Journal of International Money and Finance 132 (2023) 102811

Contents lists available at ScienceDirect

Journal of International Money and Finance

journal homepage: www.elsevier.com/locate/jimf

Currency exchange rate predictability: The new power of Bitcoin prices

Wenjun Feng [a,*], Zhengjun Zhang [b]

[a] School of Economics and Management, Beijing Jiaotong University, No.3 Shangyuancun, Beijing 100044, PR China
[b] Department of Statistics, University of Wisconsin at Madison, 1300 University Avenue, Madison, WI 53706, United States

ARTICLE INFO

Article history:
Available online 10 February 2023

JEL:
F31
F47
G12

Keywords:
Bitcoin
Exchange rate
Present-value model

ABSTRACT

We show that Bitcoin prices have surprisingly predictive power for nominal currency exchange rates, both in-sample and out-of-sample. The predictability follows from the fact that Bitcoin prices are forward-looking: Bitcoin efficiently incorporates expectations of currency exchange rates and their drivers, as exchange rates serve as a fundamental of Bitcoin. We examine the Bitcoin-based exchange rate prediction model in the autoregressive distributed lag (ADL) specification and the error correction specification. Forecasts based on both specifications outperform different benchmarks for some of the exchange rates. The outperformance is most pronounced at the daily horizon using the ADL model. Bitcoin-based forex trading strategies generate Sharpe ratio gains relative to the US risk-free rate and the carry trade. Bitcoin returns incorporate extra knowledge of future interest rate differentials after controlling for lagged exchange rate movements. Our result is inspiring for currency market participants, given the well-documented difficulty in exchange rate prediction.

1. Introduction

Reliably predicting exchange rate movements is a crucial problem for international economists, investors, policymakers, and multinational corporations worldwide. Since Meese and Rogoff (1983a), Meese and Rogoff (1983b) documents the failure of traditional economic models in exchange rate prediction (known as "the Meese and Rogoff puzzle"), whether exchange rates are predictable remains controversial.

The recent literature has made a lot of efforts to study this question, and most of the studies are based on macroeconomic fundamentals of exchange rates. Examples of traditional exchange rate predictors include interest rate differentials (Alquist and Chinn, 2008; Amat et al., 2018; Clarida et al., 2003; Clark and West, 2006), price or inflation differentials (Ca'Zorzi and Rubaszek, 2020; Clements and Lan, 2010; Ince, 2014; Rogoff, 1996), money and output differentials (Berkowitz and Giorgianni, 2001; Chinn and Meese, 1995; Macdonald et al., 1993), productivity differentials (Cheung et al., 2005), Taylor rule fundamentals (Engel and West, 2005; Engel and West, 2006; Molodtsova and Papell, 2009), external imbalance measures (Della Corte et al., 2012; Gourinchas and Rey, 2007), commodity prices (Chen and Rogoff, 2003; Chen et al., 2010; Ferraro et al., 2015), order flows (Rime et al., 2010), fundamental equilibrium exchange rates (Clark and MacDonald, 1999; Jordà and Taylor, 2012), and time serial predictors (Engel and Hamilton, 1990; Engel, 1994). However, another strand

* Corresponding author.
E-mail addresses: fengwj@bjtu.edu.cn (W. Feng), zjz@stat.wisc.edu (Z. Zhang).

https://doi.org/10.1016/j.jimonfin.2023.102811
0261-5606/

of literature argues that, many forecasting models based on macroeconomic fundamentals and well-established theories, empirically fail to beat the random walk (RW) (Berkowitz and Giorgianni, 2001; Chinn and Meese, 1995; Diebold et al., 1994; Diebold and Nason, 1990; Engel et al., 2019; Faust et al., 2003; Groen, 1999; Kilian, 1999; Rogoff and Stavrakeva, 2008; Rossi and Sekhposyan, 2011). The existing exchange rate prediction models are carefully summarized in Cheung et al. (2005), Cheung et al. (2019) and Rossi (2013).

This paper uncovers a surprising and unexamined predictor of currency exchange rates: Bitcoin prices. Bitcoin is an emerging and globally traded asset characterized by decentralization. We show that lagged Bitcoin prices have short-term predictive power for currency exchange rates of numerous countries.

The success that Bitcoin prices forecast exchange rates is not a coincidence. It results from the fact that Bitcoin prices are *forward-looking* and *efficiently* incorporate market expectations about their future fundamentals. Currency exchange rates influence the demand for Bitcoin (details in Section 2.2) and serve as such a fundamental of Bitcoin. Therefore, when Bitcoin market participants anticipate future shocks to exchange rates, their views are priced into Bitcoin.

The Bitcoin market provides a unique trading environment to *efficiently* price such views. The Bitcoin market is poorly regulated (Foley et al., 2019) and offers a 24/7 trading scheme. Any market opinion on exchange rate fluctuations or future value of exchange rates' fundamentals can be reflected immediately in Bitcoin prices without being manipulated by a central authority. In contrast, exchange rates are a crucial macroeconomic variable for national economies. Governments have more or less power over the exchange rates, even for floating exchange rate regimes (Calvo and Reinhart, 2002). Compared with Bitcoin, exchange rates respond less sharply to future expectations. As a result, Bitcoin prices contain information that cannot be captured by simple time series models of exchange rates. As supporting evidence for Bitcoin's incorporation of future shocks to exchange rates, we show that Bitcoin returns predict one of the exchange rate fundamentals, the interest rate differentials, for a noticeable part of currencies. We also find that in the cross-section, the forecastability is better in countries with higher inflation volatility, providing suggestive evidence for another potential mechanism of predictability: Bitcoin returns might correlate with the expected currency premium or its determinants, such as convenience yield differentials.

To describe the relation between the *forward-looking* Bitcoin prices and their expected fundamentals, we offer a theoretical pricing model based on the present-value approach (e.g., Campbell and Shiller, 1987; Chen et al., 2010; Dahlquist and Pénasse, 2022; Engel and West, 2005) in the asset pricing theory. The present-value model suggests that Bitcoin prices should predict the relevant fundamentals, including exchange rates.

Bitcoin provides an ideal and unique opportunity to test the present-value model, as the causality between exchange rates and Bitcoin is clear. Although exchange rates are also a fundamental determinant of many other macroeconomic variables or traditional assets (e.g., interest rates, stock indices, etc.), an issue faced by previous studies to verify the present-value model is reciprocal causations (Chen et al., 2010; Engel and West, 2005). Specifically, the observed predictability could result from market responses or policy responses of exchange rates to that macroeconomic variable or traditional assets, rather than resulting from the present-value specification. Bitcoin is such a unique asset that avoids the reverse causality problem: Exchange rates are a fundamental determinant of Bitcoin prices, while the Bitcoin market size is too small compared with the foreign exchange market,[1] and supply or demand for Bitcoin can hardly influence the currency exchange rates; meanwhile, it is reasonable to assume policymakers do not refer to Bitcoin prices when adjusting exchange rates. Therefore, predictability can be viewed as evidence of the present-value model. We quantitatively examine the exogeneity in the robustness analysis.

Our work provides an important supplement for *managed fixed* and *managed floating* exchange rate prediction. Most previous studies focus on forecasting (free) floating exchange rates, as floating exchange rates are more sensitive to the market demands for the currencies. Our forecasts are not subject to this restriction, as the expectations of managed fixed or managed floating exchange rates can also be priced into Bitcoin. In this study, we examine the Bitcoin-based exchange rate predictability of 33 currencies, including all the exchange rates with available IMF daily data, and only excluding strictly fixed exchange rate regimes.

We estimate the Bitcoin-based exchange rate prediction model in the autoregressive distributed lag (ADL) specification and the error correction model (ECM) specification. Both specifications are standard tools in the exchange rate prediction literature (e.g., Chen and Tsang, 2013; Rossi, 2013; Ferraro et al., 2015; Mark, 1995), and both specifications provide true *ex-ante* out-of-sample forecasts without assuming knowledge of contemporaneous values of predictors.

Both the ADL and the ECM specifications demonstrate remarkable in-sample and out-of-sample exchange rate predictability of Bitcoin. In the in-sample tests of both specifications (including the Granger causality tests), we find significant predictive power of Bitcoin for all 33 exchange rates for all three horizons, at least for a period of time. The predictability favorably supports the present-value model. The out-of-sample predictability is particularly pronounced at the daily horizon and using the ADL specification: According to the direction of change statistics, for 32 out of 33 currencies, we successfully forecast the direction of exchange rate movement more than half the time, and 22 outperformance cases are significant at the 10% level; according to the Clark-West statistics (Clark and West, 2006; Clark and West, 2007), 31 series of the forecasts outperform the RW (the toughest benchmark in the literature), and 23 outperformance cases are significant at the 10% level.

[1] The foreign exchange market is the largest financial market in the world, with average daily volumes of \$5.36 trillion, \$5.07 trillion, and \$6.60 trillion in 2013, 2016, and 2019 respectively (Bank for International Settlements, 2013). The average daily volume of Bitcoin is 14.42 billion in our sample, according to the Coinmarketcap data.

For weekly and monthly forecasts, the ECM works slightly better than the ADL model, and significantly outperforms the RW benchmark in forecasting 9–15 currencies.

To evaluate the economic gains of the forecastability for currency market practitioners, we test the performance of two strategies based on the daily ADL forecasting model: The first strategy goes long on a foreign currency if our model predicts its appreciation and otherwise deposits the US dollar; the strategy earns higher returns than the US risk-free rate benchmark for 30 (out of 32) currencies; the annualized return of the strategy can be up to 10.81% (the Russian Ruble); The second strategy is the carry trade based on the Bitcoin-implied forecastability, and it outperforms the standard carry trade for 29 currencies; the annualized return of the strategy can reach 20.44% (the Columbia Peso); the mean return of the strategy (7.02%) is also economically higher than the mean return of the carry-trade benchmark (0.27%).

We conduct two robustness analyses. First, we test alternative benchmarks: random walk with drift and AR(1). We confirm the superiority of the Bitcoin-based model again, addressing concerns that the out-of-sample outperformance is attributed to the constant term or the lagged exchange rate in the forecasting equations. Second, we conduct Wooldridge, 1995's (Wooldridge, 1995) score tests to strictly address potential concerns on reverse causality between Bitcoin prices and exchange rates, supporting the interpretation of the present-value model.

Our paper contributes to the literature in three ways. First, we find a new predictor of currency exchange rates: Bitcoin prices. Our model provides *ex-ante* out-of-sample forecasts and achieves outperformance compared with several tough benchmarks. We complement the sizable body of studies on exchange rate prediction from three aspects: (1) *New mechanism.* Most traditional predictors are based on macroeconomic fundamentals of exchange rates. Our predictor, Bitcoin prices, is not a fundamental determinant of exchange rates, but reflects market expectations about them. (2) *Wider applicability.* The target exchange rates of most previous studies are the free floating ones, while our predictor also works for managed fixed and managed floating exchange rates. (3) *Shorter horizons.* The majority of previous studies forecast at the monthly, quarterly, and longer horizons; one reason is that macroeconomic data are not released at a high frequency. Our forecasts are most favorable at a daily horizon, and daily or even intra-day Bitcoin prices are available.

Second, we show that Bitcoin prices incorporate expectations about macroeconomic variables and can help predict macroeconomic variables; the perspective is new and inspiring to the Bitcoin studies. Our results imply that Bitcoin price movements are not simply speculative or random fluctuations, but absorb some information more efficiently than the established currency market. To some extent, our study also uncovers which countries are "important" for Bitcoin supply and demand. Our study enriches the growing strand of literature that analyzes the relation between Bitcoin prices and traditional asset prices or macroeconomic variables (e.g., Dyhrberg, 2016; Guesmi et al., 2019; Makarov and Schoar, 2020; Shahzad et al., 2020). Previous studies mainly focus on analyzing the statistical relations or portfolio diversification implications, and few studies use Bitcoin prices for out-of-sample macroeconomic variable forecasting. Most directly related to our research, Urquhart and Zhang (2019) shows that Bitcoin can be an intraday hedge or a diversifier for some currencies; they focus on the contemporaneous correlations, while our work focus on the lead-lag relations and forecast implications. Salisu et al. (2019) empirically shows that Bitcoin prices help improve the G7 stock return predictability; our analysis framework may be similarly applied and may provide theoretical support for their conclusion.

Third, our work offers an ideal laboratory for examining the present-value model, circumventing the reciprocal causation problem. The present-value model (e.g., Campbell and Shiller, 1987; Engel and West, 2005) delivers valuable insights by showing that asset prices reflect expectations of future fundamentals and should be able to predict the fundamentals. However, as Chen et al. (2010) points out, previous tests of the present-value model are easily exposed to the reciprocal causation problem between the asset prices and the fundamentals, making causal interpretation spurious. Based on the economic analysis and the exogeneity tests, we show that exchange rate shocks are exogenous to Bitcoin. The exogeneity allows us to attribute the predictability to the present-value specification.

In sum, our results show that Bitcoin prices help predict many currency exchange rates. The predictability has important implications not only for currency market participants, policymakers, and multinational corporations, but also for Bitcoin asset pricing research. Our results motivate future studies on Bitcoin pricing models that explicitly incorporate currency exchange rates.

The remainder of the paper proceeds as follows. Section 2 briefly introduces Bitcoin and offers theoretical resolutions on the predictability. Section 3 describes our data. Section 4 presents the forecasting specifications and the evaluation methods. Section 5 evaluates the empirical in- and out-of-sample forecasting performances and the performance of related strategies. Section 6 tests two hypothetical mechanisms of the forecastability. Section 7 conducts two robustness analyses on alternative benchmarks and on the exogeneity assumption. Section 8 concludes.

2. Background and theoretical analysis

In this section, we give a brief introduction about Bitcoin, and discuss the mechanisms to explain the exchange rate predictability of Bitcoin prices.

2.1. Background about Bitcoin

Bitcoin is a new international "currency" invented by Nakamoto (2008). Bitcoin is a decentralized cryptocurrency, which is not backed by any central authority but backed by blockchain technology and those willing to recognize its value worldwide. Compared with traditional financial assets whose trading is heavily monitored, the Bitcoin market is much less regulated (Foley et al., 2019). The transaction anonymity imposes technical difficulty for regulation (Feng et al., 2018b). Meanwhile, the Bitcoin market offers a 24/7 trading scheme. Therefore, any market opinion about its determinants can be priced into Bitcoin immediately without being manipulated by a central authority.

From the supply side, the speed of supply is pre-defined in Bitcoin's white paper. From the demand side, Bitcoin is widely used for dark marketplace dealings and cross-border transactions, providing a covert way of transactions, and allowing sellers of illegal goods and services to reach buyers around the globe (Foley et al., 2019). For example, in June 2019, China customs busted a cross-border drug trafficking, featuring Bitcoin payment on the dark web.[2] Bitcoin also serves as a new means of cross-border capital flight, especially from strictly capital regulated regions (Ju et al., 2016). Makarov and Schoar (2020) finds higher convenience yields for Bitcoin in countries with tight capital controls.

A growing body of literature has studied the financial and statistical characteristics of Bitcoin (e.g., Böhme et al., 2015; Cong et al., 2019; Easley et al., 2019; Gandal et al., 2018; Griffin and Shams, 2020; Leshno and Strack, 2020; Mai et al., 2018; Makarov and Schoar, 2020; Schilling and Uhlig, 2019; Yin et al., 2019) and the correlation between Bitcoin prices and traditional asset prices or macroeconomic factors (e.g., Dyhrberg, 2016; Guesmi et al., 2019; Makarov and Schoar, 2020; Shahzad et al., 2020). We extend the literature by showing that Bitcoin prices embody market views about macroeconomic variables and can help with macroeconomic variable prediction.

2.2. Bitcoin and currency exchange rates: the present value approach

Motivated by the present-value approach in the asset pricing theory (e.g., Campbell and Shiller, 1987; Chen et al., 2010; Engel and West, 2005), we use two steps to describe the theoretical mechanism of why Bitcoin prices predict currency exchange rates. First, we show that exchange rates are a fundamental determinant of Bitcoin. Second, we use a present-value model to describe the pricing relation between Bitcoin and the expectations about its future fundamentals, including exchange rates. The predictability is implied by the present-value model, and we explain why Bitcoin offers an ideal laboratory to test the present-value model.

We put forward three possible channels to explain why currency exchange rates are a fundamental determinant of Bitcoin. First, depreciation of the fiat currency and currency crisis in a country can greatly increase the demand for Bitcoin and hence its prices, as Bitcoin acts as both a medium of exchange for foreign currency and an alternative store of value. For example, the Russian ruble crisis in 2014 greatly increased Bitcoin demand.[3] Meanwhile, there is not a well-recognized approach to calculate Bitcoin's intrinsic value (Detzel et al., 2021). As a result, Bitcoin prices are sensitive to demand shocks from exchange rates.

Second, it is well-studied in the literature that currency exchange rates have a major influence on globally traded assets, like gold (Sjaastad and Scacciavillani, 1996). Bitcoin is also a global asset traded continuously and liquidly in many exchanges worldwide, against most currencies (Makarov and Schoar, 2020). The analyses in Sjaastad and Scacciavillani (1996) can be similarly applied to Bitcoin and demonstrate that currency exchange rates influence Bitcoin prices and the extent of the impact depends on the market power (regarding supply and demand) in each country.[4]

Third, the Bitcoin users involved in multi-currency transactions or cross-border remittances are concerned about the currency exchange rates. They should have their views about the short-term trend of the bilateral exchange rates and choose an appropriate time to convert their money/deposit from one currency to another. Nominal exchange rates directly influence how much home currency one should pay. In this way, currency exchange rates influence the short-term demand for Bitcoin and its prices.

According to these three channels, the exchange rates of the countries where Bitcoin mining prevails and where Bitcoin is widely used for cross-border remittance, are supposed to have a larger impact on Bitcoin prices. To some extent, our predictability analyses could help identify these large Bitcoin "importer" and "exporter" countries, which are otherwise hard to recognize because of the transaction anonymity.

We consider a general model in which log Bitcoin prices p_t can be expressed as its fundamentals $\boldsymbol{f_t}$ and expectations of its future values:

$$p_t = (1-\theta)\boldsymbol{\beta}^{\boldsymbol{T}}\boldsymbol{f_t} + \theta E_t(p_{t+1}), \tag{1}$$

[2] http://www.xinhuanet.com/english/2019-06/24/c_138170221.htm (Accessed: Aug. 25, 2021)

[3] https://www.cnbc.com/2014/12/17/russians-move-into-bitcoin-as-ruble-tanks.html (Accessed: Aug. 25, 2021)

[4] Following the analysis of Sjaastad and Scacciavillani (1996), if we make a hypothetical assumption that all other fundamentals and market environment about Bitcoin remain unchanged, and supposing, for example, when the Japanese yen (JPY) appreciates against the US dollar (USD), the Bitcoin price based on JPY tends to fall, or the Bitcoin price based on USD tends to rise; otherwise, there will be an arbitrage opportunity. According to the market-clearing condition described in Sjaastad and Scacciavillani (1996), the extent of the impact depends on the market power (regarding supply and demand) in each country.

where the log exchange rates are components of the fundamentals $\boldsymbol{f_t}; E_t$ is the expectation operator given information at time $t; \theta \in (0, 1)$ measures the Bitcoin price elasticity of its market expectations. The forward-looking component $E_t(p_{t+1})$ is commonly modeled in the asset-pricing theory, for example, for stock prices (Campbell and Shiller, 1987), interest rates (Campbell and Shiller, 1987), exchange rates (Chen et al., 2010; Engel and West, 2005), and also for Bitcoin pricing (Biais et al., 2022).

Eq. (1) leads to a pricing relation between the current log Bitcoin price and its expected future fundamentals,

$$p_t = (1-\theta)\sum_{i=0}^{\infty}\theta^i \boldsymbol{\beta^T} E_t(\boldsymbol{f_{t+i}}) + \lim_{n\to\infty}\theta^{n+1}E_t p_{t+n+1}. \tag{2}$$

For preciseness, we do not impose a "no bubble" condition and still keep the potential bubble component $\lim_{n\to\infty}\theta^{n+1}E_t p_{t+n+1}$, which is not, however, our focus. The present-value model in Eq. (2) shows that Bitcoin prices reflect market expectations about future fundamentals of Bitcoin. Therefore, Bitcoin prices should help predict the fundamentals, including exchange rates.[5]

Although the present-value model theoretically offers an insightful representation that asset prices absorb expectations of their future fundamentals, there is little evidence for its application in exchange rate prediction yet. A hard issue faced by previous studies is the reverse causality problem (Chen et al., 2010; Engel and West, 2005). Besides Bitcoin, exchange rates are also a fundamental of many other macroeconomic variables and traditional asset prices, such as interest rates, inflation rates, growth rates, and stock indices. However, there could be reciprocal causations between exchange rates and these macroeconomic variables or traditional asset classes: Exchange rates not only influence these macroeconomic variables or traditional assets, but also react to changes in these variables through market responses or policy responses. Even if we observe that an exchange rate predicts a macroeconomic variable or a traditional asset's price, this could result from market responses or policy responses of the exchange rate to that variable, rather than resulting from the present-value specification. In such cases, empirical predictability cannot be easily treated as evidence of the present-value specification.

Bitcoin is such a unique asset that avoids the reciprocal causation problem, and provides an ideal opportunity to examine the present-value model. The causality is clear, and predictability can be viewed as evidence of the present-value specification. It is reasonable to assume that exchange rate market participants typically do not refer to Bitcoin prices when making decisions, as the size of the Bitcoin market is far too small compared with the forex market (refer to footNote 1). It is also reasonable to assume that policymakers do not refer to Bitcoin prices when adjusting exchange rates. Therefore, exchange rate fluctuations are an *exogenous* shock to Bitcoin prices. We quantitatively test the exogeneity in the robustness analyses.

2.3. The potential mechanisms that Bitcoin prices predict exchange rates[6]

We have shown that Bitcoin prices incorporate information of future exchange rates. To more explicitly describe why Bitcoin predicts exchange rates, we discuss and test two potential mechanisms: The first mechanism is that Bitcoin prices incorporate future fundamentals of the exchange rate more efficiently than the exchange rate itself. The second mechanism is that Bitcoin returns correlate with the expected currency premium.

Let $\lambda_{t+1} = s_{t+1} - s_t + (i_t^* - i_t)$ be the equilibrium excess return on the non-USD currency over the USD, where s_t is the log exchange rate in terms of USD price of 1 unit of non-USD currency; i_t and i_t^* are interest rates of the USD and non-USD currencies, respectively. Let $\tilde{E}_t(\cdot)$ denote the expectational operator that prices the exchange rates based on information of $\tilde{\mathscr{F}}_t$. By iterating forward and taking expectations, the equilibrium exchange rate can be expressed as:

$$s_t = -\sum_{k=0}^{\infty}\widetilde{E}_t(i_{t+k} - i_{t+k}^*) - \sum_{k=0}^{\infty}\widetilde{E}_t(\lambda_{t+k+1}) + \lim_{k\to\infty}\widetilde{E}_t(s_{t+k}), \tag{3}$$

Let $E_t(\cdot)$ be the optimal expectational operator which uses all current available information $\mathscr{F}_t$. By definition, the filtrations satisfy: $\tilde{\mathscr{F}}_t \subset \mathscr{F}_t$; without loss of generality,[7] assuming $\mathscr{F}_t \subset \tilde{\mathscr{F}}_{t+1}$, and then we have:

$$\begin{aligned} E_t(\Delta s_{t+1}) = {} & (i_t - i_t^*) + \widetilde{E}_t\lambda_{t+1} - \sum_{k=1}^{\infty}\left(E_t - \widetilde{E}_t\right)(i_{t+k} - i_{t+k}^*) \\ & -\sum_{k=1}^{\infty}\left(E_t - \widetilde{E}_t\right)\lambda_{t+k+1} + \lim_{k\to\infty}\left(E_t - \widetilde{E}_t\right)(s_{t+k}). \end{aligned} \tag{4}$$

If the forex market is efficient, the exchange rates are set using the optimal forecasts of future fundamentals, i.e., $\tilde{E}_t = E_t$, and then $E_t(\Delta s_{t+1}) = (i_t - i_t^*) + E_t\lambda_{t+1}$; in this case, any forecastability of Δs_{t+1} arises from $E(\lambda_{t+1})$. But if the forex market is not

[5] The implications of the present-value model is well-studied Campbell and Shiller (1987),Chen et al. (2010), and Engel and West (2005).

[6] We thank an anonymous reviewer for detailed suggestions on the two possible mechanisms discussed in this section, as well as on the methods to test the mechanisms in Section 6.

[7] One can reasonably assume $\mathscr{F}_t \subset \tilde{\mathscr{F}}_{t+h}$, and derive $E_t(\Delta s_{t+h})$ accordingly.

efficient, i.e., $\tilde{E}_t \neq E_t$, the forecastability could also comes from extra knowledge of $\mathscr{F}_t$. Based on the above reasoning, the exchange rate forecastability of Bitcoin could either comes from:

(i) *Bitcoin return efficiently captures short-term inefficiency of exchange rates.* The Bitcoin market is less regulated than the currency market; unlike the exchange rates, there is no central authority to monitor or manipulate Bitcoin. So the Bitcoin returns could reflect information of future exchange rate fundamentals in a faster manner than the exchange rate itself.
(ii) *Bitcoin return correlates with either the expected currency premium $E_t(\lambda_{t+1})$, or its determinants,* including risks of foreign currency investment, convenience yield differentials between the non-USD currency and the USD, the fundamentals of the relevant stochastic discount factors that prices the exchange rate, etc.

In Section 6, we test whether the two potential mechanisms work. In Section 6.1, we test (i) by testing whether Bitcoin returns predict a future fundamental of the exchange rate. In Section 6.2, we test (ii) by testing whether the convenience yields of currencies are related to the forecastability.

3. Data

We obtain daily Bitcoin prices (in USD) from Coinmarketcap[8]. The Coinmarketcap data is widely used in the Bitcoin literature (e.g., Feng et al., 2018a; Gandal et al., 2018). Our sample period is Jan. 1, 2014, to Aug. 31, 2022, including 3166 Bitcoin price observations. Although Bitcoin was invented in 2009, its liquidity was not good in the early years.

We examine the nominal exchange rate predictability of 32 currencies, plus a nominal effective exchange rate (NEER) of the USD. We obtain the exchange rate data from the International Monetary Fund (IMF) database and convert the exchange rates to be quoted in USD per 1 unit of each currency, such that a higher value indicates an appreciation of the currency. IMF provides exchange rate data of 39 currencies; we only exclude strictly fixed exchange rates and keep the floating, managed floating, and managed fixed exchange rates. We use the Nominal Broad Dollar Index (daily)[9] provided by the US Federal Reserve as a measure of the NEER of the USD. Although the analysis in Section 2.2 can be similarly applied to real exchange rates, we focus on nominal exchange rates because they are directly observable at a relatively high frequency. Meanwhile, we do not focus only on large countries, as expectations of a small country's exchange rate could also be priced into Bitcoin if either Bitcoin demand or supply is high in the small country.

Table 1 presents the descriptive statistics of Bitcoin and the selected exchange rates, as well as the exchange rate regimes. According to the augmented Dickey-Fuller (ADF) test, we can treat the log return series of all the selected exchange rates/Bitcoin as stationary.

Our study offers a way of forecasting managed fixed and managed floating exchange rates. Previous studies based on macro fundamentals usually focus on forecasting the currencies with long histories of (free) floating exchange rates. Our methods are not restricted to the floating exchange rates because Bitcoin prices can also absorb expectations of managed floating and managed fixed exchange rates.

Our forecasts are conducted at the daily, weekly, and monthly horizons. The Bitcoin market fast incorporates market expectations of its fundamentals, so we focus on short-term forecasts. The majority of the previous literature on exchange rate prediction forecast at the monthly (e.g., Abhyankar et al., 2005; Chinn and Meese, 1995; Chinn and Moore, 2011; Clark and West, 2006; Giacomini and Rossi, 2010), quarterly (e.g., Alquist and Chinn, 2008;Berkowitz and Giorgianni, 2001; Chen et al., 2010;Cheung et al., 2005; Cheung et al., 2019;Chinn, 1991; Della Corte et al., 2012;Engel and Hamilton, 1990; Engel, 1994) and longer horizons up to 5 years (e.g., Meese and Rogoff, 1983a; Meese and Rogoff, 1983b; Cerra and Saxena, 2010), and one reason is that data of macroeconomic variables are usually released monthly or quarterly. However, exchange rate prediction at short horizons is of interest to practitioners in the foreign exchange market. Our study provides a supplement to the studies on exchange rate prediction at shorter horizons (e.g., Ferraro et al., 2015; Foroni et al., 2018; Zhang et al., 2016).

We also collect daily interest data for strategy construction and mechanism test. Following Ferraro et al. (2015), we generally use the daily overnight money market financing rates as the daily interest rates for the non-US currencies; the data are collected from the central banks of the selected countries.[10] We use the daily effective federal funds rate (EFFR) from the Federal Reserve as the daily interest rate of the USD (Ferraro et al., 2015). We collect interest rates of all currencies except that we do not find reliable daily interest rate data for the Algerian Dinar (DZD).

[8] https://coinmarketcap.com (Accessed: Sep. 12, 2022)
[9] The Nominal Broad Dollar Index is a weighted average of the foreign exchange value of the USD against the currencies of a broad group of major US trading partners.
[10] For a few currencies whose daily money market overnight financing rates are not available, we use other daily or weekly interest rates of daily-frequency provided by the central banks instead.

Table 1
Exchange rate regimes and descriptive statistics.

	Country/region	Regime	Obs.	ADF	ADF(Δ)	L-B	Mean (%)	Std. (%)	Skew.	Kurt.	Min. (%)	Med. (%)	Max. (%)
BTC			3165	0.8882	0.0000	0.0918	0.1030	3.9241	−0.7657	10.3493	−46.4730	0.1438	22.5119
AUD	Australia	Floating	2064	0.1917	0.0000	0.1155	−0.0124	0.6711	−0.4131	10.2270	−7.7180	−0.0140	4.9380
BRL	Brazil	Floating	2081	0.6341	0.0000	0.1296	−0.0381	0.9972	−0.1844	4.3261	−8.2915	−0.0188	6.0686
BWP	Botswana	Crawling band	2024	0.5687	0.0000	0.9789	−0.0186	0.5513	−0.3550	2.0158	−3.1405	0.0000	3.0425
CAD	Canada	Floating	2022	0.0341	0.0000	0.0412	−0.0104	0.4715	0.0468	2.3759	−2.3632	−0.0078	2.8697
CHF	Switzerland	Floating[1]	2097	0.0355	0.0000	0.0000	−0.0042	0.6107	7.8487	197.5867	−2.6560	−0.0158	15.4705
CLP	Chile	Floating	2049	0.4956	0.0000	0.0000	−0.0254	0.7037	0.0157	2.5947	−3.5905	−0.0015	4.9068
CNY	China, P.R.: Mainland	Managed floating	2011	0.3044	0.0000	0.0015	−0.0061	0.2317	−0.4090	8.3743	−1.8403	−0.0065	1.3798
COP	Colombia	Floating	2153	0.5193	0.0000	0.0000	−0.0384	0.8122	−0.2829	3.4799	−5.9307	0.0000	3.5333
CZK	Czech Rep.	Floating[2]	1268	0.0588	0.0000	0.0011	0.0004	0.5884	−0.5228	3.5131	−3.9891	0.0043	2.2627
DZD	Algeria	Managed floating	2029	0.1279	0.0000	0.0000	−0.0288	0.2354	−2.2805	28.1843	−3.5031	−0.0145	1.0418
EUR	Europe	Floating	2126	0.2893	0.0000	0.4310	−0.0147	0.4971	−0.2226	3.6379	−3.6820	−0.0175	2.4664
GBP	United Kingdom	Floating	2119	0.5492	0.0000	0.0029	−0.0166	0.5852	−1.4983	20.8957	−8.3209	−0.0113	2.5517
ILS	Israel	Floating	1993	0.5090	0.0000	0.2070	0.0021	0.4732	−0.9847	10.9147	−3.6663	0.0284	3.8354
INR	India	Floating	1971	0.9006	0.0000	0.4946	−0.0128	0.3391	0.1036	1.9902	−1.3743	−0.0070	1.7752
JPY	Japan	Floating	2035	0.8555	0.0000	0.0021	−0.0138	0.5573	0.4525	7.3101	−3.8503	−0.0099	4.8969
KRW	Korea, Rep. of	Floating	2022	0.6104	0.0000	0.1007	−0.0121	0.4775	−0.1812	2.6674	−3.3603	−0.0091	2.0520
KWD	Kuwait	Composite anchor	1856	0.0595	0.0000	0.0129	−0.0046	0.0808	−2.1378	36.3467	−1.2828	0.0000	0.4643
MUR	Mauritius	Managed floating	1976	0.9297	0.0000	0.0000	−0.0201	0.2159	−0.3543	10.0985	−1.7704	−0.0143	1.6274
MXN	Mexico	Floating	2014	0.1912	0.0000	0.0076	−0.0213	0.7957	−0.7574	7.6705	−7.3724	0.0171	5.0560
MYR	Malaysia	Managed floating	2001	0.2575	0.0000	0.0014	−0.0157	0.4177	−0.0233	5.9706	−2.6385	−0.0225	2.4892
NOK	Norway	Floating	2059	0.2409	0.0000	0.3613	−0.0233	0.7598	−0.4325	5.3196	−6.3501	−0.0342	3.8172
NZD	New Zealand	Floating	2063	0.2545	0.0000	0.2310	−0.0140	0.6879	−0.1635	2.3783	−5.3003	−0.0251	2.9344
PEN	Peru	Floating	1861	0.6606	0.0000	0.0000	−0.0169	0.3959	0.5070	11.3625	−3.0694	−0.0302	3.7740
PHP	Philippines	Floating	1991	0.8876	0.0000	0.0002	−0.0119	0.2586	−0.3754	2.0926	−1.8533	−0.0020	1.0386
PLN	Poland, Rep. of	Floating	2077	0.4239	0.0000	0.0004	−0.0215	0.6400	−0.5522	3.4856	−4.0437	−0.0065	2.9055
RUB	Russian Federation	Floating	2011	0.0534	0.0000	0.0010	−0.0297	1.4380	−1.1474	18.5486	−11.8120	0.0000	12.8638
SEK	Sweden	Floating	2069	0.3049	0.0000	0.2268	−0.0241	0.6294	−0.1283	4.0450	−4.3806	−0.0124	4.6603
SGD	Singapore	Managed floating	2057	0.0814	0.0000	0.4501	−0.0048	0.3093	−0.0415	2.3817	−1.7858	0.0000	1.4677
THB	Thailand	Floating	1994	0.6841	0.0000	0.0000	−0.0052	0.3172	0.0431	1.9210	−1.4326	−0.0032	1.6843
TTD	Trinidad and Tobago	Managed floating	2055	0.5446	0.0000	0.0000	−0.0018	0.3362	0.3819	1.7724	−1.7343	−0.0267	1.4839
UYU	Uruguay	Floating	1909	0.4470	0.0000	0.0000	−0.0338	0.4816	−0.5517	6.4463	−3.6756	−0.0170	2.6541
ZAR	South Africa	Floating	2009	0.2715	0.0000	0.0000	−0.0234	1.2435	0.3404	34.4461	−15.3773	0.0000	17.0565
USD	United States	Floating	2155	0.2377	0.0000	0.0521	0.0128	0.3134	0.1731	3.5670	−2.0885	−0.0013	1.8760

Notes: This table summarizes the exchange rate regimes and descriptive statistics of Bitcoin, the selected exchange rates denominated in USD, and the NEER of the USD. Column "Obs" reports the number of return observations between 01/2014 and 08/2022. Column "ADF" and "ADF(Δ)" report the *p*-values of ADF tests for the log exchange rates and log returns, respectively. Column "L-B" represents the *p*-values of Ljung-Box tests of autocorrelations, and the lag is the nearest integer of $ln(T)$ (Tsay, 2005). The last seven columns report the mean, the standard deviation, the skewness, the excess kurtosis, the minimum, the median, and the maximum values of daily log returns. The returns are not annualized.

[1]Switzerland maintained a minimum exchange rate against the euro between 09/2011–01/2015 and moved to a floating exchange rate regime afterward.

[2]Czech pegged the Czech Koruna to the euro before 04/2017 and moved to a floating exchange rate regime afterward. We only keep the data after 04/2017.

4. Forecasting specifications and the evaluation methods

In this section, we consider two Bitcoin-based linear predicting specifications of exchange rates: the autoregressive distributed lag (ADL) specification and the error correction model (ECM) specification. Both specifications are widely used in the exchange rate prediction literature (e.g., the ADL specification is used in Chen et al., 2010; Clark and West, 2006; Della Corte et al., 2012; Gourinchas and Rey, 2007; the ECM is used in Abhyankar et al., 2005; Alquist and Chinn, 2008; Chinn and Meese, 1995; Mark, 1995). We use linear models as previous literature shows that linear specification performs generally better than non-linear models in exchange rate prediction (e.g., Rossi, 2013).

We measure both the in-sample and out-of-sample predictive abilities of the two specifications. As is discussed in Section 2.2, the in-sample predictability can be viewed as evidence of the present-value model. The out-of-sample forecastability is a tougher challenge and is more meaningful in practice.

Both the ADL and the ECM specifications in our study provide true *ex-ante* out-of-sample forecasts, without the necessity to assume knowledge on contemporaneous values of the predictors. The *ex-ante* forecasts reflect the real-time data constraint of forecasting, having an informational advantage over the *pseudo* or *ex-post* out-of-sample forecasts in some studies, which use contemporaneous values of predictors.

The out-of-sample performances of our forecasts are evaluated with two different metrics (the direction of change statistic and the Clark-West statistic) and compared with three different benchmarks (the random walk with/without drift and the AR(1) model).

4.1. The ADL specification

Under the ADL specification, the explained variable is the first difference of log exchange rate ($\Delta s_t = s_t - s_{t-h}$), where h is the forecasting horizon; and the explanatory variables include its own lags and lags of log Bitcoin returns (Δp_{t-kh}):

$$\Delta s_t = \alpha_0 + \alpha_1 \Delta s_{t-h} + \alpha_2 \Delta s_{t-2h} + \cdots + \alpha_q \Delta s_{t-qh} + \beta_1 \Delta p_{t-h} + \beta_2 \Delta p_{t-2h} + \cdots + \beta_q \Delta p_{t-qh} + u_t.$$

The Granger causality (GC) test is a standard tool for measuring the in-sample predictability under the ADL specification. To test whether lagged Bitcoin returns provide additional explanatory power for the variation in exchange rates, we compute F-statistics to test the null hypothesis that all βs are jointly zero. If the null hypothesis is rejected, then lagged Bitcoin returns provide additional information for forecasting the exchange rate. We use the Bayesian Information Criterion (BIC; Schwarz et al., 1978) to determine the appropriate number of lags in the GC tests.[11]

For out-of-sample forecasts, we estimate Eq. (5) ($q = 1$) via rolling robust linear regression[12], and we use the estimated parameters ($\hat{\alpha}_0, \hat{\alpha}_1$ and $\hat{\beta}_1$) to calculate the out-of-sample predicted exchange rate movement as:

$$\Delta s^f_{t+h} = \hat{\alpha}_0 + \hat{\alpha}_1 \Delta s_t + \hat{\beta}_1 \Delta p_t. \tag{6}$$

We only keep one lagged term of both exchange rate returns and Bitcoin returns for estimation and forecasting, to avoid overfitting and to increase out-of-sample robustness.[13]

4.2. The ECM specification

The ECM assumes a long-run cointegrating relation between the log exchange rate s_t and the log Bitcoin price p_t. The system dynamically corrects the disequilibrium[14]:

$$E_{t-h}(\Delta s_t) = \beta_0 + \beta_1 (s_{t-h} - \gamma_0 - \gamma_1 p_{t-h}), \tag{7}$$

where β_1 reflects the speed at which s_t reverts back to its long-run equilibrium value: $\gamma_0 + \gamma_1 p_t$.

In the previous studies of exchange rate prediction, the cointegration parameters γ_0 and γ_1 can be either calibrated (e.g., Mark, 1995; Chinn and Meese, 1995) or estimated (e.g., Chinn and Moore, 2011; Alquist and Chinn, 2008). Here we estimate all the parameters in rolling windows, as calibration could potentially bring the model an "ad hoc" unfair advantage regarding the choice of calibrated parameters (Rossi, 2013).

We follow a classical two-step procedure to estimate the parameters in the ECM. First, the cointegrating relation,

$$s_t = \gamma_0 + \gamma_1 p_t + v_t, \tag{8}$$

is estimated using dynamic OLS (DOLS, Stock and Watson, 1993) in rolling windows. Next, the estimated parameters $\hat{\gamma}_0$ and $\hat{\gamma}_1$ are incorporated into Eq. (7), and β_0, β_1 in Eq. (7) are estimated via robust linear regressions in rolling windows. t-tests

[11] The empirical results are very similar if we choose q = 1 instead of using the BIC for in-sample GC tests.

[12] We use robust linear regressions to mitigate the influence of extreme values.

[13] One could include more lagged terms for estimation and forecasting (e.g., use BIC to select lag lengths) and may get better results. Our empirical forecasts only provide an achievable and conservative out-of-sample performance result.

[14] Technically, the ECM can model both long-run and short-run effects between two variables, where short-run effects could be described by adding the first-difference term of the explained variable. Following previous works (e.g., Cheung et al., 2019), we only focus on the long-run cointegrating relation for brevity and model stability.

($H_0 : \beta_1 = 0$) can be conducted to test the in-sample predictability of the error correction term. For out-of-sample forecasts, we use the estimated parameters and lagged values of s_t and p_t to calculate the predicted exchange rate movement Δs^f_{t+h}:

$$\Delta s^f_{t+h} = \hat{\beta}_0 + \hat{\beta}_1 (s_t - \hat{\gamma}_0 - \hat{\gamma}_1 p_t). \tag{9}$$

4.3. Out-of-sample performance evaluation

4.3.1. Benchmark selection

We consider three benchmarks. For the baseline analysis, we use the random walk without drift (RW) as the benchmark. In the robustness check, we consider alternative benchmarks: the random walk with drift (RWWD) and the AR(1), to address the concern that the out-of-sample outperformance is attributed to the constant term or the lagged exchange rate in the forecast equations.

RW is the most widely used benchmark and is empirically examined to be the most challenging benchmark in the exchange rate forecasting literature. Forecasts based on many popular economic models cannot beat the RW (e.g., Rossi, 2013). Therefore, it is a challenging and productive job to find a true *ex-ante* predictor with out-of-sample superiority over the RW.

Under the specification of RW, the expected value of tomorrow's exchange rate is the exchange rate today: $\Delta s^f_{t+h} = 0$. Under the RWWD: $\Delta s^f_{t+h} = \alpha$. Under the autoregressive model AR(1): $\Delta s^f_{t+h} = \alpha_0 + \alpha_1 \Delta s_t$.

4.3.2. Performance evaluation criteria

We use two different metrics, the *direction of change* statistic and the *Clark-West* statistic, to compare the out-of-sample forecasting performance of our Bitcoin-based models and the benchmarks.

The *direction of change* statistic calculates the proportion of predictions that correctly predict the direction of exchange rate movements. The statistic focuses on whether the sign of the forecast is correct, rather than the magnitude of the error. A value larger (smaller) than 50% indicates a better (worse) performance of the proposed model than a simple model that predicts an equal probability of exchange rate movement in each direction. Diebold and Mariano (1995) provides a statistic to test the null that the direction of change statistic equals 50%. For many practitioners, for example, for those who need to decide whether to use derivative contracts to hedge the exchange rate risks, correctly forecasting the direction of change could be more important than achieving a low forecast error. Meanwhile, policymakers are also concerned about whether the currency of a country will experience an appreciation or a depreciation.

The *Clark-West* (Clark and West, 2006; Clark and West, 2007) statistic is based on adjusted mean squared prediction errors (MSPEs).[15] A positive (negative) Clark-West statistic indicates a better (worse) performance of the proposed model compared with the benchmark. The statistic tests the null of no improved predictability in the larger model, against the alternative that the larger model has a smaller MSPE. Note that a model that perfectly forecasts the direction of change could still have a negative Clark-West statistic, if it over-predicts the absolute values of changes to a large extent. The Clark-West statistic is widely used to compare the forecast errors of nested models, as is the case for our comparisons.

5. Empirical results

As is discussed in Section 2.2, the exchange rate predictability of Bitcoin can be treated as evidence for the theoretical present-value model. In this section, we empirically examined the predictability. We adopt a rolling forecasting scheme for both the ADL and ECM specification (including the cointegrating equation and the error correction equation): we estimate the model over a given in-sample window and then make an out-of-sample forecast for one day, one week, or one month ahead of the window; next, we roll the estimation window forward one day, repeating the process until using up all observations.[16] The rolling scheme takes into account potential parameter instabilities, which is a serious concern in both exchange rate prediction (Chen et al., 2010) and Bitcoin price movements (Feng et al., 2018a). The weekly and monthly estimations and forecasts are performed on overlapping observations implied by the daily data. We use the heteroskedasticity and autocorrelation consistent (HAC) covariance correction (Newey and West, 1987)[17] in all the in- and out-of-sample statistical inferences. Overall, we show the exchange rate predictability of Bitcoin both in-sample and out-of-sample. For all three horizons, the in-sample predictability exists for all currencies, and out-of-sample forecastability exists for part of the currencies.

[15] The Diebold and Mariano (1995) and West (1996) (DMW) statistic, which directly compares the out-of-sample MSPE of two models, is also broadly used in the forecasting literature. However, Clark and McCracken (2001) points out that the DMW statistic has a nonstandard asymptotic distribution when comparing nested models. Clark and West (2006), Clark and West (2007) point out that if we compare two nested models and given that the two models provide the same predictive ability, there is an expected upward shift in the larger model's MSPE. Therefore, Clark and West (2006), Clark and West (2007) propose test statistics that account for this influence. Under the null hypothesis, the Clark-West statistics are asymptotic normal. Comparing the MSPEs of nested models, in Clark and West (2006) the parsimonious model is RW, while Clark and West (2007) allows a general parametric specification for the parsimonious model. Following Clark and West (2006), Clark and West (2007) and other studies on comparing nested models, we use one-sided tests for out-of-sample and strategy comparisons.

[16] For both the ADL and the ECM specification, our rolling windows are 180 trading days.

[17] For the HAC correction, we use a conservative number of lags equal to $\max\left(\left[4(T/100)^{2/9}\right], h\right)$, where T is the sample length and h is the horizon.

The out-of-sample forecastability is most pronounced at the daily horizon using the ADL model. We further test the performance of two trading strategies exploiting the forecastability.

5.1. In-sample predictability

5.1.1. The ADL specification

We use rolling Granger causality (GC) tests[18] to analyze the in-sample predictability of the ADL specification. Table 2 (Panel A: h = 1 day, Panel B: h = 1 week, and Panel C: h = 1 month) reports the results of rolling GC tests, as well as the average estimated β_1 and the average R^2 of the rolling in-sample robust linear regression: $\Delta s_t = \alpha_0 + \alpha_1 \Delta s_{t-h} + \beta_1 \Delta p_{t-h} + u_t$, where Δs_t and Δp_t are the log exchange rate return and log Bitcoin return. To illustrate the dynamic goodness of fit, the orange lines in Figure A1 of Online Appendix D plot the R^2 of the rolling in-sample ADL regressions.

The GC test results favorably prove the in-sample exchange rate predictability from Bitcoin, suggesting that Bitcoin returns contain information of future exchange rates, which cannot be captured by exchange rates' own lagged values. At the 5% significance level, for all three predicting horizons, Bitcoin returns significantly Granger-cause all 33 selected exchange rates, at least for a period of time. The average significant GC percentage of selected currencies are 17.38%, 21.79%, and 46.14% at the daily, weekly, and monthly horizons, respectively, all higher than the significance level of the test.

Using a 5% significance level, at the daily horizon, the two highest significant GC percentages are that of the South Korean won (KRW) and the Norwegian krone (NOK) prediction. At the weekly horizon, the highest significant GC percentages are that of the NOK and the Swiss franc (CHF) prediction. At the monthly horizon, the highest significant GC percentages are for the Canadian Dollar (CAD) and the Swiss franc (CHF) prediction. These countries all play important roles in the Bitcoin market: South Korea covered a large percentage of total Bitcoin trading volume (Makarov and Schoar, 2020). Norway and Canada both take up a large share in Bitcoin mining, due to the cold weather to cool devices and low electricity prices;[19] the Norwegian government once provided considerable subsidies for Bitcoin mining to attract mining pools.[20] Switzerland has long been famous for banking secrecy, and more than half of the managed wealth in Switzerland is thought to be foreign-originated;[21] Bitcoin provides an ideal way of secretly transferring foreign wealth to Switzerland. The average R^2 of all currencies are 2.97%, 4.15%, and 14.42%, at the daily, weekly, and monthly horizons, respectively. The in-sample goodness of fit (measured by R^2) improve when the forecast horizon increases, and a similar phenomenon is also demonstrated in other studies (e.g., Mark, 1995).

5.1.2. The ECM specification

Table 3 reports the ECM (Eq. 7) estimation results, and Table A1 in Online Appendix A reports the DOLS estimation results of the long-term cointegrating relation (Eq. 8). The blue lines in Figure A1 of Online Appendix D plot the dynamic goodness of fit (measured with R^2) of the in-sample ECM estimation.

The ECM estimation results also support the exchange rate predictability of Bitcoin. At the significance level of 5%, the percentages of significant $\hat{\beta}_1$ (among all the rolling ECM regressions) are positive for all 33 exchange rates and all three horizons, with a minimum value of 10.54%. The average percentages of significant $\hat{\beta}_1$ are 43.80%, 62.94%, and 76.92% at the daily, weekly, and monthly horizons, respectively, much greater than the significance level (5%). If we relax the significance level to 10%, the results are more favorable: The average percentages of significant $\hat{\beta}_1$ are 58.07%, 72.28%, and 81.36% at the daily, weekly, and monthly horizons, respectively, all much greater than the significance level (10%).

The estimated coefficients of the error correction term $\hat{\beta}_1$ are between -1 and 0 for all 33 exchange rates and all three predicting horizons, supporting the error correction scheme. The magnitudes of $\hat{\beta}_1$ reflect the speed of error correction. The average R^2 of all currencies are 2.57%, 10.45%, and 30.34%, at the daily, weekly, and monthly horizons, respectively. Similar to the ADL specification, R^2 improves when the forecast horizon increases. With ECM and a 5% significance level, the Trinidadian dollar (TTD) has the highest percentage of significant $\hat{\beta}_1$ at all three predicting horizons.

Compared with the ADL specification, under the ECM: 1) The percentages of significant in-sample predictability are higher. 2) The average levels of the goodness of fit (R^2) are lower at the daily horizon and much higher at the weekly and monthly horizons.

[18] As Chen et al. (2010) pointed out, static Granger causality (GC) regressions may fail to capture the dynamic causality between exchange rates and other variables due to parameter instability. We use rolling GC tests to overcome this problem.

[19] https://www.cer-rec.gc.ca/en/data-analysis/energy-markets/market-snapshots/2018/market-snapshot-crypto-currency-mining-is-booming-in-canada-here-is-why.html (Aug. 25, 2021)

[20] https://www.regjeringen.no/no/aktuelt/Bitcoin-er-unntatt-fra-merverdiavgift/id2538128/ (In Norwegian, accessed: Aug. 25, 2021)

[21] https://www.nationsencyclopedia.com/economies/Europe/Switzerland-MONEY.html (Accessed Aug. 25, 2021)

Table 2
In-sample exchange rate predictability of Bitcoin: the ADL specification.

	Panel A: $h = 1$ day				Panel B: $h = 1$ week				Panel C: $h = 1$ month			
Currency	GC(0.05)	GC(0.1)	$\overline{\hat{\beta}_1}$	$\overline{R}^2$	GC(0.05)	GC(0.1)	$\overline{\hat{\beta}_1}$	$\overline{R}^2$	GC(0.05)	GC(0.1)	$\overline{\hat{\beta}_1}$	$\overline{R}^2$
AUD	23.27%	27.69%	0.0089	2.05%	27.88%	36.28%	0.0092	3.36%	40.50%	50.86%	0.0062	14.32%
BRL	5.70%	9.76%	0.0016	1.81%	19.79%	29.93%	0.0017	3.27%	44.59%	56.12%	0.0104	9.03%
BWP	15.45%	23.50%	−0.0011	1.24%	12.92%	15.54%	0.0052	2.70%	47.00%	56.80%	−0.0013	15.64%
CAD	18.19%	21.68%	0.0014	2.61%	18.92%	31.11%	0.0031	3.08%	61.07%	67.42%	0.0052	18.92%
CHF	12.66%	15.59%	0.0008	1.16%	36.12%	45.68%	−0.0028	4.46%	58.52%	67.56%	−0.0042	16.09%
CLP	23.40%	30.70%	0.0078	3.53%	11.73%	15.15%	0.0115	1.64%	41.96%	51.62%	0.0020	17.10%
CNY	13.37%	24.93%	0.0004	3.07%	11.64%	15.25%	0.0026	2.70%	54.73%	58.09%	−0.0051	17.65%
COP	13.07%	18.71%	0.0063	3.82%	21.11%	28.22%	0.0102	2.68%	37.09%	47.14%	−0.0281	13.97%
CZK	26.06%	32.62%	0.0058	1.44%	30.20%	39.40%	0.0082	2.53%	34.49%	40.04%	−0.0024	10.25%
DZD	12.26%	26.32%	0.0004	2.05%	22.47%	26.11%	0.0009	3.34%	52.17%	61.26%	0.0043	14.69%
EUR	13.71%	22.22%	0.0002	1.53%	33.80%	39.67%	0.0007	3.75%	43.64%	52.66%	−0.0009	11.63%
GBP	24.62%	29.49%	0.0020	2.50%	29.17%	42.25%	0.0020	3.30%	52.10%	59.64%	−0.0196	16.35%
ILS	20.03%	23.96%	0.0038	1.07%	13.03%	19.51%	0.0038	1.86%	45.38%	54.85%	0.0080	15.85%
INR	12.55%	17.31%	0.0012	1.34%	24.99%	35.13%	−0.0002	2.10%	48.14%	56.00%	−0.0011	15.47%
JPY	20.17%	28.93%	−0.0016	1.50%	8.03%	14.82%	0.0017	3.74%	55.24%	68.60%	−0.0043	13.28%
KRW	32.79%	36.87%	−0.0047	1.74%	16.01%	28.03%	0.0045	4.03%	47.17%	54.82%	−0.0053	13.48%
KWD	6.47%	12.04%	0.0001	1.09%	23.99%	34.55%	−0.0002	3.72%	46.16%	52.46%	−0.0008	11.93%
MUR	19.39%	22.07%	0.0006	26.04%	23.57%	35.56%	0.0003	4.40%	43.96%	55.28%	0.0000	11.51%
MXN	16.08%	20.46%	−0.0054	1.62%	20.89%	28.96%	0.0071	2.84%	37.26%	49.26%	−0.0105	13.00%
MYR	21.60%	26.72%	0.0022	1.88%	17.17%	25.12%	0.0034	4.27%	43.04%	47.74%	0.0031	14.00%
NOK	29.47%	39.08%	−0.0022	1.54%	37.17%	45.70%	0.0061	3.72%	42.67%	52.28%	−0.0097	9.95%
NZD	25.57%	30.58%	0.0138	2.41%	33.74%	38.92%	0.0144	3.57%	45.90%	54.16%	0.0180	15.75%
PEN	9.25%	17.25%	0.0020	2.06%	13.61%	18.50%	0.0029	3.12%	53.83%	60.31%	−0.0072	21.30%
PHP	15.96%	17.67%	−0.0014	1.71%	33.06%	42.52%	0.0043	2.65%	48.04%	57.39%	0.0001	13.41%
PLN	20.10%	26.55%	0.0020	1.75%	10.44%	25.18%	0.0052	2.37%	48.40%	55.34%	0.0007	12.29%
RUB	2.03%	8.33%	0.0018	1.60%	29.93%	37.04%	0.0065	4.65%	42.92%	48.92%	−0.0301	16.05%
SEK	18.37%	25.70%	0.0073	2.22%	35.77%	42.32%	0.0067	3.33%	51.10%	60.33%	−0.0005	15.44%
SGD	20.68%	21.91%	0.0028	1.97%	22.07%	32.35%	0.0024	3.37%	45.16%	56.28%	−0.0021	15.60%
THB	28.71%	34.90%	0.0045	2.96%	28.72%	43.43%	0.0010	2.62%	45.30%	51.99%	0.0034	10.70%
TTD	13.91%	17.39%	0.0012	11.61%	6.60%	15.44%	−0.0001	35.21%	36.10%	40.45%	0.0001	20.06%
UYU	3.13%	8.07%	−0.0004	2.31%	17.76%	22.75%	−0.0017	3.26%	41.39%	51.84%	−0.0103	10.28%
ZAR	15.58%	23.26%	−0.0039	1.10%	2.35%	6.49%	0.0089	2.28%	40.69%	49.83%	0.0020	17.29%
USD	19.96%	21.84%	−0.0001	1.62%	24.54%	26.29%	−0.0019	2.89%	46.94%	59.81%	0.0039	13.50%
Mean	17.38%	23.16%	0.0018	2.97%	21.79%	29.79%	0.0039	4.15%	46.14%	54.76%	−0.0023	14.42%

Notes: This table reports the in-sample exchange rate predictability of Bitcoin of the ADL specification at three predicting horizons (h = 1 day, 1 week, or 1 month). The Granger causality (GC) tests are conducted in a rolling scheme, and the null hypothesis is "Δp_t does not Granger-cause Δs_t", where Δp_t and Δs_t are the log Bitcoin return and the log exchange rate return, respectively. Column "GC(0.05)"/"GC(0.1)" reports the percentage of all rolling regressions when the null of no Granger causality is rejected at the 5%/10% significance level. The GC inferences are HAC. Column "$\overline{\hat{\beta}_1}$" and $\overline{R}^2$ report the average estimated β_1 and average R^2 of the rolling in-sample robust linear regression: $\Delta s_t = \alpha_0 + \alpha_1 \Delta s_{t-h} + \beta_1 \Delta p_{t-h} + u_t$.

Table 3
In-sample exchange rate predictability of Bitcoin: the ECM specification.

	Panel A: $h = 1$ day				Panel B: $h = 1$ week				Panel C: $h = 1$ month			
	$p < 0.05$	$p < 0.1$	$\overline{\hat{\beta}_1}$	$\overline{R}^2$	$p < 0.05$	$p < 0.1$	$\overline{\hat{\beta}_1}$	$\overline{R}^2$	$p < 0.05$	$p < 0.1$	$\overline{\hat{\beta}_1}$	$\overline{R}^2$
AUD	59.33%	78.79%	−0.0462	2.52%	73.11%	81.79%	−0.1894	9.53%	79.83%	83.93%	−0.5575	30.57%
BRL	44.15%	55.32%	−0.0260	1.45%	60.83%	68.10%	−0.1364	7.69%	68.20%	75.51%	−0.4625	27.18%
BWP	51.39%	63.50%	−0.0419	2.31%	65.30%	74.00%	−0.2058	11.46%	77.44%	81.92%	−0.5475	33.07%
CAD	53.29%	73.19%	−0.0429	2.31%	81.48%	87.84%	−0.2250	12.62%	86.38%	89.05%	−0.6216	33.67%
CHF	57.84%	75.50%	−0.0474	2.27%	80.89%	85.47%	−0.2483	12.39%	87.86%	90.47%	−0.6827	37.12%
CLP	38.91%	50.00%	−0.0335	1.81%	57.07%	64.52%	−0.1853	9.59%	73.24%	75.81%	−0.5857	33.27%
CNY	26.26%	46.83%	−0.0186	1.21%	47.41%	62.68%	−0.1143	7.03%	81.49%	87.24%	−0.4613	33.53%
COP	32.39%	46.19%	−0.0273	1.53%	59.80%	71.00%	−0.1668	8.76%	81.11%	86.40%	−0.5757	32.66%
CZK	37.88%	64.88%	−0.0388	2.30%	65.05%	81.40%	−0.1886	9.71%	92.47%	95.04%	−0.5983	31.79%
DZD	31.31%	39.06%	−0.0283	1.85%	46.23%	53.55%	−0.1425	8.40%	61.32%	65.39%	−0.3908	24.48%
EUR	50.28%	66.55%	−0.0440	2.38%	68.36%	74.01%	−0.2066	11.02%	78.31%	84.00%	−0.4905	26.80%
GBP	42.72%	56.40%	−0.0447	2.55%	67.83%	77.51%	−0.2040	10.49%	85.13%	87.88%	−0.6071	36.06%
ILS	54.92%	69.50%	−0.0455	2.46%	68.17%	77.24%	−0.1941	9.84%	87.59%	90.92%	−0.6025	33.62%
INR	38.76%	52.01%	−0.0287	1.52%	58.70%	70.25%	−0.1300	6.68%	70.63%	76.98%	−0.5191	28.57%
JPY	53.51%	63.98%	−0.0426	2.46%	63.66%	70.51%	−0.1866	10.24%	82.30%	85.85%	−0.5217	31.61%
KRW	42.41%	58.24%	−0.0370	2.20%	68.55%	75.34%	−0.1723	9.77%	73.92%	78.80%	−0.5097	30.73%
KWD	41.60%	53.80%	−0.0302	2.07%	61.55%	69.92%	−0.1576	9.64%	79.60%	82.84%	−0.4510	29.42%
MUR	10.54%	17.46%	−0.0130	1.68%	44.10%	55.51%	−0.1173	7.58%	67.71%	74.27%	−0.3670	25.80%
MXN	39.65%	55.76%	−0.0378	2.38%	56.19%	73.03%	−0.1768	9.61%	81.11%	85.84%	−0.5820	33.40%
MYR	24.04%	40.32%	−0.0215	1.56%	45.29%	59.19%	−0.0978	6.30%	72.72%	76.28%	−0.4388	29.46%
NOK	57.25%	69.56%	−0.0428	2.35%	65.09%	73.52%	−0.1825	8.91%	81.39%	85.61%	−0.5439	27.58%
NZD	61.33%	68.94%	−0.0541	3.02%	68.27%	77.92%	−0.2159	11.01%	75.83%	83.65%	−0.5964	29.50%
PEN	45.23%	55.96%	−0.0249	1.28%	61.98%	69.85%	−0.1479	7.56%	68.79%	75.39%	−0.4705	27.08%
PHP	31.58%	45.85%	−0.0254	1.65%	55.69%	62.37%	−0.1186	6.63%	55.89%	60.80%	−0.4072	22.78%
PLN	33.69%	54.28%	−0.0395	2.11%	67.46%	78.58%	−0.2087	10.99%	84.32%	89.38%	−0.5582	29.50%
RUB	36.93%	53.88%	−0.0356	2.20%	61.74%	69.90%	−0.1799	11.03%	76.08%	80.37%	−0.5157	30.11%
SEK	41.25%	61.93%	−0.0358	1.90%	60.54%	68.50%	−0.1657	8.83%	69.06%	73.92%	−0.4926	28.40%
SGD	52.13%	66.38%	−0.0381	2.25%	63.98%	76.72%	−0.1627	9.09%	78.87%	83.82%	−0.5234	32.68%
THB	33.19%	52.40%	−0.0242	1.73%	61.21%	73.96%	−0.1228	7.88%	75.10%	79.31%	−0.4604	30.60%
TTD	100.00%	100.00%	−0.4150	20.53%	98.12%	99.52%	−0.9786	49.00%	92.81%	93.98%	−0.6674	34.71%
UYU	28.27%	35.69%	−0.0182	1.19%	35.41%	48.54%	−0.0962	6.05%	56.68%	60.91%	−0.3379	22.55%
ZAR	59.80%	73.66%	−0.0467	2.06%	79.03%	84.16%	−0.2211	11.74%	80.91%	84.40%	−0.5887	35.17%
USD	33.57%	50.35%	−0.0265	1.62%	58.87%	68.93%	−0.1387	7.77%	74.10%	79.06%	−0.4593	27.83%
Mean	43.80%	58.07%	−0.0461	2.57%	62.94%	72.28%	−0.1935	10.45%	76.92%	81.36%	−0.5210	30.34%

Notes: This table reports the rolling estimation results of the ECM specification: $s_t - s_{t-h} = \beta_0 + \beta_1(s_{t-h} - \hat{\gamma}_0 - \hat{\gamma}_1 p_{t-h})$, at three predicting horizons (h = 1 day, 1 week, or 1 month), where s_t is the exchange rate and p_t is Bitcoin price, and $\hat{\gamma}_0, \hat{\gamma}_1$ are estimated via DOLS (see Table A1 in Online Appendix A). $\overline{\hat{\beta}_1}$ reports the average estimated β_1 of the rolling regressions. Columns "$p < 0.05$" and "$p < 0.1$" report the percentage when the Newey and West (1987) HAC p-value of β_1 is less than 0.05 and 0.1, respectively. $\overline{R}^2$ reports the average R^2 of the rolling ECM regressions.

5.2. Out-of-sample predictability

5.2.1. The ADL specification

Table 4 reports the out-of-sample exchange rate forecasting performance of the ADL specification. We report the direction of change statistics, the Clark-West statistics (benchmark: the RW), and corresponding Newey-West robust p-values. To illustrate the dynamic out-of-sample performance of the ADL specification, the orange lines in Figure A2 of Online Appendix E plot the cumulative differences between the numbers of forecasts that predict the direction of change correctly and incorrectly; a positive end value indicates the overall outperformance of the proposed model.

The out-of-sample results of the ADL specification deliver remarkably supporting evidence for the predictability at the *daily* forecasting horizon, and part of the exchange rates are also forecastable at weekly or monthly horizons. The average direction of change statistics of the 33 selected exchange rates are larger than 50% for all three horizons, and the average Clark-West statistics are positive for all three horizons.

At the daily forecasting horizon, according to the direction of change statistics, for 32 out of 33 (96.97%) currencies, we successfully forecast the direction of change more than half the time. At the significance level of 10%, among the 32 successful cases, 22 are significantly greater than 50%, which represents 66.67% (22/33) of statistical outperformance, and the percentage is much greater than the significance level (10%). The direction of change statistics of different currencies range from 49.97% to 64.97%, with an average value of 52.84%. According to the Clark-West statistics, the results are similar. 31 out of 33 (93.94%) series of the forecasts have positive Clark-West statistics and outperform the RW benchmark. Among the 31 positive cases, 23 are significantly positive at the 10% level, representing 69.70% (23/33) of statistical outperformance. The Clark-West statistics range from −0.7798 to 9.1116, with an average value of 2.2459.

At the weekly forecasting horizon, 20 out of 33 (60.61%) direction of change statistics are greater than 50%, and 10 (10/33 = 30.30%) direction of change statistics are significantly larger than 50%, using a 10% significance level. The direction

Table 4
Out-of-sample exchange rate predictability of Bitcoin: the ADL specification (benchmark: RW).

	Panel A: $h = 1$ day		Panel B: $h = 1$ week		Panel C: $h = 1$ month		Currency	Panel A: $h = 1$ day		Panel B: $h = 1$ week		Panel C: $h = 1$ month	
Currency	DoC	CW	DoC	CW	DoC	CW	(*Continued*)	DoC	CW	DoC	CW	DoC	CW
AUD	52.63%	0.9620	48.35%	1.3045	52.92%	0.4908	MUR	64.97%	4.8390	54.13%	1.2007	53.60%	−0.1606
	(0.0114)	(0.1680)	(0.8226)	(0.0960)	(0.1863)	(0.3118)		(0.0000)	(0.0000)	(0.0158)	(0.1149)	(0.1692)	(0.5638)
BRL	52.63%	0.8912	52.79%	1.0309	49.56%	−0.2997	MXN	51.09%	1.3121	49.86%	0.5015	55.29%	−0.8276
	(0.0109)	(0.1864)	(0.0741)	(0.1513)	(0.5503)	(0.6178)		(0.1812)	(0.0948)	(0.5321)	(0.3080)	(0.0523)	(0.7961)
BWP	50.65%	1.0879	48.20%	−0.5445	51.12%	0.1012	MYR	52.52%	0.2934	54.29%	1.0009	47.76%	−0.0259
	(0.2928)	(0.1383)	(0.8333)	(0.7070)	(0.3667)	(0.4597)		(0.0228)	(0.3846)	(0.0152)	(0.1584)	(0.7371)	(0.5103)
CAD	54.21%	2.9349	48.63%	−1.0889	55.80%	1.1396	NOK	53.44%	2.8374	51.37%	0.5547	48.05%	−0.0760
	(0.0001)	(0.0017)	(0.7846)	(0.8619)	(0.0497)	(0.1272)		(0.0009)	(0.0023)	(0.2228)	(0.2895)	(0.7257)	(0.5303)
CHF	51.51%	0.7218	51.42%	0.5944	53.70%	1.2618	NZD	53.97%	3.7768	49.41%	0.3667	50.31%	0.6689
	(0.0973)	(0.2352)	(0.2039)	(0.2761)	(0.1008)	(0.1035)		(0.0002)	(0.0001)	(0.6254)	(0.3569)	(0.4615)	(0.2518)
CLP	54.60%	3.4477	51.71%	−0.7853	50.67%	1.2618	PEN	55.33%	2.6593	56.18%	0.1645	58.92%	0.1073
	(0.0000)	(0.0003)	(0.1945)	(0.7838)	(0.4164)	(0.1035)		(0.0000)	(0.0039)	(0.0012)	(0.4347)	(0.0032)	(0.4573)
CNY	53.73%	1.5341	53.27%	1.2499	55.25%	1.7581	PHP	51.23%	2.3722	52.64%	1.6577	59.83%	1.9072
	(0.0005)	(0.0625)	(0.0509)	(0.1057)	(0.0759)	(0.0394)		(0.1295)	(0.0088)	(0.0982)	(0.0487)	(0.0019)	(0.0282)
COP	53.53%	5.7159	51.35%	0.6811	49.37%	0.8744	PLN	50.16%	2.3816	49.25%	−1.0964	52.45%	1.7187
	(0.0009)	(0.0000)	(0.2336)	(0.2479)	(0.5746)	(0.1910)		(0.4449)	(0.0086)	(0.6595)	(0.8635)	(0.2236)	(0.0428)
CZK	51.71%	0.9058	50.80%	−0.8584	49.75%	0.1231	RUB	49.97%	0.7183	52.32%	0.3799	48.17%	−1.4404
	(0.1380)	(0.1825)	(0.3702)	(0.8047)	(0.5218)	(0.4510)		(0.5097)	(0.2363)	(0.1117)	(0.3520)	(0.7025)	(0.9251)
DZD	52.96%	2.9204	56.35%	2.3504	59.44%	2.3871	SEK	51.52%	2.3370	48.81%	0.1033	53.90%	1.6399
	(0.0054)	(0.0017)	(0.0006)	(0.0094)	(0.0022)	(0.0085)		(0.0970)	(0.0097)	(0.7372)	(0.4589)	(0.1305)	(0.0505)
EUR	51.79%	2.0081	51.16%	−0.3938	53.49%	1.1038	SGD	52.24%	1.6068	48.96%	−0.5747	53.18%	−0.4031
	(0.0511)	(0.0223)	(0.2530)	(0.6531)	(0.1258)	(0.1348)		(0.0254)	(0.0541)	(0.7146)	(0.7173)	(0.1711)	(0.6566)
GBP	52.88%	2.5849	49.51%	−0.1520	55.04%	1.9905	THB	53.88%	4.1062	54.46%	1.4057	47.34%	−1.9630
	(0.0058)	(0.0049)	(0.6093)	(0.5604)	(0.0515)	(0.0233)		(0.0005)	(0.0000)	(0.0159)	(0.0799)	(0.7635)	(0.9752)
ILS	50.43%	1.3546	49.56%	−0.8753	53.67%	0.8375	TTD	56.71%	9.1116	71.93%	15.1832	64.04%	6.2129
	(0.3678)	(0.0878)	(0.5894)	(0.8093)	(0.1292)	(0.2011)		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
INR	51.40%	−0.2171	49.97%	−0.2115	55.42%	1.1607	UYU	54.31%	2.5025	51.53%	0.6813	52.66%	2.1461
	(0.1165)	(0.5859)	(0.5060)	(0.5838)	(0.0503)	(0.1229)		(0.0003)	(0.0062)	(0.2311)	(0.2478)	(0.2544)	(0.0159)
JPY	50.77%	0.6024	52.59%	−0.3658	45.91%	−0.9433	ZAR	50.22%	−0.7798	47.59%	−0.5166	48.69%	−0.6736
	(0.2517)	(0.2735)	(0.0697)	(0.6427)	(0.8908)	(0.8272)		(0.4229)	(0.7822)	(0.9136)	(0.6973)	(0.6526)	(0.7497)
KRW	50.96%	1.6210	51.72%	0.0241	54.74%	0.4141	USD	53.28%	2.5008	51.46%	0.5334	55.38%	0.8735
	(0.2046)	(0.0525)	(0.1760)	(0.4904)	(0.0769)	(0.3394)		(0.0015)	(0.0062)	(0.2151)	(0.2969)	(0.0619)	(0.1912)
KWD	52.62%	2.4650	49.80%	0.9155	51.60%	1.3787	Mean	52.84%	2.2459	51.86%	0.7400	52.94%	0.7498
	(0.0367)	(0.0069)	(0.5378)	(0.1800)	(0.3292)	(0.0840)							

Notes: This table reports the out-of-sample performance of the Bitcoin-based exchange rate forecasting model using the ADL specification. "h" denotes the forecasting horizon. "DoC" denotes the direction of change statistics: a value larger than 50% indicates outperformance compared with a naïve model that predicts an equal probability of exchange rate movement in each direction; p-values (Diebold and Mariano, 1995) are reported in the parentheses. "CW" denotes the Clark-West test statistics: a positive value indicates outperformance compared with the RW; p-values (Clark and West, 2006; Clark and West, 2007) are reported in the parentheses. All tests are implemented with HAC covariance matrices(Newey and West, 1987).

of change statistics range from 47.59% to 71.93%, with an average value of 51.86%. According to the Clark-West statistics, 21 out of 33 (63.64%) series of the forecasts outperform the RW benchmark; 5 forecasts (5/33 = 15.15%) significantly outperform the RW at a 10% significance level. The Clark-West statistics range from −1.0964 to 15.1832, with an average value of 0.7400.

When the forecasting horizon increases to one month, 24 out of 33 (72.73%) direction of change statistics are greater than 50%, and 11 (11/33 = 33.33%) direction of change statistics are significantly larger than 50%, at the 10% level. The direction of change statistics range from 45.91% to 64.04%, with an average value of 52.94%. According to the Clark-West statistics, 23 out of 33 (69.70%) series of the forecasts have positive Clark-West statistics. Among the 23 positive cases, 9 are significant at the 10% level, representing a 27.27% rate of statistical outperformance. The Clark-West statistics range from −1.9630 to 6.2129, with an average value of 0.7498.

In terms of different currencies, using a 10% significance level, the ADL forecasts significantly outperform the benchmarks at least at one horizon and at least based on one metric for 29 out of 33 currencies. The most successful forecast is the Trinidadian dollar (TTD) forecast, based on both criteria and at all three horizons, except that the most successful daily forecast based on the direction of change statistics is the Mauritian rupee (MUR) forecast. In terms of different forecasting horizons, although the in-sample goodness of fit improves when the forecast horizon increases (see Section 5.1.1), the out-of-sample performance is most favorable at a daily horizon. At the significance level of 10%, according to the direction of change criterion (Clark-West criterion), our Bitcoin-based ADL forecasts achieve significant outperformance for 22 (23), 10 (5), 11 (9) exchange rates, at daily, weekly, and monthly horizons, respectively.

5.2.2. The ECM specification

Overall, the ECM forecasts also favorably support the out-of-sample exchange rate forecastability of Bitcoin, based on either the direction of change criterion or the Clark-West criterion. Table 5 reports the out-of-sample forecasting results of the ECM (Eq. 9). The blue lines in Figure A2 of Online Appendix E plot the cumulative differences between the numbers of forecasts that the ECM predicts the direction of change correctly and incorrectly. The average direction of change statistics of the 33 selected currencies are larger than 50% and the average Clark-West statistics are positive at all three horizons. The number of forecastable currencies is generally similar across three forecasting horizons.

At the daily forecasting horizon, for 25 out of 33 (75.76%) currencies, the direction of change statistics exceed 50%, and 15 (15/33 = 45.45%) direction of change statistics are significantly greater than 50%, at the 10% significance level. The direction of change statistics range from 46.31% to 64.31%, with an average value of 51.34%. According to the Clark-West criterion, 23 out of 33 (69.70%) series of the forecasts outperform the RW benchmark, and 11 (11/33 = 33.33%) forecasts significantly outperform the RW, at the 10% significance level. The Clark-West statistics range from −1.7871 to 13.8862, with an average value of 1.0839.

At the weekly forecasting horizon, 27 out of 33 (81.82%) series of the forecasts have a direction of change statistic above 50%, and 15 (15/33 = 45.45%) direction of change statistics are significantly greater than 50%, at the 10% significance level. The direction of change statistics range from 47.32% to 73.62%, with an average value of 52.45%. According to the Clark-West test, 20 out of 33 (60.61%) series of the forecasts outperform the RW, and 12 (12/33 = 36.36%) forecasts significantly outperform the RW, at the 10% significance level. The Clark-West statistics range from −1.7223 to 13.5003, with an average value of 0.8917.

When the forecasting horizon increases to one month, 25 out of 33 (25/33 = 75.76%) series of the forecasts achieve a direction of change statistic above 50%, and among the 25 cases, 12 (12/33 = 36.36%) are significant at the 10% level. The direction of change statistics range from 47.23% to 66.82%, with an average value of 53.18%. According to the Clark-West test, 24 out of 33 (24/33 = 72.73%) series of the forecasts outperform the RW benchmark, and 9 cases (9/33 = 27.27%) significantly outperform the RW, at the 10% significance level. The Clark-West statistics range from −1.7609 to 5.5153, with an average value of 0.8068.

At the 10% level, the Bitcoin-based ECM forecasts achieve significant outperformance at least at one horizon and at least based on one metric for 23 currencies. The forecast for the Trinidadian dollar (TTD) exchange rate is most successful, based on both criteria and at all three horizons. For ECM, the forecastability is similar across three forecasting horizons: At the significance level of 10%, according to the direction of change criterion (Clark-West criterion), the Bitcoin-based ECM forecasts achieve significant outperformance for 15 (11), 15 (12), 12 (9) exchange rates at daily, weekly, and monthly horizons, respectively. Compared with the ADL specification, the out-of-sample performance of the ECM is less favorable at the daily forecasting horizon but works slightly better at the weekly and monthly horizons.

5.3. Performance of Bitcoin-based currency trading strategy

To further evaluate the economic gains of the forecastability for currency market practitioners, we test the performance of two currency trading strategies based on the daily forecastability using the ADL model. The first strategy goes long on the currency when our Bitcoin-based ADL model predicts the currency to appreciate and clears the position if not. We define the buy indicator of the strategies as:

$$\xi^{FX}_{BTC,t} = \begin{cases} 1, & \text{if } \Delta s^f_t > 0 \\ 0, & \text{otherwise} \end{cases}. \tag{10}$$

Table 5
Out-of-sample exchange rate predictability of Bitcoin: the ECM specification (benchmark: RW).

	Panel A: $h = 1$ day		Panel B: $h = 1$ week		Panel C: $h = 1$ month		Currency	Panel A: $h = 1$ day		Panel B: $h = 1$ week		Panel C: $h = 1$ month	
Currency	DoC	CW	DoC	CW	DoC	CW	(*Continued*)	DoC	CW	DoC	CW	DoC	CW
AUD	50.81%	2.5369	52.97%	1.5575	55.57%	2.3111	MUR	50.53%	1.4276	48.14%	−0.3775	49.33%	−0.6283
	(0.2353)	(0.0056)	(0.0672)	(0.0597)	(0.0457)	(0.0104)		(0.3631)	(0.0767)	(0.8141)	(0.6471)	(0.5669)	(0.7351)
BRL	52.41%	0.7680	51.92%	0.6002	50.96%	0.1891	MXN	53.11%	0.4447	53.81%	−0.2424	56.82%	0.8253
	(0.0209)	(0.2213)	(0.1613)	(0.2742)	(0.3975)	(0.4250)		(0.0048)	(0.3283)	(0.0244)	(0.5958)	(0.0148)	(0.2046)
BWP	50.41%	0.2980	51.70%	1.3177	50.52%	−0.2736	MYR	50.42%	−0.2118	51.32%	−0.3983	50.00%	−0.5778
	(0.3656)	(0.3829)	(0.1976)	(0.0938)	(0.4390)	(0.6078)		(0.3637)	(0.5839)	(0.2667)	(0.6548)	(0.5000)	(0.7183)
CAD	51.94%	0.9704	53.83%	0.3266	59.60%	1.7152	NOK	52.16%	2.7580	52.69%	2.1336	55.38%	1.9671
	(0.0556)	(0.1659)	(0.0208)	(0.3720)	(0.0023)	(0.0432)		(0.0268)	(0.0029)	(0.0791)	(0.0164)	(0.0604)	(0.0246)
CHF	51.88%	0.9274	53.99%	1.8445	55.16%	1.8683	NZD	51.82%	3.1377	51.19%	2.0706	51.28%	0.9492
	(0.0517)	(0.1769)	(0.0171)	(0.0326)	(0.0478)	(0.0309)		(0.0571)	(0.0009)	(0.2730)	(0.0192)	(0.3474)	(0.1713)
CLP	49.86%	0.1520	51.35%	0.4259	51.54%	0.6313	PEN	52.60%	−0.8506	52.88%	−0.0854	57.50%	1.4727
	(0.5438)	(0.4396)	(0.2462)	(0.3351)	(0.3260)	(0.2639)		(0.0249)	(0.8025)	(0.0819)	(0.5340)	(0.0206)	(0.0704)
CNY	50.69%	−1.4781	47.32%	−1.7223	49.40%	0.2823	PHP	46.31%	−1.7871	48.35%	−0.9484	51.22%	0.0481
	(0.2706)	(0.9303)	(0.9056)	(0.9575)	(0.5607)	(0.3888)		(0.9997)	(0.9630)	(0.8028)	(0.8285)	(0.3680)	(0.4808)
COP	50.40%	−0.2429	50.26%	−0.3839	55.70%	1.2445	PLN	50.79%	0.8319	54.36%	2.1841	56.51%	1.9811
	(0.3711)	(0.5959)	(0.4475)	(0.6495)	(0.0497)	(0.1067)		(0.2421)	(0.2027)	(0.0110)	(0.0145)	(0.0219)	(0.0238)
CZK	52.08%	1.2791	57.29%	1.8698	56.99%	1.5140	RUB	49.64%	−0.7198	49.67%	−1.2672	47.45%	0.5146
	(0.0754)	(0.1004)	(0.0015)	(0.0308)	(0.0511)	(0.0650)		(0.6175)	(0.7642)	(0.5642)	(0.8975)	(0.7600)	(0.3034)
DZD	52.25%	2.2012	54.06%	0.3387	53.94%	−0.2978	SEK	49.49%	1.2979	51.45%	1.0455	47.23%	0.2228
	(0.0288)	(0.0139)	(0.0241)	(0.3674)	(0.1307)	(0.6171)		(0.6671)	(0.0972)	(0.2338)	(0.1479)	(0.7878)	(0.4118)
EUR	52.30%	1.6908	52.54%	1.7577	49.60%	0.9308	SGD	49.22%	−0.1114	50.84%	−0.4408	53.72%	0.5028
	(0.0197)	(0.0454)	(0.0861)	(0.0394)	(0.5476)	(0.1760)		(0.7602)	(0.5444)	(0.3299)	(0.6703)	(0.1470)	(0.3075)
GBP	50.70%	1.7199	52.67%	1.4717	56.08%	2.8853	THB	49.64%	−0.0555	48.97%	−0.6240	49.16%	−1.7609
	(0.2667)	(0.0427)	(0.0740)	(0.0706)	(0.0387)	(0.0020)		(0.6111)	(0.5221)	(0.6890)	(0.7337)	(0.5884)	(0.9609)
ILS	51.85%	2.3496	51.53%	1.3237	51.86%	−0.2073	TTD	64.31%	13.8862	73.62%	13.5003	66.82%	5.5153
	(0.0623)	(0.0094)	(0.2211)	(0.0928)	(0.3090)	(0.5821)		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
INR	49.83%	−1.5458	50.54%	−1.1110	53.45%	0.3697	UYU	51.14%	0.4462	50.47%	−0.3419	52.42%	−0.1942
	(0.5540)	(0.9389)	(0.3931)	(0.8667)	(0.1746)	(0.3558)		(0.2054)	(0.3277)	(0.4131)	(0.6338)	(0.2655)	(0.5770)
JPY	50.61%	1.1880	52.88%	0.1511	50.00%	−0.1494	ZAR	51.67%	1.9987	53.29%	2.4784	52.49%	−0.1041
	(0.2931)	(0.1174)	(0.0699)	(0.4400)	(0.5000)	(0.5594)		(0.0665)	(0.0228)	(0.0488)	(0.0066)	(0.2449)	(0.5415)
KRW	49.20%	−0.6604	48.73%	−0.5025	52.16%	0.8860	USD	51.60%	0.4568	52.15%	0.2949	55.00%	1.1648
	(0.7602)	(0.7455)	(0.7476)	(0.6924)	(0.2705)	(0.1878)		(0.0774)	(0.3239)	(0.1362)	(0.3841)	(0.0874)	(0.1220)
KWD	52.47%	0.6657	54.03%	1.1785	50.26%	0.8265	Mean	51.34%	1.0839	52.45%	0.8917	53.18%	0.8068
	(0.0592)	(0.2528)	(0.0273)	(0.1193)	(0.4727)	(0.2042)							

Notes: This table reports the out-of-sample performance of the Bitcoin-based exchange rate forecasting model using the ECM specification. "h" denotes the forecasting horizon. "DoC" denotes the direction of change statistics: a value larger than 50% indicates outperformance compared with a naïve model that predicts an equal probability of exchange rate movement in each direction; p-values (Diebold and Mariano, 1995) are reported in the parentheses. "CW" denotes the Clark-West test statistics: a positive value indicates outperformance compared with the RW; p-values (Clark and West, 2006; Clark and West, 2007) are reported in the parentheses. All tests are implemented with HAC covariance matrices(Newey and West, 1987).

The linear return of the strategy on each day t is:

$$r^{FX}_{BTC,t} = \exp\left(\xi^{FX}_{BTC,t} \cdot \left(\Delta s_t + i^*_{t-1}\right) + \left(1 - \xi^{FX}_{BTC,t}\right) \cdot i_{t-1}\right) - 1 \tag{11}$$

where Δs_t is the change of log exchange rate, and i_t and i^*_t are the US and non-US interest rate transformed by $\log(1+\cdot)$, respectively. We use the US risk-free interest rate (i.e. $\xi_t = 0$ for all t) as the benchmark for this strategy.

The second strategy is a (zero-cost) Bitcoin-based carry trade, which takes into account the financing cost. When the forecasted exchange rate change plus the interest rate differential is positive, we borrow USD, converts USD into foreign currency, and then collect the foreign interest rate; otherwise, we borrow foreign currency to finance the risk-free investment in USD. The buy indicator of the strategy is:

$$\xi^{Carry}_{BTC,t} = \begin{cases} 1, & \text{if } \Delta s^f_t + i^*_{t-1} - i_{t-1} > 0 \\ 0, & \text{if } \Delta s^f_t + i^*_{t-1} - i_{t-1} = 0 \\ -1, & \text{if } \Delta s^f_t + i^*_{t-1} - i_{t-1} < 0 \end{cases}. \tag{12}$$

The linear return of the strategy is:

$$r^{Carry}_{BTC,t} = \xi^{Carry}_{BTC,t} \cdot \left(\exp\left(\Delta s_t + i^*_{t-1}\right) - \exp\left(i_{t-1}\right)\right) \tag{13}$$

The benchmark of the second strategy is the standard carry trade strategy, where we borrow the low-interest-rate currency to invest in the high-interest-rate currency, assuming no knowledge on the future exchange rate changes:

$$\xi^{Carry}_{t} = \begin{cases} 1, & \text{if } i^*_{t-1} - i_{t-1} > 0 \\ 0, & \text{if } i^*_{t-1} - i_{t-1} = 0 \\ -1, & \text{if } i^*_{t-1} - i_{t-1} < 0 \end{cases}. \tag{14}$$

The linear return of the carry-trade benchmark is:

$$r^{Carry}_{t} = \xi^{Carry}_{t} \cdot \left(\exp\left(\Delta s_t + i^*_{t-1}\right) - \exp\left(i_{t-1}\right)\right) \tag{15}$$

Table 6 describes the performance of the four strategies, and Table A5 in Online Appendix C provides supplementary statistics (drawdowns and skewness) of the strategies.[22] We use the full sample period except for the first rolling in-sample estimation window.

Both of our proposed strategies produce higher returns than their benchmarks for most of the currencies (Column 1–6 of Table 6). The Bitcoin-based (long-only) forex trading strategy (ξ^{FX}_{BTC}) produces positive returns for all 32 currencies[23], and outperform the US risk-free rate (r^{USD}_f) for 30 currencies. Using HAC-robust t-tests, the differences of returns ($r^{FX}_{BTC} - r^{USD}_f$) is significant for 14 (13) currencies at a 10% (5%) significance level. The average annualized return of our strategy (3.41%) is economically higher than the average risk-free rate (0.85%).

The Bitcoin-based carry trade (ξ^{Carry}_{BTC}) produces positive returns for 30 currencies, and outperforms the standard carry trade (ξ^{Carry}) benchmark for 29 currencies. ($r^{Carry}_{BTC} - r^{Carry}$) is significant for 14 (10) currencies using a 10% (5%) significance level. The average annualized returns of ξ^{Carry}_{BTC} (7.02%) is also economically higher than the standard carry trade (0.27%). Both of the BTC-based strategies (ξ^{FX}_{BTC} and ξ^{Carry}_{BTC}) produce the highest annualized returns on the Russian ruble (10.81%, 16.15%), the Columbian peso (8.64%, 20.44%) and the Chilean peso (7.43%, 16.65%).

Fig. 1 plots the cumulative returns of the four strategies for 4 representative currency pairs.[24] The lead of our strategies compared with corresponding benchmarks is relatively stable over time. In 2022 (January to August), for RUB/USD, the strategies ξ^{FX}_{BTC} and ξ^{Carry}_{BTC} produce accumulative returns of 69.90% and 120.83%, respectively, while the standard carry trade has a cumulative return of 31.17%, and the performance is perhaps associated with the capital control and Bitcoin-based cross-border capital flows in 2022.

Our strategies also have higher risk-adjusted returns compared with the carry-trade benchmark. The average Sharpe ratio[25] (column 7–9 of Table 6) for ξ^{FX}_{BTC}, ξ^{Carry}_{BTC}, and ξ^{Carry}, is 0.53, 0.76, and −0.13, respectively. The Bitcoin-based carry trade earns higher Sharpe ratios than the carry-trade benchmark for 29 currencies. According to the Ledoit and Wolf (2008) test (robust to heteroskedasticity and serial correlation) of equal Sharpe ratios (column 10), the Sharpe ratio gain is significant for 14 (10) currencies using a 10% (5%) significance level.

[22] We follow the common practice since Sharpe (1966) to analyze Sharpe ratio and drawdowns in the form of simple returns, instead of log returns.

[23] We test all currency pairs except that we fail to find reliable interest rate data for the Algerian dinar. Regarding the row "USD" in Table 6, the strategies are hypothetical: we use NEER as the effective exchange rate and ignore the interest rate differential. As a result, when we calculate the "mean" for each column in Table 6, the "USD" is not used.

[24] EUR/USD is the most traded currency pair on the forex market. CAD is a representative commodity currency. Our strategies ξ^{FX}_{BTC} and ξ^{Carry}_{BTC} produce the highest cumulative returns on RUB/USD and COP/USD, respectively.

[25] We use the daily EFFR of the USA as the risk-free rate to calculate Sharpe ratios. It makes little sense to compute the Sharpe ratio of the benchmark strategy r^{USD}_f.

Table 6
Performance of the Bitcoin-based currency trading strategies: full sample.

	Mean (ann., %)						Sharpe ratio (ann.)				Win rate (12 m, %)			Volatility (ann., %)			
	(1) r^{FX}_{BTC}	(2) r^{USD}_{f}	(3) (1)-(2)	(4) r^{Carry}_{BTC}	(5) r^{Carry}	(6) (4)-(5)	(7) r^{FX}_{BTC}	(8) r^{Carry}_{BTC}	(9) r^{Carry}	(10) (8)-(9)	(11) r^{FX}_{BTC}	(12) r^{Carry}_{BTC}	(13) r^{Carry}	(14) r^{FX}_{BTC}	(15) r^{USD}_{f}	(16) r^{Carry}_{BTC}	(17) r^{Carry}
AUD	3.02*	0.84***	2.18	6.85**	4.40*	2.45	0.36	0.57	0.34	0.23	34.91	45.92	81.95	6.09	0.04	10.52	10.52
BRL	3.63	0.84***	2.78	12.80**	−5.71	18.51**	0.31	0.75	−0.41	1.17**	49.01	64.21	40.02	8.96	0.04	15.86	15.88
BWP	1.26	0.84***	0.42	3.94*	0.96	2.97	0.07	0.36	0.01	0.35	57.50	60.57	64.07	5.76	0.04	8.61	8.61
CAD	3.70***	0.84***	2.86**	7.44***	−1.31	8.75**	0.70	0.90	−0.29	1.20**	80.56	79.05	47.42	4.12	0.04	7.31	7.32
CHF	1.95	0.84***	1.11	3.23	1.36	1.87	0.14	0.24	0.05	0.19	49.84	39.67	60.37	7.95	0.04	10.04	10.04
CLP	7.43***	0.84***	6.59***	16.65***	−3.36	20.01***	0.97	1.43	−0.38	1.81***	84.29	81.55	41.63	6.77	0.04	11.03	11.06
CNY	1.35*	0.85***	0.50	0.70	0.68	0.02	0.20	−0.04	−0.05	0.01	62.05	59.14	44.29	2.52	0.04	3.69	3.69
COP	8.64***	0.84***	7.81***	20.44***	−5.22	25.66***	0.96	1.49	−0.46	1.95***	96.37	98.50	39.16	8.09	0.04	13.17	13.21
CZK	3.97	1.08***	2.89	7.06**	3.34	3.72	0.44	0.65	0.24	0.40	65.98	66.97	75.19	6.61	0.05	9.23	9.24
EUR	2.35*	0.84***	1.51	7.50***	3.88*	3.62	0.32	0.84	0.38	0.45	64.24	84.18	60.48	4.71	0.04	7.97	7.98
GBP	1.34	0.84***	0.50	5.38**	−2.02	7.40*	0.08	0.48	−0.30	0.79*	57.93	55.87	42.11	6.33	0.04	9.41	9.41
ILS	1.61	0.85***	0.76	0.27	0.01	0.26	0.14	−0.08	−0.12	0.04	54.05	36.16	51.36	5.53	0.04	7.35	7.07
INR	0.82	0.85***	−0.03	−1.49	1.35	−2.84	−0.01	−0.47	0.10	−0.57	65.29	34.67	66.33	2.79	0.04	5.01	5.01
JPY	1.22	0.84***	0.37	4.79*	3.80	0.99	0.07	0.45	0.34	0.11	59.36	59.17	51.81	5.50	0.04	8.74	8.74
KRW	2.31*	0.84***	1.47	4.45**	1.16	3.29	0.33	0.48	0.04	0.44	60.07	64.29	67.91	4.41	0.04	7.45	7.45
KWD	1.21***	0.85***	0.36*	1.18***	−0.22	1.40***	0.61	0.28	−0.90	1.18***	94.98	81.02	55.46	0.59	0.04	1.19	1.19
MUR	6.69***	0.85***	5.84***	15.67***	−4.45	20.12***	2.86	4.51	−1.58	6.09***	87.68	100.00	25.91	2.05	0.04	3.29	3.36
MXN	2.26	0.85***	1.42	5.43	0.69	4.74	0.17	0.36	−0.01	0.38	61.04	61.36	58.36	8.23	0.04	12.56	12.56
MYR	1.44	0.85***	0.60	3.51*	−1.68	5.19	0.18	0.41	−0.39	0.81	64.09	61.42	46.27	3.37	0.04	6.43	6.43
NOK	5.77***	0.84***	4.92**	15.28***	−5.78	21.05***	0.68	1.20	−0.55	1.75***	70.03	76.62	30.33	7.26	0.04	12.02	12.05
NZD	5.42**	0.84***	4.58**	12.01***	4.39	7.62*	0.66	1.03	0.33	0.71*	71.67	59.25	75.91	6.95	0.04	10.80	10.81
PEN	3.51***	0.85***	2.67**	5.70***	−1.37	7.06**	0.68	0.80	−0.37	1.17**	88.68	94.42	39.59	3.91	0.04	6.03	6.04
PHP	2.56***	0.85***	1.72**	3.11**	−0.74	3.85**	0.70	0.58	−0.41	0.99**	86.12	88.92	39.43	2.45	0.04	3.89	3.90
PLN	0.76	0.84***	−0.08	4.90*	−1.29	6.19	−0.01	0.40	−0.21	0.61	43.95	50.61	48.00	6.51	0.04	10.15	9.98
RUB	10.81**	0.84***	9.96**	16.15**	5.53	10.61	0.67	0.68	0.21	0.47	68.72	55.75	58.69	14.80	0.04	22.58	22.60
SEK	1.43	0.84***	0.59	8.00**	4.68*	3.33	0.10	0.72	0.38	0.33	37.61	53.80	60.12	6.09	0.04	9.98	9.97
SGD	1.90**	0.84***	1.06	3.40**	0.10	3.30*	0.36	0.52	−0.15	0.68*	70.74	66.20	59.40	2.95	0.04	4.87	4.88
THB	2.89***	0.85***	2.04**	5.20***	1.66	3.54	0.66	0.89	0.17	0.72	79.00	72.62	59.98	3.11	0.04	4.89	4.89
TTD	6.90***	0.84***	6.06***	12.79***	−0.03	12.81***	2.09	2.36	−0.17	2.53***	94.08	91.53	66.72	2.90	0.04	5.06	5.10
UYU	5.19***	0.85***	4.34***	8.51***	2.22	6.29*	0.95	1.05	0.19	0.86*	76.54	82.88	47.37	4.56	0.04	7.27	7.29
ZAR	2.25	0.84***	1.41	−3.19	1.45	−4.64	0.11	−0.20	0.03	−0.24	52.49	27.40	53.48	13.41	0.04	19.66	19.66
USD	5.65***	0.84***	4.81***	6.49***			1.14	1.11			86.31	88.33		4.21	0.04	5.10	
Mean	3.41	0.85	2.55	7.02	0.27	6.75	0.53	0.76	−0.13	0.89	67.38	66.25	53.52	5.65	0.04	8.91	8.90

Notes: This table compares the performance of four strategies. The BTC-based forex trading strategy: $r^{FX}_{BTC,t} = \exp(\Delta s_t + i^*_{t-1}) - 1$ if $\Delta s^f_t > 0$, and otherwise $\exp(i_{t-1}) - 1$ VS the US risk-free rates during the same period; the Bitcoin-based carry trade: $r^{Carry}_{BTC,t} = \exp(\Delta s_t + i^*_{t-1}) - \exp(i_{t-1})$ if $\Delta s^f_t + i^*_{t-1} - i_{t-1} > 0$, and otherwise $\exp(i_{t-1}) - \exp(\Delta s_t + i^*_{t-1})$VS the standard carry trade: $r^{Carry}_t = \exp(\Delta s_t + i^*_{t-1}) - \exp(i_{t-1})$ if $\Delta i^*_{t-1} - i_{t-1} > 0$, and otherwise $\exp(i_{t-1}) - \exp(\Delta s_t + i^*_{t-1})$. We use HAC t-tests to test whether the strategies produce positive returns over zero (Column 1, 2, 4, and 5) or over the corresponding benchmarks (Column 3 and 6); and we use Ledoit and Wolf (2008) test (Column 10) to test whether the Sharpe ratios of the BTC-based carry trade are higher than the carry-trade benchmark; asterisks behind each number indicate significance at 1% (***), 5% (**), and 10% (*) levels. For the row "USD", the strategy is hypothetical: we use NEER as the effective exchange rate and ignore the interest rate differential. When we calculate the "mean" for each column, the "USD" is not used.

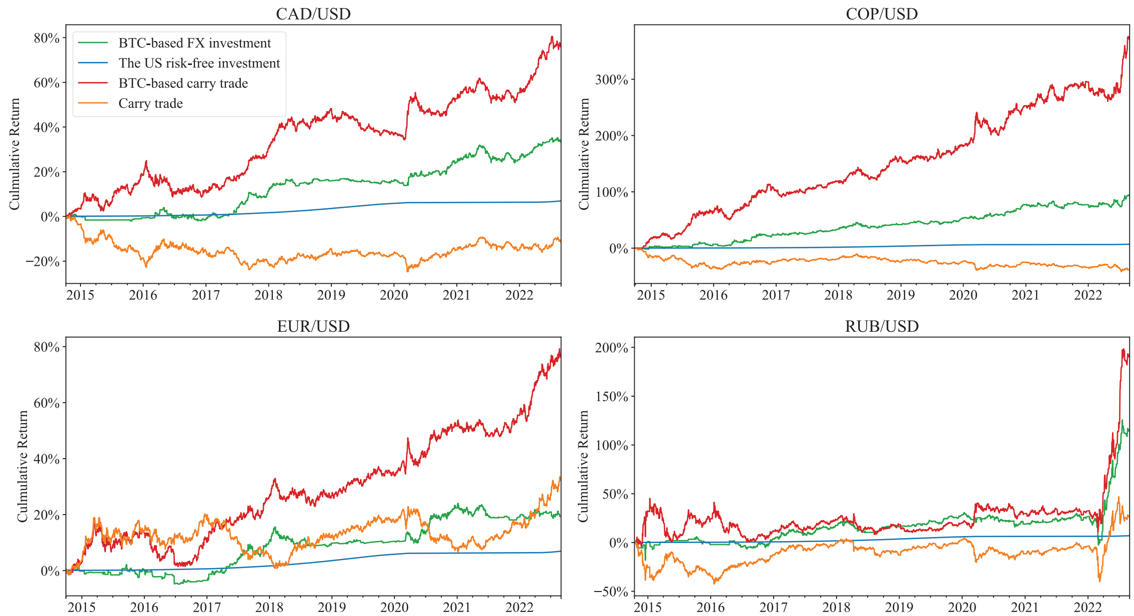

Fig. 1. Cumulative returns of each strategy performed on the representative currencies.

We also present the 12-month win rates (column 11–13, Table 6), which measure the chances of profiting if one performs a strategy for 12 consecutive months. The average win rate for $\xi_{BTC}^{FX}, \xi_{BTC}^{Carry}$, and ξ^{Carry}, is 67.38%, 66.25%, and 53.52%, respectively. The average volatility (column 14–17, Table 6) of $\xi_{BTC}^{FX}, \xi_{BTC}^{Carry}$, and ξ^{Carry}, is 5.65%, 8.91%, and 8.90% respectively. Table A5 in Online Appendix C presents four drawdown criteria, which measure the percentage of decline from a historical peak.[26] On average, compared with the carry trade, the Bitcoin-based strategies ξ_{BTC}^{FX} and ξ_{BTC}^{Carry} have lower maximum drawdowns, lower average drawdowns, lower average drawdown days, and higher Calmar ratios.

In Table 7, we further test whether our strategy survives the periods of Bitcoin price crashes. Although Bitcoin achieved an impressive return of 2499.14% during our sample period (2014/1/1–2022/8/31), there are four noticeable crashes (the grey areas of Fig. 2). As the first crash period is mainly for estimation, we compare the performance of the Bitcoin-based carry trade versus the standard carry trade during three subsamples of Bitcoin price crashes. Overall, the Bitcoin-based carry trade has higher returns than the benchmark for a majority of the currencies during each Bitcoin price crash. The performance is better in the last two Bitcoin crashes than in the first crash.

6. Tests on the mechanisms of the forecastability[27]

In this section, we test whether the two potential mechanisms described in Section 2.3 work.

6.1. Bitcoin return and a fundamental of exchange rate

To test the mechanism (i) of Section 2.3, that is, to test whether the exchange rate forecastability of Bitcoin returns partly arises from their fast incorporation of future fundamentals of exchange rates, we test whether Bitcoin returns forecast the future fundamental of exchange rates when controlling for lags of exchange rates. As observed by Engel and West (2005), exchange rates themselves are forward-looking and embody information about their future fundamentals. Such fundamentals of exchange rates include interest rate differentials, money differentials, price differentials, output differentials, etc. If Bitcoin returns could also predict such variables, it would partly support the view that Bitcoin returns incorporate future fundamentals of exchange rates in a faster manner so that they can predict exchange rates. Among the four differentials mentioned above, only interest rate differential data are available at the daily frequency, so we focus on the interest rate differential predictability of Bitcoin returns.

[26] Mathematically speaking, the drawdown series D(t) of the price series P(t) is defined as $DD(t) = \max_{s\in[0,t]}(P(s) - P(t))/P(s)$. The maximum drawdown $MDD(T) = \max_{t\in[0,T]}DD(t)$. The average drawdown $AvDD(T) = \sum_0^T DD(t)/T$. The average drawdown days are the average days between a high-water mark and the recovery time (or, if none, the end of the period). The Calmar ratio is the average annual return divided by the maximum drawdown.

[27] We thank an anonymous reviewer for the suggestions on this section.

Table 7
Performance of the Bitcoin-based currency carry trade strategy VS the standard carry trade strategy: subsamples of Bitcoin crashes.

	12/16/17∼ 12/15/18	6/26/19∼ 3/12/20	11/8/21∼ 6/18/22		12/16/17∼ 12/15/18	6/26/19∼ 3/12/20	11/8/21∼ 6/18/22
	(1)	(2)	(3)		(1)	(2)	(3)
AUD	−13.6617	−3.0455	39.9442**	(continued)			
BRL	34.2843*	74.1277***	37.3549*	MXN	−10.6159	42.9418**	6.6862
BWP	−8.3196	−1.2702	16.6924	MYR	3.4598	5.6284	18.2629**
CAD	10.3712*	6.6505	22.1657**	NOK	−6.9134	23.1331	57.9127***
CHF	0.2383	−3.8385	17.9991	NZD	−25.9508	−0.7556	65.8898***
CLP	31.1734**	65.2443***	25.9315	PEN	4.3705	20.6923**	−14.3297
CNY	3.4243	0.1601	−1.4949	PHP	3.7494	1.0594	10.2541
COP	18.0003	49.8075**	2.3227	PLN	−4.2007	11.8692	59.3674**
CZK	−15.4985	−2.2064	28.2499*	RUB	0.3713	35.5050*	18.6294
EUR	−4.5745	6.6017	7.2189	SEK	−4.8656	1.4666	28.9522**
GBP	−11.6374	11.7810	44.6830***	SGD	−1.3198	2.1206	13.6744**
ILS	−11.8543	−11.8423	32.6380**	THB	−7.2535	−5.7234	17.2770
INR	6.5479	−6.1089	21.8783***	TTD	2.0288	16.2937***	4.5668
JPY	4.4017	7.1820	1.4867	UYU	7.6164	35.9224*	0.1753
KRW	−11.8115	−1.2384	6.2680	ZAR	4.4928	6.0413	35.4408
KWD	0.6001	0.3368	3.0385**	USD	10.9404***	1.7464	13.0589**
MUR	35.9303***	18.4115***	4.2815	Mean	1.0511	13.1274	20.4328

Notes: This table reports the differences between average returns of the Bitcoin-based carry trade and the standard carry-trade benchmark during three periods of Bitcoin crashes. A positive value indicates outperformance. The returns are in percentages and are annualized. Asterisks behind each number indicate outperformance at 1% (***), 5% (**), and 10% (*) significance levels based on the t-test with HAC covariance correction.

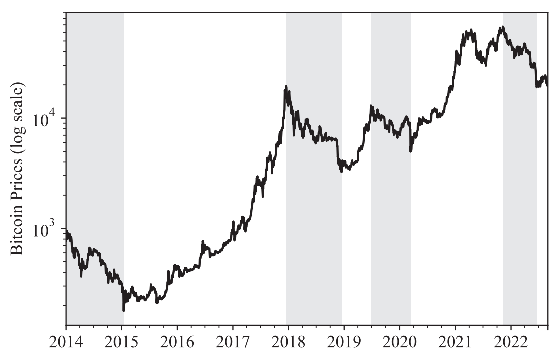

Fig. 2. Bitcoin prices.

Implied by a variety of economic models (e.g. UIRP), the level of interest rate differential is a fundamental of exchange rates. However, using ADF tests, we are generally unable to reject the null of a unit root in $i_t - i_t^*$. Following Engel and West (2005), we present statistics for both levels and the first differences of interest rate differentials. In line with the designs of earlier works (Campbell and Shiller, 1987; Chen et al., 2010; Engel and West, 2005), if Bitcoin returns Δp_t efficiently incorporates some information in addition to that included in past values of interest rate differentials (and exchange rates), Δp_t should Granger-cause $i_t - i_t^*$ (after controlling for past values of Δs_t). A finding of Granger causality after controlling for lags of Δs_t will partly stand for the view that Bitcoin captures information on future fundamentals of exchange rates in a faster manner than the exchange rate itself.

Table 8 reports the results of the Granger causality (GC) tests on interest rate predictability of Bitcoin returns, and the results provide support for the mechanism (i) of Section 2.3. The lags of GC tests are selected using BIC. At a significance level of 5%, the null that Δp_t does not Granger cause $i_t - i_t^*$ is rejected for 19/31 (61.29%) currencies (column 1), and the null that Δp_t does not Granger cause $\Delta(i_t - i_t^*)$ is rejected for 14/31 (45.16%) currencies (column 2). After controlling for the lag values of exchange rates, the null that Δp_t does not Granger cause $i_t - i_t^*$ is rejected for 18/31 (58.06%) currencies (column 3), and the null that Δp_t does not Granger cause $\Delta(i_t - i_t^*)$ is rejected for 14/31 (45.16%) currencies (column 4). The percentage of Granger causality is much higher than what would be expected from the random chances with simply no predictability (i.e., the significance level 5%). The result of Table 8 provides evidence that Bitcoin returns incorporate extra knowledge on future interest differentials, one of the exchange rate fundamentals.

Table 8
Interest rate differential predictability of Bitcoin returns: the Granger causality test.

	(1) Δp_t	(2) Δp_t	(3) Δp_t	(4) Δp_t		(1) Δp_t	(2) Δp_t	(3) Δp_t	(4) Δp_t
GC	$i_t - i_t^*$	$\Delta(i_t - i_t^*)$	$i_t - i_t^*$	$\Delta(i_t - i_t^*)$		$i_t - i_t^*$	$\Delta(i_t - i_t^*)$	$i_t - i_t^*$	$\Delta(i_t - i_t^*)$
Control FX			Yes	Yes				Yes	Yes
AUD	0.0005***	0.8347	0.0001***	0.8306		(Continued)			
BRL	0.0000***	0.0000***	0.0000***	0.0000***	MUR	0.2152	0.0000***	0.2766	0.0000***
BWP	0.0000***	0.0001***	0.0000***	0.0002***	MXN	0.0000***	0.0000***	0.0001***	0.0000***
CAD	0.0378**	0.5402	0.0366**	0.5615	MYR	0.7884	0.6859	0.4871	0.6771
CHF	0.0790*	0.1541	0.2497	0.1868	NOK	0.3021	0.4307	0.3223	0.4025
CLP	0.0000***	0.1818	0.0000***	0.1845	NZD	0.0320**	0.0699*	0.0405**	0.0661*
CNY	0.5570	0.2792	0.5372	0.2864	PEN	0.0315**	0.4908	0.0624*	0.5255
COP	0.0000***	0.0000***	0.0000***	0.0001***	PHP	0.0000***	0.0000***	0.0000***	0.0001***
CZK	0.0004***	0.8014	0.0008***	0.8428	PLN	0.1990	0.2340	0.3797	0.2510
EUR	0.0000***	0.0000***	0.0000***	0.0000***	RUB	0.7147	0.8230	0.6031	0.7799
GBP	0.0002***	0.0000***	0.0009***	0.0000***	SEK	0.6694	0.8250	0.6316	0.8415
ILS	0.0000***	0.5577	0.0001***	0.6257	SGD	0.6079	0.9455	0.3509	0.9372
INR	0.0684*	0.2120	0.0931*	0.2341	THB	0.0000***	0.0000***	0.0000***	0.0000***
JPY	0.0000***	0.0000***	0.0000***	0.0000***	TTD	0.9891	0.6590	0.9719	0.6571
KRW	0.0000***	0.0000***	0.0000***	0.0000***	UYU	0.0685*	0.0055***	0.0302**	0.0046***
KWD	0.0000***	0.0000***	0.6612	0.0000***	ZAR	0.0000***	0.0000***	0.0000***	0.0000***

Notes: This table reports the Granger causality tests on interest rate differential predictability of Bitcoin returns. The lags of the GC tests are selected using the BIC. Δp_t is the daily Bitcoin log return; i_t and i_t^* are interest rates on the USD and non-USD currencies, respectively. The null hypothesis for each columns is $\beta_{p,1} = \ldots = \beta_{p,k} = 0$ in the regression: (1) $i_t - i_t^* = \alpha + \beta_{p,1}\Delta p_{t-1} + \ldots + \beta_{p,k}\Delta p_{t-k} + \beta_{i,1}(i_{t-1} - i_{t-1}^*) + \ldots + \beta_{i,k}(i_{t-k} - i_{t-k}^*) + \varepsilon_t$, (2) $\Delta(i_t - i_t^*) = \alpha + \beta_{p,1}\Delta p_{t-1} + \ldots + \beta_{p,k}\Delta p_{t-k} + \beta_{i,1}\Delta(i_{t-1} - i_{t-1}^*) + \ldots + \beta_{i,k}\Delta(i_{t-k} - i_{t-k}^*) + \varepsilon_t$, (3) $i_t - i_t^* = \alpha + \beta_{p,1}\Delta p_{t-1} + \ldots + \beta_{p,k}\Delta p_{t-k} + \beta_{i,1}(i_{t-1} - i_{t-1}^*) + \ldots + \beta_{i,k}(i_{t-k} - i_{t-k}^*) + \beta_{s,1}\Delta s_{t-1} + \ldots + \beta_{s,k}\Delta s_{t-k} + \varepsilon_t$, (4) $\Delta(i_t - i_t^*) = \alpha + \beta_{p,1}\Delta p_{t-1} + \ldots + \beta_{p,k}\Delta p_{t-k} + \beta_{i,1}\Delta(i_{t-1} - i_{t-1}^*) + \ldots + \beta_{i,k}\Delta(i_{t-k} - i_{t-k}^*) + \beta_{s,1}\Delta s_{t-1} + \ldots + \beta_{s,k}\Delta s_{t-k} + \varepsilon_t$. The values in each cell are the p-values of the F-test. Asterisks behind each number indicate significance at 1% (***), 5% (**), and 10% (*) levels.

6.2. The heterogeneity of the forecastability

To test the mechanism (ii) of Section 2.3, we test whether the exchange rate forecastability of Bitcoin returns arises from their reflection of convenience yield differentials between the currencies and the USD. We analyze the cross-sectional heterogeneity as well as the panel heterogeneity of the forecastability. If Bitcoin returns correlate with the expected currency risk premium through their correlation with the convenience yield differentials, the forecastability would probably be more pronounced where convenience yields play a more important role, through the investors' demand for liquid (medium of exchange) or safe (store of value) currency. If the mechanism works, we could possibly find better forecastability on the countries with tighter capital controls, higher inflations, or higher inflation volatility.

In Table 9, we regress the forecastability over capital control, inflation, and inflation volatility. The forecastability is represented by (1) *RMSER* (root mean squared error ratio), which is the ratio of the Bitcoin-based ADL model's RMSE to the RMSE of the RW, and (2) *DoC*, which is the direction of change statistic of the Bitcoin-based ADL model. We use the Chinn and Ito (2006) *KAOPEN* index to measure the capital control, and a higher value indicates more financially open. *INFLATION* is the annual percentage change of the end-of-period consumer price index, and the data is from the IMF. *INFLTN_VOL* (inflation volatility) is the yearly standard deviation of monthly inflation rates. Panel A reports the results of cross-sectional regressions, where both the explained and explanatory variables are average values across years; Panel B reports the results of panel regressions, where both the explained and explanatory variables are in a country-year fashion.

Based on the results of Table 9, higher inflation volatility is significantly associated with higher direction-of-change statistics, both in the cross-section regression (Column 3,4 of Panel A) and in the panel regression with year-fixed effect (that is, to focus on the same-year cross-sectional forecastability, Column 3,4 of Panel B). The result becomes insignificant when we include both country- and year-fixed effect and all three explanatory variables in the panel regression (Column 5 of Panel B). Higher inflation volatility is also associated with lower RMSER (Column 8, 9, 10 of Panel A and B), but in a less significant or insignificant manner. We do not find significant evidence that either capital control or the level of inflation explains the forecastability in the cross-sectional regressions or in the panel regressions.

The results of Table 9 only provide some suggestive evidence that Bitcoin returns reflect convenience yields of selected currencies, by showing significantly higher direction of change statistics in countries with higher inflation volatility. We admit that part of the other insignificant result may result from limited cross-sectional and yearly data. We also admit that the expected currency premiums or convenience yield differentials still reflect a lot of information besides the selected explanatory variables, and we cannot rule out the possibility that Bitcoin returns may correlate with such information.

Table 9
The cross-sectional and panel heterogeneity of the forecastability.

Panel A: Cross-sectional regressions										
			DoC					*RMSER*		
	(1)	(2)	(3)	(4)		(6)	(7)	(8)	(9)	
KAOPEN	−0.0492			0.4435		0.0078			−0.2304	
	(0.8390)			(0.2386)		(0.9606)			(0.4117)	
INFLATION		0.1146		−0.2035			0.0157		0.5064	
		(0.5256)		(0.5537)			(0.8791)		(0.1346)	
INFLTN_VOL			11.7192*	15.9022**				−10.1770	−13.9505*	
			(0.0578)	(0.0209)				(0.1497)	(0.0644)	
Constant	Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes	
Panel B: Panel regressions										
			DoC					*RMSER*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
KAOPEN	−0.0012			0.2874	0.2826	−0.0492			−0.1640	−1.4246
	(0.9955)			(0.2261)	(0.7948)	(0.6726)			(0.4228)	(0.1847)
INFLATION		0.0933		−0.0996	0.0656		0.0372		0.2861	0.1720
		(0.5916)		(0.5628)	(0.7741)		(0.4611)		(0.1350)	(0.2472)
INFLTN_VOL			8.5685**	11.1229**	−0.2721			−6.2806	−8.9184*	−2.6198
			(0.0223)	(0.0299)	(0.9277)			(0.1572)	(0.0863)	(0.2015)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE					Yes					Yes

Notes: This table tests whether the exchange rate forecastability can be explained by capital control, inflation, or inflation volatility. Panel A reports the results of cross-sectional regressions, where both the explained and explanatory variables are averaged across years, and the *p*-values in parentheses are heteroskedasticity-robust. Panel B reports the results of panel regressions, and the *p*-values in parentheses are based on standard errors clustered at both country and year levels. *RMSER* (root mean squared error ratio, in percent) is the ratio of the Bitcoin-based ADL model's RMSE to the RMSE of the RW benchmark, and a lower value indicates better forecastability. *DoC* (in percent) is the direction of change statistic of the Bitcoin-based ADL model, and a higher value indicates better forecastability. *KAOPEN* is the Chinn and Ito (2006) index, and a higher value indicates more financially open. *INFLATION* is the annual percentage change of the end-of-period consumer price index. *INFLTN_VOL* (inflation volatility) is the yearly standard deviation of monthly inflation rates.

7. Robustness analyses

7.1. Alternative benchmarks

Although the RW is considered the most challenging benchmark for forecasting exchange rates (e.g., Rossi, 2013; Cheung et al., 2019) and our model outperforms the RW, to strictly address the concerns that the superiority of our model may arise from the constant term or the lagged exchange rate in the ADL specification (Eq. 6), or the constant term in the ECM specification (Eq. 9), we test alternative benchmarks.

We compare the out-of-sample performance of our ADL-based exchange rate forecasts, with the random walk with drift (RWWD) model (Table A2 in Online Appendix B), and with the autoregressive model AR(1) (Table A3 in Online Appendix B); and we compare our ECM-based forecasts with the RWWD model (Table A4 in Online Appendix B). The parameters in the alternative benchmarks are also estimated in a rolling scheme. Similar to the baseline comparison, three forecasting horizons (h = 1 day, 1 week, 1 month) are reported in Panel A, B, and C respectively, and both the direction of change criterion and the Clark-West criteria are evaluated.

Comparisons with alternative benchmarks do not change the primary observation. Our Bitcoin-based exchange rate forecasting models still beat the new benchmarks for many currencies; the forecastability is still most favorable at the daily horizon using the ADL model. The results confirm that the outperformance of our model is attributed to the predictability of Bitcoin, rather than the drift term or the lagged exchange rates.

7.2. Exogeneity

As is discussed in Section 2.2, given the clear one-way causality relationship between exchange rates and Bitcoin, the in-sample predictability of Bitcoin can be treated as evidence of the present-value specification, although the out-of-sample superiority of our model does not rely on the exogeneity assumption. For large economies, reverse causality is not a concern, as the Bitcoin trading volume is far too less compared with the size of the foreign exchange market (see footNote 1). For managed fixed exchange rate regimes, reverse causality is also not a concern, as the exchange rates are adjusted by the governments, and the governments do not adjust the exchange rates according to Bitcoin prices.

One might still be concerned that for some small economies with (managed-) floating exchange rates, Bitcoin supply or demand is so large that Bitcoin price movements may influence the demand for the currency and the exchange rate. To strictly address this concern, we test the exogeneity assumption in five small economies with (managed-) floating exchange rates. The examined currencies are the Chilean peso (CLP), the Mauritian rupee (MUR), the New Zealand dollar (NZD), the

Table 10
Wooldridge's score test of exogeneity.

	CLP	MUR	NZD	TTD	UYU
	Panel A: Wooldridge's score test using $(i_{t-1} - i^*_{t-1})$ as the IV				
Wooldridge test statistic	1.2224	0.6848	1.2686	1.2869	0.0743
p-value	(0.2689)	(0.4079)	(0.2600)	(0.2566)	(0.7851)
	Panel B: Wooldridge's score test using $\Delta(i_{t-1} - i^*_{t-1})$ as the IV				
Wooldridge test statistic	0.0181	1.5694	0.2152	0.1818	0.8454
p-value	(0.8930)	(0.2103)	(0.6427)	(0.6698)	(0.3579)

Notes: This table reports the Wooldridge's score test result. The test examines the exogeneity of the exchange rate from the regression: $\Delta p_t = \alpha + \beta\Delta s_t + u_t$, where Δp_t and Δs_t are the log Bitcoin returns and the log exchange rate returns respectively. The test uses the lagged interest rate differentials $(i_{t-1} - i^*_{t-1})$ and their first-differences $\Delta(i_{t-1} - i^*_{t-1})$ as instrument variables of Δs_t in Panel A and B, respectively.

Trinidadian dollar (TTD), and the Uruguayan peso (UYU). The average official reserve assets [28] of each of the countries is less than three times the daily trading volume of Bitcoin during the sample period.

We verify the exogeneity assumption using the Wooldridge, 1995's (Wooldridge, 1995) score test. Different from the Durbin (1954) and Wu-Hausman (Wu, 1974; Hausman, 1978) test of exogeneity, the Wooldridge, 1995's (Wooldridge, 1995) score test is robust to heteroskedastic and autocorrelated errors. The test compares the OLS estimator with an instrumental variable (IV) estimator. We use the lagged interest rate differential or its first difference as the instrument variables of the test.[29] Table 10 reports the results of the Wooldridge's score test. The null hypothesis that the exchange rate return is exogenous to Bitcoin return is not rejected for all the five exchange rates at 10%.

8. Conclusions

In this study, we uncover a surprising and unexamined predictor of currency exchange rates: Bitcoin prices. We model the relation between Bitcoin prices and exchange rates through a forward-looking pricing model of Bitcoin. The model describes the facts that currency exchange rates serve as a fundamental of Bitcoin, and that Bitcoin prices efficiently incorporate future expectations of exchange rates and their drivers. As a result, Bitcoin prices can help predict future exchange rate movements. The economic insight of our study is in line with Chen et al. (2010). From a theoretical perspective, different from previous studies, our predictor, Bitcoin prices, is not a macroeconomic fundamental of exchange rates, but efficiently incorporates market expectations about exchange rate movements. This new perspective contributes to the exchange rate prediction literature. As supporting evidence for the forecasting mechanism, we show that compared with the exchange rate itself, Bitcoin return incorporates extra information of future interest rate differential. In the cross-section, the forecastability (measured by the direction of change statistic) is more pronounced in countries with higher inflation volatility, partly suggesting a possible link between Bitcoin returns and the currency premium or convenience yields.

We provide empirical evidence of the predictive power of Bitcoin for numerous currency exchange rates. The fact that exchange rate movements are exogenous to Bitcoin returns provides an ideal opportunity that we can treat empirical predictability as evidence of the theoretical present-value model. Both the ADL and the ECM specifications demonstrate in-sample and out-of-sample exchange rate predictability of Bitcoin. In the in-sample tests, predictability of both specifications exists at all three horizons. In the out-of-sample tests, different evaluation methods (the direction of change statistics and the Clark-West statistics) and different benchmarks (RW, RWWD, AR(1)) are scrupulously tested. The out-of-sample forecastability is most strong at the daily horizon using the ADL specification, and there are also a number of significantly forecastable currencies at weekly and monthly horizons or using the ECM. Trading strategies based on the daily forecastability produce risk-adjusted return gains compared with the US risk-free-rate or carry-trade benchmarks. Alternative forecasting specifications, possibly in a multi-equation fashion or a nonlinear fashion, are possible candidates to improve forecasting performance. We leave these potential issues for future research.

Given the well-documented difficulty and the practical importance of exchange rate prediction, the forecastability provided by Bitcoin (especially at the daily horizon) is of particular interest to currency market practitioners, and possibly provides policymakers and multinational corporations with more information about short-term exchange rate movements. Meanwhile, our results motivate Bitcoin asset pricing models that explicitly incorporate currency exchange rates.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

[28] The data of the official reserve assets (in USD) are from the IMF and the European Commission Website.

[29] An IV is supposed to meet the requirements of relevance and exogeneity. Concerning relevance, interest rate differentials are related to future exchange rate movement, as suggested by UIRP and some empirical evidence (although empirically the correlation may be significantly negative, see Froot and Thaler, 1990). Concerning exogeneity, lagged interest rate differentials cannot be influenced by future Bitcoin prices. We use the first difference of interest rate differentials as another IV to address the potential concern of nonstationarity of interest rate differentials.

Acknowledgements

We are grateful to the editor (Menzie David Chinn) and an anonymous referee for highly insightful and valuable suggestions, especially the suggestions on the mechanisms of forecastability, the methods to test the mechanisms, and the trading strategies. All errors are our own. Wenjun Feng acknowledges financial support from the Fundamental Research Funds for the Central Universities [grant number 2020RCW002] and the China Postdoctoral Science Foundation [grant numbers 2019M660442, 2020T130051]. Zhengjun Zhang acknowledges financial support from the National Science Foundation [grant number NSF-DMS-2012298].

Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.jimonfin.2023.102811.

References

Abhyankar, A., Sarno, L., Valente, G., 2005. Exchange rates and fundamentals: Evidence on the economic value of predictability. J. Int. Econ. 66, 325–348.
Alquist, R., Chinn, M.D., 2008. Conventional and unconventional approaches to exchange rate modelling and assessment. Int. J. Financ. Econ. 13, 2–13.
Amat, C., Michalski, T., Stoltz, G., 2018. Fundamentals and exchange rate forecastability with simple machine learning methods. J. Int. Money Financ. 88, 1–24.
Bank for International Settlements, 2013, 2016, and 2019. Triennial Central Bank Survey of Foreign Exchange and Over-the-counter (OTC) Derivatives Markets. Basel, Switzerland.
Berkowitz, J., Giorgianni, L., 2001. Long-horizon exchange rate predictability? Rev. Econ. Statistics 83, 81–91.
Biais, B., Bisiere, C., Bouvard, M., Casamatta, C., Menkveld, A.J., 2022. Equilibrium Bitcoin pricing. J. Financ., forthcoming.
Böhme, R., Christin, N., Edelman, B., Moore, T., 2015. Bitcoin: Economics, technology, and governance. J. Econ. Perspect. 29, 213–238.
Calvo, G.A., Reinhart, C.M., 2002. Fear of floating. Q.J. Econ. 117, 379–408.
Campbell, J.Y., Shiller, R.J., 1987. Cointegration and tests of present value models. J. Polit. Econ. 95, 1062–1088.
Ca'Zorzi, M., Rubaszek, M., 2020. Exchange rate forecasting on a napkin. J. Int. Money Financ. 102168.
Cerra, V., Saxena, S.C., 2010. The monetary model strikes back: Evidence from the world. J. Int. Econ. 81, 184–196.
Chen, Y.C., Rogoff, K., 2003. Commodity currencies. J. Int. Econ. 60, 133–160.
Chen, Y.C., Rogoff, K.S., Rossi, B., 2010. Can exchange rates forecast commodity prices? Q.J. Econ. 125, 1145–1194.
Chen, Y.C., Tsang, K.P., 2013. What does the yield curve tell us about exchange rate predictability? Rev. Econ. Statistics 95, 185–205.
Cheung, Y.W., Chinn, M.D., Pascual, A.G., 2005. Empirical exchange rate models of the nineties: Are any fit to survive? J. Int. Money Financ. 24, 1150–1175.
Cheung, Y.W., Chinn, M.D., Pascual, A.G., Zhang, Y., 2019. Exchange rate prediction redux: New models, new data, new currencies. J. Int. Money Financ. 95, 332–362.
Chinn, M.D., 1991. Some linear and nonlinear thoughts on exchange rates. J. Int. Money Financ. 10, 214–230.
Chinn, M.D., Ito, H., 2006. What matters for financial development? Capital controls, institutions, and interactions. J. Dev. Econ. 81, 163–192.
Chinn, M.D., Meese, R.A., 1995. Banking on currency forecasts: How predictable is change in money? J. Int. Econ. 38, 161–178.
Chinn, M.D., Moore, M.J., 2011. Order flow and the monetary model of exchange rates: Evidence from a novel data set. J. Money, Credit, Bank. 43, 1599–1624.
Clarida, R.H., Sarno, L., Taylor, M.P., Valente, G., 2003. The out-of-sample success of term structure models as exchange rate predictors: A step beyond. J. Int. Econ. 60, 61–83.
Clark, P.B., MacDonald, R., 1999. Exchange rates and economic fundamentals: A methodological comparison of beers and feers. Equilibrium Exchange Rates. Springer, 285–322.
Clark, T.E., McCracken, M.W., 2001. Tests of equal forecast accuracy and encompassing for nested models. J. Econometrics 105, 85–110.
Clark, T.E., West, K.D., 2006. Using out-of-sample mean squared prediction errors to test the martingale difference hypothesis. J. Econometrics 135, 155–186.
Clark, T.E., West, K.D., 2007. Approximately normal tests for equal predictive accuracy in nested models. J. Econometrics 138, 291–311.
Clements, K.W., Lan, Y., 2010. A new approach to forecasting exchange rates. J. Int. Money Financ. 29, 1424–1437.
Cong, L.W., He, Z., Li, J., 2019. Decentralized mining in centralized pools. Rev. Financ. Stud..
Dahlquist, M., Pénasse, J., 2022. The missing risk premium in exchange rates. J. Financ. Econ. 143, 697–715.
Della Corte, P., Sarno, L., Sestieri, G., 2012. The predictive information content of external imbalances for exchange rate returns: How much is it worth? Rev. Econ. Statistics 94, 100–115.
Detzel, A., Liu, H., Strauss, J., Zhou, G., Zhu, Y., 2021. Learning and predictability via technical analysis: Evidence from bitcoin and stocks with hard-to-value fundamentals. Financ. Manage. 50, 107–137.
Diebold, F.X., Gardeazabal, J., Yilmaz, K., 1994. On cointegration and exchange rate dynamics. J. Financ. 49, 727–735.
Diebold, F.X., Mariano, R.S., 1995. Comparing predictive accuracy. J. Bus. Econ. Stat., p. 13.
Diebold, F.X., Nason, J.A., 1990. Nonparametric exchange rate prediction? J. Int. Econ. 28, 315–332.
Durbin, J., 1954. Errors in variables. Rev. Inst. Int. Stat., 23–32
Dyhrberg, A.H., 2016. Hedging capabilities of Bitcoin. Is it the virtual gold? Financ. Res. Lett. 16, 139–144.
Easley, D., O'Hara, M., Basu, S., 2019. From mining to markets: The evolution of Bitcoin transaction fees. J Financ. Econ. 134, 91–109.
Engel, C., 1994. Can the markov switching model forecast exchange rates? J. Int. Econ. 36, 151–165.
Engel, C., Hamilton, J.D., 1990. Long swings in the dollar: Are they in the data and do markets know it? Am. Econ. Rev., 689–713
Engel, C., Lee, D., Liu, C., Liu, C., Wu, S.P.Y., 2019. The uncovered interest parity puzzle, exchange rate forecasting, and taylor rules. J. Int. Money Financ. 95, 317–331.
Engel, C., West, K.D., 2005. Exchange rates and fundamentals. J. Polit. Econ. 113, 485–517.
Engel, C., West, K.D., 2006. Taylor rules and the deutschmark: Dollar real exchange rate. J. Money, Credit, Bank. 38, 1175–1194.
Faust, J., Rogers, J.H., Wright, J.H., 2003. Exchange rate forecasting: The errors we've really made. J. Int. Econ. 60, 35–59.
Feng, W., Wang, Y., Zhang, Z., 2018a. Can cryptocurrencies be a safe haven: A tail risk perspective analysis. Appl. Econ. 50, 4745–4762.
Feng, W., Wang, Y., Zhang, Z., 2018b. Informed trading in the Bitcoin market. Financ. Res. Lett. 26, 63–70.
Ferraro, D., Rogoff, K., Rossi, B., 2015. Can oil prices forecast exchange rates? An empirical analysis of the relationship between commodity prices and exchange rates. J. Int. Money Financ. 54, 116–141.
Foley, S., Karlsen, J.R., Putniņš, T.J., 2019. Sex, drugs, and Bitcoin: How much illegal activity is financed through cryptocurrencies? Rev. Financ. Stud. 32, 1798–1853.

Foroni, C., Ravazzolo, F., Sadaba, B., 2018. Assessing the predictive ability of sovereign default risk on exchange rate returns. J. Int. Money Financ. 81, 242–264.
Froot, K.A., Thaler, R.H., 1990. Anomalies: Foreign exchange. J. Econ. Perspect. 4, 179–192.
Gandal, N., Hamrick, J., Moore, T., Oberman, T., 2018. Price manipulation in the Bitcoin ecosystem. J. Monetary Econ. 95, 86–96.
Giacomini, R., Rossi, B., 2010. Forecast comparisons in unstable environments. J. Appl. Economet. 25, 595–620.
Gourinchas, P.O., Rey, H., 2007. International financial adjustment. J. Polit. Econ. 115, 665–703.
Griffin, J.M., Shams, A., 2020. Is Bitcoin really untethered? J. Financ. 75, 1913–1964.
Groen, J.J., 1999. Long horizon predictability of exchange rates: Is it for real? Empir. Econ. 24, 451–469.
Guesmi, K., Saadi, S., Abid, I., Ftiti, Z., 2019. Portfolio diversification with virtual currency: Evidence from Bitcoin. Int. Rev. Financ. Anal. 63, 431–437.
Hausman, J.A., 1978. Specification tests in econometrics. Econometrica 46, 1251–1271.
Ince, O., 2014. Forecasting exchange rates out-of-sample with panel methods and real-time data. J. Int. Money Financ. 43, 1–18.
Jordà, Ò., Taylor, A.M., 2012. The carry trade and fundamentals: Nothing to fear but feer itself. J. Int. Econ. 88, 74–90.
Ju, L., Lu, T., Tu, Z., 2016. Capital flight and Bitcoin regulation. Int. Rev. Financ. 16, 445–455.
Kilian, L., 1999. Exchange rates and monetary fundamentals: What do we learn from long-horizon regressions? J. Appl. Economet. 14, 491–510.
Ledoit, O., Wolf, M., 2008. Robust performance hypothesis testing with the Sharpe ratio. J. Empir. Financ. 15, 850–859.
Leshno, J.D., Strack, P., 2020. Bitcoin: An axiomatic approach and an impossibility theorem. Am. Econ. Rev.: Insights 2, 269–286.
Macdonald, R., Taylor, M.P., et al, 1993. The monetary approach to the exchange rate: Rational expectations, long-run equilibrium, and forecasting. IMF Staff Papers 40, 89–107.
Mai, F., Shan, Z., Bai, Q., Wang, X., Chiang, R.H., 2018. How does social media impact Bitcoin value? A test of the silent majority hypothesis. J. Manage. Inform. Syst. 35, 19–52.
Makarov, I., Schoar, A., 2020. Trading and arbitrage in cryptocurrency markets. J Financ. Econ. 135, 293–319.
Mark, N.C., 1995. Exchange rates and fundamentals: Evidence on long-horizon predictability. Am. Econ. Rev., 201–218
Meese, R., Rogoff, K., 1983a. The out-of-sample failure of empirical exchange rate models: Sampling error or misspecification? In: Exchange Rates and International Macroeconomics. University of Chicago Press, pp. 67–112.
Meese, R.A., Rogoff, K., 1983b. Empirical exchange rate models of the seventies: Do they fit out of sample? J. Int. Econ. 14, 3–24.
Molodtsova, T., Papell, D.H., 2009. Out-of-sample exchange rate predictability with taylor rule fundamentals. J. Int. Econ. 77, 167–180.
Nakamoto, S., 2008. Bitcoin: A peer-to-peer electronic cash system. Available at. Available at https://bitcoin.org/bitcoin.pdf.
Newey, W.K., West, K.D., 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55, 703–708.
Rime, D., Sarno, L., Sojli, E., 2010. Exchange rate forecasting, order flow and macroeconomic information. J. Int. Econ. 80, 72–88.
Rogoff, K., 1996. The purchasing power parity puzzle. J. Econ. Lit. 34, 647–668.
Rogoff, K.S., Stavrakeva, V., 2008. The continuing puzzle of short horizon exchange rate forecasting. NBER working paper.
Rossi, B., 2013. Exchange rate predictability. J. Econ. Lit. 51, 1063–1119.
Rossi, B., Sekhposyan, T., 2011. Understanding models' forecasting performance. J. Econometrics 164, 158–172.
Salisu, A.A., Isah, K., Akanni, L.O., 2019. Improving the predictability of stock returns with Bitcoin prices. North Am. J. Econ. and Financ. 48, 857–867.
Schilling, L., Uhlig, H., 2019. Some simple Bitcoin economics. J. Monetary Econ. 106, 16–26.
Schwarz, G. et al, 1978. Estimating the dimension of a model. Ann. Stat. 6, 461–464.
Shahzad, S.J.H., Bouri, E., Roubaud, D., Kristoufek, L., 2020. Safe haven, hedge and diversification for G7 stock markets: Gold versus Bitcoin. Econ. Model. 87, 212–224.
Sharpe, W.F., 1966. Mutual fund performance. J. Bus. 39, 119–138.
Sjaastad, L.A., Scacciavillani, F., 1996. The price of gold and the exchange rate. J. Int. Money Financ. 15, 879–897.
Stock, J.H., Watson, M.W., 1993. A simple estimator of cointegrating vectors in higher order integrated systems. Econometrica 61, 783–820.
Sun Yin, H.H., Langenheldt, K., Harlev, M., Mukkamala, R.R., Vatrapu, R., 2019. Regulating cryptocurrencies: A supervised machine learning approach to de-anonymizing the Bitcoin blockchain. J. Manage. Inform. Syst. 36, 37–73.
Tsay, R.S., 2005. Analysis of Financial Time Series, volume 543. John Wiley & Sons.
Urquhart, A., Zhang, H., 2019. Is Bitcoin a hedge or safe haven for currencies? An intraday analysis. Int. Rev. Financ. Anal. 63, 49–57.
West, K.D., 1996. Asymptotic inference about predictive ability. Econometrica 64, 1067–1084.
Wooldridge, J.M., 1995. Score diagnostics for linear models estimated by two stage least squares. In: Maddala, G.S., Srinivasan, T.N., Phillips, P.C.B. (Eds.), Advances in Econometrics and Quantitative Economics. Blackwell, Oxford, UK, pp. 66–87.
Wu, D.M., 1974. Alternative tests of independence between stochastic regressors and disturbances: Finite sample results. Econometrica 42, 529–546.
Zhang, H.J., Dufour, J.M., Galbraith, J.W., 2016. Exchange rates and commodity prices: Measuring causality at multiple horizons. J. Empir. Financ. 36, 100–120.