquident de manière optimale leurs réserves excédentaires pour répondre à la demande de MNBC des ménages. Sans limites, ce processus pourrait affecter négativement les prêts et rendre problématique un resserrement quantitatif. Cependant, il est toujours possible de trouver des conditions spécifiques pour lesquelles l'émission d'une MNBC est neutre pour l'économie.

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Chapter 1

FX Hedging, Currency Choice and Dollar Dominance

with Martina Fraschini

1.1 Introduction

The currency choice of firms has important implications for understanding currency internationalization and for the transmission of exchange rate shocks.[1] Generally, exporters can price their goods in three currencies. For instance, when a French winemaker sells a bottle of champagne to Brazil, they may price it in euros (i.e., producer's currency), Brazilian reals (i.e., local currency), or U.S. dollars (i.e., vehicle currency). Their choice mainly depends on the local demand elasticity and on how much they want to be exposed to currency risk.

Yet, the existing literature has largely ignored the role of foreign exchange (FX) derivatives markets, which allow firms to hedge their revenues from currency risk while pricing in foreign currency.[2] This is important to consider as hedging is widespread; for example, in France, 24.6% of export transactions are made by hedging firms,[3] while the turnover of FX forward derivatives traded by non-financial counterparties has increased by 147% since the global financial crises.[4] The choice of the French winemaker in our example thus also depends on her ability to hedge the currency risk, fully or partially, with an FX forward contract. Indeed, if the cost of FX forwards is low and the payment is in Brazilian reals, they could sell forward Brazilian reals in exchange for euros at the due date to sterilize currency risk. Alternatively, if hedging in the Brazilian real is too expensive, they could price in dollars. This way, the revenues would not be affected by adverse shocks in the exchange rate, since the winemaker would receive a predetermined amount of euros at maturity, and they would be able to keep the price more stable for the buyer.

Thus, three fundamental questions arise: do FX derivatives affect firms' currency choice? What are the implications for dollar dominance? And, is FX hedging associated with stickier prices?

We show that hedging firms price more their goods in foreign currency, especially in dollars. Arguably, this is because dollar markets are better at serving firms' hedging needs, rendering dollar pricing more appealing. Furthermore, we exploit an exogenous increase in dollar FX trading costs to test how access to hedging products affects exporters' currency choices. We find that higher FX trading costs (i.e., lower access to FX forward markets) reduce the use of both dollar and local currency pricing, consistent with the idea that dollar

[1] See, for instance, Amiti et al., 2022; Gopinath et al., 2010, 2020a; Maggiori et al., 2019.

[2] A notable exception is Lyonnet et al., 2020.

[3] In addition, Adams et al., 2022 show that 25% of the Japanese firms reporting any FX position (including zero) have more than 17% of their incomes exposed to exchange-rate risk.

[4] BIS Triennial Central Bank Survey of FX and Over-the-counter (OTC) Derivatives Markets in 2022: https://www.bis.org/statistics/rpfx22.htm.

products are used as a reference in FX forward markets (e.g., see Somogyi, 2021). Finally, we document that FX hedging is associated with lower levels of exchange-rate pass-through into export prices. Hence, we conclude that FX hedging contributes to the exchange-rate disconnect puzzle and that more accessible derivatives markets nurture dollar dominance.

In our analysis, we extend a standard currency choice model to account for the possibility of hedging currency risk via FX forward contracts. Our framework features a representative, financially constrained firm that optimally chooses the price and the invoicing currency -namely, the producer or the foreign (i.e., local or vehicle) currency. The model provides three main insights. First, access to FX hedging favors foreign currency pricing because it enables dealing with currency risk while pricing to market. Second, when we consider the possibility of using the dollar as a vehicle currency, theory predicts that firms favor the dollar over local currency pricing when it provides better services (i.e., when it is cheaper, when its markets are more liquid, and so forth). Third, hedging firms that opt for pricing in foreign currency (instead of producer currency) can attain lower levels of pass-through.

We test these hypotheses using a comprehensive transactional dataset on French exports to extra-EU countries and firms' FX derivatives positions. Our empirical design exploits the sudden deterioration in 2011 of the covered interest parity (CIP) deviation in the euro-dollar market, which was triggered by U.S. investors' growing concerns about the creditworthiness of southern European countries, notably Greece.[5] A negative euro-dollar CIP deviation increases the costs of underwriting FX forward products and thus reduces firms' access to hedging (Alfaro et al., 2022; Berthou et al., 2022; Hong et al., 2021; Ivashina et al., 2015). Although French public debt sustainability was never in question, French firms were affected by the consequences of such a shock as the euro-dollar is the most traded currency pair in France.

First, we find that greater access to hedging increases the use of both local currency and US dollar pricing. Our estimates show that a deterioration of the CIP deviation (i.e., higher trading costs) of 125 basis points leads to a 26% decrease in the probability of pricing in dollars and a 44% decrease in the likelihood of local currency pricing for hedging firms. As expected, we observe

[5]The covered interest parity (or basis) is a non-arbitrage condition that states that the return of investing in dollar markets (e.g., interbank or treasury) should be the same as that of investing in euro markets while hedging the position from currency risk. Therefore, a negative basis implies an unexploited arbitrage opportunity, which –in the case we consider– was mainly due to the reluctance of US money market funds to lend dollars to European banks potentially exposed to Greek default risk (Ivashina et al., 2015).

a larger impact on small firms, which are less able to internalize higher costs of hedging, than on big firms, which are not significantly affected by the shock.

Second, we observe that hedging firms price more their goods in dollars than in local currency in the cross-section. These results imply that dollar markets can serve firms' hedging needs better than local currency markets. If there were no differences in trading costs, hedging firms would probably rely less on the dollar as vehicle currency because they would be able to hedge their exposure in local currency. However, the difference in trading costs across currency pairs (coupled with extended price discrimination) leads hedging firms to resort to dollar pricing. Therefore, our results corroborate the idea that the development of dollar FX markets is important for explaining the widespread adoption of the dollar (a finding consistent with Boz et al., 2019; Maggiori et al., 2019).[6]

Third, we also investigate whether FX hedging firms have different exchange-rate pass-through dynamics. We focus on the price adjustments up to eight quarters after an FX shock between FX hedging and non-hedging firms using different currency pricing. As expected, we do not find any difference between FX hedging and non-hedging firms using producer currency pricing, as there is no currency risk involved. On the other hand, there are significant differences between hedging and non-hedging firms for goods denominated in local currency and U.S. dollars. Our results show that hedging firms have lower levels of exchange-rate pass-through, meaning that their prices are more stable because they price more their goods in foreign currency. Furthermore, we find that the persistence and magnitude of the difference between hedging and non-hedging firms depend on their size. We conclude that FX hedging makes real variables more *disconnected* from exchange-rate movements.

It is worth highlighting that France is the ideal setting for studying the link between FX hedging and invoicing currency choice. First, it is an advanced economy with large and diversified industries; and second, it adopted the euro, the second world reserve currency.[7] French firms, unlike those operating within many other economies, have a potentially viable alternative to the U.S. dollar.

[6] In our analysis, we control for a large set of covariates that the literature has proven to be related to currency choice, namely the firm's weighted-average export share, the share of imports in foreign currency, the firm's size, and the firm's degree of sophistication (Amiti et al., 2014, 2022; Corsetti et al., 2018; Lyonnet et al., 2020). In addition, we account for currency pegs by using the classification of Ilzetzki et al., 2019. Finally, our findings hold to a wide range of robustness tests for misspecification, selection, and omitted-variable bias, among others.

[7] See the IMF World Currency Composition of Official Foreign Exchange Reserves. Link: https://data.imf.org/regular.aspx?key=41175. See also Adler et al., 2020 for the role of the euro as invoicing currency.

Hence, our findings about the dollar are likely to be even stronger in the case of developing and emerging countries.

Finally, our paper contributes to the debate about dollar dominance and, more generally, currency internationalization. More developed and accessible FX forward markets are important for currency internationalization, in line with the requirement of the IMF Board for the inclusion of a currency in the special drawing rights basket (Bahaj et al., 2020; Eichengreen et al., 2014; IMF, 2011). In addition, our results are particularly relevant in light of the efforts to internationalize the Chinese renminbi[8] and given the advent of private stablecoins sponsored by large entities (Gopinath et al., 2020a). Finally, FX hedging tends to render prices stickier, undermining the effectiveness of monetary policy (Chen et al., 2021). In other words, FX derivatives markets contribute to the exchange-rate disconnect puzzle as they reduce the sensitivity of prices to currency shocks (Meese et al., 1983).

The rest of the paper is organized as follows. Section 1.2 reviews the literature. Section 1.3 develops the theoretical model. Section 1.4 describes the data, whereas Section 1.5 reports relevant summary statistics. Section 1.6 empirically investigates how access to hedging relates to currency choice, while Section 1.7 exploits a natural experiment to identify the mechanisms. Section 1.8 estimates the effects of FX hedging on exchange-rate pass-through dynamics. Finally, Section 1.9 concludes.

1.2 Literature Review

This paper contributes to the extensive literature on how internationally active firms choose their invoicing currencies and the consequences in terms of exchange-rate pass-through.[9] Firms' choice is driven by multiple factors: the extent of price rigidity, which depends on the adjustment costs (e.g., menu costs) or on the type of traded goods (e.g., commodities are adjusted more frequently); the cost structure, as firms with a large fraction of foreign-denominated inputs or financing are incentivized to price their products in the same currencies to shield their profits from adverse currency movements (i.e., operational or *natural* hedging); the curvature of the demand function for prices (i.e., demand elasticity), as highly elastic demands discourage upward price adjustments making

[8]The Chinese share of the world's GDP is booming while its currency is experiencing a series of structural developments, such as establishing multiple central bank swap lines and issuing its retail digital version (e.g., see Bahaj et al., 2020; Eichengreen, 2013).

[9]The first paper on the topic is Betts et al., 1996.

prices stickier.[10] Goldberg et al., 2016 use Canadian invoice-level data to empirically pinpoint determinants of invoicing currency choice. At the macro level, FX volatility and exchange rate regimes are significantly correlated with firms' choices, whereas, at the micro level, market share, absolute, and relative size matter.[11] At the transaction level, large deals tend to be priced more in foreign currency, probably because hedging costs are relatively smaller.[12] Furthermore, invoicing currency choice directly impacts the exchange-rate pass-through into prices e.g., see Amiti et al., 2022; Corsetti et al., 2018; Friberg et al., 2008; Gopinath et al., 2010.[13] For instance, Amiti et al., 2022 show that invoicing currencies are crucial in determining the degree of exchange-rate pass-through. They also document the causal effects of strategic complementarities for currency choice. Finally, the literature has shown that firms' characteristics are also important for FX shock transmissions beyond the invoicing currency. In particular, variables like size, market power, or asymmetric information have relevant explanatory power for quantifying the degree of exchange rate pass-through (e.g., see Amiti et al., 2014; Berman et al., 2012; Corsetti et al., 2018; Garetto, 2016). We contribute to this strand of literature by studying the impact of FX hedging on both currency choice and exchange-rate pass-through.

Our paper also relates to the literature on dollar dominance.[14] The debate revolves around the fact that the US dollar is broadly used in trade and finance, even for transactions in which the United States are not involved (e.g., see Adler et al., 2020; Boz et al., 2019; Cook et al., 2018; Eichengreen et al., 2009; Gopinath, 2015; Gopinath et al., 2020a; Maggiori et al., 2019, 2020; Somogyi, 2021). In her influential contribution, Gopinath, 2015 argues that the extensive use of vehicle currency, namely the US dollar, changes how international shocks are transmitted into prices. Using UK firm-level data, Chen et al., 2018 find that the pass-through amplifies once vehicle currencies are considered.[15] Using

[10] Bacchetta et al., 2005, and Burstein et al., 2014 formalize this framework using general equilibrium models to study the elasticity of local prices to exchange rate shocks. In their setting, firms' currency choice depends on the curvature of the demand function, the sensitivity of marginal costs to exchange rates, and the type of returns to scale. This strand of literature departs from the standard Mundell-Fleming framework in which exporters price only in their currency.

[11] Their findings are consistent with Devereux et al., 2015 who argue that pass-through is non-monotonic and U-shaped in exporters' market share but monotonically decreasing in importers' market share.

[12] Chung, 2016 also supports that invoicing currency choice is related to the dependence on foreign currency-denominated inputs.

[13] Gopinath et al., 2010 estimate that the average pass-through for non-dollar (foreign) denominated goods in the US is 95%, whereas it is 25% for dollar (local) denominated ones.

[14] Gopinath et al., 2021 provide a broad review of the topic.

[15] Interestingly, Cook et al., 2018 also document that dollar invoicing has real implications for international trade flows.

Belgian invoicing data, Amiti et al., 2022 argue that large import-intensive firms use more foreign currency pricing, especially in US dollars. Such firms also show lower levels of pass-through of the euro-destination exchange rate and a high elasticity to the dollar-destination country exchange rate. In addition, Maggiori et al., 2020 argue that vehicle currencies, especially the US dollar, are more used because they have larger and more liquid financial markets. We relate to this literature by arguing that the cost of hedging influences currency adoption and in particular the favorable features of dollar FX forward markets contribute to its dominant status.

Finally, our results also speak to the literature on FX hedging. Foreign currency risk is one of the biggest concerns of companies trading internationally (Aabo et al., 2010). More generally, from a theoretical standpoint, a firm may want to hedge for various reasons, such as costly external finance (Froot et al., 1993; Rampini et al., 2010), risk aversion (Stulz, 1984), financial distress, or convex taxes (Smith et al., 1985). Nevertheless, the literature on FX risk and currency adoption is still relatively limited. Lyonnet et al., 2020 explore the link between invoicing currency and financial hedging using cross-sectional survey data of roughly three thousand European companies. They conclude that large companies are more likely to price their products in foreign currency because they can easily cover (fixed) hedging costs. In addition, using bank-firm relationship data, Berthou et al., 2022 show a reduction in export growth to "US dollar destinations" after the 2011 dollar funding shortage. Furthermore, Hau et al., 2022 study how the currency- and firm-specific trading costs of European OTC FX forward markets deter firms' hedging choices. Alfaro et al., 2022 use a unique dataset on Chilean FX derivatives transactions to study the hedging behavior of firms. They find that operational FX risk hedging is limited, larger firms are more likely to hedge and do it for large amounts, and firms are more likely to hedge their gross exposures independently (i.e., exports and imports separately). Jung, 2022 exploits a quasi-natural experiment to examine the real effects of FX hedging and shows that a shortage in the supply of FX products results in a substantial reduction in exports. Finally, Adams et al., 2022 use publicly available balance sheet data to proxy for FX exposure of Japanese and US companies. They show that exchange rate fluctuations influence the stock returns of Japanese firms with FX exposures. Differently from the existing literature, we exploit a natural experiment to study how changes in trading costs impact firms' currency choices. Although we do not observe the intensive margin of hedging, we contribute to this strand of literature by showing the reals effect of having access to FX forward markets on export currency choice and international shock propagation.

1.3 Theoretical Framework

We use a standard theoretical framework to study the interaction between FX hedging and currency choice. The model features a representative exporting firm with endogenous currency choice and exchange pass-through in a staggered price-setting environment. The desired ERPT determines the currency choice of the firm during the period of price stickiness. The representative firm is financially constrained and therefore has a motive to hedge its profits from currency risk. However, hedging is costly, and the firm has limited access to FX forward markets. We are interested in studying how the firm's currency choice changes with exogenous changes in its access to hedging products (i.e., FX forward derivatives). Note that we do not model the optimal hedging choice of the firm to keep the model tractable.[16]

1.3.1 Model Setup

We develop a model of endogenous currency choice in a static price-setting environment. The model features a representative firm optimally choosing its prices when exporting to another currency area. The exporting firm decides whether to price its product in producer or foreign[17] currency. Let p^P be the log price of the product in producer, or exporter, currency (PCP), and p^F the equivalent log price in foreign currency (FCP). We define the log exchange rate $e^{F/P}$ such that an increase in the exchange rate corresponds to an appreciation of the producer currency: $p^F = p^P + e^{F/P}$.

The exporting firm can enter an FX hedging contract to better deal with currency risk. Since access to FX forward markets is limited, and the firm faces hedging costs, it can hedge only a fraction $h \in [0, 1]$ of its exports. The parameter h is equal to zero when the firm does not have access to FX forward markets and to one when it fully hedges. The FX hedging strategy reduces currency risk by fixing the forward rate $f^{F/P}$ with a contract. This operation

[16]Our approach is similar to Adams et al., 2022, who do the opposite by modelling the firm's hedging choice given the invoicing currency.

[17]At the moment, we do not differentiate between local and vehicle currency (see Section 1.3.4).

gives the following equivalent foreign currency price:

$$p^{hF} = p^P + e^{F/P} + h\left(f^{F/P} - e^{F/P}\right) \tag{1.1}$$

$$= p^F + h\left(f^{F/P} - e^{F/P}\right). \tag{1.2}$$

It is worth noting that, when the firm does not hedge, and $h = 0$, then $p^{hF} = p^F$.

Finally, we define the firm's profit function $\Pi\big(p^P|S\big)$ such that it depends on the correspondent price expressed in producer currency and on a state vector S. The state vector can include demand conditions, cost shocks, competitors' prices, and exchange rates.

1.3.2 Optimal Pricing

We define the desired price of the firm in producer currency as the price it would set if it could frictionlessly adjust its price in state S:

$$\tilde{p}^P = \arg\max_{p^P} \ \Pi\big(p^P|S\big). \tag{1.3}$$

We introduce price stickiness as in Calvo, 1983: the firm readjusts its price with probability $1-\phi$ each period, where ϕ is the degree of price stickiness. Therefore, the firm presets the price $\bar{p}^{hF}$ in foreign currency before observing the state S, and it will remain with probability ϕ. In this case, the realized price for the firm will be $p^P = \bar{p}^{hF} - e^{F/P} - h\left(f^{F/P} - e^{F/P}\right)$. With probability $1-\phi$, the firm is able to adjust its price to the desired level, and the realized price is $p^P = \tilde{p}^P$.

The optimal preset price in foreign currency is obtained from a first-order approximation of the first-order condition that characterizes the maximization problem of the exporting firm:

$$\bar{p}^{hF} = \arg\max_{p^{hF}} \ E\left[\Pi\left(p^{hF} - e^{F/P} - h\left(f^{F/P} - e^{F/P}\right)|S\right)\right] \tag{1.4}$$

$$= E\left[\tilde{p}^P + e^{F/P} + h\left(f^{F/P} - e^{F/P}\right)\right] = E\left[\tilde{p}^{hF}\right]. \tag{1.5}$$

The firm chooses its preset price to target the average desired price expressed in foreign currency and considering FX hedging. When $h = 0$, there is no hedging, and the results boil down to ones of Amiti et al., 2022, and Gopinath et al., 2010 in one period.

1.3.3 Currency Choice

Following the results in Amiti et al., 2022, the optimal currency choice for the firm is the one that minimizes the variance of the desired price expressed in currency i:

$$i = \arg\min_{i} \operatorname{var}\left(\tilde{p}^{i}\right). \tag{1.6}$$

The choice of currency i ensures that the firm minimizes the loss from price stickiness. The variance comes from the second-order approximation of the profit function, as shown in Engel, 2006, Gopinath et al., 2010, Amiti et al., 2022, among others. If there is no price stickiness ($\phi = 0$), prices adjust every period, and currency choice is irrelevant. On the contrary, when prices are sticky, the firm chooses the currency with the lowest variance of the desired price.

Hence, foreign currency pricing (without hedging) is favoured over producer currency pricing when $\operatorname{var}\left(\tilde{p}^{F}\right) < \operatorname{var}\left(\tilde{p}^{P}\right)$, that translates in the condition:

$$\frac{\operatorname{cov}\left(\tilde{p}^{P} + e^{F/P}, e^{F/P}\right)}{\operatorname{var}(e^{F/P})} < \frac{1}{2}. \tag{1.7}$$

The left-hand side of the condition is the projection of the desired price in foreign currency on the corresponding exchange rate or the exchange rate pass-through (ERPT) elasticity for the desired price. It is worth noting that, as in Engel, 2006, Gopinath et al., 2010, and Amiti et al., 2022, foreign currency pricing is favored if the exchange rate pass-through into $\tilde{p}^{F}$ is low, which means that the desired price expressed in FCP does not vary closely with the exchange rate. In the opposite scenario, the optimal choice for the firm is producer currency, which ensures a high (or complete) ERPT.

Following the same logic, we can find similar conditions for a hedging firm. When the firm has access to FX forward markets, it prefers foreign currency over producer currency when $\operatorname{var}\left(\tilde{p}^{hF}\right) < \operatorname{var}\left(\tilde{p}^{P}\right)$. Expanding the variance of the desired price of a hedging firm, this condition is equivalent to:

$$\frac{\operatorname{cov}\left(\tilde{p}^{P} + e^{F/P}, e^{F/P}\right)}{\operatorname{var}(e^{F/P})} < \frac{1+h}{2}. \tag{1.8}$$

PROPOSITION 1. *FX hedging favours foreign currency pricing.*

Proof. As $h \in [0, 1]$, the threshold at which a hedging firm prefers producer currency is higher than for a non-hedging firm $\left(\frac{1+h}{2} > \frac{1}{2}\right)$. Consequently, having access to FX forward markets can increase the probability of choosing foreign currency pricing. □

On the other hand, foreign currency pricing with hedging is preferred to simple foreign currency pricing whenever $\mathrm{var}\big(\tilde{p}^{hF}\big) < \mathrm{var}\big(\tilde{p}^{F}\big)$, which means:

$$\frac{\mathrm{cov}\big(\tilde{p}^{P} + e^{F/P}, e^{F/P}\big)}{\mathrm{var}\big(e^{F/P}\big)} > \frac{h}{2}. \tag{1.9}$$

Figure 1.1 shows a summary of the optimal choices for the exporting firm. We can observe that the parameter h increases the threshold under which the firm starts to optimally choose foreign currency, as observed in Proposition 1. The higher the fraction of exports hedged (h), the higher the probability of choosing foreign currency.

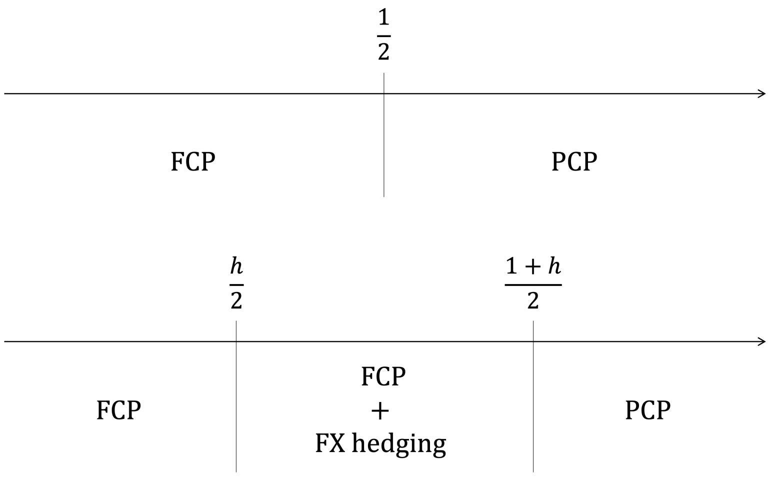


FIGURE (1.1) Conditions for optimal currency choice

Notes: The horizontal axis represent $\mathrm{cov}\big(\tilde{p}^{F}, e^{F/P}\big) / \mathrm{var}\big(e^{F/P}\big)$. The graph above (below) represents the currency choice without (with) FX hedging. PCP and FCP stand for producer and foreign currency pricing, respectively.

1.3.4 Local and Vehicle Currency Pricing

Let's now assume that the exporting firm can choose among producer, local and vehicle currency pricing. As before, the firm will optimally choose the currency with the lowest variance of the desired price.

DEFINITION 1. *We say that currency markets A offer better services than currency markets B when they provide more accessible products that are cheaper and more liquid. For this reason, access to markets A is greater than access to markets B:* $h^{A} > h^{B}$.

PROPOSITION 2. *Firms prefer vehicle over local currency pricing when the vehicle currency markets offer better services.*

Proof. Following Proposition 1, we know that the higher the access to hedging h, the higher is foreign currency pricing. Now, assume that the vehicle currency has more accessible markets than the local currency, i.e., $h^V > h^L$. Then, without loss of generality, we can say that firms prefer vehicles over local currency pricing when the vehicle currency markets offer better services. □

1.3.5 Empirical Implications

In the model, the hedging parameter represents the fraction of exports hedged by the representative firm. Empirically, we interpret it as access to FX hedging markets. More practically, it could be akin to the inverse function of hedging costs: the higher the trading costs, the lower is firms' access to hedging products.[18]

Overall, the model provides three main insights. First, hedging firms resort more to local currency and US dollar pricing (see Proposition 1). Second, firms also choose dollar pricing as dollar FX forward markets are relatively more developed than the ones of other currencies (see Proposition 2). Third, hedging firms that opt for pricing in foreign currency (instead of producer currency) can attain lower levels of pass-through (see Figure 1.1).

1.4 Data

The empirical analysis mainly relies on French firms' FX forward positions, their customs declarations,and exchange-rate regimes from Ilzetzki et al., 2019. Specifically, our data contains information regarding FX forward exposure at the firm-currency-time level and the entire universe of French customs declarations. For this latter, we know the identity of the firm, currency, date, quantity, FOB value in euro, FOB value in foreign currency, number of units, destination/source country, and CN8 product code.[19] The dataset by Ilzetzki et al., 2019 gathers a comprehensive recollection of rate regimes, anchors, currency arrangements, and all the exchange rate restrictions for all currency pairs.[20] In addition, they render the bilateral arrangements comparable by classifying them into fifteen different categories (e.g., "Currency Union", "De facto peg").

[18]Hau et al., 2022 study how expected firm-level hedging costs affect firms' market participation, whereas Somogyi, 2021 investigates how differences in trading costs leads to more dollar trading as the dollar is used as a vehicle currency to indirectly exchange two non-dollar currencies.

[19]The first 6-digits of the CN codes (CN6) correspond to the World Harmonized System (HS6).

[20]The authors published their dataset on Ilzetski's website: https://www.ilzetzki.com/irr-data.

We focus on French exports to extra-EU countries and FX forward positions, including the forward leg of FX swaps. We exclude international trades with intra-EU countries because the currency variable is unavailable for these transactions.[21] Finally, we complement the data with exchange rates and additional firm characteristics from Thomson Reuters/Eikon API and INSEE API, respectively.

The French economy is ideal for studying the link between FX hedging, foreign currency pricing, and exchange-rate pass-through dynamics. It is a developed country with a matured manufacturing sector, plenty of diversity, and an advanced financial industry. It has 93 FX dealers, and access to financial services does not depend on the geographical location of firms. In addition, France has the euro, the second largest reserve currency after the US dollar,[22] meaning that French companies have a viable alternative to the US dollar when they choose the denomination of their exports. Hence, this setting is optimal for investigating how FX hedging interacts with the international dominance of the US dollar in terms of currency choice and exchange rate pass-through.

We clean the data by following Bergounhon et al., 2018. We drop non-financial and non-governmental companies as they potentially have different incentives and motives when choosing a currency of invoicing, with consequent peculiar exchange-rate pass-through dynamics.[23] Furthermore, we exclude all siren codes (i.e., firm IDs), CN8 product codes, and country codes that do not conform with the definition of the variable (e.g., when a siren code contains a letter) or that are missing values. We filter out outliers or implausible entries such as European countries wrongly registered in the extra-EU dataset (e.g., Germany, Spain, and Italy). Finally, we drop all countries with the US dollar as official currency, mainly the US, as the US dollar would be considered both local and vehicle currency simultaneously.

Since we are interested in studying firms' currency choice, we correct for currency pegs, namely the instances in which the exchange rate is artificially kept fixed by some official agreement or de facto policies. Specifically, we consider a currency as "pegged" when it is classified as "no separate legal tender or currency union", "pre-announced peg or currency board arrangement", "pre-announced horizontal band that is narrower than or equal to +/-2%", or "de facto peg" by

[21] We argue that this does not imply any sample bias as transactions within the EU are likely to be denominated in euros. In such a context, researching invoicing currency choices is not informative.

[22] Source: World Currency Composition of Official Foreign Exchange Reserves - International Monetary Fund. Link: https://data.imf.org/regular.aspx?key=41175. See also Adler et al., 2020 for the role of the euro as invoicing currency.

[23] Specifically, we drop Naf2 $\in [64, 66] \vee [84]$.

Ilzetzki et al., 2019. For example, when a French firm prices in local currency but such currency is pegged to the euro, we consider this transaction as if it was in producer currency (i.e., euro). We apply similar adjustments for currency pegs with the US dollar for dollarized economies.[24] Such adjustments allow us to thoroughly isolate the cases in which firms are effectively exposed to currency risk and the instances in which they are not.

Customs declarations do not provide product prices, so we compute them by dividing the euro-equivalent value of the transaction by the number of units (similarly to Amiti et al., 2022). We also drop all the transactions with missing prices. Finally, in the derivatives dataset, we consider the following currencies vis-à-vis the euro: Australian dollar (AUD), Canadian dollar (CAD), Swiss franc (CHF), Chinese yuan renminbi (CNY), British pound (GBP), Hong Kong dollar (HKD), Korean won (KRW), Japanese yen (JPY), Russian ruble (RUB), Singapore dollar (SGD), Turkish lira (TRY), and US dollar (USD). Overall, they account for roughly 96% of the transactions.

The final sample comprises almost 55'000 firms distributed in 705 French geographical areas, 19 NAF2 industries, and trading 2'316 different CN8 product codes with 125 countries in 67 currencies. Notably, almost a quarter of the transactions (24%) are by FX hedging firms. We define a firm as hedging if it has an outstanding FX forward position for at least one month. Table 1.1 reports the number of unique values for some characteristics of the firms in the sample.

Table (1.1) Summary statistics by firm type

	Firms	Currencies	Industries	Sizes	Products	Countries
Non-Hedging	52'589	61	19	17	2'308	125
Hedging	2'391	48	16	17	2'009	119

Notes: This table reports the number of unique values for some characteristics of the firms in each sub-sample. The *Hedging* sample includes all firms with an outstanding FX forward exposure for at least one month. *Firms* refers to the number of unique firms in each sub-sample. *Currencies* is the number of unique trading currencies. *Industries* refers to the number of unique Naf2 section classifications. *Sizes* is the number of different size bin classifications according to the number of employees. *Products* refers to the number of unique CN8 product codes exported to extra-EU countries. Finally, *Countries* is the number of extra-EU countries to which the firms in the sub-sample exported.

FX hedging firms cover almost the same spectrum of the non-hedging sample. The difference in the number of unique currencies does not pose any concern

[24] We also account for indirect pegs, namely when a currency is not directly pegged to the euro (or the US dollar) but to a currency that is pegged to the euro (or the US dollar).

as most of the exports are concentrated in a limited number of currencies common to both samples. In addition, in both samples, there are companies of all size categories, which is an important feature since the literature has established that size is a prime determinant of currency choice and is usually correlated with a wide range of unobservables (e.g. Döhring, 2008; Goldberg et al., 2016; Lyonnet et al., 2020). Furthermore, hedging firms are present in most industries and trade with almost as many countries as non-hedging firms. The difference in the number of unique exported products is arguably explained by the fact that there are three more industries among non-hedging firms. Hence, Table 1.1 shows that the two sub-samples are relatively similar, suggesting that hedging firms do not inherently differ from non-hedging ones. Nevertheless, we further discuss this aspect in the next section and the robustness tests of our empirical analysis.

1.5 Summary Statistics

Our dataset is highly heterogeneous and captures several cross-sectional dimensions relevant for studying invoicing currency choice. At the same time, there is a remarkable persistency in time-varying variables as firms do not often switch to different pricing or hedging strategies. In this section, we first document the extent to which currency pairs and FX hedging firms operate. Secondly, we show how FX hedging firms differ in their pricing strategies.

Figure 1.2 shows the percentage of FX hedging firms trading a given currency vis-à-vis the euro and the annualized realized volatility of each currency pair. Consistently with Maggiori et al., 2020, the US dollar is highly appreciated among hedging firms as 90% have traded the EUR-USD at least once. The remaining currency pairs are traded by less than 20% of the firms. As expected, there is a negative correlation between the usage of a currency and its volatility. Nonetheless, the coefficient is not very high (-16.5%), suggesting that other determinants might explain the distribution's skewness.[25]

[25] If we exclude the RUB-EUR, the two variables are uncorrelated.

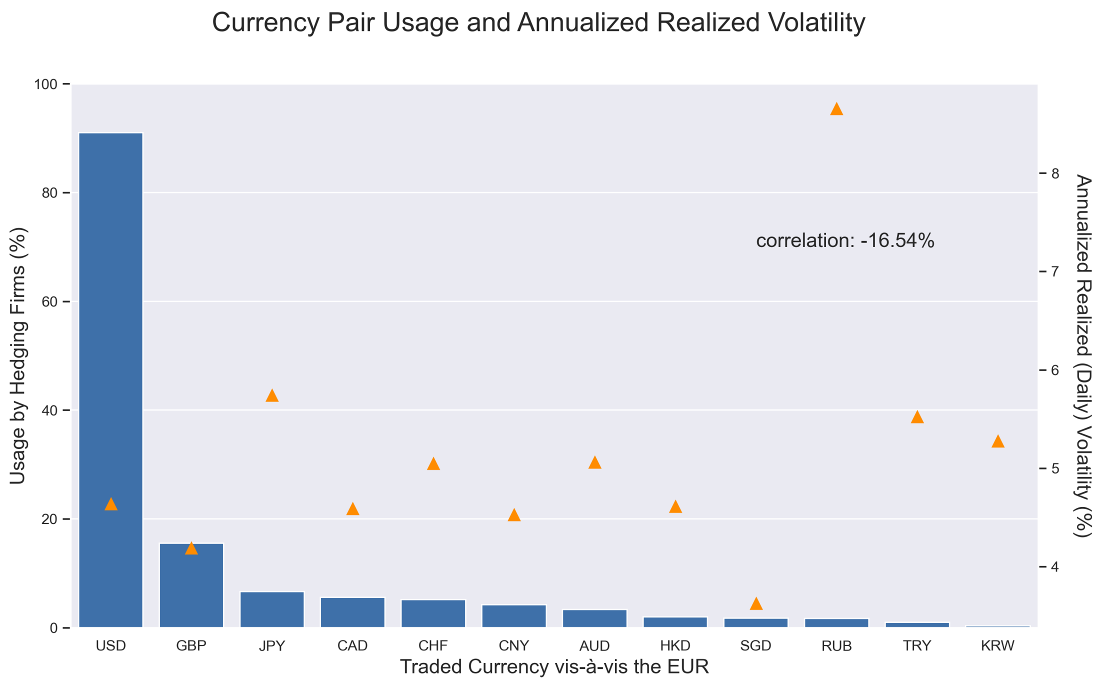


FIGURE (1.2) Currency pairs traded in OTC FX forward markets and realized volatility

Notes: The chart plots the percentage use of a currency vis-à-vis the euro by FX hedging firms (bar plot) as well as the correspondent level of annualized realized (daily) volatility from 2010 to 2017 (scatter plot).

Figure 1.3 shows the percentage of hedging firms by size category. Consistently with the literature, the number of hedging firms is limited, and they tend to be larger than non-hedging ones. We focus on the extensive margins as firms face high fixed costs to enter such markets (e.g., see Hau et al., 2021; Lyonnet et al., 2020). Using a broad survey dataset, Lyonnet et al., 2020 find that large firms are more likely to use hedging instruments, as they can internalize the fixed costs better than smaller ones e.g., see also Adams et al., 2022; Hau et al., 2022. In addition, it is worth noting that currency risk management is not a trivial activity. Thus only sophisticated firms may be able to do it effectively, and these are usually large.

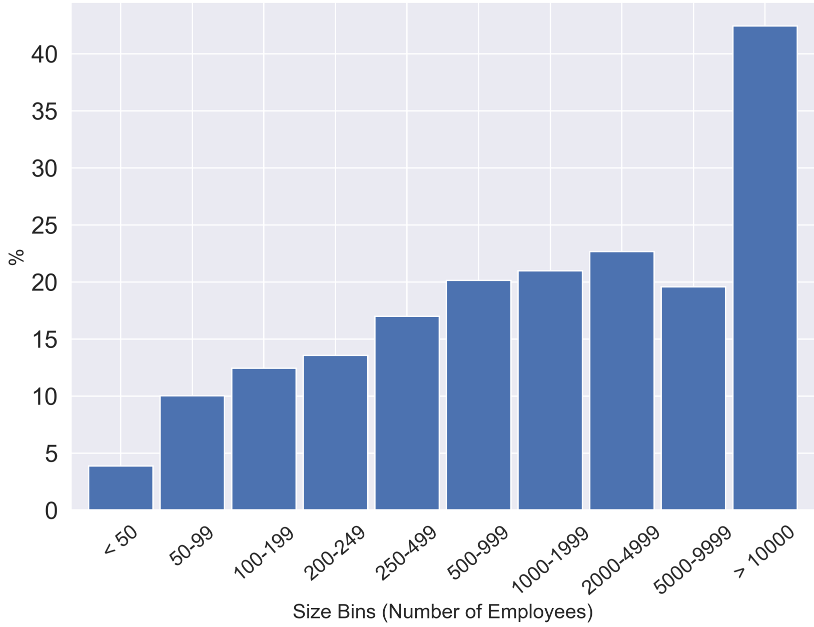


FIGURE (1.3) Share of hedging firms by size bins

Data also shows a remarkable persistence of FX hedging over time. More precisely, if a firm has an outstanding FX contract in a given period and currency pair, it will likely have an FX forward position in the next period. This persistence is evident in Table 1.2, which reports the transition probabilities of the variable *Hedge* at the firm-currency-month level. The rows represent the firms' status at time t, whereas the columns at time $t+1$. Firms that do not hedge have a low probability of underwriting an FX forward contract in the next period. However, once they start, they keep doing it more than 95% of the time. Interestingly, the transition probabilities are essentially the same when dropping the US dollar or considering only the firm-month variation.

TABLE (1.2) Transition probability matrix of the variable Hedge_{fct}

	$\text{Not-Hedging}_{fc,t+1}$	$\text{Hedging}_{fc,t+1}$
$\text{Not-Hedging}_{fc,t}$	86.2%	13.8%
$\text{Hedging}_{fc,t}$	4.6%	95.4%

Notes: The matrix reports the probability of hedging or not-hedging next month (columns), given the status of the current month (rows).

Figure 1.4 focuses the destination markets to which hedging and non-hedging firms export their goods. The top (bottom) panel shows the export countries with which non-hedging (hedging) firms do business. The darker the color, the higher the trading volume, whereas grey countries do not trade with the firms we consider.[26] The correlation between the two sets is higher than 90%, indicating that hedging and non-hedging firms do not differ substantially in terms of countries with which they trade. Nevertheless, this is only suggestive evidence. We formally discuss and test the differences in export countries (before and after the shock) in Section 1.7.3.

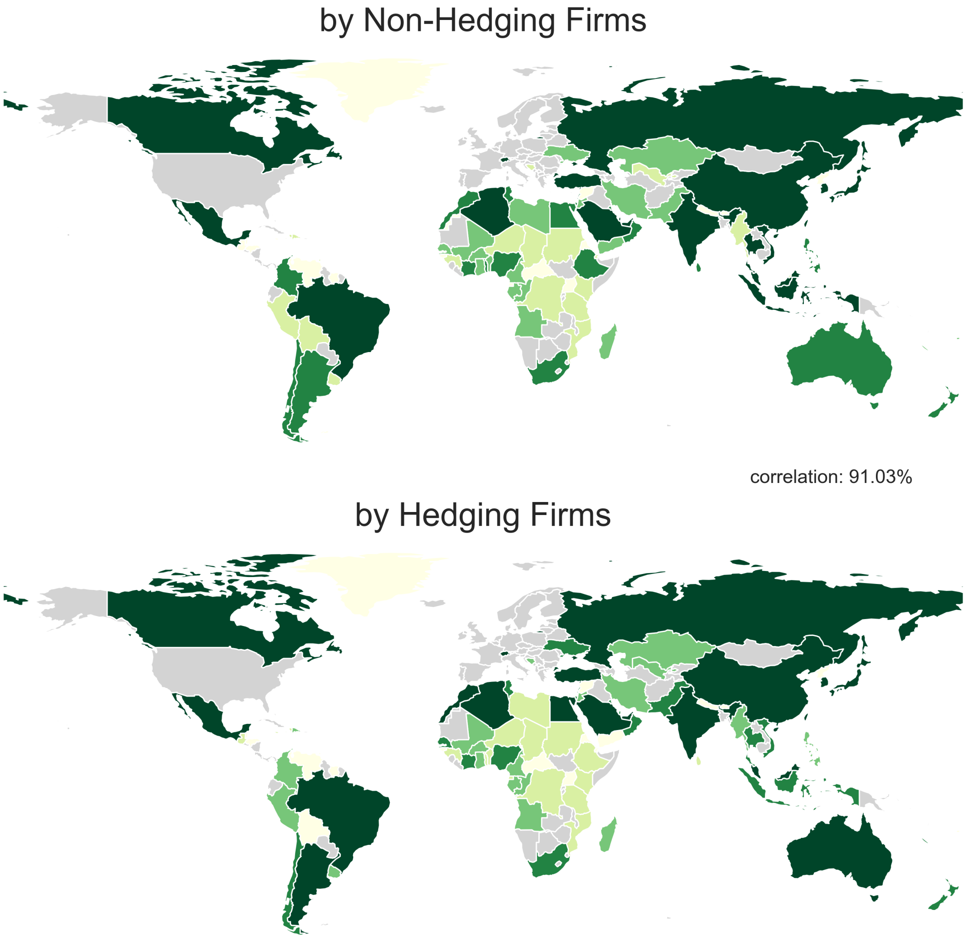


FIGURE (1.4) Exports to extra-EU countries by hedging type

Notes: The pictures show the destinations and export intensities of hedging and non-hedging firms. Darker tones indicate higher export volumes. Grey countries are either excluded from our dataset (i.e., the United States and EU members) or do not engage in trade with French firms.

Finally, we investigate how firms' pricing strategies evolve through time. Table 1.3 reports the transition matrices of switching from one invoicing strategy to another, from one month to the next at the firm-country-product level. Consistently with Corsetti et al., 2018 and Barbiero, 2019, the probability of moving from one regime to another is relatively low. Notably, hedging and non-hedging firms have almost the same transition probabilities. We notice that the

[26]The United States and Europe are excluded from the sample at the beginning of the analysis. For further details, please refer to Section 1.4.

dynamic choices are between the euro and either the local currency or the US dollar, meaning that firms rarely decide between the US dollar and other currencies once the currency choice is made. Moreover, firms are unlikely to switch to another currency once they start invoicing in euros. This fact is consistent with the intuition that French firms would prefer to use the euro in the absence of frictions and other strategic considerations.

TABLE (1.3) Transition probability matrices of firms' pricing strategies by hedging type

Full Sample

	EUR_{t+1}	USD_{t+1}	LCP_{t+1}
EUR_t	96.0%	1.9%	2.2%
USD_t	15.8%	81.7%	2.5%
LCP_t	16.4%	2.2%	81.4%

Non-Hedging Sample

	EUR_{t+1}	USD_{t+1}	LCP_{t+1}
EUR_t	96.6%	1.5%	1.9%
USD_t	16.7%	80.8%	2.5%
LCP_t	17.0%	1.7%	81.3%

Hedging Sample

	EUR_{t+1}	USD_{t+1}	LCP_{t+1}
EUR_t	93.9%	3.1%	3.0%
USD_t	14.4%	83.0%	2.5%
LCP_t	15.3%	3.3%	81.4%

Notes: The panels report the transition probabilities of moving from a pricing strategy at time t (rows) to a pricing strategy at $t+1$ (columns). The first matrix considers the whole sample, the second only non-hedging firms, and the third only hedging ones. A firm is classified as hedging if it has an outstanding FX forward position for at least one month.

1.6 FX Hedging and Currency Choice

In this section, we formally test proposition (1) which states that hedging firms resort more to local currency and US dollar pricing, given the amount of local currency volatility of their export countries. Our baseline specification exploits the cross-sectional variation between hedging and non-hedging firms to document their different export currency strategies. Specifically, we estimate the following regression:

$$\begin{aligned} \mathrm{Y}_{ft} = \beta_0 + \beta_1 \mathrm{Hedge}_f + \beta_2 \mathrm{LC\ Volatility}_{ft} \\ + \beta_3 \mathrm{Hedge}_f \times \mathrm{LC\ Volatility}_{ft} + X_{ft} + \mathrm{FEs}_{ft} + \epsilon_{ft} \end{aligned} \tag{1.10}$$

where f stands for firm, and t for year-quarter.[27] The dependent variable is the export-weighted percentage of local currency pricing or US dollar pricing of a firm in a given quarter, corrected for direct and indirect currency pegs, i.e., the instances in which the local currency is artificially kept fixed either to the euro or to the US dollar by the central bank or any other institution (see Section 1.4 for an extensive discussion).[28] We drop all countries with the US dollar as official currency; thus, in our setting, the US dollar always represents a vehicle currency.

Intuitively, higher local currency volatility should be associated with less local currency pricing (i.e., $\beta_2 < 0$) and more dollar pricing (i.e., $\beta_2 > 0$), regardless of whether the firm is hedging or not. However, hedging firms arguably resort more to foreign currency pricing (i.e., $\beta_1 > 0$) as they are better equipped to deal with currency risk. β_3 compares the pricing strategy between hedging and non-hedging firms as it represents their extensive margin difference per unit of local currency volatility. In other words, if a hedging firm exports to country A and a non-hedging one exports to country B, β_3 would capture the difference in their currency choice, accounting for possible differences in local currency volatility between country A and B. Therefore, we ensure that our estimate is not biased by potential differences in the set of countries to which hedging and non-hedging firms sell their goods.

It is worth noting that, ex-ante, it is not clear if we should expect hedging firms to do more or less dollar pricing. If currency markets had the same characteristics, hedging firms would likely rely less on the dollar as vehicle currency and more on local currency pricing as they could hedge their exposure in local currency. Nevertheless, the large difference in trading costs across currency pairs (coupled with extended price discrimination) makes dollar markets cheaper and more liquid, which in turn might lead hedging firms to resort more to dollar pricing (Hau et al., 2022; Maggiori et al., 2019; Somogyi, 2021).

Importantly, equation (1.10) does not allow for any causal interpretation. In principle, a firm could prefer local currency pricing because it is already a hedging firm. Conversely, a firm could decide to hedge because it is pricing its products in local currency or dollars. Nonetheless, a firm enters an FX forward

[27] We consider the time window for which we have complete derivatives data, namely from April 2016 to September 2017.

[28] Our results hold when we do not adjust for per arrangements.

contract because it intends to reduce its exposure to currency risk. We exploit a natural experiment in the next section to address such endogeneity issues.

X_{ft} is a set of control variables that are likely to be correlated with firms' currency choice. Specifically, we include the share of imports in foreign currency, as firms might use them to *naturally* hedge their export exposure in foreign currency. Furthermore, we add the weighted-average firm's export share with respect to all other French exports of the same product to the same country as in Amiti et al., 2022. We also control for the firm's degree of sophistication by adding the number of unique countries to which the firm exports, the number of unique products it exports, and its total number of transactions. In addition, we control for dollar quarterly volatility, as it might influence the choice both directly and indirectly. An increase in dollar volatility might directly discourage dollar pricing, and, at the same time, it would proxy for global market conditions (e.g., see Bruno et al., 2021). We complement the specification with industry-time and size-time fixed effects. The first set absorbs common industry practices related to currency choice and time-varying market conditions. The second set directly controls for firm size, which the literature has established to be an important determinant for firms' currency choice (e.g., see Amiti et al., 2014, 2022; Corsetti et al., 2018; Lyonnet et al., 2020). We interacted it with time to capture time-varying events that might influence a firm's choice, i.e., financing conditions, strategic considerations, and so forth. Standard errors are clustered at size bins level, and summary statistics are reported in Appendix A.2 Table A.3.

Table 1.4 reports the estimates of equation (1.10) across difference specifications and models. The first five regressions refer to dollar pricing, while the next five to local currency pricing. We first estimate probit and logit regressions, and then we move to OLS to be able to account for a large set of fixed effects. In columns (3) and (8), we remove the interaction term to report how the significance of the coefficients changes across specifications. In columns (4), (5), (9), and (10), we remove dollar volatility as it is collinear with the fixed effects.

Table (1.4) Currency choice and FX hedging

	US Dollar Pricing (peg-adj)					Local Currency Pricing (peg-adj)				
	Logit	Probit	OLS	OLS	OLS	Logit	Probit	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Hedge_f	0.382***	0.156***	0.0205***	-0.0123	-0.0125	0.783***	0.326***	0.0244***	0.0144**	0.0142**
	(3.22)	(2.72)	(4.37)	(-1.60)	(-1.63)	(4.79)	(4.04)	(4.23)	(2.30)	(2.28)
$\text{Hedge}_f \times \text{LC Vol.}_{ft}$	0.556**	0.454***		0.110***	0.111***	0.415	0.366		0.0273	0.0279
	(2.56)	(4.02)		(5.11)	(5.13)	(0.84)	(1.49)		(1.16)	(1.19)
LC Vol._{ft}	1.129***	0.563***	0.0398***	0.0321***	0.0324***	0.135	0.00552	-0.00710**	-0.00928***	-0.00943***
	(11.21)	(10.35)	(5.17)	(5.59)	(5.62)	(0.76)	(0.07)	(-2.29)	(-3.07)	(-3.10)
$\text{Foreign Import Share}_{ft}$	1.279***	0.640***	0.0507***	0.0493***	0.0493***	0.301***	0.149***	0.00805**	0.00712**	0.00715**
	(12.71)	(15.23)	(9.30)	(9.57)	(9.55)	(2.87)	(3.18)	(2.57)	(2.50)	(2.51)
$\text{w.a. Export Share}_{ft}$	1.243***	0.576***	0.0299***	0.0262***	0.0262***	-0.787***	-0.343***	-0.00828***	-0.0112***	-0.0112***
	(21.44)	(19.69)	(9.41)	(9.23)	(9.23)	(-3.79)	(-4.55)	(-5.27)	(-5.24)	(-5.26)
Dollar Vol._t	-0.893***	-0.430***	-0.0354***			-0.632*	-0.268*	-0.00240		
	(-3.61)	(-3.91)	(-3.66)			(-1.79)	(-1.80)	(-0.59)		
Sophistication	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time	NO	NO	NO	YES	NO	NO	NO	NO	YES	NO
Industry	NO	NO	NO	YES	NO	NO	NO	NO	YES	NO
Industry × Time	NO	NO	NO	NO	YES	NO	NO	NO	NO	YES
Size Bins	NO	NO	NO	YES	NO	NO	NO	NO	YES	NO
Size Bins × Time	NO	NO	NO	NO	YES	NO	NO	NO	NO	YES
N	117'275	117'275	117'275	117'275	117'275	117'275	117'275	117'275	117'275	117'275
R^2			0.0548	0.0643	0.0653			0.0200	0.0268	0.0278
R^2_{adj} or R^2_{pseudo}	0.264	0.267	0.0548	0.0639	0.0636	0.182	0.184	0.0199	0.0264	0.0260

Notes: The dependent variables are w.a.% USD^{peg}_{ft} and w.a.% LCP^{peg}_{ft}, which are defined as the weighted-average share of US dollar and local currency pricing for firm f in quarter t adjusted for peg arrangements, respectively. Hedge_f is equal to one if firm f has traded an FX forward contract at least once. w.a. LC Volatility_{ft} is the weighted-average local currency volatility of the countries with which firm f is trading at time t, regardless of its currency choice. Foreign Import Share_{ft} is the share of imports in foreign currency. w.a. Export Share_{ft} is the weighted-average (across countries) of the share of exports of firm f in quarter t of a given product to a given country over the total amount of export by all French firms of the same product to the same country. Sophistication controls include the number of transactions (# Transactions_f), the number of unique destination countries (# Countries_f), and unique exported products (# Products_f). Standard errors are clustered at size level, and t-statistics are in parenthesis. * p<.10, ** p<.05, *** p <.01.

Our results show that hedging firms use more foreign currency pricing than non-hedging ones. As expected, the local currency volatility is significant and positively (negatively) associated with dollar (local currency) pricing. The interaction coefficient is positive across specifications, although it is only statistically significant in dollar regressions. This means that hedging firms resort more to dollar pricing than non-hedging ones. Back-of-the-envelope calculations suggest that, on average, hedging firms price in foreign currency almost three times as much as non-hedging ones.

Overall, these regressions imply that firms with access to hedging markets rely more on foreign currency pricing, especially on dollar pricing. Arguably, this is explained by the fact that dollar markets are larger and cheaper; thus, they can better serve firms hedging needs. In other words, our results indicate that hedging firms still rely on dollar pricing, even though they can, in principle, deal with any currency risk. Consistently with the extensive literature on the topic (see, for instance, Boz et al., 2019; Maggiori et al., 2019), our results corroborate the idea that the development of USD FX markets is important in explaining the widespread adoption of the dollar.

As expected, dollar volatility negatively correlates with dollar pricing, while it is mildly significant for local currency pricing. The negative signs in columns (6) and (7) are probably due to quarters characterized by poor global market conditions. Notably, the share of firm-specific export with respect to total French exports is positive for dollar pricing and negative for local currency pricing. Arguably, it correlates with the degree of specialization and firms' export share. For instance, if a firm produces a rare bottle of champagne, it would have a high export share, and it would more easily bargain the use of the euro or the US dollar, as the demand elasticity to price would probably be lower. By contrast, if the firm produces a highly substitutable product, it would presumably be better off pricing to market.

The share of imports in foreign currency is always significant and positively correlated with foreign currency pricing. Consistently with Amiti et al., 2014, this is because exporters are usually the biggest importers, even after controlling for size-time effects. Generally, it seems that firms tend to offset their export exposure by importing in foreign currency and vice-versa. In our analysis, we follow the literature and use export currency choice as the dependent variable, also because firms do use naturally hedge their exports with imports (Alfaro et al., 2022; Gopinath et al., 2021). However, as a robustness test, we re-run the regressions of Table 1.4 by dropping the instances in which dollar or local currency imports were positive and find that the results hold (see Table A.5).

1.7 Event Study: 2011 Dollar Funding Shortage

To study the effect of the use of FX forwards on currency choice, we exploit a dollar funding shortage event that increased the cost of underwriting FX forwards in 2011. Higher trading costs reduced the accessibility (i.e., the use) of hedging products for French firms, and thus these latter reduced their use of foreign currency pricing. In Subsection 1.7.1, we describe the nature of the shock, its exogenous causes, and why it is relevant for French firms. In the following subsections, we augment our baseline specification to identify the effects of losing access to hedging on firms' currency choice, along with a broad set of robustness tests.

1.7.1 Dollar Funding Shortage Event in 2011

The European sovereign debt crisis dramatically worsened in the summer of 2011. In June, the Greek government undertook a series of austerity measures with the aim of not defaulting on their government bonds.[29] Moreover, rumors regarding the possibility of Greece abandoning the euro heightened, undermining the stability of the entire eurozone.[30] Figure 1.5 panel (a) shows the evolution of sovereign spreads, i.e., the differences between 10-year government bonds and the homologous German bund, for selected European countries. The burgeoning concerns over the sustainability of the public debt of southern countries translated into a loss of confidence that led to a steep increase in their sovereign yields.[31]

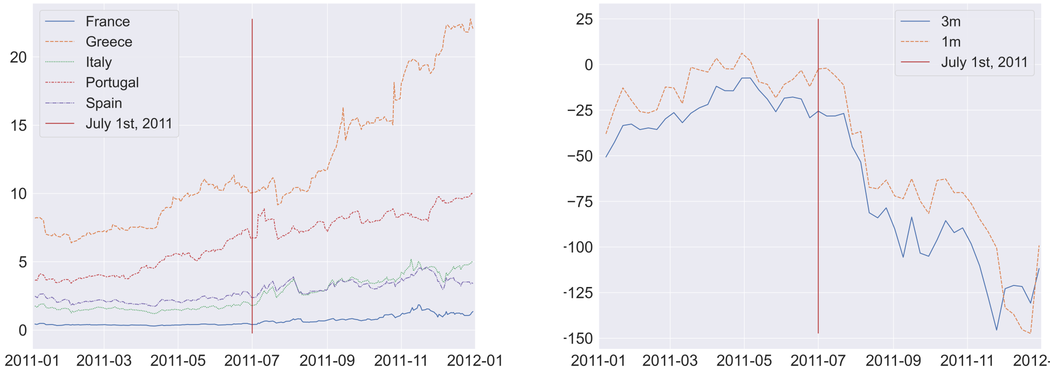
In response to the situation, in the second half of 2011, US investors significantly reduced their exposure to European counterparties (Ivashina et al., 2015). This resulted in a sharp widening of the EUR/USD covered interest rate parity (CIP) deviation (Figure 1.5 panel (b)).[32] A negative CIP (or basis) implies the existence of an arbitrage opportunity in the FX market. More precisely, the return on investing in the USD interbank market is lower than its synthetic equivalent, constructed by selling dollars for euros on the spot market, simultaneously buying forward USD, and investing in the EUR interbank market between the two dates. Therefore, a negative CIP deviation reflects the impossibility or reluctance of investors to lend dollars and take advantage of the arbitrage opportunity. In the case we are considering, the sudden shortage of dollar funding was due to the concerns of US investors over the sustainability of Greek public debt. Evidently, this episode directly affected forward markets and all European exporters, even though they did not cause the shock.

[29] BBC News, "Timeline: The unfolding eurozone crisis", June 13th, 2012. Link: https://www.bbc.com/news/business-13856580.

[30] Russell Hotten, BBC News, "Greece takes the eurozone's future to the brink," June 21st, 2011. Link: https://www.bbc.com/news/business-13842763

[31] BBC News, "Euro crisis: Barroso warns debt crisis is spreading", August 4th, 2011, Link: https://www.bbc.com/news/business-14404852.

[32] For a further discussion on the link between the European sovereign debt crisis and dollar funding, see also Miu, Sarkar, and Tepper, "The European Debt Crisis and the Dollar Funding Gap," August 8th, 2012, link: https://libertystreeteconomics.newyorkfed.org/2012/08/the-european-debt-crisis-and-the-dollar-funding-gap/.



(a) Sovereign Spreads (%) (b) EUR/USD CIP Deviations (bp)

FIGURE (1.5) European sovereign debt crisis and dollar liquidity shortage

Notes: Panel (a) reports the spread, i.e., the difference in the 10-year treasury yields with respect to the German bund, for selected European countries. Panel (b) shows the evolution of the euro-dollar covered interest parity deviation for the one-month and three-month tenor. Data is from Bloomberg. Authors' calculations.

Such a shortage of dollar funding rendered dollar borrowing more expensive (Berthou et al., 2022; Hong et al., 2021; Ivashina et al., 2015). Consequently, hedging currency risk by underwriting a EUR/USD forward also became more expensive, and higher costs reduce firms' hedging participation (Alfaro et al., 2022; Hau et al., 2022; Jung, 2022).[33] Therefore, French firms lost access (at least partially) to USD/EUR hedging in the second half of 2011. Arguably, French companies were particularly influenced by such a shock as the dollar is the most traded currency by French exporters (see Figure 1.2, and also Berthou et al., 2022; Hau et al., 2022; Jung, 2022).[34] Nevertheless, since FX dollar markets are the cheapest, and its products are often used as reference for other currencies, it is reasonable to assume that the tightening was not limited to dollar markets but to all other currency pairs (Hau et al., 2022; Somogyi, 2021). In other words, the 2011 shock was characterized by an overall increase in hedging costs for non-financial firms and consequently by a generalized reduction in their access to hedging.

[33] In addition, there is a direct effect of negative CIP deviation onto the forward value of exports denominated in foreign currency. Consider a French winemaker that exports a bottle of Champagne worth 100 dollars, with the payment due at $t+1$. Let S_t and $F_{t,t+1}$ be the spot and forward rates in dollars per euro, respectively (e.g., $S_t = 1.1$ USD/EUR). If the winemaker fully hedges her revenues, they will receive $100/F_{t,t+1}$ euros at $t+1$. Given the formula of the CIP deviation, i.e., $x_t = (1 + y^{USD}) - (1 + y^{EUR})S_t/F_{t,t+1}$, we can express the value of the bottle of Champagne as a function of the cross-currency basis: bottle $= 100(x_t + 1 + y^{USD})/(S_t(1 + y^{EUR}))$. Therefore, a worsening of the CIP deviation $\Delta x_t < 0$ mechanically implies a decrease in the forward value of the bottle of Champagne.

[34] If was not the case, French firms would not be affected by the shock, and we would not observe any significant result in our analysis. Therefore, if these considerations were incorrect, our results would simply be insignificant.

As mentioned above, the dollar shortage was not caused by French firms, but stemmed from concerns over the creditworthiness of southern countries, especially Greece. During the European crisis, the French government debt was under control and considered fairly safe by financial markets. This view is supported by the fact that the spread between the French OAT and the German bund always remained flat (see Figure 1.5, panel (a), blue line). Therefore, we conclude that the 2011 shock was exogenous and relevant to French firms, making this event ideal for investigating the effects of FX forward markets on firms' currency choice.

1.7.2 Identification Strategy

To identify the causal effects of having access to FX forward markets, we employ a triple-difference strategy by augmenting the equation (1.10) with the dummy variable $Shock2011_t$, which switches to one in the second semester of 2011.[35][36] Formally,

$$\begin{aligned} \mathrm{Y}_{ft} = \alpha_0 + \alpha_1\ \mathrm{Shock2011}_t \times \mathrm{Hedge}_f \times \mathrm{LC\ Volatility}_{ft} \\ + \mathrm{Other\ Interactions}_{ft} + X_{ft} + \mathrm{FEs}_{ft} + \epsilon_{ft} \end{aligned} \tag{1.11}$$

Our identification strategy exploits the fact that hedging firms had harder times in underwriting forward contacts in the second half of 2011. The sudden increase in trading costs made hedging more expensive, and arguably changed the extent to which hedging firms resorted to it. Therefore, equation (1.11) relies on the fact that higher trading costs are associated with lower market participation (Alfaro et al., 2022; Hau et al., 2021, 2022). In other words, we leverage on the exogenous difference in hedging costs over time to investigate how lower access to hedging (i.e., higher trading costs) influences firms' currency choice.

It is worth noting that the triple difference approach allows to tightly control for several potential confounding factors, such as contemporaneous common events, differences across local currency volatility exposures as well as differences across hedging and non-hedging firms. Nevertheless, we run a large set of robustness tests to ensure the solidity of our results (see below).

[35] The Other Interactions$_{ft}$ are Hedge$_f$ × LC Volatility$_{ft}$, $Shock2011_t$ × Hedge$_f$, and $Shock2011_t$ × LC Volatility$_{ft}$.

[36] We consider only the time range that goes from January to December 2011 and not longer, because French customs data do not provide invoicing currency before 2011, and in 2012 the shortage of dollar funding ended thanks to the intervention of the Federal Reserve (FED). Since we do not have hedging data for 2011, we assume that the firms that were hedging in 2016 also did so in 2011. Given the high persistence of hedging choice (see Table 1.2), this is a rather mild assumption.

Table 1.5 reports the regression results of equation (1.11) using different combinations of fixed effects. All specifications lead to conclude that limited access to hedging reduced both dollar and local currency pricing. Specifically, our estimates show that a deterioration of the CIP deviation by 125 basis points led to a 23% decrease in the probability of pricing in dollars, and to a 44% decrease in the probability of local currency pricing for hedging firms. Furthermore, the magnitudes of the coefficients suggest that the cost shock in the euro-dollar market spread to other currency markets, arguably because dollar products are used as a vehicle to trade other currencies (Somogyi, 2021). Put differently, our results indicate that there was a shift in the entire distribution of both foreign currency pricing. This is consistent with our theoretical model, as a decrease in h would correspond to a reduction in foreign currency pricing (see Figure 1.1).

Our results imply that developed financial markets contribute to explaining the dominant role of the dollar in international markets. In other words, firms choose the dollar also because its markets offer cheaper products and can better accommodate their needs as in Gopinath et al., 2020a; Maggiori et al., 2019. These findings complement the current literature on dollar dominance which typically focuses on less complex products such as loans and bonds. Furthermore, our results relate more generally to the broader literature on the future of the international monetary system. Such a debate has recently been revived by efforts of the People's Bank of China to internationalize the Chinese renminbi (e.g., see Bahaj et al., 2020; Georgiadis et al., 2021), by the slow, but steady, erosion of dollar reserves (Arslanalp et al., 2022), as well as by privately sponsored stablecoins (Gopinath et al., 2020a). Our analysis documents the importance of FX trading costs for currency internationalization.

In the remaining subsections, we show that results are robust to common endogeneity concerns that might undermine our identification, such as differences between hedging and non-hedging firms not related to their hedging activity, other strategic responses to the shock (e.g., different sourcing of products), as well as spurious time correlations.

Table (1.5) Tripe-difference regressions

	US Dollar Pricing (peg-adj)			Local Currency Pricing (peg-adj)		
	OLS	OLS	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Shock2011}_t \times \text{Hedge}_f \times \text{LC Vol.}_{ft}$	-0.0482***	-0.0394**	-0.0373**	-0.0497***	-0.0470**	-0.0460**
	(-2.96)	(-2.37)	(-2.25)	(-3.14)	(-2.88)	(-2.79)
Other Interactions	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES
Time	YES	YES	NO	YES	YES	NO
Industry	NO	YES	NO	NO	YES	NO
Industry × Time	NO	NO	YES	NO	NO	YES
Size Bins	NO	YES	NO	NO	YES	NO
Size Bins × Time	NO	NO	YES	NO	NO	YES
N	57'255	57'255	57'252	57'255	57'255	57'252
R^2	0.0524	0.0605	0.0617	0.0283	0.0340	0.0355
R^2_{adj}	0.0522	0.0597	0.0593	0.0281	0.0332	0.0331

Notes: The dependent variables are w.a.% USD_{ft}^{peg} and w.a.% LCP_{ft}^{peg}, which are defined as the weighted-average share of US dollar and local currency pricing for firm f in quarter t adjusted for peg arrangements, respectively. Hedge_f is equal to one if firm f has traded an FX forward contract at least once. w.a. LC Volatility_{ft} is the weighted-average local currency volatility of the countries with which firm f is trading at time t, regardless of its currency choice. The variable shock is equal to one in the second semester of 2011. By "Other Interactions" we mean all the non-reported interactions that characterize a triple-difference identification strategy. In the controls, we include the following variables. Foreign Import Share_{ft} is the share of imports in foreign currency. w.a. Export Share_{ft} is the weighted-average (across countries) of the share of exports of firm f in quarter t of a given product to a given country over the total amount of export by all French firms of the same product to the same country. Sophistication controls include the number of transactions (# Transactions_f), the number of unique destination countries (# Countries_f), and unique exported products (# Products_f). The time span is Jan-Dec 2011. Standard errors are clustered at size level, and t-statistics are in parenthesis. * p<.10, ** p<.05, *** p <.01 .

1.7.3 Robustness Tests and Additional Results

In this subsection, we run a battery of robustness tests to asses whether our results are biased, and driven by anything else than hedging firms temporarily losing access to FX markets. Moreover, we exploit the granularity of our data to investigate which are the characteristics of the firms that explain our results. In Appendix A.4, we report additional robustness checks.

Before exploring the heterogeneity of our findings, we test whether our results are spuriously determined by differences between hedging and non-hedging firms. Potentially, it might be that the shock affected hedging and non-hedging firms differently. Or, our estimates might be biased because being a hedging firm is not a random assignment but a strategic consideration (selection bias).

It might also be the case that there are some other characteristics driving our results that likewise explain why a firm is a hedging one. The fact that our hedging classification is time-invariant only partially alleviates this concern. Thus, in Table 1.8, we focus only on the sample of hedging firms to test whether the interaction between the shock dummy and local currency volatility is still negative and significant. By considering only hedging firms, we rule out the possibility that some inherent differences between hedging or non-hedging firms are biasing our estimates. Our results hold across different specifications. In some cases, the significance even improves, while the magnitude of the coefficients sensibly increases for dollar pricing, and slightly decreases for local currency pricing. In columns (4) and (9), we saturate the regression by looking at the within-firm variation to test whether firms' characteristics matter or not. The coefficients are both negative, although only the one attached to local currency pricing is significant. This is probably due to the fact that we do not have enough time variation and the sample size is relatively small. Finally, in columns (5) and (10), we estimate the firm fixed effect specification on the entire sample. Both coefficients are negative and significant, further supporting the idea that the results are not biased by spurious firm characteristics.

TABLE (1.6) Tripe-difference regressions with firms fixed effects

	US Dollar Pricing (ped-adj)					Local Currency Pricing (ped-adj)				
	Hedging Firms				Full Sample	Hedging Firms				Full Sample
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Shock2011$_t$ × LC Vol.$_{ft}$	-0.0702***	-0.0596***	-0.0534**	0.00478	-0.0150***	-0.0552***	-0.0596***	-0.0627***	-0.0323***	-0.0141***
	(-3.29)	(-2.71)	(-2.31)	(0.22)	(-2.84)	(-3.70)	(-3.89)	(-3.75)	(-2.68)	(-5.35)
Other Interactions	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time	NO	YES	NO	NO	NO	NO	YES	NO	NO	NO
Industry	NO	YES	NO	NO	NO	NO	YES	NO	NO	NO
Industry × Time	NO	NO	YES	YES	YES	NO	NO	YES	YES	YES
Size Bins	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO
Size Bins × Time	NO	NO	YES	NO	NO	NO	NO	YES	NO	NO
Firm	NO	NO	NO	YES	YES	NO	NO	NO	YES	YES
N of Unique Firms	1'697	1'696	1'695	1'249	15'229	1'697	1'696	1'695	1'249	15'229
N	4717	4716	4709	4262	47805	4717	4716	4709	4262	47805
R^2	0.0449	0.0565	0.0802	0.751	0.758	0.0512	0.0566	0.0845	0.776	0.737
R^2_{adj}	0.0431	0.0517	0.0574	0.642	0.644	0.0493	0.0517	0.0618	0.678	0.613

Notes: The dependent variables are w.a.% USD_{ft}^{peg} and w.a.% LCP_{ft}^{peg}, which are defined as the weighted-average share of US dollar and local currency pricing for firm f in quarter t adjusted for peg arrangements, respectively. w.a. LC Volatility_{ft} is the weighted-average local currency volatility of the countries with which firm f is trading at time t, regardless of its currency choice. The variable shock is equal to one in the second semester of 2011. By "Other Interactions" we mean all the non-reported interactions that characterize a triple-difference identification strategy. In the controls, we include the following variables. Foreign Import Share_{ft} is the share of imports in foreign currency. w.a. Export Share_{ft} is the weighted-average (across countries) of the share of exports of firm f in quarter t of a given product to a given country over the total amount of export by all French firms of the same product to the same country. Sophistication controls include the number of transactions (# Transactions_f), the number of unique destination countries (# Countries_f), and unique exported products (# Products_f). The time span is Jan-Dec 2011. Standard errors are clustered at size level, and t-statistics are in parenthesis. * p<.10, ** p<.05, *** p <.01 .

We now discuss possible endogeneity concerns related to firms' exposure to the European economies and their strategic reactions to the 2011 shock. First of all, if there was a generalized loss of confidence in the solidity of the European Union, we should observe less euro pricing, but data actually shows an increase in producer currency pricing. Therefore, if anything, our results are underestimated. Anyway, it is not clear why such a loss of credibility would affect hedging and non-hedging firms differently. Nonetheless, it might be that hedging firms reacted strategically to the shock by changing their sourcing and export countries. Although the correlation of export destination countries served by hedging and non-hedging firms is more than 90% (see Figure 1.4), we formally test these hypotheses by re-estimating our triple-difference specifications on three subsets. It is worth highlighting that none of the exporting firms in our sample was trading with Greece or Portugal, i.e., the two countries that posed the largest debt risk in 2011 (see Figure 1.5 panel (a)). Therefore, we can rule out any possible confounding factor related to a direct exposure of the French firms we consider to those countries, such as a supply chain disruption or other contagious mechanisms. In columns (3) and (4), we restrict the sample to the firms that in Europe were only trading with Germany, which was the country with the most solid financial conditions. Therefore, these specifications ensure sure that our results are not biased by the indirect exposure to southern countries via similarly distressed nations, e.g., Italy. The significance of the coefficients indicates that, also in this case, our results hold. Finally, we check the robustness of our estimates on a rather restricted subsample (columns (7) and (8)). For each firm, we recorded the country-CN8 products it imported and exported in the first half of 2011, and we consider only the firms that kept on buying and selling the same country-CN8 product pairs in the second half of 2011. Since we consider a relatively short time window, this is a rather conservative subsample as the actual share of firms that kept on trading the same country-product pairs is likely to be larger. It is indeed plausible that a firm might not receive or ship the same foreign products so frequently. Anyway, within this subsample, we are sure that firms had not changed their input sourcing or export destinations to cope with the dollar funding shortage. We also make sure that our results are not capturing the effect of specialized bank lending targeted to specific export markets (as in Paravisini et al., 2015). Our estimates hold fairly well considering the large number of observations that we drop. Thus, we conclude that firms' strategic reactions to the shock are not biasing our results.

TABLE (1.7) Value chain regressions

	Full Sample		Only Germany in EU		Same Value Chain	
	USD	LCP	USD	LCP	USD	LCP
	(1)	(2)	(3)	(4)	(5)	(6)
Shock2011$_t$ × Hedge$_f$ × LC Vol.$_{ft}$	-0.0373**	-0.0460**	-0.0382**	-0.0357**	-0.400**	-0.161*
	(-2.25)	(-2.79)	(-2.33)	(-2.37)	(-2.26)	(-2.07)
Other Interactions	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES
Time	NO	NO	NO	NO	NO	NO
Industry	NO	NO	NO	NO	NO	NO
Industry × Time	YES	YES	YES	YES	YES	YES
Size Bins	NO	NO	NO	NO	NO	NO
Size Bins × Time	YES	YES	YES	YES	YES	YES
N	57252	57252	52073	52073	1483	1483
R^2	0.0617	0.0355	0.0464	0.0236	0.110	0.0675
R^2_{adj}	0.0593	0.0331	0.0438	0.0209	0.0470	0.00152

Notes: The dependent variables are w.a.% USD^{peg}_{ft} and w.a.% LCP^{peg}_{ft}, which are defined as the weighted-average share of US dollar and local currency pricing for firm f in quarter t adjusted for peg arrangements, respectively. Hedge$_f$ is equal to one if firm f has traded an FX forward contract at least once. w.a. LC Volatility$_{ft}$ is the weighted-average local currency volatility of the countries with which firm f is trading at time t, regardless of its currency choice. The variable shock is equal to one in the second semester of 2011. By "Other Interactions" we mean all the non-reported interactions that characterize a triple-difference identification strategy. In the controls, we include the following variables. Foreign Import Share$_{ft}$ is the share of imports in foreign currency. w.a. Export Share$_{ft}$ is the weighted-average (across countries) of the share of exports of firm f in quarter t of a given product to a given country over the total amount of export by all French firms of the same product to the same country. Sophistication controls include the number of transactions (# Transactions$_f$), the number of unique destination countries (# Countries$_f$), and unique exported products (# Products$_f$). The time span is Jan-Dec 2011. Standard errors are clustered at size level, and t-statistics are in parenthesis.

In columns (3) and (4), we keep only firms that in EU trade with Germany. In columns (5) and (6), we keep only firms that in 2011S2 traded at least all product-country pairs they traded in 2011S1. * p<.10, ** p<.05, *** p <.01 .

In the following set of regressions, we concentrate on firms' size. Several papers have pointed out that size is a powerful explanatory variable for both currency choice and access to hedging (Amiti et al., 2014; Hau et al., 2021, 2022; Lyonnet et al., 2020). Throughout our analysis, we have accounted for size×time fixed effects to compare firms with similar sizes within the same quarter. In Table 1.8, we seek to dissect the size dimension by looking at the subsample of small firms, i.e., that have less than 200 employees, and of large ones, i.e., that have more than 500 employees.[37] We remove the size×time effects as we want the size variation to be absorbed by our triple interaction term. Nevertheless, we keep industry×time effects to compare firms within the same industry, in the same quarter. Results show that small firms were the ones that suffered the most from the cost heightening, whereas large firms were not significantly affected. Consistently with Hau et al., 2022; Lyonnet et al., 2020, small firms are less profitable and thus are less capable of internalizing a sudden increase in trading costs.

Table (1.8) Tripe difference regressions by firm size

	US Dollar Pricing (peg-adj)				Local Pricing (peg-adj)			
	Small Firms		Large Firms		Small Firms		Large Firms	
	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{Shock2011}_t \times \text{Hedge}_f \times \text{LC Vol.}_{ft}$	-0.0451**	-0.0443**	0.105	0.105	-0.0436**	-0.0436**	0.0973	0.102
	(-2.53)	(-2.48)	(1.58)	(1.44)	(-2.61)	(-2.58)	(1.02)	(1.04)
Sample	<200e	<200e	>=500e	>=500e	<200e	<200e	>=500e	>=500e
Other Interactions	YES	YES	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Time	YES	NO	YES	NO	YES	NO	YES	NO
Industry	YES	NO	YES	NO	YES	NO	YES	NO
Industry × Time	NO	YES	NO	YES	NO	YES	NO	YES
Size Bins	NO	NO	NO	NO	NO	NO	NO	NO
Size Bins × Time	NO	NO	NO	NO	NO	NO	NO	NO
N	52168	52166	2289	2281	52168	52166	2289	2281
R^2	0.0431	0.0441	0.101	0.109	0.0154	0.0160	0.112	0.114
R^2_{adj}	0.0425	0.0427	0.0895	0.0845	0.0148	0.0145	0.100	0.0903

[37] Results are robust to different classifications, although the statistical power is affected by sample sizes.

Notes: The dependent variables are w.a.% USD_{ft}^{peg} and w.a.% LCP_{ft}^{peg}, which are defined as the weighted-average share of US dollar and local currency pricing for firm f in quarter t adjusted for peg arrangements, respectively. Hedge_f is equal to one if firm f has traded an FX forward contract at least once. w.a. LC Volatility_{ft} is the weighted-average local currency volatility of the countries with which firm f is trading at time t, regardless of its currency choice. The variable shock is equal to one in the second semester of 2011. By "Other Interactions" we mean all the non-reported interactions that characterize a triple-difference identification strategy. In the controls, we include the following variables. Foreign Import Share_{ft} is the share of imports in foreign currency. w.a. Export Share_{ft} is the weighted average (across countries) of the share of exports of firm f in quarter t of a given product to a given country over the total amount of export by all French firms of the same product to the same country. Sophistication controls include the number of transactions ($\#$ Transactions_f), the number of unique destination countries ($\#$ Countries_f), and unique exported products ($\#$ Products_f). The time span is Jan-Dec 2011. Standard errors are clustered at size level, and t-statistics are in parenthesis. Firms with less than 200 employees are classified as small, while the ones with more than 500 are classified as large. * p$<$.10, ** p$<$.05, *** p $<$.01 .

1.7.4 Dynamic Effects

We now widen the time window to study the effects of the shock over time, by replacing the variable $Shock2011_t$ in equation (1.11) with a set of quarterly dummies. Since there is no currency choice data for 2010, we focus on the triple interaction term over the two years after the shock.

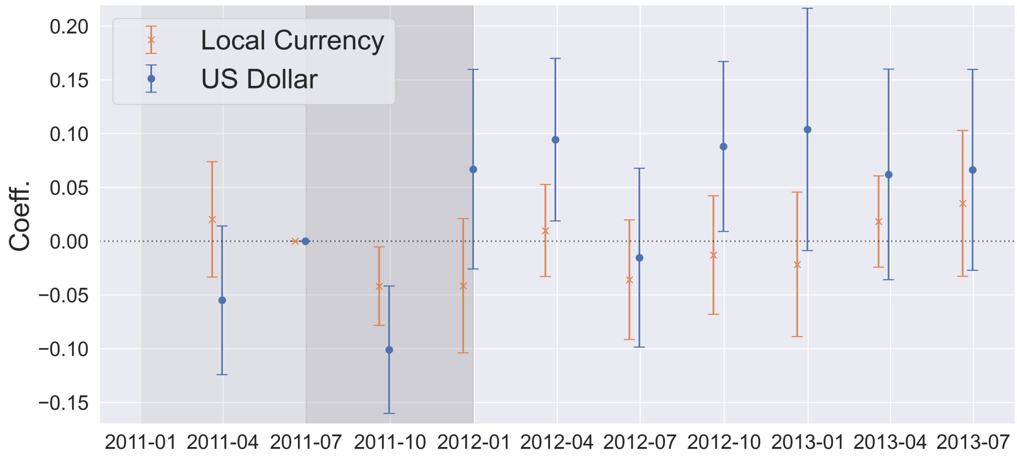
Figure 1.6 panel (a) shows the evolution of the dollar and local currency coefficients over time by taking the second quarter of 2011 as a reference period. As expected, for both pricing strategies, the coefficient is more precisely estimated right after the shock, whereas standard errors increase starting from 2012 onwards. For local currency pricing, the coefficient is only significant in the third quarter of 2011, suggesting that access to hedging shrank only temporarily.

The dollar coefficient shows a more complex pattern. The reduction in dollar pricing in the third quarter of 2011 is massive, but the coefficient becomes insignificant in the fourth quarter. Therefore, the short-term impact of the shock is almost twice as large as the one reported in Table 1.5. After that, the coefficient essentially goes back to zero. The only exceptions are the first and third quarters of 2012. If our identification strategy is correct, this implies that there was an easiness of dollar funding in the FX forward markets. Indeed, the FED intervened in international dollar markets to inject liquidity in December 2011. Figure 1.6 panel (b) reports the policy rate and the amounts of new trades of the euro-dollar central bank swap line between the FED and the European Central Bank (ECB). These kinds of swap facilities were set up to improve liquidity market conditions, by allowing foreign central banks, i.e., the

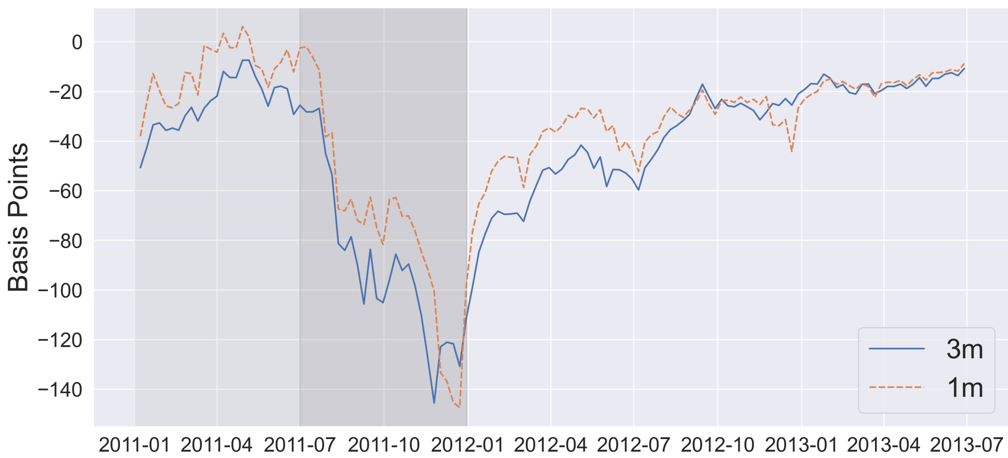
ECB, to borrow dollars from the FED and lend them locally. In principle, the swap rate serves as a ceiling in the secured interbank dollar markets (Bahaj et al., 2021). However, during the dollar shortage of the second half of 2011, market rates went above the ceiling as the fear of being stigmatized as in distress prevented private banks from using the swap facility. Consequently, the FED decided to intervene to minimize the risk that such tensions would spread to US households. On December 5th, the Board of Governors slashed the policy rate by 50 basis points to ease strains in international dollar markets (see Figure 1.6 panel (b) blue line).[38] The market rate went back below the ceiling policy rate, and the 3-month EUR/USD CIP deviation improved from -146 basis points as of November 25th, to -70 basis points at the end of January 2012, to eventually settle around -25 basis points in the fourth quarter of 2012 (see Figure 1.6 panel (c)). The outstanding amount of dollar funding peaked at USD 109 billion in January 2012, and normal market conditions were restored. Our results show that the FED intervention had a significant positive impact also on dollar adoption by French firms.[39]

[38] The December 5th cut was announced on November 30th. See the FED press release: https://www.federalreserve.gov/newsevents/pressreleases/monetary20111130a.htm.

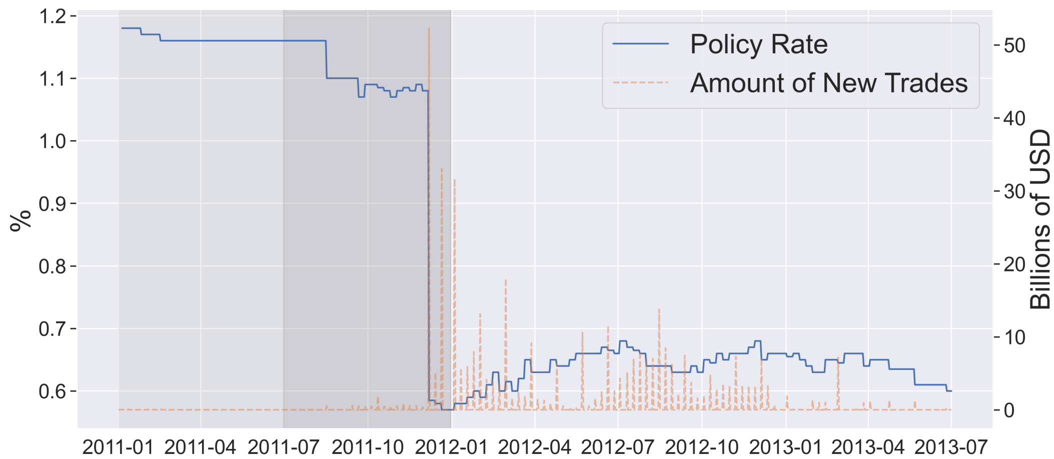
[39] Our findings are consistent with Bahaj et al., 2020 that investigate the establishment of swap lines with the People's Bank of China and find that they increased the international use of the Renminbi.



(a) Triple interaction coefficient



(b) EUR/USD CIP deviation



(c) EUR/USD central bank swap line

FIGURE (1.6) FED intervention and firms' currency choice

Notes: Panel (a) plots the triple interaction coefficient of specification (1.11) over time. Panel (b) shows the evolution of the euro-dollar CIP deviation (authors' calculations from Bloomberg data). Panel (c) reports the EUR/USD central bank swap line policy rate and new loans traded (data from New York FED). Lighter and darker shaded areas represent the semester before and after the shock, respectively.

1.8 FX Hedging and Exchange-Rate Pass-Through

Results of Section 1.7 show that lower access to hedging, i.e., higher trading costs, affects firms' currency choice. Therefore, FX hedging is also likely to influence the transmission of shocks across countries. In this section, we move a step forward to test the insights of Figure 1.1 that state that hedging firms can attain lower levels of exchange-rate pass-through.

The literature has extensively documented how exchange-rate pass-through depends on currency denomination, with effects on the terms of trade, defined as the value of exports divided by the value of imports (i.e., Gopinath et al., 2010). When a firm prices its exports in producer currency, a depreciation of the home currency deteriorates its terms of trade and vice versa (Obstfeld et al., 2001). However, when exports are invoiced in a vehicle currency, the pass-through also depends on the vehicle currency's bilateral exchange rate (Gopinath et al., 2020b). Moreover, firms may be reluctant to pass through the entire exchange rate shock to their customers, leading to deviations from their optimal pricing. In a highly elastic product market with monopolistic competition, we expect firms to partially incorporate the exchange rate shock into prices to maintain the same market share (Corsetti et al., 2018). These effects accumulate to other rigidities potentially disjoint from the invoicing currency, such as menu costs. For these reasons, understanding the dynamics of exchange-rate pass-through and international spillovers has important policy implications, especially for developing countries that heavily use the US dollar and other reserve currencies (Adler et al., 2020).

1.8.1 Price Adjustment Results: Baseline

We investigate the different price adjustments of French hedging firms to FX shocks that translate into their exchange-rate pass-through.[40] In our analysis,

[40] Similarly to Amiti et al., 2022, we extend the sample up to 2014 to focus on a longer time horizon as the price reaction to FX shocks does not fully materialize in the short term. Our results also hold when considering a longer horizon (see Table A.11). However, we do not include earlier observations as we do not want temporary dollar market conditions to influence our estimates (see Figure 1.6).

we augment the standard price adjustments regression by adding the interactions with the variable $Hedge_f$.

$$\begin{aligned}\Delta_\ell p_{d,t} = {} & \alpha_0 \\ & + \alpha_1 \cdot \text{PCP} \cdot \Delta_\ell e_t^{j/€} + \alpha_2 \cdot \text{PCP} \cdot \text{Hedge}_f \cdot \Delta_\ell e_t^{j/€} \\ & + \alpha_3 \cdot \text{FCP} \cdot \Delta_\ell e_t^{j/€} + \alpha_4 \cdot \text{FCP} \cdot \text{Hedge}_f \cdot \Delta_\ell e_t^{j/€} \\ & + \text{Industry}\times\text{Country}\times\text{Year} + \text{ Size Bins} + \ u_{d,t}\end{aligned} \tag{1.12}$$

where d represents the product-country-firm-currency dimension. The time period is in quarters, and $\Delta_\ell x_t = \log(x_t) - \log(x_{t-\ell})$. The exchange rates $e_t^{j/i}$ are expressed in currency j per unit of currency i. Thus, the estimated coefficients represent the price elasticities to a 1% appreciation of the euro or the dollar after ℓ quarters. Similarly to Amiti et al., 2022, we include industry-country-time fixed effects to absorb a wide array of time-varying dominants, such as differences across countries and sectors, growth or inflation rates, and the average industry degree of good differentiation, among others. Moreover, we saturate the specification with size bins effects as larger firms usually have higher markups and thus could absorb exchange-rate shocks differently. Finally, standard errors are clustered at product level, and summary statistics are reported in Table A.9 in Appendix A.5.

The regression estimates represent the degree of firms' price adjustments after an FX shock. Conventionally, the exchange-rate pass-through is defined as the change of import prices (expressed in local currency) after a one percent change in the bilateral exchange rate (Goldberg et al., 1997). Therefore, in our setting, the exchange-rate pass-through is the complement to one of our point estimates.[41]

Table 1.9 shows the results of regression (1.12) four quarters after the exchange rate shock, i.e., $\ell = 4$, and using different fixed effects combinations. The first row reports a small price change for exporting firms with products invoiced in producer currency, i.e., the euro. This result is consistent with the literature (e.g. Gopinath et al., 2010), as a small price adjustment means that the buyer absorbs the entirety of the shock and, consequently, the exchange-rate

[41] Consider the following example. Let the price of a bottle of Champagne be 100 Brazilian reals and assume that at time t 1 euro is equal to 1 real. At time $t+1$, 1 euro is equal to 2 reals, and the exporter adjusts the price to 120 reals (60 euro equivalent). In local currency, the price change has been 20% $(= (120 - 100)/100)$, and the exchange rate change has been 100% $(= (2-1)/1)$; thus, the ERPT is 20% $(= 20\%/100\%)$. It is possible to reach the same result by taking the complement to one of the price elasticity in producer currency. In euro equivalent, the price change has been -40% $(= (60 - 100)/100)$, and the exchange rate change has been -50% $(= (0.5-1)/1)$, thus the adjustment is 80% $(= -40\%/-50\%)$, and the ERPT is 20% $(= 100\% - 80\%)$.

pass-through is complete (almost 100%). As expected, the second row is never significant. For euro-denominated exports, there is no currency risk involved, so hedging and non-hedging firms should similarly adjust their prices.

The third row documents a larger price adjustment for goods denominated in foreign currency (as in Barbiero, 2019) that translates into a lower exchange-rate pass-through than for euro-denominated goods. Moreover, we find that hedging firms have smaller price adjustments for foreign currency-denominated products than non-hedging firms (fourth row). These results are consistent with our theoretical model (Figure 1.1), which states that hedging firms can attain a lower pass-through when they opt for foreign currency pricing over producer currency pricing. Therefore, FX hedging might contribute to rendering exchange rates less correlated with economic fundamentals. Notably, our estimates hold throughout different specifications, regardless of whether we account for peg arrangements.

TABLE (1.9) Price adjustments regressions

	$\Delta_4 p_{d,t}$					
	not adjusting for peg arrangements			adjusting for peg arrangements		
	(1)	(2)	(3)	(4)	(5)	(6)
PCP$\times\Delta_4 e_t^{j/€}$	0.0334***	0.0795***	0.0867***	0.0332***	0.0793***	0.0865***
	(2.86)	(6.14)	(4.60)	(2.83)	(6.13)	(4.58)
Hedge$_f\times$PCP$\times\Delta_4 e_t^{j/€}$	-0.0143	-0.0112	-0.0253	-0.0150	-0.0119	-0.0258
	(-0.67)	(-0.52)	(-1.13)	(-0.70)	(-0.55)	(-1.16)
FCP$\times\Delta_4 e_t^{j/€}$	0.452***	0.487***	0.493***	0.453***	0.488***	0.494***
	(20.88)	(22.06)	(18.67)	(20.92)	(22.09)	(18.70)
Hedge$_f\times$FCP$\times\Delta_4 e_t^{j/€}$	-0.0934***	-0.0647**	-0.0804***	-0.0929***	-0.0640**	-0.0799***
	(-3.21)	(-2.23)	(-2.69)	(-3.19)	(-2.21)	(-2.67)
Size Bins	✓		✓	✓		✓
Year		✓			✓	
Year-Qarter	✓			✓		
Size Bins × Year-Quarter						
Industry × Country		✓			✓	
Industry × Country × Year			✓			✓
R^2_{adj}	0.00194	0.00229	0.00481	0.00194	0.00230	0.00481
N	691'332	705'786	690'875	691'332	705'786	690'875
F	188.1	206.3	141.1	189.2	207.3	141.9

Notes: This table reports the results of regressing (log) price changes on a set of covariates, i.e., specification (1.13) with $\ell = 4$. PCP stands for producer currency pricing, and FCP for foreign currency (i.e., local and dollar) pricing. The bilateral exchange rate $e_t^{j/€}$ is expressed in euro per unit of currency j. Thus, the estimated coefficients represent the price elasticities to a 1% depreciation of the euro after ℓ quarters. $Hedge_f$ is a binary variable that switches to one if the firm has an outstanding forward exposure for at least one month in our sample. Size Bins classify the size of the firm into sixteen categories according to its number of employees. The time span is 2014-2017. Standard errors are clustered at product level, and t-statistics are in parenthesis. * p < 10%, ** p < 5%, *** p < 1%.

1.8.2 Dynamic Exchange-Rate Pass-Through

We now extend the analysis and explore the dynamics of exchange-rate pass-through into prices (similarly to Amiti et al., 2022). Specifically, We augment specification (1.12) by splitting the foreign currency pricing into local and dollar pricing. Furthermore, we consider changes in three exchange rates, namely the bilateral one between the euro and the local country currency, and its decomposition into local currency-dollar and dollar-euro for dollar-denominated exports (as in Barbiero, 2019). Therefore, the new specification is the following:

$$\begin{aligned}\Delta_\ell p_{d,t} = {} & \alpha_0 \\ & + \alpha_1 \cdot \text{PCP} \cdot \Delta_\ell e_t^{j/€} + \alpha_2 \cdot \text{PCP} \cdot \text{Hedge}_f \cdot \Delta_\ell e_t^{j/€} \\ & + \alpha_3 \cdot \text{LCP} \cdot \Delta_\ell e_t^{j/€} + \alpha_4 \cdot \text{LCP} \cdot \text{Hedge}_f \cdot \Delta_\ell e_t^{j/€} \\ & + \alpha_5 \cdot \text{USD} \cdot \Delta_\ell e_t^{j/\$} + \alpha_6 \cdot \text{USD} \cdot \text{Hedge}_f \cdot \Delta_\ell e_t^{j/\$} \\ & + \alpha_7 \cdot \text{USD} \cdot \Delta_\ell e_t^{\$/€} + \alpha_8 \cdot \text{USD} \cdot \text{Hedge}_f \cdot \Delta_\ell e_t^{\$/€} \\ & + \text{Industry} \times \text{Country} \times \text{Year} + \text{ Size Bins} + u_{d,t}\end{aligned} \tag{1.13}$$

as before, d represents the product-country-firm-currency dimension. The time period is in quarters, and $\Delta_\ell x_t = \log(x_t) - \log(x_{t-\ell})$.[42] We estimate equation (1.13) at different horizons, i.e., from one quarter until two years after the shock, and report the levels of exchange-rate pass-through in Figure 1.7.[43]

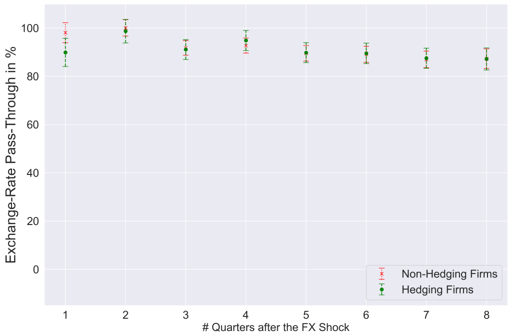
Figure 1.7 panel (a) shows that the price adjustment for PCP is very low and relatively stable over time. Thus, the exchange-rate pass-through is almost complete, even after two years, and there is no difference in the elasticities between hedging and non-hedging firms. This behavior is trivially explained by the fact that the euro entails no currency risk for French companies, regardless

[42] Table A.8 in Appendix A.5 reports the estimate of equation (1.13) for $\ell = 4$.
[43] The tables with all the regression coefficients are in Appendix A.5.

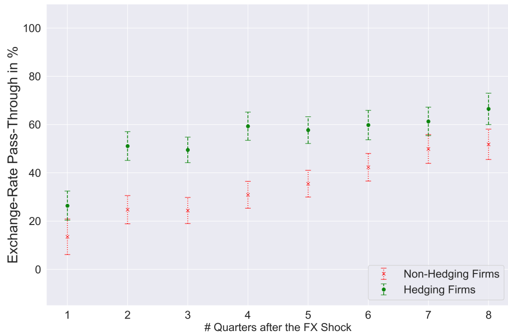
of their type. The absence of currency risk mechanically implies no difference in shock transmission between hedging and non-hedging firms.

For local currency pricing (Figure 1.7, panel (b)), non-hedging firms transmit significantly smaller amounts of shocks to their prices than hedging companies. Remarkably, the difference persists even after two years. This pattern is consistent with our theoretical model, which states that the pass-through in local currency with hedging is smaller than in producer currency but larger than in local currency without hedging (see Figure 1.1). In other words, our results show that thanks to hedging, firms are able to transfer part of their currency risk to the dealer and keep their prices more stable with respect to exchange rate fluctuations (i.e., stickier).

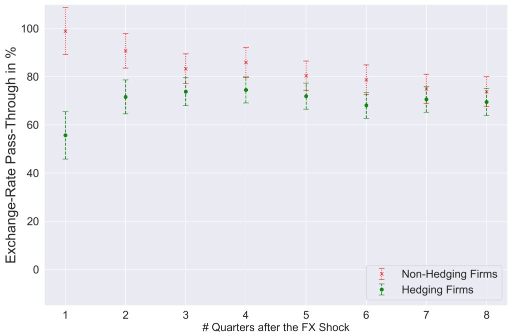
The lower price sensitivity of FX hedging firms directly relates to the literature on the exchange-rate disconnect puzzle pioneered by the contribution of Meese et al., 1983. The latter paper documents that short-term economic fundamentals hardly correlate with exchange rates (see also Lilley et al., 2022, for a more recent discussion). Although this might be due to multiple factors, we argue that FX hedging is one of them, with sizable implications for spillovers across economies and optimal policy design.



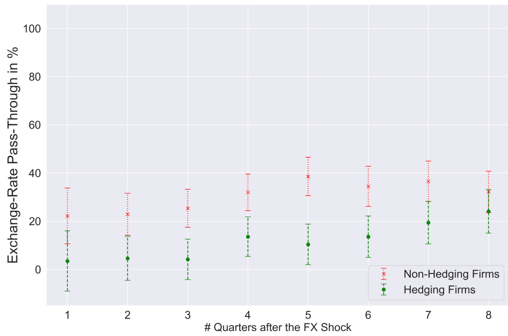
(a) PCP with respect to the LC/EUR rate.



(b) LCP with respect to the LC/EUR rate.



(c) USD with respect to the LC/USD rate.



(d) USD with respect to the USD/EUR rate.

FIGURE (1.7) Dynamic exchange-rate pass-through by hedging type

Notes: The graph reports the exchange-rate pass-through to prices to a one percent exchange-rate depreciation at different time horizons for non-hedging firms and hedging firms. The coefficients are estimated with size and industry×country×year fixed effects. Green dashed and red dotted marks represent the reactions of hedging and non-hedging firms, respectively. The time span is 2014-2017. Standard errors are clustered at the product level, while confidence intervals are at 90% level.

The dynamics of US dollar pricing are depicted in Figure 1.7, panels (c) and (d). Specifically, panel (c) reports the ERPT of dollar-denominated goods with respect to the local currency-dollar rate. Here, the difference between hedging and non-hedging firms is sizable and significant in the first periods, but it fades away five quarters after the exchange-rate shock. These patterns suggest that the choice is made between the dollar and the local currency, which is why dollar pricing without hedging has a higher pass-through. It is also worth noting that the coefficients in panels (b) and (c) tend to converge. Finally, panel (d) shows the reaction of dollar-denominated products to the dollar-euro rate. Not surprisingly, the pass-through is very low at all time horizons. Noticeably, hedging firms show transmit a small bit of the FX shock to their buyers, similarly to panel (c).

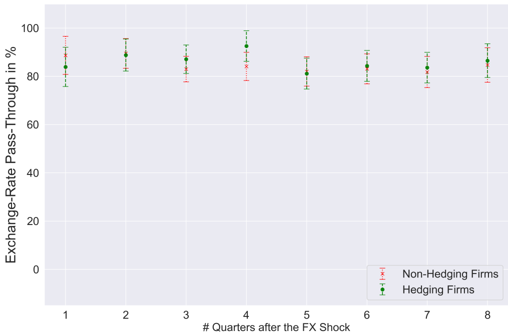
1.8.3 Additional Results

In this subsection, we further explore the price adjustment dynamics to understand the underlying determinants of the pass-through differences between hedging and non-hedging firm.

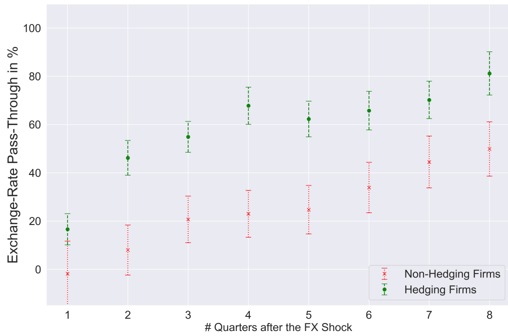
In Figure 1.8, we plot the change-rate pass-through coefficients of firms with more than 1'000 employees.[44] In panels (b) and (c), the differences between hedging and non-hedging firms broaden and become significant even two years after the shock. However, standard errors of the coefficients of dollar adjustments with respect to the euro-dollar rate (panel (d)) increase so that there is no statistical difference between hedging and non-hedging firms. Nothing changes for euro-denominated goods. These results for large firms are consistent with the idea that these firms are more sophisticated and thus better at managing currency risk and pricing to market. Indeed, the differences between hedging and non-hedging types almost disappear when considering only small firms (see Figure A.2 in Appendix A.5).

In addition, Figure 1.9 shows the estimates for differentiated goods. The results in panels (a) and (c) remain essentially the same as the baseline, whereas the coefficients in panel (d) shift upwards at all horizons. Finally, panel (b) shows a sizable and persistent difference lasting for two years. Not surprisingly, most of these differences fade away for undifferentiated goods, as firms have less leeway in setting their prices (see Figure A.7 in Appendix A.5).

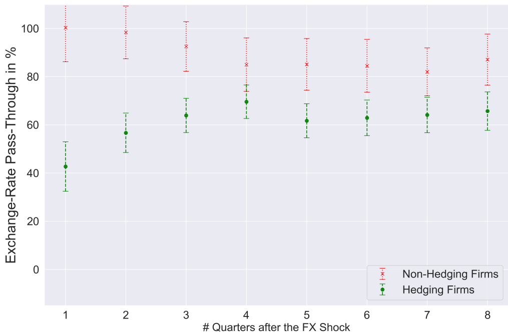
[44] In Figure A.2 in Appendix A.5, we report the pass-through coefficients of small firms.



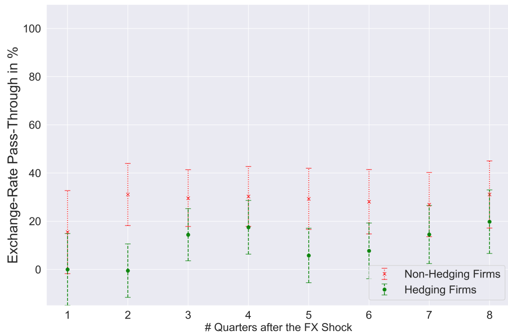
(a) PCP with respect to the LC/EUR rate.



(b) LCP with respect to the LC/EUR rate.



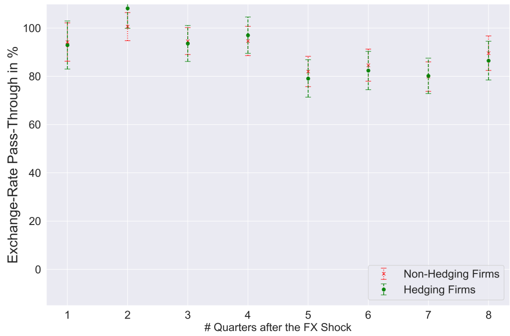
(c) USD with respect to the LC/USD rate.



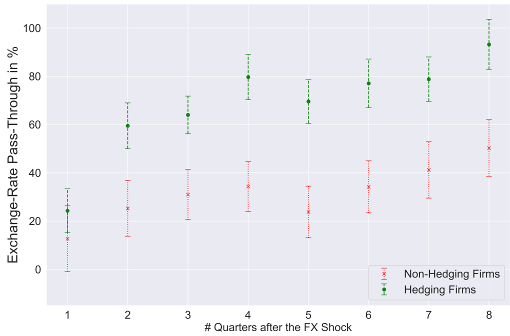
(d) USD with respect to the USD/EUR rate.

FIGURE (1.8) Dynamic exchange-rate pass-through for large firms by hedging type

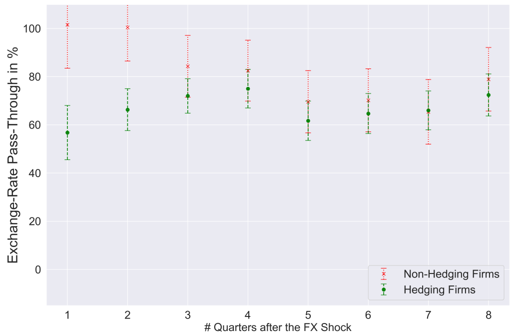
Notes: The graph reports the exchange-rate pass-through to prices to a one percent exchange-rate depreciation at different time horizons for non-hedging firms and hedging firms. The coefficients are estimated with size and industry×country×year fixed effects. Green dashed, and red dotted marks represent the reactions of hedging and non-hedging firms, respectively. The time span is 2014-2017. Standard errors are clustered at the product level, while confidence intervals are at 90% level. In these regressions, we only consider firms with more than 1'000 employees.



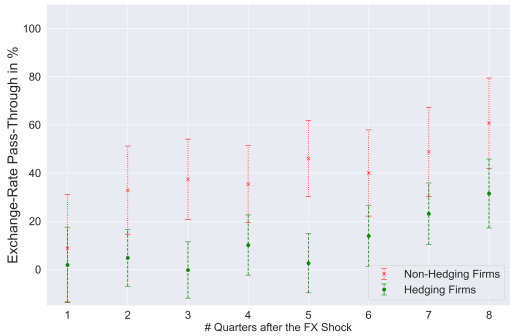
(a) PCP with respect to the LC/EUR rate.



(b) LCP with respect to the LC/EUR rate.



(c) USD with respect to the LC/USD rate.



(d) USD with respect to the USD/EUR rate.

FIGURE (1.9) Dynamic exchange-rate pass-through for differentiated products by hedging

Notes: The graph reports the exchange-rate pass-through to prices to a one percent exchange-rate depreciation at different time horizons for non-hedging firms and hedging firms. The coefficients are estimated with size and industry×country×year fixed effects. Green dashed and red dotted marks represent the reactions of hedging and non-hedging firms, respectively. The time span is 2014-2017. Standard errors are clustered at the product level, while confidence intervals are at 90% level. In these regressions, we only consider differentiated products (according to Rauch, 1999 classification).

1.9 Conclusions

Macroeconomic literature has long departed from the standard Mundell-Fleming framework in which firms price their exports only in producer currency. Broad empirical evidence has shown that firms' currency choice depends on several aspects related to market conditions and on firms' intrinsic characteristics. Studying invoice currency choice is essential to understand issues related to currency internationalization and how shocks propagate across economies.

Although we carry out a partial-equilibrium analysis, we provide evidence of the causal effects of financial development on currency internationalization. The numerous initiatives of governments and private companies to internationalize their own currencies, popular technological innovation, along with the stealth but steady erosion of the status of the dollar has renewed the interests of scholars and policymakers on the matter (Arslanalp et al., 2022; Gopinath et al., 2020a). Looking forward, these topics are likely to become more relevant also in light of the fast-changing international political equilibria and the consequent promotion of the use of other currencies.

This paper contributes to the literature by investigating how FX derivatives markets affect firms' currency choice and exchange-rate pass-through, focusing on the dollar's special role in this setting. Consistently with our theoretical insights, we find that access to FX hedging not only favors local currency pricing but also dollar pricing. In addition, we document that hedging firms have lower levels of exchange-rate pass-through, i.e., their prices are more sticky to exchange-rate shocks.

Our results suggest that FX hedging strengthens the exchange-rate disconnect puzzle as it reduces the price-elasticity to currency shocks, with important implications for optimal policy design (Meese et al., 1983). Furthermore, our findings corroborate the view that the development of financial markets fosters currency internationalization (e.g., see IMF, 2011). This is especially the case for settings with no viable alternatives to the dollar, e.g., developing countries. More generally, we can conclude that access to financial markets is likely to play an important role not only for the dollar but for all the currencies that long to become widespread.

Chapter 2

The Crypto Cycle and US Monetary Policy

with Natasha Che, Alexander Copestake, and Davide Furceri[1]

[1] The views expressed in this paper are those of the authors and should not be attributed to the IMF, its Executive Board, or IMF management.

2.1 Introduction

Crypto assets vary substantially in their design and value propositions, yet their prices have moved in common cycles.[2] Total crypto market capitalization boomed from US$20 billion in 2016 to almost US$3 trillion in November 2021, before collapsing to below US$1 trillion in the latest crypto 'winter'.[3] Periods of exponential returns have attracted retail and institutional investors alike (Auer et al., 2021b, 2022; Benetton et al., 2022), while subsequent crashes have drawn increasing attention from politicians and regulators. These fluctuations in crypto markets may also be increasingly synchronized with other asset classes: prior to 2020, Bitcoin provided a partial hedge against market risk, yet it has since become increasingly correlated with the S&P500 (Adrian et al., 2022).

However, we know relatively little about the common drivers of crypto asset prices or the factors affecting the correlation between crypto and equity markets, including US monetary policy. This paper tries to shed light on these issues by answering the following questions. To what extent is there a common cycle across crypto assets? Are crypto markets becoming more synchronized with global equity markets? If so, why? Given that US monetary policy has been identified as a key driver of the global financial cycle (Miranda-Agrippino et al., 2020), does US monetary policy influence the crypto cycle to a similar extent? If so, through which channels?

We start answering these questions by using a dynamic factor model to identify a single dominant trend in crypto-asset prices. Using a panel of daily prices for seven tokens created before 2018, which together account for approximately 75% of total crypto market capitalization, we decompose their variation into asset-specific idiosyncratic disturbances and an AR(q) common component. We find that the resulting "crypto factor" explains approximately 80% of the variance in the crypto price data. This is substantially larger than the 20% figure for global equities calculated by Miranda-Agrippino et al., 2020, which also reflects the greater concentration of market capitalization in the largest crypto assets relative to that in the largest equities. This figure is robust for various lag orders q, and we find a similarly high degree of correlation when broadening

[2] For instance, the white papers of prominent crypto assets include aims to provide peer-to-peer electronic cash, more efficient transactions, censorship-resistant decentralized computing, and functionality within a financial services ecosystem (Binance, 2017; Buterin, 2014; Nakamoto, 2008; Ripple Labs Inc., 2014; Sun, 2018). We exclude stablecoins from our analysis, as they are intended to maintain a constant price.

[3] Source: CoinMarketCap.com.

the panel to include more crypto assets.[4]

In a second step, we study the relationship of this crypto factor to a set of global equity factors, constructed using the equity indices of the largest countries by GDP (in the spirit of Miranda-Agrippino et al., 2020; Rey, 2013). We find a positive correlation over the entire sample, driven by a particularly strong correlation since 2020. The increasing co-movement is not limited to Bitcoin vis-a-vis the S&P500, but pertains more broadly to the crypto and global equity factors. Disaggregating across equity markets, we find that the crypto factor correlates most strongly with the global tech factor and the small-cap factor since 2020, while it is surprisingly less correlated with the global financial factor.

The increased correlation between crypto and equities coincides with the growth in the participation of institutional investors in crypto markets since 2020. Although institutions' exposure is small relative to their balance sheets, their absolute trading volume is much larger than that of retail traders. In particular, the volume of trading by institutional investors in crypto exchanges increased by more than 1700% (from roughly $25 billion to more than $450 billion) from 2020Q2 to 2021Q2 (Auer et al., 2022). Since institutional investors trade both stocks and crypto assets, this has led to a progressive increase in the correlation between the risk profiles of marginal equity and crypto investors, which in turn is associated with a higher correlation between the global equity and crypto factors. When decomposing factor movements following Bekaert et al., 2013, we find that correlation in the aggregate effective risk aversion of crypto and equities can explain a large share (up to 65%) of the correlation between the two factors.

Since US monetary policy affects the global financial cycle (Miranda-Agrippino et al., 2020), the high correlation between equities and crypto suggests a similar impact on crypto markets. We test this hypothesis using a daily VAR with the shadow federal funds rate (SFFR) by Wu et al., 2016 to account for the important role of balance sheet policy over our sample period. Our identification of the impact of monetary policy shocks is based on a Cholesky decomposition with the following ordering: the SFFR; the Treasury 10Y2Y spread, reflecting expectations of future growth; the dollar index, oil and gold prices, as proxies for international trade, credit and commodity cycles; the VIX, reflecting expected future uncertainty; and finally the equity and crypto factors. In this setup, endogeneity is not likely to be an issue as it is implausible that the Federal

[4]Since most crypto assets have been created only in the last couple of years, a broader panel of assets also implies a shorter time dimension—hence we focus on the seven main assets in our baseline measure.

Reserve adjusts its monetary policy according to crypto price movements and that it does so at the daily level.[5]

We find that US monetary policy affects the crypto cycle, as it does with the global equity cycle, contrasting starkly with claims that crypto assets provide a hedge against market risk. A one percentage point rise in the SFFR leads to a persistent 0.15 standard deviation decline in the crypto factor over the subsequent two weeks, relative to a 0.1 standard deviation decline in the equity factor.[6] Interestingly, as with the global financial cycle (Rey, 2013), we find that only the US Fed's monetary policy matters, and not that of other major central banks—likely reflecting that crypto markets are highly dollarized.[7]

We find evidence that the risk-taking channel of monetary policy is an important channel driving these results, paralleling the findings of Miranda-Agrippino et al., 2020 for global equity markets. In particular, we find that a monetary contraction leads to a reduction of the crypto factor that is accompanied by a surge in a proxy for the aggregate effective risk aversion in crypto markets. Put differently, restrictive policies render the risk positions of investors less sustainable, and thus they reduce their exposure to crypto assets. When splitting the sample in 2020, we find that the impact on risk aversion in crypto markets is significant only for the post-2020 period, consistent with the entry of institutional investors reinforcing the transmission of monetary policy to the crypto market. More formally, we find the same result when testing this hypothesis using a smooth transition VAR following Auerbach et al., 2012, where the transition variable is the share of institutional investors.

Next, we rationalize our results in a model with two heterogeneous agents, namely crypto and institutional investors. The former are retail investors who only invest in crypto assets, while the latter can invest in both stocks and crypto assets. Crucially, crypto investors are risk averse, while institutional investors are risk-neutral but face a value-at-risk constraint. We can rewrite the equilibrium returns on the crypto assets as a linear combination of their variance and

[5]Note that our results are also robust to relaxing the aforementioned variable ordering. When we invert the order of the variables to allow the policy rate to be the *most endogenous* one, we find similar results. As expected, we also find that the policy rate does not respond to changes in the crypto factor. Thus, our findings do not depend on an arbitrary ordering of the variables. In addition, using the available Bu et al., 2021 monetary policy shocks; we still find a significant negative effect of US monetary policy on the crypto cycle at the monthly level.

[6]This refers to standard deviations of variation in crypto or equities over 2018-2023, the period for which we can construct the crypto factor.

[7]For instance, the two largest stablecoins Tether and USD Coin are pegged to the dollar, while Coinbase, the largest centralized crypto exchange, is listed on the New York Stock Exchange.

their covariance with stocks' returns, scaled by the aggregate effective risk aversion. The latter can be interpreted as the average risk aversion of the agents, weighted by their wealth. This implies that the higher the relative wealth of institutional investors, the more similar the crypto aggregate effective risk aversion becomes to their risk appetite and the more correlated are crypto and equity markets. Since the presence of institutional investors in crypto markets decreases the aggregate effective risk aversion, we interpret the increasing reaction of crypto prices to monetary contraction as reflecting that more levered investors are more sensitive to the economic cycle (Adrian et al., 2014; Coimbra et al., 2022). Finally, we note that spillovers from crypto to equities can arise even in our simple framework: if institutions' crypto holdings become large, a crash in crypto prices reduces equilibrium returns in equities.

Overall, our results highlight that the crypto cycle is remarkably synchronized with global equity markets and reacts similarly to monetary policy shocks. Despite the range of explanations for crypto asset values—e.g., as an inflation hedge or as a provider of more efficient payments, censorship-resistant computing or property rights—most variation in crypto markets is highly correlated with equity prices and highly influenced by Fed policies. This also suggests emerging crypto ventures that benefited from high crypto returns were concomitantly supported by the low interest-rate environment. Finally, we find that growth in institutional participation has strengthened these conclusions and increased the risk of spillovers from crypto markets to the broader economy.

Literature: This paper contributes to the burgeoning literature on crypto assets by connecting work on specific crypto prices and the composition of crypto investors to the established literature on the global financial cycle.

First, our paper builds on work assessing the drivers of the prices of specific crypto assets. The primary aim of early developers, led by Nakamoto, 2008, was to provide a new form of decentralized electronic cash that people could freely access. Several scholars have studied the matter through these lenses (Auer et al., 2021a; Biais et al., 2018; Brunnermeier et al., 2019a; Cong et al., 2021; Pagnotta, 2022; Schilling et al., 2019), yet the high price volatility and the relatively low scalability of existing distributed ledger technology have led researchers to think of most crypto tokens as assets rather than currencies (see for instance Liu et al., 2022; Makarov et al., 2020; Scaillet et al., 2020).[8] Indeed,

[8]Indeed, to address such high volatility, the industry developed stablecoins, such as Tether or USD Coin, which are pegged to another currency (most commonly the US dollar).

many crypto assets lack explicit fundamental value or cash-flows (Makarov et al., 2020), and are subject to fragmentation, arbitrage opportunities and market manipulation (Foley et al., 2019; Gandal et al., 2018; Griffin et al., 2020). In this paper, we abstract from crypto-asset-specific pricing considerations, and instead consider the common movement in the entire asset class. In doing so, we build on Iyer, 2022, who provides evidence of the positive correlation between US equity markets and Bitcoin and Ether prices, and Corbet et al., 2020 who assess the impact of macroeconomic news on Bitcoin returns.

Second, we draw on an emerging empirical literature examining the composition and motivations of crypto investors, including the increased participation of institutions. Auer et al., 2021b study the profile of US crypto investors and highlight that they are in general less motivated by distrust in the traditional financial system than by the prospects for high returns.[9] 2022 are the first to focus on the role of institutional investors in crypto markets, and show that traditional financial institutions, especially lightly regulated banks, are starting to hold crypto assets.[10] We use this literature to help explain the co-movement between crypto and equities, and to construct a stylized framework for investigating potential spillovers between the two.

Third, we contribute to the literature on the global financial cycle.[11] In her seminal contribution, Rey, 2013 shows the existence of a single factor that explains 20% of the variation in global asset prices. In more recent works, Miranda-Agrippino et al., 2020 and Miranda-Agrippino et al., 2021 highlight how US monetary policy affects this global financial cycle through the risk-taking channel. A change in interest rates forces financial intermediaries to change their leverage and thus the effective risk appetite of the marginal investor. A US monetary contraction thus negatively affects global equity prices, eroding the independence of other central banks and reinforcing the dominant role of the US dollar (Farhi et al., 2018; Passari et al., 2015). Within this literature, we particularly focus on the risk-taking channel of monetary policy. Coimbra et al., 2022 develop a comprehensive dynamic model with heterogeneous intermediaries, which features time-varying endogenous macroeconomic risk. In their framework, the variation in risk-aversion across agents determines the aggregate risk of the economy. Relatedly, Adrian et al., 2014 highlight how the cyclicality of leverage depends on the constraints of financial intermediaries.

[9]Similarly Hackethal et al., 2021 and Didisheim et al., 2022 document the behaviour of crypto retail investors and their portfolio allocation between equity and crypto assets.

[10]Nonetheless, banks' exposure remains limited with respect to the size of their balance sheets. In addition, Cornelli et al., 2023 document differences in trading behaviour between small and large investors during crisis episodes.

[11]For early discussions, see: Calvo et al., 1996; Diaz-Alejandro, 1985.

Fostel et al., 2008 show how leverage cycles can be explained by differences in agents' beliefs, whereas Kekre et al., 2018 and Gourinchas et al., 2010 focus on heterogeneity in risk aversion. We contribute to this literature by incorporating analysis of the crypto cycle.

The rest of this paper proceeds as follows. Section 2.2 derives the crypto factor, then Section 2.3 investigates its relationship to equity prices and the global financial cycle. Section 2.4 examines the impact of US monetary policy on the crypto factor, and Section 2.5 rationalizes our findings in a heterogeneous-agent model. Section 2.6 concludes.

2.2 The Crypto Factor

The prices of crypto assets are highly correlated. Table 2.1 reports the cross-correlations among the crypto assets with the largest market capitalization. These are remarkably high, and much larger than the correlations documented across equity markets (see, for instance, Rey, 2013). For example, Bitcoin has a 52% average correlation with other crypto assets. We thus conjecture the existence of a common crypto factor that co-moves with crypto prices, in the same spirit as the global equity factor pioneered by Rey, 2013.

Table (2.1) Correlations among crypto assets

	Bitcoin	Ethereum	Binance Coin	Ripple	Cardano	Solana	Dogecoin	Polkadot	Tron	Shiba Inu	Maker Dao	Avalanche	Uniswap	Litecoin	FTX	Chainlink	Monero	THETA
Bitcoin	1.00																	
Ethereum	0.82	1.00																
Binance Coin	0.64	0.64	1.00															
Ripple	0.62	0.67	0.52	1.00														
Cardano	0.69	0.75	0.56	0.65	1.00													
Solana	0.47	0.57	0.51	0.42	0.48	1.00												
Dogecoin	0.34	0.31	0.24	0.26	0.30	0.16	1.00											
Polkadot	0.64	0.70	0.58	0.49	0.63	0.52	0.23	1.00										
Tron	0.59	0.61	0.47	0.58	0.59	0.37	0.25	0.56	1.00									
Shiba Inu	0.49	0.47	0.46	0.41	0.42	0.34	0.51	0.43	0.34	1.00								
Maker Dao	0.38	0.45	0.32	0.33	0.38	0.43	0.15	0.54	0.27	0.32	1.00							
Avalanche	0.55	0.59	0.55	0.48	0.64	0.54	0.21	0.59	0.44	0.34	0.51	1.00						
Uniswap	0.53	0.63	0.47	0.44	0.54	0.47	0.14	0.60	0.46	0.43	0.54	0.51	1.00					
Litecoin	0.80	0.82	0.63	0.67	0.72	0.49	0.33	0.66	0.58	0.45	0.38	0.53	0.56	1.00				
FTX	0.03	0.00	0.03	0.00	-0.01	0.52	0.00	0.52	0.00	0.31	-0.01	0.48	0.45	-0.01	1.00			
Chainlink	0.59	0.66	0.51	0.53	0.58	0.53	0.27	0.70	0.52	0.42	0.33	0.59	0.59	0.60	-0.01	1.00		
Monero	0.75	0.73	0.59	0.59	0.66	0.43	0.30	0.55	0.55	0.39	0.34	0.46	0.44	0.72	0.04	0.54	1.00	
THETA	0.55	0.56	0.48	0.46	0.53	0.43	0.22	0.60	0.48	0.40	0.27	0.50	0.49	0.55	-0.01	0.48	0.53	1.00

Notes: This table shows pairwise correlations between selected crypto-asset returns. Data is from January 2018 to March 2023.

To summarize the fluctuations in crypto markets into one variable, we use dynamic factor modelling, a dimensionality reduction technique.[12] This allows us to decompose a set of prices into their idiosyncratic components and a common trend. Specifically, we start with the daily prices of the largest crypto assets that were created before January 2018 (excluding stablecoins). This leaves us with seven crypto assets, accounting for 75% of total market capitalization in June 2022.[13] We then write this panel of crypto prices p_{it} as a linear combination of an AR(q) common factor f_t and an asset-specific idiosyncratic disturbance ϵ_{it} (which in turn follows an AR(1) process):

$$\begin{aligned} p_{it} &= \lambda_i(L) f_t + \epsilon_{it} & & \\ f_t &= A_1 f_{t-1} + ... + A_q f_{t-q} + \eta_t & \eta_t &\sim \mathcal{N}(0, \Sigma) \\ \epsilon_{it} &= \rho_i \epsilon_{it-1} + e_{it} & e_{it} &\sim \mathcal{N}(0, \sigma^2_{it}) \end{aligned} \tag{2.1}$$

where L is the lag operator and $\lambda_i(L)$ is a q-order vector of factor loadings for asset i. Estimating this system using maximum likelihood, selecting q using information criteria, produces our common factor f_t.[14] It is also possible to specify multiple factors that affect prices differently, and we use this latter specification when we consider multiple distinct sub-classes of crypto assets.

Figure 2.1 shows the crypto factor and the underlying price series from which we extract it. The crypto factor effectively captures the salient phases that characterized crypto markets—such as the decline at the beginning of 2018, the subsequent 'crypto winter', the latest boom with the peaks in Bitcoin and Dogecoin, and finally the slump of Terra and FTX of 2022—without being overly influenced by isolated spikes like those of Ripple and Tron.

[12] For the evolution of the method, see, among others: Bai et al., 2002; Forni et al., 2000; Geweke, 1977; Miranda-Agrippino et al., 2020; Sargent et al., 1977; Stock et al., 2002.

[13] These are: Bitcoin, Ethereum, Binance Coin, Ripple, Cardano, DogeCoin, and Tron.

[14] We use the Python package STATSMODELS/DYNAMICFACTOR. For further information about the model and algorithm, see https://www.statsmodels.org/dev/examples/notebooks/generated/statespace_dfm_coincident.html.

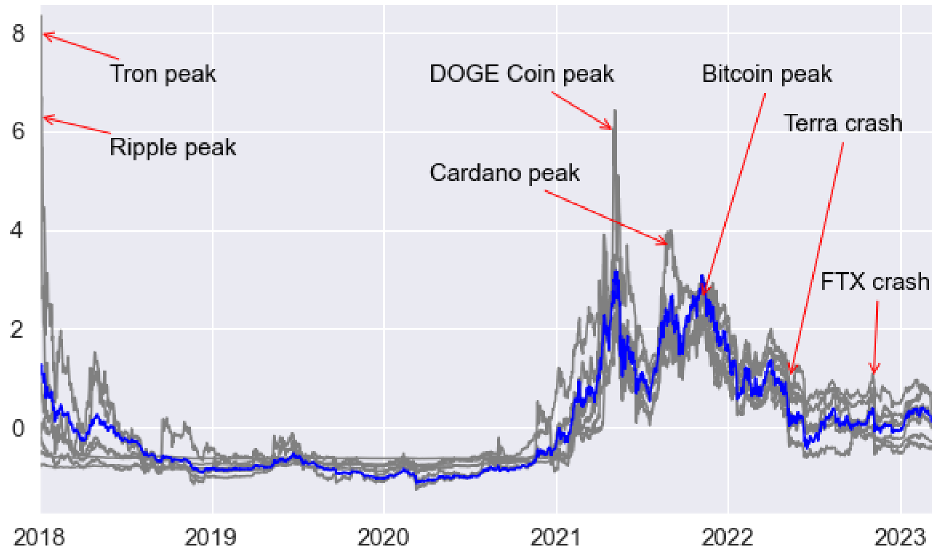


FIGURE (2.1) The crypto factor

Notes: This figure shows the crypto factor (blue) and the standardized crypto prices from which it is constructed (grey) using a dynamic factor model.

To gauge the importance of this factor more systematically, we regress each price series in turn on the crypto factor. On average, 80% of variation in the underlying series is explained by our crypto factor.[15] This figure is above 68% for all seven assets, underscoring the high degree of co-movement over our sample period. For comparison, the global equity factor calculated by Miranda-Agrippino et al., 2020 explains only 20% of global equity prices, highlighting the greater co-movement and concentration of market capitalization in the crypto market. Our findings thus strongly corroborate the hypothesized existence of a single crypto factor that drives the prices of the entire crypto market.

Given the limited range of assets used to calculate our factor, we also confirm that our crypto factor reflects more recent trends in newer assets.[16] To do so, we examine a broader sample of assets, grouped into five categories: First Generation tokens (Bitcoin, Ripple and Dogecoin), Smart Contracts platform tokens (Ethereum, Binance Coin, Cardano, Solana and Polkadot), DeFi tokens (Chainlink, Uniswap, Maker and Aave), Metaverse tokens (Flow, Ape Coin, the Sandbox, Decentraland and Theta Network) and Internet of Things tokens (Helium, Iota, IoTex and MXC). We then estimate a new model with five different factors, where each factor can only affect one class. The results are shown in Figure 2.2, along with the general crypto factor estimated above.[17] All classes

[15] See Appendix Figure B.1 for the breakdown across individual crypto assets.

[16] We do not include these newer assets in the calculation of the main factor, as they would further limit the timespan of our sample.

[17] Note that the timespan for each of the new factors is substantially shorter, given that many were created only in 2021.

are highly correlated with the general crypto cycle, validating our focus on the common trend.[18]

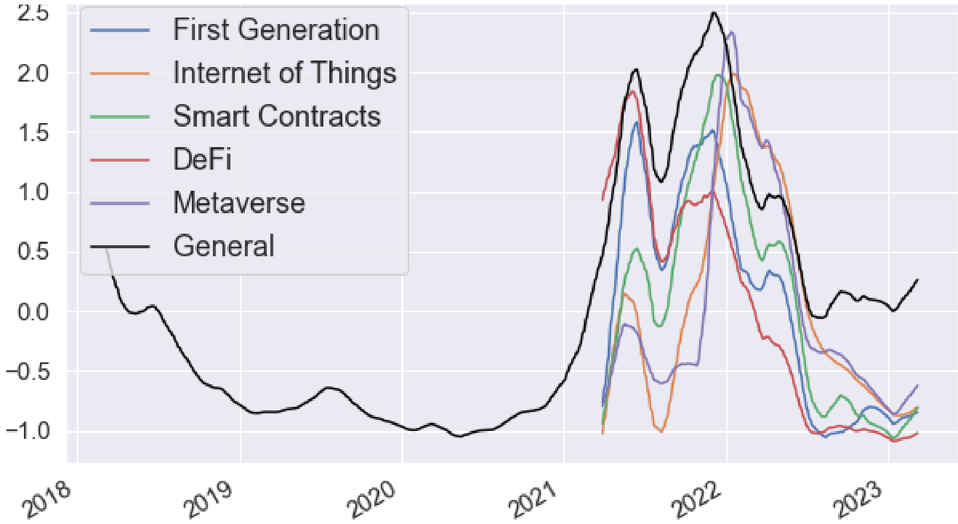


FIGURE (2.2) Crypto sub-factors

Notes: This graph shows the overall crypto factor and five crypto sub-factors, standardized and smoothed. The sub-factors are constructed from the following assets: First Generation tokens—Bitcoin, Ripple and Dogecoin; Smart Contract platform tokens—Ethereum, Binance Coin, Cardano, Solana and Polkadot; DeFi tokens—Chainlink, Uniswap, Maker and Aave; Metaverse tokens—Flow, Ape Coin, the Sandbox, Decentraland and Theta Network; and Internet of Things tokens—Helium, Iota, IoTex and MXC.

Finally, and consistent with anecdotal evidence, the crypto factor correlates with a proxy for leverage in crypto markets. Figure 2.3 plots the crypto factor against crypto leverage, defined using the total value locked (TVL) in decentralized finance ("DeFi") contracts normalized by total crypto market capitalization.[19] This shows that the system was relatively unlevered until the end of the 2018-2019 crypto winter, after which leverage increased substantially and the correlation with the general crypto factor increased.

[18]The main exception is the jump in the Metaverse factor in late 2021, when Facebook re-branded to Meta. Outside of this idiosyncratic shock, movements in the Metaverse factor also follow the general trend.

[19]TVL data from https://defillama.com/. While this measure of leverage is incomplete, since it does not capture the indebtedness present in exchanges or due to bilateral loans, it is indicative of total leverage in the system. We normalize by total crypto market capitalization to control for the fact that a large share of DeFi lending is denominated in crypto assets, so a rise in the price of these assets increases nominal leverage, and hence would generate a mechanical correlation with our crypto factor in the absence of the normalization.

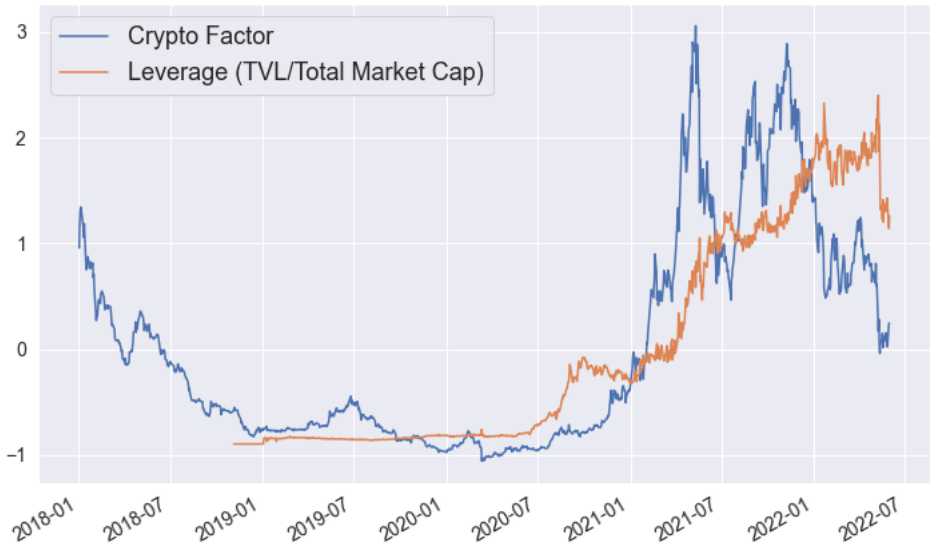


FIGURE (2.3) De-fi leverage

Notes: This graph shows the overall crypto factor and a proxy for total DeFi leverage, defined as the total value locked (TVL) in decentralized finance contracts normalized by total crypto market capitalization. The TVL data is downloaded from `https://defillama.com/`.

2.3 Crypto and the Global Financial Cycle

We now turn to the relationship between the crypto factor and global equities. Iyer, 2022 has documented an increase in correlation between Bitcoin and S&P500 returns since 2020. We therefore conjecture that crypto markets have become more integrated and synchronized with the equity cycle. To assess this, in this section we compute a global equity factor, then examine its relationship to the crypto factor.

We construct the global equity factor using all the equity indices available on Eikon/Thomson Reuters for the largest fifty countries by GDP.[20] We then follow the same methodology as in the previous section to compute: a general factor using all major stock indices, a factor for small capitalization stocks, and separate factors for each of the technology and financial sectors. Figure 2.4 shows both the equity and the crypto factors. As with the crypto factor, the equity factor credibly replicates the dynamics of global markets, with the sharp decline during the COVID-19 shock, the subsequent recovery and the downturn in early 2022. Generally speaking, the two series are fairly uncorrelated before 2020, then increasingly correlated from the second half of 2020. More formally, in Table 2.2, we regress changes in the crypto factor on changes in each of the other factors. Model (1) shows that, in general, the correlation between

[20]Table B.1 in Appendix B.1 details the full list of indices used.

the crypto and the equity factor is highly significant, while models (2) and (7) specifically highlight that this relationship is driven by the technology and small-cap components.

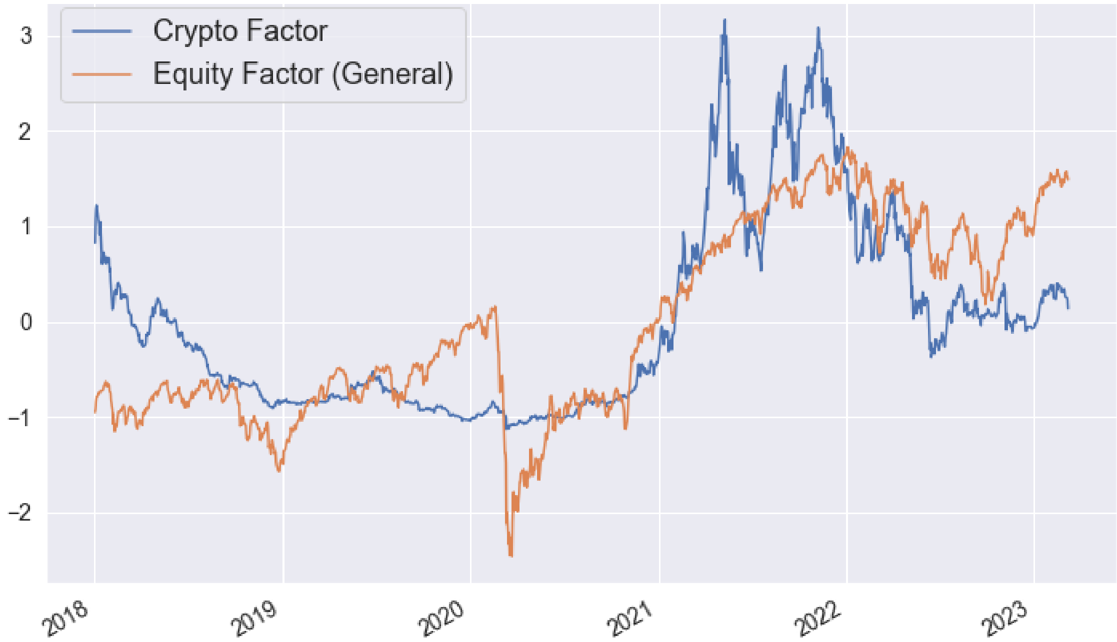


Figure (2.4) Crypto and equity factors

Notes: This figure shows the standardized time series of the crypto and equity factors, derived using dynamic factor modelling from a large range of crypto prices and equity indices respectively, as described in Section 2.2.

Table (2.2) Factor regressions

	Δ Crypto Factor						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Δ Global Equity Factor	0.310***						
	(6.57)						
Δ Global Tech Factor		0.627***				0.663***	
		(8.76)				(6.73)	
Δ Global Equity Factor excl. Tech			0.00916				
			(0.10)				
Δ Global Financial Factor				0.158***		-0.0226	
				(5.55)		(-0.61)	
Δ Global Equity Factor excl. Financials					0.519***		
					(4.90)		
Δ Global Small Caps Factor							0.385***
							(6.61)
Constant	-0.00111	-0.00161	-0.000529	-0.000552	-0.000529	-0.00167	-0.000926
	(-0.43)	(-0.63)	(-0.20)	(-0.21)	(-0.20)	(-0.65)	(-0.36)
Observations	1302	1302	1302	1302	1302	1302	1302
R-squared	0.047	0.069	0.000	0.026	0.027	0.069	0.050

Notes: This table reports the results from regressing the crypto factor on different combinations of equity factors. Data is from January 2018 to March 2023. Variables are standardized. t-statistics are in parentheses. *, **, and *** correspond to significance at the 10%, 5%, and 1% levels respectively.

In Table 2.3, we report the correlation matrices for a wide range of crypto and equity variables before and after 2020. Consistent with Iyer, 2022, the correlation between Bitcoin and the S&P500 was low before 2020 but increased significantly afterward. This is also the case for the correlation between the crypto and global equity factors. In particular, the crypto factor correlated increasingly strongly with the small cap and technology factors, and relatively less so with the financial factor. In Table B.2 in Appendix B.1, we report the p-values of such differences in correlations, computed by regressing the different crypto factors on equity factors (or other variables, e.g., gold and oil prices), a time dummy and their interactions.

Table (2.3) Cross-correlations between factors before and after 2020

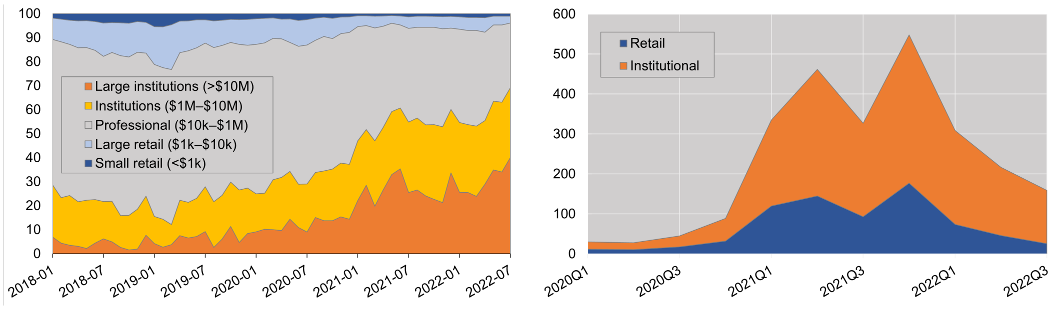
	Before 2020						
Bitcoin	1.00						
Crypto F	0.76	1.00					
First Gen							
IoTs							
Smart C.							
DeFi							
Metaverse							
S&P 500	0.01	0.09					
Equity F	0.00	0.07					
Small Caps F	0.01	0.09					
Tech Factor	-0.01	0.06					
Equity F (no Tech)	0.01	0.04					
Financials F	-0.03	0.03					
Equity F (no Fin)	0.05	0.09					
Dollar Index	-0.05	0.00					
VIX	-0.08	-0.19					
Oil	0.01	0.04					
Gold	0.08	0.03					
	Bitcoin	Crypto F	First Gen	IoTs	Smart C.	DeFi	Metaverse

	After 2020						
Bitcoin	1.00						
Crypto F	0.85	1.00					
First Gen	0.80	0.91	1.00				
IoTs	0.65	0.78	0.76	1.00			
Smart C.	0.80	0.97	0.80	0.73	1.00		
DeFi	0.65	0.85	0.76	0.69	0.85	1.00	
Metaverse	0.40	0.45	0.38	0.43	0.47	0.38	1.00
S&P 500	0.29	0.28	0.26	0.28	0.36	0.24	0.27
Equity F	0.25	0.24	0.23	0.24	0.33	0.23	0.23
Small Caps F	0.26	0.24	0.22	0.23	0.32	0.24	0.23
Tech Factor	0.30	0.29	0.25	0.26	0.35	0.23	0.25
Equity F (no Tech)	0.00	0.00	-0.02	-0.02	-0.02	0.01	-0.02
Financials F	0.19	0.18	0.17	0.16	0.24	0.17	0.17
Equity F (no Fin)	0.17	0.18	0.14	0.17	0.22	0.13	0.14
Dollar Index	-0.14	-0.16	-0.14	-0.09	-0.19	-0.13	-0.09
VIX	-0.26	-0.24	-0.28	-0.29	-0.37	-0.26	-0.26
Oil	0.05	0.05	0.05	0.01	0.08	0.05	0.06
Gold	0.05	0.06	0.05	0.02	0.07	0.04	0.01
	Bitcoin	Crypto F	First Gen	IoTs	Smart C.	DeFi	Metaverse

Notes: The tables above show the cross-correlations between the crypto and equity factors and sub-factors, before and after 2020. Note that we cannot compute correlations for crypto sub-factors before 2020, as most of the constituent assets from which they are derived did not exist at that time. p-values are reported in Table B.2 in Appendix B.1.

What drove the increased correlation between crypto and equities? Previous literature suggests a range of possible (and mutually compatible) explanations. Retail investors increased their trading during the COVID-related lockdowns, including in crypto assets (Schwab, 2021; Vanda Research, 2021). Indeed, Toczynski, 2022 estimates that roughly US$15 billion of the federal stimulus checks was spent on trading crypto assets. New on-ramps also opened to cater for the growing demand. For instance, popular mobile payment applications (e.g., Revolut, Paypal) and trading platforms (e.g., Robinhood) allowed their clients to trade crypto assets. Coinbase, a centralized crypto exchange, was listed on the Nasdaq in April 2021. New investment products, such as the Grayscale Bitcoin Trust, were created to give investors exposure to crypto assets without holding tokens.

Against this backdrop, institutional investors also increased their exposure to crypto assets. Using a novel supervisory database, Auer et al., 2022 document the growing importance of traditional financial intermediaries in crypto markets. They show that banks' exposure to crypto assets has increased, and that, while it remains small relative to their balance sheets, it is significant for the crypto market, which was previously populated predominantly by retail investors. Using data scraped from public blockchains by Chainalysis, 2021, we find similarly that institutional investors' share of crypto trading volumes has risen dramatically since 2020 (Figure 2.5 Panel (a)). While this method relies on proxying for investor type by the size of on-chain transactions (for example, transactions under $10k are classified as trades by retail traders), we see a similar pattern in self-reported data from centralized exchanges (Figure 2.5 Panel (b)). By 2022, institutional investors made up a substantial majority of total trading volumes.



(A) Share of on-chain trading volumes (B) Trading volumes on Coinbase ($bn)

FIGURE (2.5) Increasing institutional participation in crypto markets

Notes: Panel (a) shows the share of on-chain trading volumes by investor type over time, using data scraped by Chainalysis, 2021. Investor types are proxied by transactions sizes, e.g. trades under $10k are classified as trades by retail traders. Panel (b) shows the relative trading volumes on Coinbase of retail and institutional investors, reported in the company's public financial statements (available at https://investor.coinbase.com/financials/quarterly-results/).

In Table 2.4, we further investigate the relationship between the share of institutional investors and the correlation between equity and crypto factors. Consistent with previous findings, the correlation between Bitcoin and the S&P500 is positive and significant only after 2020 (columns (1) and (2)), and the same applies to the crypto and equity factors (columns (3) and (4)). Finally, column (5) shows that the share of institutional investors plays a significant and important role in explaining the correlation between the two factors. Arguably, the growing participation of institutional investors that are also heavily exposed to traditional stocks creates a direct link between equity and crypto markets.

Table (2.4) Factor regressions and participation of institutional investors

	Δ Bitcoin		Δ Crypto Factor		
	(1)	(2)	(3)	(4)	(5)
Δ SP500	0.268***	0.00378			
	(8.72)	(0.10)			
Δ SP500 # After 2020		0.304***			
		(5.88)			
After 2020		0.0268		0.0544	
		(0.60)		(1.18)	
Δ Global Equity Factor			0.217***	0.0437	0.180***
			(6.57)	(1.39)	(7.23)
Δ Global Equity Factor # After 2020				0.206***	
				(4.08)	
Δ Global Equity Factor # Share of Institutionals					0.226***
					(5.02)
Share of Institutionals					0.00302
					(0.08)
Constant	-5.45e-10	-0.0163	-1.17e-09	-0.0338	-0.00284
	(-0.00)	(-1.03)	(-0.00)	(-1.81)	(-0.10)
Observations	1302	1302	1302	1302	1148
R^2	0.0721	0.0825	0.0472	0.0535	0.0854
R^2 (adj)	0.0714	0.0804	0.0465	0.0513	0.0830

Notes: This table reports the results from regressing the bitcoin and the crypto factor on the S&P500 and the equity factor along with different interactions with time dummies and the share of institutional investors. Variables are standardized. Data is from January 2018 to March 2023. Standard errors are in parentheses. *, **, *** correspond to 10%, 5%, and 1% significance, respectively.

Given the importance of institutions, we now investigate their role in changing the profile of the marginal crypto investor. To examine this empirically, we follow Bekaert et al., 2013 and Miranda-Agrippino et al., 2020 in decomposing movements in the factors into two elements: (i) changes in market risk, and (ii) changes in market attitudes towards risk, i.e., 'aggregate effective risk aversion', defined as the wealth-weighted average risk aversion of investors. Proxying (i) with realized market risk, measured by the 90-day variance of the MSCI World index as in Miranda-Agrippino et al., 2020, we can then estimate (ii) as (an inverse function of) the residual ϵ of the following regression in logarithms:

$$f_t^{Equities} = \alpha + \beta_1 \cdot Var(\text{MSCI World})_t + \epsilon_t \tag{2.2}$$

and similarly for crypto:

$$f_t^{Crypto} = \alpha' + \beta_1' \cdot Var(\text{MSCI World})_t + \beta_2' \cdot Var(\text{BTC})_t + \epsilon_t' \tag{2.3}$$

where: f_t are the factors estimated using the methodology in Equation 2.1 above; we repeat the MSCI World term in the crypto regression to control for overall global market risk; and we add the 90-day variance of the Bitcoin price in the crypto regression as an analogous proxy for realized crypto market risk.[21]

The effective equity risk aversion extracted from Equation 2.2 is consistent with other proxies of investors' risk-taking in literature. The correlation (in changes) of the 90-day equity risk aversion with the intermediary capital ratio and the square of the intermediary leverage ratio developed by He et al., 2017 are -0.292 and 0.434, respectively (see Table B.4 in Appendix B.1). The interpretation of these proxies is the following: when a negative shock hits the equity capital of the intermediaries, their leverage increases; thus, their risk-bearing capacity is impaired, and the effective risk-aversion rises. The correlations are relatively high, given that He et al., 2017 use a very different methodology and we are comparing daily measures. Indeed, their proxies are constructed using capital ratios only for the primary dealer counterparties of the New York Federal Reserve, and not from (a dynamic factor computed from) global equity prices (see Equation 6 of their paper).

Figure 2.6 shows the resulting aggregate effective risk aversion for the marginal crypto investor, along with the crypto factor. We identify two main phases, before and after the late 2019 peak. At the beginning of our sample, the effective risk aversion of crypto investors was more volatile and characterized by a somewhat increasing trend. Notably, this coincided with the 'crypto winter', an extensive period of relatively flat or negative returns. After 2020, the effective risk aversion declined fairly steadily and the crypto factor exhibited large returns and high volatility. Interestingly, since the collapse of Terra/Luna in May 2022, the crypto factor is almost a mirror image of effective risk aversion, implying that crypto prices have been driven primarily by changes in the risk appetite of

[21] Regression results are reported in Appendix Table B.3. Note that we include both equity and crypto measures of market variance in order to account for *all* risks and to be more conservative about the price variation that we ascribe to the aggregate risk aversion. Such considerations are even more relevant if crypto investors are exposed to both equity and crypto markets.

crypto investors. Finally, we note that the decline in the effective risk aversion corresponded with the increase in the participation of institutional investors, who can bear more risk than retail investors and thus change the profile of the marginal crypto investor.

FIGURE (2.6) Aggregate effective crypto risk aversion

Notes: This figure shows the crypto factor and the aggregate effective risk aversion in crypto markets, estimated following Bekaert et al., 2013 and Miranda-Agrippino et al., 2020 as described in the text. Both variables are standardized.

Comparing the estimated risk aversion in crypto to that for equities, we see an increase in correlation since 2020 (Figure 2.7, orange line). At its peak in 2022, the correlation was more than 40%. This implies that the risk profiles of the marginal crypto and marginal equity investors have become more similar, again coinciding with increased institutional entry into crypto markets (Figure 2.5). This rise also parallels the aforementioned increasing correlation between the overall crypto and equity factors (Figure 2.7, blue line).

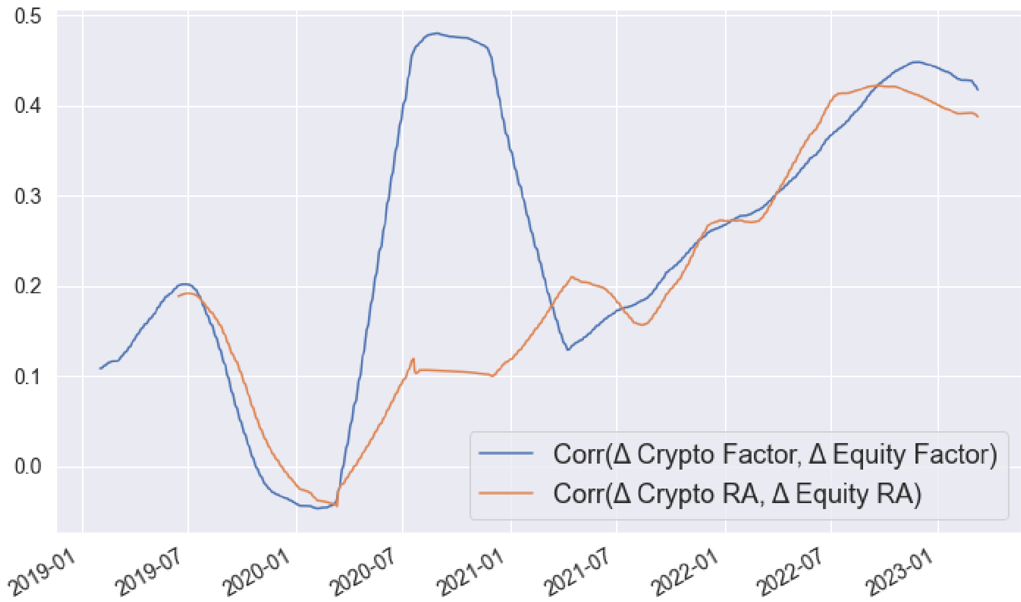


FIGURE (2.7) Rolling correlations between crypto and equities

Notes: This graph shows the 180-day rolling correlations between the crypto and equity factors (blue) and between the risk aversions of the marginal investors in each of the two asset classes (orange), where the risk aversions are calculated following Bekaert et al., 2013 and Miranda-Agrippino et al., 2020 as described in the text.

To assess the strength of this possible relationship, in Table 2.5 we regress the rolling correlation between the equity and crypto factors on the correlation between their respective effective risk aversions. The coefficients are positive and highly significant across all specifications and the R^2s are relatively high, even reaching 65% for the 30-day window. This further suggests that the correlation between effective risk aversions can explain a substantial share of the variation in the factors' correlation.

TABLE (2.5) Correlations regressions

	Corr(Δ Crypto Factor, Δ Equity Factor)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Corr(Δ Crypto RA, Δ Equity RA)	0.854***	0.833***	0.802***	0.773***	0.705***	0.633***	0.473***
	(0.016)	(0.018)	(0.021)	(0.023)	(0.027)	(0.027)	(0.018)
Constant	0.036***	0.046***	0.074***	0.091***	0.116***	0.130***	0.154***
	(0.006)	(0.007)	(0.008)	(0.008)	(0.009)	(0.008)	(0.005)
Rolling window	30	45	90	120	180	240	360
Observations	1,183	1,168	1,123	1,093	1,033	973	853
R-squared	0.648	0.564	0.455	0.408	0.356	0.364	0.434

Notes: This table reports the results of regressing the rolling correlation between the delta crypto and the delta equity factors on the rolling correlation between the delta crypto and delta equity aggregate effective risk aversions.

Data is from January 2018 to March 2023. Standard errors are in parentheses. *, **, *** correspond to 10%, 5%, and 1% significance, respectively.

Overall, our findings are consistent with the hypothesis that the entry of institutional investors was a major factor driving the increase in correlation between crypto and equity markets. At the same time as many traditional financial institutions entered crypto markets, the risk aversion of the marginal crypto investor became increasingly similar to that of the marginal equity investor, and this correlation in turn can explain an important share of the correlation between the crypto and equity factors.

2.4 Crypto and US Monetary Policy

In the first part of the paper, we documented the existence of a single crypto factor that explains a large share of the variation in crypto prices, and highlighted that it is increasingly correlated with the global equity factor. Since the literature has shown that US monetary policy influences the global financial cycle (Miranda-Agrippino et al., 2020; Rey, 2013), it is plausible that it might also affect the crypto cycle. In this section, we therefore assess the impact of US monetary policy on the crypto cycle, and the channels through which this occurs.

2.4.1 The impact of monetary policy on the crypto factor

To assess the impact of monetary policy on crypto markets, we use a daily vector autoregressive model (similarly to Miranda-Agrippino et al., 2020). Table 2.6 shows the order of the variables and the various controls that we include in each of our main specifications. We identify monetary policy shocks using a Cholesky decomposition in which the policy variable and controls are ordered first. In this setup, endogeneity is not likely to be an issue as the Fed does not tune interest rates or its open market operations in response to the evolution of crypto markets. Furthermore, we use variables at a daily frequency, such that reverse causation would only occur if the Fed adjusted its policy in response to the crypto market on a day-to-day basis. Nonetheless, among the battery of robustness tests we run, we also invert the order of the variables to allow the policy rate to be the most endogenous with respect to all other variables. We find that results are robust, i.e., do not depend on an arbitrary ordering of the variables, and—as expected—that the policy rate does not respond to changes in the crypto factor.[22]

We measure the monetary policy stance using the shadow federal funds rate developed by Wu et al., 2016, as it reflects that balance sheet policy is now part of the conventional tool kit of modern central banking. If we only used the federal funds rate, we would omit relevant information. This is especially the case given our recent sample period, with the primary response to the COVID shock occurring through balance sheet policies.

In our specifications, beyond the variables related to equity and crypto prices, we account for a set of variables that proxy for global economic activity. Specifically, we include: (i) the spread between ten- and two-year yields on US government bonds, reflecting investors' expectations of future economic growth; (ii) the dollar index, to proxy for the status of international trade and credit flows—which the literature has shown to be cyclical (e.g., Bruno et al., 2022); (iii) oil and gold prices, as they are usually associated with the economic cycle; and (iv) the VIX to capture anticipated future uncertainty and effective risk-aversion.

[22] In addition, in Table B.5 in Appendix B.1, we estimate a simple monthly regression of the crypto factor and bitcoin on the Wu et al., 2016 shadow rate and on monetary policy shocks from Bu et al., 2021. For the latter, we use latest updated series, which includes data up to end-2021. Although the sample size is very small, we still find a significant negative effect of US monetary policy on the crypto cycle.

Table (2.6) VAR specifications

Variable Ordering	(1)	(2)	(3)	(4)	(5)
Interest Rates					
Wu-Xia Shadow FFR	✓	✓		✓	✓
Average S-FFR (BOE,ECB,Fed)			✓		
Conjuncture					
10-2 Y Treasury Yield Spread	✓	✓	✓	✓	✓
Dollar Index	✓	✓	✓	✓	✓
VIX	✓	✓	✓	✓	
Oil	✓	✓	✓	✓	✓
Gold	✓	✓	✓	✓	✓
Equity Variables					
Aggregate Equity Risk Aversion					✓
S&P500		✓			
Global Equity Factor	✓		✓	✓	✓
Crypto Factors					
Aggregate Crypto Risk Aversion					✓
Bitcoin		✓			
Crypto Factor	✓		✓		✓
First Generation Factor				✓	
Smart Contracts Factor				✓	
DeFi Factor				✓	
Metaverse Factor				✓	
IoT Factor				✓	

Notes: This table shows the selection and ordering of variables in each of our VAR specifications. Column (1) is our baseline specification. Column (2) tests whether the baseline results are determined by the construction of the crypto and equity factors. Column (3) explores if the crypto factor is affected by other (major) monetary policies. Column (4) investigates the heterogeneous effects of the responses by crypto sub-classes. Finally, column (5) tests whether US monetary policy affects the crypto factor via the risk-taking channel as in Miranda-Agrippino et al., 2020. Data is from January 2018 to March 202, with the exception of column (4) which is from 2021 due to data availability.

Figure 2.8 reports the most relevant cumulative impulse response functions for the first specification in Table 2.6. Overall, the signs of the responses are consistent with the literature. A Fed monetary contraction leads to an increase in the VIX and to a decline in the global equity factor as in Miranda-Agrippino et al., 2020. Importantly, we also find that Fed monetary policy has a large and persistent impact on the crypto factor, as with traditional stocks. Specifically, the crypto factor declines by 0.15 standard deviations, while the equity factor declines only by 0.1 standard deviation.[23] This indicates that crypto assets are subject to US monetary policy and the economic cycle similarly to traditional investments, in contrast to claims of orthogonality to the traditional financial system or usefulness as a hedge against market risk. We postpone the discussion of the drivers of these findings to Sections 2.4.2 and 2.4.3.

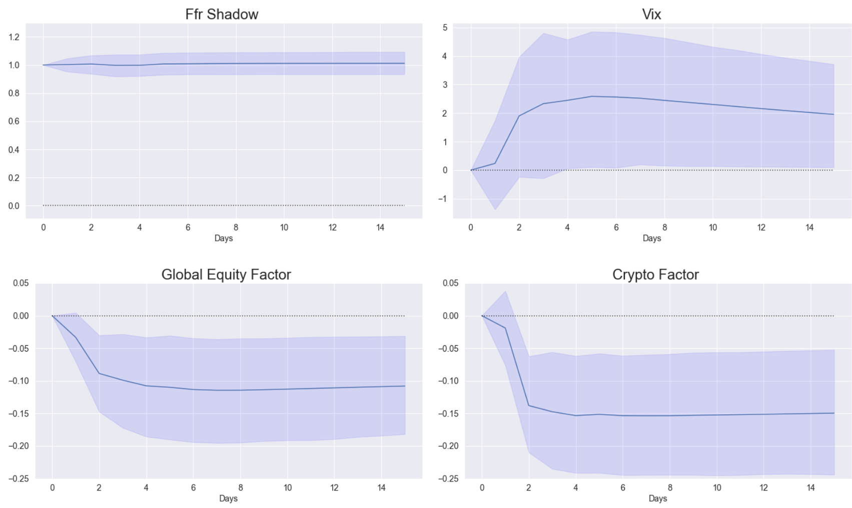


FIGURE (2.8) Baseline VAR results

Notes: This figure shows the cumulative 15-day impulse response functions for a one percentage point rise in the shadow FFR when estimating VAR specification (1) (see Table 2.6 for details). We report 90% confidence intervals computed from 1000 Monte Carlo simulations. Factors are standardized over the sample period.

To confirm that our results are not biased by the construction of the factors, we re-estimate the impulse responses using the S&P500 and the Bitcoin price instead of the factors (specification (2) in Table 2.6). The estimates in Figure 2.9 are very similar to the responses in Figure 2.8, reassuring us that the previous results are not artifacts of our particular methodology for deriving the factors, nor are they due to the selection of assets we considered.

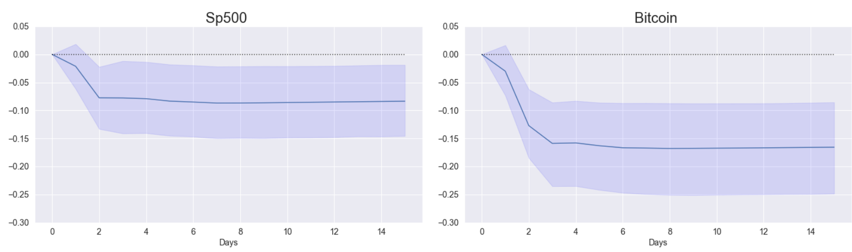


FIGURE (2.9) Robustness to factor construction

[23]Note that for comparability the factors are both standardized with respect to the same sample period. The magnitudes of the effects can therefore be interpreted as the responses—measured in 2018-2023 standard deviations—of the factors to a hypothetical one percentage point hike in the shadow FFR.

Notes: This figure shows the cumulative 15-day impulse response functions for a one percentage point rise in the shadow FFR when estimating VAR specification (2) (see Table 2.6). We report 90% confidence intervals computed from 1000 Monte Carlo simulations. Variables are standardized over the sample period.

We also check whether our results are specific to Fed policy, or hold equally across major central banks. In specification (3), we instead define the policy variable as the average shadow rate of the Fed, the Bank of England and the European Central Bank, weighted by the size of their balance sheets. Consistent with the extensive literature on dollar dominance, we find much weaker responses to this broader policy tightening (see Figure 2.10). There is no longer a significant impact on the global equity factor, and this is also the case for the crypto factor, possibly reflecting that crypto markets are increasingly dollarized. For instance, the largest stablecoins are USD-denominated, most crypto borrowing and lending occurs in USD stablecoins, and crypto prices are usually expressed in dollars. Indeed, Auer et al., 2022 document that a large share of total global crypto trading occurs in North America.

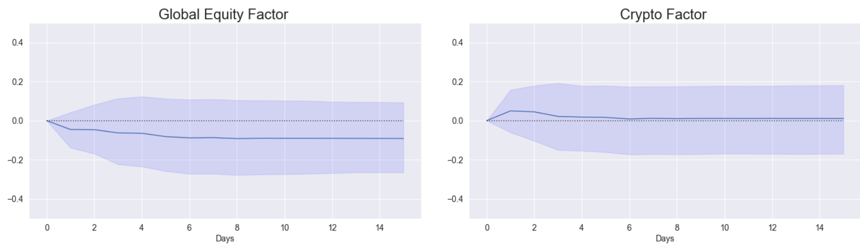


FIGURE (2.10) Impacts of global tightening

Notes: This figure shows the cumulative 15-day impulse response functions for a one percentage point rise in the shadow FFR when estimating VAR specification (3) (see Table 2.6). We report 90% confidence intervals computed from 1000 Monte Carlo simulations. Factors are standardized over the sample period.

Next, we disaggregate across the different crypto sub-classes, as described in Section 2.2. Figure 2.11 shows the results from running VAR specification (4). Since many of the tokens did not exist in 2018, we shorten the sample in each case to start from the first date for which the respective prices are available. Overall, our results show that the reaction of First Generation coins is consistent with our baseline. However, while the other sub-factors show a similar shape, their response is insignificant, in part reflecting the shorter estimation sample. The category that is farthest from having a significant reaction is the Metaverse, possibly because such tokens are relatively newer with smaller market caps and a mostly retail investor base.

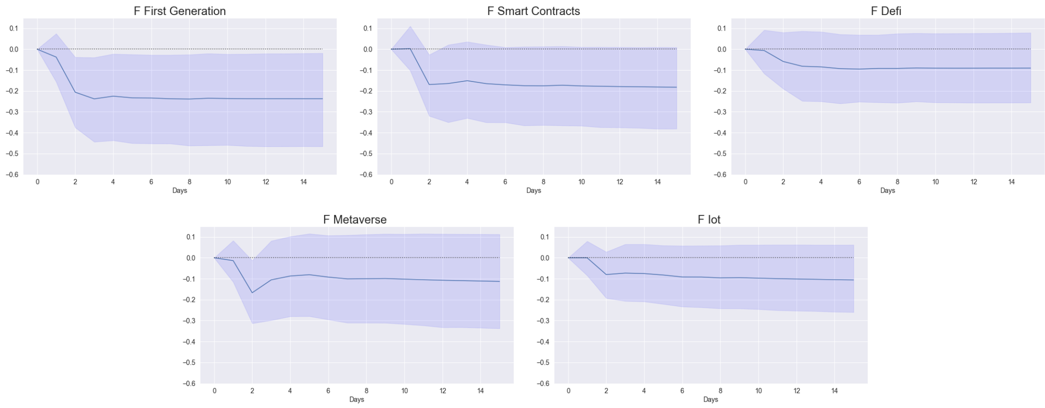


Figure (2.11) Impacts on crypto sub-factors

Notes: This figure shows the cumulative 15-day impulse response functions for a one percentage point rise in the shadow FFR when estimating VAR specification (4) (see Table 2.6). Clockwise from the top-left, the figures show the results respectively for the First Generation, Smart Contracts, DeFi, Internet of Things and Metaverse factors. We report 90% confidence intervals computed from 1000 Monte Carlo simulations. Factors are standardized over the sample period.

2.4.2 The risk-taking channel and institutional investors

Given this impact of monetary policy on the crypto factor, we now consider potential transmission channels. Following Miranda-Agrippino et al., 2020, we investigate the risk-taking channel of monetary policy, where a monetary policy shock changes the effective risk aversion of the marginal investor. Using specification (5) of Table 2.6, we include our proxies for the aggregate effective risk aversion of both equity and crypto investors. The results in Figure 2.12 show that a monetary policy contraction leads to a persistent increase in the effective risk aversion of the marginal crypto investor as well as to lower crypto prices (as described in the previous section). This suggests that the marginal crypto investor reduces their risky positions as they cannot tolerate the same amount of risk given the new rates. In other words, a higher cost of capital leads crypto investors to deleverage and this in turn is associated with lower crypto prices. This interpretation is also consistent with the fact that leveraged investors are more sensitive to the economic cycle (Adrian et al., 2014; Coimbra et al., 2022).[24]

[24] In addition, the global equity factor responds negatively to the monetary tightening, as expected, while we do not observe any significant effect on the aggregate effective risk aversion of the marginal equity investor. This may simply reflect that equity investors are more sophisticated and thus better anticipate monetary policy changes.

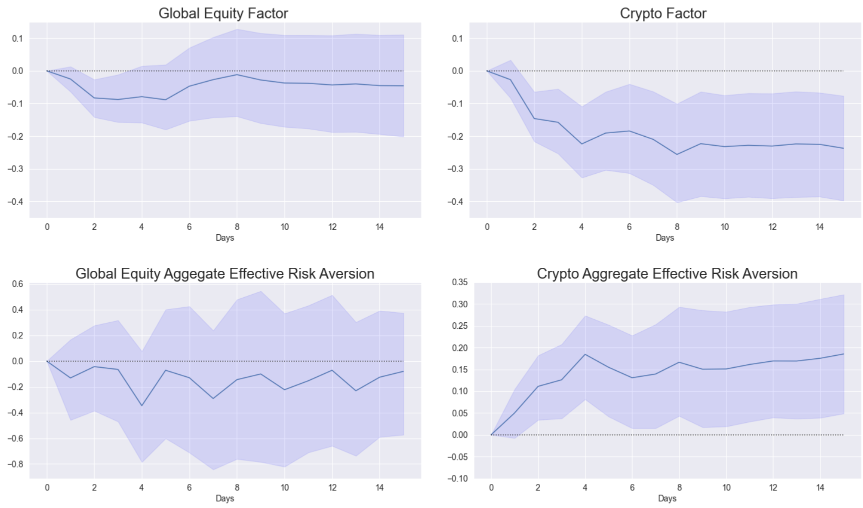


FIGURE (2.12) Impacts on aggregate effective risk aversion

Notes: This figure shows the cumulative 15-day impulse response functions for a one percentage point rise in the shadow FFR when estimating VAR specification (5) (see Table 2.6). We report 90% confidence intervals computed from 1000 Monte Carlo simulations. All variables are standardized over the sample period.

Furthermore, when estimating the model before and after 2020, we find that the response of crypto risk aversion is only significant in the post-2020 period and the response of crypto prices to monetary policy is larger in the post-2020 period (see Figure 2.13). This suggests that the participation in crypto markets of institutional investors who take on more leverage not only increased the correlation between equity and crypto prices, but also reinforced the transmission of monetary policy to crypto markets.

(A) Before 2020 (B) After 2020

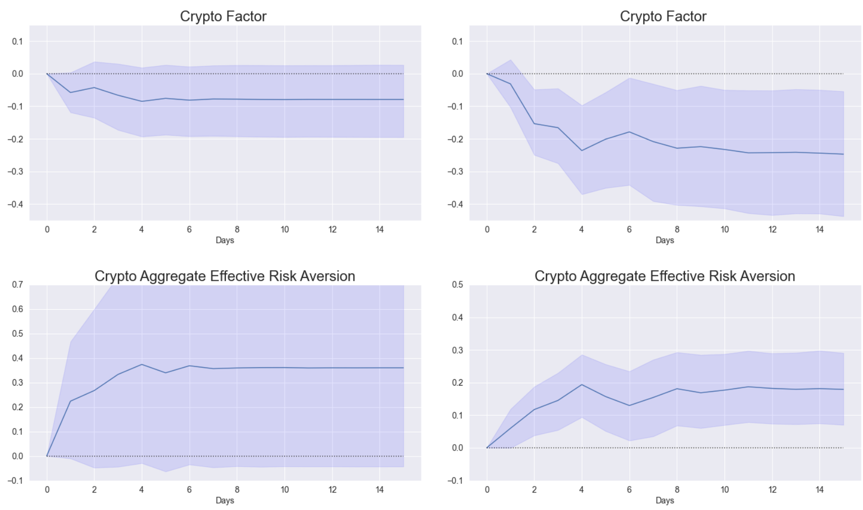


FIGURE (2.13) Impacts of monetary policy before and after 2020

Notes: This figure shows the cumulative 15-day impulse response functions for a one percentage point rise in the shadow FFR when estimating VAR specification (5) (see Table 2.6 for details) before 2020 (left-hand charts) and after 2020 (right-hand charts). We report 90% confidence intervals computed from 1000 Monte Carlo simulations. All variables are standardized over the full sample period, while the VAR models are estimated on each sub-sample.

We test this hypothesis more formally by estimating a logistic smooth transition VAR with two states à la Auerbach et al., 2012, where the transition variable is the share of institutional investors.[25] Specifically, we run

$$Y_t = \underbrace{(1 - F(s_{t-1}))}_{\text{prob. of state 1}} \overbrace{\left[\sum_{j=1}^{p} A_{1j} Y_{t-j}\right]}^{\text{VAR in state 1}} + \underbrace{F(s_{t-1})}_{\text{prob. of state 2}} \overbrace{\left[\sum_{j=1}^{p} A_{2j} Y_{t-j}\right]}^{\text{VAR in state 2}} + u_t$$

where Y_t is the stacked vector of variables, s_t the transition state variable and $F(\cdot)$ a logistic function. Intuitively, we estimate a linear combination of two VARs, one when the share of institutional investors is low and one when it is high, where the weights are the probability of being in that state. The approach is similar to considering a dummy variable that takes value 1 when the share of institutional investors is above the sample median. The difference is that, instead of considering two discrete values (0 and 1), the smooth transition approach allows the regimes to continuously vary between 0 and 1. Such a methodology has two main advantages compared to standard approaches to model interactions and assess non-linearities. First, compared to a linear interaction model, it allows the magnitude of the effect of monetary policy shocks to vary non-linearly as a function of the share of institutional investors. Hence, it is possible to compute the impulse response functions when the share of institutional investors is high or low. Second, compared to estimating structural vector autoregressions for each regime, it allows the effect of monetary policy shocks to change smoothly between regimes by considering a continuum of states to compute the impulse response functions, thus making the response more stable and precise.

Figure 2.14 reports the evolution of the share of institutional investors as well as the state transition variable which determines the state of the economy.[26] The correlation between the two is 96%, and when the latter is equal to one (zero) the share of institutional investors is high (low).

[25]We use the *macrometrics* toolbox of Gabriel Zuelling, which is based on the replication code of Auerbach et al., 2012. Link: `https://gabrielzuellig.ch/macrometrics/`.

[26]The transition variable is computed using a logistic function with $\gamma = 3$. Yet, results are robust to using a different γ (e.g., $\gamma = 1.5$).

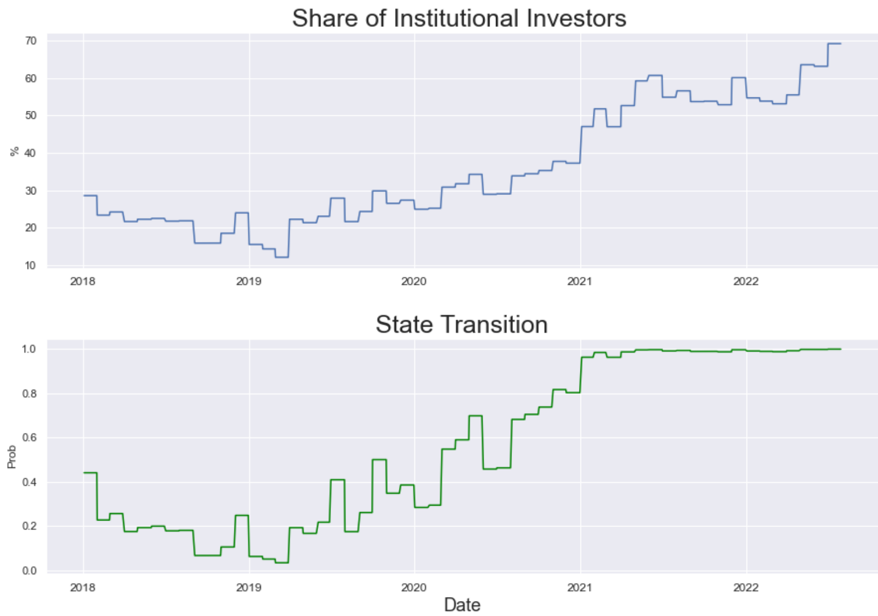


FIGURE (2.14) Transition variable

Notes: The share of institutional investors is from Chainalysis, 2021. The state transition is a logistic transformation of the (standardized) share of institutional investors (with $\gamma = 3$), thus, when it is equal to one (zero), the share of institutional investors is high (low). The correlation between the two is 96%.

The results are reported in Figure 2.15 and corroborate the findings of previous specifications. When the share of institutional investors is low, US monetary policy does not significantly affect crypto prices and the response of the aggregate risk aversion is not significant. However, when the share of institutional investors is high, we observe a significant negative effect on crypto prices and a significant change in the risk appetite of the marginal crypto investor.

(A) Lower Share (B) Higher Share

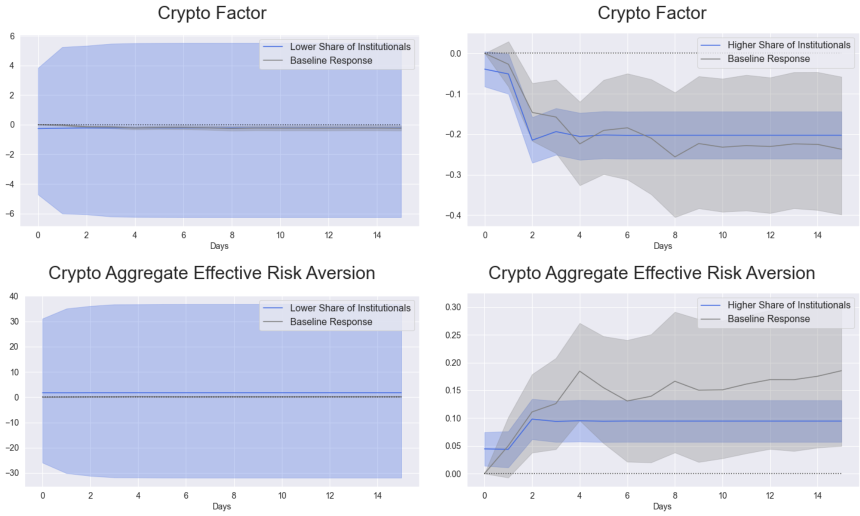


FIGURE (2.15) Impacts of monetary policy depending on the share of institutional investors

Notes: This figure shows the cumulative 15-day impulse response functions for a one percentage point rise in the shadow FFR when estimating a logistic smooth transition VAR (as in Auerbach et al., 2012). The STVAR includes the shadow FFR, the crypto aggregate risk aversion, and the crypto factor. We report 90% confidence intervals computed using Markov chain Monte Carlo techniques. For comparison, we also report the baseline responses of the linear VAR estimated in Section 2.4.2. All variables are standardized over the sample period.

2.4.3 Other mechanisms

Our analysis does not rule out the existence of additional mechanisms that could influence the responses of crypto markets to monetary policy. Here we discuss three: lower liquidity, USD appreciation and an alternative valuation model.

First, the lower liquidity of crypto markets may drive different responses to monetary policy. Specifically, illiquid securities may react more strongly to monetary policy shocks, regardless of the composition of the investor base. To test the liquidity hypothesis, we sort crypto assets by the number of units traded daily, extracting factors for the most and least liquid securities, and then repeat our previous analysis. We do not find significant differences between the two factors in their response to monetary policy, suggesting that differences in liquidity do not explain our results. In addition, we note that the crypto market became increasingly liquid from 2020 as more investors entered the asset class. According to the liquidity channel above, this would reduce the responsiveness to monetary policy –whereas we find that in fact the responsiveness to monetary policy has increased (Figure 2.13).

US monetary policy could also indirectly affect the crypto market via the USD valuation channel, with the dollar being the main funding currency and unit of account in the crypto market. Crypto tokens are mostly priced in dollars, USD stablecoins account for 95% of stablecoins issued, and DeFi lending is largely executed in USD stablecoins. When USD appreciates, tokens become de facto more expensive for non-US investors whose purchasing power is based in other fiats, which mechanically reduces inflows into the crypto market. USD stablecoin borrowing also becomes more expensive as the dollar appreciates, potentially reducing the demand for leverage. However, we do not find strong evidence for this channel in our empirical analysis: our VARs do not show significant responses of the crypto factors to shocks in the DXY index.

Finally, investors may have a different valuation model for crypto assets. If investors price crypto assets as bubbles, a rise in discount rates would compress risk premia, leading more investors to divest, putting downward pressure on the price.[27] However, this channel does not explain the increase in responsiveness of crypto to monetary policy since 2020, as with the liquidity channel, nor does it account for the increased synchronization of the crypto and equity cycles. We therefore retain our focus on a change in the underlying composition of the crypto investor base.

2.5 Model

In this section, we provide a stylized model to help interpret our empirical results, building on the literature on heterogeneous risk-taking intermediaries (see, for instance: Adrian et al., 2014; Danielsson et al., 2010; Miranda-Agrippino et al., 2021). We derive an expression for crypto excess returns as a function of the aggregate effective risk aversion (Γ_t^c) in the crypto market. Changes in the composition of the market then affect Γ_t^c, and hence crypto prices. Specifically, the entry of more institutional investors implies that crypto prices are increasingly correlated with those in equity markets, as in our empirical results in Section 2.3. A US monetary contraction disproportionately reduces the wealth of institutional investors, reducing crypto demand and prices, and does so to a greater extent the larger the share of institutional investors in the market, as in Section 2.4.[28]

[27] Nevertheless, there is relatively little consensus in the literature on the effects of monetary policy on bubbles. For a discussion see Brunnermeier et al., 2015 and Dong et al., 2020.

[28] For a sophisticated model of heterogeneous agents and monetary policy, see Coimbra et al., 2017.

Our framework features two representative heterogeneous agents and two asset classes, namely crypto and equity. Crypto investors c can only invest in crypto markets, whereas institutional investors i can invest in both crypto and equity markets.[29] Crypto investors are retail investors that trade using their disposable income and personal savings (see, for instance, Toczynski, 2022). Institutional investors are banks and similar financial intermediaries that operate in multiple sectors (Auer et al., 2022). Crypto investors maximize a mean-variance portfolio and can borrow at the US risk-free rate to leverage up their positions.[30] By contrast, institutional investors are risk-neutral agents that maximize the expected return of their portfolio, given a value-at-risk constraint.[31] The outside option of both agents is to invest in risk-free deposits, which pay zero excess return. Without loss of generality, we interpret the model as having only one crypto asset and only one global stock, which respectively represent the crypto and global equity factors in the empirical analysis.[32]

Crypto investors: Crypto investors maximize a mean-variance portfolio and have a constant risk aversion coefficient σ. They can hold only crypto assets, which pay an excess return R^c_{t+1}. They, therefore, face the following problem:

$$\max_{x^c_t} \ \mathbb{E}_t(x^c_t R^c_{t+1}) - \frac{\sigma}{2}\mathbb{V}ar_t(x^c_t R^c_{t+1})$$

where x^c_t is the share of wealth w^c_t invested in the crypto asset, while $\mathbb{E}_t$ and $\mathbb{V}ar_t$ represent the expected value and the variance, respectively. The first order condition is simply $x^c_t = \frac{1}{\sigma}\mathbb{E}_t(R^c_{t+1}) \left[\mathbb{V}ar_t(R^c_{t+1})\right]^{-1}$. Thus, crypto investors increase their holdings proportionally with the expected return on the crypto asset and decrease them proportionally with their risk aversion and the variance of their portfolio.

[29]We make this simplifying assumption to clarify the exposition of the model, while noting that, empirically, retail investors also have access to the equity market (e.g., through mobile trading apps), but less so than larger institutional investors. Our main results would be unaffected by extending the model to allow both types of investor to participate in both asset classes, with the only constraint that institutional investors are initially under-represented in the crypto market. The key feature of the model is not the difference in the investable universes but the difference in investors' constraints/risk appetite.

[30]This is a simplifying assumption: arguably, such investors are not granted loans at the risk-free rate but at a rate proportional to it. Indeed, introducing heterogeneous borrowing costs—where borrowing is more expensive for small crypto investors—would support our findings, as the entry of institutional investors would imply an even greater increase in crypto leverage.

[31]We also note that a setup with two risk-averse agents would generate similar results.

[32]We can equivalently interpret the model as featuring vectors of securities.

Institutional investors: Institutional investors are risk-neutral agents that maximize the expected returns on their portfolios given a value-at-risk constraint.[33] They invest in both crypto assets and equity, and thus choose their holdings of crypto assets to solve the following maximization problem:

$$\max_{x_t^i} \mathbb{E}_t \left(x_t^i R_{t+1}^c + y_t R_{t+1}^e \right)$$

$$\text{subject to: } \underbrace{\theta w_t^i \sqrt{\mathbb{V}ar_t \left(x_t^i R_{t+1}^c + y_t R_{t+1}^e \right)} \leq w_t^i}_{\text{value-at-risk constraint}}$$

where x_t^i is the share of wealth w_t^i invested in crypto and y_t is the share invested in equities, and R_{t+1}^e is the excess return on equity investments. Similarly to Miranda-Agrippino et al., 2020, the value-at-risk constraint is expressed in terms of a multiple θ of the investors' portfolio. The first order condition is

$$x_t^i = \frac{1}{2\theta^2 \lambda_t} \left[\mathbb{E}_t(R_{t+1}^c) - 2\theta^2 \lambda_t \mathbb{C}ov_t(R_{t+1}^c, R_{t+1}^e) y_t \right] \left[\mathbb{V}ar_t \left(R_{t+1}^c \right) \right]^{-1}$$

where λ_t is the Lagrange multiplier. Institutional investors' optimal investment in crypto is positively related to the expected payoff of crypto assets and negatively related to (i) the variance of crypto returns, (ii) the covariance of crypto returns with returns on equities, and (iii) the tightness of their financial constraints.[34]

Equilibrium: Equilibrium in the crypto market requires that the total supply of crypto assets (normalized by total wealth) s_t equals total holdings: $s_t = x_t^c \frac{w_t^c}{w_t^c + w_t^i} + x_t^i \frac{w_t^i}{w_t^c + w_t^i}$. Similarly, we impose the equity market clearing condition that the total supply of equities (normalized by institutional investors' wealth) y_t^{tot} equals total holdings: $y_t^{tot} = y_t$. By combining these conditions with the first-order conditions of the investors, we derive the following propositions.

Proposition 1: **Crypto excess returns are a function of the time-varying aggregate risk aversion in the market.** *The excess return on crypto assets can be rewritten as:*

$$\mathbb{E}_t \left(R_{t+1}^c \right) = \Gamma_t^c \mathbb{V}ar_t \left(R_{t+1}^c \right) s_t + \Gamma_t^c \mathbb{C}ov_t \left(R_{t+1}^c, R_{t+1}^e \right) y_t^{tot} \frac{w_t^i}{w_t^c + w_t^i} \tag{2.4}$$

[33] See for instance Adrian et al., 2014.

[34] We assume that institutional investors are able to take on more risk than the average crypto investor, i.e. $2\theta^2 \lambda_t < \sigma$.

where $\Gamma_t^c = (w_t^c + w_t^i)\left[\frac{w_t^c}{\sigma} + \frac{w_t^i}{2\theta^2\lambda_t}\right]^{-1}$ *is the aggregate effective risk aversion. In equilibrium, crypto excess returns must be higher to compensate for their variance, in proportion to the average degree of risk aversion in the market. Similarly, a higher correlation with equities implies lower diversification benefits for institutional investors, increasing the required return on crypto assets in equilibrium, and this matters more the larger the share of wealth held by institutional investors.*

Proposition 2: **Equity excess returns are a function of the financial constraints of institutional investors and of their portfolio allocation to crypto assets.** *The expected excess equity return can be rewritten as the sum of an equity and a crypto component:*

$$\mathbb{E}_t\left(R_{t+1}^e\right) = 2\theta^2\lambda_t\mathbb{V}ar_t\left(R_{t+1}^e\right)y_t^{tot} + 2\theta^2\lambda_t\mathbb{C}ov_t\left(R_{t+1}^c, R_{t+1}^e\right)x_t^i \tag{2.5}$$

Once again, in equilibrium investors must be compensated for higher variance or lower diversification benefits in proportion to their financial constraint.

Comparing Equations 2.4 and 2.5, we note three results. Firstly, as institutional wealth w_t^i makes up an increasing share of the crypto market, the risk-taking profile of the crypto market converges on that of the equity market. For instance, in the extreme case where institutions entirely dominate the crypto market, the aggregate effective risk aversion converges to the financial constraint of the institutional investors—i.e., as $\frac{w_t^i}{w_t^i+w_t^c} \to 1$, $\Gamma_t^c \to 2\theta^2\lambda_t$. Crypto and equity returns in this case only differ based on the relative supplies and relative variances of the two assets. More generally, the aggregate effective risk aversion depends on the relative wealth of the investors, so greater participation of institutional investors in crypto markets renders the effective risk aversion more similar to that of equity investors and increases the correlation between equity and crypto prices, in line with our empirical findings (e.g., Figure 2.7).

Secondly, since our stylized framework focuses on excess returns, a rise in the risk-free rate of interest mechanically reduces real returns for both crypto and equities. To proceed further, we note existing evidence that more levered agents are more sensitive to the economic cycle (Adrian et al., 2014; Coimbra et al., 2022). Increased institutional entry reduces aggregate effective risk aversion (since $\Gamma_t \geq 2\theta^2\lambda_t$), in line with Figure 2.6. Since the marginal crypto investor is less risk averse, they take on more leverage, since borrowing at the risk-free rate to invest in risky returns is increasingly attractive. Thus, following Coimbra et al., 2022 and Adrian et al., 2014, institutional entry could increase the sensitivity of crypto markets to the economic cycle—as observed in Figure 2.13 and 2.15.

Thirdly, this framework implies the potential for future spillovers from crypto markets onto equities. Currently the second term in Equation 2.5 is negligible, as traditional financial institutions' holdings of crypto assets x_t^i are very small relative to their holdings of equities y_t (Auer et al., 2022). However, if such holdings became significant, a subsequent crash in crypto markets that led to a reduction in x_t^i implies a decline in equity returns $\mathbb{E}_t\left(R_{t+1}^e\right)$ —and by more, the larger are pre-crash crypto holdings. Such potential spillovers could motivate a cap $\bar{x}_t^i$ or other risk-based constraints on crypto holdings by traditional financial institutions (as discussed in, for instance, Bains et al., 2022; Basel Committee on Banking Supervision, 2021, 2022).

2.6 Conclusion

Crypto assets vary substantially in their design and value propositions, yet their prices largely move together. A single crypto factor can explain 80% of the variation in crypto prices, and has become more correlated with the global financial cycle since 2020, particularly with technology and small-cap stocks. We provide evidence that such correlations are driven by the increased presence of institutional investors in crypto markets, which has made the risk profile of the marginal equity and crypto investors increasingly similar. Furthermore, crypto markets are very sensitive to US monetary policy, with a monetary contraction significantly reducing the crypto factor, similarly to global equities.

We outline a minimal theoretical framework that can explain our empirical results. We show that crypto returns can be expressed as a function of the time-varying aggregate risk aversion in the crypto market, which in turn is affected by the changing composition of the crypto investor base. As institutional investors make up an increasing share of the crypto market, the risk-taking profile of the marginal investor in crypto converges on that in equities. A rise in the risk-free rate reduces returns, and increasingly so if institutional investors hold a larger share of crypto and more levered agents are more sensitive to the economic cycle (Adrian et al., 2014; Coimbra et al., 2022).

Our results also inform the policy debate about crypto assets.[35] We find that these assets do not provide a hedge against the economic cycle—in contrast, our estimates suggest they respond even more than stocks. Furthermore, the increasing correlation between crypto and equity markets, coupled with the fact that institutional investors trade both crypto assets and stocks, implies potential spillover effects that could eventually raise systemic risk concerns. In particular, our framework implies that—in a possible future world where crypto makes up a substantial share of institutional investors' portfolios—a crash in the crypto market could have significant negative repercussions in equity markets. For these reasons, policymakers could take advantage of the fact that institutional investors' exposure to crypto is still limited to develop and implement an improved regulatory framework.

[35]See, for instance, International Monetary Fund, 2021, 2023.

Chapter 3

Central Bank Digital Currency and Quantitative Easing

with Martina Fraschini and Luciano Somoza

3.1 Introduction

Most major central banks are considering introducing a retail central bank digital currency (CBDC), i.e., a digital payment instrument, denominated in the national unit of account, that is a direct liability of the central bank (BIS, 2020). Advocates of CBDC projects argue that they would strengthen monetary sovereignty, enrich monetary policy toolkits, and foster financial innovation and inclusion.[1] Nonetheless, the introduction of a CBDC would lead central banks into uncharted territory as they would directly compete with banks for deposits, raising concerns about financial stability as well as privacy issues (Armelius et al., 2020). The burgeoning literature on the topic focuses on several aspects, such as disintermediation risk, deposit competition, and optimal design (see, e.g., Agur et al., 2022; Fernández-Villaverde et al., 2021b).

However, the interaction between a CBDC and current monetary policy remains an open question (see, e.g., BOE, 2020; ECB, 2020). This is particularly relevant, as the balance sheets of central banks reached record levels after the global financial crisis and expanded even further, due to COVID-19 relief programs. Therefore, CBDCs are likely to be introduced before central banks have fully reverted their Quantitative Easing (QE) programs. We address these issues by asking the following questions: Do current monetary policies matter for the introduction of a CBDC? What are the equilibrium outcomes of introducing a CBDC in a QE environment?

We find that the equilibrium impact of a CBDC depends on the ongoing monetary policy. Under quantitative easing, the economy reaches different equilibrium allocations than under conventional monetary policy. We show that commercial banks optimally liquidate their excess reserves to accommodate households' demand for CBDC. Such mechanism can lead to households replacing banks as counterparts on the liability side of the central bank's balance sheet. As retail deposits are typically inelastic (Chiu et al., 2018), reverting QE policies might become more difficult. We also show that, under both monetary policies, there exist conditions for which issuing a CBDC is neutral to the economy. If the central bank conducts QE, the introduction of a CBDC can only be neutral when the demand for CBDC is smaller than the amount of excess reserves in the system.[2]

[1] G7 Finance Ministers and Central Bank Governors' Communiqué, Art. 17, June 5th 2021, www.g7uk.org/g7-finance-ministers-and-central-bank-governors-communique.

[2] Excess reserves are the amount of reserves that exceeds liquidity requirement.

We obtain these results by extending the model proposed by 2020. This framework features a central bank that implements two different monetary policies. The first is standard monetary policy, where the central bank holds government bonds, their interest rate is kept above the one on reserves, and liquidity requirements are binding. The second is QE policy, where the central bank holds risky securities, the interest rates on treasuries and reserves are equal, and there are excess reserves in the system.

We introduce a CBDC under two main assumptions. First, the central bank holds assets to back CBDC deposits (consistently with ECB, 2020). Even if it were possible for a central bank to issue an unbacked CBDC, it would result in a decline in central bank equity and would be akin to helicopter money, which is not currently an option (BIS, 2020). Second, bank deposits and CBCD deposits are not perfect substitutes. While they can both be remunerated, they have different technological features and a plethora of complimentary services (e.g., programmability, smart contracts). It is plausible that a CBDC would rely on more efficient technology, allowing for faster, smoother digital payments, while the banking sector is better suited to providing complimentary services and is more efficient at targeting customers. A good example of such complementarity is given by the co-existence of traditional banks and numerous fintech companies, which provide deposits and payment solutions. For instance, the average PayPal user also has a bank account and keeps only a small sum in their PayPal account.[3] We assume that a CBDC would work in a similar way, offering better technological solutions for payments and that banks will simultaneously leverage their existing relationships, deposit rates, and commercial skills to retain depositors.[4]

We find that under standard policy the introduction of a CBDC is neutral to the economy only when managing a CBDC is as expensive as managing bank deposits (consistently with Brunnermeier et al., 2019b). More interestingly, the equilibrium outcomes are not straightforward if the central bank issues a CBDC while conducting QE programs. The impact mainly depends on the amount of bank deposits converted into CBDC as well as on the amount of the excess reserves in the system. When depositors decide to convert one unit of bank deposits into one of CBDC, commercial banks will have to transfer one unit of resources to the central bank. When converting bank deposits into CBDC deposits, the commercial bank will optimally decide to reduce its excess

[3]Source: Demos, T. June 1st 2016, *PayPal Isn't a Bank, But It May Be the New Face of Banking*, The Wall Street Journal.

[4]For simplicity, the main version of the model does not account for cash. However, when we include it, our findingds not change.

reserves. The size of the central bank's balance sheet remains the same, as one unit of reserves is simply transferred from the commercial bank's account to the households' CBDC account. Thus, as long as the amount of CBDC deposits does not exceed the amount of excess reserves, the introduction of a CBDC leads to a reduction in both deposits and reserves, without real consequences for lending to the economy.

It is worth noting that if large amounts of bank deposits are converted into CBDC deposits through this mechanism, it will arguably be harder for the central bank to reverse its expansionary policies. Reverting an asset purchase program implies selling the assets back to the banking sector in exchange for central bank reserves. If the banking sector does not have excess reserves because they have been transferred to households that hold CBDC deposits, it would be more difficult for the central bank to tighten its balance sheet. Facing financial intermediaries is not the same as facing retail depositors, as they tend to be inelastic (Chiu et al., 2018). In other words, the widespread adoption of a CBDC might render current quantitative easing programs quasi-permanent.

When the demand for CBDC deposits exceeds the amount of excess reserves, the introduction of a CBDC changes the equilibrium outcomes of the economy. In this case, the reduction in deposits leads to a reduction in reserves due to liquidity requirements and the liquidation of other assets in favor of the central bank. The central bank, therefore, has to issue new liabilities in form of CBDC deposits. Since in this monetary policy regime the central bank holds risky securities, the changes in its holdings do not influence the amount of safe assets available in the economy. For this reason, the central bank is not able to channel funds back to the banking sector via open market operations, and the amount of loans to the economy shrinks. Moreover, the additional purchases of risky securities by the central bank increase its size and level of risk-taking. Even if seigniorage revenues are more volatile, they increase in expectation allowing the government sector to levy lower taxes.

Although our model encompasses important real-world features, such as liquidity and capital requirements, explicit and implicit deposit guarantees, and shortage of safe assets, it has some limitations. First, the state of the economy is exogenous and taken as given by the actors. Second, monetary policies, including the introduction of a CBDC, are exogenous. Third, all interest rates in the model are real rates, and thus there is no inflation from one period to the next. Our analysis is a comparative statistics exercise focused on the balance sheet effects of introducing a CBDC during QE. Providing an exhaustive theoretical account of the general equilibrium effects of introducing a CBDC is beyond the scope of this paper.

Our results directly inform the debate about CBDCs in two ways. First, our findings suggest that the decision to issue a CBDC should consider the ongoing monetary policy. While the direction of the effects can be easily determined under standard monetary policy, it is largely ambiguous under QE. Second, if a central bank launches a CBDC while pursuing QE policies, it should consider the amount of excess reserves in the banking system, as the impact on lending is neutral only insofar the demand for CBDC deposits is lower than the amount of excess reserves. Moreover, the fact that a CBDC might render the reversion of QE policies harder to implement undermines any commitment to return to a pre-QE world.

Related literature. Our paper contributes to the burgeoning literature that studies the introduction of a CBDC, its design and the implications for the banking sector.[5] To the best of our knowledge, we are the first to focus on the interaction with ongoing monetary policies. A notable exception is Minesso et al., 2022, who study the open-economy implications of the introduction of a CBDC and how it amplifies international spillovers.

We contribute to the literature related to the disintermediation risk of the banking sector due to the introduction of a CBDC. For instance, Whited et al., 2022 estimate a structural model that highlights how a CBDC would reduce banks' deposit funding. Fernández-Villaverde et al., 2021a and Fernández-Villaverde et al., 2021b focus on these issues by using a modified version of the model by Diamond et al., 1983, where a central bank engages in large-scale intermediation by competing with private financial intermediaries for deposits and investing in long term projects. They find that the set of allocations achieved with private financial intermediation is also achieved with a CBDC and that, during a run, the central bank is more stable than the commercial banking sector. For this reason, they conclude that the central bank would arise as a deposit monopolist. Brunnermeier et al., 2019b and Niepelt, 2020 provide conditions under which swapping private money with public money (e.g., CBDC) is indifferent for equilibrium allocations. In their setting, the central bank collects retail deposits and lends them to commercial banks to compensate for missing funding, de facto eliminating any disintermediation effect. Chiu et al., 2023 focus on banks' market power and show that when banks have no market power, issuing a CBDC would crowd out private banking. However, when banks have

[5] Notably, Barrdear et al., 2016 are among the first to study CBDCs, by focusing on their potential as additional monetary policy tools to stabilize the business cycle. For a more extensive review of the literature, please refer to Ahnert et al., 2022; Carapella et al., 2020; Chapman et al., 2023.

deposit market power, a CBDC with a reasonable interest rate would encourage banks to pay higher interests or offer better services to keep their customers (see also Andolfatto, 2021). We contribute to this strand of literature by showing that the general equilibrium effects that might render a CBDC neutral for the banking sector largely depend on the amount of excess reserves in the system and on baseline monetary policy.

Furthermore, we contribute to the literature on CBDC design. The choice of CBDC design has sizeable real effects on the economy in terms of technological innovation, users' privacy, and the bank's ability to intermediate. A comprehensive BIS report by Auer et al., 2020 studies the differences between three main architectural choices: account- vs token-based system, one- or two-tier distribution, and whether to adopt a decentralized ledger technology (see also Armelius et al., 2020). Agur et al., 2022 studies the relation between preferences over anonymity and security by developing a theoretical model where depositors can choose between cash, CBDC, and bank deposits. They conclude that the optimal CBDC design trades off bank intermediation against the social value of maintaining diverse payment instruments. By contrast, Keister et al., 2021 study CBDC optimal design in a setting with financially constrained banks and with a liquidity premium on bank deposits. They highlight an important policy trade-off: while a digital currency tends to promote efficiency, it may also crowd out bank deposits, raise banks' funding costs, and decrease investment. They also find that despite these effects, introducing a CBDC often increases welfare. Our approach is rather agnostic as our model allows for different kinds of CBDC designs (i.e., token-based, account-based, interest-bearing and so forth). Indeed, we focus on the imperfect substitutability between CBDC and bank deposits, and not on the CBDC design features per se.

Finally, note that there is still limited empirical research on CBDC as only a few CBDC projects are in advanced stages, and data is not yet available for research (e.g., see Auer et al., 2020; Kosse et al., 2022).

The rest of the paper is organised as follows. Section 3.2 describes the model setup. Section 3.3 reviews the possible mechanisms to issue new CBDC deposits and introduce them in the economy. Sections 3.4 presents the equilibrium conditions. Section 3.5 discusses the implications of introducing a CBDC under different policy regimes, and the neutrality conditions. Finally, Section 3.6 concludes.

3.2 Model

For our analysis, we extend the model developed by 2020 by adding a one-tier interest-bearing CBDC. The model has two periods and an economy with a private and a public sector. The private sector consists of agents and a representative commercial bank, whereas the public sector consists of a central bank (CB) and a fiscal authority, which are treated as a single actor, the government.

Agents are households, investors, and institutional cash pools. Households and cash pools are infinitely risk-averse and only lend to banks if they are sure of having their funds returned. Deposits are explicitly insured (e.g., DGS in the Eurozone or FDIC in the US). In addition to the deposit interest rate, households benefit from the payment services provided by the banks. Cash pools invest indifferently in public and bank debt and consider the latter to be implicitly insured by the government. This belief was essentially confirmed in 2008 when the government bailed out most failing financial institutions or provided relief by purchasing assets through the central bank. Because of the public insurance on the bank liabilities, there is no possibility of bank runs. On the other hand, investors are the only agents willing to accept risk and therefore invest in bank equity.

Banks have a unique technology that allows them to invest in risky ventures and perform maturity transformation. They channel funds from savers to entrepreneurs and allow savers to transfer funds from one period to the next. We do not explicitly model entrepreneurs' decision-making. We assume that banks invest in productive ventures without explicitly modelling the bank's screening process. The government regulates banks, bails them out of bankruptcy when needed, issues debt to fund its spending, and collects taxes from investors to repay its debt.

In this setting, we include a CBDC, by which households have the option to deposit their funds at the central bank. CBDC deposits pay an interest and provide payment services.

3.2.1 Households

The representative household is infinitely risk averse and receives an endowment $w_{h,0}$ at time 0 and no endowment in period 1. The household can place their funds either in a commercial bank (as a standard bank deposit) or in the central bank (as a CBDC deposit) to transfer them to time 1 for consumption. They also benefit from the payment services provided by the bank and the central bank.[6]

The agent's utility derives from the consumption stream x_h, which consists of $x_{h,0}$ at time 0 and the random consumption $\tilde{x}_{h,1}$ at time 1. The total utility is given by:

$$u_h(x_{h,0}) + \min \tilde{x}_{h,1} + \rho \min \tilde{x}_{h,1}, \tag{3.1}$$

where u_h is a concave increasing function, $\min \tilde{x}_{h,1}$ represents the household's infinite risk aversion, and ρ captures the convenience yield obtained from the transaction services at time 1. We assume that the convenience yield is linear. If R^h denotes the deposit interest paid by banks, a bank deposit h generates a consumption $R^h h$ at time 1. Similarly, if R^d denotes the deposit interest paid by the central bank, d worth of CBDC deposit generates a consumption $R^d d$ in period 1. The total consumption is therefore $x_h = (w_{h,0} - h - d, R^h h + R^d d)$ and the household utility is $u_h(w_{h,0} - h - d) + (1+\rho_h)R^h h + (1+\rho_d)R^d d$, where ρ_h and ρ_d are the convenience yields from bank and central bank services respectively.

If in time 0 the utility function of households u_h satisfies the Inada conditions $\frac{\partial u_h(x_{h,0})}{\partial h} \to \infty$ as $x_{h,0} \to 0$ and $\frac{\partial u_h(x_{h,0})}{\partial d} \to \infty$ as $x_{h,0} \to 0$, then the solutions to the maximization problem are characterized by the following first-order conditions:

$$\frac{\partial u_h(w_{h,0} - h - d)}{\partial h} = (1 + \rho_h)R^h, \tag{3.2}$$

$$\frac{\partial u_h(w_{h,0} - h - d)}{\partial d} = (1 + \rho_d)R^d. \tag{3.3}$$

PROPOSITION 3. *If the utility function of households u_h satisfies the Inada conditions, then positive funds allocations in bank and CBDC deposits, $(h, d) > 0$, are guaranteed if and only if*

$$(1 + \rho_h)\, R^h = (1 + \rho_d)\, R^d. \tag{3.4}$$

Proof. Using Leibniz's notation, $\frac{\partial u_h}{\partial h} = \frac{\partial u_h}{\partial x_{h,0}} \frac{\partial x_{h,0}}{\partial h}$ and $\frac{\partial u_h}{\partial d} = \frac{\partial u_h}{\partial x_{h,0}} \frac{\partial x_{h,0}}{\partial d}$. In this model, it holds that $\frac{\partial x_{h,0}}{\partial h} = \frac{\partial x_{h,0}}{\partial d}$ and, therefore, that $\frac{\partial u_h}{\partial h} = \frac{\partial u_h}{\partial d}$. Applying this result to (3.2) and (3.3), it follows (3.4). □

In other words, there is no corner solution for households if the unitary utilities, considering interest rates and convenience yields, for deposits in bank and

[6] Note that in the main version of the model we do not include cash. However, when we allow households to hold it, the implications of the model do not change; only the magnitudes of the effects are different.

deposits in CBDC are the same. This condition guarantees that, at equilibrium, households holds both bank and CBDC deposits, even if interest rates are set to zero.

3.2.2 Cash Pools

The cash pool agents represent the wholesale money market, which includes money market funds, wealth managers, and the like. Just like households, cash pools are infinitely risk averse and invest only in safe and liquid assets. The representative cash pool has an endowment $w_{c,0}$ only at time 0, and it has a utility function $u_c(x_{c,0}) + \min \tilde{x}_{c,1}$, where u_c is an increasing concave function that captures the opportunity cost of the cash pool funds.

During the 2008 financial crisis, the actions by the central bank and the treasury prevented runs and confirmed the perception that bank liabilities are implicitly insured by the government. Since cash pools invest only in safe assets, they choose between government and bank liabilities, which have to be interpreted as short-term debt, either loans or bonds. [7] When treasuries are not enough to satisfy the demand of cash pools, part of their savings is therefore absorbed by the bank (c_b). The representative cash pool chooses how much to invest (c) in order to maximize $u_c(w_{c,0} - c) + R^c c$, where R^c is the interest received by the bank or the government.

If in time 0 the utility function of cash pools u_c satisfies the Inada conditions $\frac{\partial u_c(x_{c,0})}{\partial c} \to \infty$ as $x_{c,0} \to 0$, then the solution to their maximization problem is characterized by the first-order condition:

$$\frac{\partial u_c(w_{c,0} - c)}{\partial c} = R^c. \tag{3.5}$$

3.2.3 Investors

Investors play two roles in the model. They are long-term investors who take risks, and they act as taxpayers.[8] Investors receive an endowment in both periods $w_i = (w_{i,0}, w_{i,1})$ and are risk neutral. Their utility function is $u_i(x_{i,0}) + E(\tilde{x}_{i,1})$, where u_i is an increasing concave function that satisfies the Inada conditions. Investors can place their funds in safe assets (either government bonds or bank debt that we denote by c_i), and bank equity (that we denote by e). If they invest in safe assets, they receive the same return R^c as cash pools. The payoff of bank equity is $V(y)$ per unit of equity, where y is the realization of the

[7] Potentially, they could invest also in bank and CBDC deposits. Since cash pools do not benefit from the payment services, these options are not attractive enough.

[8] We better describe taxes in section 3.2.5.

random payoff $\tilde{y}$ per unit of investment in risky projects. The investor problem is to choose (c_i, e) to maximize

$$u_i(w_{i,0} - c_i - e) + E(w_{i,1} - t(y) + V(y)e + R^c c_i), \tag{3.6}$$

where $t(y)$ is a lump-sum tax due to the government at time 1. Given the expected return on equity $R^E = E\left[V(\tilde{y})\right]$, we exclude the case where $R^c > R^E$ for which $c_i > 0$ and $e = 0$, since banks must have positive equity in equilibrium. We assume that when $R^E = R^c$, investors choose to invest only in equity. Finally, when $R^E > R^c$, investors prefer to invest only in equity and $c_i = 0$.

Therefore, the first-order condition that characterizes the solution of the investor maximization problem is:

$$\frac{\partial u_i(w_{i,0} - e)}{\partial e} = R^E. \tag{3.7}$$

3.2.4 Commercial Bank

The banking sector is modeled with a representative commercial bank that can either store funds in reserves (M) at the central bank or invest (K) in a productive risky technology. To finance its assets, the bank collects deposits from households (h), obtains financing from cash pools (c_b), and issues equity (E). Hence, it holds that $M + K = h + c_b + E$.

The commercial bank is the only one that can perform risk and maturity transformation: it borrows short safe deposits and lends long risky loans to entrepreneurs. It offers bank deposits with a series of complimentary services and faces a unitary cost μ_h at time 1, which represents the cost of maintenance of the infrastructure, managing of accounts, and so forth. In light of what occurred in the aftermath of the 2008 crisis, our model encompasses two kinds of insurances. The first one is explicit and refers to the households, featuring the deposit guarantee schemes of major economies. The second one is implicit and applies only to cash pools, who believe that, in case of crisis, the government would bail out the banking sector following the too-big-to-fail argument.[9]

The central bank pays an interest rate R^M on reserves, while the risky technology delivers $\tilde{y}$ at time 1. The distribution of returns is characterized by the density function $f(y)$ on $R_{\geqslant 0}$, and it is different from zero for $\tilde{y} > \underline{y} > 0$.[10]

[9]It is worth mentioning that cash pools receive $\underline{y}K$ as collateral from the bank. Thus, in case of default, they are only interested in the fact that the government would repay them the difference between what they lent out and the collateral value.

[10]As in Magill et al., 2020, we assume that all shocks are perfectly correlated and, due to the law of large numbers, we can treat $\tilde{y}$ as an aggregate shock for the economy.

Our model also incorporates current banking regulations with liquidity and capital requirements. The bank is forced to store at least δ of its deposits in reserves to satisfy the liquidity requirement and finance at least $\bar{\alpha}$ of the risky projects with equity for the capital requirement.

The representative bank optimally chooses the items of its balance sheet $(M,\ K,\ h,\ c_b,\ E)$ taking as given the interest rates in the economy $(R^M,\ R^h,\ R^c,\ R^E)$, and it maximizes the shareholders' expected profit:

$$\max_{h,\, c_b,\, E,\, M,\, K} \int_{\hat{y}}^{\infty} [R^M M + yK - (1+\mu_h)R^h h - R^c c_b] f(y) dy - R^E E, \tag{3.8}$$

subject to

$$h + c_b + E = K + M, \quad \text{(balance sheet constraint)} \tag{3.9}$$

$$M \geqslant \delta h, \quad \text{(liquidity requirement)} \tag{3.10}$$

$$E \geqslant \bar{\alpha} K, \quad \text{(capital requirement)} \tag{3.11}$$

where $\hat{y}$ is the minimum return on the risky technology that allows the bank to repay its creditors, i.e., $R^M M + \hat{y}K = (1+\mu_h)R^h + R^c c_b$. The bank is solvent for $y > \hat{y}$.

3.2.5 Government

We consider the fiscal authority and the central bank as a single entity (i.e., the government) that conducts guarantee, prudential, interest rate, and balance sheet policies. Similarly, to the commercial bank, the central bank offers CBDC deposits facing a unitary cost μ_d at time 1. To finance its expenditure G, the government issues bonds $(B = G)$ at time 0, on which it pays an interest R^B at time 1. The central bank can influence this interest rate via open market operations, namely repos and reverse-repos with cash pools.[11] The interest rate takes different values according to the monetary policy regime. At time 1, the government levies taxes on the investors to service its bonds. We make the strong assumption that prices are fully rigid as it allows us to work with a real variable model.

As mentioned before, the government provides explicit and implicit insurance to households and cash pools to avoid bank runs, and it sets the liquidity (δ) and capital $(\bar{\alpha})$ requirements.

[11] We consider only two periods, so we interpret B as very short-term bonds.

The central bank manages the funds coming from reserves (M) and CBDC deposits (d) by deciding the compositions of its assets. Hence, it either invests in government bonds (B^{CB}) or in risky securities (E^{CB}), which in our model are represented by the bank's equity. We define a baseline *standard policy* where the central bank holds government bonds against its reserves and a *quantitative easing (QE) policy* setting where the reserves are backed by risky assets (i.e., bank equity, which is the only risky asset in the model). It is worth noting that purchasing distressed assets from the banking sector is economically equivalent to recapitalize banks by injecting equity. When the central bank issues CBDC deposits, it also decides which type of assets to hold against the new liabilities. This decision is explained in detail in Section 3.3.

In standard policy, the liquidity requirement is always binding ($M = \delta h$), and the interest rate on government bonds is larger than the one on reserves, $R^B > R^M$. In a QE setting, the amount of reserves usually exceeds the liquidity requirement ($M \geqslant \delta h$), and the banking sector holds excess reserves ($M - \delta h$) at the central bank. In our model, the amount of excess reserves can be considered as exogenous to the banking sector, as it is solely due to the asset purchase programs of the central bank. Finally, under QE, there is a low interest rate environment with the interest rate on reserves equal to the one on government bonds, $R^B = R^M$.

Finally, when the commercial bank is solvent ($y > \hat{y}$), the tax is equal to the difference between the bondholders' repayment and the net seignorage revenue (θ). In case the bank goes bankrupt ($y \leqslant \hat{y}$), the tax also includes the repayment of bank's guaranteed liabilities (household's deposits and cash pools' funds) after the liquidation of the assets. Thus, we define the bankruptcy costs as $\phi = (1 + \mu_h)R^h h + R^c c_b - (yK + R^M M)$. Taxes are given by:

$$t = R^B B - \theta + \phi 1_{y \leqslant \hat{y}}. \tag{3.12}$$

3.3 CBDC Introduction Mechanism

3.3.1 Institutional Settings

In standard times, the central bank conducts a conventional monetary policy, regulating the commercial banks and setting the short-term interest rates to stimulate or slow down the economy. However, in times of crisis, lowering the interest rates might not be enough. In these cases, the central bank could implement an unconventional monetary policy, called quantitative easing (QE). When conducting quantitative easing policies, the central bank creates new reserves[12] and uses them to purchase assets. Normally, the asset purchases programmes focus on longer-term securities or distressed assets, with the purpose of manipulating the longer maturities of the yield curve. Such policies aim to support the financial system and ease the pressure on governments and banks.

The result is an increase in the central bank's balance sheet size and an abundance of reserves in the banking system (Joyce et al., 2012). As banks are subject to liquidity requirements, the abundance of reserves should help to boost lending. However, in the US, the launch of quantitative easing programs in 2008 has led to a significant amount of excess reserves, i.e., reserves above liquidity requirements. Figure 3.1 shows the evolution of the FED's balance sheet size and the amount of excess reserves in the system between 2006 and 2021. The strong link between quantitative easing and excess reserves is clearly visible.

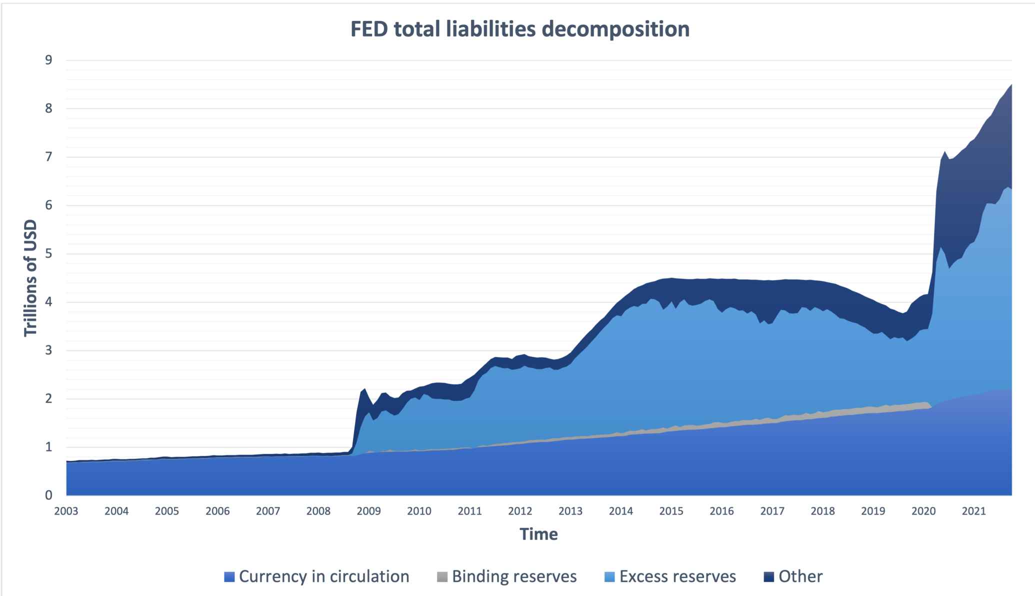


FIGURE (3.1) FED's total liabilities decomposition

Notes: Source: FRED, Federal Reserve Bank of St. Louis, December 2021.

Other central banks that implemented quantitative easing over the years show a similar pattern. Figure 3.2 exhibits the liabilities decomposition for the Bank of England (BoE) and the ECB, with an increase of excess reserves after each asset purchase round.

Notes: (a) Bank of England's total liabilities decomposition. Source: Bank of England. (b) ECB's total liabilities decomposition. Source: ECB.

[12] Reserves are direct central bank liabilities available only to financial institutions.

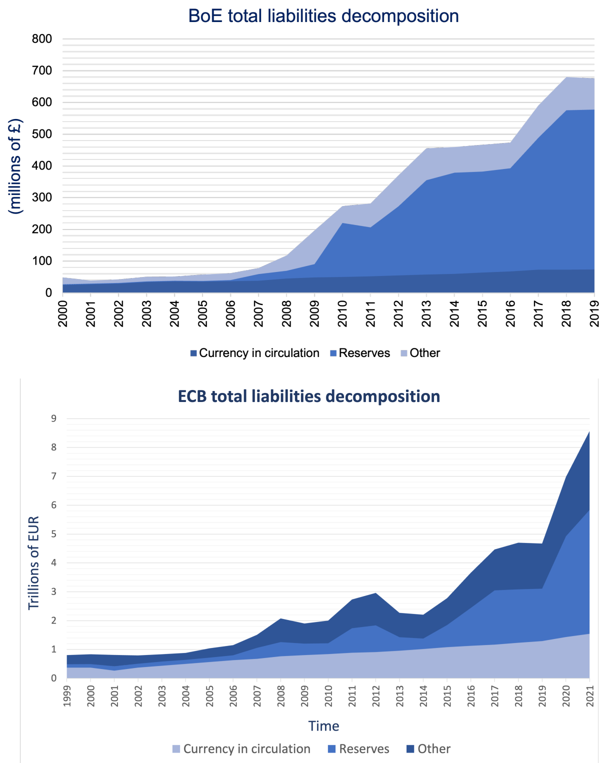


FIGURE (3.2) Central banks' liabilities

Quantitative tightening (QT) is the reversion of quantitative easing policies to go back to a standard regime. When central banks want to tighten, they sell assets to the market and cancel outstanding reserves in exchange, effectively decreasing the size of their balance sheets. As the balance sheet constraint applies to central banks as well, reducing the balance sheet implies reducing both assets and liabilities at the same time.

3.3.2 Transferring Money into a CBDC Deposit

With the introduction of a CBDC, households will want to transfer part of their savings from bank deposits into CBDC deposits. By definition, a CBDC is a direct liability of the central bank, like cash (banknotes). From an accounting perspective, it is reasonable to assume that transferring money into a CBDC deposit will work similarly to withdrawing cash from an ATM. In both cases, households exchange a liability of the commercial bank (private money) for a liability of the central bank (public money). The commercial bank must pass resources to the central bank to accommodate the household's demand for public money, either cash or CBDC.

Under QE, when the liquidity requirement is not binding ($M > \delta h$), the commercial bank easily exchanges part of its excess reserves for the central bank liabilities. After the swap, the commercial bank reduces the household's deposit account and delivers the banknotes or the CBDC. The operation is neutral for the size of the central bank's balance sheet, as one type of liabilities (excess reserves) is transformed into another (CBDC deposits). On the other hand, when the liquidity requirement is binding ($M = \delta h$), the commercial bank needs to keep reserves on its balance sheet and cannot swap them for cash or CBDC. In this case, it is forced to liquidate the other assets in favour of the central bank, leading to an increase in the size of the central bank's balance sheet.

Figure 3.3 provides a graphical representation of the mechanism described. As long as there are enough excess reserves in the system, the transfer is neutral for the size of the central bank's balance and the central bank's liabilities only change in type. Once excess reserves are exhausted, and the liquidity requirement is binding, the commercial bank liquidates assets in favor of the central bank, that in turn can create new liabilities in the form of CBDC. This operation increases the size of the central bank's balance sheet.

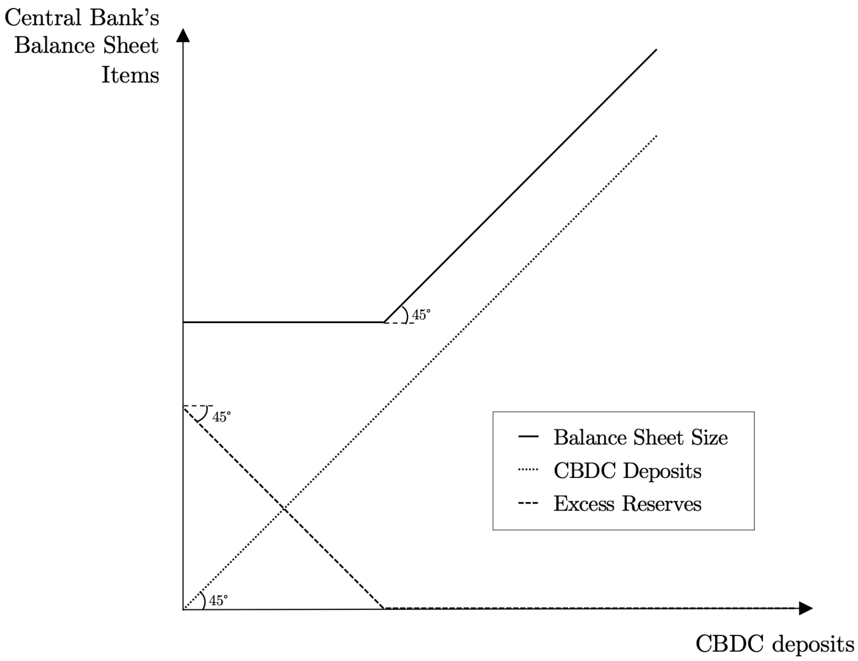


FIGURE (3.3) Relationships between CBDC deposits, excess reserves, and central bank's balance sheet size.

Notes: If the liquidity requirement is not binding, the commercial bank swaps excess reserves for CBDC deposits. In this case, the size of the central bank does not change as one type of liability is simply transformed into another. Once the liquidity requirement is met, the commercial bank liquidates assets in favor of the central bank, increasing its size.

Let the representative commercial bank be a profit maximizer as described in Section 3.2. The optimal choice for accommodating the households' demand for CBDC is to exchange reserves rather than liquidating other assets, unless the liquidity requirement is binding.

Proof. When the commercial bank transfer the households' savings into CBDC deposits, it can stop paying the interest on the lost deposits and their cost of maintenance. When it accommodates the households' demand by exchanging reserves for CBDC deposits, it loses the interest on the swapped reserves. The difference in the expected profit is

$$\Delta\pi' = d\left[(1+\mu_h)R^h - R^r\right]. \tag{3.13}$$

On the other hand, when the commercial bank liquidates other assets than reserves in favor of the central bank, its expected profits change accordingly:

$$\Delta\pi'' = d\left[(1+\mu_h)R^h - \int_{\hat{y}}^{\infty} yf(y)dy\right]. \tag{3.14}$$

It must hold that $R^r < \int_{\hat{y}}^{\infty} yf(y)dy$ as an incentive for the commercial bank to invest in risky projects, implying $\Delta\pi' > \Delta\pi''$. Since the commercial bank is a profit maximizer, whenever it is possible, it optimally chooses to reduce its excess reserves to accommodate the demand for CBDC. □

The commercial bank can reduce its reserves only until the liquidity requirement is binding. After that point, the commercial bank has no choice but to liquidate its assets in favor of the central bank. We define $\bar{d}$ as the maximum demand for CBDC deposits for which the commercial bank can swap excess reserves. This amount is such that the liquidity requirement is binding, $M - \bar{d} = \delta(h - \bar{d})$, i.e., the maximum amount for which the reduction in reserves fully compensates the reduction in deposits.

COROLLARY 1. *The commercial bank can swap a maximum of $\bar{d}$ reserves into CBDC deposits, where $\bar{d}$ is defined such that the liquidity requirement becomes binding:*

$$\bar{d} = \frac{M - \delta h}{1 - \delta}. \tag{3.15}$$

If the demand for CBDC deposits exceeds the threshold ($d > \bar{d}$), then the commercial bank swaps as many reserves as possibile. Only when it runs out of excess reserves, i.e., the liquidity requirement is binding, the commercial bank then liquidates assets in favor of the central bank. We define $\tilde{d} = d - \bar{d}$ as the demand of CBDC that that the commercial bank accommodates by liquidating assets. In this case, since the liquidity requirement is binding, the bank compensate the loss in deposits by partly reducing its reserves by an additional $\delta\tilde{d}$, on top of the $\bar{d}$ optimally used.

3.3.3 Central Bank's Balance Sheet

When there is an abundance of excess reserves, the commercial bank optimally swaps them for CBDC deposits, without altering the size of the central bank's balance sheet. The composition of the central bank's liabilities change, but the asset side of its balance sheet is left unaltered.

This is not the case when the central bank issues new liabilities in the form of CBDC deposits, as CBDCs must always be backed by assets (ECB, 2020). The central bank could acquire either treasuries or risky securities to be held against the CBDC deposits. In theory, holding risky securities against households' deposits could be justified by the fact that there might not be sufficient safe assets (i.e., government bonds) to fully absorb the overall demand. However, backing the issuance of new liabilities with the purchase of risky securities corresponds to a new quantitative easing round, should be a measure for times of crisis.

Nevertheless, if the commercial bank converted its excess reserves into CBDC deposits, it would be much harder for the central bank to revert QE programs. The central bank would go from having a limited number of financial institutions as counterparts to having a large number of small households. Households would use a CBDC for payments and savings and would probably be much less elastic than financial institutions. It is reasonable to assume that the CBDC deposits' elasticity would be similar to the bank deposits' one, which tends to be low (Chiu et al., 2018). Quantitative tightening means selling assets on the one side and canceling liabilities on the other. An inelastic liability side would render quantitative easing policies semi-permanent.

The adoption of a CBDC under quantitative easing might render this policy quasi-permanent, as it will be even more difficult to revert.

3.4 Equilibrium

In this section, we study how introducing a CBDC under different monetary policy scenarios changes the respective equilibrium allocations. We first outline assumptions to ensure that banks fund themselves with households' deposits and wholesale funding at equilibrium. Then we define the equilibria in different monetary policy regimes. Finally, we briefly discuss the Pareto-optimality of our equilibrium allocations.

3.4.1 Assumptions

Investors.

(a) Investors are better off investing in bank equity: $\frac{\partial u_i(w_{i,0})}{\partial w_{i,0}} < E[\tilde{y}]$.

(b) Investors have enough endowment at time 1 to pay the tax: $w_{i,1} > (w_{d,0}(1+\mu_d) + w_{c,0}) E[\tilde{y}]$.

The first part of the assumption guarantees that investors do not prefer to consume all their endowment at time 0 but always want to invest in the technology. It is worth noting that it also ensures that bank equity is never zero, especially under standard monetary policy. The second part of the assumption guarantees that investors have enough resources to repay households and cash pools (investors pay the tax to the government, including the cost of bankruptcy). The condition considers even the limit case in which at date 0 households store all their endowment in deposits, and cash pools invest all their endowment in wholesale funds.

Cash pools.

(a) Cash pools want to buy both government bonds and bank debt: $\frac{\partial u_c(w_{c,0}-B)}{\partial w_{c,0}} < R^B \leqslant E[\tilde{y}]$.

This assumption ensures that at equilibrium there is a shortage of safe assets. Cash pools want to invest an amount bigger than the amount of government bonds in the economy. For this reason, cash pools resolve to wholesale funding at the commercial bank.

Households.

(a) Households prefer bank deposits to government bonds: $\rho_h > \mu_h$, $0 \leqslant \delta \leqslant \frac{\rho_h - \mu_h}{1+\rho_h}$.

(b) Households would want treasuries if they had no other choice: $\frac{\partial u_h(w_{h,0})}{\partial w_{h,0}} < \frac{\partial u_c(w_{c,0}-B)}{\partial w_{c,0}}$.

This assumption guarantees positive bank deposits at equilibrium. The first part ensures that households get a greater utility from the saving technology and payment services offered by bank deposits, rather than investing in government bonds. The second part states that, in an economy without bank and CBDC deposits, households would prefer treasuries rather than consume all their endowment in time 0.

3.4.2 Equilibrium definition

In equilibrium, we consider an economy with scarcity of safe assets (i.e., government bonds), which are not enough to satisfy the demand of cash pools. Therefore, it must hold that

$$R^c = R^B \tag{3.16}$$

to make bank debt attractive enough to cash pools. It is worth noting that, this way, the central bank can influence the cost of bank funding by setting R^B.

Moreover, the commercial bank keeps both bank deposits and wholesale funds as a source of funding in terms of debt. Intuitively, when the commercial bank wants to invest its debt and lend money to entrepreneurs, it consider 1 unit of bank deposits equivalent to $(1-\delta)$ unit of wholesale funding, because of the liquidity requirement in equation (3.10). Therefore, they must also have the same opportunity costs[13]: $(1+\mu_h)R^h - \delta R^r = (1-\delta)R^B$. We get that

$$R^h = \frac{(1-\delta)R^B + \delta R^r}{1+\mu_h}. \tag{3.17}$$

We define the investable debt of the bank as all the debt that can be invested in the risky technology, excluding reserves:

$$D = h + c_b - M. \tag{3.18}$$

Replacing equation (3.18) into the bank's balance sheet constraint (3.9), we obtain:

$$K = E + D. \tag{3.19}$$

Let's now define $\alpha \geq \bar{\alpha}$ as $\alpha = E/K$. From equation (3.19), we have that $D = (1-\alpha)K$. Substituting the previous results into the first order conditions, we find the bank's maximization problem is reduced to the choice of $(\alpha,\ E)$ that maximizes $E\left(\frac{1}{\alpha}\int_{(1-\alpha)R^B}^{\infty}\left[y-(1-\alpha)R^B\right]f(y)dy - R^E\right)$, where $\hat{y} = (1-\alpha)R^B$ comes from the bankruptcy definition at equilibrium. This problem has solution if and only if the capital requirement (3.11) is binding:

$$E = \bar{\alpha}K, \tag{3.20}$$

[13]The equation comes from one of the first order conditions of the commercial bank's maximization problem.

and the zero profit condition is satisfied:

$$R^E = \frac{1}{\bar{\alpha}} \int_{(1-\bar{\alpha})R^B}^{\infty} \left[y - (1-\bar{\alpha})R^B\right] f(y)dy. \tag{3.21}$$

Finally, from equations (3.20) and (3.19), we find that $D = (1-\bar{\alpha})K$, from which we derive

$$E = \frac{\bar{\alpha}}{1-\bar{\alpha}} D. \tag{3.22}$$

We now define the equilibrium conditions under the two monetary policy regimes. For simplicity, we consider that when the central bank chooses the type of assets to back the issuance of CBDCs, it carries on with the ongoing monetary policy. Therefore, it chooses treasuries under standard policy and risky securities in QE. We always use the same structure for the equilibria definitions. Conditions *(i)* are the common ones we discussed above. Condition *(ii)* specifies the agents' optimal choices. Condition *(iii)* refers to whether the liquidity requirement is binding or not. Condition *(iv)* derives from the dynamics of the money market, in which cash pools invest in (short-term) government bonds, and they lend the remaining part to the bank. Finally, condition *(v)* imposes market clearing for bank equity.

DEFINITION 2. ***Standard policy with CBDCs backed by treasuries.***
Given the central bank standard monetary policy $(R^B,\ R^r,\ \delta,\ \bar{\alpha})$, with interest rate policy $R^B > R^r$ and balance sheet policy $(B^{CB},\ E^{CB}) = (M + d,\ 0)$, the banking equilibrium consists of rates of return $(R^h,\ R^d,\ R^c,\ R^E)$ and choices $(h,\ d,\ c,\ e,\ E,\ D,\ M,\ K)$ such that:

(i) *Conditions (3.4), (3.16), (3.17), (3.18), (3.19), (3.22), (3.21) hold;*

(ii) *(h, d) is optimal for households, given (R^h, R^d); c is optimal for cash pools, given R^c; e is optimal for investors, given (R^B, R^E);*

(iii) $M = \delta h$;

(iv) $c_b = c - (B - M - d)$;

(v) $e = E$.

DEFINITION 3. ***Quantitative easing with CBDCs backed by risky securities.***
If the demand for CBDC deposits is such that $d > \bar{d}$, given the central bank quantitative easing policy $(R^B,\ R^r,\ \delta,\ \bar{\alpha})$, with interest rate policy $R^B = R^r$ and

balance sheet policy $(B^{CB},\ E^{CB}) = (0,\ M+\tilde{d})$*, then the banking equilibrium consists of rates of return* $(R^h,\ R^d,\ R^c,\ R^E)$ *and choices* $(h,\ d,\ c,\ e,\ E,\ D,\ M,\ K)$ *such that:*

(i) *Conditions (3.4), (3.16), (3.17), (3.18), (3.19), (3.22), (3.21) hold;*

(ii) (h, d) *is optimal for households, given* (R^h, R^d)*;* c *is optimal for cash pools, given* R^c*;* e *is optimal for investors, given* (R^B, R^E)*;*

(iii) $M \geqslant \delta h$*;*

(iv) $c_b = c - B$*;*

(v) $e + M + \tilde{d} = E$.

Figure 3.4 depicts the balance sheets at equilibrium at time 1.

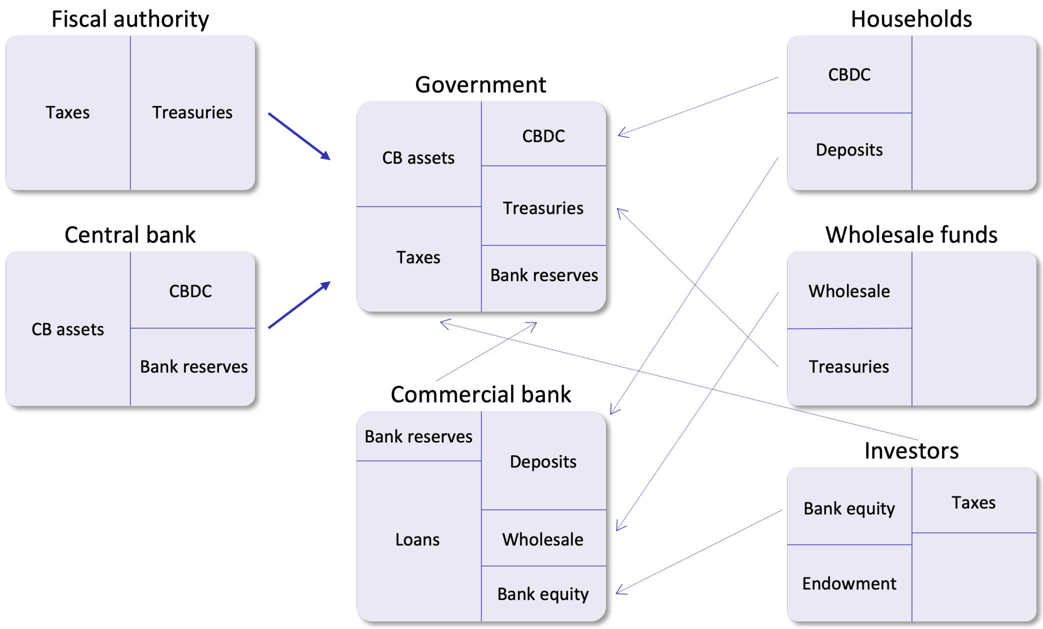


FIGURE (3.4) Actors' balance sheets and relationships at time 1.

3.4.3 Pareto Optimal Allocations

The maximization of social welfare determines the optimal allocations of resources at time 0 and the optimal weight of each agent. The Pareto problem can be written as:

$$\max_{x_{h,0},\, x_{h,1}^h,\, x_{h,1}^d,\, x_{c,0},\, x_{c,1},\, x_{i,0},\, \{x_{i,1}(y)\}_{y\in Y},\, K} \quad \beta_h\Big[u_h(x_{h,0}) + (1+\rho_h)x_{h,1}^h + (1+\rho_d)x_{h,1}^d\Big] + \\ + \beta_c\Big[u_c(x_{c,0}) + x_{c,1}\Big] + \\ + \beta_i\Big[u_i(x_{i,0}) + \int_0^\infty x_{i,1}(y)f(y)dy\Big] \tag{3.23}$$

subject to

$$x_{h,0} + x_{c,0} + x_{i,0} + K + G = w_{d,0} + w_{c,0} + w_{i,0}, \tag{3.24}$$

$$(1+\mu_h)x_{h,1}^h + (1+\mu_d)x_{h,1}^d + x_{c,1} + x_{i,1}(y) = w_{i,1} + Ky, \tag{3.25}$$

$$x_{h,1} = x_{h,1}^h + x_{h,1}^d, \tag{3.26}$$

where $(\beta_h,\ \beta_c,\ \beta_i) > 0$ are the relative weights of the agents, and equations (3.24) and (3.25) represent the resource constraints at time 0 and 1, respectively. Substituting $x_{i,1}(y)$[14] in the maximization problem and computing the first order conditions with respect to $x_{h,1}^h$, $x_{h,1}^d$, and $x_{c,1}$, we find that a solution exists only if

$$\beta_c = \beta_i = \frac{1+\rho_h}{1+\mu_h}\beta_h = \frac{1+\rho_d}{1+\mu_d}\beta_h. \tag{3.27}$$

Interestingly, equation (3.27) shows that, at Pareto optimum, the ratio between the benefits and the costs of CBDC and bank deposits have to be the same, i.e., $\frac{1+\rho_h}{1+\mu_h} = \frac{1+\rho_d}{1+\mu_d}$.

The necessary and sufficient conditions for a Pareto optimal equilibrium can be summarized by

$$\frac{1+\mu_h}{1+\rho_h}\frac{\partial u_h(x_{h,0})}{\partial x_{h,0}} = \frac{\partial u_c(x_{c,0})}{\partial x_{c,0}} = \frac{\partial u_i(x_{i,0})}{\partial x_{i,0}} = E\left[\tilde{y}\right], \tag{3.28}$$

and the resource constraints (3.24) and (3.25).[15]

---

[14] We derive the equation for $x_{i,1}(y)$ from the resource constraint (3.25).

[15] Equation (3.28) derives from the first order conditions with respect to $x_{d,0}$, $x_{c,0}$, $x_{i,0}$, and K.

Furthermore, the implicit contributions (d^*, h^*, c^*, e^*) of all the agents are given by:

$$\begin{aligned}
\frac{\partial u_h(w_{h,0} - h^* - d^*)}{\partial h^*} &= \frac{1+\rho_h}{1+\mu_h} E\left[\tilde{y}\right], \\
\frac{\partial u_h(w_{h,0} - h^* - d^*)}{\partial d^*} &= \frac{1+\rho_d}{1+\mu_d} E\left[\tilde{y}\right], \\
\frac{\partial u_c(w_{c,0} - c^*)}{\partial c^*} &= E\left[\tilde{y}\right], \\
\frac{\partial u_i(w_{i,0} - e^*)}{\partial e^*} &= E\left[\tilde{y}\right].
\end{aligned}$$

PROPOSITION 4. *In any Pareto optimal allocation, the implicit rates of return are:*

$$(1+\mu_h) R^h = (1+\mu_d) R^d = R^c = R^E = E\left[\tilde{y}\right]. \tag{3.29}$$

Proof. It follows from the combination of the Pareto optimal allocations and the first order conditions of the single agents' maximization. □

3.5 Results

In this section, we analyze the first-order effect of introducing a CBDC in the economy either under standard policy or quantitative easing. Because of the introduction of a CBDC, households will transfer part of their bank deposits toward the central bank to convert them into CBDC. Hence, the main mechanism driving the results in Sections 3.5.1 and 3.5.2 is the reduction in bank deposits (as in Klein et al., 2020; Kumhof et al., 2018).[16] Appendix C.2 shows the proofs of these results.

The second part of this section focuses on finding the conditions for each monetary policy scenario under which the introduction of a CBDC will be neutral for the economy.

3.5.1 Introduction of a CBDC under Standard Policy

The introduction of a CBDC under standard monetary policy leads to a decline in deposits by the amount of households' savings placed in CBDC (d). Since in equilibrium the liquidity constraint is binding, the bank reserves held at the central bank decline by δd, and the size of the commercial bank's balance sheet (S) shrinks. Furthermore, since net liabilities shrink and equity remains unchanged,

[16]Note that the main version of our model does not include cash, however, our findings do not change when we account for it.

the commercial bank's leverage declines.[17] The central bank's treasuries holding increases by d and declines by δd, as the reduction in bank deposits is followed by a decrease in central bank reserves (M) by the commercial bank. This additional demand for treasuries, $(1-\delta)d$, from the central bank to back CBDC deposits crowds out cash pools that cannot buy as many treasuries as they desire. Consequently, cash pools compensate by investing $(1-\delta)d$ more in bank debt. The amount of investable funds D for the bank does not change, as the decrease in deposits $(-d)$ is fully compensated by the reduction in reserves $(-\delta)$ and the increase in cash pool funding $(1-\delta)$. In other words, the expansion of the central bank balance sheet generates a general equilibrium effect for which wholesale funding substitutes deposits on the commercial bank balance sheet. The result of this general equilibrium effect is that the bank does not change the amount invested in risky loans (K). Bankruptcy costs (ϕ) are unchanged.

The effect on the government sector depends on the cost of issuing CBDC deposits, namely interest rate (R^d) and management cost $(1+\mu_d)$. The impact on seignorage revenues is determined by the difference between the cost of deposits for the central bank, $(1+\mu_d)R^d$, and the commercial bank, $(1+\mu_h)R^h$. When the cost of deposits for the central bank is higher than for the commercial bank (i.e., $(1+\mu_d)R^d > (1+\mu_h)R^h$), seignorage revenues decrease, and taxes increase. Vice versa when $(1+\mu_d)R^d < (1+\mu_h)R^h$.

3.5.2 Introduction of a CBDC under Quantitative Easing

Under quantitative easing, there is an abundance of excess reserves and the reserve requirement is not binding. As shown in section 3.3.2, when the demand for CBDC remains under the threshold $\bar{d}$, the commercial bank optimally chooses to swap reserves for CBDC deposits. In this scenario, the size of the commercial bank decreases but everything else remains equal. The reduction in bank deposits is fully compensated by the reduction in excess reserves and loans are not affected. Furthermore, the size of the central bank's balance sheet does not change, as there are no additional asset purchases. Nevertheless, the composition of the central bank balance sheet changes, as commercial bank reserves are converted into CBDC deposits. The government asks the investors to pay higher or lower taxes depending on the relative costs of reserves and CBDC deposits that the central bank needs to sustain. If the cost for CBDC deposits is higher than the one for reserves, than taxes increase, and viceversa.

[17] We define leverage as bank liabilities divided by the size of the balance sheet, i.e., $(h+c_b)/(h+c_b+E)$.

When the demand for CBDC exceeds the amount of excess reserves, i.e., $d > \bar{d}$, the commercial bank swaps reserves for CBDC deposits until the liquidity requirement is binding. At that point, the reduction in deposits cannot be fully compensated by the reduction of reserves anymore. The central bank needs to issue new liabilities to satisfy the demand for CBDC deposits and holds risky securities against them. Therefore, the commercial bank loses deposits, which are a cheap source of funding, and receives equity injections, which are more costly. The result is a reduction in lending, due to the replacement of a cheap source of funding by a more expensive one.

As in Magill et al., 2020, for $\bar{\alpha} > \alpha_c$ the bank has enough capital to absorb the losses even when $\tilde{y}$ is $\underline{y}$, its lowest possible realization. With such a macroprudential policy, there are no bankruptcies, and the equilibrium is Pareto optimal. The central bank holds riskier assets on its balance sheet, with higher expected seignorage revenues. Seignorage volatility increases as the central bank holds more risky assets on its balance sheet. Consequently, taxes are lower in expectation but more volatile. When $\bar{\alpha} < \alpha_c$, the impact on the government sector depends on the relative levels of R^B, R^h, and $V(y)$. In this case, the impact on seignorage is ambiguous.

PROPOSITION 5. *A different monetary policy in place when introducing a CBDC determines different equilibrium allocations and, consequently, a different impact of the CBDC on the economy.*

Proof. The result comes from the derivation shown in Appendix C.2 and the analysis in Sections 3.5.1 and 3.5.2. □

Our analysis shows that the effects of introducing a CBDC depend on the ongoing monetary policy. Specifically, the equilibrium depends on interest rates and on the composition of the central bank balance sheet. Such a relationship highlights an unappreciated problem. Currently, the central bank balance sheet has been a function of monetary policy and financial stability. Issuing a CBDC would add an additional layer of complexity by permanently locking assets on central bank balance sheet, in so inevitably interacting with ongoing monetary policies.

While our model is static and does not capture transition dynamics, in Appendix C.1 we model a hybrid scenario where the central bank conducts QE policy, but it backs the CBDC with treasuries (as in standard policy). In such a scenario, the central bank holds risky assets on its balance sheet but, once absorbed excess reserves, it decides to accommodate the inflows of CBDC deposits by purchasing treasuries, as it does not want to pursue further QE expansions. In such a scenario, we find that introducing a CBDC increases the speed of transition towards standard policy by pushing the sales of risky assets as households convert bank deposits into CBDC.

3.5.3 Neutrality

In this Section, we analyze whether it is possible to have an introduction of a CBDC neutral to the economy. We define neutrality in our model in the following way.

DEFINITION 4. *The introduction of a CBDC is neutral for equilibrium economic allocations when it has no impact both on the commercial bank's lending* ($\Delta_K = 0$) *and on taxes* ($\Delta_t = 0$).

Under standard policy, the central bank indirectly channels funds back to the commercial bank via open-market operations. Since the new CBDC deposits increase the amount of liabilities on its balance sheet, when the central bank holds treasuries against CBDC deposits, it decreases the amount of safe assets available to cash pools. This mechanism allows the commercial bank to receive part of the cash pools' savings in the form of debt funding. Thus, when the central bank only holds treasuries on its asset side of the balance sheet, its pass-through policy is complete as the increase in cash pools funding can fully compensate for the reduction in bank deposits. For this reason, the bank's lending to the economy is not affected by the introduction of a CBDC. However, to have an introduction fully neutral for the economy, the cost of issuing CBDC deposits for the central bank must be equal to the cost of issuing bank deposits for the commercial bank. This condition leaves the seigniorage unchanged, with no consequences for the taxes.

PROPOSITION 6. *Under standard policy, introducing a CBDC is neutral for equilibrium economic allocations when:*

(i) the cost of issuing CBDC deposits for the central bank is equal to the cost of issuing bank deposits for the commercial bank:

$$(1 + \mu_d)R^d = (1 + \mu_h)R^h.$$

Proof. See Appendix C.2 for $\Delta_K^{sB} = 0$ and $\Delta_t^{sB} = \left[(1 + \mu_d)R^d - (1 + \mu_h)R^h\right]h$, under standard policy. Therefore, $\Delta_t^{sB} = 0$ when $(1 + \mu_d)R^d = (1 + \mu_h)R^h$. □

It is worth noting that our results are consistent with Brunnermeier et al., 2019b.[18] In our model, the CBDC design assures liquidity and span neutrality since CBDC deposits have the same liquidity properties as bank deposits and the same payoffs of a portfolio of existing securities. If we remove all the frictions and consider no convenience yields ($\rho_d = \rho_h = 0$) and no maintenance costs ($\mu_d = \mu_h = 0$), we directly find that $\Delta_K^{sB} = 0$ and $\Delta_t^{sB} = 0$.

Under QE, the central bank keeps risky securities on its balance sheet. This means that it does not influence the amount of safe assets available in the economy. For this reason, the central bank does not indirectly channel funds back to the commercial bank, contrary to standard policy. As long as the demand for CBDC remains below the threshold $\bar{d}$, the reduction in deposits is fully compensated by the reduction in reserves without affecting the bank's lending. In this case, it is possible to find the conditions for a neutral introduction of CBDC in the economy. However, once the commercial bank has to liquidate some other assets in favor of the central bank ($d > \bar{d}$), then lending decreases automatically and neutrality is impossible.

PROPOSITION 7. *Under QE policy, the introduction of a CBDC is neutral for equilibrium economic allocations when:*

(i) the demand for CBDC deposits is lower than the amount of excess reserves:

$$d < \bar{d};$$

(ii) the cost of reserves for the central bank is equal to the cost of CBDC deposits:

$$R^r = (1 + \mu_d)R^d.$$

Proof. If the demand for CBDC deposits is lower than the amount of excess reserves, the commercial bank can swap excess reserves for CBDC deposits. In this way, the amount of lending to the economy remains unchanged because the reduction in reserves fully compensates for the reduction in deposits ($\Delta_K^q = 0$). Since the central bank transforms one type of liabilities into another, the impact on taxes is given by: $\Delta_t^q = \left[(1 + \mu_d)R^d - R^r\right] h$. This is null only when $R^r = (1 + \mu_d)R^d$. □

[18] In a rather different framework, Brunnermeier et al., 2019b pinpoint the conditions under which the introduction of a CBDC does not change the equilibrium allocations in the economy. Their equivalence theorem states that neutrality can be obtained only through liquidity and span-neutral open-market operations with compensating transfers and a corresponding central bank pass-through policy. In our framework, once we consider some frictions as convenience yields, maintenance costs for deposits, or quantitative easing policies, their theorem does not hold anymore, and we need to impose some conditions to achieve neutrality.

In the real world, the central bank could keep the demand for CBDC low enough for neutrality by designing it to meet its needs. For example, it could offer a very low interest rate to make the CBDC less attractive, or impose a cap on the amount of money that households can keep in their CBDC deposits.

3.6 Conclusions

When central banks issue a CBDC, the equilibrium effects on the economy largely depend on the ongoing monetary policy. In this paper, we investigate and compare two illustrative cases, the first where the central bank pursues standard monetary policy and the second where it implements QE. Our paper sheds light on the key equilibrium mechanisms that affect the bank and government sectors.

First, we find that the economic effects do indeed differ depending on the interaction between the ongoing monetary policy. For instance, introducing a CBDC under standard policy does not affect lending to the economy, but it can reduce it under QE. This fact can be regarded as a warning that the debate over CBDCs cannot be held in a vacuum, as a CBDC will interact with the other central bank policies.

Second, the impact of introducing a CBDC while the central bank is conducting QE depends on the amount of excess reserves in the system. Banks optimally transfer excess reserves to households when creating new CBDC deposits. Therefore, a CBDC has no impact on the banking sector as long as the demand for CBDC does not exceed excess reserves. Above this threshold, introducing a CBDC is problematic as banks lose a cheap source of funding, which is not replaced. Furthermore, it is worth noting that substituting banks with households on the liability side of the central bank's balance sheet is not without consequences. Households tend to be inelastic, so it would be difficult for the central bank to reduce the size of its balance sheet when reverting QE policies. In this sense, introducing a CBDC might render QE quasi-permanent.

These findings are relevant for policymakers in charge of designing future digital currencies. CBDCs have the potential to radically change monetary policy transmission, and central banks should have a comprehensive approach that considers the interaction with current monetary policies.

Appendix A

Appendices of Chapter 1

A.1 Main Variables Definition

Weighted-Average US Dollar and Local Currency Pricing. We define the currency choice variables are the weighted-average share of exports done in currency x by firm f in quarter t, where x is either US dollar pricing, local currency pricing, or euro pricing. We also adjust for peg arrangements with both the euro and the US dollar, following the definition of Ilzetzki et al., 2019. We consider a currency as "pegged" when it is classified as either "no separate legal tender or currency union", or "pre-announced peg or currency board arrangement", or "pre-announced horizontal band that is narrower than or equal to $+/$-2%", or "de facto peg". For instance, if a firm sells in a currency that is either pegged with the euro or the US dollar, we consider such a sale as it was directly done in euros or dollars. If a currency is pegged to both the euro and the US dollar, we consider it as was pegged only to the euro. Mathematically,

$$\text{Weighted-Average USD}_{ft}^{peg} = \frac{\sum \text{Export}_{USD}}{\text{Tot Firm Exp}_{ft}}$$

$$\text{Weighted-Average LCP}_{ft}^{peg} = \frac{\sum \text{Export}_{LCP}}{\text{Tot Firm Exp}_{ft}}$$

Weighted-Average Local Currency Volatility. Furthermore, we build a measure of local currency volatility to account for country-specific differences which may influence currency choice. Intuitively, if the local currency volatility is very high, French firms might be incentivized to either price in euro or US dollars. By converse, if the local currency volatility is very low (at the extreme, if the currency is pegged to the euro), French firms would be (almost) indifferent between using the two currencies. In order to control for the exposure of single firms to different countries, we compute the export-weighted measure of realized (daily) currency volatility between the local currency and the euro. Specifically, we compute it as follows:

$$\text{W.A. Local Currency Volatility}_{ft} = \sum_h \sum_c \underbrace{\frac{\text{Firm Exp}_{fthc}}{\text{Tot Firm Exp}_{ft}}}_{\text{Weight}_{fthc}} \times \text{LC Vol}(e_t^{j/€})$$

where h stands for product, c for country, and:

$$\underbrace{\text{LC Vol}(e_t^{j/€})}_{\text{Realized Local Currency Volatility}} = \sqrt{\frac{252}{4} \sum_t log \left(\frac{e_{day}^{j/€}}{e_{day-1}^{j/€}} \right)}$$

Our measure of weighted-average local currency volatility has two main advantages. First, it provides an objective measure to relate different export destinations. In other words, this measure captures the magnitude of being exposed to one local currency with respect to another. From a firm's perspective, this is arguably more meaningful than using country-fixed effects as it allows us to compare countries that share similar characteristics instead of focusing only on within-country variation. Second, currency volatility is exogenous for single French firms as it would not depend on firms' currency choices, and it is arguably impossible for them to influence it (Adams et al., 2022).

Nevertheless, our weighted average LC volatility measure presents a limitation. In principle, a firm could influence the weights by changing the export amounts to specific countries. However, it is reasonable to believe that if a firm has the chance to export to a country that has a very volatile currency, it will probably price in a currency different from the local one (so the phenomenon in which we are interested), instead of entirely refusing to do business with that country. Nevertheless, we also test for this possibility in Table 1.7.

Foreign Import Share. We construct a variable that proxies for the operational exposure to currency risk unrelated to financial hedging. Following Amiti et al., 2014, we define the foreign import share as the fraction of imports in foreign currency over the total amount of imports of a given firm in a given quarter. Quantitatively, it is given by:

$$\text{Foreign Import Share}_{ft} = \frac{\text{Imports not in Euro}_{ft}}{\text{Total Imports}_{ft}}$$

A firm can potentially hedge its foreign currency exposure by matching its foreign imports and exports. If this was the case, we should expect the marginal effects of foreign import share to be highly significant for the firm's currency choice, both in statistical and economic terms. Alfaro et al., 2022 show that operational hedging is often incomplete, and it is due to several factors.

It is worth noting that in our empirical analysis, we show that our specification is robust to different definitions of our currency choice variable. In particular, we show that the results hold very well when we weigh firms' currency choice by the difference between exports and imports in foreign currency.

Weighted-Average Export Share. The literature has shown that currency choice also depends on the relative bargaining power of the exporter and importer. In turn, this might correlate with several aspects such as the size of the firm, its level of sophistication, or its market share (e.g., see Alfaro et al., 2022; Amiti et al., 2014; Lyonnet et al., 2020). Following the intuition of Amiti et al., 2014, 2022, we construct a variable that accounts for the share of exports of firm f in time t of a given product h to a given country c over the amount of exports by all French firms. Mathematically,

$$\text{Weighted-Average Export Share}_{ft} = \sum_h \sum_c \underbrace{\frac{\text{Firm Exp}_{fthc}}{\text{Tot Firm Exp}_{ft}}}_{\text{Weight}_{fthc}} \times \underbrace{\frac{\text{Firm Exp}_{fthc}}{\text{Tot Exp}_{thc}}}_{\text{Export Share}_{fthc}}$$

where c is the country, and h is the product.

Dollar Volatility. In our analysis, we also use the quarterly volatility of the US dollar as it is likely to influence firms' currency choice, both directly and indirectly, as it proxies for global market conditions. Consistently with our measure of weighted-average local currency volatility, we compute dollar volatility as follows:

$$\text{Dollar Volatility}_t = \sqrt{\frac{252}{4} \sum_t log \left(\frac{e_{day}^{\$/€}}{e_{day-1}^{\$/€}} \right)}$$

A.2 Additional Summary Statistics

We now present additional summary statistics about the event study we consider in the paper. Specifically, we are interested in understanding whether the shock resulted in a structural change, whether hedging firms could have been affected differently, or whether they had different characteristics, to begin with. Table A.1 reports the transition probability of currency choice from one month to the other, before and after the 2011 shock (similarly to Table 1.3). The table should be read as follows: the cells contain the probability of firm pricing in currency j next period (columns), given that it prices in i today (rows). As for the baseline, we do not observe a substantial variation between hedging and non-hedging firms. More importantly, the two sets of matrices are very similar before and after the shock. This means that the shock did not cause (at least in the period we consider) a structural change in how firms choose their invoicing currency over time. In other words, data shows that the limited access to forward markets, due to dollar shortage, shifted the distribution of currency choice, but not the dynamics with which firms change their strategy over time.

TABLE (A.1) Transition probability matrices of firms' pricing strategies by hedging type

Before the Shock				After the Shock			
Full Sample				*Full Sample*			
	EUR_{t+1}	USD_{t+1}	LCP_{t+1}		EUR_{t+1}	USD_{t+1}	LCP_{t+1}
EUR_t	92.6%	4.5%	2.9%	EUR_t	94.6%	3.1%	2.2%
USD_t	16.8%	81.8%	1.4%	USD_t	16.8%	82.2%	1.0%
LCP_t	25.6%	1.5%	72.8%	LCP_t	20.5%	1.1%	78.4%
Non-Hedging Sample				*Non-Hedging Sample*			
	EUR_{t+1}	USD_{t+1}	LCP_{t+1}		EUR_{t+1}	USD_{t+1}	LCP_{t+1}
EUR_t	93.5%	4.1%	2.4%	EUR_t	95.4%	2.8%	1.8%
USD_t	17.1%	81.8%	1.2%	USD_t	17.0%	81.9%	1.1%
LCP_t	24.6%	1.7%	73.7%	LCP_t	19.6%	1.2%	79.2%
Hedging Sample				*Hedging Sample*			
	EUR_{t+1}	USD_{t+1}	LCP_{t+1}		EUR_{t+1}	USD_{t+1}	LCP_{t+1}
EUR_t	89.5%	5.6%	4.8%	EUR_t	91.9%	4.3%	3.8%
USD_t	16.3%	81.9%	1.8%	USD_t	16.3%	82.8%	1.0%
LCP_t	27.7%	1.2%	71.1%	LCP_t	22.0%	1.0%	76.9%

Notes: The two set of matrices are computed before in the first and second semester of 2011, i.e., before and after the dollar funding shortage in FX markets. The panels report the transition probabilities of moving from a pricing strategy at time t (rows) to a pricing strategy at $t+1$ (columns). The first matrix considers the full sample, the second only non-hedging firms, and the third only hedging ones. A firm is classified as hedging if it has an outstanding FX forward position for at least one month.

In Table A.2, we compute the mean by hedging type for the most relevant variables of our analysis. In columns (3) and (4), we report the differences in mean, both unconditional and when controlling for industry-quarter and size bins-quarter effects. As expected, hedging firms price more in foreign currency (both in local currency and dollars). Hedging firms face slightly higher local currency volatility, whereas they import more inputs in foreign currency. As expected, hedging firms are more sophisticated than non-hedging ones and have a higher export share, possibly because they produce more differentiated goods.

TABLE (A.2) Balanced table

	Non-Hedging	Hedghing	Difference	
	Mean/SE	Mean/SE	Unconditional	with Fixed Effects
	(1)	(2)	(3)	(4)
w.a.% USD_{ft}^{peg}	0.022	0.064	-0.042***	-0.0320***
	(0.001)	(0.003)		
w.a.% LCP_{ft}^{peg}	0.011	0.036	-0.025***	-0.0198**
	(0.000)	(0.002)		
w.a. LC Volatility_{ft}	0.415	0.39	0.024***	0.0108**
	(0.001)	(0.003)		
Foreign Import Share_{ft}	0.113	0.418	-0.305***	-0.258***
	(0.001)	(0.007)		
w.a. Export Share_{ft}	0.279	0.419	-0.140***	-0.0666***
	(0.002)	(0.005)		
# of Transactions_f	198.261	858.699	-660.438**	-415.9*
	(40.121)	(281.040)		
# of Countries_f	9.596	17.542	-7.946***	-4.005***
	(0.896)	(1.774)		
# of Products_f	14.486	33.600	-19.114***	-11.20***
	(1.252)	(4.526)		

Notes: This table reports the mean and the standard errors of the variables used in our empirical analysis for the subsample of non-hedging and hedging firms, respectively column (1) and (2). Column (3) reports the unconditional difference between columns (1) and (2), whereas the difference in column (4) accounts for industry × quarter and size bins × quarter fixed effects. w.a.% USD_{ft}^{peg} (w.a.% LCP_{ft}^{peg}) is the weighted-average share of US dollar (local currency) pricing for firm f in quarter t adjusted for peg arrangements. w.a. LC Volatility_{ft} is the weighted-average local currency volatility of the country with which firm f is trading, regardless of its currency choice. Foreign Import Share_{ft} is the share of imports in foreign currency. w.a. Export Share_{ft} is the weighted-average (across countries) of the share of exports of firm f in quarter t of a given product to a given country over the total amount of export by all French firms of the same product to the same country. # Transactions_f, # Countries_f, # Products_f represent the number of transactions, unique destination countries, and unique exported products. * p<.10, ** p<.05, *** p <.01 .

Finally, we report the summary statistics of the main variables we use for different time windows. The sample for which we have complete derivatives data is from 2016 to 2017. For periods outside this window, we simply assume that the firms that were hedging in this period were doing so also before. This is a rather mild assumption as the hedging choice is highly sticky, as shown in Table 1.2. It is worth noting that the summary statistics are essentially the same across time windows, suggesting that there are no structural changes in the data.

Table (A.3) Summary statistics (2016-2017)

	obs.	mean	std	min	5%	25%	50%	75%	95%	max
w.a.% LCP_{ft}	117'275	0.02	0.11	0.00	0.00	0.00	0.00	0.00	0.00	1.00
w.a.% LCP_{ft}^{peg}	117'275	0.01	0.10	0.00	0.00	0.00	0.00	0.00	0.00	1.00
w.a.% USD_{ft}	117'275	0.02	0.13	0.00	0.00	0.00	0.00	0.00	0.00	1.00
w.a.% USD_{ft}^{peg}	117'275	0.02	0.14	0.00	0.00	0.00	0.00	0.00	0.00	1.00
w.a. LC Volatility_{ft}	117'275	0.28	0.16	0.00	0.07	0.17	0.27	0.33	0.55	1.24
w.a. Export Share_{ft}	117'275	0.26	0.34	0.00	0.00	0.01	0.07	0.45	1.00	1.00
US Dollar Volatility_t	117'275	0.31	0.04	0.24	0.24	0.30	0.32	0.32	0.37	0.37
Foreign Import Share_{ft}	117'275	0.14	0.33	0.00	0.00	0.00	0.00	0.00	1.00	1.00

Notes: Weighted-average % USD^i_{ft} and weighted-average % LCP^i_{ft}, which are defined as the weighted-average share of US dollar and local currency pricing for firm f in quarter t. If $i = peg$, the measure is adjusted for peg arrangements. Weighted-average LC Volatility_{ft} is the weighted-average local currency volatility of the countries with which firm f is trading at time t, regardless of its currency choice. Foreign Import Share_{ft} is the share of imports in foreign currency. w.a. Export Share_{ft} is the weighted-average (across countries) of the share of exports of firm f in quarter t of a given product to a given country over the total amount of export by all French firms of the same product to the same country. The time span is April 2016 - September 2017.

Table (A.4) Summary statistics (2011)

	obs.	mean	std	min	5%	25%	50%	75%	95%	max
w.a.% LCP_{ft}	57'255	0.02	0.11	0.00	0.00	0.00	0.00	0.00	0.00	1.00
w.a.% LCP_{ft}^{peg}	57'255	0.01	0.10	0.00	0.00	0.00	0.00	0.00	0.00	1.00
w.a.% USD_{ft}	57'255	0.02	0.14	0.00	0.00	0.00	0.00	0.00	0.02	1.00
w.a.% USD_{ft}^{peg}	57'255	0.03	0.14	0.00	0.00	0.00	0.00	0.00	0.03	1.00
w.a. LC Volatility_{ft}	57'255	0.41	0.23	0.00	0.08	0.26	0.42	0.49	1.09	1.61
w.a. Export Share_{ft}	57'255	0.29	0.35	0.00	0.00	0.01	0.10	0.54	1.00	1.00
US Dollar Volatility_t	57'255	0.47	0.04	0.40	0.40	0.47	0.50	0.50	0.51	0.51
Foreign Import Share_{ft}	57'255	0.14	0.33	0.00	0.00	0.00	0.00	0.00	1.00	1.00

Notes: Weighted-average % USD^i_{ft} and weighted-average % LCP^i_{ft}, which are defined as the weighted-average share of US dollar and local currency pricing for firm f in quarter t. If $i = peg$, the measure is adjusted for peg arrangements.

Weighted-average LC Volatility$_{ft}$ is the weighted-average local currency volatility of the countries with which firm f is trading at time t, regardless of its currency choice. Foreign Import Share$_{ft}$ is the share of imports in foreign currency. w.a. Export Share$_{ft}$ is the weighted-average (across countries) of the share of exports of firm f in quarter t of a given product to a given country over the total amount of export by all French firms of the same product to the same country. Data refers to 2011.

A.3 Additional Currency Choice Results

This section presents alternative specifications of our baseline regressions to show that the results are robust. Specifically, we focus on the role of foreign import share. In Table A.5, we re-run the same set of regressions of Table 1.4, but we drop all the instances in which firms are importing inputs either in dollars (from column (1) to (5)) or in local currency (from column (6) to (10)). Results hold across specifications.

Table (A.5) Currency choice regressions with no foreign imports

	US Dollar Pricing (peg-adj)					Local Currency Pricing (peg-adj)				
	Logit	Probit	OLS			Logit	Probit	OLS		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Hedge$_f$	0.901***	0.390***	0.0365***	0.00123	0.00104	0.927***	0.387***	0.0238***	0.0173**	0.0171**
	(4.63)	(4.11)	(6.45)	(0.13)	(0.11)	(5.57)	(4.98)	(4.94)	(2.87)	(2.85)
Hedge$_f$ × LC Vol.$_{ft}$	0.325	0.375**		0.106***	0.107***	0.421	0.361*		0.0149	0.0155
	(0.84)	(1.98)		(3.61)	(3.64)	(0.99)	(1.77)		(0.87)	(0.90)
LC Vol.$_{ft}$	1.250***	0.581***	0.0273***	0.0243***	0.0247***	0.259	0.0582	-0.00689**	-0.00813**	-0.00820**
	(12.79)	(10.38)	(4.51)	(4.99)	(5.02)	(1.39)	(0.67)	(-2.30)	(-2.57)	(-2.58)
Foreign Import Share$_{ft}$	0.642***	0.321***	0.0129***	0.00893**	0.00870**	-0.102	-0.0301	0.00104	0.000820	0.000841
	(4.56)	(4.57)	(3.15)	(2.31)	(2.21)	(-0.78)	(-0.53)	(0.36)	(0.31)	(0.31)
w.a. Export Share$_{ft}$	1.433***	0.620***	0.0236***	0.0199***	0.0199***	-0.939***	-0.396***	-0.00796***	-0.0106***	-0.0106***
	(17.19)	(16.90)	(10.13)	(8.41)	(8.43)	(-3.89)	(-4.43)	(-5.38)	(-5.52)	(-5.54)
Dollar Vol.$_t$	-1.023**	-0.448**	-0.0199***			-1.070**	-0.436**	-0.00473		
	(-1.98)	(-2.08)	(-3.24)			(-2.58)	(-2.56)	(-1.15)		
Zero Foreign Imports	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Sophistication Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time	NO	NO	NO	YES	NO	NO	NO	NO	YES	NO
Industry	NO	NO	NO	YES	NO	NO	NO	NO	YES	NO
Industry × Time	NO	NO	NO	NO	YES	NO	NO	NO	NO	YES
Size Bins	NO	NO	NO	YES	NO	NO	NO	NO	YES	NO
Size Bins × Time	NO	NO	NO	NO	YES	NO	NO	NO	NO	YES
N	97'857	97'857	97'857	97'857	97'856	112'035	112'035	112'035	112'035	112'035
R^2			0.0200	0.0270	0.0289			0.0123	0.0183	0.0195
R^2_{adj} or R^2_{pseudo}	0.181	0.184	0.0199	0.0265	0.0268	0.143	0.144	0.0122	0.0179	0.0177

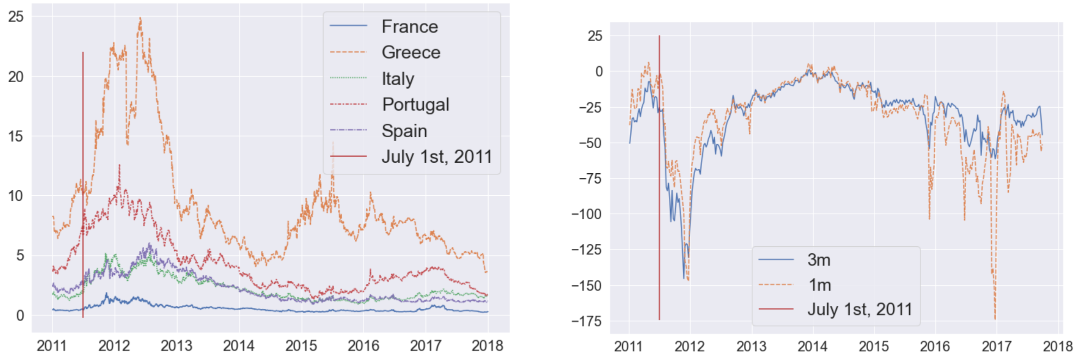
Notes: This table reports a set of currency choice regressions. The dependent variables are w.a.% USD_{ft}^{peg} and w.a.% LCP_{ft}^{peg}, which are defined as the weighted-average share of US dollar and local currency pricing for firm f in quarter t adjusted for peg arrangements, respectively. Hedge_f is equal to one if firm f has traded an FX forward contract at least once. w.a. LC Volatility_{ft} is the weighted-average local currency volatility of the countries with which firm f is trading at time t, regardless of its currency choice. Foreign Import Share_{ft} is the share of imports in foreign currency. w.a. Export Share_{ft} is the weighted-average (across countries) of the share of exports of firm f in quarter t of a given product to a given country over the total amount of export by all French firms of the same product to the same country. Sophistication controls include the number of transactions (# Transactions_f), the number of unique destination countries (# Countries_f), and unique exported products (# Products_f). In all regressions, we restrict the sample to the instances in which imports in USD or in LCP are zero. The time span is April 2016 - September 2017. Standard errors are clustered at size level, and t-statistics are in parenthesis. * p<.10, ** p<.05, *** p <.01 .

A.4 Additional Experimental Results

In this section, we report additional results regarding the natural experiment as well as further considerations about the event.

Figure A.1 shows the time series of main European government spreads with respect to the German bund and the CIP deviation at different tenors. Differently from Figure 1.5, here we report a longer time span to show what happened after the shock we consider. As far as spreads are concerned, the spike of the second half of 2011 in Greek yields essentially persisted until 2013, when they fell back below 10%. Notably, French rates were rather flat even years after the window we consider for the experiment. This corroborates our assumption about the exogeneity of the shock. Panel (b) shows that at the end of 2011, there was a progressive decrease in the absolute value of the deviation, probably ascribable to the intervention of the FED, the one of the ECB, as well as to the signature of the Greek rescue package (see Subsection 1.7.1 for a more detailed discussion).

The deviations that occurred from 2016 onward are likely to be due to the US money market fund reforms (see Anderson et al., 2021). In an unreported set of regressions, we investigated whether those events could serve as an additional natural experiment. Although the deviations were clearly exogenous to French exporters, they failed to be relevant for their currency choice. This is arguably due to two main reasons. The first is that the tenors that were hit the most were relatively short-term, e.g., one-week rates, and probably these horizons were not long enough to affect firms' currency choice. Second, the deviations were mainly due to US money managers' window dressing activity, making the deviations somewhat predictable. Hence, it is also possible that CFOs understood the phenomenon and timed their trading activity accordingly.



(a) Sovereign Spreads (%) (b) EUR/USD CIP deviations (bp)

FIGURE (A.1) European sovereign crisis and CIP deviation

Notes: Panel (a) reports the spread, i.e., the difference in the 10-year treasury yields with respect to the German bund, for selected European countries. Panel (b) shows the evolution of the euro-dollar covered interest parity deviation for the one-month and three-month tenor. Data is from Bloomberg. Authors' calculations.

Table A.6 simply replicates the baseline results of our experimental design by using the producer currency pricing (i.e., euro) choice as a dependent variable. In all specifications, we observe an increase in the amount of producer currency pricing, consistently with the main regression results that show a significant decrease in foreign currency pricing. In columns (4) to (6), we also re-run the same set of regression by controlling for currency arrangements, and regression coefficients are essentially the same.

TABLE (A.6) Placebo regressions

	Producer Currency Pricing			Producer Currency Pricing (ped-adjusted)		
	OLS	OLS	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)	(6)
Shock2011 × Hedge$_f$ × LC Vol.$_{ft}$	0.0962***	0.0835***	0.0822***	0.0984***	0.0866***	0.0837***
	(4.24)	(3.61)	(3.66)	(4.46)	(3.97)	(3.95)
Other Interactions	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES
Time	YES	YES	NO	YES	YES	NO
Industry	NO	YES	NO	NO	YES	NO
Industry × Time	NO	NO	YES	NO	NO	YES
Size Bins	NO	YES	NO	NO	YES	NO
Size Bins × Time	NO	NO	YES	NO	NO	YES
N	57'255	57'255	57'252	57'255	57'255	57'252
R^2	0.0661	0.0774	0.0784	0.0684	0.0789	0.0802
R^2_{adj}	0.0658	0.0766	0.0761	0.0682	0.0782	0.0779

Notes: The dependent variables are w.a.% PCP_{ft} with and without adjusting for peg arrangements. Hedge_f is equal to one if firm f has traded an FX forward contract at least once. w.a. LC Volatility_{ft} is the weighted-average local currency volatility of the countries with which firm f is trading at time t, regardless of its currency choice. The variable shock is equal to one in the second semester of 2011. By "Other Interactions" we mean all the non-reported interactions that characterize a triple-difference identification strategy. In the controls, we include the following variables. Foreign Import Share_{ft} is the share of imports in foreign currency. w.a. Export Share_{ft} is the weighted average (across countries) of the share of exports of firm f in quarter t of a given product to a given country over the total amount of export by all French firms of the same product to the same country. Sophistication controls include the number of transactions (# Transactions_f), the number of unique destination countries (# Countries_f), and unique exported products (# Products_f). The time span is Jan-Dec 2011. Standard errors are clustered at size level, and t-statistics are in parenthesis. * $p<.10$, ** $p<.05$, *** $p<.01$.

Finally, Table A.7 investigates whether there are differences in the extensive margin variation around the 2011 shock. The dependent variables are the quarter-over-quarter growth rate of total exports, exports in local currency, and in dollars, respectively.[1] Although their medium-run (two-year) growth rates are significant (Berthou et al., 2022), the short-run effect is statistically insignificant. The absence of a significant difference in growth rates -before and after, but mainly between hedging and non-hedging firms- reassures us that our experimental strategy is robust.

[1]Due to data limitation, we cannot compare growth rates at longer horizons differently from Berthou et al., 2022. The reason is that there is no currency choice data before 2011.

Table (A.7) Export growth regressions

	Quarter-over-Quarter Export Growth					
	Total		in Local Currency		in US Dollars	
	(1)	(2)	(3)	(4)	(5)	(6)
Hedge_f	-0.0168	-0.00165	0.203	0.239	0.0174	0.0527
	(-0.50)	(-0.04)	(1.27)	(1.29)	(0.14)	(0.56)
Shock2011_t	0.852***		-1.669		0.781	
	(7.06)		(-1.36)		(0.96)	
$\text{Shock2011}_t \times \text{Hedge}_f$	0.0607	0.0509	-0.428	-0.524	0.110	0.0980
	(1.43)	(0.96)	(-1.69)	(-1.73)	(0.76)	(0.86)
LC Vol._{ft}	0.0360	0.0380	-0.252	-0.194	0.396	0.437*
	(1.41)	(1.35)	(-0.62)	(-0.46)	(1.73)	(1.80)
Controls	YES	YES	YES	YES	YES	YES
Time	NO	NO	NO	NO	NO	NO
Industry × Time	NO	YES	NO	YES	NO	YES
Industry	NO	NO	NO	NO	NO	NO
Size Bins	NO	NO	NO	NO	NO	NO
Size Bins × Time	NO	YES	NO	YES	NO	YES
N	29611	29607	1119	1117	1759	1754
R^2	0.00926	0.0155	0.0157	0.0830	0.0105	0.0595
R^2_{adj}	0.00892	0.0120	0.00682	0.0103	0.00481	0.0122
F	136.9	161.6	4.162	3.416	13.42	5.254

Notes: The dependent variables are quarter-over-quarter export growth of total exports, exports in local currency, and in dollars . Hedge_f is equal to one if firm f has traded an FX forward contract at least once. w.a. LC Volatility_{ft} is the weighted-average local currency volatility of the countries with which firm f is trading at time t, regardless of its currency choice. The variable shock is equal to one in the second semester of 2011. In the controls, we include the following variables. Foreign Import Share_{ft} is the share of imports in foreign currency. w.a. Export Share_{ft} is the weighted-average (across countries) of the share of exports of firm f in quarter t of a given product to a given country over the total amount of export by all French firms of the same product to the same country. Sophistication controls include the number of transactions (# Transactions_f), the number of unique destination countries (# Countries_f), and unique exported products (# Products_f). The time span is Jan-Dec 2011. Standard errors are clustered at size level, and t-statistics are in parenthesis. * p<.10, ** p<.05, *** p <.01 .

A.5 International Shock Propagation

E.1 Additional Results on Price Adjustment Regressions

In this subsection, we report additional results on the price adjustment regressions.

Table A.8 shows the results of regression (1.13) four quarters after the exchange rate shock, i.e., $\ell = 4$, across different specifications. Notably, the estimates hold throughout different specifications, regardless of whether we account for peg arrangements. The only exception is the hedging firms' sensitivity to the euro-dollar shock of dollar products.

Consistently with Gopinath et al., 2010, we observe a small price change for exporting firms with products invoiced in producer currency, i.e., the euro. This implies that the buyer absorbs the whole shock and, thus, the exchange-rate pass-through is complete (almost 100%). Noticeably, where there is no currency risk, i.e., for euro-denominated exports, hedging is never significant.

As in Barbiero, 2019, the adjustment for goods denominated in local currency is large, which means that the pass-through is lower with respect to euro-denominated goods. In addition, we find that hedging firms have smaller price adjustments for local currency-denominated products than non-hedging firms (fourth row). Intuitively, non-hedging firms are more exposed to exchange-rate shocks, so they tend to re-adjust their prices more than hedging firms, which are less exposed to currency risk. When an FX shock occurs, they are able to transmit a part of the shock to the dealer using their FX forward contracts. This arguably helps them to set an optimal price that maximizes local demand, so buyers face more stable prices in local currency.

As we can see from the fifth row, dollar-denominated goods have higher levels of pass-through with respect to the local currency-dollar rate (as in Barbiero, 2019; Giuliano et al., 2020). The coefficients are similar to the ones for producer currency, as prices tend to be more stable in units of invoice currency exchange-rate shocks. Nonetheless, we observe higher price adjustments for dollar-denominated goods with respect to the euro-dollar rate (seventh row). Hedging firms, however, always show higher price adjustments or lower degrees of exchange-rate transmission (rows six and eight).

Table (A.8) Price adjustments regressions

	$\Delta_4 p_{d,t}$					
	non adjusting for peg arrangements			adjusting for peg arrangements		
	(1)	(2)	(3)	(4)	(5)	(6)
PCP$\times\Delta_4 e_t^{j/€}$	0.0526***	0.0825***	0.0726***	0.0531***	0.0832***	0.0737***
	(4.52)	(6.41)	(3.85)	(4.56)	(6.47)	(3.90)
Hedge$_f\times$PCP$\times\Delta_4 e_t^{j/€}$	-0.0165	-0.0116	-0.0210	-0.0172	-0.0125	-0.0215
	(-0.78)	(-0.54)	(-0.94)	(-0.81)	(-0.58)	(-0.97)
LCP$\times\Delta_4 e_t^{j/€}$	0.683***	0.708***	0.691***	0.633***	0.652***	0.645***
	(22.62)	(23.36)	(20.63)	(19.05)	(19.54)	(17.68)
Hedge$_f\times$LCP$\times\Delta_4 e_t^{j/€}$	-0.315***	-0.291***	-0.284***	-0.254***	-0.224***	-0.228***
	(-7.57)	(-6.85)	(-6.50)	(-5.78)	(-5.02)	(-4.99)
USD$\times\Delta_4 e_t^{j/\$}$	0.166***	0.149***	0.141***	0.191***	0.178***	0.172***
	(5.42)	(4.62)	(3.73)	(6.38)	(5.63)	(4.62)
Hedge$_f\times$USD$\times\Delta_4 e_t^{j/\$}$	0.0716*	0.139***	0.114***	0.0363	0.101**	0.0755*
	(1.75)	(3.42)	(2.67)	(0.90)	(2.52)	(1.79)
USD$\times\Delta_4 e_t^{\$/€}$	0.690***	0.715***	0.680***	0.731***	0.759***	0.720***
	(16.51)	(17.20)	(14.72)	(20.09)	(20.95)	(17.69)
Hedge$_f\times$USD$\times\Delta_4 e_t^{\$/€}$	0.154***	0.170***	0.184***	0.0697	0.0805	0.0997*
	(2.61)	(2.90)	(2.98)	(1.26)	(1.46)	(1.71)
Size Bins	✓		✓	✓		✓
Year		✓			✓	
Year-Quarter	✓			✓		
Industry × Country		✓			✓	
Industry × Country × Year			✓			✓
R^2_{adj}	0.00257	0.00294	0.00536	0.00254	0.00291	0.00532
N	691’054	705’507	690’597	691’054	705’507	690’597
F	153.8	167.0	119.1	149.5	161.8	114.4

Notes: This table reports the results of regressing (log) price changes on a set of covariates, i.e., specification (1.13) with $\ell = 4$. PCP stands for producer currency pricing, LCP for local currency pricing, and USD for US dollar currency pricing. The bilateral exchange rate $e_t^{j/€}$ is expressed in euro per unit of currency j. Thus, the estimated coefficients represent the price elasticities to a 1% depreciation of the euro after ℓ quarters. $Hedge_f$ is a binary variable that switches to one if the firm has an outstanding forward exposure for at least one month in our sample. Size Bins classify the size of the firm into sixteen categories according to its number of employees. The time spans is 2014-2017. Standard errors are clustered at product level, and t-statistics are in parenthesis. * p < 10%, ** p < 5%, *** p < 1%.

In the rest of the subsection, we report a summary statistics table of the price adjustment regressions, as well as the point estimates of the regression coefficients, plotted in Section 1.8.

Table (A.9) Summary Statistics for Price Adjustment Regressions

	obs.	mean	std	10%	25%	50%	75%	90%
PCP	1'908'166	0.84	0.37	0.00	1.00	1.00	1.00	1.00
PCP^{peg}	1'908'166	0.85	0.36	0.00	1.00	1.00	1.00	1.00
USD	1'908'166	0.07	0.26	0.00	0.00	0.00	0.00	0.00
USD^{peg}	1'908'166	0.09	0.29	0.00	0.00	0.00	0.00	0.00
LCP	1'908'166	0.08	0.27	0.00	0.00	0.00	0.00	0.00
LCP^{peg}	1'908'166	0.06	0.23	0.00	0.00	0.00	0.00	0.00
$\Delta_1 p_{d,t}$	791'043	0.00	0.64	-0.67	-0.19	0.00	0.20	0.66
$\Delta_2 p_{d,t}$	750'683	0.00	0.67	-0.69	-0.21	0.00	0.22	0.70
$\Delta_3 p_{d,t}$	708'798	0.01	0.68	-0.71	-0.22	0.00	0.23	0.72
$\Delta_4 p_{d,t}$	708'845	0.01	0.68	-0.69	-0.21	0.01	0.24	0.72
$\Delta_5 p_{d,t}$	642'535	0.02	0.71	-0.74	-0.23	0.01	0.26	0.77
$\Delta_6 p_{d,t}$	614'490	0.02	0.73	-0.75	-0.24	0.01	0.28	0.79
$\Delta_7 p_{d,t}$	587'131	0.02	0.74	-0.76	-0.24	0.02	0.28	0.81
$\Delta_8 p_{d,t}$	584'437	0.03	0.73	-0.75	-0.23	0.02	0.28	0.81
$\Delta_1 e_t^{j/\$}$	790'950	-0.01	0.04	-0.05	-0.02	0.00	0.01	0.02
$\Delta_2 e_t^{j/\$}$	750'542	-0.02	0.07	-0.09	-0.04	-0.01	0.01	0.04
$\Delta_3 e_t^{j/\$}$	708'660	-0.03	0.09	-0.13	-0.06	-0.01	0.01	0.04
$\Delta_4 e_t^{j/\$}$	708'565	-0.05	0.11	-0.17	-0.08	-0.02	0.00	0.04
$\Delta_5 e_t^{j/\$}$	642'301	-0.06	0.12	-0.19	-0.10	-0.03	0.00	0.04
$\Delta_6 e_t^{j/\$}$	614'147	-0.07	0.14	-0.22	-0.12	-0.03	0.00	0.05
$\Delta_7 e_t^{j/\$}$	586'795	-0.09	0.15	-0.25	-0.15	-0.05	0.00	0.05
$\Delta_8 e_t^{j/\$}$	583'954	-0.10	0.16	-0.28	-0.17	-0.06	0.00	0.04
$\Delta_1 e_t^{j/€}$	791'043	0.00	0.05	-0.04	-0.02	0.00	0.01	0.04
$\Delta_2 e_t^{j/€}$	750'683	-0.01	0.07	-0.08	-0.04	0.00	0.02	0.08
$\Delta_3 e_t^{j/€}$	708'798	-0.01	0.09	-0.10	-0.05	0.00	0.03	0.11
$\Delta_4 e_t^{j/€}$	708'845	-0.01	0.11	-0.12	-0.05	0.00	0.04	0.12
$\Delta_5 e_t^{j/€}$	642'535	-0.01	0.12	-0.14	-0.05	0.00	0.04	0.13
$\Delta_6 e_t^{j/€}$	614'490	-0.02	0.14	-0.16	-0.06	0.00	0.05	0.14
$\Delta_7 e_t^{j/€}$	587'131	-0.02	0.15	-0.18	-0.07	0.00	0.06	0.14
$\Delta_8 e_t^{j/€}$	584'437	-0.02	0.16	-0.20	-0.07	0.00	0.09	0.15
$\Delta_1 e_t^{\$/€}$	791'043	0.01	0.04	-0.03	-0.01	0.00	0.02	0.06
$\Delta_2 e_t^{\$/€}$	750'683	0.02	0.07	-0.07	-0.03	0.01	0.05	0.12
$\Delta_3 e_t^{\$/€}$	708'798	0.03	0.08	-0.09	-0.02	0.01	0.06	0.18
$\Delta_4 e_t^{\$/€}$	708'845	0.04	0.09	-0.05	-0.02	0.02	0.09	0.20
$\Delta_5 e_t^{\$/€}$	642'535	0.05	0.10	-0.05	-0.01	0.00	0.12	0.21
$\Delta_6 e_t^{\$/€}$	614'490	0.06	0.10	-0.06	-0.04	0.03	0.16	0.21
$\Delta_7 e_t^{\$/€}$	587'131	0.07	0.11	-0.07	-0.02	0.04	0.16	0.22
$\Delta_8 e_t^{\$/€}$	584'437	0.08	0.11	-0.07	-0.05	0.15	0.18	0.22

Notes: f stands for firm, t for quarter, and d represents the product-country-firm-currency dimension. $\Delta_\ell x_t$ means $\log(x_t) - \log(x_{t-\ell})$. The bilateral exchange rate $e_t^{j/€}$ is expressed in euro per unit of currency j. The time spans is 2013-2017.

TABLE (A.10) Price adjustment regressions (coefficients)

	$\Delta_1 p_{d,t}$ (1)	$\Delta_2 p_{d,t}$ (2)	$\Delta_3 p_{d,t}$ (3)	$\Delta_4 p_{d,t}$ (4)	$\Delta_5 p_{d,t}$ (5)	$\Delta_6 p_{d,t}$ (6)	$\Delta_7 p_{d,t}$ **(5)**	$\Delta_8 p_{d,t}$ **(6)**
$\text{Hedge}_f = 0 - PCP \times \Delta_\ell e_t^{j/€}$	0.0194	-0.000672	0.0822	0.0726	0.105	0.109	0.13	0.127
	[-0.022,0.061]	[-0.035,0.033]	[0.052,0.113]	[0.042,0.104]	[0.073,0.137]	[0.075,0.142]	[0.095,0.164]	[0.086,0.168]
$\text{Hedge}_f = 1 - PCP \times \Delta_\ell e_t^{j/€}$	0.101	0.0129	0.0891	0.0516	0.102	0.105	0.125	0.128
	[0.042,0.159]	[-0.036,0.062]	[0.048,0.130]	[0.010,0.093]	[0.060,0.143]	[0.062,0.147]	[0.084,0.167]	[0.082,0.174]
$\text{Hedge}_f = 0 - LCP \times \Delta_\ell e_t^{j/€}$	0.865	0.753	0.756	0.691	0.645	0.577	0.501	0.482
	[0.791,0.938]	[0.695,0.812]	[0.702,0.810]	[0.636,0.747]	[0.590,0.701]	[0.520,0.634]	[0.442,0.561]	[0.419,0.545]
$\text{Hedge}_f = 1 - LCP \times \Delta_\ell e_t^{j/€}$	0.736	0.489	0.505	0.407	0.423	0.402	0.387	0.335
	[0.676,0.797]	[0.430,0.549]	[0.452,0.558]	[0.349,0.466]	[0.367,0.478]	[0.341,0.463]	[0.328,0.446]	[0.270,0.400]
$\text{Hedge}_f = 0 - USD \times \Delta_\ell e_t^{j/\$}$	0.0109	0.0928	0.167	0.141	0.196	0.213	0.251	0.262
	[-0.086,0.108]	[0.021,0.164]	[0.106,0.229]	[0.079,0.203]	[0.135,0.257]	[0.151,0.275]	[0.190,0.312]	[0.200,0.325]
$\text{Hedge}_f = 1 - USD \times \Delta_\ell e_t^{j/\$}$	0.443	0.284	0.262	0.255	0.281	0.319	0.294	0.305
	[0.344,0.542]	[0.214,0.355]	[0.204,0.321]	[0.201,0.309]	[0.227,0.335]	[0.265,0.373]	[0.241,0.348]	[0.249,0.362]
$\text{Hedge}_f = 0 - USD \times \Delta_\ell e_t^{\$/€}$	0.778	0.771	0.746	0.68	0.614	0.655	0.634	0.678
	[0.662,0.893]	[0.684,0.858]	[0.667,0.825]	[0.604,0.756]	[0.535,0.694]	[0.572,0.738]	[0.550,0.717]	[0.592,0.764]
$\text{Hedge}_f = 1 - USD \times \Delta_\ell e_t^{\$/€}$	0.965	0.954	0.958	0.864	0.896	0.864	0.806	0.759
	[0.840,1.090]	[0.862,1.045]	[0.874,1.042]	[0.782,0.946]	[0.812,0.980]	[0.778,0.950]	[0.718,0.894]	[0.668,0.849]
R^2	0.00414	0.00548	0.0076	0.00893	0.00911	0.0101	0.0102	0.0102
N	768'023	730'126	689'847	690'597	626'740	599'894	573'698	571'425

Notes: f stands for firm, t for quarter, and d represents the product-country-firm-currency dimension. $\Delta_\ell x_t$ means $\log(x_t) - \log(x_{t-\ell})$. The bilateral exchange rate $e_t^{j/€}$ is expressed in euro per unit of currency j. All regressions include industry×country×year fixed effects. Standard errors are at country×product level. Data is from 2014 to 2017.

TABLE (A.11) Price adjustment regressions (coefficients) - full sample

	$\Delta_1 p_{d,t}$ (1)	$\Delta_2 p_{d,t}$ (2)	$\Delta_3 p_{d,t}$ (3)	$\Delta_4 p_{d,t}$ (4)	$\Delta_5 p_{d,t}$ (5)	$\Delta_6 p_{d,t}$ (6)	$\Delta_7 p_{d,t}$ **(5)**	$\Delta_8 p_{d,t}$ **(6)**
$\text{Hedge}_f = 0 - PCP \times \Delta_\ell e_t^{j/€}$	0.0159	-0.00932	0.0693	0.0561	0.0681	0.0734	0.129	0.136
	[-0.020,0.052]	[-0.040,0.021]	[0.041,0.097]	[0.027,0.085]	[0.039,0.097]	[0.043,0.104]	[0.098,0.161]	[0.098,0.173]
$\text{Hedge}_f = 1 - PCP \times \Delta_\ell e_t^{j/€}$	0.0749	-0.00998	0.062	0.032	0.0655	0.0646	0.124	0.144
	[0.022,0.128]	[-0.054,0.034]	[0.024,0.100]	[-0.006,0.070]	[0.027,0.104]	[0.026,0.104]	[0.085,0.162]	[0.102,0.187]
$\text{Hedge}_f = 0 - LCP \times \Delta_\ell e_t^{j/€}$	0.893	0.727	0.737	0.673	0.625	0.545	0.512	0.501
	[0.830,0.956]	[0.676,0.778]	[0.688,0.785]	[0.623,0.723]	[0.574,0.675]	[0.492,0.598]	[0.457,0.568]	[0.441,0.561]
$\text{Hedge}_f = 1 - LCP \times \Delta_\ell e_t^{j/€}$	0.759	0.537	0.562	0.461	0.446	0.416	0.423	0.376
	[0.703,0.814]	[0.483,0.591]	[0.512,0.612]	[0.405,0.516]	[0.393,0.499]	[0.358,0.474]	[0.365,0.480]	[0.313,0.439]
$\text{Hedge}_f = 0 - USD \times \Delta_\ell e_t^{j/\$}$	0.00637	0.0571	0.141	0.126	0.167	0.162	0.242	0.265
	[-0.084,0.096]	[-0.008,0.122]	[0.082,0.199]	[0.068,0.183]	[0.110,0.224]	[0.104,0.220]	[0.184,0.299]	[0.206,0.324]
$\text{Hedge}_f = 1 - USD \times \Delta_\ell e_t^{j/\$}$	0.389	0.253	0.256	0.233	0.256	0.275	0.299	0.32
	[0.296,0.482]	[0.186,0.319]	[0.201,0.311]	[0.180,0.285]	[0.203,0.308]	[0.222,0.327]	[0.248,0.351]	[0.266,0.374]
$\text{Hedge}_f = 0 - USD \times \Delta_\ell e_t^{\$/€}$	0.89	0.835	0.798	0.731	0.657	0.657	0.659	0.718
	[0.788,0.991]	[0.756,0.914]	[0.725,0.871]	[0.660,0.801]	[0.582,0.731]	[0.578,0.735]	[0.580,0.737]	[0.636,0.800]
$\text{Hedge}_f = 1 - USD \times \Delta_\ell e_t^{\$/€}$	0.958	0.903	0.937	0.842	0.866	0.817	0.798	0.774
	[0.842,1.075]	[0.817,0.989]	[0.858,1.017]	[0.764,0.919]	[0.785,0.947]	[0.734,0.900]	[0.714,0.883]	[0.687,0.861]
R^2	0.00435	0.00588	0.00776	0.0088	0.00955	0.0104	0.0105	0.0102
N	1'193'681	1'098'605	1'004'365	970'353	847'758	779'696	715'680	685'048

Notes: f stands for firm, t for quarter, and d represents the product-country-firm-currency dimension. $\Delta_\ell x_t$ means $\log(x_t) - \log(x_{t-\ell})$. The bilateral exchange rate $e_t^{j/€}$ is expressed in euro per unit of currency j. All regressions include industry×country×year fixed effects. Standard errors are at country×product level. Data is from 2011 to 2017.

TABLE (A.12) Price adjustment regressions (coefficients) - large firms

	$\Delta_1 p_{d,t}$ (1)	$\Delta_2 p_{d,t}$ (2)	$\Delta_3 p_{d,t}$ (3)	$\Delta_4 p_{d,t}$ (4)	$\Delta_5 p_{d,t}$ (5)	$\Delta_6 p_{d,t}$ (6)	$\Delta_7 p_{d,t}$ (5)	$\Delta_8 p_{d,t}$ (6)
$\text{Hedge}_f = 0 - PCP \times \Delta_\ell e_t^{j/€}$	0.113	0.105	0.17	0.159	0.18	0.169	0.182	0.153
	[0.034,0.192]	[0.043,0.166]	[0.117,0.223]	[0.101,0.218]	[0.120,0.241]	[0.107,0.231]	[0.117,0.246]	[0.081,0.224]
$\text{Hedge}_f = 1 - PCP \times \Delta_\ell e_t^{j/€}$	0.161	0.112	0.129	0.0745	0.189	0.157	0.164	0.135
	[0.080,0.243]	[0.046,0.179]	[0.070,0.188]	[0.011,0.138]	[0.125,0.253]	[0.093,0.221]	[0.101,0.228]	[0.065,0.205]
$\text{Hedge}_f = 0 - LCP \times \Delta_\ell e_t^{j/€}$	1.018	0.92	0.793	0.77	0.753	0.661	0.555	0.501
	[0.883,1.153]	[0.816,1.023]	[0.697,0.890]	[0.673,0.867]	[0.653,0.854]	[0.557,0.766]	[0.447,0.662]	[0.388,0.613]
$\text{Hedge}_f = 1 - LCP \times \Delta_\ell e_t^{j/€}$	0.834	0.538	0.451	0.322	0.377	0.342	0.298	0.188
	[0.770,0.899]	[0.466,0.610]	[0.387,0.515]	[0.245,0.399]	[0.303,0.451]	[0.262,0.422]	[0.221,0.376]	[0.099,0.278]
$\text{Hedge}_f = 0 - USD \times \Delta_\ell e_t^{j/\$}$	-0.00323	0.0162	0.0747	0.15	0.149	0.155	0.18	0.129
	[-0.145,0.138]	[-0.093,0.126]	[-0.028,0.178]	[0.039,0.261]	[0.042,0.256]	[0.045,0.264]	[0.081,0.280]	[0.023,0.235]
$\text{Hedge}_f = 1 - USD \times \Delta_\ell e_t^{j/\$}$	0.573	0.433	0.361	0.304	0.383	0.371	0.359	0.343
	[0.470,0.675]	[0.351,0.515]	[0.290,0.432]	[0.234,0.373]	[0.313,0.454]	[0.297,0.445]	[0.286,0.433]	[0.263,0.423]
$\text{Hedge}_f = 0 - USD \times \Delta_\ell e_t^{\$/€}$	0.845	0.689	0.704	0.697	0.707	0.719	0.731	0.689
	[0.672,1.017]	[0.560,0.818]	[0.586,0.822]	[0.573,0.821]	[0.580,0.834]	[0.586,0.853]	[0.598,0.865]	[0.550,0.829]
$\text{Hedge}_f = 1 - USD \times \Delta_\ell e_t^{\$/€}$	1	1.005	0.856	0.825	0.942	0.923	0.855	0.802
	[0.851,1.149]	[0.894,1.116]	[0.748,0.964]	[0.714,0.937]	[0.829,1.055]	[0.808,1.039]	[0.735,0.976]	[0.670,0.934]
R^2	0.00961	0.0155	0.0225	0.0267	0.0269	0.0272	0.0266	0.0289
N	187'546	173'889	166'867	164'268	152'830	145'023	140'676	137'241

Notes: f stands for firm, t for quarter, and d represents the product-country-firm-currency dimension. $\Delta_\ell x_t$ means $\log(x_t) - \log(x_{t-\ell})$. The bilateral exchange rate $e_t^{j/€}$ is expressed in euro per unit of currency j. Data is from 2014 to 2017. All regressions include industry×country×year fixed effects. Standard errors are at country×product level. We only consider large firms, i.e., the ones that have more than 1000 employees.

Table (A.13) Price adjustment regressions (coefficients) - small firms

	$\Delta_1 p_{d,t}$ (1)	$\Delta_2 p_{d,t}$ (2)	$\Delta_3 p_{d,t}$ (3)	$\Delta_4 p_{d,t}$ (4)	$\Delta_5 p_{d,t}$ (5)	$\Delta_6 p_{d,t}$ (6)	$\Delta_7 p_{d,t}$ (5)	$\Delta_8 p_{d,t}$ (6)
$\text{Hedge}_f = 0 - PCP \times \Delta_\ell e_t^{j/€}$	-0.02	0.000471	0.0848	0.0412	0.0501	0.0648	0.102	0.144
	[-0.076,0.036]	[-0.048,0.049]	[0.041,0.128]	[-0.002,0.085]	[0.007,0.093]	[0.018,0.111]	[0.052,0.151]	[0.084,0.204]
$\text{Hedge}_f = 1 - PCP \times \Delta_\ell e_t^{j/€}$	0.101	0.0149	0.122	0.0704	0.0337	0.0512	0.0879	0.135
	[0.002,0.200]	[-0.069,0.098]	[0.053,0.192]	[0.005,0.136]	[-0.031,0.098]	[-0.015,0.118]	[0.024,0.152]	[0.065,0.205]
$\text{Hedge}_f = 0 - LCP \times \Delta_\ell e_t^{j/€}$	0.875	0.64	0.664	0.58	0.478	0.437	0.37	0.392
	[0.780,0.970]	[0.559,0.721]	[0.591,0.736]	[0.508,0.652]	[0.405,0.551]	[0.361,0.513]	[0.292,0.447]	[0.305,0.480]
$\text{Hedge}_f = 1 - LCP \times \Delta_\ell e_t^{j/€}$	0.404	0.441	0.739	0.667	0.666	0.675	0.76	0.795
	[0.242,0.566]	[0.318,0.565]	[0.619,0.859]	[0.543,0.792]	[0.547,0.784]	[0.549,0.800]	[0.631,0.889]	[0.660,0.930]
$\text{Hedge}_f = 0 - USD \times \Delta_\ell e_t^{j/\$}$	0.101	0.175	0.216	0.108	0.179	0.212	0.236	0.312
	[-0.045,0.246]	[0.073,0.278]	[0.129,0.303]	[0.021,0.195]	[0.094,0.263]	[0.131,0.294]	[0.149,0.324]	[0.222,0.403]
$\text{Hedge}_f = 1 - USD \times \Delta_\ell e_t^{j/\$}$	0.0557	0.0892	0.151	0.184	0.18	0.273	0.243	0.318
	[-0.255,0.367]	[-0.088,0.266]	[0.000,0.303]	[0.046,0.323]	[0.042,0.319]	[0.143,0.404]	[0.109,0.378]	[0.178,0.457]
$\text{Hedge}_f = 0 - USD \times \Delta_\ell e_t^{\$/€}$	0.898	0.968	0.782	0.566	0.481	0.548	0.433	0.584
	[0.688,1.108]	[0.809,1.126]	[0.631,0.932]	[0.424,0.709]	[0.333,0.630]	[0.401,0.696]	[0.287,0.579]	[0.432,0.735]
$\text{Hedge}_f = 1 - USD \times \Delta_\ell e_t^{\$/€}$	1.03	0.838	0.948	0.742	0.678	0.601	0.636	0.529
	[0.729,1.330]	[0.637,1.039]	[0.771,1.126]	[0.561,0.924]	[0.491,0.865]	[0.412,0.789]	[0.438,0.835]	[0.326,0.731]
R^2	0.00495	0.00619	0.00788	0.00885	0.00944	0.0105	0.011	0.0106
N	436'332	423'509	399'472	405'298	365'298	352'695	336'484	339'424

Notes: f stands for firm, t for quarter, and d represents the product-country-firm-currency dimension. $\Delta_\ell x_t$ means $\log(x_t) - \log(x_{t-\ell})$. The bilateral exchange rate $e_t^{j/€}$ is expressed in euro per unit of currency j. Data is from 2014 to 2017. All regressions include industry×country×year fixed effects. Standard errors are at country×product level. We only consider small firms, i.e., the ones that have less than 200 employees.

TABLE (A.14) Price adjustment regressions (coefficients) - differentiated goods

	$\Delta_1 p_{d,t}$ (1)	$\Delta_2 p_{d,t}$ (2)	$\Delta_3 p_{d,t}$ (3)	$\Delta_4 p_{d,t}$ (4)	$\Delta_5 p_{d,t}$ (5)	$\Delta_6 p_{d,t}$ (6)	$\Delta_7 p_{d,t}$ (7)	$\Delta_8 p_{d,t}$ (8)
$\text{Hedge}_f = 0 - PCP \times \Delta_\ell e_t^{j/€}$	0.058	-0.00577	0.0541	0.0535	0.18	0.154	0.201	0.104
	[-0.022,0.137]	[-0.064,0.052]	[-0.001,0.110]	[-0.007,0.114]	[0.117,0.243]	[0.088,0.221]	[0.140,0.262]	[0.032,0.175]
$\text{Hedge}_f = 1 - PCP \times \Delta_\ell e_t^{j/€}$	0.0704	-0.0818	0.0638	0.0296	0.209	0.176	0.198	0.135
	[-0.029,0.170]	[-0.165,0.001]	[-0.011,0.138]	[-0.046,0.105]	[0.131,0.286]	[0.097,0.256]	[0.124,0.271]	[0.055,0.216]
$\text{Hedge}_f = 0 - LCP \times \Delta_\ell e_t^{j/€}$	0.873	0.747	0.69	0.657	0.762	0.658	0.588	0.497
	[0.737,1.009]	[0.632,0.863]	[0.585,0.794]	[0.554,0.760]	[0.655,0.869]	[0.550,0.766]	[0.472,0.705]	[0.380,0.615]
$\text{Hedge}_f = 1 - LCP \times \Delta_\ell e_t^{j/€}$	0.757	0.405	0.36	0.203	0.304	0.229	0.212	0.0677
	[0.666,0.848]	[0.310,0.500]	[0.282,0.438]	[0.109,0.296]	[0.213,0.395]	[0.129,0.330]	[0.120,0.304]	[-0.036,0.172]
$\text{Hedge}_f = 0 - USD \times \Delta_\ell e_t^{j/\$}$	-0.0157	-0.00452	0.157	0.175	0.304	0.298	0.346	0.211
	[-0.196,0.165]	[-0.144,0.135]	[0.028,0.285]	[0.048,0.301]	[0.175,0.433]	[0.167,0.429]	[0.212,0.480]	[0.079,0.343]
$\text{Hedge}_f = 1 - USD \times \Delta_\ell e_t^{j/\$}$	0.432	0.337	0.28	0.25	0.383	0.353	0.34	0.276
	[0.319,0.544]	[0.250,0.424]	[0.208,0.351]	[0.170,0.330]	[0.302,0.465]	[0.270,0.436]	[0.259,0.420]	[0.189,0.363]
$\text{Hedge}_f = 0 - USD \times \Delta_\ell e_t^{\$/€}$	0.912	0.671	0.626	0.646	0.54	0.6	0.512	0.393
	[0.690,1.135]	[0.488,0.854]	[0.459,0.793]	[0.486,0.805]	[0.382,0.698]	[0.421,0.779]	[0.326,0.697]	[0.206,0.580]
$\text{Hedge}_f = 1 - USD \times \Delta_\ell e_t^{\$/€}$	0.981	0.952	1.002	0.899	0.974	0.861	0.769	0.685
	[0.825,1.138]	[0.834,1.070]	[0.885,1.119]	[0.774,1.024]	[0.851,1.097]	[0.733,0.988]	[0.642,0.897]	[0.542,0.828]
R^2	0.0116	0.0173	0.0221	0.0279	0.0286	0.0308	0.0344	0.0348
N	165'367	153'011	141'490	141'208	124'987	118'764	111'350	110'730

Notes: f stands for firm, t for quarter, and d represents the product-country-firm-currency dimension. $\Delta_\ell x_t$ means $\log(x_t) - \log(x_{t-\ell})$. The bilateral exchange rate $e_t^{j/€}$ is expressed in euro per unit of currency j. Data is from 2014 to 2017. All regressions include industry×country×year and size bins fixed effects. Standard errors are clustered at country×product level. We consider only differentiated products as per Rauch (1999) classification.

TABLE (A.15) Price adjustment regressions (coefficients) - undifferentiated goods

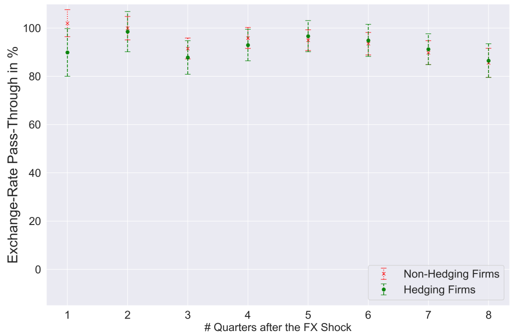
	$\Delta_1 p_{d,t}$ (1)	$\Delta_2 p_{d,t}$ (2)	$\Delta_3 p_{d,t}$ (3)	$\Delta_4 p_{d,t}$ (4)	$\Delta_5 p_{d,t}$ (5)	$\Delta_6 p_{d,t}$ (6)	$\Delta_7 p_{d,t}$ (7)	$\Delta_8 p_{d,t}$ (8)
$\text{Hedge}_f = 0 - PCP \times \Delta_\ell e_t^{j/€}$	0.00198	0.000551	0.0918	0.0798	0.0881	0.0999	0.115	0.142
	[-0.047,0.051]	[-0.041,0.042]	[0.056,0.128]	[0.044,0.116]	[0.051,0.125]	[0.061,0.139]	[0.074,0.156]	[0.093,0.191]
$\text{Hedge}_f = 1 - PCP \times \Delta_\ell e_t^{j/€}$	0.109	0.0508	0.104	0.0641	0.0751	0.088	0.111	0.136
	[0.037,0.181]	[-0.009,0.110]	[0.054,0.154]	[0.015,0.114]	[0.026,0.124]	[0.038,0.138]	[0.061,0.160]	[0.080,0.191]
$\text{Hedge}_f = 0 - LCP \times \Delta_\ell e_t^{j/€}$	0.864	0.756	0.766	0.691	0.593	0.539	0.452	0.454
	[0.778,0.951]	[0.688,0.823]	[0.703,0.829]	[0.625,0.756]	[0.528,0.659]	[0.472,0.606]	[0.383,0.521]	[0.379,0.529]
$\text{Hedge}_f = 1 - LCP \times \Delta_\ell e_t^{j/€}$	0.726	0.523	0.564	0.49	0.479	0.473	0.458	0.442
	[0.648,0.803]	[0.449,0.597]	[0.497,0.631]	[0.418,0.561]	[0.411,0.547]	[0.399,0.547]	[0.384,0.532]	[0.361,0.522]
$\text{Hedge}_f = 0 - USD \times \Delta_\ell e_t^{j/\$}$	0.0104	0.111	0.171	0.132	0.167	0.19	0.223	0.283
	[-0.105,0.125]	[0.028,0.194]	[0.101,0.242]	[0.060,0.204]	[0.098,0.236]	[0.120,0.259]	[0.156,0.290]	[0.211,0.354]
$\text{Hedge}_f = 1 - USD \times \Delta_\ell e_t^{j/\$}$	0.439	0.238	0.226	0.23	0.216	0.292	0.257	0.291
	[0.292,0.586]	[0.134,0.342]	[0.140,0.312]	[0.157,0.304]	[0.142,0.290]	[0.220,0.365]	[0.184,0.329]	[0.216,0.366]
$\text{Hedge}_f = 0 - USD \times \Delta_\ell e_t^{\$/€}$	0.735	0.796	0.777	0.677	0.627	0.662	0.651	0.742
	[0.601,0.869]	[0.697,0.895]	[0.688,0.866]	[0.591,0.764]	[0.536,0.717]	[0.568,0.755]	[0.558,0.745]	[0.644,0.839]
$\text{Hedge}_f = 1 - USD \times \Delta_\ell e_t^{\$/€}$	0.951	0.945	0.913	0.83	0.849	0.878	0.811	0.763
	[0.774,1.127]	[0.816,1.075]	[0.797,1.029]	[0.719,0.942]	[0.732,0.965]	[0.760,0.996]	[0.689,0.933]	[0.642,0.884]
R^2	0.0044	0.00561	0.00754	0.00877	0.00891	0.0101	0.0101	0.01
N	602'355	576'860	548'050	549'065	501'414	480'823	462'096	460'410

Notes: f stands for firm, t for quarter, and d represents the product-country-firm-currency dimension. $\Delta_\ell x_t$ means $\log(x_t) - \log(x_{t-\ell})$. The bilateral exchange rate $e_t^{j/€}$ is expressed in euro per unit of currency j. Data is from 2014 to 2017. All regressions include industry×country×year and size bins fixed effects. Standard errors are clustered at country×product level. We only consider undifferentiated products as per Rauch (1999) classification.

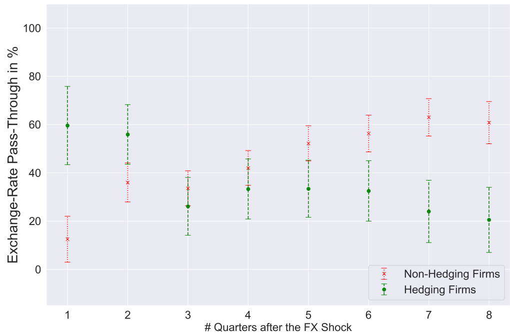
E.2 Additional Results on Exchange-Rate Pass-Through

In this subsection, we report the exchange-rate pass-through coefficients of small firms (Figure A.2) and undifferentiated goods (Figure A.3). Interestingly, we do not observe significant differences between the price adjustment of small hedging and non-hedging firms. Perhaps, this is because small firms cannot effectively hedge their currency risk. Alternatively, it is possible that the fraction of revenues that they hedge is not large enough to result in a significant difference in exchange-rate pass-through.

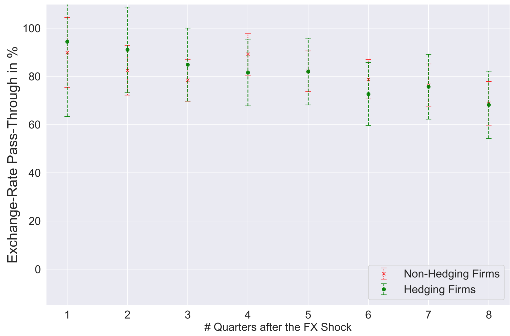
Finally, the dynamics of the adjustments of undifferentiated products still show differences among hedging and non-hedging firms, although less pronounced. Arguably, this can be ascribed to the fact that it is harder for firms to influence the adjustment of these kinds of products as they are by definition more substitutable.



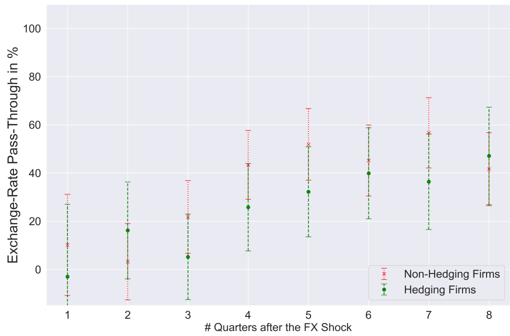
(a) PCP with respect to the LC/EUR rate.



(b) LCP with respect to the LC/EUR rate.



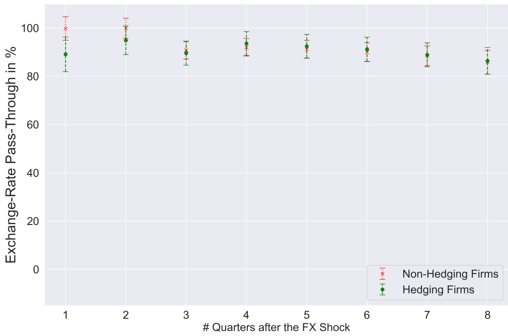
(c) USD with respect to the LC/USD rate.



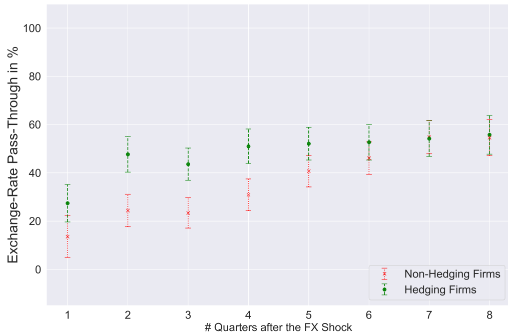
(d) USD with respect to the USD/EUR rate.

FIGURE (A.2) Dynamic exchange-rate pass-through for small firms by hedging type.

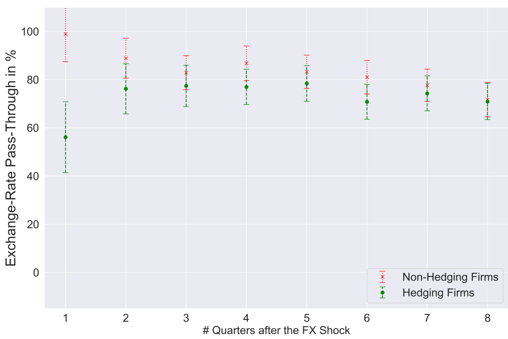
Notes: The graph reports the exchange-rate pass-through to prices to a one percent exchange-rate depreciation at different time horizons for non-hedging firms and hedging firms. The coefficients are estimated with size and industry×country×year fixed effects. Green dashed and red dotted marks represent the reactions of hedging and non-hedging firms, respectively. The time span is 2014-2017. Standard errors are clustered at the product level, while confidence intervals are at 90% level. In these regressions, we only consider firms with less than 200 employees.



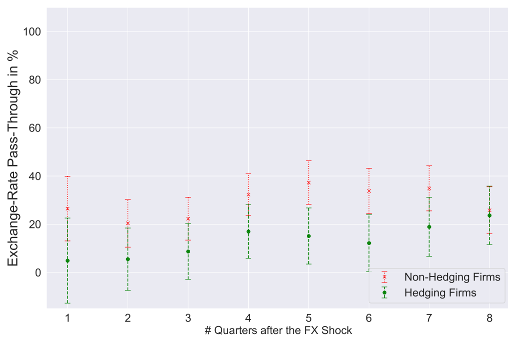
(a) PCP with respect to the LC/EUR rate.



(b) LCP with respect to the LC/EUR rate.



(c) USD with respect to the LC/USD rate.



(d) USD with respect to the USD/EUR rate.

FIGURE (A.3) Dynamic exchange-rate pass-through for undifferentiated products by hedging type

Notes: The graph reports the exchange-rate pass-through to prices to a one percent exchange-rate depreciation at different time horizons for non-hedging firms and hedging firms. The coefficients are estimated with size and industry×country×year fixed effects. Green dashed and red dotted marks represent the reactions of hedging and non-hedging firms, respectively. The time span is 2014-2017. Standard errors are clustered at the product level, while confidence intervals are at 90% level. In these regressions, we only consider undifferentiated products (according to Rauch, 1999 classification)

E.3 Exchange-Rate Pass-Through Quantities

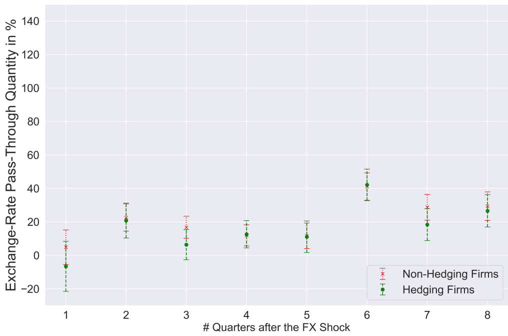
In this subsection, we extend the analysis and focus on export quantities. To do so, we regress changes in quantities onto the same covariates of Section 1.8. Specifically, we estimate the following equation:

$$
\begin{aligned}
\Delta_\ell quantity_{d,t} = \alpha_0 & \qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad \text{(A.1)} \\
& + \alpha_1 \cdot \text{PCP} \cdot \Delta_\ell e_t^{j/€} + \alpha_2 \cdot \text{PCP} \cdot \text{Hedge}_f \cdot \Delta_\ell e_t^{j/€} \\
& + \alpha_3 \cdot \text{LCP} \cdot \Delta_\ell e_t^{j/€} + \alpha_4 \cdot \text{LCP} \cdot \text{Hedge}_f \cdot \Delta_\ell e_t^{j/€} \\
& + \alpha_5 \cdot \text{USD} \cdot \Delta_\ell e_t^{j/\$} + \alpha_6 \cdot \text{USD} \cdot \text{Hedge}_f \cdot \Delta_\ell e_t^{j/\$} \\
& + \alpha_7 \cdot \text{USD} \cdot \Delta_\ell e_t^{\$/€} + \alpha_8 \cdot \text{USD} \cdot \text{Hedge}_f \cdot \Delta_\ell e_t^{\$/€} \\
& + \text{Industry} \times \text{Country} \times \text{Year} + \text{ Size Bins} + \ u_{d,t}
\end{aligned}
$$

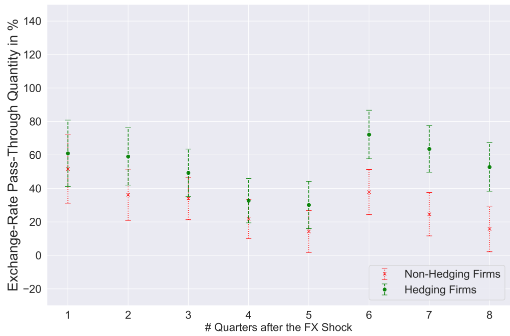
where d represents the product-country-firm-currency dimension. The time period is in quarters, and $\Delta_\ell x_t$ means $\log(x_t) - \log(x_{t-\ell})$. The exchange rates $e_t^{j/i}$ is expressed in currency i per unit of currency j. Thus, the estimated coefficients represent the price elasticities to a 1% depreciation of the euro or of the dollar after ℓ quarters. Similarly to Amiti et al., 2022, we include industry×country×time to absorb a wide array of time-varying dominants, such as differences across countries and sectors, different growth or inflation rates, the average industry degree of good differentiation, and so forth. Moreover, we saturate the specification with size bins effects as larger firms usually have bigger markups and thus could absorb exchange-rate shocks differently. Finally, standard errors are clustered at the product level, and summary statistics are reported at the beginning of this appendix.

Overall, we do not observe significant differences in quantity responses between hedging and non-hedging firms. The only exception are goods denominated in local currency. For these latter, hedging firms adjust their quantity more than non-hedging ones, six quarters after the exchange-rate shock (see Figure A.4 panel (b)).

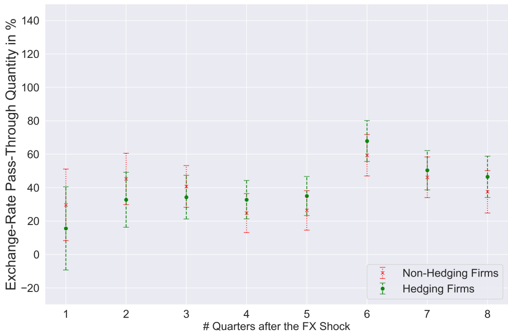
In the subsequent figures, we report the results by size (small vs large firms) and by product type (differentiated vs undifferentiated goods) in the same spirit of the analyses carried out for the price dynamics. The sample split shows interesting patterns, however, their interpretation is not trivial. Arguably, they should be read through the lenses of theory, and thus we leave these aspects for future research.



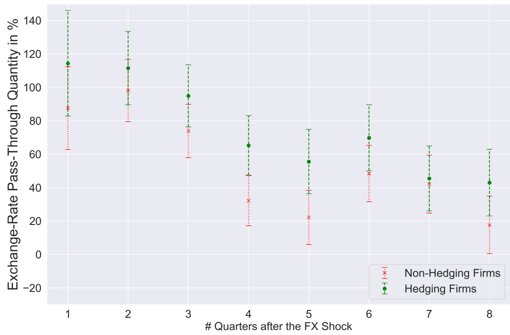
(a) PCP with respect to the LC/EUR rate.



(b) LCP with respect to the LC/EUR rate.



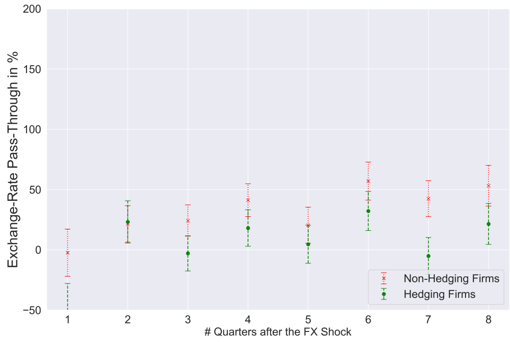
(c) USD with respect to the LC/USD rate.



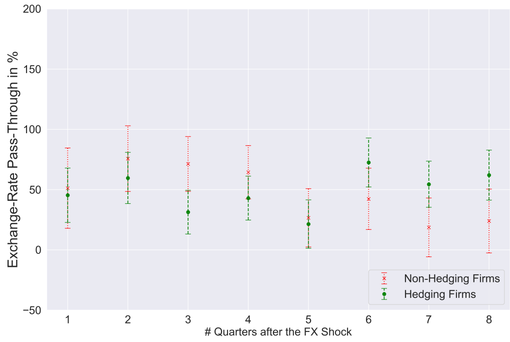
(d) USD with respect to the USD/EUR rate.

FIGURE (A.4) Dynamic exchange-rate pass-through quantity by hedging type

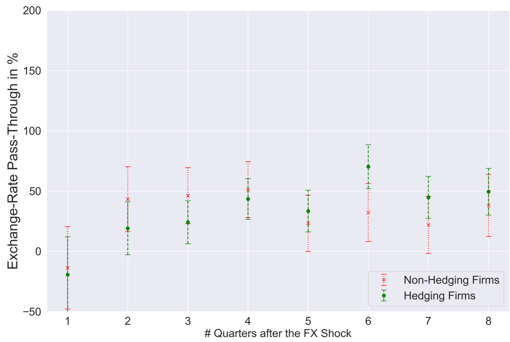
Notes: The graph reports the exchange-rate pass-through to quantities to a one percent exchange-rate depreciation at different time horizons for non-hedging firms and hedging firms. The coefficients are estimated with size and industry×country×year fixed effects. Green dashed, and red dotted marks represent the reactions of hedging and non-hedging firms, respectively. The time span is 2014-2017. Standard errors are clustered at the product level, while confidence intervals are at 90% level.



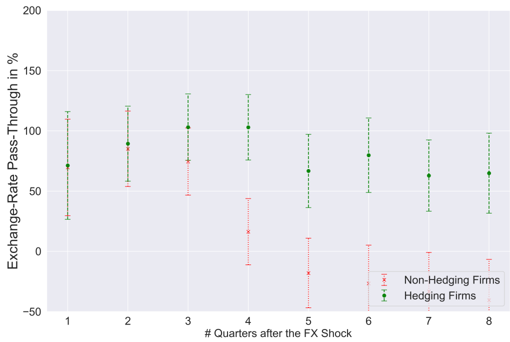
(a) PCP with respect to the LC/EUR rate.



(b) LCP with respect to the LC/EUR rate.



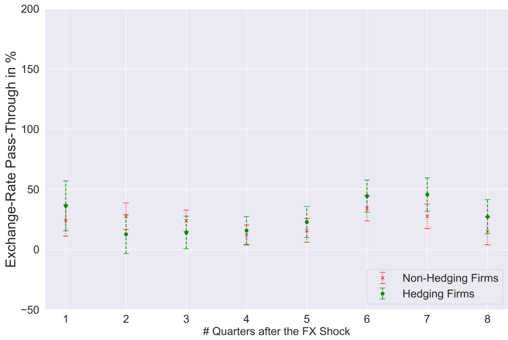
(c) USD with respect to the LC/USD rate.



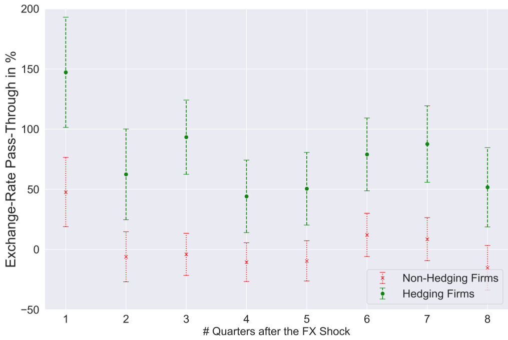
(d) USD with respect to the USD/EUR rate.

FIGURE (A.5) Dynamic exchange-rate pass-through quantity for large firms by hedging type

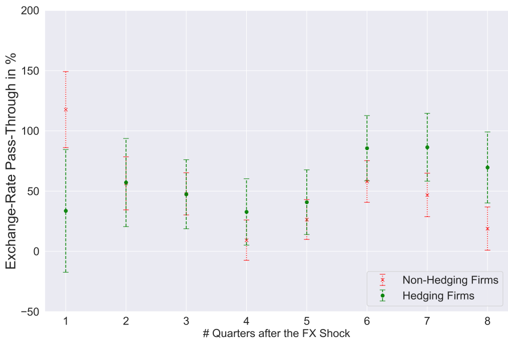
Notes: The graph reports the exchange-rate pass-through to quantities to a one percent exchange-rate depreciation at different time horizons for non-hedging firms and hedging firms. The coefficients are estimated with size and industry×country×year fixed effects. Green dashed and red dotted marks represent the reactions of hedging and non-hedging firms, respectively. The time span is 2014-2017. Standard errors are clustered at the product level, while confidence intervals are at 90% level. We only consider large firms, i.e., the ones that have more than 1000 employees.



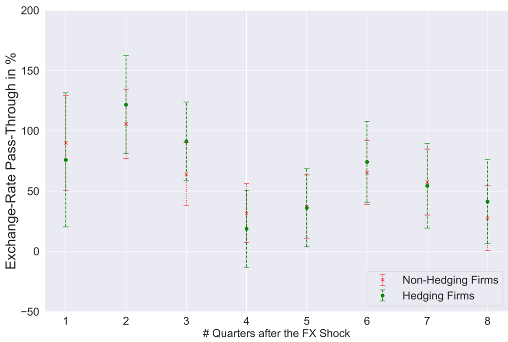
(a) PCP with respect to the LC/EUR rate.



(b) LCP with respect to the LC/EUR rate.



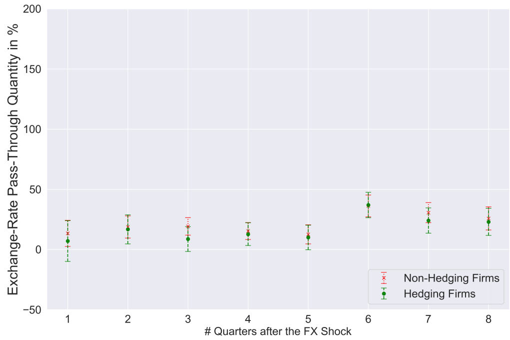
(c) USD with respect to the LC/USD rate.



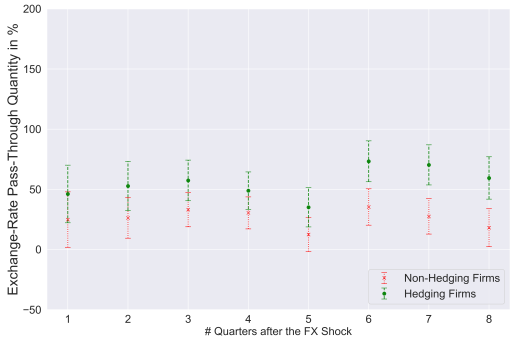
(d) USD with respect to the USD/EUR rate.

FIGURE (A.6) Dynamic exchange-rate pass-through quantity for small firms by hedging type

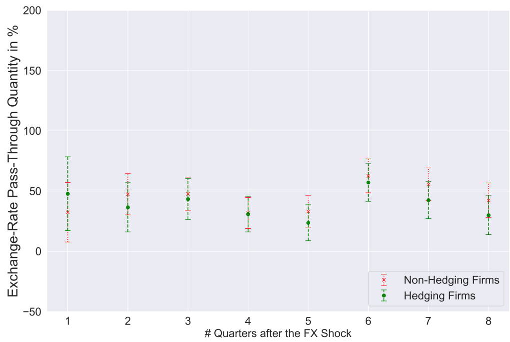
Notes: The graph reports the exchange-rate pass-through to quantities to a one percent exchange-rate depreciation at different time horizons for non-hedging firms and hedging firms. The coefficients are estimated with size and industry×country×year fixed effects. Green dashed and red dotted marks represent the reactions of hedging and non-hedging firms, respectively. The time span is 2014-2017. Standard errors are clustered at the product level, while confidence intervals are at 90% level. We only consider small firms, i.e., the ones that have less than 200 employees.



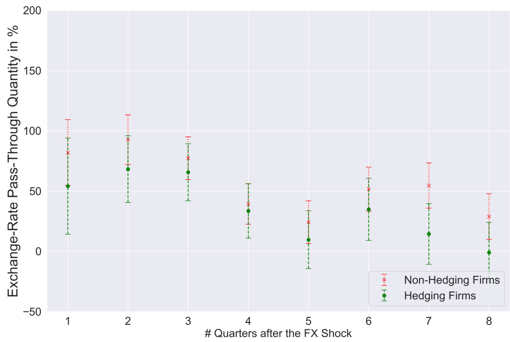
(a) PCP with respect to the LC/EUR rate.



(b) LCP with respect to the LC/EUR rate.



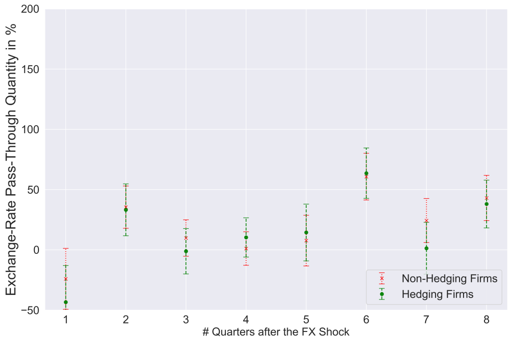
(c) USD with respect to the LC/USD rate.



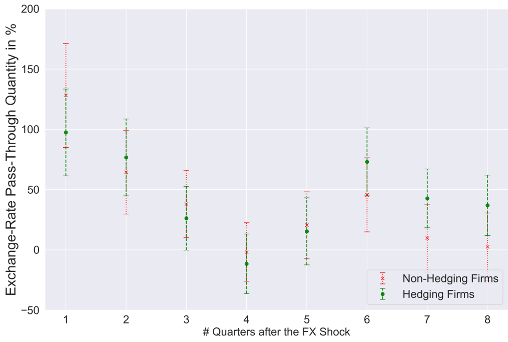
(d) USD with respect to the USD/EUR rate.

FIGURE (A.7) Dynamic exchange-rate pass-through quantity for undifferentiated products by hedging type

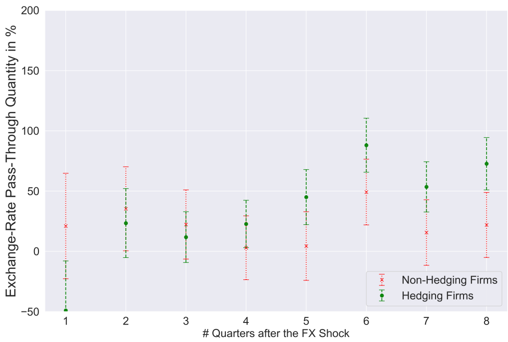
Notes: The graph reports the exchange-rate pass-through to quantities to a one percent exchange-rate depreciation at different time horizons for non-hedging firms and hedging firms. The coefficients are estimated with size and industry×country×year fixed effects. Green dashed and red dotted marks represent the reactions of hedging and non-hedging firms, respectively. The time span is 2014-2017. Standard errors are clustered at the product level, while confidence intervals are at 90% level. We only consider undifferentiated products as per Rauch (1999) classification.



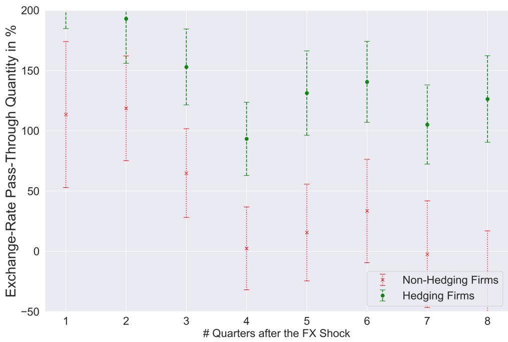
(a) PCP with respect to the LC/EUR rate.



(b) LCP with respect to the LC/EUR rate.



(c) USD with respect to the LC/USD rate.



(d) USD with respect to the USD/EUR rate.

FIGURE (A.8) Dynamic exchange-rate pass-through quantity for differentiated products by hedging type

Notes: The graph reports the exchange-rate pass-through to quantities to a one percent exchange-rate depreciation at different time horizons for non-hedging firms and hedging firms. The coefficients are estimated with size and industry×country×year fixed effects. Green dashed and red dotted marks represent the reactions of hedging and non-hedging firms, respectively. The time span is 2014-2017. Standard errors are clustered at the product level, while confidence intervals are at 90% level. We only consider differentiated products as per Rauch (1999) classification.

Appendix B

Appendices of Chapter 2

B.1 Additional Descriptives and Results

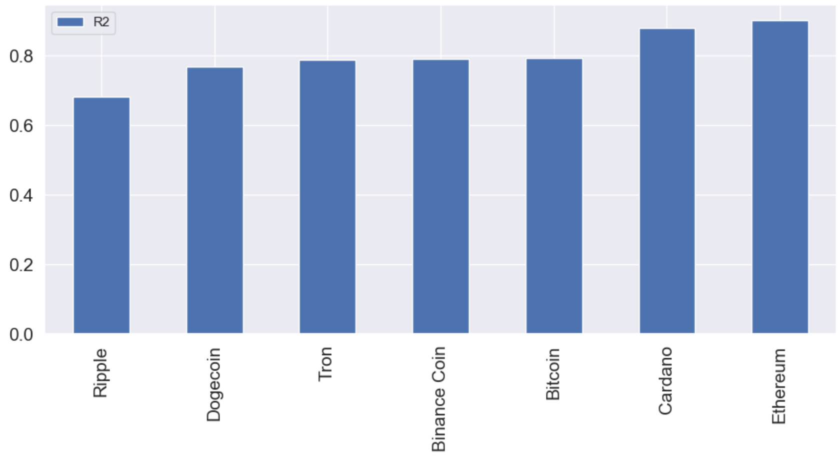


FIGURE (B.1) Reverse regressions

Notes: This figure shows the R^2s from regressions of the crypto factor on each of the input price series, as described in Section 2.2.

TABLE (B.1) Equity Eikon RICs by country

Country	Equity Indexes	Tech Indexes	Financial Indexes	Small Caps Indexes
United States	.SPX	.SPLRCT	.SPSY	.SPCY
China	.SSEC	.SZFI	.SZFI	
Japan	.JPXNK400			.TOPXS
Germany	.GADXHI	.CXPHX	.CXPVX	
India	.BSESN	.BSETECK	.BSEBANK	
UK	.FTSE	.FTTASX		.FTSC
France	.FCHI	.FRTEC	.FRFIN	.CACS
Brazil	.BVSP		TRXFLDBRPFIN	.SMLL
Italy	.FTMIB			.FTITSC
Canada	.GSPTSE	.SPTTTK	.SPTTFS	.SPTSES
Russia	.IRTS		.RTSFN	
South Korea	.KS11	.KRXIT	.KRXBANK	

Australia	.AXJO	.AXIJ	.AXFJ	.AXSO
Spain	.IBEX		.IFNC.MA	.IBEXS
Mexico	.MXX		.MXSE07	.MXXSM
Indonesia	.JKSE			
Turkey	.XU100		.XUMAL	
Netherlands	.AEX		.SXFP	.ASCX
Saudi Arabia	.TASI			
Switzerland	.SSHI	.C9500T	.C8700T	.SSCC
Argentina	.IBG		.TRXFLDARPFIN	
Sweden	.OMXS30			.OMXSSCPI
Poland	.WIG	.COMP	.BNKI	
Belgium	.BFX	.BETEC	.BEFIN	.BELS
Thailand	.SET100	.THTECH	.THFINCIAL	
Iran				
Austria	.ATX		.TRXFLDATPFIN	
Norway	.OBX			.OSESX
UAE	.DFMGI		.DFMIF	
Nigeria	.NGSEINDEX			
Israel	.TRXFLDILT			
South Africa	.JALSH	.JTECH	.JFINA	.JSMLC
Hong Kong	.HSI	.HSCIIT	.HSCIF	.HSSI
Ireland	.ISEQ			
Denmark	.OMXCBPI			
Singapore	.STI			.FTFSTS
Malaysia	.KLSE	.KLTE	.KLFI	.KLFTSC
Colombia	.COLCAP			
Philippines	.PSI		.PSFI	
Pakistan	.KSE		.TRXFLDPKPFIN	
Chile	.SPCLXIGPA		.TRXFLDCLPFIN	
Finland	.OMXHPI			
Bangladesh	.dMIBD00000P			
Egypt	.EGX30		.TRXFLDEGPFIN	
Vietnam	.VNI			
Portugal	.PSI20	.PTTEC	.PTFIN	
Czech Republic	.PIX			
Romania	.BETI			
Peru	.SPBLPGPT			
New Zealand	.NZ50			.NZSC

Notes: This table lists the indices used for constructing the global equity factor and each of the equity sub-factors. The selected countries are the fifty largest by GDP. All indices are from Eikon/Thomson Reuters.

Table (B.2) p-values of the differences in correlation before and after 2020

	Bitcoin	Crypto F	First Gen	IoTs	Smart C.	DeFi	Metaverse
Bitcoin	n.a.						
Crypto F	0.390	n.a.					
First Gen	n.a.	n.a.	n.a.				
IoTs	n.a.	n.a.	n.a.	n.a.			
Smart C.	n.a.	n.a.	n.a.	n.a.	n.a.		
DeFi	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	
Metaverse	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
S&P 500	0.000	0.005	n.a.	n.a.	n.a.	n.a.	n.a.
Equity F	0.000	0.006	n.a.	n.a.	n.a.	n.a.	n.a.
Small Caps F	0.000	0.012	n.a.	n.a.	n.a.	n.a.	n.a.
Tech Factor	0.000	0.001	n.a.	n.a.	n.a.	n.a.	n.a.
Equity F (no Tech)	0.876	0.765	n.a.	n.a.	n.a.	n.a.	n.a.
Financials F	0.004	0.029	n.a.	n.a.	n.a.	n.a.	n.a.
Equity F (no Fin)	0.037	0.090	n.a.	n.a.	n.a.	n.a.	n.a.
Dollar Index	0.060	0.010	n.a.	n.a.	n.a.	n.a.	n.a.
VIX	0.000	0.008	n.a.	n.a.	n.a.	n.a.	n.a.
Oil	0.673	0.890	n.a.	n.a.	n.a.	n.a.	n.a.
Gold	0.962	0.544	n.a.	n.a.	n.a.	n.a.	n.a.

Notes: The matrix reports the p-values of the interaction coefficient of the following set of regressions: y = constant $+\beta_1$x + β_2After2020 + β_3xAfter2020 + ϵ. After2020 is equal to one from January 2020. Standard errors are robust. Data is from January 2018 to March 2023.

Table (B.3) Risk-aversion regressions

		Global Crypto Factor				Global Equity Factor			
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	30 days	2.061***							
		(0.315)							
	45 days		1.711***						
			(0.265)						
	60 days			1.763***					
				(0.245)					
Var(Bitcoin)	90 days				1.851***				
					(0.249)				
	30 days	-27.939***				-63.585***			
		(1.686)				(4.020)			
	45 days		-22.804***				-49.620***		
			(1.290)				(2.813)		
	60 days			-21.133***				-41.336***	
				(1.141)				(2.245)	
Var(MSCI World)	90 days				-18.727***				-30.706***
					(1.006)				(1.876)
Constant		-0.163***	-0.172***	-0.200***	-0.266***	70.975***	55.650***	46.562***	34.904***
		(0.022)	(0.025)	(0.028)	(0.037)	(4.421)	(3.095)	(2.471)	(2.067)
Observations		1,273	1,258	1,243	1,213	1,275	1,261	1,246	1,217
R-squared		0.084	0.1	0.121	0.159	0.176	0.185	0.182	0.163

Notes: The table reports the results of regressing the equity and the crypto factor on the variances of the MSCI World Index and Bitcoin. Standard errors are in parentheses. *, **, and *** correspond to significance at the 10%, 5%, and 1% levels respectively.

TABLE (B.4) Correlations across risk-taking proxies

	Δ 30-day Crypto Risk Aversion	Δ 45-day Crypto Risk Aversion	Δ 60-day Crypto Risk Aversion	Δ 90-day Crypto Risk Aversion	Δ 30-day Global Equity Risk Aversion	Δ 45-day Global Equity Risk Aversion	Δ 60-day Global Equity Risk Aversion	Δ 90-day Global Equity Risk Aversion	Δ Intermediary Capital Ratio	Δ Intermediary Leverage Ratio Squared
Δ 30-day Crpyto Risk Aversion	1.000									
Δ 45-day Crpyto Risk Aversion	0.791	1.000								
Δ 60-day Crpyto Risk Aversion	0.798	0.820	1.000							
Δ 90-day Crpyto Risk Aversion	0.761	0.787	0.821	1.000						
Δ 30-day Global Equity Risk Aversion	0.181	0.176	0.190	0.205	1.000					
Δ 45-day Global Equity Risk Aversion	0.124	0.156	0.154	0.170	0.973	1.000				
Δ 60-day Global Equity Risk Aversion	0.090	0.110	0.124	0.133	0.951	0.992	1.000			
Δ 90-day Global Equity Risk Aversion	0.050	0.062	0.066	0.079	0.900	0.959	0.984	1.000		
Δ Intermediary Capital Ratio	-0.122	-0.144	-0.170	-0.182	-0.485	-0.414	-0.366	-0.292	1.000	
Δ Intermediary Leverage Ratio Squared	0.110	0.116	0.172	0.197	0.613	0.551	0.510	0.434	-0.872	1.000

Notes: This table shows pairwise daily correlations between changes in the measures of risk aversion, computed using Equations 2.2 and 2.3, and changes in the intermediary risk-appetite measures by He et al., 2017 available at https://voices.uchicago.edu/zhiguohe/data-and-empirical-patterns/intermediary-capital-ratio-and-risk-factor/. Series are standardized, and data is from January 2018 to March 2023.

TABLE (B.5) Crypto returns and US monetary policy

	Δ Bitcoin		Δ Crypto Factor	
	(1)	(2)	(3)	(4)
Δ Shadow FFR	-0.0531		-0.101*	
	(-1.41)		(-2.00)	
BRW Shocks		-0.0613*		-0.0791**
		(-1.75)		(-2.28)
Constant	0.0366	0.0366	0.0141	0.0141
	(0.78)	(0.78)	(0.26)	(0.26)
N	48	48	48	48
R^2	0.0263	0.0351	0.0705	0.0431
R^2 (adj)	0.00516	0.0141	0.0503	0.0223

Notes: Variables are standardized. Frequency is monthly and data is from January 2018 to December 2021. Shadow FFR are from Wu et al., 2016 and BRW shocks are from Bu et al., 2021. Standard errors are robust and t-statistics are parentheses. *, **, *** correspond to 10%, 5%, and 1% significance, respectively.

Appendix C

Appendices of Chapter 3

C.1 Extension: Introduction of a CBDC Backed by Treasuries under Quantitative Easing

DEFINITION 5. *If the demand for CBDC deposits is such that $d > \bar{d}$, given the central bank quantitative easing policy $(R^B,\ R^r,\ \delta,\ \bar{\alpha})$, with interest rate policy $R^B = R^r$ and balance sheet policy $(B^{CB},\ E^{CB}) = (d,\ M - \bar{d})$, the banking equilibrium consists of rates of return $(R^h,\ R^d,\ R^c,\ R^E)$ and choices $(h,\ d,\ c,\ e,\ E,\ D,\ M,\ K)$ such that:*

(a) Conditions (3.4), (3.16), (3.17), (3.18), (3.19), (3.22), (3.21) hold;

(b) (h, d) is optimal for households, given (R^d, R^h); c is optimal for cash pools, given R^c; e is optimal for investors, given (R^B, R^E);

(c) $M \geqslant \delta h$;

(d) $c_b = c - (B - d)$;

(e) $e + M - \bar{d} = E$.

Under QE policy, there is a positive amount of excess reserves in the system due to the asset-purchase programs. Thus, the liquidity requirement is not binding. When the central bank decides to hold treasuries against CBDC deposits, the amount of risky investments in the economy (K) increases but not the size of the bank (S). This happens because the decrease in deposits is fully offset by increased cash pools' funding as there are $\tilde{d}$ less bonds available in the economy. At the same time, the reduction in deposits allows the commercial bank to further decrease its reserves, increasing the amount of investable debt. Thus, the commercial bank has more funding to allocate in risky loans. The difference with the standard policy setting is that, in this scenario, bank reserves are not backed by treasuries but by bank equity. Therefore, a reduction in bank reserves has no impact on the treasury market, and it does not allow cash pools to purchase more treasuries. We find that the bank's leverage decreases and that the larger investable debt increases bankruptcy costs.

In this scenario, since some bank reserves are swapped into CBDC deposits, and some are simply reduced, the central bank asset side is less risky. Therefore, the introduction of CBDCs backed by treasuries, under QE policy, reduces the seigniorage volatility. Consequently, the economy benefits from more stable taxes.

C.2 CBDC Equilibrium Effects - Proofs

The superscripts s and q denote the standard policy and the QE policy scenarios, respectively, without the CBDC. In this section, we always consider the QE policy when the amount of CBDC deposits exceeds the amount of excess reserves in the economy ($h > \bar{h}$) and the liquidity requirement is binding. With the introduction of a CBDC, a B superscript indicates when the central bank decides to hold government bonds against CBDC deposits and a E superscript when the CBDC is backed by bank equity (risky securities). The Δ_x^{sB} is defined as the difference between the generic variable x in the case of standard policy with CBDC backed by treasuries and the same variable in a scenario with the same policy but no CBDC: $\Delta_x^{sB} = x^{sB} - x^s$. Similarly, the differences $\Delta_x^{sE} = x^{sE} - x^s$, $\Delta_x^{qB} = x^{qB} - x^q$, and $\Delta_x^{qE} = x^{qE} - x^q$ illustrate the variation with the respective baseline scenarios.

C.2.1 Agents' optimal choices

We assume that the monetary policy interest rates (R^r, R^B), the amount of treasuries in the economy (B), and the convenience yield of deposits (ρ_h) do not change with the introduction of a CBDC. If we also assume that the initial endowments of the agents do not change, it implies that the optimal amounts of savings for depositors and cash pools remain the same with the introduction of a CBDC.

C.2.2 Bank deposits and reserves

In scenarios without the CBDC, bank deposits are the same: $h^s = h^q$. With the introduction of a CBDC, we always have that part of the depositors' savings goes to the central bank and, therefore, bank deposits decrease:

$$h^{sB} = h^{sE} = h^s - d,$$
$$h^{qB} = h^{qE} = h^q - d,$$

with $\Delta_h^{sB} = \Delta_h^{sE} = \Delta_h^{qB} = \Delta_h^{qE} = -d < 0$.

The amount of bank reserves in standard policy is given by $M^{sB} = M^{sE} = \delta(h^s - d) = M^s - \delta d$, because the liquidity requirement is binding. Under QE policy, the commercial bank swaps $\bar{d}$ excess reserves into CBDC deposits. After this point, the liquidity requirement is binding, and at each further unit of bank deposits reduction corresponds δ units of reserves reduction. We have that $M^{qB} = M^{qE} = M^q - \bar{d} - \delta\tilde{d}$, where $\tilde{d} = d - \bar{d}$. We obtain $\Delta_M^{sB} = \Delta_M^{sE} = -\delta d < 0$, and $\Delta_M^{qB} = \Delta_M^{qE} = -d + (1-\delta)\tilde{d} < 0$.

C.2.3 Wholesale funding

The wholesale funding is given by the cash pool demand of savings, minus all the available government bonds in the economy. The amount of treasuries available for cash pools is given by the amount of bonds issued by the government minus the ones bought by the central bank. In standard policy $c_b^s = c - (B - M^s)$, while under QE policy the central bank does not hold any bond and $c_b^q = c - B$.

With the introduction of a CBDC backed by treasuries in standard policy, the cash pool funding becomes $c_b^{sB} = c^s - (B^s - M^{sB} - d)$, which translate in an increase of $\Delta_{c_b}^{sB} = c_b^{sB} - c_b^s = (1-\delta)d > 0$. When the CBDC deposits are backed by equity, the mechanism is similar to before, i.e., $c_b^{sE} = c^s - (B^s - M^{sE})$, which corresponds to a decline of $\Delta_{c_b}^{sE} = c_b^{sE} - c_b^s = -\delta d < 0$, given by the decrease in the reserves. Under QE policy, the bank's wholesale funding when the central bank holds bonds against CBDC deposits is $c_b^{qB} = c^q - (B^q - d)$, with an increase of $\Delta_{c_b}^{QB} = c_b^{qB} - c_b^q = \tilde{d} > 0$. The funding does not change if the central bank decides to hold only equity: $c_b^{qE} = c^q - B^q$, with $\Delta_{c_b}^{qE} = c_b^{qE} - c_b^q = 0$.

C.2.4 Investable debt, bank equity and risky investment

As in equation (3.18), we define the investable debt of the bank as all the debt fundings that can be invested in the risky technology, excluding the reserves. In all scenarios, the investable debt is determined by:

$$D = h + c_b - M.$$

Under standard policy with CBDC backed by treasuries, there is no difference with the baseline: $\Delta_D^{sB} = 0$. However, if the central bank decides to allocate these funds in bank equity, then the investable debt declines by $\Delta_D^{sE} = -d < 0$. On the other hand, under quantitative easing policy, the CBDC investment in the safe asset translates in an increase in the debt that the banks can use to fund the risky technology, $\Delta_D^{qB} = d - (1-\delta)\tilde{d} > 0$, while an investment in bank equity decreases it, $\Delta_D^{qE} = -(1-\delta)\tilde{d} < 0$.

Let's define $\gamma = \frac{\bar{\alpha}}{1-\bar{\alpha}}$ for simplicity in the notation. At equilibrium, as in equation (3.22), the amount of bank equity is fixed at $E = \gamma D$, and, because of condition (3.19), the risky investment is always given by $K = (1+\gamma)D$. For both equity and risky investment, the results are the same as for the investment debt, but scaled by γ and $1+\gamma$, respectively.

C.2.5 Commercial bank size

We measure the bank size as the sum of all its liabilities or all its assets:

$$S = h + c_b + E = M + K.$$

The introduction of a CBDC in standard policy always leads to a decline in the bank size. In fact, $\Delta_S^{sB} = -\delta d < 0$ and $\Delta_S^{sE} = -(1+\delta+\gamma)d < 0$. Instead, in a QE policy setting, we have that $\Delta_S^{qB} = \gamma[d - (1-\delta)\tilde{d}] > 0$ and $\Delta_S^{qE} = -d - \gamma(1-\delta)\tilde{d} < 0$.

C.2.6 Bankruptcy costs

Let $\hat{y}$ be the minimum return on the risky technology that allows the bank to repay its creditors. It follows that $\hat{y}$ is such that $K\hat{y} + MR^r = hR^h(1+\mu_h) + c_bR^c$, and the bank is solvent for $y > \hat{y}$. The bankruptcy costs are then given by:

$$\phi = hR^h(1+\mu_h) + c_bR^c - MR^r - Ky,$$

when $y \leqslant \hat{y}$. At equilibrium, it holds that $R^c = R^B$ as in (3.16), $R^h(1+\mu_h) = (1-\delta)R^B + \delta R^r$ for condition (3.17), and $D = h + c_b - M = \frac{K}{(1+\gamma)}$ as defined in section C.2.4. This implies that $\phi = DR^B - Ky$ and $\hat{y} = \frac{R^B}{1+\gamma}$. Hence, the bankruptcy costs can be written as:

$$\phi = \left[R^B - (1+\gamma)y\right]D.$$

For this reason, all the results are the same as for the investable debt D, but scaled by $\big[R^B - (1+\gamma)y\big]$, that is always positive in bankruptcy because $y \leqslant \hat{y}$.

C.2.7 Seignorage

The seignorage is defined as the profit made by the government. In standard policy, this profit is given by $\theta^s = \big(R^B - R^r\big)M^s$, while under quantitative easing policy we have $\theta^q = \big(V(y) - R^B\big)M^q$. With the introduction of a CBDC, there is an additional term that depends on what the central bank decides to hold against the new funds. If CBDC deposits are backed by bonds, then the seignorage has an additional profit of $\big(R^B - (1+\mu_d)R^d\big)$ per unit of CBDC. Instead, if it they are backed by bank equity, then the additional profit per unit of CBDC becomes $\big(V(y) - (1+\mu_d)R^d\big)$.

Therefore, with the introduction of the CBDC in the standard policy we have that $\theta^{sB} = \big(R^B - R^r\big)M^{sB} + \big(R^B - (1+\mu_d)R^d\big)d$, and $\theta^{sE} = \big(R^B - R^r\big)M^{sE} + \big(V(y) - (1+\mu_d)R^d\big)d$, with a difference from the baseline of $\Delta_\theta^{sB} = \big[(1+\mu_h)R^h - (1+\mu_d)R^d\big]d$, and $\Delta_\theta^{sE} = -\big(R^B - R^r\big)\delta d + \big(V(y) - (1+\mu_d)R^d\big)d$, respectively. Similarly, under quantitative easing policy the seignorage is computed as $\theta^{qB} = \big(V(y) - R^B\big)M^{qB} + \big(R^B - (1+\mu_d)R^d\big)h$ in the scenario with a CBDC backed by safe assets, and as $\theta^{qE} = \big(V(y) - R^B\big)M^{qE} + \big(V(y) - (1+\mu_d)R^d\big)d$ for equity held against the CBDC. The differences with the baseline scenario are respectively $\Delta_\theta^{qB} = \big(R^B - (1+\mu_d)R^d\big)d - \big(V(y) - R^B\big)\big(d - (1-\delta)\tilde{d}\big)$, and $\Delta_\theta^{qE} = \big(R^B - (1+\mu_d)R^d\big)d + \big(V(y) - R^B\big)(1-\delta)\tilde{d}$.

In the quantitative easing policy, Pareto-optimum can be achieved. As $E\big[V(y)\big] = R^E$ by definition, $R^c = R^B$ at the banking equilibrium, and $R^E = R^c = (1+\mu_d)R^d$ at Pareto-optimum, it follows that:

$$E\big[\Delta_\theta^{qB}\big] = E\big[\Delta_\theta^{qE}\big] = 0.$$

It is worth noting that whenever the central bank decides to invest in bank equity, the seignorage is no more deterministic because it depends on the realization of the payoff of the risky technology. Therefore, the only scenarios in which the seigniorage volatility is null are standard policy without CBDC and with CBDC backed by bonds: $\sigma_\theta^s = \sigma_\theta^{sB} = 0$. If the central bank decides to hold equity against CBDC deposits, we have that $\sigma_\theta^{sE} = d\,\sigma_{V(y)}$, where $\sigma_{V(y)}$ is the volatility of the equity payoff. Under quantitative easing policy, the seigniorage is always volatile and, specifically, we have that $\sigma_\theta^q = M^q\,\sigma_{V(y)}$.

Introducing a CBDC has opposite effects to the seigniorage volatility depending on where the central bank decides to invest the funds. If the CBDC deposits are backed by treasuries, then $\sigma_\theta^{qB} = M^{qB}\,\sigma_{V(y)}$, reducing the volatility: $\Delta_{\sigma_\theta}^{qB} = -(d - (1-\delta)\tilde{d})\,\sigma_{V(y)} < 0$. On the other hand, holding bank equity increases the volatility of the seigniorage, as $\sigma_\theta^{qE} = M^{qE}\,\sigma_{V(y)}$, and $\Delta_{\sigma_\theta}^{qE} = (1-\delta)\tilde{d}\,\sigma_{V(y)} > 0$.

C.2.8 Taxes

Taxes are defined in Section 3.2.5:

$$t(y) = \begin{cases} R^B B - \theta, & \text{if } y > \hat{y} \\ R^B B - \theta + \phi, & \text{if } y \leqslant \hat{y} \end{cases} = R^B B - \theta + \phi\, 1_{y \leqslant \hat{y}}.$$

For this reason, all the differences in all scenarios can be determined as $\Delta_t = \Delta_\phi\, 1_{y\leqslant\hat{y}} - \Delta_\theta$.

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