

Inflation Expectation and Cryptocurrency Investment^{*}

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Abstract

Using proprietary data from the predominant crypto exchange in India and the country's Household Inflation Expectations Survey, we document a significantly positive correlation between inflation expectations and individual cryptocurrency purchases. Higher inflation expectations are also associated with more new cryptocurrency investors. Investigating heterogeneity in multiple dimensions, we find that the effect is concentrated in Bitcoin (BTC) and Tether (USDT) investments. The findings are also robust after controlling for speculative demand captured by surveys of investors' expected cryptocurrency returns, and have causal interpretations confirmed using instrumental variables. Our findings provide direct evidence that households already adopt cryptocurrencies for inflation hedging, which in turn rationalizes their high adoption in developing countries without a globally dominant currency.

Keywords: FinTech, Household Finance, Inflation, Stablecoins, Surveys.

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1 Introduction

A fundamental question in cryptocurrency research examines the origins of global demand for cryptocurrencies (e.g., [Weber, Candia, Coibion, and Gorodnichenko, 2023](#)). Answers to this question may help us better appreciate why crypto-assets without fiat backing or underlying cash flows ever accrue value. Over the years, the literature has developed a myriad of possible explanations for cryptocurrency demands, yet there is still little direct evidence for arguably one of the most oft-advocated advantages of cryptocurrencies: inflation hedging. Specifically, unlike fiat currencies which have potentially unlimited supplies and may be subject to discretionary monetary policy expansions, many cryptocurrencies feature fixed quantities and predetermined monetary policies (e.g., Bitcoin has a fixed maximum supply of 21 million coins and hard-coded halving schedules) that are credible thanks to the underlying decentralized ledger technology. This inherent scarcity has thus led to the belief that cryptocurrencies may serve as a hedge against erosion in fiat currency values.¹

Understandably, given ample noise, establishing a clear empirical relationship between inflation hedging and cryptocurrency demand is challenging. For example, a simple correlation exercise between cryptocurrency returns and inflation expectations (or realized inflations) has rendered mixed results.² Therefore, we still need *direct* evidence to answer (1) do households indeed perceive cryptocurrency investments as inflation hedges, and if so, do they behave accordingly in their investment decisions? In case of positive answers, we may also be interested in many follow-up questions. For example, (2) quantitatively, how much does inflation expectation drive cryptocurrency investment? (3) which cryptocurrencies do households view as inflation hedges? (4) do higher inflation expectations attract more new investors into cryptocurrencies? (5) how do answers change across different demographic groups, if at all? Finally, given that cryptocurrencies are global assets, evidence from emerging economies with relatively high inflation would also be particularly informative.

¹This point has been widely discussed in popular media, see, for example, Shevlin, R. (2021). “[Bitcoin or Ethereum: Which Cryptocurrency Is The Best Hedge Against Inflation?](#)” *Forbes*. Cryptocurrency adoptions are also high in countries such as India and Turkey which suffer from high domestic inflation.

²See e.g., [Conlon, Corbet, and McGee \(2021\)](#).

From a theoretical perspective, answers to the above questions are not clear *ex ante* either. For example, for Question (1), despite what people may discuss or respond in surveys (Stix, 2021), it is unclear if people do put money where their mouths are. For Question (3), it is also unclear if all coins will be regarded similarly for inflation hedging: While Bitcoin, the first and largest cryptocurrency, has a fixed supply and may thus be used as a potentially good inflation hedge, it is less clear for other coins which may either have increasing supplies or non-deterministic coin issuance schedules.³ In sum, answering the various questions above requires access to granular trader/coin-level information to link inflation expectations and specific cryptocurrency investment decisions.

We overcome the data challenges by exploiting a micro-level dataset from India, one of the largest emerging economies perennially gripped by high inflation, to establish direct evidence of the relation between inflation expectation and cryptocurrency investment. Our proprietary data come from the largest Indian cryptocurrency exchange which provides detailed masked individual-level trading records. In addition to the timestamp, size, price, market (the pair of the exchanged assets), and involved trader IDs of each transaction, each trader ID is also accompanied by rich demographic information, including gender, age, city, and pincode (similar to zip code in the United States). We then match the trading records to localized demographic-level data on inflation expectations from India’s Inflation Expectations Survey of Households (IESH) conducted roughly every two months by the Reserve Bank of India (India’s central bank), and investigate the direct relationship between inflation expectations and trading decisions across different cryptocurrencies.

We find that on average, a 1% increase in one-year ahead inflation expectation is associated with more than ₹1,000 increase in a single investor’s net cryptocurrency purchase before the next inflation expectation survey (roughly two months later). This positive relationship also has causal interpretations as it persists when we repeat our regressions using current inflation as an instrumental variable for inflation expectation, as used in Weber, Gorodnichenko, and Coibion (2023). The results are robust when we control for investors’

³For example, significant changes in Ethereum’s EIP-1559 converts it from an inflationary asset to a likely deflationary one whose issuance schedule depends on onchain activities. See Jermann (2023) for analysis.

speculation motives toward cryptocurrency investment, using a subsample of our data in which we have results from a survey that explicitly asks investors about their expected returns in cryptocurrencies. We also complement our findings on the intensive margin (that is, more cryptocurrency investment in response to higher inflation expectations) with results from an extensive margin specification, establishing a significantly positive relationship between inflation expectations and the number of new cryptocurrency investors joining the exchange.

We further investigate the heterogeneity of our findings across different dimensions: First, across cryptocurrencies, we find the effect to be concentrated within Bitcoin, the first and largest cryptocurrency with a fixed supply, as well as Tether (USDT), a stablecoin whose value is pegged to the US dollar; other cryptocurrencies, however, do not show clear patterns of more investment following high inflation expectations. Second, across the demographic dimension, we find that although within the whole population men (young people) tend to have lower inflation expectations on average than women (old people), there is no significant difference among crypto investors in their cryptocurrency investment decisions in responses to inflation expectations. Finally, across the geographic dimension, we find that the positive relationship between inflation expectations and cryptocurrency investments tends to be more salient in semi-urban areas as compared to their urban or rural counterparts, where the urban/semi-urban/rural designations follow classifications by the Reserve Bank of India.⁴

Overall, our findings confirm that inflation expectations have a significant impact on households' purchase decisions in Bitcoin and Tether (USDT). Hence, some cryptocurrencies, though not all of them, have already been perceived and adopted by households as inflation hedges.⁵ This is consistent with the high cryptocurrency adoptions observed in countries like Argentina, India, and Turkey (Chainalysis, 2023). In sum, using granular micro-level evidence, our study highlights the macro-level implications of cryptocurrencies within the broader economy. It also points to that some cryptocurrencies, even though not as means of

⁴See details at rbidocs.rbi.org.in/rdocs/Content/PDFs/RBILIS130910.PDF

⁵Both BTC and Tether did turn out to be effective hedges against INR inflation *ex post*. Indeed, Bitcoin appreciated 17.11% in USD price during our sample period, while INR experienced a similar magnitude of inflation as its depreciation against the USD (and thus Tether) without extreme value fluctuations.

payment or units of account, are widely used as stores of value.

Literature. Harnessing granular individual-level trading data allows us to exploit macro-level implications with micro-level evidence. In particular, our paper contributes to the literature on the economic implications of inflation expectations and household investment in cryptocurrencies for inflation hedging. [Coibion, Gorodnichenko, and Weber \(2022\)](#) study the repercussions of inflation expectations on consumer behaviors and corporate decisions. We further this narrative by soliciting firsthand inflation expectations from households and exploring their impact on cryptocurrency investments. [Weber et al. \(2023\)](#) conduct surveys of U.S. households about their cryptocurrency investment decisions and relate to inflation hedging motives, while [Schnorpfeil, Weber, and Hackethal \(2024\)](#) conduct surveys in partnership with a bank to investigate how inflation expectations affect general trading decisions. Similarly, [Aiello, Baker, Balyuk, Di Maggio, Johnson, Kotter, and Williams \(2023\)](#) study the relationship between cryptocurrency investment with stimulus checks and inflation expectations in the United States.⁶ Our direct evidence from the actual trading behaviors of the entire cryptocurrency investor population on the largest cryptocurrency exchange in India complements their focus on U.S. households. Our study also broadly relates to inflation-related macroeconomic perspectives of cryptocurrency pricing. For example, [Jermann \(2021\)](#) develops a theoretical model to relate cryptocurrency prices with Cagan’s model of hyperinflation. [Choi and Shin \(2022\)](#) estimate a Vector Autoregression model to suggest Bitcoin as an inflation hedge. The interaction among the US dollar, the Indian Rupee, and cryptocurrencies also echoes the theoretical framework of [Cong and Mayer \(2022\)](#).

Our study advances our understanding of cryptocurrency demand too. Prior research offers various rationales for cryptocurrency demand, including their use for illicit activities and cybercrimes ([Foley, Karlsen, and Putniņš, 2019](#); [Li, Baldimtsi, Brandao, Kugler, Hualays, Showers, Ali, and Chang, 2021](#); [Cong, Harvey, Rabetti, and Wu, 2023](#)), circumventing

⁶They measure cryptocurrency investment by fiat transfers to crypto exchanges and thus cannot distinguish what coins are being purchased (nor the potential gap between fiat deposit to exchanges and actual investment); we directly observe investors’ trading decisions on the exchange and can explore the rich heterogeneity in cryptocurrencies and households.

capital control measures (Makarov and Schoar, 2020; Yu and Zhang, 2022), promoting financial autonomy (Choi, Lehar, and Stauffer, 2022; Pagnotta, 2022), and underpinning various digital platforms (Cong, Li, and Wang, 2021; Li and Mann, 2018; Sockin and Xiong, 2023). Shams (2020) and Benetton and Compiani (2024) relate crypto-asset returns to demands and general optimism of future valuation. Leveraging detailed transaction data from cryptocurrency exchanges and insights from household surveys, our investigation provides the earliest direct evidence that cryptocurrencies serve as an inflation hedge for households, a benefit frequently touted but rarely verified. Underscoring the important role of inflation expectations in driving cryptocurrency pricing, our study is also the first to combine trading data with household surveys to analyze cryptocurrency investments in emerging economies.

Our results thus add to an emerging literature on cryptocurrency investor trading behaviors. For example, Kogan, Makarov, Niessner, and Schoar (2023) compare retail investors' trading behaviors of different assets, but does not speak to the effects of inflation expectations on cryptocurrency investment, which is the focus of our research. Other research such as Divakaruni and Zimmerman (2023) examines the effects of COVID-19 stimulus checks on Bitcoin trading activities, while studies like Cong, Li, Tang, and Yang (2021), Aloosh and Li (2023), and Amiram, Lyandres, and Rabetti (2020) focus on the phenomena of crypto wash trading. Moreover, Li, Shin, and Wang (2019) investigates the dynamics of pump-and-dump schemes in the crypto market. Finally, our findings also contribute to the emerging literature on cryptocurrency markets in general. For example, Makarov and Schoar (2020), Choi, Lehar, and Stauffer (2020), and Yu and Zhang (2022) document large and recurrent arbitrage opportunities across exchanges and especially across borders. Li and Yi (2019), Liu and Tsyvinski (2021), Liu, Tsyvinski, and Wu (2022), and Cong, Karolyi, Tang, and Zhao (2022) study the factor structures in cryptocurrency returns. Schwenkler and Zheng (2021) relate crypto returns to co-mentions in news.

The rest of the paper is organized as follows: Section 2 motivates our focus on India and describes the data. Section 3 explains our empirical specifications and presents our empirical findings. Section 4 concludes. The appendix discusses the institutional background of IESH

surveys, robustness of identification, temporal dynamics in the extensive margin, and a theoretical framework for our findings.

2 Institutional Background and Data Description

Before diving into our analysis, this section first provides some institutional background to help readers appreciate why India is a particularly relevant market for studying the relationship between inflation expectations and cryptocurrency investment. Readers more interested in our main analysis may skip this section entirely without loss of continuity.

2.1 Inflation and Cryptocurrency Adoption in India

India holds a significant position in the global cryptocurrency landscape: Chainalysis 2023 Global Crypto Adoption Index ranks the country the first for cryptocurrency adoptions.⁷ A Statista survey projects that by the end of 2023, over 11% of India’s population will have ventured into the cryptocurrency sector, surpassing the adoption the United States, the United Kingdom, Japan, and Russia.⁸ In December 2023, IMF chief Kristalina Georgieva also specifically brought up India when highlighting the high level of cryptoasset adoption in emerging market economies.⁹ Additionally, India’s prominent role in the global cryptocurrency market is underpinned by its demographics, as the most populous country in the world with a projected population surpassing 1.39 billion by the end of 2023, and more than half of its residents no older than 28, an age group inclined to be more digitally literate.

India also has many distinct features that make it particularly relevant for understanding the link between cryptocurrency investment and inflation. First, India has historically been plagued by high inflation. Indeed, its average inflation rate over the past decade hovers over 6.32%, peaking at 10.91% in 2013 and bottoming at 3.59% in 2017. Such high inflation is largely due to monetary oversupply rather than shortages of goods in the supply chain, as

⁷See <https://www.chainalysis.com/blog/2023-global-crypto-adoption-index/>. This is a bump from its 4th position in 2022. See [chainalysis.com/blog/2022-global-crypto-adoption-index/](https://www.chainalysis.com/blog/2022-global-crypto-adoption-index/).

⁸See cryptopotato.com/india-to-have-over-150-million-crypto-users-by-the-end-of-2023-study/.

⁹See imf.org/en/News/Articles/2023/12/13/sp121423-leaving-the-wild-west-kordigitalmoney.

evidenced by a comparison with the US dollar presented in Table 1. Specifically, Table 1 presents for Indian rupee (INR) its inflation rates, its exchange rates (against the US dollar), year-over-year changes in its exchange rates, and the difference between its inflation rates and exchange rate changes from 2011 to 2023. As Table 1 shows, while INR’s inflation rate and depreciation rate (compared to USD) are both high, their differences are much smaller. Therefore, cryptocurrencies like Bitcoin (which does not suffer from oversupply thanks to its fixed quantity by design) or stablecoins like Tether (which is pegged to USD) may both appear as attractive alternatives for Indian households to preserve the value of their wealth.

[Table 1 about here.]

Second, it is difficult for Indian households to hedge inflation via other (more stable) fiat currencies. Arguably, other fiat currencies (e.g., USD) could serve as a hedge against inflation in the Indian Rupee. However, strict capital controls managed by the Reserve Bank of India (RBI) under the Foreign Exchange Management Act (FEMA) have limited households’ access to foreign currencies. Therefore, cryptocurrency transactions that are not restricted by FEMA would be expected to serve as a viable alternative.¹⁰

2.2 Data

Our study utilizes data mainly from two sources: (1) granular individual-level trading data from the largest cryptocurrency exchange in India and (2) survey data on inflation expectations from the Inflation Expectation Survey of Households (IESH) conducted by the Reserve Bank of India. Combining the two datasets enables us to uniquely analyze the interplay between inflation expectations, cryptocurrency trading behaviors, and demographic attributes.

Cryptocurrency exchange dataset. We use proprietary individual-trader-level data from a dominant cryptocurrency exchange in India to gauge investors’ cryptocurrency trading decisions. As the predominant cryptocurrency trading venue in India, it has a wide

¹⁰Admitted, non-fiat real assets or commodities may also be used as inflation hedges, albeit with nontrivial carry costs. To the extent that other inflation-hedging properties exist, they will bias us against finding results in cryptocurrencies.

geographic coverage and operates in all states in India. Figure 1 illustrates the geographic coverage by presenting the Pincode location of cryptocurrency investors in our sample during the period from January 2018 to June 2022 (our sample period).

[Figure 1 about here.]

Our dataset encompasses in total of 85,785,078 transactions, spanning from January 2018 to June 2022. Each transaction contains detailed information on transaction specifics (timestamp, price, size, trading pair), pseudonymized investor IDs on each side of the transaction, and their demographic attributes. Key demographic attributes include Age, Gender, City, Country (since the exchange also has customers from countries other than India, although a majority of 93.79% of all customers are located in India), Pincode, and Date of joining. Table 2 presents more detailed information on all the available variables.

[Table 2 about here.]

Our data also contains many trading pairs with different base currencies (for example, in the trading pair BTC-INR, Indian rupee, or INR, is the base currency). The predominant base currency is India’s local fiat currency INR, which accounts for 76.53% among all transactions. This is succeeded by Tether (USDT) which accounts for 21.36% among all transactions. The exchange’s native token accounts for 1.16% of all transactions, and Bitcoin (BTC) constitutes a minor proportion, accounting for 0.95% of all transactions. Because our interest is in relating cryptocurrency investments with inflation expectations in rupees, unless otherwise specified, our subsequent analyses will focus on trades with INR as their base currencies, which are the majority of the trades in our sample.

IESH dataset. We use India’s Inflation Expectation Survey of Households (IESH) to evaluate investors’ inflation expectations.¹¹ Initiated in November 2006, each entry in the IESH dataset contains survey periods, city, the respondent’s demographics (age and gender), perceived current inflation rates, and projected three-month-ahead and one-year-ahead inflation

¹¹Agarwal, Chua, Ghosh, and Song (2022) also use this dataset to investigate the impact of inflation expectations on households’ consumption and portfolio decisions.

rates. The IESH records inflation expectations in intervals of full percentage points (e.g., 1% - 2%), except for those above 16%, for which the actual number is recorded. The average (median) numbers recorded in the IESH dataset are 10% (9%), 11% (10%), 11% (10%) for current perceived inflation, three-month ahead inflation expectations, and one-year ahead inflation expectations, respectively. Table 3 provides a tabulated overview of all included variables in the IESH dataset.¹²

[Table 3 about here.]

Data matching. For subsequent analyses, we match the exchange data with the IESH data by pincode and period, leading to 650,973 total observations.¹³ Because the inflation expectations in the IESH dataset mostly come with intervals rather than precise numbers (except for extreme values above 16%), we first replace each interval with its midpoint and then compute the average inflation expectation for each pincode-period pair. We also perform demographic matching, and the results remain consistent. As emphasized by Garcia-Lembergman, Hajdini, Leer, Pedemonte, and Schoenle (2023), the expectations of others can become a significant source driving individual inflation expectations, illustrating the suitability of our method of using local average inflation expectations. This transformation allows us to obtain the average inflation expectation in every pair.

[Table 4 about here.]

Table 4 presents summary statistics of the variables in our match sample. The average (median) age of cryptocurrency investors in our sample is 32.26 (31) years, ranging from

¹²Throughout the paper, we use aggregate inflation expectations over the next three months or the next year. Although IESH contains more detailed categories such as food or housing, it does not provide exact inflation expectation values for them (instead only coarse information about whether the values go up or down from the last period). We are thus prevented from following the approach in Dietrich, Knotek II, Myrseth, Rich, Schoenle, and Weber (2023), who find that aggregated inflation expectations (from category-specific) tend to see less disagreement and volatility and are stronger predictors of consumers' spending plans than aggregate expectations. We also note that the IESH is not conducted across all pincodes in India, and hence matching the IESH dataset with our cryptocurrency exchange data will see a reduction in the number of observations.

¹³An alternative approach is to match the two datasets by all available demographic information, that is, pincode, period, gender, and age. However, this alternative approach would result in too few variations within each match. We therefore make the compromise and match by pincode and period, while controlling for gender and age in later regressions.

18 to 87 years with a standard deviation of 7.80 years. About 86% of all investors in our sample identify themselves as male. Regarding inflation expectations, the average current perceived inflation in the matched sample is at 13.48%, accompanied by a standard deviation of 6.27%. The average three-month ahead inflation expectation stands at 15.94% with a standard deviation of 7.73%, and the average one-year ahead inflation expectation stands at 15.63% with a deviation of 7.94%. Recall that in the entire IESH dataset (not matched to our investors), the average (median) numbers are 10% (9%), 11% (10%), 11% (10%) for current perceived inflation, three-month ahead inflation expectations, and one-year ahead inflation expectations, respectively. Hence, as a piece of suggestive evidence relating inflation expectations and cryptocurrency investments, we note that cryptocurrency investors in our sample do tend to reside in pincodes with relatively higher average inflation expectations.

Regarding the amount of cryptocurrency purchases, the variable `inr_amount_net` calculates an individual investor’s net purchase volume of cryptocurrencies in units of Indian rupees (INR). The mean purchase amount is negative 5236.227 INR with a large variation across investors, captured by a standard deviation of 2.84 million INR. Indeed, the range of net purchase amounts across individuals stretches from as low as negative 1.58 billion INR to as high as 755 million INR.

3 Empirical Specifications and Results

We first motivate and formulate our main empirical specifications before presenting the key empirical results. We then conduct several auxiliary tests to further corroborate the robustness of our key findings regarding the relationship between inflation expectations and cryptocurrency investment decisions. Finally, we report additional results to shed light on how the relationship between inflation expectations and cryptocurrency investments differs across various heterogeneity groups.

3.1 Main Empirical Specifications

Since our dataset features a large cross-section of investors each with infrequent transactions over time, our main empirical specification employs the Fama-MacBeth regression (Fama and MacBeth, 1973), originally developed for testing asset pricing models within a large cross-section of stocks whose returns feature insignificant intertemporal autocorrelations. This approach has several advantages for our analysis. First, it does not require each investor to have multiple time-series observations, making it well-suited for our data which features a large number of investors with infrequent trading activities. Second, it allows us to extract cross-sectional relationships between households’ inflation expectations and their cryptocurrency purchase decisions. Finally, it enables us to estimate time-varying coefficients, capturing the potentially dynamic nature of the relationship between inflation expectations and cryptocurrency investment decisions.

Specifically, our baseline regression model is given by:

$$\text{Inr_Amount_Net}_{i,t+1} = \alpha + \beta \times \text{Inflation_Expectation}_{i,t} + \gamma \times \text{Age}_{i,t} + \lambda \times \text{Male}_{i,t} + \epsilon_{i,t+1}, \quad (1)$$

where i indexes investors and t indexes the periods in which inflation expectation surveys are conducted. On the left-hand side, the dependent variable $\text{Inr_Amount_Net}_{i,t+1}$ denotes investor i ’s net cryptocurrency purchase amount in Indian Rupees within period $t + 1$. On the right-hand side, the main variable of interest is $\text{Inflation_Expectation}_{i,t}$, investor i ’s inflation expectation in period t , controlling for investor i ’s age and gender.

To identify the causal relationship between inflation expectations and net cryptocurrency purchase volumes, we also adopt an instrumental variable (IV) approach. Inspired by Weber et al. (2023), we employ (current) perceived inflation as the IV for inflation expectations, either for three months or one year ahead. This IV satisfies the relevance criteria as Table 6 shows significant first-stage regression results. The IV is also expected to satisfy the exogeneity criteria once we control for demographic variables such as age, gender, rural/semi-urban/urban residency, and income categories: As Weber et al. (2023) explain, inflation

perceptions are shaped by a myriad of factors, many of which are idiosyncratic. These factors might encompass individual experiences with price changes, such as personal shopping experiences, or sector-specific inflationary pressures that do not necessarily resonate with broader economic trends. Given this idiosyncratic nature, it is reasonable to posit that such perceptions are not directly implicated in subsequent cryptocurrency investment decisions. Therefore, based on the assumption that the personal experiences affecting current inflation expectations are unique to the individual, conditional on demographic variables such as age, gender, rural/semi-urban/urban residency, and income categories, we leverage the inherent randomness of individual experiences in shaping current perceptions of inflation to ensure the exogeneity of the perceived inflation and mitigate concerns about omitted variable bias or reverse causality that might confound the relationship between inflation expectations and cryptocurrency investments.

3.2 Key Empirical Findings

Table 5 presents the regression results and takeaways from our main specification in (1):

[Table 5 about here.]

First, in terms of *statistical significance*, all inflation/expectation-related variables, namely current inflation, three-month head inflation expectation, and one-year ahead inflation expectation, exhibit statistically significant correlations with the next-period net cryptocurrency purchase volumes.

Second, in terms of *economic magnitude*, for each investor in our sample, a one percentage point increase in current inflation is associated with an average ₹1,112 (about 13.4 USD as of Feb 15, 2024) increase in the net cryptocurrency purchase volume before the next inflation expectation survey (typically in two or three months). Similarly, a one percentage point increase in the three-month (one-year) ahead inflation expectation is associated with a ₹819.3 (₹998.5) increase in the net cryptocurrency purchase volume before the next inflation expectation survey. To help appreciate the economic significance of these numbers, we note

that India’s national income per capita (at current prices) for 2022-23 stands at ₹172,000. Therefore, a one percentage point increase in inflation expectations is associated with an annualized increase in cryptocurrency investment of about 3.2% to 3.9% national income per capita in India (depending on whether IESH actually conducts five or six inflation surveys in that particular year).

Third, in terms of *casual interpretations*, the last two columns in Table 5 (Columns (4) and (5)) present the IV regression results using the current perceived inflation as instrumental variables for three-month and one-year inflation expectations (first-stage regression results are significant as presented in Table 6). We find that the instrumented three-month inflation expectation and one-year inflation expectation both have positive and significant effects on cryptocurrency investment in the period before the next inflation expectation survey. The coefficients of IV regressions are slightly larger than the coefficients in the non-IV regressions presented in Columns (2) and (3) of Table 5. Specifically, a one percentage point increase in three-month (one-year) inflation expectation leads to a ₹965 (₹1,069) in the net cryptocurrency purchase volume before the next inflation expectation survey.

[Table 6 about here.]

3.3 Discussion and Robustness

To lend further support to our key empirical findings above, we conduct several additional tests. Our goal is to (1) mitigate concerns over confounding forces, and (2) relate inflation expectations and cryptocurrency investment in both the intensive and extensive margin.

Accounting for cryptocurrency speculation motives. One potential concern against our key empirical findings is whether investors’ speculation motives in cryptocurrencies may confound their inflation-hedging motives. While our IV specification should already mitigate omitted variable biases, we nevertheless provide another piece of direct evidence in this respect.

For this purpose, we take advantage of an investor survey conducted by the same leading cryptocurrency exchange in our study among a small subsample of its investors. The resulting survey comprises 898 unique cryptocurrency investors on the exchange and records their expectations of cryptocurrency returns over the following 12 months. The survey additionally collected the respondents’ annual income information. Because the expected return survey was conducted over weeks in October 2021, we match the expected return survey data with the IESH inflation survey data from September 30, 2021, and cryptocurrency purchase records spanning from September 30 to November 30, 2021 (the next IESH survey date). This matched sample forms the basis for the regression analysis in this section.

[Table 7 about here.]

Table 7 presents results from a regression similar to that in Equation (1) on the subsample, but with additional controls for investors’ expectations for cryptocurrency returns. We also control for the additional information on investors’ income levels available within the survey. As Table 7 shows, even when controlling for expected returns, the net amount of cryptocurrency investment still consistently exhibits a positive and significant relationship with inflation expectations, with or without instrumental variables.

Placebo tests. Since the survey only covers a small subset of all investors in our sample, we also conduct an additional placebo test to assess the robustness of our key findings. Specifically, we repeat our analysis among trading pairs with USDT (instead of INR) as base currencies. Since trading between USDT (rather than INR) with other cryptocurrencies does not help with hedging inflation in INR, we should expect no significant relationship between investors’ inflation expectations and cryptocurrency investments that involve USDT as base currencies. As Table 8 reports, we indeed no longer find any significant relationship between inflation expectations and cryptocurrency investments among trading pairs denominated in USDT. This finding contrasts sharply with the significantly positive relationships among trading pairs denominated in INR, and such a contrast further strengthens our main result that investors view cryptocurrencies as hedges against inflation risks in the INR.

[Table 8 about here.]

Inflation expectations and cryptocurrency market participation Our main results so far concern the relationship between inflation expectations and cryptocurrency investment along the intensive margin — how much more money do customers on the cryptocurrency exchange invest when they have higher inflation expectations? One may also be interested in the relationship along the extensive margin – how many more new customers does the cryptocurrency exchange attract when the overall inflation expectations among the general population increase? We now answer this question.

To investigate whether new investors are driven by inflation expectations onto the cryptocurrency exchange, we calculate the new customer count at each pincode-period combination and match it with the average inflation expectations within the same pincode and period. We then regress the number of new customers on inflation expectations:

$$New_Customer_{p,t+1} = \alpha + \beta \times Inflation_Expectation_{p,t} + \gamma \times Controls_{p,t} + \epsilon_{p,t}, \quad (2)$$

where $New_Customer_{p,t}$ is the dependent variable representing the number of new customers at pincode p in period t and $Inflation_Expectation_{p,t}$ is the inflation expectation at pincode p in period t . Control variables include the number of respondents to the IESH inflation expectations survey at pincode p in period t , which serves as a proxy for the total population at pincode p in period t , as well as the proportion of self-employed individuals in the IESH survey at pincode p in period t . $\epsilon_{p,t}$ denotes the error term.

[Table 9 about here.]

Table 9 reports the regression results. Column (1) shows that a one percentage increase in inflation expectations is associated with 1.149 more new cryptocurrency customers within each pincode. Given 945 total pincodes in India, the number indicates that a one percentage increase in inflation expectations corresponds to 1000 more new cryptocurrency investors onto our exchange nationwide. Besides economic significance, this result is also significantly

positive at the 1% level. The positive relationship holds after controlling for the number of surveyees in the pincode-period, as a proxy for the population of the pincode at the period, and the proportion of self-employment in labor to control for economic situations. The result continues to hold after adding fixed effects, with standard errors clustered at the pincode level. Our results employing IV in Columns (4) and (5) remain consistent.

In sum, the evidence confirms that inflation expectations are associated with more cryptocurrency investment, not only at the intensive margin by leading existing customers to invest more, but also at the extensive margin by attracting new customers into cryptocurrency investment. This extensive margin evidence is also consistent with our earlier observations that, in our sample, cryptocurrency investors have a significantly higher average one-year ahead inflation expectation of 14% versus the national level of 11%.

3.4 Heterogeneous Effects

One advantage of our granular micro-level data is that it includes detailed information on each investor’s cryptocurrency portfolio at any given time. Besides, our data also covers a large cross-section of cryptocurrency investors across a wide variety of geographic and demographic groups. This unique richness in data allows us to further break down our sample and reveal how the relationship between inflation expectations and cryptocurrency investment differs across different geographic/demographic groups as well as different cryptocurrencies.

Heterogeneous effects across different cryptocurrencies. Table 10 presents the relationship between the net purchase volume of specific cryptocurrencies and one-year ahead inflation expectations, with INR and USDT as base currencies, respectively. These results thus decompose the regression coefficient of Equation (1) in Table 5 and 8 across different cryptocurrencies.

[Table 10 about here.]

For the BTC/INR pair, we observe a significantly positive coefficient of 383.7, suggesting a strong positive relationship with inflation expectations. Similarly, USDT/INR has a

significantly positive coefficient of 818.6. None of the other cryptocurrencies, however, see significantly positive relationship with inflation expectations. Therefore, our main finding from Table 5 mainly concentrates on Bitcoin and Tether. For trades with USDT as the base currency, not surprisingly (as from Table 8) most cryptocurrencies display either negative or non-significant coefficients. These findings suggest that investors tend to view BTC and USDT as hedges against inflation risks in INR.

Heterogeneous effects across geographic locations. We further explore how the relationship between inflation expectations and cryptocurrency investments differs across different geographic locations. For this purpose, we follow the common practice in India to classify different geographic locales into three types of regions: (a) urban (b) semi-urban, and (c) rural. According to the Reserve Bank of India,¹⁴ a rural region has a population of fewer than 10,000 inhabitants and is characterized by sparse populations, agricultural land use, and limited access to modern conveniences; Examples include villages and small towns scattered across the country’s landscapes. Semi-urban regions, with populations ranging from 10,000 to less than 100,000, act as bridges between rural and urban settings; They feature evolving infrastructure, offer a growing range of services, and often include smaller cities or towns that are on the path to urbanization (these cities are often known as Tier 2 and Tier 3 cities). Urban regions, including Mumbai, Delhi, and Bangalore, are identified by populations of 100,000 and above, distinguished by higher population densities, advanced infrastructure, and greater concentrations of services and amenities.

Our field knowledge from engaging with the cryptocurrency community suggests that residents in semi-urban areas tend to be more active in the cryptocurrency market. Accordingly, we distinguish the urban/semi-urban/rural areas in India and investigate whether the link between inflation expectations and cryptocurrency investments is the strongest in semi-urban areas.

[Table 11 about here.]

¹⁴See details from <https://rbidocs.rbi.org.in/rdocs/Content/PDFs/RBILIS130910.PDF>.

Table 11 presents results from adapting the regression specification in Equation (1) by adding the interactions between semi-urban dummies and inflation expectations: Across Columns (1) - (5), we find that the relationship between inflation expectations and cryptocurrency investment is indeed significantly stronger among investors from semi-urban areas, and is robust for current inflation, three-month/one-year ahead inflation expectations, as well as their instrumented variables.

Temporal dynamics. As we have mentioned earlier, one advantage of the Fama-MacBeth specification in Equation (1) is in permitting investigations of the temporal dynamics in the regression coefficients. Although temporal dynamics is not our main focus in this paper given that the sample period is not that long, in this section we nevertheless present temporal dynamics for completeness.

[Table 12 about here.]

As Section 3.4 has already shown that the significant relationship between inflation expectations and cryptocurrency investments is mainly focused on BTC or USDT investments using INR as base currency, Table 12 presents the coefficients of one-year ahead inflation expectations from Equation (1) for BTC, USDT, and the broader cryptocurrency market from December 2017 to March 2022. These numbers are also visualized in Figure 2.

[Figure 2 about here.]

4 Conclusion

Using granular individual cryptocurrency trading data and household inflation surveys in India, we uncover a significantly positive relationship between inflation expectations and cryptocurrency investment. Our findings highlight that the pursuit of inflation hedges is an important source of the demand for certain cryptocurrencies. We also investigate the heterogeneity of inflation expectation - cryptocurrency investment relationship across different cryptocurrencies, geographic locations, demography, and time.

We provide for the first time rigorous direct evidence that cryptocurrencies, as new assets, have evolved into financial instruments for households in emerging economies aiming to counteract inflation and preserve their purchasing power. With Argentina’s annual inflation rate soaring to 211.4% in 2023, and Turkey’s hitting decades-high 61.53% in September 2023 (compared with 49.86% in the same month last year, according to the Turkish Statistical Institute), our findings offer crucial insights beyond India into the general market demand for cryptocurrencies, the structuring of household investment portfolios, and the comprehension by central banks and policymakers of the economic implications associated with inflation.

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Tables

Table 1: INR's Inflation Rate, Exchange Rate, and Comparison (2011-2023)

Year	Inflation Rate (%) (1)	FX Rate (USD/INR) (2)	FX Rate Change (%) (3)	Difference (%) (1)–(3) (4)
2011	8.87	46.67	-	-
2012	9.30	53.44	14.51	-5.21
2013	10.91	58.60	9.66	1.25
2014	6.37	61.03	4.15	2.22
2015	5.87	64.15	5.11	0.76
2016	4.94	67.19	4.74	0.20
2017	3.59	64.46	-4.06	7.65
2018	4.86	69.92	8.47	-3.61
2019	4.51	70.39	0.67	3.84
2020	6.20	74.84	6.32	-0.12
2021	4.91	73.49	-1.80	6.71
2022	6.70	82.75	12.60	-5.90
2023	5.70	83.25	0.60	5.10
Average	6.36	66.94	5.08	1.07

This table presents the inflation rates of INR, its exchange rates against the US dollar, the percentage change in its exchange rates, and the differences between inflation rates and exchange rate changes from 2011 to 2023. **Year** indicates the year the different measures are recorded. **Inflation (%)** represents the inflation rate in percentage points. **FX Rate (INR/USD)** signifies the USD/INR exchange rate, while **FX Rate Change (%)** calculates the year-to-year percentage change in the USD/INR exchange rate. **Diff. (%)** provides the difference between the inflation rates (Column 1) and percentage changes in the USD/INR exchange rates (Column 3).

Table 2: Summary of Indian Cryptocurrency Exchange Dataset Variables

Fields	Description	Format
Market	Trading Pair example BTCINR, USDTINR	Char
Price	Traded Price	Num
Volume	Trade volume (units)	Num
Trade Date	Transaction date	Date
Ask Order ID	Corresponding order ID for seller	Num
Bid Order ID	Corresponding order ID for Buyer	Num
Ask Customer ID	Seller customer ID	Char
Bid Customer ID	Buyer Customer ID	Char
Trade Volume	Price $\times$ Volume	Num

This table enumerates the available data fields from our exchange sample. Our dataset encompasses in total of 85,785,078 transactions, spanning from January 2018 to June 2022. Each transaction contains detailed information on transaction specifics such as timestamp, price, size, and trading pair (known as market), and pseudonymized investor IDs on each side of the transaction. The investor IDs are also accompanied by demographic attributes.

Table 3: IESH Inflation Expectation Survey of Households Variables

Variable
Round No
Period
City Name
PIN Code
Gender Of Respondent t
Age Group
Category of Respondent
Expectations on prices in next 3 months - General
Expectations on prices in next 3 months - Food products
Expectations on prices in next 3 months - Non food products
Expectations on prices in next 3 months - Housing
Expectations on prices in next 3 months - Services
Expectations on prices in next 1 year - General
Expectations on prices in next 1 year - Food products
Expectations on prices in next 1 year - Non food products
Expectations on prices in next 1 year - Household durables
Expectations on prices in next 1 year - Housing
Expectations on prices in next 1 year - Services
View on Current Inflation Rate
View on Current Inflation Rate - actual rate for above 16%
View on 3 Months ahead Inflation Rate
View on 3 Months ahead Inflation Rate - actual rate for above 16%
View on 1 Year ahead Inflation Rate
View on 1 Year ahead Inflation Rate - actual rate for above 16%

This table enumerates the available data fields from India's Inflation Expectation Survey of Households (IESH). Each entry in the IESH dataset contains survey periods, city, the respondent's demographics (age and gender), perceived current inflation rates, and projected three-month-ahead and one-year-ahead inflation rates. The IESH records inflation expectations in intervals of full percentage points (e.g., 1% - 2%), except for those above 16%, for which the actual number is recorded. The average (median) numbers recorded in the IESH dataset are 10% (9%), 11% (10%), 11% (10%) for current perceived inflation, three-month ahead inflation expectations, and one-year ahead inflation expectations, respectively.

Table 4: Summary Statistics of the Matched Data

	Mean	1%	25%	50%	75%	99%
Age	32.26	20	26	31	38	50
Male	0.86	0	1	1	1	1
Current_inflation	13.52	4.57	9.13	12.27	16.57	34.09
Three_month_inflation	15.99	5.45	10.50	14.40	19.51	42.86
One_year_inflation	15.69	3.23	10.17	14.10	19.43	41.97
Inr_amount_net	-5,023.26	-236,311.80	-887.80	146.44	3,204.72	237,311.60

Number of Observations: 650,973

This table presents summary statistics of the variables in our match sample. The average (median) age of cryptocurrency investors in our sample is 32.26 (31) years, ranging from 18 to 87 years with a standard deviation of 7.80 years. About 86% of all investors in our sample identify themselves as male. The average current perceived inflation in the matched sample is at 13.48%, accompanied by a standard deviation of 6.27%. The average three-month ahead inflation expectation stands at 15.94% with a standard deviation of 7.73%, and the average one-year ahead inflation expectation stands at 15.63% with a deviation of 7.94%. These numbers are all higher than those in the entire IESH dataset (not matched to our investors). The variable `inr_amount_net` calculates an individual investor's net purchase volume of cryptocurrencies in units of Indian rupees (INR) within each period (between two consecutive inflation surveys), with a mean of -5236.227 INR and a standard deviation of 2.84 million INR.

Table 5: Inflation Expectations and Cryptocurrency Investment (Jan 2018 - June 2022)

	Dependent Variable: INR_Amount_Net				
	(1)	(2)	(3)	(4)	(5)
Current Inflation	1,112** (485.0)				
Three-Month Inflation		819.3** (340.2)			
One-Year Inflation			998.5** (419.3)		
Three-month Inflation (IV)				965.0** (420.8)	
One-Year Inflation (IV)					1,069** (466.2)
Age	354.9 (402.9)	352.9 (403.6)	347.8 (404.4)	352.2 (403.2)	351.1 (403.3)
Male	-20,080 (12,745)	-20,095 (12,726)	-20,043 (12,694)	-20,015 (12,727)	-19,973 (12,716)
Constant	-12,417 (22,633)	-10,285 (22,907)	-12,276 (22,079)	-12,770 (22,608)	-14,117 (22,524)
Observations	652,168	652,164	652,152	652,168	652,168
R-squared	0.005	0.005	0.005	0.005	0.005
Number of groups	26	26	26	26	26

This table presents the regression results of

$$inr_amount_net_{i,t+1} = \alpha + \beta \times inflation_expectation_{i,t} + \gamma \times age_{i,t} + \lambda \times male_{i,t} + \epsilon_{i,t+1}.$$

Individual i denotes the investor and period t spans two or three months in the sample. The Fama-MacBeth regressions are conducted by performing sequential cross-sectional regressions for each period, with coefficients averaged over all periods. The variables *three_months_inflation (IV)* and *one_year_inflation (IV)* are fitted values from the first stage linear regression on current perceived inflation. Standard errors are in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6: First-stage Regressions of Instrumental Variables

	(1) Three-Month Inflation	(2) One-Year Inflation
Current Perceived Inflation	1.153*** (0.000544)	1.040*** (0.000890)
Age	0.00277*** (0.000438)	0.00351*** (0.000717)
Male	−0.0666*** (0.00976)	−0.100*** (0.0160)
Constant	0.366*** (0.0188)	1.590*** (0.0308)
Observations	652,164	652,152
R^2	0.873	0.677

Table 6 presents the first-stage regression results for the IV regressions. We regress three-month and one-year inflation expectations on current perceived inflation. The coefficients of current inflation are both significant at 1%. The R-square for the three-month ahead inflation expectation is 87.3% and is higher than that for one-year ahead at 67.7%, likely due to more uncertainties taken into account in longer terms. The coefficient of age is significantly positive, indicating that older individuals have higher inflation expectations, while the coefficient of gender (Male=1) is significantly negative, indicating that female individuals tend to have higher inflation expectations than males. Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7: Inflation Expectations and Cryptocurrency Investment (Expected Return Survey)

	Dependent Variable: INR_Amount_Net				
	(1)	(2)	(3)	(4)	(5)
Current Inflation	2,089** (813.2)				
Three Months Inflation		1,403** (683.6)			
One Year Inflation			1,604* (827.4)		
Three Months Inflation (IV)				1,741** (677.6)	
One Year Inflation (IV)					2,055** (800.1)
Expected Return	0.00428* (0.00219)	0.00430* (0.00227)	0.00471* (0.00240)	0.00453** (0.00226)	0.00509** (0.00242)
Annual Income (₹5-7.5×10 ⁵)	43,021* (22,250)	42,338* (22,145)	41,251* (21,759)	42,593* (22,131)	41,243* (21,762)
Annual Income (₹7.5-10×10 ⁵)	-16,428 (28,776)	-16,249 (28,858)	-16,431 (28,770)	-16,825 (28,840)	-17,155 (28,894)
Annual Income (₹10-50×10 ⁵)	15,009 (18,494)	14,666 (18,537)	15,132 (18,621)	14,820 (18,470)	15,443 (18,550)
Annual Income (> ₹50×10 ⁵)	-19,920 (27,386)	-20,727 (27,632)	-20,286 (27,885)	-19,077 (27,467)	-18,233 (27,552)
Age	-2,671** (1,356)	-2,698** (1,363)	-2,717** (1,370)	-2,700** (1,362)	-2,725** (1,367)
Male	11,691 (13,659)	10,365 (13,641)	9,870 (13,698)	10,839 (13,687)	10,285 (13,709)
Constant	33,048 (37,969)	41,181 (37,958)	39,516 (38,972)	34,690 (38,119)	31,456 (37,832)
Observations	681	681	681	681	681
R-squared	0.025	0.024	0.025	0.025	0.025

This table presents the regression results, examining the impact of inflation expectations on cryptocurrency investment decisions based on the survey sample of investor expected returns. The dependent variable is the net amount invested in cryptocurrencies, measured in INR. Independent variables include different measures of inflation expectations (current, three months, one year, and their estimates) and controls for their expected returns on cryptocurrency, income category, age, and gender. Robust standard errors are shown in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 8: Inflation Expectation & Cryptocurrency Investment (USDT as Base Currency)

	Dependent Variable: Inr_Amount_Net				
	(1)	(2)	(3)	(4)	(5)
Current Inflation	-247.9 (235.4)				
Three-Month Inflation		-257.3 (224.0)			
One-Year Inflation			-231.6 (225.0)		
Three-Month Inflation (IV)				-215.1 (204.2)	
One-Year Inflation (IV)					-238.3 (226.2)
Age	-114.1 (119.8)	-115.4 (119.5)	-118.8 (119.3)	-113.5 (119.4)	-113.2 (119.3)
Male	3,453 (2,405)	3,418 (2,392)	3,315 (2,371)	3,439 (2,403)	3,429 (2,401)
Constant	6,761 (6,524)	7,122 (6,701)	7,036 (6,803)	6,839 (6,585)	7,139 (6,821)
Observations	652,168	652,164	652,152	652,168	652,168
R-squared	0.001	0.001	0.001	0.001	0.001
Number of groups	26	26	26	26	26

This table presents results from a Fama-MacBeth regression focusing on the trading pairs using USDT as the base currency, given by:

$$Inr_Amount_Net_{i,t+1} = \alpha + \beta \times Inflation_Expectation_{i,t} + \gamma \times Age_{i,t} + \lambda \times Male_{i,t} + \epsilon_{i,t+1}.$$

Individual i denotes the investor and period t spans two or three months in the sample. The regressions are conducted by performing sequential cross-sectional regressions for each period, with coefficients averaged over all periods. The *Three-Month Inflation Fitted* and *One-Year Inflation Fitted* are fitted values from the first stage linear regression on current perceived inflation. The sample period is from January 2018 to June 2022. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 9: Impact of Inflation Expectations on New Customer Acquisition

	Dependent Variable: New_Customer				
	(1)	(2)	(3)	(4)	(5)
Current Inflation	1.149*** (0.178)				
Three Months Inflation		1.190*** (0.173)			
One Year Inflation			1.037*** (0.150)		
Three Months Inflation Fitted				1.145*** (0.178)	
One Year Inflation Fitted					1.106*** (0.172)
Number of Survey Respondents	0.611*** (0.187)	0.635*** (0.187)	0.603*** (0.187)	0.611*** (0.187)	0.610*** (0.187)
Proportion of Self Employed	20.18*** (6.536)	19.75*** (6.518)	20.19*** (6.523)	19.87*** (6.534)	20.76*** (6.541)
Constant	13.17*** (4.249)	10.27** (4.417)	12.79*** (4.308)	11.72*** (4.397)	11.00** (4.474)
Observations	7,735	7,733	7,733	7,735	7,735
R-squared	0.008	0.011	0.010	0.008	0.008
Number of pincode_index	945	944	945	945	945

This table presents Fama-MacBeth regression results examining the influence of inflation expectations on the acquisition of new customers, using various inflation metrics. Columns (1) through (5) correspond to regressions with different inflation measures as independent variables. The analysis highlights a consistent positive relationship between inflation expectations and new customer acquisition across different measures and specifications. Robust standard errors are provided in parentheses below each coefficient, indicating the precision of estimates. The significant coefficients across all models underscore the robust impact of inflation expectations on new customer acquisition in the context of cryptocurrency investments. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 10: Inflation Expectations and Investments across Different Cryptocurrencies

Token \ Base	INR		USDT	
	Coefficient	Std. Error	Coefficient	Std. Error
USDT	818.6*	(411.4)	-0.609	(0.806)
BTC	383.7**	(173.1)	-171.1	(188.7)
XRP	-16.23	(27.29)	-69.47*	(35.25)
DOGE	-5.054	(8.196)	1.264*	(0.725)
SHIB	1.186	(2.247)	0.858	(0.710)
WIN	-0.366	(0.825)	0.688	(0.688)
TRX	-29.61	(30.24)	21.19	(18.57)
ETH	-56.61	(34.94)	-66.36	(62.44)
BTT	-10.02**	(4.580)	5.444	(3.653)
ADA	1.232	(2.337)	-5.127**	(2.453)
MATIC	-3.469	(6.445)	0.628	(2.580)
WRX	-20.64	(16.29)	15.38	(11.27)
BNB	-2.797	(2.540)	2.378	(2.489)

This table showcases the regression results assessing the relationship between the one-year inflation rate and the net-buy volume of various cryptocurrencies with INR and USDT as base currencies, respectively. The coefficients indicate the change in net purchase volume (in respective base currency denominations) for a one percentage point change in the inflation rate. The base currency is represented in the column headings, and tokens in the first column denote the specific cryptocurrencies that traders use the respective base currency to trade for. The sample period is from Jan 2018 to June 2022. Standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 11: Inflation Expectations and Cryptocurrency Investment (Jan 2018 - June 2022)

	Dependent Variable: INR_Amount_Net				
	(1)	(2)	(3)	(4)	(5)
Current Inflation	1,152** (495.2)				
* Semi-Urban	1,467*** (502.3)				
Three Months Inflation		847.6** (347.3)			
* Semi-Urban		1,194*** (419.5)			
One Year Inflation			1,031** (427.6)		
* Semi-Urban			1,051*** (371.3)		
Three Months Inflation (IV)				999.3** (429.8)	
* Semi-Urban				1,237*** (422.4)	
One Year Inflation (IV)					1,108** (476.4)
* Semi-Urban					1,246*** (422.0)
Age	351.3 (411.7)	349.0 (412.7)	342.0 (414.1)	348.4 (412.0)	347.2 (412.1)
Male	-20,372 (12,931)	-20,378 (12,911)	-20,349 (12,887)	-20,305 (12,912)	-20,260 (12,899)
Rural	3,207 (2,909)	3,074 (2,894)	2,709 (2,894)	3,209 (2,910)	3,215 (2,911)
Constant	-12,864 (23,010)	-10,651 (23,321)	-12,626 (22,522)	-13,233 (22,983)	-14,641 (22,891)
Observations	638,834	638,831	638,818	638,834	638,834
R-squared	0.005	0.005	0.006	0.005	0.005
Number of groups	26	26	26	26	26

This table presents the regression results of

$$inr_amount_net_{i,t+1} = \alpha + \beta \times current_inflation_{i,t} + \gamma \times age_{i,t} + \lambda \times gender_index_{i,t} + \mu \times rural_{i,t} + \epsilon_{i,t+1}.$$

The regression incorporates both general and semi-urban inflation rates over different periods, reflecting their distinct impacts on the dependent variable. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

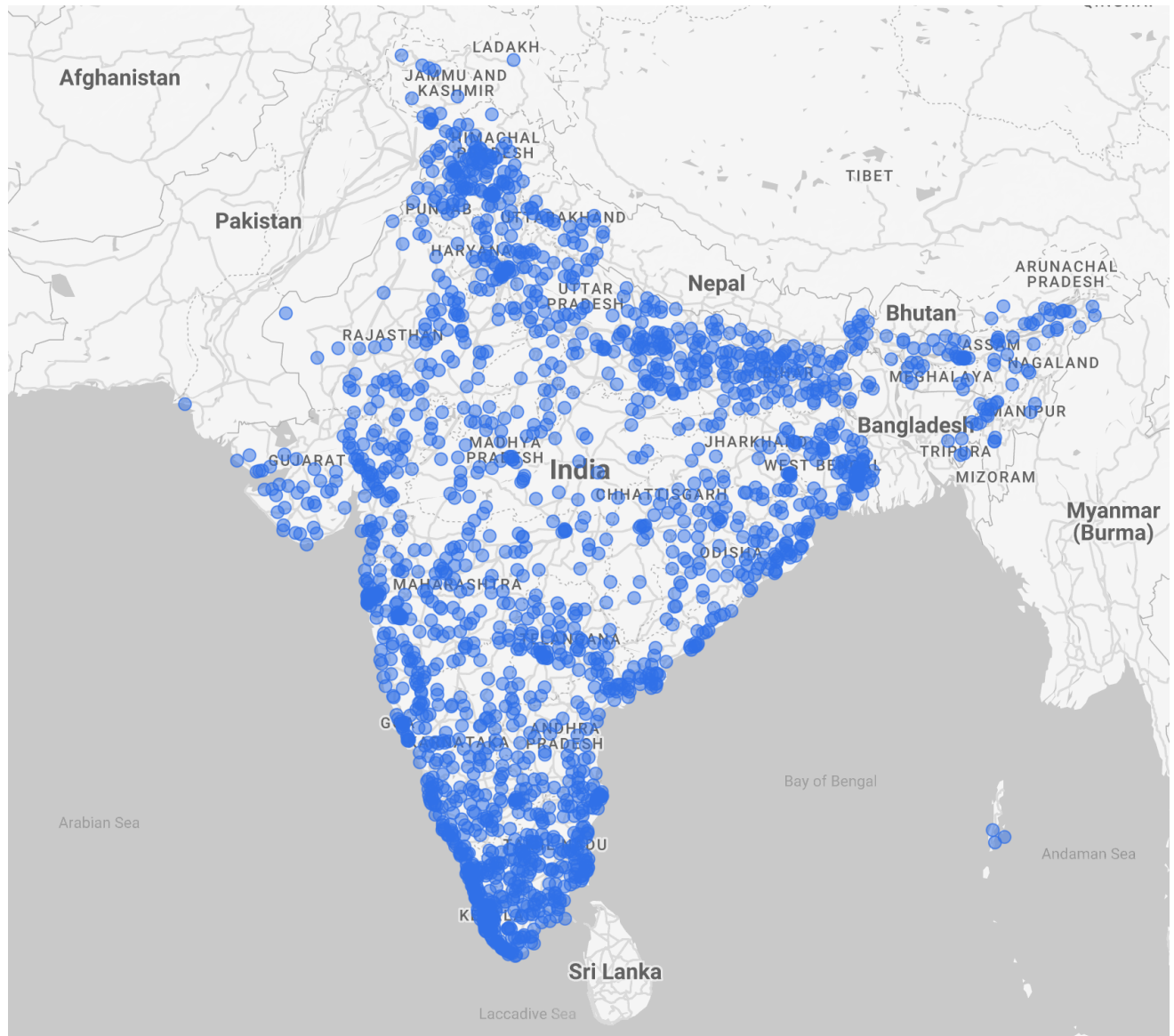
Table 12: By-Period Coefficients of One-Year Ahead Inflation Expectation

Period	BTC	USDT	All-Cryptos
Dec 2017	115.63	0.00	253.23
Mar 2018	2165.22	0.00	2839.46
May 2018	-516.41	0.00	-1325.64
Jun 2018	94.95	127.51	178.28
Sep 2018	-0.88	23.68	33.74
Nov 2018	-12.50	-13.38	-12.70
Dec 2018	-21.22	48.28	6.33
Mar 2019	18.67	-11.77	13.73
May 2019	5.26	2.97	14.52
Jul 2019	-42.65	42.00	9.41
Sep 2019	-5.18	-10.33	-20.03
Nov 2019	6.09	14.83	18.91
Jan 2020	253.21	1239.21	1415.44
Mar 2020	3557.58	-1181.63	1904.22
May 2020	1659.62	1486.87	2112.05
Jul 2020	917.97	5029.00	3526.71
Sep 2020	546.16	3823.66	3739.96
Nov 2020	864.72	8451.29	8926.02
Jan 2021	760.07	543.11	1250.26
Mar 2021	-607.57	271.80	-623.03
May 2021	-30.55	160.77	201.83
Jul 2021	56.30	-342.60	-108.96
Sep 2021	53.25	394.26	410.29
Nov 2021	107.06	2943.04	3096.51
Jan 2022	-1.58	-1074.68	-1455.95
Mar 2022	33.07	-683.93	-443.78
Average	383.70	818.61	998.49

This table presents the coefficients of one-year-ahead inflation expectations for different cryptocurrencies over various periods. The coefficients are calculated based on a model analyzing the relationship between inflation expectations and cryptocurrency market trends. This analysis offers insights into how cryptocurrency values fluctuate in response to changing inflation expectations, providing valuable information for investors and market analysts.

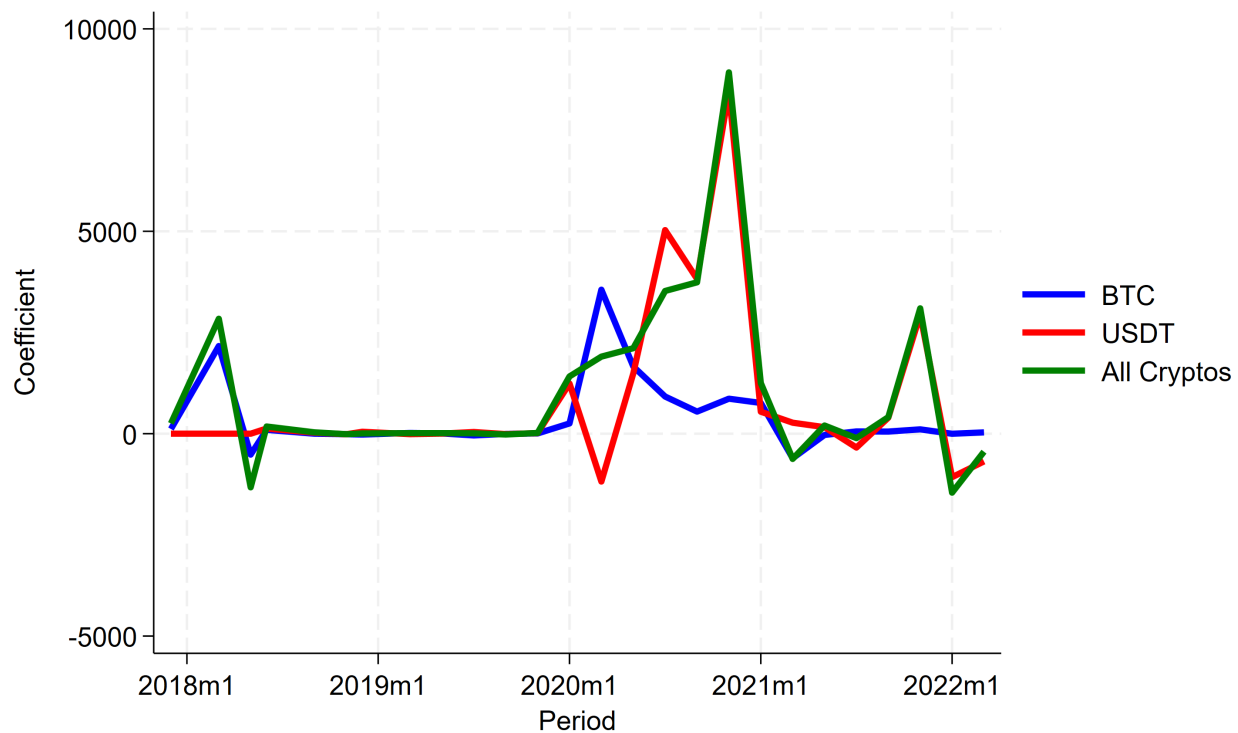
Figures

Figure 1: Cryptocurrency Investor Pincode Distribution in India



This figure illustrates the Pincode distribution of cryptocurrency investors during our sample period from January 2018 to June 2022.

Figure 2: Cryptocurrency Investment-Inflation Expectation Relationship over Time



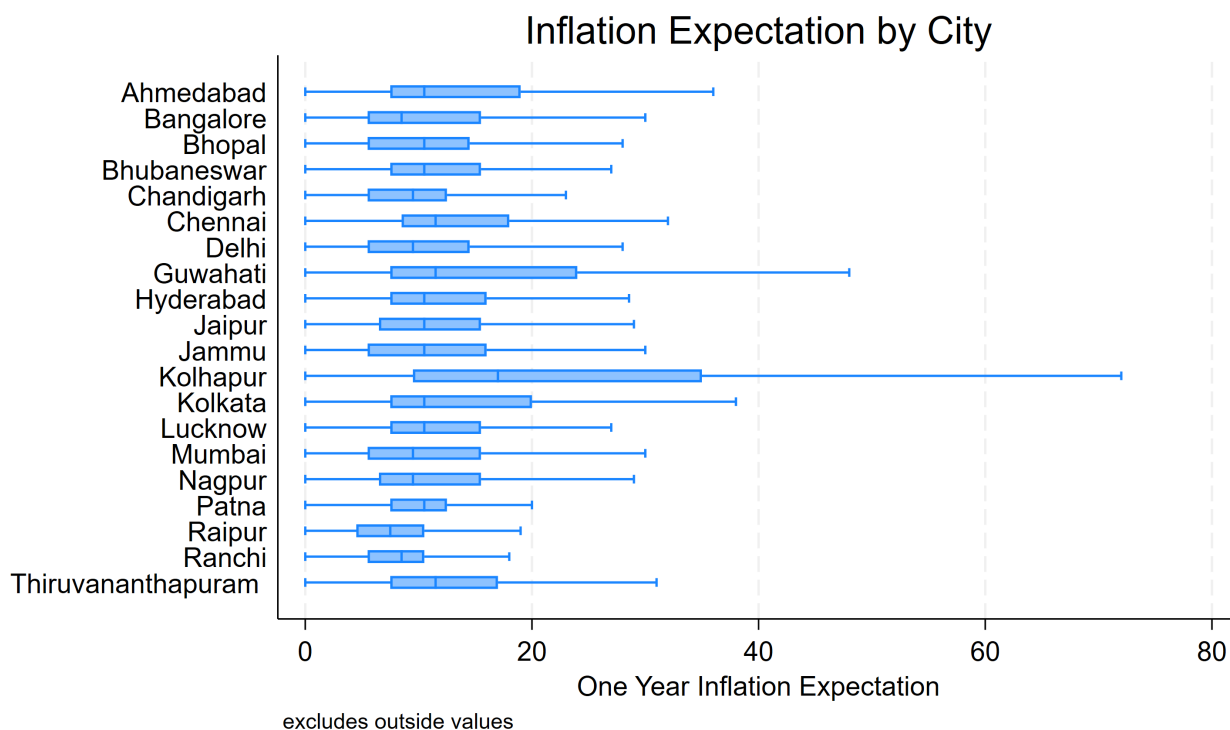
This figure showcases the evolving relationship between one-year ahead inflation expectations and the net purchase volume in Indian Rupee of BTC, USDT, and the broader cryptocurrency market from December 2017 to March 2022, as well as the change of Indian Rupee exchange rate to US dollar.

Appendix

A Additional Illustrations on the IESH Survey

Figure 3 presents multiple visualizations to illustrate how inflation expectations in the IESH household inflation expectations survey vary across cities, genders, ages, periods, and job designations, respectively. Overall, we see significant variances in inflation expectations across cities and periods. Along with formal statistic testing, we find that inflation expectations tend to be higher among women (old people) than men (young people). These patterns are consistent with the existing literature, as lucidly summarized in [D’Acunto and Weber \(2024\)](#).¹⁵

Figure 3: Inflation Expectations across Different Dimensions



¹⁵Specically, [D’Acunto and Weber \(2024\)](#) and the papers cited there illustrate how inflation expectations tend to differ across gender, income, education, age, race, and financial literacy. All demographic attributes available in both our data and existing literature see consistent patterns. [D’Acunto and Weber \(2024\)](#) and the papers cited there also explain where the cross-sectional differences in inflation expectations come from.

Figure 3: Inflation Expectations across Different Dimensions (Continued)

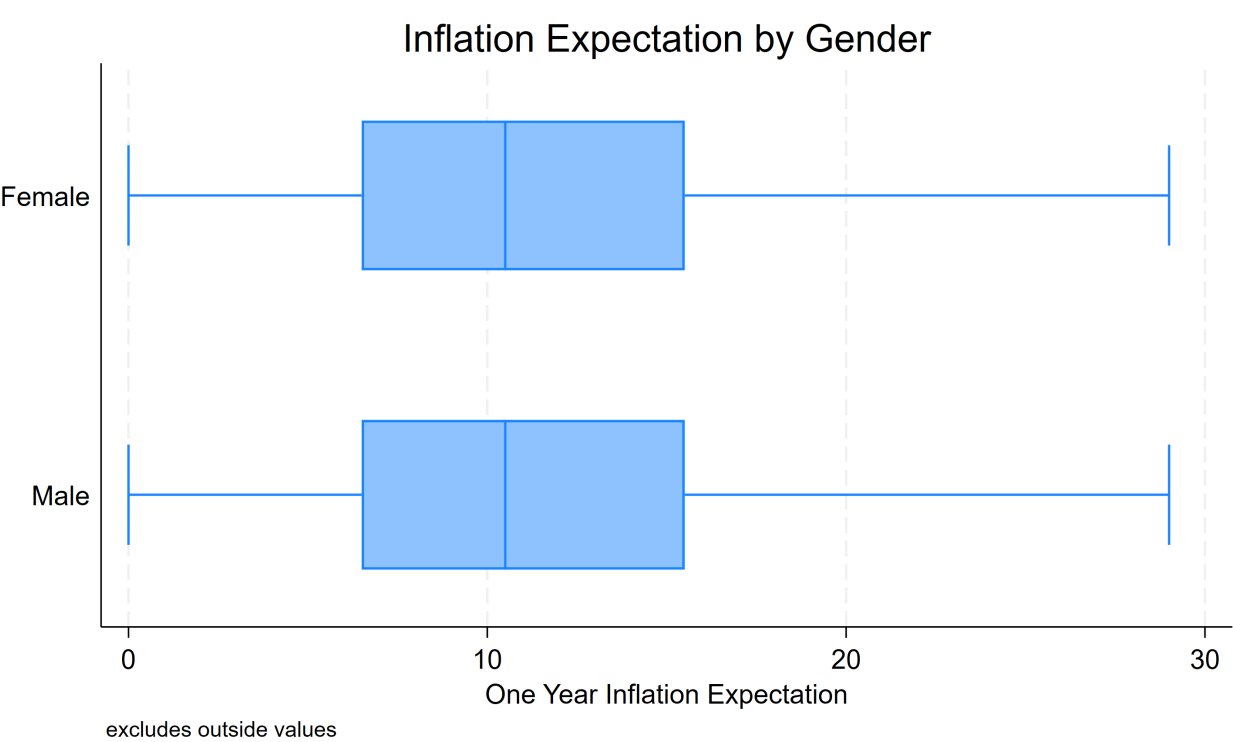


Figure 3: Inflation Expectations across Different Dimensions (Continued)

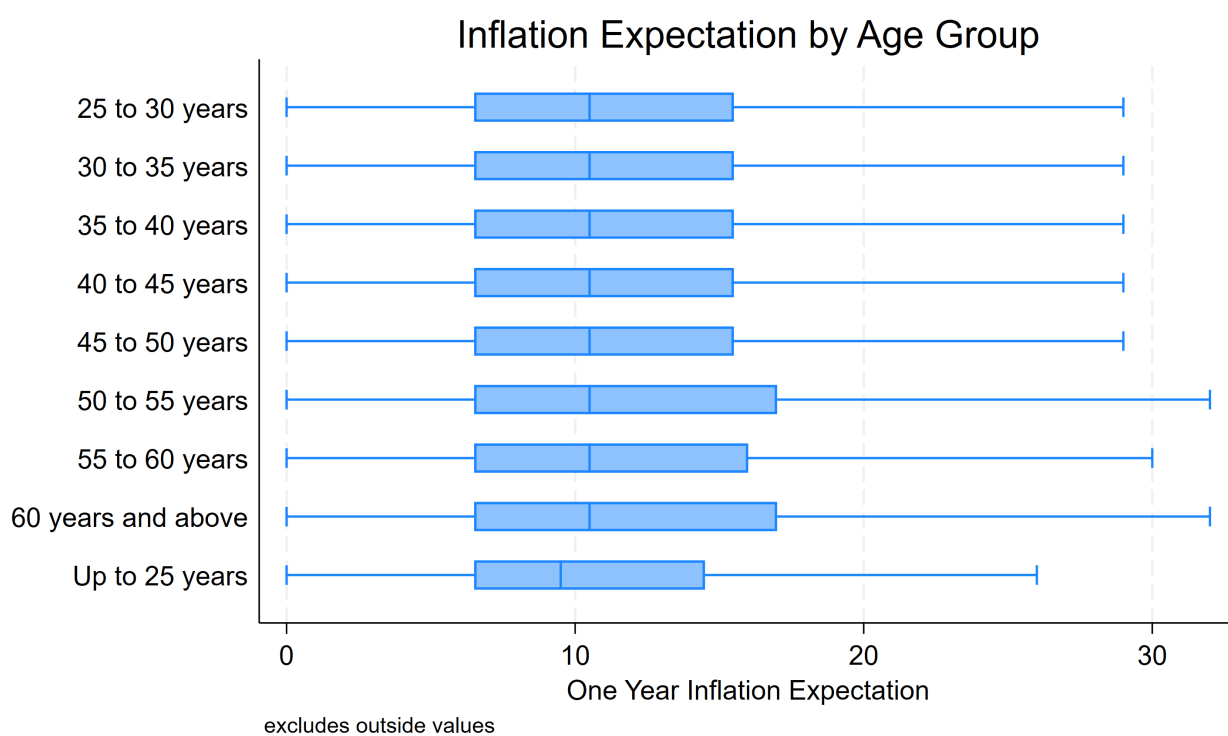


Figure 3: Inflation Expectations across Different Dimensions (Continued)

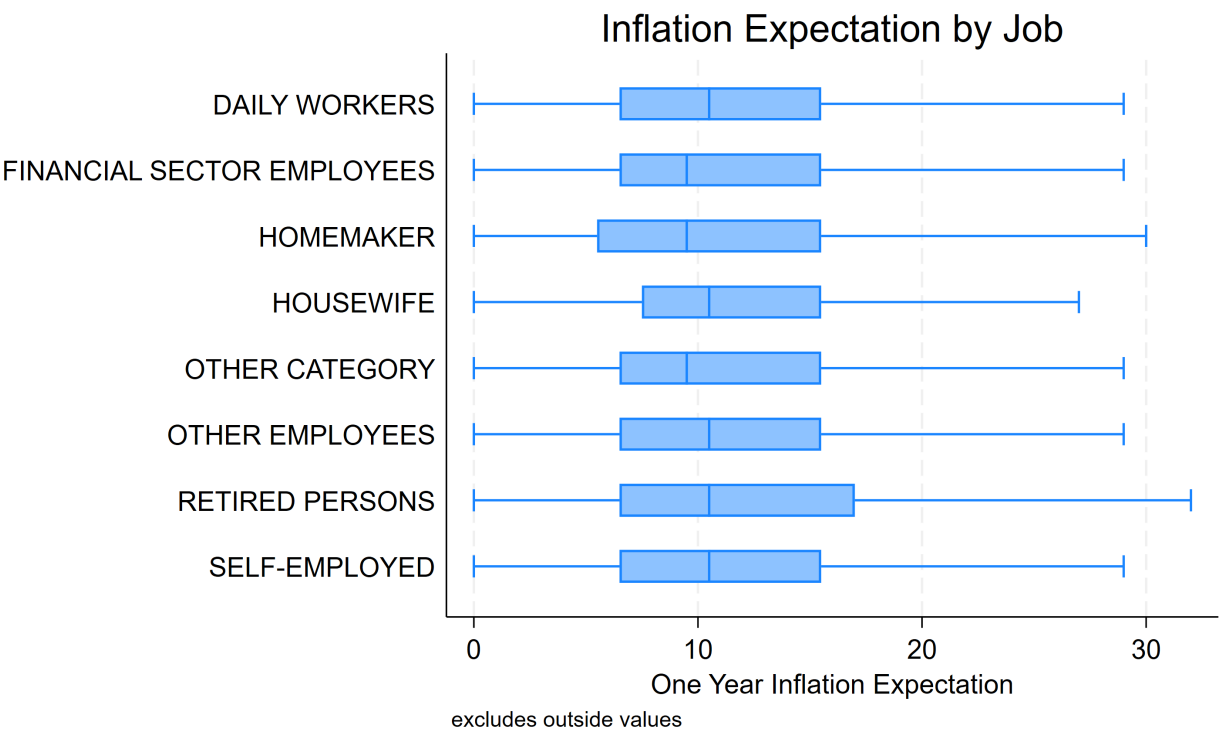
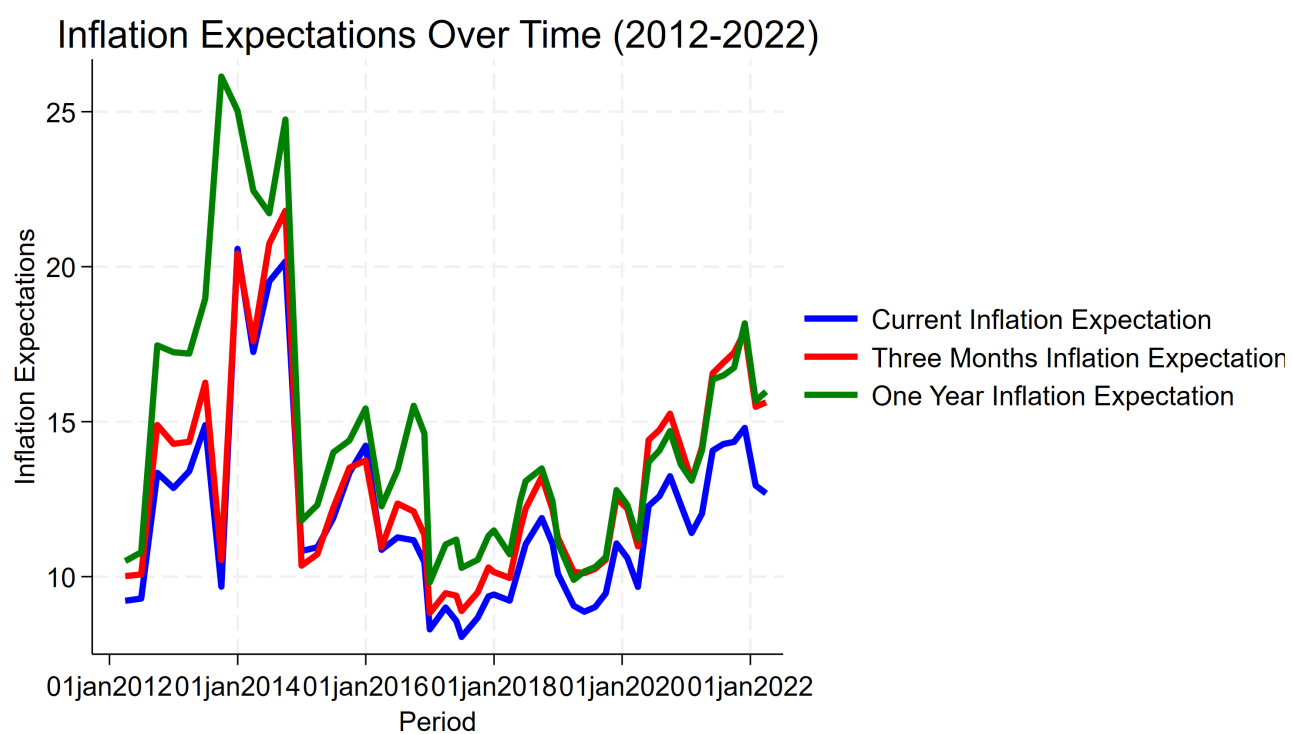


Figure 3: Inflation Expectations across Different Dimensions (Continued)



B Multiple Instrumental Variables Approach

To assess the robustness of our main results that use current inflation as the instrument, we explore alternative instrumental variables (IVs). In addition to current inflation, we consider two innovative IVs: (1) the weighted average of inflation expectations based on phone call networks and (2) the interaction term between the log of the number of gas stations per nighttime light intensity and state-level gasoline price changes.

The first IV captures the impact of information diffusion through social networks on individual expectations. This approach builds upon the seminal work of [Bartik \(1991\)](#), who introduced the shift-share IV strategy to study the impact of regional labor demand shocks on local employment growth. Following [Bartik \(1991\)](#) and recent applications of shift-share IVs in the context of social networks and economic outcomes (e.g., [Kuchler, Li, Peng, Stroebe, and Zhou \(2022\)](#); [Bailey, Cao, Kuchler, Stroebe, and Wong \(2018\)](#); [Zacchia \(2020\)](#)), we construct a social network using voice call minutes between pincodes, which captures the strength of social connections across different regions. We then use the weighted average of inflation expectations of connected pincodes as an exogenous “shift-share” to instrument for the inflation expectations of a given pincode. This approach allows us to isolate the causal effect of inflation expectations on cryptocurrency investments by exploiting the exogenous variation in inflation expectations driven by the expectations of socially connected regions ([Manski \(1993\)](#); [Kuchler, Russel, and Stroebe \(2021\)](#)).

We construct the social network using detailed call data from 2019, which provides information on the volume of calls between different pincodes in India. We measure the strength of social connections between pincodes by calculating the call concentration, which is the ratio of the minutes of calls between two pincodes to the total minutes of calls made by each pincode ([Bailey et al. \(2018\)](#); [Büchel, Puga, Viladecans-Marsal, and von Ehrlich \(2020\)](#)). This call concentration matrix serves as the “share” component of our shift-share IV. Next, for each pincode, we identify the top three most closely connected pincodes based on the call concentration matrix. We then calculate the average inflation expectation of these top three connected pincodes, excluding the pincode of interest, to ensure exogeneity. This inflation expectation of the connected pincodes serves as the “shift” component of our IV, drawing upon the idea that social connections can influence economic expectations and behaviors ([Granovetter \(2005\)](#); [Coibion, Gorodnichenko, and Weber \(2020\)](#)).

The validity of our social network shift-share IV relies on two key assumptions. First, we

assume that the social network structure, as measured by call concentrations, is exogenous to future changes in cryptocurrency investments. We argue that this assumption is likely to hold, as the call data used to construct the social network predates our sample period, and it is unlikely that cryptocurrency investment decisions would significantly influence the patterns of social connections across pincodes (Bailey et al. (2018); Chaney (2014)). Second, we assume that the inflation expectations of the connected pincodes are exogenous to the cryptocurrency investment decisions of the pincode of interest. This assumption is supported by the fact that we exclude the pincode of interest when calculating the average inflation expectation of the connected pincodes, thus mitigating potential reverse causality concerns (Borusyak, Hull, and Jaravel (2022); Goldsmith-Pinkham, Sorkin, and Swift (2020)). We also conduct robustness checks, such as controlling for pincode-specific characteristics and testing for pre-trends, to further validate our instrument (Jaeger, Ruist, and Stuhler (2018); Adao, Koles'ar, and Morales (2019)).

The second IV builds on the Bartik shift-share approach (Goldsmith-Pinkham et al., 2020). We measure a region's exposure to gasoline prices using the log of the number of gas stations divided by nighttime light intensity. Areas with a higher density of gas stations relative to economic activity are more reliant on gasoline and thus more sensitive to gasoline price changes. The shift component uses state-level gasoline price changes, as prices are clustered by state in India¹⁶. The pincode-level economic situation is unlikely to reversely affect state-level gasoline prices, making state-level changes an ideal shift variable. We use the number of gas stations at the beginning of 2018 and nightlight data from 2017, both predating our sample period, to ensure exogeneity. The gas station count exhibits a stable trend over time, independent of cryptocurrency market trends, supporting the validity of our shift-share IV. Moreover, nightlight data is widely used to measure economic activity (Henderson, Storeygard, and Weil, 2012; Donaldson and Storeygard, 2016).

Table 13 presents the first-stage IV estimation results. All three IVs have positive and significant coefficients, confirming their relevance in explaining inflation expectations. A 1% increase in current inflation is associated with a 1.148 percentage point increase in three-month ahead inflation expectations and a 1.044 percentage point increase in one-year ahead inflation expectations. The call connection weighted inflation expectation IVs also show positive and significant effects, with coefficients of 0.0845 for the three-month horizon and 0.0544 for the one-year horizon. The Bartik shift-share IV, constructed as the interaction

¹⁶See https://www.mypetrolprice.com/petrol-price-in-india.aspx#google_vignette.

term between petrol exposure and state-level petrol price changes, has coefficients of 0.639 for the three-month inflation expectation and 2.375 for the one-year inflation expectation. These results align with economic intuition: higher current inflation, greater exposure to inflation information through social networks, and stronger sensitivity to oil price shocks in economically active areas all contribute to higher inflation expectations.

Table 14 presents the second-stage results. The coefficient on the current inflation is 1,162, statistically significant at the 5% level. The coefficients on the three-month and one-year inflation expectations are 855.9 and 1,038, respectively, both statistically significant at the 5% level. When using the fitted values from the first-stage regressions as the IVs, the coefficients on the three-month and one-year inflation expectations are 1,075 and 1,187, respectively, slightly larger than the OLS estimates and statistically significant at the 10% level. This suggests that the new IVs capture additional exogenous variation in inflation expectations not fully accounted for by current inflation alone.

However, the consistency of the results across different IV combinations underscores the robustness and appropriateness of our main specification. If inflation expectations primarily affect capital reallocation through the current inflation channel, as posited in our baseline model, then the original IV specification is valid and sufficient.

The multiple IV approach allows for the possibility that inflation expectations influence capital reallocation through multiple channels beyond current inflation, providing a robustness check that accounts for potential omitted variables in the baseline specification. The slightly larger second-stage coefficient with the new IVs suggests that these alternative channels, while present, are not as quantitatively important as the current inflation channel. This is further evidenced by the insignificant second-stage coefficients when the new IVs are used individually, despite their positive and significant first-stage estimates (results available upon request).

The sample size in this robustness check is reduced from over 630,000 to around 460,000 observations due to the more stringent requirement of overlapping coverage for all three IVs. Nevertheless, the stability of the estimates reinforces the reliability of our main findings.

In conclusion, our robustness checks using multiple IVs, including the social network shift-share IV approach, confirm the paper’s main results while allowing for a more comprehensive understanding of the channels through which inflation expectations affect capital reallocation. The consistency of the estimates across different instrument choices, coupled with the positive and significant first-stage coefficients for all IVs, strengthens the credibility

of our conclusions and highlights the robustness of the relationship between inflation expectations and economic behavior. While we focus on current inflation as the primary IV in the main analysis for parsimony and comparability with previous studies, the exploration of innovative IVs and their theoretical justification adds depth to our understanding of the inflation expectation formation process and demonstrates the comprehensive nature of our empirical investigation.

Table 13: First-stage Regressions of Instrumental Variables

	(1) 3-Month Inflation	(2) 1-Year Inflation
Current Inflation	1.148*** (0.000688)	1.044*** (0.00110)
3-Month Call Connected Inflation Expectation	0.0845*** (0.00233)	
1-Year Call Connected Inflation Expectation		0.0544*** (0.00387)
Petrol Exposure*State Petrol Price Changes	0.639*** (0.0340)	2.375*** (0.0545)
Age	0.00304*** (0.000546)	0.00530*** (0.000876)
Male	-0.0682*** (0.0120)	-0.144*** (0.0193)
Semi-Urban	1.247*** (0.0382)	0.714*** (0.0613)
Rural	-0.113*** (0.0304)	-0.766*** (0.0488)
Constant	-0.805*** (0.0416)	0.926*** (0.0683)
Observations	459,969	459,956
R^2	0.864	0.672

Table 13 presents the first-stage regression results for the IV estimations. The dependent variables are three-month and one-year ahead inflation expectations. The key instrumental variables are current inflation, call connection weighted inflation expectations (for both three-month and one-year horizons), and the interaction term between petrol exposure and state-level petrol price changes, following the Bartik shift-share IV idea. Petrol exposure at pincode level is measured by $\log(\# \text{ of Petrol Station/Nightlight})$, while nightlight intensity is a proxy for economic activity. Additional control variables include age, gender index, and urban/rural classification. The coefficients of the instrumental variables are all significant at the 1% level, confirming their relevance in explaining inflation expectations. The R-squared for the three-month ahead inflation expectation is 86.4% and is higher than that for one-year ahead at 67.2%, likely due to more uncertainties taken into account in longer terms. Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 14: Inflation Expectations and Cryptocurrency Investment (Jan 2018 - June 2022)

	Dependent Variable: INR_Amount_Net				
	(1)	(2)	(3)	(4)	(5)
Current Inflation	1,162** (498.9)				
Three Months Inflation		855.9** (349.8)			
One Year Inflation			1,038** (429.7)		
Three Months Inflation (IV)				1,075* (577.7)	
One Year Inflation (IV)					1,187* (635.3)
Age	350.1 (412.1)	348.0 (413.0)	341.1 (414.2)	663.0 (518.5)	659.6 (519.1)
Male	-20,370 (12,928)	-20,379 (12,910)	-20,347 (12,886)	-22,945 (16,755)	-22,848 (16,713)
Semi-Urban	16,672*** (5,319)	15,960*** (4,903)	15,863*** (4,837)	10,983* (5,462)	11,426* (5,687)
Rural	3,258 (2,918)	3,127 (2,901)	2,773 (2,902)	2,725 (2,846)	3,472 (2,917)
Constant	-12,993 (23,010)	-10,766 (23,331)	-12,750 (22,535)	-21,500 (27,225)	-22,876 (26,956)
Observations	638,834	638,831	638,818	459,969	459,969
R-squared	0.005	0.005	0.006	0.010	0.010
Number of groups	26	26	26	25	25

This table presents the regression results of:

$$\text{INR_amount_net}_{i,t+1} = \alpha + \beta \times \text{Inflation_expectation}_{i,t} + \gamma \times \text{Age}_{i,t} \\ + \lambda \times \text{Male}_{i,t} + \mu \times \text{Semi_urban}_{i,t} + \nu \times \text{Rural}_{i,t} + \epsilon_{i,t+1}.$$

The dependent variable $\text{inr_amount_net}_{i,t+1}$ denotes investor i 's net cryptocurrency purchase amount in Indian Rupees within period $t + 1$. The main explanatory variables are current inflation, three-month ahead inflation expectation, one-year ahead inflation expectation, and their instrumented values using current perceived inflation as the instrument. Additional control variables include age, gender index, and urban/rural classification. The Fama-MacBeth regressions are conducted by performing sequential cross-sectional regressions for each period, with coefficients averaged over all periods. Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

C Temporal Dynamics in the Extensive Margin

The first panel of Figure 4 sheds light on the gender distribution of new market entrants. This gender-specific analysis aligns with the documented FinTech gender gap, as outlined in the findings of [Chen, Doerr, Frost, Gambacorta, and Shin \(2023\)](#). The data illustrate a substantial, consistent predominance of male entrants, punctuated by marked increases in female customer acquisitions during certain intervals. These escalations suggest episodic amplifications in market engagement, potentially triggered by external economic events or shifts in inflationary outlooks. Cumulatively, the aggregate trends of new customer inductions into the cryptocurrency market reveal pronounced fluctuations, potentially correlating with macroeconomic signals and investor sentiment metrics.

The second panel of Figure 5 further shows the evolution of the gender ratio of new customers, the proportion of female investors grows from 10% at the beginning of 2018 to 20% at the end of 2021. This finding sharply contrasts findings from the United States as reported in the [Aiello et al. \(2023\)](#), which suggests that only 49% of U.S. crypto investors are male, a stark contrast to the 80% in our Indian sample. Their estimate, inferred from consumer transaction data, differs from ours which is directly sourced from the crypto exchange.

The panels in Figure 6 delineate the temporal progression of new customer acquisitions across urban, semi-urban, and rural regions, along with their respective proportions over time. Specifically, the dataset comprises 340,353 investors from rural areas, constituting 17.11% of the total. From semi-urban regions, there are 497,036 investors, accounting for 24.98% of the overall cohort. The urban sector is represented by 1,151,964 investors, which corresponds to 57.91% of the total investor base.

Figure 4: New Customers By Gender Over Time

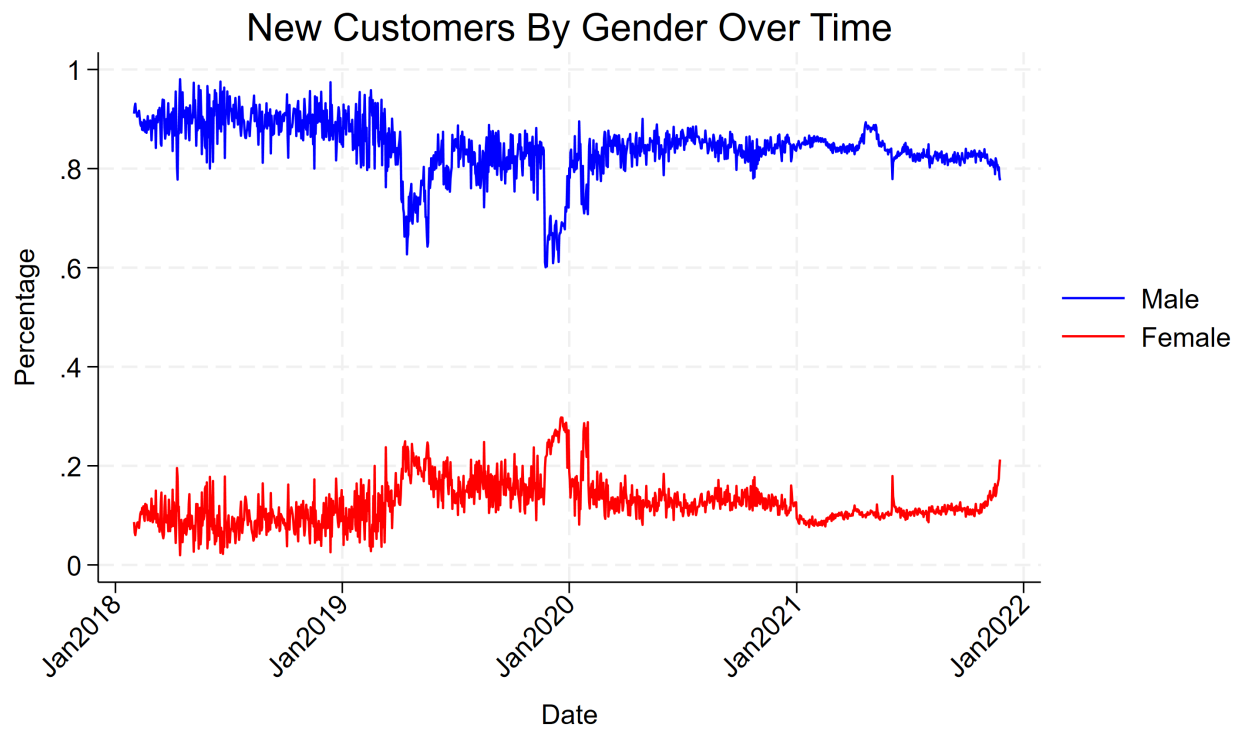
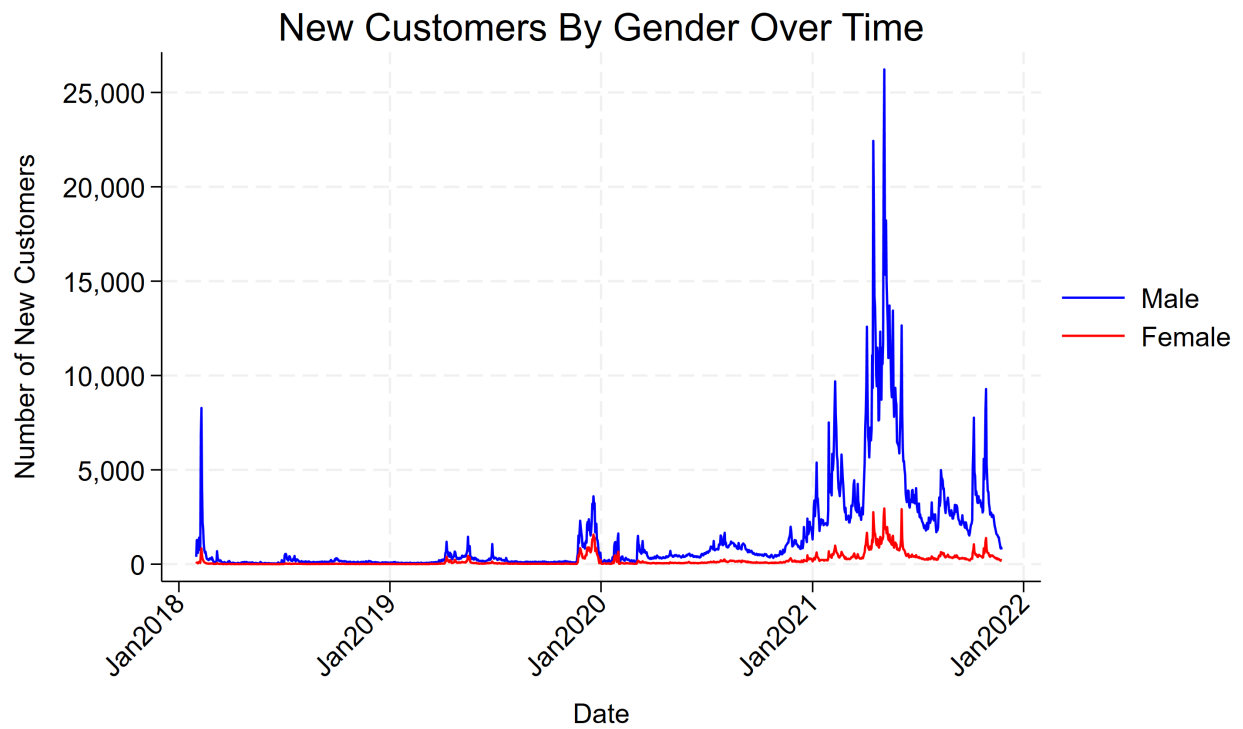
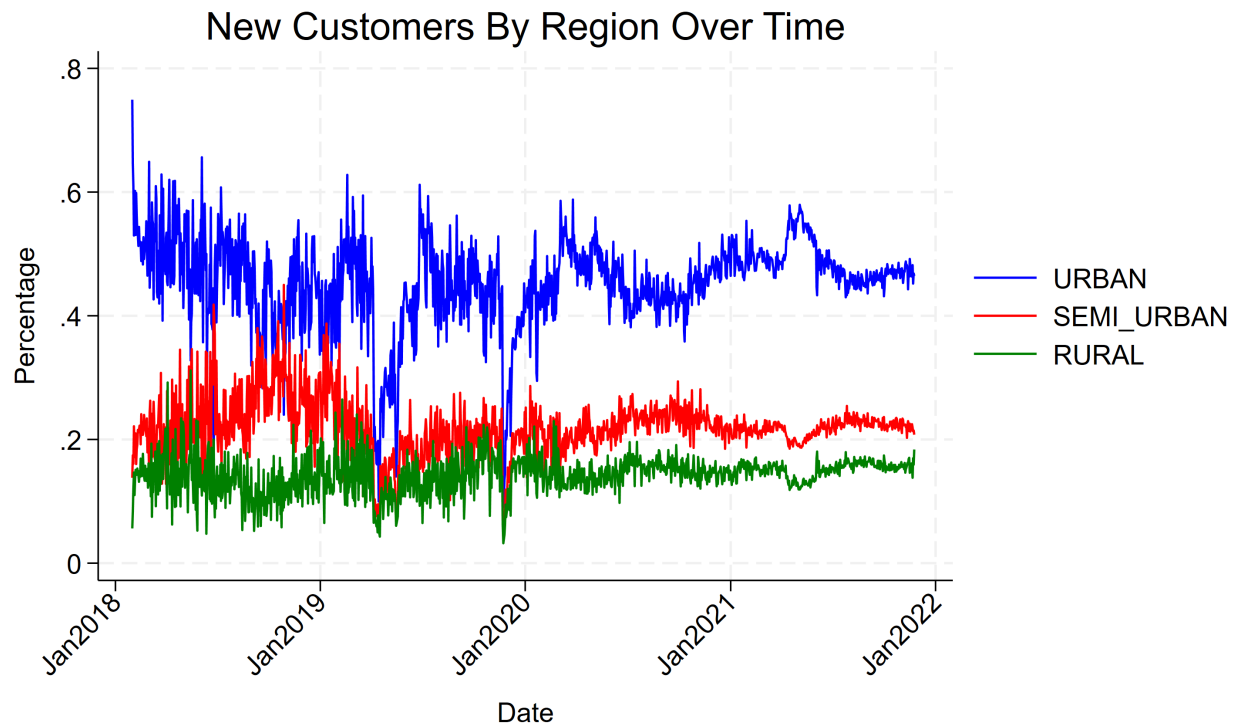
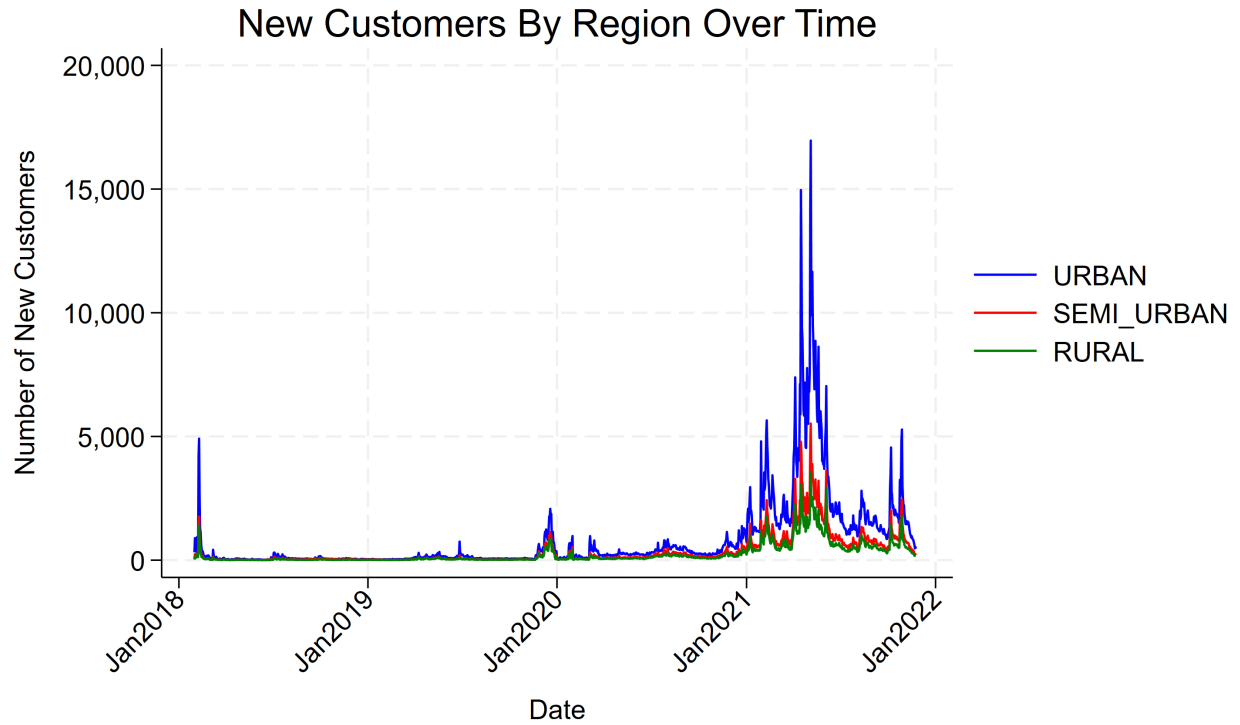


Figure 5: New Customers By Gender Over Time

Figure 6: New Customers By Region Over Time



D Theoretical Framework

This section develops a simple theoretical model based on the Euler Equation to clarify the relationship between inflation expectation and cryptocurrency investment. Having a formal theoretical framework is useful because a priori the effects of inflation expectations on cryptocurrency investment are ambiguous: On the one hand, when the dominating effect is that inflation expectations increase the relative affordability of consumption in the current period, households will spend more on consumption and less on investment, including cryptocurrency investment; On the other hand, when the dominating effect is that inflation expectations make households believe that they should save more for future consumption, then they may increase cryptocurrency investment, which serves as an inflation hedge and method of a store of value. A key parameter to determine which effect is dominating is the intertemporal elasticity of consumption, which is a common parameter in literature. Also, the (perceived) fitness of cryptocurrency as an inflation hedge also affects households' asset allocation decisions.

We formalize the above reasoning using an Euler equation that delineates a representative household's optimal intertemporal consumption trajectory, factoring in consumption smoothing. The Euler equation associates current real consumption c_t with expected future consumption $\mathbb{E}_t c_{t+1}$, nominal asset returns i_{t+1} , and projected inflation $\mathbb{E}_t \pi_{t+1}$. Assuming constant relative risk aversion (CRRA) utility, the ensuing log-linear, first-order approximation follows:

$$c_t = \mathbb{E}_t c_{t+1} - \sigma(\mathbb{E}_t i_{t+1} - \mathbb{E}_t \pi_{t+1} - \ln \beta).$$

Here, the elasticity of intertemporal substitution (EIS) between present and future consumption, denoted as σ , measures the impact of the opportunity cost incurred when opting for consumption over saving, adjusted for the household's time preference rate β .

The Euler equation can be recast in nominal terms:

$$c_t^{nominal} - p_t = \mathbb{E}_t c_{t+1}^{nominal} - \mathbb{E}_t p_{t+1} - \sigma(\mathbb{E}_t i_{t+1} - \mathbb{E}_t \pi_{t+1} - \ln \beta)$$

$$c_t^{nominal} = \mathbb{E}_t c_{t+1}^{nominal} - \sigma \mathbb{E}_t i_{t+1} + (\sigma - 1) \mathbb{E}_t (\pi_{t+1}) + \sigma \ln \beta$$

To account for an asset functioning as an inflation hedge, we introduce the relationship $i_{t+1} = \rho \pi_{t+1} + \epsilon_{t+1}$. Substituting this expression into the equation yields:

$$c_t^{nominal} = \mathbb{E}_t c_{t+1}^{nominal} - \sigma \mathbb{E}_t(\epsilon_{t+1}) + (\sigma(1 - \rho) - 1) \mathbb{E}_t(\pi_{t+1}) + \sigma \ln \beta.$$

The nominal savings $s_t^{nominal}$ equals the difference between nominal income and consumption, $y_t^{nominal} - c_t^{nominal}$.

$$s_t^{nominal} = y_t^{nominal} - \mathbb{E}_t c_{t+1}^{nominal} + \sigma \mathbb{E}_t(\epsilon_{t+1}) + (1 - \sigma + \sigma \rho) \mathbb{E}_t(\pi_{t+1}) - \sigma \ln \beta.$$

The marginal influence of inflation expectations on savings and investments can be represented by $1 - \sigma + \sigma \rho$. Without an inflation hedging asset, the effect would be $1 - \sigma$. When an asset serves as an effective inflation hedge—indicated by a larger ρ value—the impact of inflation expectations on asset acquisitions intensifies. Our model shows that an inflation-hedge asset can serve as a saving avenue and help households hedge inter-temporal consumption risks.

In our model, what characterizes an asset with a high ρ value? Essentially, ρ represents the sensitivity of asset returns to inflation. If we had used the US dollar or Bitcoin to calculate India's Consumer Price Index (CPI) since 2011, the resulting average inflation rate would have been less than when using the Indian rupee. This suggests a positive ρ value for both the US dollar and Bitcoin within our framework. Thus, during this period, both the US dollar and Bitcoin acted as effective inflation hedges.

Informed by our theoretical conclusions, we hypothesize that an increase in inflation expectations will prompt a surge in net purchases of US dollars and Bitcoin.