Commodity Prices and Currencies*

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Abstract

Currencies of countries specializing in exporting basic commodities are typically labeled commodity currencies. We identify a set of commodity currencies as those with a significant positive contemporaneous relationship with commodity price shocks, after controlling for global risk factors. We find that commodity price changes predict the returns of commodity currencies, especially in times of high aggregate currency volatility. Commodity currencies tend to offer relatively higher interest rates and are often in the long leg of a currency carry trade strategy. Commodity price changes thus also significantly predict carry trade returns, however, we show that this predictability is driven exclusively by the commodity currencies in the portfolio. We rationalize our findings with a simple model with heterogeneous agents who disagree about the informativeness of commodity price shocks. Our results shed new light on the connection between commodity and currency markets.

Keywords: Carry trade, exchange rates, commodities, FX volatility, predictability.
JEL codes: C32, F31, G15.

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1 Introduction

The last decades have been devoted to understanding two major empirical facts in currency markets. The common thread is the violation of the uncovered interest rate parity (UIP), which can be simply represented by the non-zero return of borrowing in a currency with low interest rate $r^l_{f,t}$ and lending in a currency with higher interest rate $r^h_{f,t}$:

$$r_t = r^h_{f,t} - r^l_{f,t} - \mathbb{E}_t \Delta s_{t+1} \neq 0, \tag{1}$$

where Δs_{t+1} is the rate of depreciation of the high-interest-rate currency. The first fact is that high-interest-rate currencies do not depreciate enough to wipe out any differences in interest rates, so that $r^h_{f,t} - r^l_{f,t} \neq \Delta s_{t+1}$, on average. Investors thus make money by borrowing in currencies with low interest rates and lending in currencies with high interest rates, i.e., $r_t > 0$. The second fact is that the difference in interest rates (and currency returns) is a pervasive phenomenon (Lustig and Verdelhan, 2007), such that $r_t > 0$ holds on a long-term basis. Recent studies suggest that high-interest-rate currencies are persistently riskier than low-interest-rate currencies because they have lower capital-to-output ratios (Hassan and Mano, 2019), are from decentralized countries (Richmond, 2019), and are more exposed to global risk factors,[1] among other explanations. While this literature is fundamental for understanding the cross-section of currency returns, through $r^h_{f,t} - r^l_{f,t}$, we still have limited knowledge on exchange rate predictability, i.e., $\mathbb{E}_t \Delta s_{t+1}$.

In this paper, we shift the attention to the time variation in exchange rate returns, with a particular focus on the return predictability for high-yield currencies. A notable feature of these currencies is that they are typically of countries that specialize in exporting basic commodities, such as Australia and Canada. One can then expect that currencies of commodity exporters, which we refer to as *commodity currencies*, are strongly exposed to fluctuations in commodity prices.

As an illustration, consider the performance of the Canadian dollar (CAD) during the meltdown of the COVID-19 crisis. Figure 1 shows the daily time series of the price of oil (Canada's main commodity export) and an index of the CAD relative the United States dollar (USD), Swiss franc, euro, and Japanese yen. We observe a stark pattern of CAD

[1] Unconditional currency returns reflect compensation for investors exposure to global factors, such as consumption growth risk (Lustig and Verdelhan, 2007), consumption habits (Verdelhan, 2010), average excess returns (Lustig, Roussanov, and Verdelhan, 2011), systematic FX volatility (Menkhoff, Sarno, Schmeling, and Schrimpf, 2012a), systematic liquidity (Mancini, Ranaldo, and Wrampelmeyer, 2013), global imbalance risk (Della Corte, Riddiough, and Sarno, 2016), and crash risk (Chernov, Graveline, and Zviadadze, 2018). See Hassan and Zhang (2020) for a recent literature review.

depreciating strongly as oil prices drop, particularly at the onset of the Russia-Saudi Arabia oil price war, and subsequently appreciating as the price war ends. A decrease in commodity prices translates into lower expected future export revenue and, therefore, into a deterioration in a commodity exporter's economic fundamentals. Negative commodity price shocks induce investors exposed to commodity currencies to gradually unwind their positions, thereby generating a steady currency depreciation. Thus, commodity price fluctuations are likely to affect both current and future returns of commodity currencies.[2]

Understanding the return dynamics of commodity currencies is critical for investors because popular investment strategies in the FX market, such as the carry trade, involve a direct exposure to such currencies (Ready et al., 2017). The information conveyed in commodity market prices should thus play a key role in explaining and predicting the performance of individual commodity currencies but also that of more global investment strategies.

In this regard, this paper offers three contribution to the literature. First, it considers a market-based approach, rather than an ad hoc categorization, to identify which currencies can be accurately classified as commodity currencies. Second, it develops a model that motivates how commodity price news impact contemporaneous and future returns of commodity currencies, especially in times of high FX volatility. Third, it exploits country-level commodity price shocks and provides novel evidence of unconditional and conditional return predictability for commodity currencies and the carry trade.

We start with a simple motivating model with heterogenous agents to explore how new information drives predictability in the FX market, building on existing equilibrium models with differences of opinion among traders. When there is disagreement about the informativeness of public news, agents trade on their differences in beliefs. News is, however, slowly reflected in prices, which generates exchange rate predictability. This theory predicts that commodity price changes, which can be viewed as a public and informative source of news for commodity countries, should impact both current and future returns of commodity currencies.

Based on this theoretical insight, we provide an empirical investigation of the role of commodity price fluctuations for exchange rate predictability. We first identify a set of 'true' commodity currencies, using a sample of 41 developed and emerging market currencies and

[2]Ferraro, Rogoff, and Rossi (2015) and Ready, Roussanov, and Ward (2017) find that currencies of commodity-exporting countries correlate positively with commodity price changes, although causality is yet to be established. Amano and Van Norden (1995, 1998), Chen and Rogoff (2003), and Ricci, Milesi-Ferretti, and Lee (2013) document the existence of cointegration relations between exchange rates and commodity prices. None of these studies examine the role of commodity prices for exchange rate predictability.

country-specific commodity price indexes. Thus far, there is some degree of arbitrariness in the definition of commodity currency, with many studies analyzing a small set of reasonable, but seemingly *ad hoc*, candidates.[3] In light of this, we propose to define a commodity currency as a currency whose returns have a positive and statistically significant covariance with prices of its commodity exports, i.e., the currency appreciates when commodity prices increase, and depreciates when they fall. Specifically, we regress each currency's return against the US dollar on the growth rate of the commodity price index of the corresponding country over the period January 1980 to May 2019.[4] Our procedure identifies nine countries whose currencies display a positive and statistically significant commodity exposure (or beta), namely, Australia, Brazil, Canada, Mexico, New Zealand, Norway, Peru, Russia, and the UK. Our regressions control for the dollar factor, which we argue is critical for a strict identification of commodity currencies.[5] Based on our definition, currencies of various commodity producers, such as Chile, Colombia, and South Africa, should not be categorized as commodity currencies, as their sensitivity to commodity export prices are not statistically significant, once we account for the global dollar effect. On average, the correlation between a country's primary commodity share of its exports and the sensitivity of its currency to the price of export commodities is about 70 percent. Our market-based categorization therefore lines up well with the importance of the commodity sector in a country's economic fundamentals.

We then examine the role of the country-specific commodity price shocks for exchange rate predictability in our set of identified commodity currencies. Our analysis focuses on the one-month-ahead predictability and exploits non-overlapping data. We find that commodity price shocks positively predict future exchange rate changes, both statistically and economically. A one-standard-deviation increase (decrease) in a country's commodity prices predicts a future appreciation (depreciation) for that country's currency of around 3.38 percent per annum. Predictability holds over an horizon up to 5 months. Hence, a long position in currencies of commodity exporters remains profitable for several months following an increase in the prices of the commodities they export.

[3]For example, Chen and Rogoff (2003), Chen, Rogoff, and Rossi (2010), Ferraro et al. (2015), and Ready et al. (2017) examine distinct samples of currencies.

[4]The country-specific commodity price indexes are constructed as the export-weighted changes in the international market prices of up to 45 individual commodities. Weights are time-varying to ensure that changes in the price indexes reflect variations in the relevant commodity prices for each country at each point in time.

[5]As commodity prices are typically denominated in US dollars, a dollar depreciation often mechanically leads to an increase in dollar commodity prices and an appreciation of other currencies vis-a-vis the US dollar. Estimating univariate regressions without controlling for the Dollar factor would conclude, for example, that Switzerland, a country with the second lowest ratio of commodity over total exports, is a commodity currency.

The econometric specification controls for a number of exchange rate predictors, such as each country's interest rate differential to account for UIP (Fama, 1984), aggregate FX volatility (Bakshi and Panayotov, 2013; Menkhoff et al., 2012a; Karnaukh, Ranaldo, and Söderlind, 2015), funding liquidity as measured by the TED spread (Mancini et al., 2013), aggregate market uncertainty measured by the CBOE equity-option implied volatility index (Brunnermeier, Nagel, and Pedersen, 2008; Lustig et al., 2011), and a US recession indicator to account for the aggregate decline in commodities during global economic slowdowns. Our empirical approach ensures that currency returns and commodity price shocks are thus uncorrelated with changes in financial market conditions, thereby addressing potential endogeneity concerns. So the commodity shocks we exploit contain unique information unspanned by the typical FX literature.[6]

The results are robust to the choice of the base currency. While we compute exchange rate returns from the perspective of a US investor in our benchmark analysis, we find that commodity price changes also predict the future performance of commodity currencies relative to the Swiss franc and the Japanese yen. We can thus rule out the concern that the exchange rate predictability for commodity currencies is driven by US dollar effects. A counterfactual exercise also shows the predictive relation of commodity price changes on exchange rate returns is not present in the set of non-commodity currencies. This finding mitigates the concern that omitted variables (e.g., reflecting global economic conditions), that are potentially correlated with both commodity prices and exchange rates, drive our findings. We can conclude that commodity price changes contain useful information for predicting exchange rate returns, irrespective of the base currency, and exclusively for commodity currencies.

This paper also sheds light on how the role of commodity prices in predicting future exchange rate returns varies across FX market conditions. We use our stylized model to provide useful guidance about conditional exchange rate predictability. The theory shows that commodity price shocks become relatively more informative when FX volatility increases and thus should have a greater impact on future exchange rate returns. We consider a regime-switching model to assess the conditional impact of commodity price shocks on future exchange rate returns, using the local projection method of Jordà (2005). We confirms that the predictability of commodity currencies with commodity prices news is concentrated in times of elevated FX volatility. Current FX market conditions thus dictate the informativeness of commodity price shocks for exchange rate predictability, as

[6] In addition, our results are unlikely to be capturing the potential effects stemming from investors who jointly trade commodities and currencies, and who may be simultaneously adjusting their positions in both assets as global financial conditions change.

predicted by our theory.

One may be concerned that the time-variation in FX conditions reflects changes in the global market environment and, thus, conditions that are not specifically tied to the FX market. For example, the FX market tends to display more volatile fluctuations and to become less liquid when investor fears (VIX) increase, such as during periods of financial turmoils (e.g., Menkhoff et al., 2012a). Currencies also become more volatile and liquidity evaporates when FX dealers face tighter funding constraints and money-market premiums increases (e.g., Brunnermeier et al., 2008; Ranaldo and Söderlind, 2010), as reflected by a higher TED spread. To ensure that FX volatility reflects primarily FX market conditions, we strip out the effect of such global risk conditions in our analysis. The predictability of exchange rates with commodity prices remains statistically significant and concentrated in times of elevated FX volatility, even after orthogonalizing the latter to the VIX and the TED spread. We also verify that the results continue to hold when controlling for global currency factors, which contribute to understanding the cross-section in exchange rate returns based on currency portfolios (e.g., Della Corte, Ramadorai, and Sarno, 2016; Lustig et al., 2011). Overall, FX market conditions play a robust and fundamental role in determining the conditional predictability of commodity currencies with commodity prices.

Our predictability results have critical implications for the carry trade, which is the most popular zero-cost and dollar-neutral investment strategy in the FX market. A fundamental aspect of the carry trade strategy, which consists of borrowing in low-yield currencies and investing in high-yield currencies, is the composition of the currency portfolios. Currencies with high yields are typically of countries with positive and significant commodity beta, such as Australia, Canada, and Russia, while currencies with low yields are typically countries with a low or negative commodity beta, such as Japan and Switzerland. A direct consequence is that adverse commodity price shocks constitutes bad news for high-yield currencies that are typically in the long leg of the carry trade portfolio and would, therefore, reduce the profitability of the carry trade. We find that the information conveyed in commodity prices plays a key role in explaining the future performance of the carry trade, in line with Bakshi and Panayotov (2013). Confirming our story, we show that the effect is concentrated in the long leg of the portfolio, which contains the higher-yield currencies. Furthermore, we consider a counterfactual exercise in which we recompute the returns of the carry trade strategy excluding the set of commodity currencies. In this case, commodity price shocks have no longer predictability of the carry trade returns. This exercise provides support for the finding that exposure of commodity currencies, which typically have high yields, to commodity prices plays a central role in understanding the profitability of the carry trade strategy.

This paper contributes to the FX literature in several aspects. First, while the unconditional carry trade return comes from differences in interest rates (Lustig et al., 2011), we show that the majority of the conditional carry trade returns comes from the exchange rate fluctuations, rather than from time variation in interest rates. Second, the literature has identified various common sources of risk, which proxy for changes in the stochastic discount factor of investors, that help explain unconditional return differences across currencies (Hassan and Zhang, 2020). Our work provides evidence that country-specific shocks, such as commodity price changes, can explain conditional exchange rate returns and, in turn, the carry trade performance over time. We thus identify a fundamental-sound economic force driving contemporaneous and future exchange rates.

Our findings also provide a better understanding of the relation between returns on individual exchange rates and the carry trade. Conventional wisdom is that carry trade exposes investors to global sources of risk, so that a currency that is more exposed to carry trade factor is viewed as riskier and earn higher return (Verdelhan, 2018). Complementing this view, we show that individual exchange rates are subject to currency-specific shocks that eventually affect the carry trade performance. The reason is that the long portfolio in the carry trade is heavily concentrated in a small set of commodity currencies, whose shocks cannot be truly diversified away. Hence, country-specific commodity shocks have aggregate asset pricing implications, as much as firm-specific shocks can affect the market and the economy as a whole, in the spirit of Gabaix (2011).

Overall, we demonstrate that commodity price changes predict exchange rate returns of commodity currencies. The predictability is concentrated in periods of high volatility and illiquidity in the FX market, that is when the price impact of trades becomes most prevalent. Commodity currencies tend to offer relatively higher interest rates and are often in the long leg of a currency carry trade strategy. As a result, commodity price changes also significantly predict carry trade returns, however, we show that this predictability is driven exclusively by the commodity currencies in the portfolio. This finding implies that carry traders are severely exposed to the risk of commodity price shocks. We rationalize our findings with a simple model with heterogenous agents who disagree about the informativeness of commodity price shocks. Our results shed new light on the connection between commodity and currency markets.

The remainder of the paper is organized as follows. Section 2 presents a model relating the role of commodity prices news for exchange rate predictability. Section 3 describes the data, while Section 4 determines the set of commodity currencies. Sections 5 and 6 discuss our main empirical findings regarding the unconditional and conditional exchange rate predictability with commodity prices. Section 7 extends the analysis to the carry trade. Section 8 concludes the paper.

2 Motivating theory

We present a simple, stylized model with heterogenous agents to explore how public information news drives predictability in the FX market. Our theory builds on existing equilibrium models with differences of opinion among traders.[7] In contrast to rational expectation models in which agents disagree due to asymmetric information, the basic premise of the "differences of opinion" literature is that investors interpret information differently. In our model, agents "agree to disagree" about the informativeness of public news, even if they have access to the same information, and thus trade on their differences in beliefs. We find that news is slowly reflected in prices, which generates exchange rate predictability. Furthermore, the impact of public news on exchange rates increases with the level of FX uncertainty.

The proposed framework is particularly well-suited for understanding how commodity currencies vary with commodity prices, which are arguably an important source of public news for commodity countries. The model suggests that commodity price shocks should drive both current and future exchange returns. We use the predictions of the model to guide our empirical work.

2.1 Environment

Consider a three-date, two-period economy with dates indexed by $t = 0, 1, 2$. We define the (log) exchange rate S_t as the date-t price in dollars of a unit of foreign currency. At date 2, the exchange rate is given by

$$S_2 = \bar{S} + \Phi, \tag{2}$$

where $\bar{S}$ determines the initial exchange rate level, which is known at date 0, while Φ is a normally distributed variable with mean zero and volatility σ. The component Φ reflects fundamental information determining the date-2 exchange rate level, such that $\Phi > 0$

[7] See, for example, Harrison and Kreps (1978), Harris and Raviv (1993), Kandel and Pearson (1995), Cao and Ou-Yang (2008), Banerjee, Kaniel, and Kremer (2009), Banerjee and Kremer (2010), Bhamra and Uppal (2014), Dumas, Lewis, and Osambela (2017), and Atmaz and Basak (2018) for theoretical models of stock prices.

($\Phi < 0$) represents an appreciation (depreciation) of the foreign currency. Note that risk-free rates are set to zero, i.e., we abstract away from the role of the uncovered interest rate parity condition. The distribution of S_2, including its parameters, is common knowledge to all agents.

2.2 Heterogenous beliefs

It is well established that the FX market involves different categories of market participants such as corporates, commercial banks, or asset managers.[8] Each participant has distinct objective depending on (i) the extent to which the agent exploits available information and (ii) whether the agent is a liquidity maker or taker.

Building on this insight, we consider three types of agents in the market. First, there is a research-intensive informed agent (thereafter the "Informed trader"), who learns about the fundamental exchange rate component Φ, based on public information available at date 1. Second, there is an uninformed agent ("Liquidity trader", thereafter), who offers liquidity in the market. This agent views the exchange rate as a random walk in the spirit of Meese and Rogoff (1983) and, thus, does not attempt to learn about Φ. Third, there is a "Noise trader" buying/selling currencies for exogenous reasons, which reflects any non-informational trading in the FX market.

All agents are ex ante identical, trade competitively (i.e., take prices as given), and have common knowledge about the different views. Additionally, all agents have the same initial prior of $\bar{S}$ for the future exchange rate level, so $S_0 = \bar{S}$. Heterogeneity across agents arises due to differences in beliefs about the usefulness of public information released at date 1, which we describe below.

2.3 News and expectations

At date 1, the Informed trader (identified by the subscript I) learns about the fundamental component Φ from the public news

$$p \equiv \Phi + \epsilon, \tag{3}$$

[8]Heterogeneity in agents' information is a strong feature of the FX market due to its opaque OTC nature characterized by decentralized network and dealership structure. The rise of electronic trading and settlement in recent years has also amplified market fragmentation and asymmetric information across market participants. See Ranaldo and Somogyi (2020) for recent empirical evidence and King, Osler, and Rime (2012) for a comprehensive review of the FX market structure.

where p is an unbiased, but noisy, signal about the fundamental compononent Φ, while ϵ is a normally distributed noise term with variance σ_ϵ^2.

To fix ideas, we can think of a commodity-exporting country, for example Australia, such that the spot exchange rate S is the number of US dollar per Australian dollar. A valuable source of public news for such a country is the price of its exported commodities, which is informative about the country's terms of trade and, thus, about its exchange rate.[9]

The Informed trader processes the public news p and uses Bayesian updating to form new beliefs about S_2:

$$\begin{aligned} \mathbb{E}_{I,1}[S_2] &= \bar{S} + \lambda p & (4) \\ \mathbb{V}_{I,1}[S_2] &= (1-\lambda)\,\sigma^2, & (5) \end{aligned}$$

where $\mathbb{E}_{i,1} \equiv \mathbb{E}_i[\cdot|\mathcal{F}_{i,1}]$ and $\mathbb{V}_{i,1} \equiv \mathbb{V}_i[\cdot|\mathcal{F}_{i,1}]$ denote the conditional expectation and variance given the agent i's information set $\mathcal{F}_{i,t}$ at time t, while λ is the informativeness (or signal-to-noise ratio) of the public news p:

$$\lambda = \frac{\mathbb{COV}_{I,1}[p,\Phi]}{\mathbb{V}_{I,1}[p]} = \frac{\sigma^2}{\sigma^2+\sigma_\epsilon^2} \in (0,1)\,. \tag{6}$$

The Informed trader thus learns about the fundamental part generating the future exchange rate level and takes a position in the market based on this information.

The Liquidity trader (identified by the subscript L), however, does not believe that the news p contain any value/information or, alternatively, is unable to process this public information. The expected exchange rate for the Liquidity trader at date 1 is

$$\begin{aligned} \mathbb{E}_{L,1}[S_2] &= \bar{S} \neq \mathbb{E}_{I,1}[S_2] = \bar{S} + \lambda p & (7) \\ \mathbb{V}_{L,1}[S_2] &= \sigma^2 > \mathbb{V}_{I,1}[S_2] = (1-\lambda)\,\sigma^2. & (8) \end{aligned}$$

Both agents I and L "agree to disagree" on the relevant information set and, thus, on the expected exchange rate level. Each agent believes that no other agent holds information of any additional value to his or her information set, following classic models based on difference of opinions (e.g., Harrison and Kreps, 1978). The fact that agents have heterogeneous beliefs has long been accepted as a key feature in financial and FX markets, as sophisticated rational investors, analysts, and economists often publicly disagree about their forecasts.[10]

[9]There exists a long-standing literature on the role of the terms in trade in explaining exchange rates, especially for commodity exporters. See Neary (1988) for an early discussion.

[10]Agents need not to be "behavioral" or "irrational" in the model. The seminal work of Aumann (1976)

2.4 Optimal demand and equilibrium exchange rate

All agents maximize CARA utility over terminal wealth, with risk-aversion set to one for notational simplicity, as in Banerjee and Kremer (2010). Optimal demand for agent $i = I, L$ at date 1 is

$$x_{i,1} = \frac{\mathbb{E}_{i,1}[S_2] - S_1}{\mathbb{V}_{i,1}[S_2]}, \tag{9}$$

while the aggregate demand/supply of the noise trader $x_{N,t}$ is normally distributed with mean zero and volatility σ_N. In our model, the role of the noise trader's shocks is to simply prevent prices from being fully revealing.

Imposing market clearing conditions, the equilibrium exchange rate at date 1, i.e., after the public news p is revealed, is

$$S_1 = \bar{\mu}_S + \bar{\sigma}_S^2 x_{N,1} \tag{10}$$

with

$$\bar{\mu}_S = \omega_I \mathbb{E}_{I,1}[S_2] + \omega_L \mathbb{E}_{L,1}[S_2] = \bar{S} + \underbrace{\omega_I \lambda}_{<1} p \tag{11}$$

$$\bar{\sigma}_S^2 = \omega_I \mathbb{V}_{I,1}[S_2] + \omega_L \mathbb{V}_{L,1}[S_2] = \underbrace{(1 - \omega_I \lambda)}_{<1} \sigma^2, \tag{12}$$

where ω_I and ω_L reflect relative weights of the Informed and Liquidity traders, respectively, while $\bar{\sigma}_S^2$ is the aggregate degree of uncertainty about exchange rate S_2. Observe that $\bar{\sigma}_S^2$ reflects the uncertainty perceived by the 'average' agent, which differs from the true level of exchange rate uncertainty, σ^2.

From Equation (12), the equilibrium exchange rate corresponds to the average valuation across agents and, thus, only partially reflects the available public information about Φ. With disagreement, the 'average' agent puts a weight on the public news that is lower than the informativeness of p, given that $\omega_I \lambda < 1$. Hence, the equilibrium exchange rate at date 1 underreacts to the new public information.

shows that rational people are likely to agree to disagree. Also, in the real world, agents are likely to agree on certain subjects and disagree about others. Our objective is to highlight some aspects of the world agents disagree about after having exploited the rest of the available information.

2.5 Impact on contemporaneous and future exchange rate returns

Let $r_1 \equiv S_1 - S_0$ and $r_2 \equiv S_2 - S_1$ be the first- and second-period exchange rate returns, respectively. From Equation (10) and $S_0 = \bar{S}$, it follows that:

$$
\begin{aligned}
r_1 &= \underbrace{\left(\bar{\mu}_S + \bar{\sigma}_S^2 x_{N,1}\right)}_{S_1} - \underbrace{\bar{S}}_{S_0} && (13)\\
&= \omega_I \lambda p + \bar{\sigma}_S^2 x_{N,1}. && (14)
\end{aligned}
$$

given that $\bar{\mu}_S = \bar{S} + \omega_I \lambda p$ from Equation (11). The contemporaneous impact of the public news p on the exchange rate return r_1 can be expressed as $\delta r_1/\delta p = \omega_I \lambda > 0$, which increases with the fraction of Informed traders in the market (ω_I) and with the informativeness of the news (λ). The price impact of trade is thus positively related to the asymmetric use of public information across FX traders, in line with the empirical findings of Ranaldo and Somogyi (2020).

We now discuss the implication for exchange rate predictability. The second-period exchange rate return is given by:

$$
\begin{aligned}
r_2 &= \underbrace{\bar{S} + \Phi}_{S_2} - \underbrace{\left(\bar{\mu}_S + \bar{\sigma}_S^2 x_{N,1}\right)}_{S_1} && (15)\\
&= \Phi - \omega_I \lambda p - \bar{\sigma}_S^2 x_{N,1} && (16)\\
&= \left[1 - \omega_I \lambda\right] p - \epsilon - \bar{\sigma}_S^2 x_{N,1}, && (17)
\end{aligned}
$$

as the date-2 exchange rate is $S_2 = \bar{S} + \Phi$, once the fundamental information is revealed. Given that information is gradually incorporated into prices, the public news p released at date 1 becomes useful for predicting the future exchange rate return, i.e., $\delta r_2/\delta p = 1 - \omega_I \lambda > 0$.

To explore the overall impact of public news on exchange rate predictability, it is helpful to explore the autocovariance of the exchange rate returns, which is given by

$$
\mathbb{COV}\left[r_2, r_1\right] = \underbrace{\omega_I \omega_L \lambda \sigma^2}_{\text{persistence}} - \underbrace{\bar{\sigma}_S^4 \sigma_N^2}_{\text{reversal}}. \qquad (18)
$$

A positive covariance implies that the public news p available at date 1 impacts both the contemporaneous and the future exchange rate levels with the same sign. The reason is that exchange rates are slow to aggregate new public information and, as a result, converge slowly toward their fundamental levels. This gradual diffusion of new public information into equilibrium prices is the reason for exchange rate predictability.

If the new public information is irrelevant (i.e., infinitely noisy) for learning about the fundamental component Φ, we have $\lambda = 0$ and, as a result, a negative covariance. In this case, the Informed trader will not trade with the Liquidity trader based on the public information, and the exchange rate becomes purely driven by noise trading.[11]

Hence, a positive covariance implies that (i) the public news p about the future exchange rate must be economically relevant in explaining contemporaneous exchange rate returns, and (ii) this information is slowly incorporated into the equilibrium exchange rate, leading to exchange rate predictability. In sum, our stylized model offers two key insights to guide our empirical analysis:

Insight 1: *Any public news that is informative about future exchange rates must also have a contemporaneous impact.*

Insight 2: *Exchange rates slowly reflect new available information, given the FX market consists of heterogenous participants, thereby leading to exchange rate predictability.*

These predictions are expected to be particularly relevant in the context of currencies of commodity exporters (e.g., Australia or Canada). Our theory suggests that commodity price changes, which can be viewed as a public and informative source of news for these countries, should both impact their currencies contemporaneously *and* explain their future returns. Hence, we should only label a 'commodity currency' a currency that is economically and positively exposed to contemporaneous price changes in the country's exported commodities. In contrast, we should not expect to observe any of these relations for the currencies of non-commodity exporters (e.g., Switzerland or Japan), as variations in commodity prices would not be viewed as informative for such countries. For such countries, we thus expect that their currencies are not fundamentally exposed to contemporaneous changes in commodity prices. Guided by this intuition, we provide a comprehensive analysis of how commodity price news impact contemporaneous and future exchange rate returns for commodity vs. non-commodity currencies.

3 Data

Our sample period runs from January 1980 to May 2019. Our primary data consists of individual foreign exchange rates and country-specific commodity price indexes. We

[11] One may conjecture that in the presence of noise, information is incorporated slowly into the exchange rate, thus leading to return persistence. However, the opposite happens given that noise induces a reversal in returns, as discussed in Banerjee et al. (2009).

describe these data below. We discuss the auxiliary data when we introduce it in our analysis and in the Internet Appendix.

3.1 FX data

We collect daily spot and one-month forward exchange rates relative to the US dollar from WM/Reuters via Datastream. Exchange rates are defined as units of US dollars per unit of foreign currency so that an increase in the exchange rate indicates an appreciation of the foreign currency. Monthly data are obtained by sampling end-of-month exchange rates. Our sample includes 41 developed and emerging market currencies. Namely, the currencies of Australia, Austria, Belgium, Brazil, Bulgaria, Canada, Chile, Colombia, Croatia, Czechia, Denmark, Finland, France, Germany, Greece, Hungary, India, Indonesia, Ireland, Italy, Japan, Malaysia, Mexico, the Netherlands, New Zealand, Norway, Peru, the Philippines, Poland, Portugal, Russia, Singapore, Slovenia, South Africa, South Korea, Spain, Sweden, Switzerland, Thailand, the United Kingdom, and the euro area. We filter these data following Lustig et al. (2011), and Dahlquist and Hasseltoft (2020) (the Internet Appendix provides further details). Our sample of currencies is similar to that of Lustig et al. (2011), but includes additional commodity exporters like Colombia, Chile, and Peru. Our sample, however, differs from Ready et al. (2017) who also study commodity currencies. They focus exclusively on developed countries because the equilibrium model they test requires that countries are financially integrated. We do not need to restrict our sample as our empirical analysis is guided by a differences of opinion theoretical framework which is applicable to all currencies.[12]

3.2 Commodity price data

Our commodity price data are from the International Monetary Fund (IMF) Commodity Term of Trade database which provides country-specific commodity price indexes for a large number of countries. These indexes are constructed for each country as trade-weighted changes in the international market prices of up to 45 individual commodities (including agricultural raw material, energy, food and beverages, and metals). In particular, we use the export-weighted indexes for each of the 41 countries in our sample. The weights are each country's individual commodity exports, scaled by its overall commodity trade. In order to account for variations in commodity trade over time, the weights are time-varying

[12]Our framework may be especially relevant for emerging market currencies as they are relatively less efficient, thus differences of opinion may be more prevalent (e.g., Pukthuanthong-Le and Thomas, 2008).

(specifically, lagged three-year rolling averages).[13] The index methodology ensures that changes in the price indexes reflect variations in the relevant commodity prices for each country at each point in time and is well-suited for our analysis.

4 Identifying commodity currencies

In this section we ask what constitutes a commodity currency. Countries that specialize in exporting basic commodities, such as Australia or Canada, are typically labeled commodity countries, and their respective currencies are often regarded as commodity currencies. However, there is some degree of arbitrariness in the definition, with many studies analyzing a small set of reasonable, but seemingly *ad hoc*, candidates.[14] In light of this, we propose a formal definition of a commodity currency.

Guided by our theory (in particular, prediction 1), we define a commodity currency as a currency whose returns vary positively with prices of the country's commodity exports, i.e., the currency appreciate when commodity prices increase, and depreciate when commodity prices fall. The definition is economically intuitive: if a country's exports are a key factor (valuable public information) for the traders of a country's currency, commodity price shocks must contemporaneously affect currency values. Importantly, our definition is also in line with the prediction of the general equilibrium model of Ready et al. (2017) showing that commodity price changes are positively correlated with commodity currency returns. It is an empirical question whether this relationship holds on average for any individual currency. It is possible that, empirically, some commodity currencies do not have a significant relationship with the prices of their exported commodities. In those cases, an ad hoc commodity currency categorization would not be meaningful.

To identify commodity currencies, we consider the full time series and all the currencies in our sample and estimate the following benchmark regression for each currency i:

$$\Delta s_{i,t} = \alpha_i + \beta_i \Delta \, \mathrm{Comm}_{i,t} + \gamma_i \, \mathrm{Dollar}_t + \varepsilon_{i,t}, \tag{19}$$

where $\Delta s_{i,t}$ denotes the log change in nominal bilateral exchange rate in U.S. dollar per

[13]See Gruss and Kebhaj (2019) for additional details on the data.

[14]For example, Chen and Rogoff (2003) consider Australia, Canada, and New Zealand, Chen et al. (2010) consider the three countries in the sample of Chen and Rogoff (2003) plus Chile and South Africa, while Ferraro et al. (2015) consider Australia, Canada, Chile, Norway, and South Africa. Ready et al. (2017) examine 21 developed countries and do not formally categorize currencies as commodity currencies, but refer to the familiar group of commodity exported (Australia, Canada, Norway, and New Zealand) in their discussions.

foreign currency unit (i.e., an increase corresponds to a foreign currency appreciation), $\Delta\,\mathrm{Comm}_{i,t}$ denotes the log change in the commodity price index of country i, and $\mathrm{Dollar}_{i,t}$ corresponds to the average change in exchange rates against the U.S. dollar, as in Verdelhan (2018).[15] The coefficient, β_i, is a currency's sensitivity to the changes in the prices of a basket of its basic commodity exports. To be categorized as a commodity currency, we require that a currency's commodity price sensitivity is positive and statistically significant.

Figure 2 [about here]

We present the results graphically. The top panel of Figure 2 displays the estimated coefficient, β_i, and its 90% confidence interval, based on White (1980) standard errors, for each country. Our procedure identifies nine countries whose currencies display a positive and statistically significant (at the 10% level) commodity exposure, as determined by β_i. Namely, Australia, Brazil, Canada, Mexico, New Zealand, Norway, Peru, Russia, and the UK. The results are largely in line with the priors established by the existing literature (the currencies of Australia, Canada, New Zealand, and Norway are all categorized as commodity currencies). Given that we consider a large sample of currencies including many emerging market currencies, it is reasonable that commodity exporters like Brazil, Mexico, Peru, and Russia are also categorized as commodity currencies.[16] In contrast, Chile, Colombia, or South Africa are typically referred to as commodity countries as they are major commodity producers of copper, coffee, and gold, respectively. Yet we cannot conclude that the Chilean peso, the Colombian peso, or the South Africa rand should be viewed as commodity currencies, as their sensitivity to their corresponding commodity prices are not statistically significant, although they may be economically.[17]

It is worth noting that the inclusion of the Dollar factor is paramount for correct identification of the set commodity currencies. Estimating univariate regressions, without controlling for the Dollar factor, produces nonsensical results. For example, we would conclude that Switzerland, a country with the second lowest ratio of commodity over total exports, is categorized as a commodity currency (Figure A.1 in the Internet Appendix plots these results). This is partly due to commodity prices being denominated in U.S. dollars, and thus a dollar depreciation often mechanically leads to an increase in dollar commodity

[15]See the Internet Appendix B.1 for the details on the construction of the Dollar factor.

[16]One may be potentially surprised that the UK is categorized as a commodity currency. However, it is important to note that our regressions are estimated over the full sample period and UK has historically been an important oil exporter.

[17]As a robustness, we include these two countries in some of our subsequent analysis and verify that do not materially affect our results.

prices and an appreciation of other currencies vis-a-vis the U.S. dollar. Moreover, commodity price changes are correlated with global risk factors. Inclusion of additional risk factors, however, does not significantly affect the results (see Figure A.2 in the Internet Appendix for a specification that includes the Dollar factor and return to the U.S. stock market). As there is no clear consensus on the null model for bilateral exchange rate changes, we choose the most parsimonious specification.

Importantly, our categorization lines up well with the importance of the commodity sector in a country's economic fundamentals. The middle panel of Figure 2 displays each country's average primary commodity share of its total exports. The averages are based on annual data from United Nations (UN) Comtrade Database. We observe a clear, intuitive pattern: the greater a country's primary commodity share of its exports, the greater is the sensitivity of a country's currency to the price of its export commodities. The bottom panel of Figure 2 illustrates this relationship. A cross-country regression of commodity price sensitivity on the average share of exports yields a positive and statistically coefficient and an R^2 of 49%.

In sum, we propose a new approach to determine the currencies that should reasonably be classified as commodity currencies. We find that 9 currencies are statistically exposed to commodity prices fluctuations and that these currencies are of countries exporting a large share of commodity goods. We hereafter focus on this set of commodity currencies and provide new evidence of exchange rate predictability.

5 Unconditional Predictability

In this section, we examine the role of the country-specific commodity price indices for exchange rate predictability. In particular, we investigate the predictive power of commodity price shocks on commodity currencies beyond the existing predictors, which include changes in FX market and global financial conditions. We first present the empirical approach, describe the control variables, and then discuss the results.

5.1 Baseline specification

We estimate the response of exchange rate returns to a commodity price shock by running panel regressions based on the following specification:

$$\frac{1}{k}\Delta s_{i,t+k} \quad = \quad \alpha_{i,k} + \beta_k \Delta C_{i,t} + \boldsymbol{\gamma}_k \mathbf{x}_t + u_{i,t+k}, \tag{20}$$

where the dependent variable corresponds to the log bilateral spot exchange change of country i over the k-month horizon, $\Delta C_{i,t}$ is the one-month percentage change of the country i's commodity export index observed in month t, while $\mathbf{x}_t$ denotes the set of control variables. To facilitate interpretation, we standardize each country's commodity index return. We consider the predictability of exchange rate changes for horizons up to 12 months, but focus our analysis on the one-month ahead predictability to exploit non-overlapping data. We include country fixed effects, denoted by $\alpha_{i,k}$, to control for time-invariant differences across currencies. We use standard errors that are clustered at individual currency and month levels and adjusted using the Newey-West correction with the lag equal to the forecasting horizon. Observations are monthly and the sample period ranges between January 1980 and May 2019.

In our baseline specification, we control for a number of exchange rate predictors. First, we include each country's interest rate differential to account for the UIP (see, e.g., Fama (1984), Bansal and Dahlquist (2000)). Specifically, we consider interest rate difference between each country and the US, which we derive from one-month forward exchange rates following Verdelhan (2018). Second, we consider fluctuations in aggregate FX market conditions using a measure of realized FX volatility constructed using the approach of Bakshi and Panayotov (2013).[18] This choice builds on the empirical evidence that uncertainty in the FX market helps explain the cross-section of exchange rate returns (Menkhoff et al., 2012a; Karnaukh et al., 2015) and predict future exchange rate returns (Bakshi and Panayotov, 2013). Third, we control for changes in funding liquidity as measured by the TED spread (the interest rate difference between the 3-month interbank deposits, LIBOR, and 3-month US Treasury bills). An elevated TED spread is associated with tighter funding conditions in the inter-bank market and, typically, poorer liquidity for currency traders (Mancini et al., 2013). Fourth, we control for aggregate market uncertainty, measured by the CBOE equity-option implied volatility index (VIX).[19] Both the TED and the VIX have been shown to predict exchange rate returns (see, e.g., Brunnermeier et al. (2008)). Finally, we control for a recession indicator based on the National Bureau of Economic Research (NBER) business-cycle dates to address the potential concern that variations in commodity prices reflect changes in global economic conditions, in particular the declines in commodities observed during economic slowdowns such as the Great Recession and the

[18]For each currency, we construct monthly volatility as the square root of the sum of squares of daily log currency changes against the US dollar over a month. We then average each volatility across our sample of 43 currencies to obtain the aggregate FX volatility measure.

[19]Although we refer to the VIX for convenience, we use the VXO, the old version of the VIX, to benefit from longer sample period.

COVID-19 crisis.[20]

5.2 Unconditional results

Table 1 reports the results for the one-month-ahead exchange rate predictability. We find that commodity price shocks positively predict future exchange rate changes in our set of commodity currencies. In a univariate specification, reported in Column (1), we observe an estimate $\beta_k = 0.307$ that is statistically significant at the 1% level. This result is robust to including various control predictors such as the 1-month interest rate differential (Column 2), changes in FX volatility (Column 3), changes in the TED spread (Column 4), changes in the VIX (Column 5), and the NBER recession indicator (Column 6). Accounting for all controls, the coefficient estimate is $\beta_k = 0.282$, which implies that a one-standard-deviation increase (decrease) in a country's commodity prices predicts a future appreciation (depreciation) for that country's currency of around $12 \times 0.291 = 3.38\%$ per annum. The effect is, thus, statistically and economically significant.

Table 1 [about here]

Figure 3 reports the least-squares estimates of β_k, for horizon k ranging between one month and one year. This analysis illustrates the dynamic elasticities of exchange rate returns following a commodity price shock accounting for the full set of control predictors. The predictability always remains positive and statistically significant in the short term and dissipates gradually, becoming negligible only after 5 months. This result suggests that a long position in currencies of commodity exporters could be profitable for several months following an increase in the prices of the commodities they export.

Figure 3 [about here]

Overall, our analysis indicates that an increase in commodity prices helps predict future exchange rate returns at multiple horizons. The effect is important both statistically and economically, and it is not explained by potential exchange rate predictors. With the inclusion of a battery of control variables, our empirical approach ensures that exchange rate returns and commodity price shocks are uncorrelated with changes in financial market conditions, thereby addressing potential endogeneity concerns. Specifically, the coefficient

[20]The data for the VIX, TED, and NBER recession indicator are from the Federal Reserve Bank of St. Louis. The sample spans the 1986.01–2019.05 period when we include the TED spread or the VIX as controls.

β_k is unlikely to be capturing the potential effects stemming from investors who jointly trade commodities and currencies, and who may be simultaneously adjusting their positions in both assets as global financial conditions change.

5.2.1 Alternative base currencies

We now verify that our inferences are robust to the choice of the base currency. In our benchmark analysis, we compute exchange rate returns from the perspective of a US investor, and the US dollar is, thus, the base currency. However, this choice may introduce US dollar specific effects into the analysis, making it more difficult to isolate the effect of commodity prices on commodity currencies. To address this potential concern, we also compute exchange rate returns with respect to the Swiss franc and the Japanese yen. Columns (1) and (2) of Table 2 report the results. When using these alternative base currencies, we continue to find that commodity price changes predict future exchange rate returns. Moreover, the estimates of the coefficient β_k are of a similar magnitude to the baseline case. This analysis alleviates the concern that the exchange rate predictability that we document for commodity currencies is driven by US dollar effects.

Table 2 [about here]

5.2.2 Counterfactual exercise

We consider a counterfactual exercise to better understand the mechanism behind the exchange rate predictability for commodity currencies. Economic intuition suggests that an increase (decrease) in commodity prices is good (bad) news for the economy of a commodity-exporting country. Hence, trading on expectations, FX traders would react to the news and increase (decrease) their demand for the country's currency. Therefore, following a commodity price shock, a commodity country's currency would appreciate (depreciate) with this increase in buying (selling) pressure. However, there is no obvious economic reason why this mechanism should affect currencies of non-commodity exporting countries. Guided by this logic, we test the validity of this economic channel by repeating our analysis in the previous sub-section on a sample of non-commodity currencies. If the observed exchange rate return predictability is indeed driven by economic fundamentals related to commodity exports, we should observe no predictability in the sub-sample of non-commodity currencies.

We estimate the full baseline specification (Column 6 of Table 1) for non-commodity currencies. We identify the non-commodity currencies using two approaches. First, we simply exclude from our full sample the 9 currencies that exhibit a statistically significant positive contemporaneous commodity beta. We report the result for this sub-sample in Column (3) of Table 2. Second, we adopt a more fundamentals-based approach. We sort countries on their commodity share of total exports from smallest to largest, and exclude either the top quartile (Column 4) or the top half (Column 5) of countries to isolate the non-commodity currencies. In other words, we exclude the largest commodity exporters.[21] We find that, in all cases, the results confirm our hypothesis that the predictive relation of commodity price changes on exchange rate returns is not present in the set of non-commodity currencies. Irrespective of how we identify the non-commodity currencies, the estimate of the coefficient of interest, β_k is almost two times smaller than the baseline case of the previous sub-section and is never statistically significant. This finding also mitigates the concern that omitted variables (e.g., reflecting global economic conditions), that are potentially correlated with both commodity prices and exchange rates, drive our findings. We can conclude that commodity price changes contain useful information for predicting exchange rate returns, however, in line with economic intuition, this effect holds exclusively for commodity currencies.

6 Conditional return predictability

In this section, we explore how the role of commodity prices in predicting future currency returns varies across FX market conditions. We use our stylized model developed in Section 2 to provide useful guidance about conditional exchange rate return predictability. The theory predicts that the impact of commodity price shocks on future currency returns increases with the level of FX volatility. We test this prediction with a regime-switching model and find strong support that exchange rate predictability is concentrated in times of elevated FX volatility.

6.1 Theoretical prediction

We use our simple, stylized model to provide further insights on exchange rate predictability. Recall that the period 2's exchange rate return r_2 depends on the public news p, here the commodity price shocks, as evidenced in this paper.

Consistent with our regression-based approach, the exposure of r_2 to the commodity

[21] Given our results of Section 4, the three sets of non-commodity currencies that we consider are similar, however they are not identical.

price shocks p can be expressed as a commodity price beta (see Internet Appendix A.2):

$$\beta \;=\; \frac{\mathbb{COV}\left[r_2, p\right]}{\mathbb{V}\left[p\right]} = \frac{\sigma^2}{\sigma^2 + \sigma_\epsilon^2}(1 - \omega_I). \tag{21}$$

Our model thus predicts that the impact of commodity price shocks on future currency returns increases with the level of FX volatility σ, as $\frac{\partial \beta}{\partial \sigma} > 0$. To grasp the intuition, recall that the signal-to-noise ratio of the news, given by $\lambda = \frac{\sigma^2}{\sigma^2 + \sigma_\epsilon^2}$, increases with σ. In other words, the commodity price shocks p becomes relatively more informative when FX volatility increases. Conversely, in the case of negligible FX volatility, news becomes of limited use to FX participants and exchange rate predictability vanishes, i.e. $\beta \to 0$ when $\sigma \to 0$. We now present the empirical approach that we develop to test this prediction.

6.2 Non-linear specification

We consider a regime-switching model to assess the conditional impact of commodity price shocks on future currency returns. Specifically, we use the local projection method of Jordà (2005) in a system that admits a smooth transition across two regimes, namely a high (H) and a low (L) FX volatility regime.[22] We estimate, in a panel, the response of a country i's currency return to a commodity price shock in that country in state $j = \{L, H\}$. The specification extends the unconditional case (20) to capture conditional predictability as follows:

$$\begin{aligned} \frac{1}{k}\Delta s_{i,t+k} \;&=\; F_{t-1}\underbrace{(\alpha_{i,k,H} + \beta_{k,H}\Delta C_{i,t} + \boldsymbol{\gamma}_H \mathbf{x}_t)}_{\textit{High FX volatility}} \\ &\quad + (1 - F_{t-1})\underbrace{(\alpha_{i,k,L} + \beta_{k,L}\Delta C_{i,t} + \boldsymbol{\gamma}_L \mathbf{x}_t)}_{\textit{Low FX volatility}} + v_{i,t+k}, \end{aligned} \tag{22}$$

where F_{t-1} is a smooth transition function reflecting the FX market conditions in the previous month. The transition function F_t from the low volatility regime (L) to the high volatility regime (H) is given by:

$$F_t = \frac{\exp\left(\theta \frac{\ell_t - c}{\sigma_\ell}\right)}{1 + \exp\left(\theta \frac{\ell_t - c}{\sigma_\ell}\right)}, \tag{23}$$

[22] This approach is similar to the smooth-transition-local projection model used in Tenreyro and Thwaites (2016) and Ramey and Zubairy (2018), who analyze monetary and fiscal policies.

where the state variable ℓ_t corresponds to the level of FX volatility, and σ_ℓ is the standard deviation of ℓ_t. The parameter θ determines the speed of transition across regimes, while the parameter c fixes the threshold between the two regimes.

Following the literature, we fix rather than estimate the parameters of the transition function (23). We calibrate the speed of transition across regimes, θ, and the threshold, c, to obtain a proper interpretation of the FX regimes. We set $\theta = 3$ as in Tenreyro and Thwaites (2016) and determine c such that probability that $F_t > 0.8$ is 0.2, thus ensuring that the FX market is in the high FX volatility regime 20 percent of the time.

Equation (22) expands the predictability specification proposed in the previous section by separating the forecasting power of commodity returns on the k-month-ahead exchange rate returns by the level of FX volatility. Specifically, the coefficients $\beta_{k,H}$ and $\beta_{k,L}$ capture whether the price changes of each country's export commodities at time t predict future exchange rate returns, conditional on the aggregate FX volatility at time t being high and low, respectively. It is important to note that to categorize FX volatility at time t, we use only the information available at time $t-1$ i.e., the transition function F_{t-1} is lagged by one period. This adjustment serves two purposes. First, the lag structure avoids inadvertently capturing potential predictive effects of changes in FX volatility. Second, it alleviates the concern of reverse causality as individual exchange rate returns could affect FX market conditions.

It is worth noting that the local projection model has several advantages to a regime-switching vector autoregressive model (VAR) that is typically used in the literature. First, it does not impose the dynamic restrictions that are implicit in a VAR. Second, we can employ a large set of controls to ensure that the shocks to commodity prices are exogenous to changes in global financial conditions, which is challenging in a VAR due to the practical limits on the number of parameters one can estimate with precision. Third, given that the transition between regimes is a key feature of the data, a VAR model has an inconvenient, rigid property that its impulse response functions assume that one remains in the same regime for the k forecasting periods. In contrast, multi-period forecasts using the local projection model accounts for future regimes changes. Finally, the local projection model is computationally simpler than a VAR as it can be estimated as a set of individual regressions for each horizon k by ordinary least squares (Jordà, 2005).

6.3 Results of the conditional case

Panel A of Figure 4 displays the probability of being in the high FX volatility regime, which is elevated in many instances outside of the 2007-9 financial crisis.

Figure 4 [about here]

Table 4 reports the regression results, which indicate that the predictability coefficients are asymmetric, as they vary across FX market conditions. In times of high FX volatility, the estimate of $\beta_{k,H}$ is positive and statistically significant, while there is no apparent predictability when the FX market has a low volatility (i.e., $\beta_{k,L}$ is not statistically significant from zero). This asymmetry remains similar when controlling for changes in uncertainty in the FX market and variations in financial market conditions. Accounting for all controls, the coefficient estimate is $\beta_{k,H} = 0.457$ ($\beta_{k,L} = 0.037$), which implies that a one-standard-deviation increase in a country's commodity prices predicts a future currency appreciation for that country of about 5.5% (0.4%) per annum when FX volatility is high (low).

Table 4 [about here]

In line with our unconditional predictability results, we find that there is some persistence to the predictability. Figure 5 reports the estimates of $\beta_{k,H}$ and $\beta_{k,L}$, for horizon k ranging between one month and one year, accounting for the full set of control predictors. We observe that, in the high volatility periods, predictability remains positive and statistically significant for horizons up to three months. We do not see any significant predictability during low volatility periods. The short persistence of predictability is consistent with underreaction to material information that we would expect to disappear fairly quickly. This contrasts the predictability of excess returns arising due to changes in risk premiums that is more persistent and typically increases with forecast horizon (see, e.g., Lettau and Ludvigson (2001)).

Figure 5 [about here]

In sum, these results provide evidence that the exchange rate predictability for commodity currencies is concentrated in times of high FX volatility. We now consider various tests to assess the robustness of our findings.

6.4 Stripping out global market conditions

One may be concerned that the time-variation in FX volatility reflects changes in the global market environment and, thus, conditions that are not specifically tied to the FX market. For example, the FX market tends to display more volatile fluctuations and to become less liquid when investor fears (VIX) increase, such as during periods of financial turmoils (e.g., Menkhoff et al., 2012a). Currencies also become more volatile and liquidity evaporates when FX dealers face tighter funding constraints and money-market premiums increases (e.g., Brunnermeier et al., 2008; Ranaldo and Söderlind, 2010), as reflected by a higher TED spread. Over our sample period, the correlation between FX volatility and the VIX and TED spread is 0.56 and 0.40, respectively. Hence, FX volatility indeed varies with these global risk indicators.

To ensure that FX volatility reflects primarily FX market conditions, we strip out the effect of such global risk conditions in our analysis. Specifically, we orthogonalize the monthly measure of FX volatility to the VIX or the TED spread, respectively, and reestimate the transition functions. Columns (1) and (2) of Table 3 report the results when we eliminate the part of FX volatility that covaries with aggregate uncertainty (VIX) and funding liquidity conditions (TED spread), respectively. In both cases, the predictability of exchange rates with commodity prices remains statistically significant and concentrated in times of elevated FX volatility.[23] This analysis confirms the primary role of FX market conditions in driving the asymmetric predictability of exchange rate returns.

6.5 Global currency factors

We then examine whether changes in commodity prices reflect variations in existing currency factors. A large stream of the literature highlights the role of global currency factors for understanding exchange rate returns based on currency portfolios (e.g., Della Corte et al., 2016; Lustig et al., 2011). It is worth noting that while the FX factors are known to help explain the cross-section of currency returns, their ability for exchange rate predictability is less clear. Nevertheless, we follow Della Corte, Jeanneret, and Patelli (2020) and include several widely considered portfolio-based currency factors as additional predictors, namely Lustig et al. (2011)'s dollar factor, the momentum factor based on previous rate of returns of a currency following (Asness, Moskowitz, and Pedersen, 2013; Menkhoff, Sarno, Schmeling, and Schrimpf, 2012b), and the valuation factor based on the degree of

[23] Results are qualitatively and quantitatively similar when orthogonalizing FX volatility to aggregate stock market excess returns.

under(over)-valuation of a currency (Asness et al., 2013).[24] Column (3) shows that the exchange rate predictability for commodity currencies remains robust to considering these additional controls, which implies that fluctuations commodity prices are not spanned by standard currency risk factors.[25]

6.6 Alternative FX volatility measures

Another robustness check involves comparing the predictability results across different measures of aggregate FX conditions. Our benchmark FX volatility measure corresponds to the average return volatility of 43 currencies. This sample includes various highly-traded currencies that we do not classify as commodity currencies (e.g., the Japanese Yen, the Swiss Franc, or the Euro). As an alternative measure of FX volatility, we consider the average return volatility of the 9 commodity currencies that we use in the panel regressions. Column (4) indicates that the coefficients associated with the conditional impact of commodity prices remain similar in magnitude relative to our baseline regression. This result indicates that the role of FX volatility in conditioning the predictability is not driven by the volatility of non-commodity currencies. We also consider a measure of forward-implied FX volatility (VXY), using the J.P. Morgan FX Volatility Index based on at-the-money options for a basket of the G7 currencies. Column (5) shows that the predictability relation is only statistically significant when the forward-looking measure of FX volatility is high, in line with our baseline results.[26]

6.7 FX illiquidity conditions

Alternatively, we measure FX conditions based on the level of liquidity, as a substantial body of research suggests that FX volatility and illiquidity are highly interlinked. The lack of liquidity, as reflected in bid-ask spreads, should be positively affected by return volatility due to higher adverse selection and inventory risk (e.g., Stoll, 1978). Empirically, Karnaukh et al. (2015) confirm that liquidity of currencies tends to evaporate when FX volatility increases, while Ranaldo and Santucci de Magistris (2019) show that higher FX volatility and illiquidity arise jointly when there is more disagreement among traders.

Given the tight link between periods of volatile exchange rates and market dry-outs,

[24] Appendix B.1 describes the construction of these factors.

[25] Results are qualitatively and quantitatively similar when we further include the carry factor as a fourth control.

[26] This analysis also indicates that the results are robust to a change in sample period, as the VXY series starts in 1992. The date are from Bloomberg.

we now condition the predictability analysis based on the level of FX illiquidity, as a robustness check. We use the systematic FX illiquidity index proposed by Karnaukh et al. (2015), which is constructed as the average level of illiquidity of 33 currency pairs, mostly based on bid-ask spreads. This index is informative about the global level of FX illiquidity, as it captures the average transaction costs of the most traded currencies, but reduces our sample period.[27] The bottom panel of Figure 4 displays the conditional probability of being in the high FX illiquidity regime.[28] As expected, periods of distressed market conditions are characterized by high probabilities of being in the high volatility and high illiquidity regimes. Note however that the correlation between the two transition probabilities is 64%, which indicates that most but not all months of high FX volatility correspond to months of high illiquidity.

The results presented in Column (6) indicate that the predictability of commodity currencies is also concentrated when FX liquidity dries out, i.e., in times of adverse FX market conditions, thereby confirming our previous findings. This analysis indicates that currency volatility captures more than the level of uncertainty in the FX market, as volatility is itself a strong determinant of a currency's transaction costs and, thus, of its trading liquidity (Bollerslev and Melvin, 1994). Hence, both aspects of FX market conditions play a fundamental role in determining the conditional predictability of commodity currencies with commodity prices.

7 Implications for the carry trade

Our predictability results have critical implications for the carry trade, which is the most popular zero-cost and dollar-neutral investment strategy in the FX market. A fundamental aspect of the carry trade strategy, which consists of borrowing in low-yield currencies and investing in high-yield currencies, is the composition of the currency portfolios. Currencies with high yields are typically of countries with positive and significant commodity beta, such as Australia, Canada, and Russia, while currencies with low yields are typically countries with a low or negative commodity beta, such as Japan and Switzerland. Figure 6 presents the relationship between each country's estimated commodity price sensitivity coefficient and its average monthly forward premium. Although there is some heterogeneity,

[27] The index, which is available from January 1991, largely reflects illiquidity of developed and emerging currencies. The emerging countries present in the index are Hungary, India, Mexico, Poland, South Africa, and Turkey. We use the updated series, which is kindly shared by Angelo Ranaldo.

[28] In the transition function (23), we redefine the state variable as the (standardized) measure of FX illiquidity, and we recalibrate the speed of transition such that the FX market remains about 20 percent of the time in the high-illiquidity regime.

we observe a positive and statistically significant relationship ($R^2 = 0.23$).[29]

Figure 6 [about here]

A direct consequence in this regularity is that adverse commodity price shocks constitutes bad news for high-yield currencies that are typically in the long leg of the carry trade portfolio and would, therefore, reduce the profitability of the carry trade. Additionally, given our findings on predictability, the information conveyed in commodity prices should also play a key role in explaining the future performance of the carry trade, particularly in times of high FX volatility. This is what we investigate in this section.

7.1 Carry trade and aggregate commodity index construction

We explore the carry trade strategy from the perspective of a US investor. Following Menkhoff et al. (2012a), at the end of each month t, we allocate all the available currencies in our sample into five portfolios based on their forward discounts $f_t - s_t$, where f_t and s_t denote the logarithm of the spot and 1-month forward exchange rates, respectively. Exchange rates are in units of foreign currency per US dollar.[30] Portfolio 1 (P1) contains currencies with the smallest forward discounts (or lowest interest rates), and portfolio 5 (P5) contains currencies with the largest forward discounts (or highest interest rates). We rebalance portfolios at the end of each month. Returns for P1 (i.e., the funding currencies in the carry trade) are adjusted for transaction costs in short positions, whereas returns for P2–5 (investment currencies) are adjusted for transaction costs in long positions, as detailed in the Internet Appendix. We compute portfolio returns by taking the (equally weighted) average of the returns of each currency in the portfolio. The return of the carry trade is the return difference between the high-yield portfolio (P5) and the low-yield portfolio (P1). We report the descriptive statistics for the currency portfolios in the Internet Appendix.

We construct an aggregate series of commodity price shocks relevant for the commodity currencies. This series is an equal-weighted average of the percentage changes in each of the nine commodity country's commodity indexes. We refer to it as the 'average commodity price index', and denote it as $\Delta Comm$ in the regression tables.

[29] This observation is also consistent with theory, as Ready et al. (2017) find that currencies that deliver high (low) yields are of countries that specialize in exporting (importing) commodities in equilibrium.

[30] Sorting on forward discounts is equivalent to sorting on interest rate differentials under the covered interest rate parity: $i_t^* - i_t - \Delta s_{t+1} \cong f_t - s_{t+1}$, where i_t^* and i_t denote the 1-month foreign and US dollar nominal risk-free rates, respectively.

7.2 Carry trade predictability

We first assess the predictability of the carry trade returns with linear specification described in Section 5. We simply replace a country i's currency return by the one-month carry trade return over the k-month horizon, and the individual country commodity index returns with the average commodity price index return.

Panel A of Table 5 reports the results for the one-month-ahead carry trade return predictive regression. We find that commodity price shocks positively predict future carry trade returns. In a univariate specification, reported in Column (1), we observe an estimate $\beta = 0.091$ that is statistically significant at the 1% level. The predictability of carry trade returns is economically significant. This coefficient implies that a one standard deviation decrease in the average commodity prices leads to a 0.34% reduction in carry trade returns in the following month (around 4% on an annualized basis). The statistical and economic significance of Δ Comm remains unaffected when we control for changes in aggregate FX volatility (Column 2), changes in the TED spread (Column 3), changes in the VIX (Column 5), and the NBER recession indicator (Column 6). Among the control predictors, we find that only the changes in FX volatility have statistically significant predictive ability for the carry trade returns (the estimated coefficient is positive, which is in line with Menkhoff et al. (2012a) who find that shocks to FX volatility are a priced risk factor in the cross-section of interest rate sorted portfolios).

Table 5 [about here]

Having established that average commodity price index changes forecast carry trade returns, we examine the source of this predictability. First, we consider the returns on P5 (the high interest currencies) as the dependent variable. Second, we reevaluate the predictive regression with the returns on P1 (the low interest currencies) as the dependent variable. The regression results are reported in Panel B of Table 5. We find that Δ Comm strongly predicts the returns of P5 ($\beta = 0.1241$ and is statistically significant at the 1% level), and does not predict the returns of P1 (($\beta = 0.0221$ and is statistically insignificant). Noting that P5 typically contains most, if not all, of the commodity currencies, these results suggest that predictive power of commodity price index changes for carry trade returns stems from its predictive ability of individual commodity currency returns, and not, for example, due to correlation with omitted risk factors. As an additional test of this intuition, we construct a carry trade portfolio with a sub-sample of currencies that excludes the nine commodity currencies, and then reestimate the predictive regression on the new carry trade returns. These results, reported in Column (3), confirm that commodity price changes have no predictive ability on carry trade returns if we exclude commodity currencies from the carry trade portfolio. Lastly, to further reiterate this point, we compare the baseline results with those obtained using alternative global commodity price indexes. We consider the percentage changes of Commodity Research Bureau (CRB) Raw Industrials subindex of the CRB commodity index as it has been used in the literature and shown to be relevant for exchange rates (see, e.g., Bakshi and Panayotov (2013), and Ready et al. (2017)), and the Goldman Sach commodity index as it is well-known benchmark in practice. Columns (4) and (5) report the results when we replace the average commodity price index by percentage changes in the CRB and Goldman Sachs indexes, respectively. The predictability results become substantially weaker than in the baseline specification. This analysis confirms the importance of the information content of a commodity country's individual commodity price shocks in forecasting its returns, and in turn those of the carry trade.

8 Conclusion

In this paper, we examine how commodity price fluctuations affect the future performance of individual commodity currencies. We first identify a set of 9 currencies that one can reasonably classify as 'commodity currencies' using a market-based approach, among currencies of 41 emerging and developed countries. We determine each currency's commodity beta from the exposure of a country's currency to variations in the country-specific commodity index prices after controlling for the dollar effect.

We find that a country's commodity price shocks predict positively one-month-ahead currency returns of the same country, after controlling for standard currency and financial predictors. The predictability strengthens when FX volatility is elevated or market liquidity evaporates, that is when the price impact of news is most severe.

Our results have direct implications for the carry trade, which is the most popular zero-cost and dollar-neutral investment strategy in the FX market. The carry trade consists of borrowing in low-yield currencies, which are typically of countries with highly positive commodity beta, such as Australia and Canada, and investing in low-yield currencies, which are typically of countries with a low or negative commodity beta, such as Japan and Switzerland. Our empirical analysis reveals that commodity price shocks have predictive power for carry trade returns. In addition, the effect is concentrated in the long side of the portfolio, confirming that the information conveyed in commodity prices plays a key role in explaining future currency returns. This paper thus sheds new light on the strong connection between commodity and currency markets, which has been clearly illustrated during the COVID-19 crisis. Future research could exploit options prices and explore how tail risk in commodities helps explain currency crash risk, thereby contributing to our comprehension of the implied volatility surface in the FX option market.

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Table 1: Commodity currency predictability – unconditional model

This table reports results from panel regressions investigating the unconditional predictability of bilateral exchange rates with changes in commodity prices. All exchange rates are against US dollar. The dependent variable is the one-month-ahead return of each commodity currency. The variable Δ Comm is the return of the corresponding country's commodity price index, which is export-weighted and rebalanced monthly. Model (1) is the univariate regression with country fixed effects, Model (2) controls for the 1-month interest rate differential (IRD) relative to the US dollar, Model (3) includes changes in aggregate FX volatility, Model (4) and (5) include changes in funding liquidity (TED) and changes in aggregate uncertainty in the US market (VIX), respectively. Model (6) includes an indicator variable which equal to one during NBER recessions and zero otherwise. All specifications include currency fixed effects. The standard errors in parentheses are clustered by currency and time, and adjusted using the Newey and West (1987) kernel where the bandwidth is equal to the forecasting horizon. Section 5 describes the econometric specification and the controls. The sample consists of monthly observations between January 1980 to May 2019.

	(1)	(2)	(3)	(4)	(5)	(6)
Δ Comm	0.343**	0.339**	0.337**	0.343***	0.343***	0.334***
	(0.140)	(0.136)	(0.131)	(0.133)	(0.132)	(0.125)
IRD		−0.149	−0.149	−0.334	−0.333	−0.312
		(0.298)	(0.298)	(0.284)	(0.284)	(0.276)
Δ FX Vol			−0.027	−0.070	−0.074	−0.069
			(0.160)	(0.164)	(0.155)	(0.153)
Δ TED				−0.437	−0.450	−0.477
				(1.160)	(1.120)	(1.110)
Δ VIX					0.003	0.003
					(0.031)	(0.031)
NBER						−0.394
						(0.662)
N	3,048	3,048	3,048	2,806	2,806	2,806
Countries	9	9	9	9	9	9
R^2 %	0.88	0.88	0.85	1.21	1.18	1.27

Table 2: Robustness analysis – unconditional model

This table reports results from panel regressions investigating the unconditional predictability of bilateral exchange rates with changes in commodity prices. The dependent variable is the one-month-ahead return of each commodity currency. The variable Δ Comm is the return of the corresponding country's commodity price index, which is export-weighted and rebalanced monthly. Columns (1) and (2) report results for individual currency returns with respect to the Swiss franc and the Japanese yen, respectively. Column (3) includes currencies exhibiting a non-statistically significant positive commodity beta. In Columns (4) and (5), we first sort countries according to their commodity share of total exports and exclude the top quartile and the top half of countries, respectively. All specifications include currency fixed effects. The standard errors in parentheses are clustered by currency and time, and adjusted using the Newey and West (1987) kernel where the bandwidth is equal to the forecasting horizon. Section 5 describes the econometric specification and the controls. The sample consists of monthly observations between January 1980 to May 2019.

	Commodity		Non-commodity		
	(1)	(2)	(3)	(4)	(5)
Δ Comm	0.293**	0.346*	0.197	0.157	0.149
	(0.146)	(0.180)	(0.123)	(0.103)	(0.111)
N	2,810	2,810	6,969	7,300	4,767
Countries	9	9	34	33	21
R^2 %	1.88	3.79	0.43	0.38	0.24
Controls	Yes	Yes	Yes	Yes	Yes
Base currency	CHF	JPY	USD	USD	USD

Table 3: Commodity currency predictability – conditional model

This table reports results from panel regressions investigating the conditional predictability of bilateral exchange rates with changes in commodity prices across FX market conditions. All exchange rates are against US dollar. The dependent variable is the one-month-ahead return of each commodity currency. The variable Δ Comm is the return of the corresponding country's commodity price index, which is export-weighted and rebalanced monthly, while F(z) reflects the probability of being in a high FX volatility regime. Column (1) is the conditional univariate regression with country fixed effects, Column (2) controls for the 1-month interest rate differential (IRD) relative to the US dollar, Model (3) includes changes in aggregate FX volatility, Columns (4) and (5) include changes in funding liquidity (TED) and changes in aggregate uncertainty in the US market (VIX), respectively. Column (6) includes an indicator variable which equal to one during NBER recessions and zero otherwise.The standard errors in parentheses are clustered by currency and time, and adjusted using the Newey and West (1987) kernel where the bandwidth is equal to the forecasting horizon. Section 4 presents the commodity price indices, while Section 5 describes the econometric specification and the controls. The sample consists of monthly observations between January 1980 to May 2019.

	(1)	(2)	(3)	(4)	(5)	(6)
Δ Comm $\times$ F(z)	0.468***	0.435**	0.429***	0.450**	0.457***	0.436***
	(0.169)	(0.171)	(0.163)	(0.177)	(0.172)	(0.156)
Δ Comm $\times$ (1–F(z))	0.064	0.060	0.060	0.045	0.037	0.042
	(0.193)	(0.222)	(0.222)	(0.230)	(0.226)	(0.227)
IRD		−0.129	−0.130	−0.279	−0.275	−0.260
		(0.232)	(0.233)	(0.224)	(0.222)	(0.216)
Δ FX Vol			−0.047	−0.081	−0.102	−0.098
			(0.153)	(0.147)	(0.148)	(0.148)
Δ TED				−0.700	−0.756	−0.781
				(1.270)	(1.244)	(1.227)
Δ VIX					0.012	0.011
					(0.029)	(0.029)
NBER						−0.430
						(0.600)
N	3,412	3,038	3,038	2,810	2,810	2,810
Countries	9	9	9	9	9	9
Countries	9	9	9	9	9	9
R^2 %	0.71	0.79	0.77	1.29	1.29	1.41
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 4: Robustness analysis – conditional model

This table reports robustness results from panel regressions investigating the conditional predictability of bilateral exchange rates with changes in commodity prices across FX market conditions. All exchange rates are against US dollar. The dependent variable is the one-month-ahead return of each commodity currency. The variable Δ Comm is the return of the corresponding country's commodity price index, which is export-weighted and rebalanced monthly, while F(z) reflects the probability of being in a high FX volatility regime. Columns (1) and (2) report the predictability results conditional on the level of FX volatility orthogonalized with respect to the VIX and the TED spread, respectively. Column (3) controls for global currency factors (dollar, momentum, and value). Column (4) reports the predictability results conditional on the level of FX volatility of the 9 commodity currencies considered in the panel, while Column (5) conditional the results using a measure of forward-implied FX volatility (VXY) based on at-the-money options. Column (6) conditional the results based on the level of systematic FX illiquidity of Karnaukh et al. (2015). The standard errors in parentheses are clustered by currency and time, and adjusted using the Newey and West (1987) kernel where the bandwidth is equal to the forecasting horizon. Section 4 presents the commodity price indices, while Section 5 describes the econometric specification and the controls. The sample consists of monthly observations between January 1980 to May 2019.

	(1) $\perp$ VIX	(2) $\perp$ TED	(3) Globals	(4) FX Vol^{CC}	(5) VXY	(6) FX Liq
Δ Comm $\times$ F(z)	0.423***	0.379***	0.359**	0.418***	0.364***	0.280**
	(0.154)	(0.141)	(0.162)	(0.156)	(0.139)	(0.129)
Δ Comm $\times$ (1–F(z))	0.135	0.170	0.060	0.065	0.194	0.317
	(0.162)	(0.173)	(0.224)	(0.157)	(0.183)	(0.203)
N	2,810	2,810	2,810	2,810	2,435	2,510
Countries	9	9	9	9	9	9
Countries	9	9	9	9	9	9
R^2 %	1.39	1.32	1.79	1.42	1.89	1.96
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Table 5: Carry trade predictability – linear model

This table reports the predictive regression results of monthly currency carry trade returns on commodity price shocks. Five equally weighted portfolios are formed every month, with portfolio 1 (P1) containing the currencies with the lowest interest rates and portfolio 5 (P5) containing those with the highest. Carry is the return to a long-short portfolio that is long in portfolio 5 and short in portfolio 1. Panel A reports the results of a regression of Carry at time $t+1$ on Δ Comm at time t. Δ Comm is the average of the percentage changes in each commodity country's export-weighted commodity index. Columns (1)reports the univariate specification, Columns (2), (3), and (4) report specifications which include controls for changes in aggregate FX volatility, changes in funding liquidity (TED), and changes in aggregate uncertainty in the US market (VIX), respectively. Specification in column (5) includes an indicator variable which is equal to one during NBER recessions and zero otherwise. Panel B reports specifications for alternative dependent variables, columns (1) to (3), and alternative measures of commodity price shocks, columns (4) and (5). Carry ex. CC denotes the return to a carry trade portfolio constructed only from currencies that are not categorized as commodity currencies. Δ CRB and Δ GSCI are the percentage change in Commodity Research Bureau (CRB) and Goldman Sachs commodity index, respectively. All the specifications in Panel B include an intercept and controls. The standard errors in parentheses are adjusted using the Newey and West (1987) kernel where the bandwidth is equal to the forecasting horizon. The sample consists of monthly observations between January 1980 to May 2019.

Panel A

	(1)	(2)	(3)	(4)	(5)
Δ Comm	0.091***	0.097***	0.102***	0.102***	0.102***
	(0.032)	(0.032)	(0.033)	(0.033)	(0.033)
Δ FX Vol		0.325**	0.319**	0.326**	0.327**
		(0.132)	(0.151)	(0.160)	(0.160)
Δ TED			−1.203*	−1.187	−1.188
			(0.694)	(0.742)	(0.748)
Δ VIX				−0.004	−0.004
				(0.030)	(0.030)
NBER					−0.024
					(0.506)
Constant	0.678***	0.678***	0.714***	0.714***	0.716***
	(0.120)	(0.121)	(0.136)	(0.136)	(0.142)
N	471	471	399	399	399
R^2 %	1.56	2.39	3.07	2.83	2.59

Panel B

	(1)	(2)	(3)	(4)	(5)
	P5	P1	Carry ex. CC	Carry	Carry
Δ Comm	0.124***	0.022	0.067		
	(0.043)	(0.032)	(0.045)		
Δ CRB				0.074	
				(0.050)	
Δ GSCI					0.031
					(0.027)
N	399	399	399	399	399
R^2 %	1.49	0.63	1.42	0.78	0.65
Controls	Yes	Yes	Yes	Yes	Yes

Figure 1: CAD exchange rate and oil price during the COVID-19 crisis

The figure shows the daily time series of the Canadian dollar (CAD) index and West Texas Intermediate crude oil price (in USD per barrel) over a short period around the Russia - Saudi Arabia oil price war in 2020. The CAD index is constructed using the average changes of CAD/USD, CAD/CHF, CAD/EUR, and CAD/JPY exchange rates. Each exchange rate is expressed as foreign currency unit (FCU) per CAD, i.e., a decrease in the index implies an average depreciation of CAD. The index value on 1 February 2020 is set to 100. The two vertical dashed lines denote the start of the price war (8 March 2020) when Saudi Arabia announced a significant oil price reduction to its customers, and its unofficial end (3 April 2020) when Russian President Putin made a public announcement that global production could be cut.

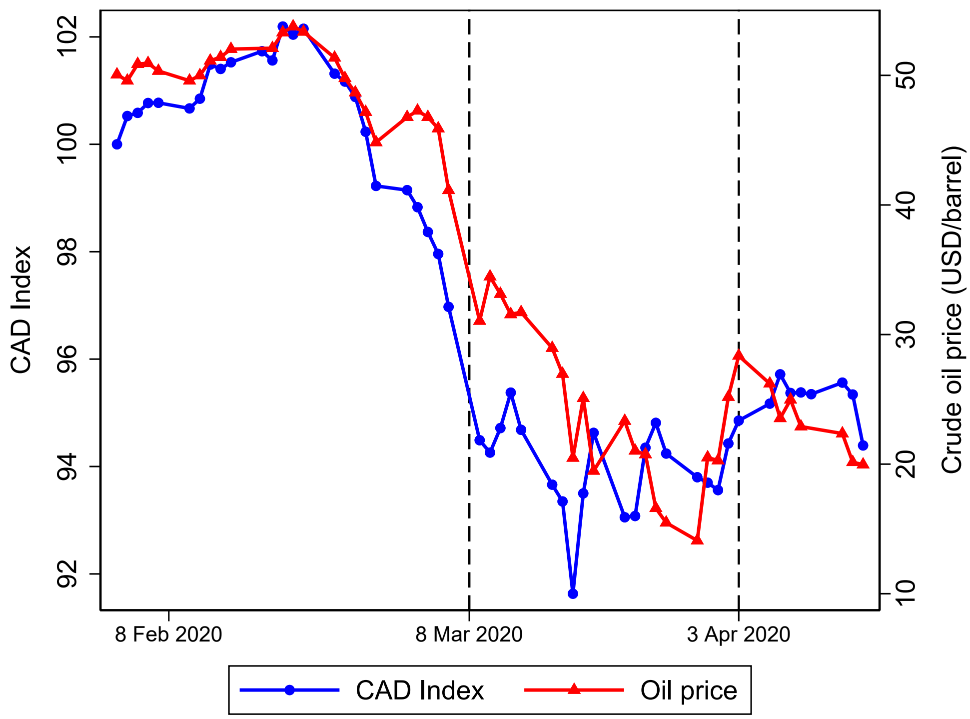


Figure 2: Exchange rate commodity price sensitivity

The top panel of the figure shows the estimated commodity price sensitivity coefficient from a contemporaneous, country-level regression of bilateral spot exchange rate changes on the changes of a country's standardized commodity price index and the dollar factor. Country-specific commodity price indexes are export-weighted and monthly rebalanced. The dollar factor is the average change in exchange rates against the US dollar. The 90% confidence intervals based on White (1980) standard errors are also displayed. Coefficients that are positive and statistically significant at the 10% level are shown as red diamonds. The estimated commodity price sensitivity coefficients are expressed in % per month. The middle panel shows the average share (in %) of raw commodity exports of each country's total exports. In the top and middle panels, the countries are displayed in an ascending order based on their estimated commodity price sensitivities. The bottom figure shows a scatter plot and a fitted regression line of each country's commodity price sensitivity and the share of raw commodity exports of each country's total exports (OLS standard errors are used for the construction of the confidence interval). The sample consists of monthly observations between January 1980 to May 2019.

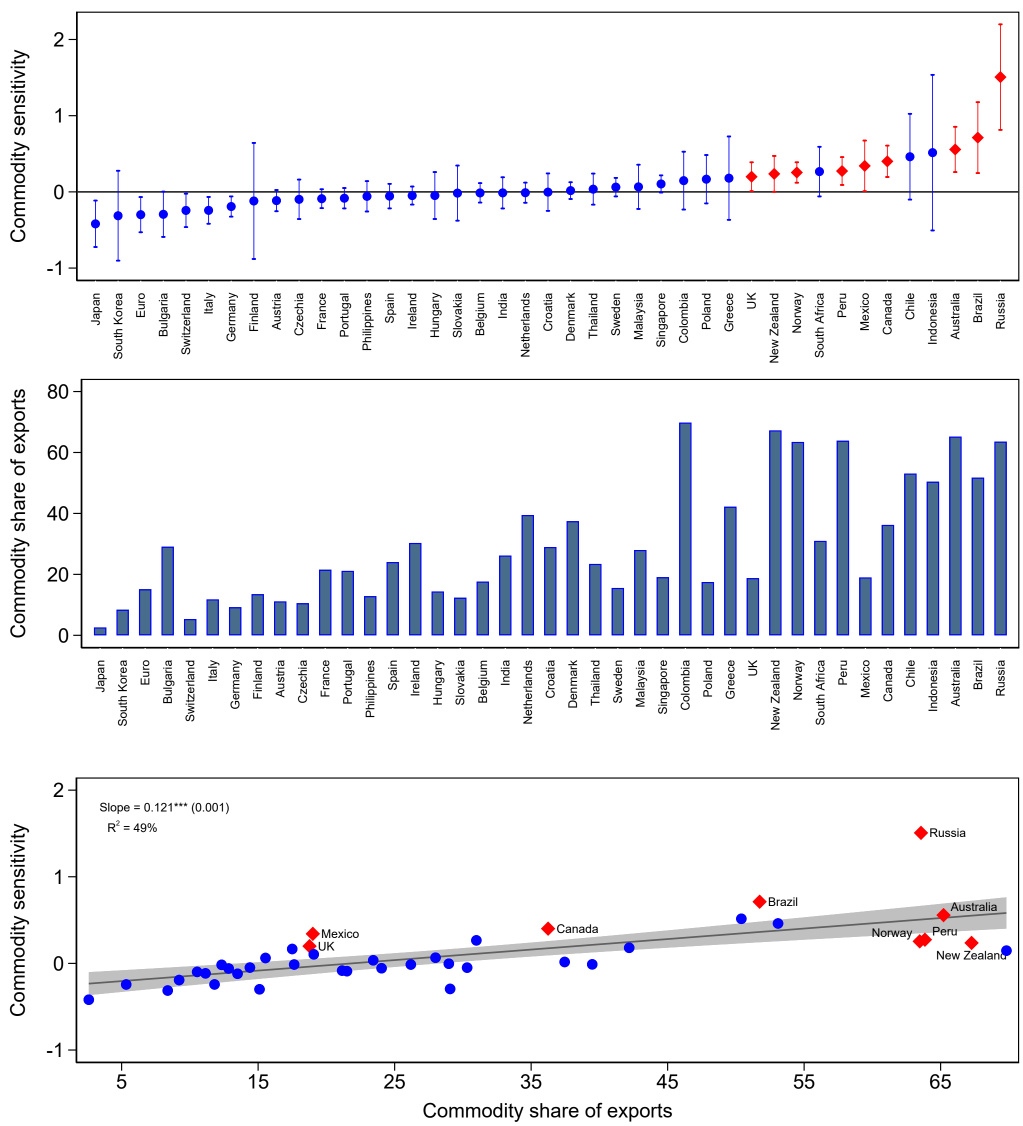


Figure 3: Multiple horizon predictability

This figure presents the average impact of commodity price changes on bilateral exchange rates of commodity currencies over different horizons. The main dependent variable is the return of country-level commodity currencies over horizons between 0 month (contemporaneous) and 12 months ahead. Commodity price changes are measured by country-specific standardized commodity price indexes, that are export-weighted and monthly rebalanced. Regression specification includes a set of alternative predictors. Control predictors are the 1-month interest rate differential, changes in aggregate FX volatility, changes in funding liquidity (TED spread), changes in aggregate uncertainty in the US market (VIX), and an NBER recession indicator. The plotted 90% confidence intervals use standard errors that are clustered by currency and time, and adjusted using the Newey and West (1987) kernel where the bandwidth is equal to the forecasting horizon. Section 5 describes the econometric specification and the controls. The sample consists of monthly observations between January 1980 to May 2019.

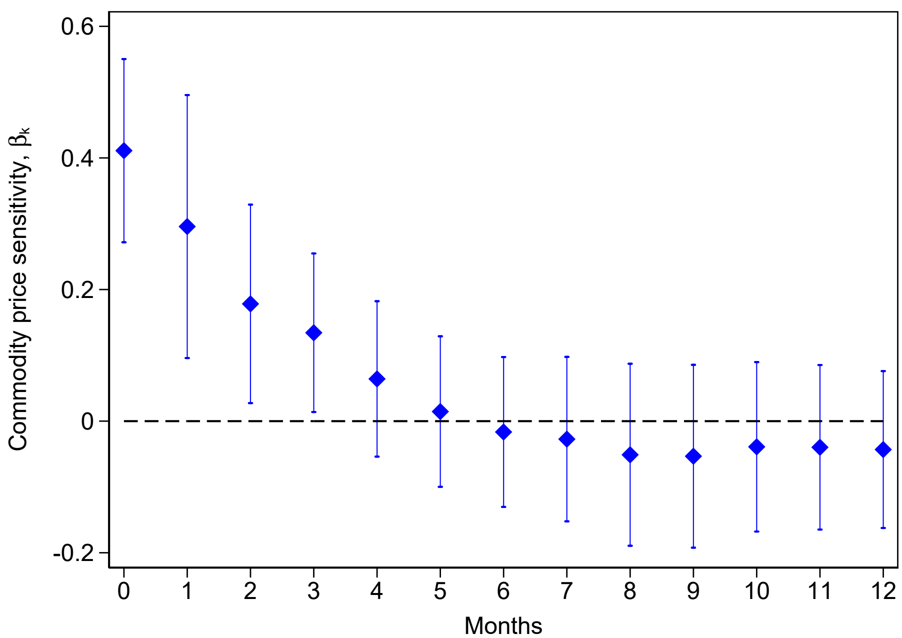


Figure 4: FX market conditions

The figure shows the probability of being in a regime of poor FX market conditions. The top and bottom panels correspond to the probability of being in high FX volatility and illiquidity regimes, respectively. FX volatility is constructed as the average realized volatility across 43 currencies against the US dollar. FX illiquidity is the average level of illiquidity of 33 currency pairs, following Karnaukh et al. (2015). Grey areas indicate NBER recession periods. The sample consists of monthly observations between January 1980 to May 2019.

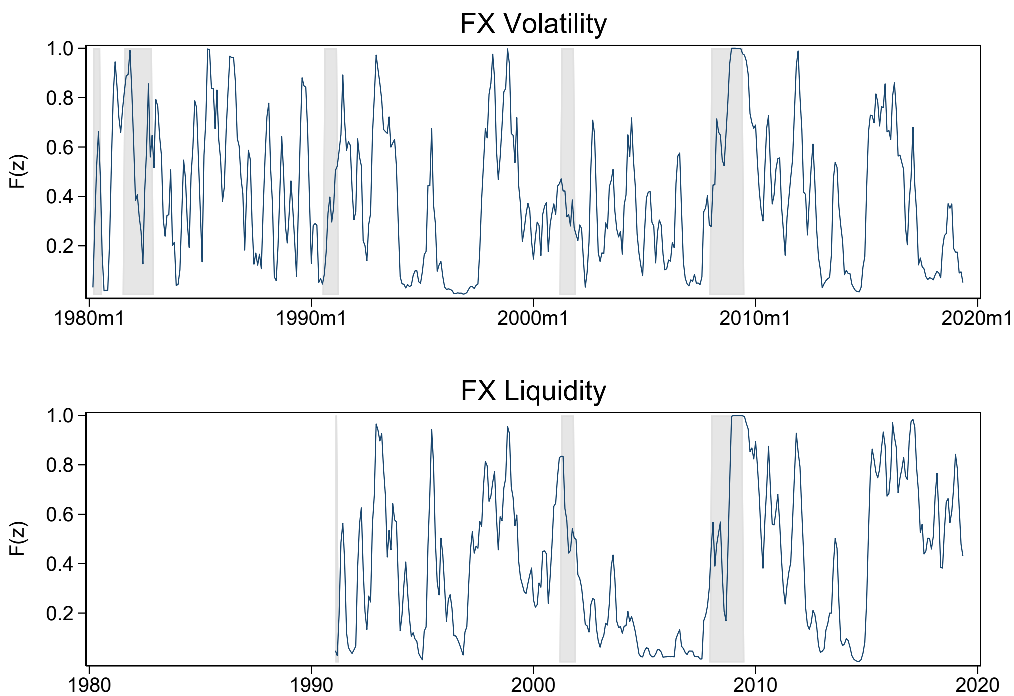
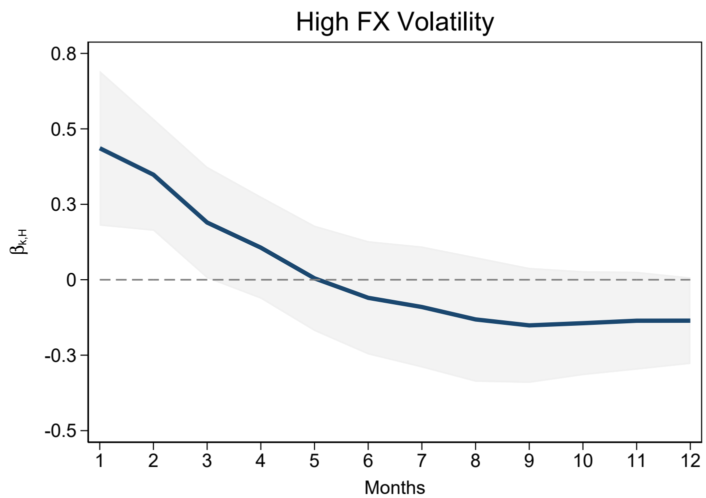


Figure 5: Multiple horizon predictability: conditional model

This figure presents the average impact of commodity price changes on bilateral exchange rates of commodity currencies over different forecast horizons, conditional on aggregate FX market volatility. The main dependent variable is the return of country-level commodity currencies over an horizon between 1 month and 12 months. Commodity price changes are measured by country-specific standardized commodity price index, that are export-weighted and monthly rebalanced. Regression specification includes a set of alternative predictors. Control predictors are the 1-month interest rate differential, changes in aggregate FX volatility, changes in funding liquidity (TED spread), changes in aggregate uncertainty in the US market (VIX), and an NBER recession indicator. The 90% confidence intervals reported in grey use standard errors that are clustered by currency and time, and adjusted using the Newey and West (1987) kernel where the bandwidth is equal to the forecasting horizon. Section 5 describes the econometric specification and the controls. The sample consists of monthly observations between January 1980 to May 2019.



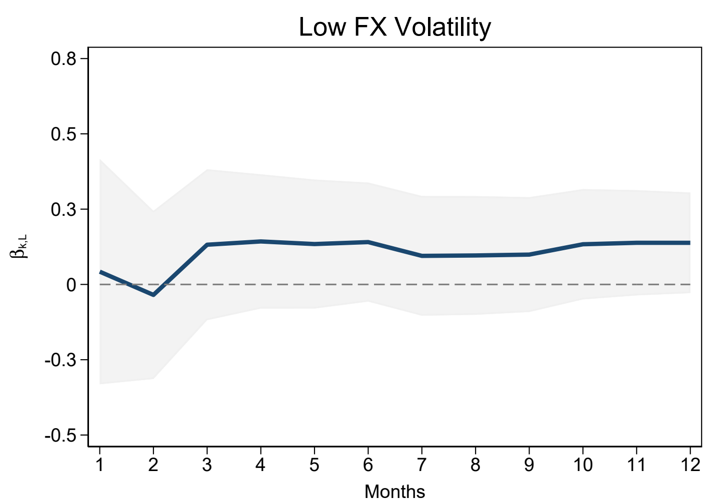
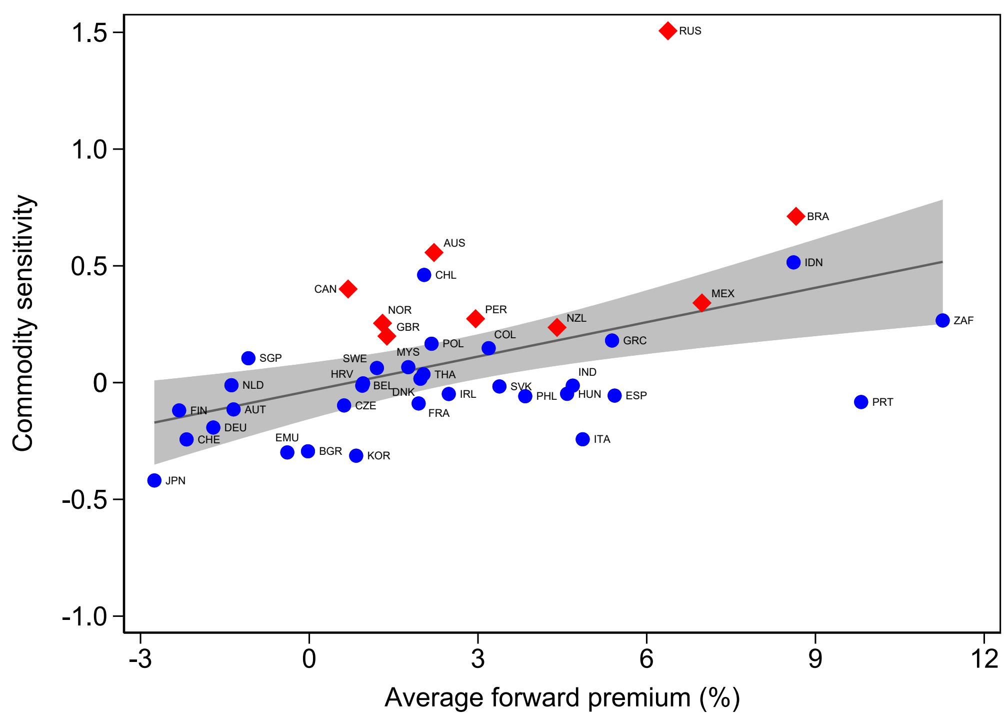


Figure 6: Commodity price sensitivity and forward premium

This figure presents the relationship between estimated commodity price sensitivity coefficient (in % per month) and average monthly forward premium (in % and annualized). Commodity price sensitivity is estimated by contemporaneous, country-level regression of bilateral spot exchange rate changes on the changes of a country's standardized commodity price index and the dollar factor. Country-specific commodity price indexes are export-weighted and monthly rebalanced. The dollar factor is the average change in exchange rates against the US dollar. Coefficients that are positive and statistically significant at the 10% level are shown as red diamonds. The figure also presents a fitted regression line of each country's commodity price sensitivity and each country's forward premium (OLS standard errors are used for the construction of the confidence interval). The sample consists of monthly observations between January 1980 to May 2019.



Internet Appendix to

"Commodity Prices and Currencies"

(not for publication)

Abstract

This Internet Appendix presents supplementary material and results not included in the main body of the paper.

August 20, 2021

A Theoretical derivation

A.1 Autocovariance of the exchange rate returns

We here derive the autocovariance of the exchange rate returns presented in Equation (18). From Equations (14) and (16), the first- and second-period exchange rate returns are, respectively, given by

$$\begin{aligned} r_1 &= \omega_I \lambda p + \bar{\sigma}_S^2 x_{N,1} && \text{(A.1)} \\ r_2 &= \Phi - \omega_I \lambda p - \bar{\sigma}_S^2 x_{N,1}. && \text{(A.2)} \end{aligned}$$

The covariance between r_2 and r_1 is then determined by

$$\begin{aligned} \mathbb{COV}\left[r_2, r_1\right] &= \mathbb{COV}\left[\Phi - \omega_I \lambda p - \bar{\sigma}_S^2 x_{N,1}, \omega_I \lambda p + \bar{\sigma}_S^2 x_{N,1}\right] && \text{(A.3)} \\ &= \mathbb{COV}\left[\Phi - \omega_I \lambda (\Phi + \epsilon) - \bar{\sigma}_S^2 x_{N,1}, \omega_I \lambda (\Phi + \epsilon) + \bar{\sigma}_S^2 x_{N,1}\right] && \text{(A.4)} \\ &= \mathbb{COV}\left[\Phi - \omega_I \lambda (\Phi + \epsilon), \omega_I \lambda (\Phi + \epsilon)\right] - \bar{\sigma}_S^4 \sigma_N^2 && \text{(A.5)} \\ &= \omega_I \lambda \sigma^2 - \omega_I^2 \lambda^2 \left(\sigma^2 + \sigma_\epsilon^2\right) - \bar{\sigma}_S^4 \sigma_N^2 && \text{(A.6)} \\ &= \omega_I \lambda \sigma^2 - \omega_I^2 \lambda \sigma^2 - \bar{\sigma}_S^4 \sigma_N^2 && \text{(A.7)} \\ &= \omega_I (1 - \omega_I) \lambda \sigma^2 - \bar{\sigma}_S^4 \sigma_N^2 && \text{(A.8)} \\ &= \omega_I \omega_L \lambda \sigma^2 - \bar{\sigma}_S^4 \sigma_N^2 && \text{(A.9)} \end{aligned}$$

using $\sigma^2 + \sigma_\epsilon^2 = \frac{\sigma^2}{\lambda}$ from Equation (6) and $\omega_I + \omega_L = 1$.

A.2 Commodity beta

We here derive the commodity price beta discussed in Section 6. The exposure of the second-period exchange rate return r_2 to the public news p, denoted by the commodity price beta β, can be expressed as follows:

$$\beta = \frac{\mathbb{COV}\left[r_2, p\right]}{\mathbb{V}\left[p\right]} = \frac{\sigma^2}{\sigma^2 + \sigma_\epsilon^2}(1 - \omega_I), \qquad \text{(A.10)}$$

where the covariance between r_2 and p satisfies

$$\begin{aligned}
\mathbb{COV}\left[r_2, p\right] &= \mathbb{COV}\left[\Phi - \omega_I \lambda p - \bar{\sigma}_S^2 x_{N,1}, p\right] && \text{(A.11)}\\
&= \mathbb{COV}\left[\Phi - \omega_I \lambda (\Phi + \epsilon) - \bar{\sigma}_S^2 x_{N,1}, \Phi + \epsilon\right] && \text{(A.12)}\\
&= \sigma^2 - \omega_I \lambda \left(\sigma^2 + \sigma_\epsilon^2\right) && \text{(A.13)}\\
&= \sigma^2 - \omega_I \sigma^2 && \text{(A.14)}\\
&= \sigma^2 (1 - \omega_I) && \text{(A.15)}
\end{aligned}$$

using Equation (16) for r_2 and $\sigma^2 + \sigma_\epsilon^2 = \frac{\sigma^2}{\lambda}$ from Equation (6), while the variance of p equals

$$\begin{aligned}
\mathbb{V}\left[p\right] &= \mathbb{V}\left[\Phi + \epsilon\right] && \text{(A.16)}\\
&= \sigma^2 + \sigma_\epsilon^2. && \text{(A.17)}
\end{aligned}$$

B Data description

B.1 Global currency factors

This section presents the construction of the global currency factors. Each strategy is rebalanced each month t and the returns are calculated the following month $t + 1$.

Following Verdelhan (2018), we compute a currency-specific dollar factor such that we do not include the bilateral exchange rate that is the dependent variable in the predictability regression. At each month t, we allocate currencies to five portfolios on the basis of their forward premiums (or interest rate differential relative to the US): 20% of all currencies with the highest forward premiums are assigned to Portfolio 1, whereas 20% of all currencies with the lowest forward premiums are assigned to Portfolio 5. We compute the return for each portfolio as an equally weighted average of individual currency returns within that portfolio. The dollar factor is computed as an equally weighted average of these portfolios, as in Lustig et al. (2011).

B.2 Construction of the carry trade

We use the logarithm of the spot exchange rates, s_t, and the logarithm of the 1-month forward exchange rates, f_t. Exchange rates are in units of foreign currency per US dollar.

To compute the carry trade performance, we determine the (log excess) return, r_{t+1}, of buying a foreign currency in the forward market and then selling it in the spot market after one month. We adjust the return for transaction costs using the bid-ask quotes for spot and forward contracts and assume that bid-ask spreads are deducted from returns whenever a currency enters and/or exits a portfolio, as in **?**. Accordingly, the adjusted return for a currency that enters a portfolio at month t and exits the portfolio at the end of the month is computed as $r^l_{t+1} = f^b_t - s^a_{t+1}$ for a long position. The investor buys the foreign currency or equivalently sells the dollar forward at the bid price, f^b_t, in month t, and sells the foreign currency or equivalently buys dollars at the ask price, s^a_{t+1}, in the spot market in month $t+1$. Conversely, the return is $r^s_{t+1} = -f^a_t + s^b_{t+1}$ for a short position.

A currency that enters a portfolio but stays in the portfolio at the end of the month t has a return of $r^l_{t+1} = f^b_t - s_{t+1}$ for a long position and $r^s_{t+1} = -f^a_t + s_{t+1}$ for a short position, whereas a currency that exits a portfolio at the end of month t but already was in the current portfolio the month before $(t-1)$ has a return of $r^l_{t+1} = f_t - s^a_{t+1}$ for a long position and $r^s_{t+1} = -f_t + s^b_{t+1}$ for a short position. A currency that was in a portfolio and that remains in this portfolio has a return $r^l_{t+1} = f_t - s_{t+1}$ for a long position and $r^s_{t+1} = -f_t + s_{t+1}$ for a short position.

Figure A.1: Exchange rate commodity price sensitivity without the dollar factor

The top panel of the figure shows the estimated commodity price sensitivity coefficient from a contemporaneous, univariate, country-level regression of bilateral spot exchange rate changes on the changes of a country's standardized commodity price index. Country-specific commodity price indexes are export-weighted and monthly rebalanced. The 90% confidence intervals based on White (1980) standard errors are also displayed. Coefficients that are positive and statistically significant at the 10% level are shown as red diamonds. The estimated commodity price sensitivity coefficients are expressed in % per month. The bottom panel shows the average share (in %) of raw commodity exports of each country's total exports. In both panels, the countries are displayed in an ascending order based on their estimated commodity price sensitivities. The sample consists of monthly observations between January 1980 to May 2019.

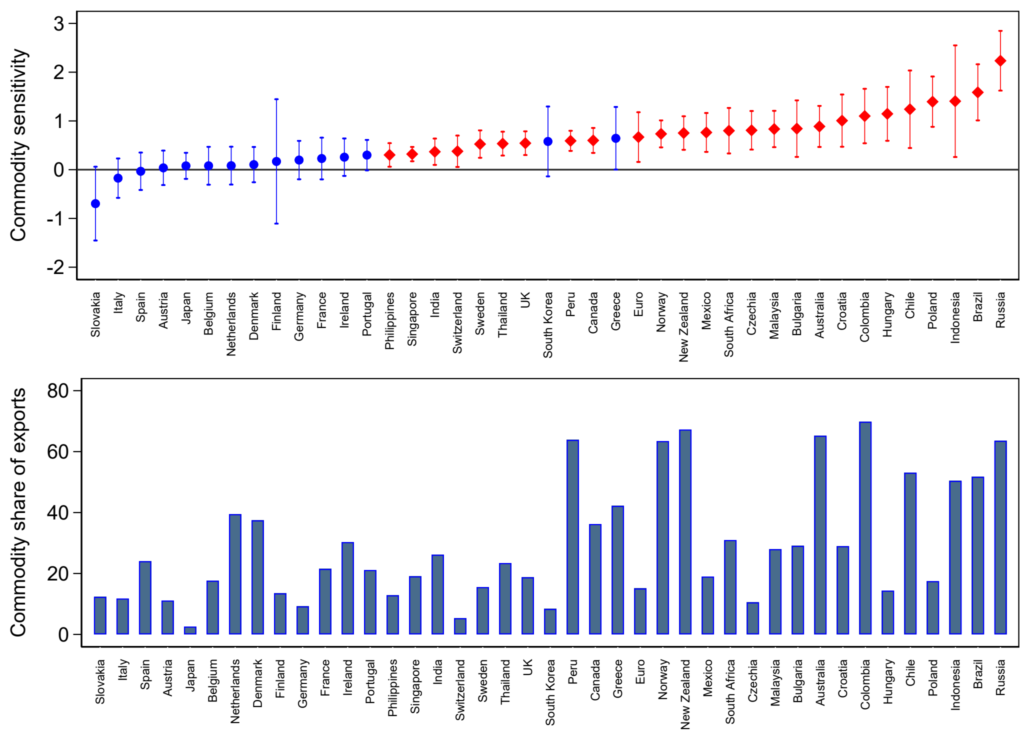


Figure A.2: Exchange rate commodity price sensitivity controlling for dollar and market

The top panel of the figure shows the estimated commodity price sensitivity coefficient from a contemporaneous, country-level regression of bilateral spot exchange rate changes on the changes of a country's standardized commodity price index, the dollar factor, and US aggreagate stock market return. Country-specific commodity price indexes are export-weighted and monthly rebalanced. The dollar factor is the average change in exchange rates against the US dollar. The 90% confidence intervals based on White (1980) standard errors are also displayed. Coefficients that are positive and statistically significant at the 10% level are shown as red diamonds. The estimated commodity price sensitivity coefficients are expressed in % per month. The bottom panel shows the average share (in %) of raw commodity exports of each country's total exports. In both panels, the countries are displayed in an ascending order based on their estimated commodity price sensitivities. The sample consists of monthly observations between January 1980 to May 2019.

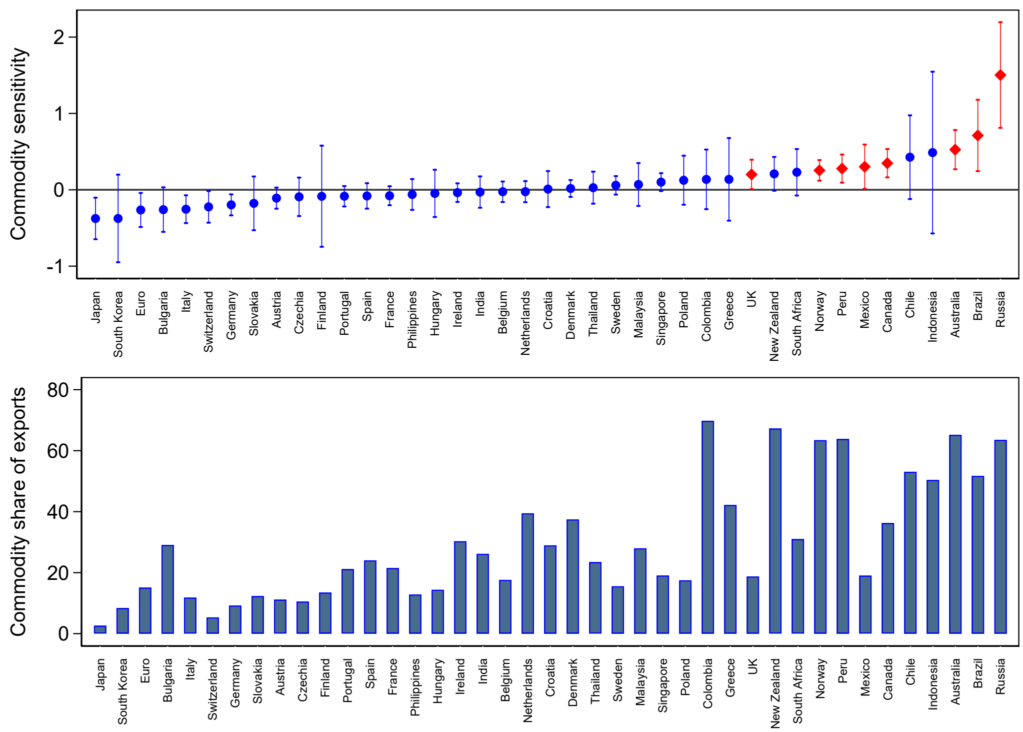


Figure A.3: Robustness

The figure shows the to the exclusion of countries from the original data sample. We plot the parameter estimate sensitivity of the estimate for the parameter, which results from dropping each country one at a time. We report 1% confidence bands, and indicate the original estimate with a gray dashed line. The sample consists of monthly observations between January 1980 to May 2019.