Inflation Expectation and Cryptocurrency Investment*

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Abstract

Using proprietary data from the predominant cryptocurrency exchange in India together with the country's Household Inflation Expectations Survey, we document a significantly positive association between inflation expectations and individual cryptocurrency purchases. Higher inflation expectations are also associated with more new investors in cryptocurrencies. We investigate investment heterogeneity in multiple dimensions, and find the effect to be concentrated in Bitcoin (BTC) and Tether (USDT) trading. The results are robust after controlling for speculative demand captured by surveys of investors' expected cryptocurrency returns, and admit causal interpretations as confirmed using multiple 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: Bitcoin, Crytocurrency, Household Finance, Inflation, Stablecoin.

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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 help us better appreciate why some digital 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 explanation: 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, against the backdrop of noise and speculative trading, 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] We 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 differ

[1] This 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.

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

across 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.

Theory offers limited insights into these inquiries. 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 aformentioned questions requires granular trader/coin-level data to link inflation expectations and specific cryptocurrency investment decisions.

We tackle the empirical challenge 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 as-

[3]For 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.

sociated with more than ₹1,000 increase in a single investor's net cryptocurrency purchase before the next inflation expectation survey (roughly two months later). The results are robust when we control for investors' 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. These results also have causal interpretations as they persist when we repeat our regressions using current inflation as an instrumental variable for inflation expectation (as in Weber, Gorodnichenko, and Coibion, 2023).

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,

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

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 with high inflations such as 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 crypotcurrencies, even though not as means of 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 inflation expectations from household surveys 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 research aligns with broader investi-

[5] Both 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.

[6] They 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.

gations into digital currencies in India, such as Di Maggio, Ghosh, Ghosh, and Wu (2024)'s analysis of CBDC impacts on traditional banking and payment systems. 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 the 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, Hulays, Showers, Ali, and Chang, 2021; Cong, Harvey, Rabetti, and Wu, 2023), circumventing 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 (2024) compare retail investors' trading behaviors of different assets, without jointly considering inflation expectations as we do.[7] We also add to the emerging literature on cryptocurrency markets in general, Makarov and Schoar (2020), Choi et al. (2022), 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 presents our model specifications. 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

We first provide some institutional background to help readers appreciate why India is a particularly relevant market for studying the relationship between inflation expectations and cryptocurrency investment.

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.[8] A Statista survey estimated that by the end of 2023, over 11% of India's population would have ventured into the cryptocurrency sector, surpassing the adoption rates in the United

[7]Other research examines the effects of COVID-19 stimulus checks on Bitcoin trading activities (Divakaruni and Zimmerman, 2023), the phenomena of crypto wash trading (Cong, Li, Tang, and Yang, 2023; Aloosh and Li, 2023; Amiram, Lyandres, and Rabetti, 2020) the dynamics of crypto pump-and-dump (e.g., Li, Shin, and Wang, 2019).

[8]See 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/.

States, the United Kingdom, Japan, and Russia.[9] In December 2023, IMF chief Kristalina Georgieva also specifically brought up India when highlighting the high level of cryptoasset adoption in emerging market economies.[10] 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 population of over 1.39 billion as 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 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) of 1999 have

[9]See cryptopotato.com/india-to-have-over-150-million-crypto-users-by-the-end-of-2023-study/.
[10]See imf.org/en/News/Articles/2023/12/13/sp121423-leaving-the-wild-west-kordigitalmoney.

limited households' access to foreign currencies. Therefore, cryptocurrency transactions not restricted by FEMA could serve as a viable alternative.

Third, while Inflation-indexed Bonds (IIBs) exist in India, they may not be effective inflation hedges for households. The RBI introduced IIBs in 2013 to provide investors with an inflation-protected investment option. However, these bonds face several challenges limiting their effectiveness and accessibility. Primary issues include low liquidity in the secondary market, complex pricing mechanisms, and limited issuance. Additionally, the inflation adjustment is based on the Wholesale Price Index rather than the Consumer Price Index, potentially misaligning the protection offered with actual consumer inflation. IIBs in India typically have long maturities, often 10 years or more, making them less suitable for households needing more flexible investment options. Furthermore, these bonds are not always accessible to retail investors, as they are sometimes only issued to specific categories of investors or in limited quantities. These factors, combined with a general lack of awareness among retail investors, have resulted in low participation and reduced effectiveness of IIBs as inflation hedges for Indian households.[11]

2.2 Data

Our study leverages data from two primary sources: (1) granular individual-level trading data from India's largest cryptocurrency exchange, and (2) inflation expectations data from the Inflation Expectation Survey of Households (IESH) conducted by the central bank of India, the Reserve Bank of India. This unique combination of datasets enables us to analyze the interplay between inflation expectations, cryptocurrency trading behaviors, and demographic attributes.

[11] Admitted, 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.

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 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.[12] 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 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 the variables in the IESH dataset.[13]

[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.[14] 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-

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

[13] Throughout 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. Note also that the IESH is not conducted across all pincodes, and hence matching the IESH dataset with our cryptocurrency exchange data reduces the number of observations.

[14] An 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.

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 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` measures an individual investor's net purchase volume of cryptocurrencies in Indian rupees (INR). The mean net purchase amount is $-5,023.26$ INR, with substantial heterogeneity across investors. The distribution of net purchases exhibits wide dispersion, ranging from $-236,311.80$ INR at the 1% percentile to $237,311.60$ INR at the 99% percentile.

3 Empirical Specifications and Findings

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 $\texttt{Inr\_Amount\_Net}_{i,t+1}$ 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 $\texttt{Inflation\_Expectation}_{i,t}$, 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.[15] 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.

[15] More complicated IV designs will also give consistent results, as we report in Appendix B.

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:

$$New\_Customer_{p,t+1} = \alpha + \beta \times \text{Inflation\_Expectation}_{p,t} + \gamma \times \text{Controls}_{p,t} + \epsilon_{p,t}, \quad (2)$$

where $\texttt{New\_Customer}_{p,t}$ is the dependent variable representing the number of new customers at pincode p in period t and $\texttt{Inflation\_Expectation}_{p,t}$ 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. A one percentage point increase in inflation expectations is associated with approximately 1,000 additional new cryptocurrency investors joining our exchange, based on data from 945 pincodes in our sample, a subset of India's total 19,000 pincodes. 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,[16] 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.

To explore potential heterogeneity in the relationship between inflation expectations and cryptocurrency investments, we disaggregate our analysis across urban, semi-urban, and rural areas. This stratification allows us to examine whether the sensitivity of cryptocurrency adoption to inflation expectations varies with the degree of urbanization, potentially

[16]See details from https://rbidocs.rbi.org.in/rdocs/Content/PDFs/RBILIS130910.PDF.

reflecting differences in financial infrastructure, economic conditions, and information dissemination across these distinct geographic segments.

[Table 11 about here.]

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. We explore the temporal dynamics of the regression coefficients using the Fama-MacBeth specification in Equation (1). This analysis provides insights into how the relationship between inflation expectations and cryptocurrency investments evolves over our sample period.

[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, especially in Bitcoins and Tethers, which is consistent with expected inflation increases causing households to purchase more cryptocurrencies, as confirmed by intrumental variable analyses. 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.

References

Agarwal, S., Y. H. Chua, P. Ghosh, and C. Song (2022). Inflation expectations of households and portfolio rebalancing: Evidence from inflation targeting in india. *Available at SSRN 4069564*.

Aiello, D., S. R. Baker, T. Balyuk, M. Di Maggio, M. J. Johnson, J. Kotter, and E. Williams (2023). Cryptocurrency investing: Stimulus checks and inflation expectations. Technical report, Working Paper.

Aloosh, A. and J. Li (2023). Direct evidence of bitcoin wash trading. *Management Science*.

Amiram, D., E. Lyandres, and D. Rabetti (2020). Competition and product quality: Fake trading on crypto exchanges. *Available at SSRN 3745617*.

Bailey, M., R. Cao, T. Kuchler, J. Stroebel, and A. Wong (2018). Social connectedness: Measurement, determinants, and effects. *Journal of Economic Perspectives 32*(3), 259–80.

Bartik, T. J. (1991). *Who benefits from state and local economic development policies?* W.E. Upjohn Institute for Employment Research.

Benetton, M. and G. Compiani (2024). Investors' beliefs and cryptocurrency prices. *The Review of Asset Pricing Studies*, raad015.

Büchel, K., D. Puga, E. Viladecans-Marsal, and M. von Ehrlich (2020). Calling from the outside: The role of networks in residential mobility. *Journal of Urban Economics 119*, 103277.

Chen, S., S. Doerr, J. Frost, L. Gambacorta, and H. S. Shin (2023). The fintech gender gap. *Journal of Financial Intermediation 54*, 101026.

Choi, K. J., A. Lehar, and R. Stauffer (2022). Bitcoin microstructure and the kimchi premium. *Available at SSRN 3189051*.

Choi, S. and J. Shin (2022). Bitcoin: An inflation hedge but not a safe haven. *Finance Research Letters 46*, 102379.

Coibion, O., Y. Gorodnichenko, and M. Weber (2022). Monetary policy communications and their effects on household inflation expectations. *Journal of Political Economy 130*(6), 1537–1584.

Cong, L. W., H. Gao, J. Ponticelli, and X. Yang (2019). Capital reallocation and productivity: Evidence from a quasi-natural experiment. *The Review of Financial Studies 32*(9), 3412–3460.

Cong, L. W., C. R. Harvey, D. Rabetti, and Z.-Y. Wu (2023). An anatomy of crypto-enabled cybercrimes.

Cong, L. W., G. A. Karolyi, K. Tang, and W. Zhao (2022). Value premium, network adoption, and factor pricing of crypto assets. *working paper*.

Cong, L. W., X. Li, K. Tang, and Y. Yang (2023). Crypto wash trading. *Management Science 69*(11), 6427–6454.

Cong, L. W., Y. Li, and N. Wang (2021). Tokenomics: Dynamic adoption and valuation. *The Review of Financial Studies 34*(3), 1105–1155.

Cong, L. W. and S. Mayer (2022). The coming battle of digital currencies. *The SC Johnson College of Business Applied Economics and Policy Working Paper Series* (2022-04).

Conlon, T., S. Corbet, and R. J. McGee (2021). Inflation and cryptocurrencies revisited: A time-scale analysis. *Economics Letters 206*, 109996.

Di Maggio, M., P. Ghosh, S. Ghosh, and A. Wu (2024, May). Impact of retail cbdc on digital payments, and bank deposits: Evidence from india. *NBER Working Paper* (32457). Available at SSRN: https://ssrn.com/abstract=4833933.

Dietrich, A., E. S. Knotek II, K. O. Myrseth, R. W. Rich, R. Schoenle, and M. Weber (2023). Greater than the sum of its parts: Aggregate vs. aggregated inflation expectations. Technical report, National Bureau of Economic Research.

Divakaruni, A. and P. Zimmerman (2023). Uncovering retail trading in bitcoin: The impact of covid-19 stimulus checks. *Management Science*.

D'Acunto, F. and M. Weber (2024). Why survey-based subjective expectations are meaningful and important. Technical report, National Bureau of Economic Research.

Fama, E. F. and J. D. MacBeth (1973). Risk, return, and equilibrium: Empirical tests. *Journal of political economy 81*(3), 607–636.

Foley, S., J. R. Karlsen, and T. J. Putniņš (2019). Sex, drugs, and bitcoin: How much illegal activity is financed through cryptocurrencies? *The Review of Financial Studies 32*(5), 1798–1853.

Garcia-Lembergman, E., I. Hajdini, J. Leer, M. O. Pedemonte, and R. S. Schoenle (2023). The expectations of others. *Federal Reserve Bank of Cleveland Working Paper* (23-22).

Goldsmith-Pinkham, P., I. Sorkin, and H. Swift (2020). Bartik instruments: What, when, why, and how. *American Economic Review 110*(8), 2586–2624.

Jermann, U. J. (2021). Cryptocurrencies and cagan's model of hyperinflation. *Journal of Macroeconomics 69*, 103340.

Jermann, U. J. (2023). A macro finance model for proof-of-stake ethereum. *Available at SSRN 4335835*.

Kogan, S., I. Makarov, M. Niessner, and A. Schoar (2024). Are cryptos different? evidence from retail trading. *Journal of Financial Economics 159*, 103897.

Li, J., F. Baldimtsi, J. P. Brandao, M. Kugler, R. Hulays, E. Showers, Z. Ali, and J. Chang (2021). Measuring illicit activity in defi: The case of ethereum. In *Financial Cryptography and Data Security. FC 2021 International Workshops: CoDecFin, DeFi, VOTING, and WTSC, Virtual Event, March 5, 2021, Revised Selected Papers 25*, pp. 197–203. Springer.

Li, J. and W. Mann (2018). Digital tokens and platform building.

Li, J. and G. Yi (2019). Toward a factor structure in crypto asset returns. *The Journal of Alternative Investments 21*(4), 56–66.

Li, T., D. Shin, and B. Wang (2019). Cryptocurrency pump-and-dump schemes. *Available at SSRN 3267041*.

Liu, Y. and A. Tsyvinski (2021). Risks and returns of cryptocurrency. *The Review of Financial Studies 34*(6), 2689–2727.

Liu, Y., A. Tsyvinski, and X. Wu (2022). Common risk factors in cryptocurrency. *The Journal of Finance 77*(2), 1133–1177.

Makarov, I. and A. Schoar (2020). Trading and arbitrage in cryptocurrency markets. *Journal of Financial Economics 135*(2), 293–319.

Pagnotta, E. S. (2022). Decentralizing money: Bitcoin prices and blockchain security. *Review of Financial Studies 35*(2), 866–907.

Schnorpfeil, P., M. Weber, and A. Hackethal (2024). Inflation and trading. Technical report, National Bureau of Economic Research.

Schwenkler, G. and H. Zheng (2021). Peer co-movement in crypto markets.

Shams, A. (2020). The structure of cryptocurrency returns. *Charles A. Dice Center Working Paper* (2020-11).

Sockin, M. and W. Xiong (2023). A model of cryptocurrencies. *Management Science*.

Stix, H. (2021). Ownership and purchase intention of crypto-assets: Survey results. *Empirica 48*(1), 65–99.

Weber, M., B. Candia, O. Coibion, and Y. Gorodnichenko (2023). Do you even crypto, bro? cryptocurrencies in household finance. Technical report, National Bureau of Economic Research.

Weber, M., Y. Gorodnichenko, and O. Coibion (2023). The expected, perceived, and realized inflation of us households before and during the covid19 pandemic. *IMF Economic Review 71*(1), 355.

Yu, G. Y. and J. Zhang (2022). Flight to bitcoin. *Available at SSRN 3278469*.

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 matched sample. The average (median) age of cryptocurrency investors in our sample is 32.26 (31) years, ranging from 18 to 87 years. About 86% of all investors in our sample identify themselves as male. The average current perceived inflation in the matched sample is at 13.52%. The average three-month ahead inflation expectation stands at 15.99%, and the average one-year ahead inflation expectation stands at 15.69%. 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 $-5,023.26$ 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	352.9	347.8	352.2	351.1
	(402.9)	(403.6)	(404.4)	(403.2)	(403.3)
Male	-20,080	-20,095	-20,043	-20,015	-19,973
	(12,745)	(12,726)	(12,694)	(12,727)	(12,716)
Constant	-12,417	-10,285	-12,276	-12,770	-14,117
	(22,633)	(22,907)	(22,079)	(22,608)	(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

$$Inr\_Amount\_Net_{i,t+1} = \alpha + \beta \times \text{Inflation\_Expectation}_{i,t} + \gamma \times \text{Age}_{i,t} + \lambda \times \text{Male}_{i,t} + \epsilon_{i,t+1}.$$

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***	1.040***
	(0.000544)	(0.000890)
Age	0.00277***	0.00351***
	(0.000438)	(0.000717)
Male	−0.0666***	−0.100***
	(0.00976)	(0.0160)
Constant	0.366***	1.590***
	(0.0188)	(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*	0.00430*	0.00471*	0.00453**	0.00509**
	(0.00219)	(0.00227)	(0.00240)	(0.00226)	(0.00242)
Annual Income (₹5-7.5$\times 10^5$)	43,021*	42,338*	41,251*	42,593*	41,243*
	(22,250)	(22,145)	(21,759)	(22,131)	(21,762)
Annual Income (₹7.5-10$\times 10^5$)	-16,428	-16,249	-16,431	-16,825	-17,155
	(28,776)	(28,858)	(28,770)	(28,840)	(28,894)
Annual Income (₹10-50$\times 10^5$)	15,009	14,666	15,132	14,820	15,443
	(18,494)	(18,537)	(18,621)	(18,470)	(18,550)
Annual Income ($>$ ₹50$\times 10^5$)	-19,920	-20,727	-20,286	-19,077	-18,233
	(27,386)	(27,632)	(27,885)	(27,467)	(27,552)
Age	-2,671**	-2,698**	-2,717**	-2,700**	-2,725**
	(1,356)	(1,363)	(1,370)	(1,362)	(1,367)
Male	11,691	10,365	9,870	10,839	10,285
	(13,659)	(13,641)	(13,698)	(13,687)	(13,709)
Constant	33,048	41,181	39,516	34,690	31,456
	(37,969)	(37,958)	(38,972)	(38,119)	(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	-115.4	-118.8	-113.5	-113.2
	(119.8)	(119.5)	(119.3)	(119.4)	(119.3)
Male	3,453	3,418	3,315	3,439	3,429
	(2,405)	(2,392)	(2,371)	(2,403)	(2,401)
Constant	6,761	7,122	7,036	6,839	7,139
	(6,524)	(6,701)	(6,803)	(6,585)	(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:

$$Inr\_Amount\_Net_{i,t+1} = \alpha + \beta \times \text{Inflation\_Expectation}_{i,t} + \gamma \times \text{Age}_{i,t} + \lambda \times \text{Male}_{i,t} + \epsilon_{i,t+1}.$$

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 (IV)				1.145***	
				(0.178)	
One Year Inflation (IV)					1.106***
					(0.172)
Number of Survey Respondents	0.611***	0.635***	0.603***	0.611***	0.610***
	(0.187)	(0.187)	(0.187)	(0.187)	(0.187)
Proportion of Self Employed	20.18***	19.75***	20.19***	19.87***	20.76***
	(6.536)	(6.518)	(6.523)	(6.534)	(6.541)
Constant	13.17***	10.27**	12.79***	11.72***	11.00**
	(4.249)	(4.417)	(4.308)	(4.397)	(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

Base / Token	INR Coefficient	INR Std. Error	USDT Coefficient	USDT 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	349.0	342.0	348.4	347.2
	(411.7)	(412.7)	(414.1)	(412.0)	(412.1)
Male	-20,372	-20,378	-20,349	-20,305	-20,260
	(12,931)	(12,911)	(12,887)	(12,912)	(12,899)
Rural	3,207	3,074	2,709	3,209	3,215
	(2,909)	(2,894)	(2,894)	(2,910)	(2,911)
Constant	-12,864	-10,651	-12,626	-13,233	-14,641
	(23,010)	(23,321)	(22,522)	(22,983)	(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 Fama-MacBeth regression results of:

$$Inr\_Amount\_Net_{i,t+1} = \alpha + \beta \times \text{Inflation\_Expectation}_{i,t} \times \text{Semi\_Urban}_{i,t} + \gamma \times \text{Age}_{i,t} + \lambda \times \text{Male}_{i,t} + \mu \times \text{Rural}_{i,t} + \epsilon_{i,t+1},$$

where Inflation_Expectation$_{i,t}$ represents the inflation expectation of agent i at time t, and Semi_Urban$_{i,t}$ and Rural$_{i,t}$ are indicator variables for agents located in semi-urban and rural areas, respectively. Age$_{i,t}$ and Male$_{i,t}$ denote the age and gender of agent i at time t. Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

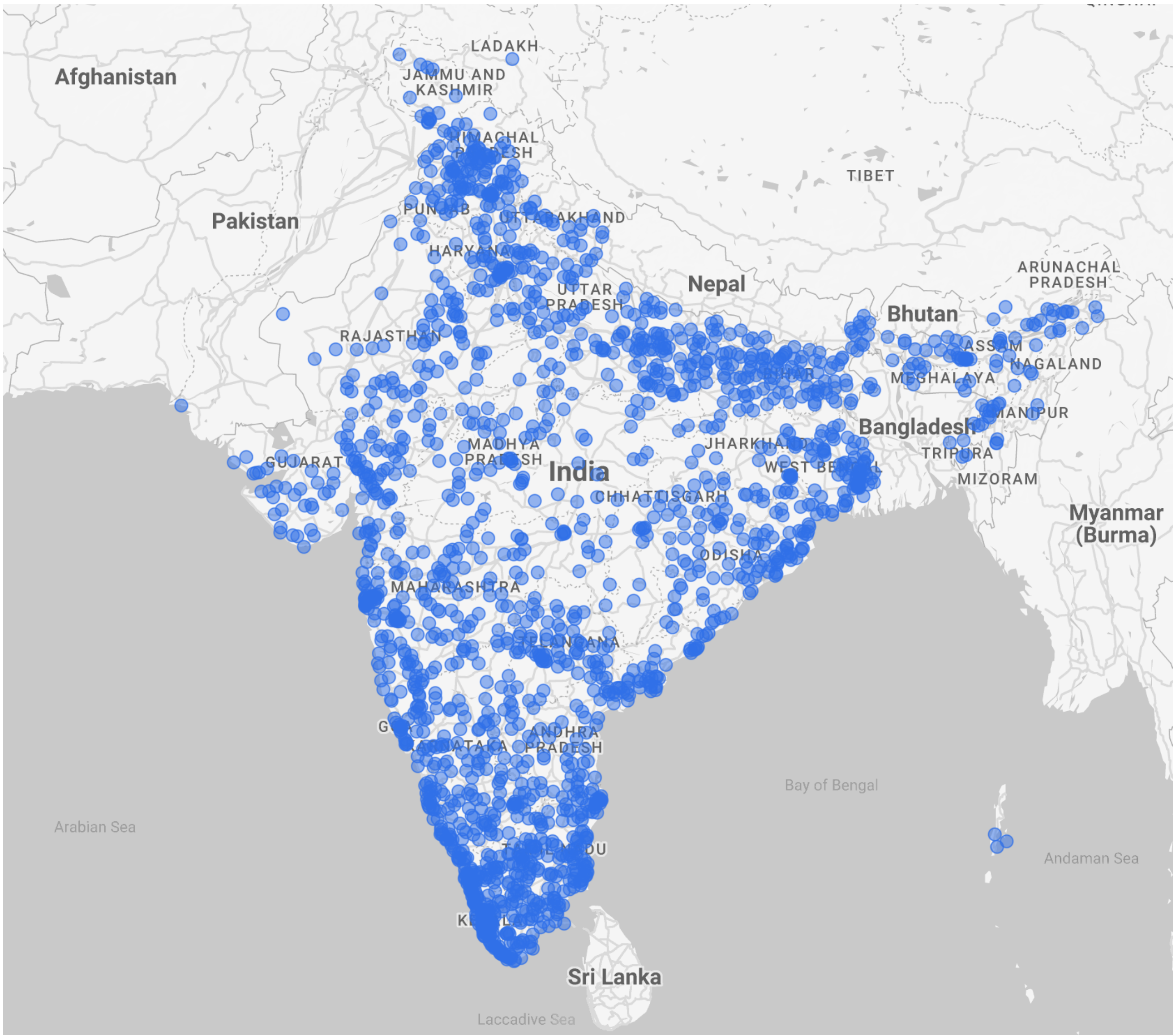
Table 12: By-Period Coefficients of One-Year Ahead Inflation Expectation

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 from Equation (1), for BTC, USDT, and the broader cryptocurrency market (All-Cryptos) over various periods from December 2017 to March 2022.

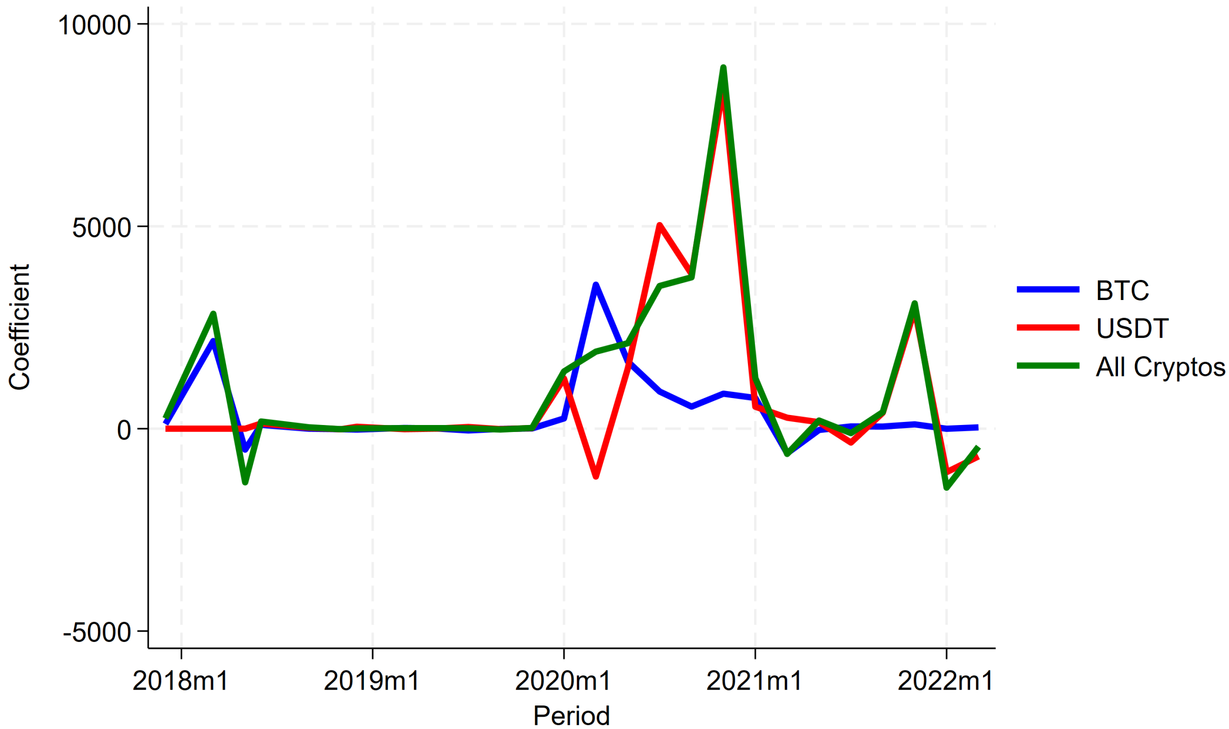
Figures

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. As the figure shows, our data has wide coverage over all regions in India.

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 of the IESH Survey

This section provides additional illustrations of the inflation expectation survey data in India. We demonstrate that the patterns identified in the Indian household inflation expectation surveys, conducted by the Reserve Bank of India (RBI) as part of their Inflation Expectations Survey of Households (IESH)[17], are largely consistent with those documented in the literature from other countries.

Figure A1 presents multiple visualizations to illustrate how surveyed household inflation expectations in IESH vary across cities, genders, ages, periods, and job designations, respectively. Overall, we observe significant variances in inflation expectations across cities and periods. Along with formal statistical testing, we find that inflation expectations tend to be higher among women (older people) than men (younger people). These patterns are consistent with the existing literature, as lucidly summarized in D'Acunto and Weber (2024).

[17] rbi.org.in/Scripts/QuarterlyPublications.aspx?head=Inflation%20Expectations%20Survey%20of%20Households

Figure A1: Inflation Expectations across Different Dimensions

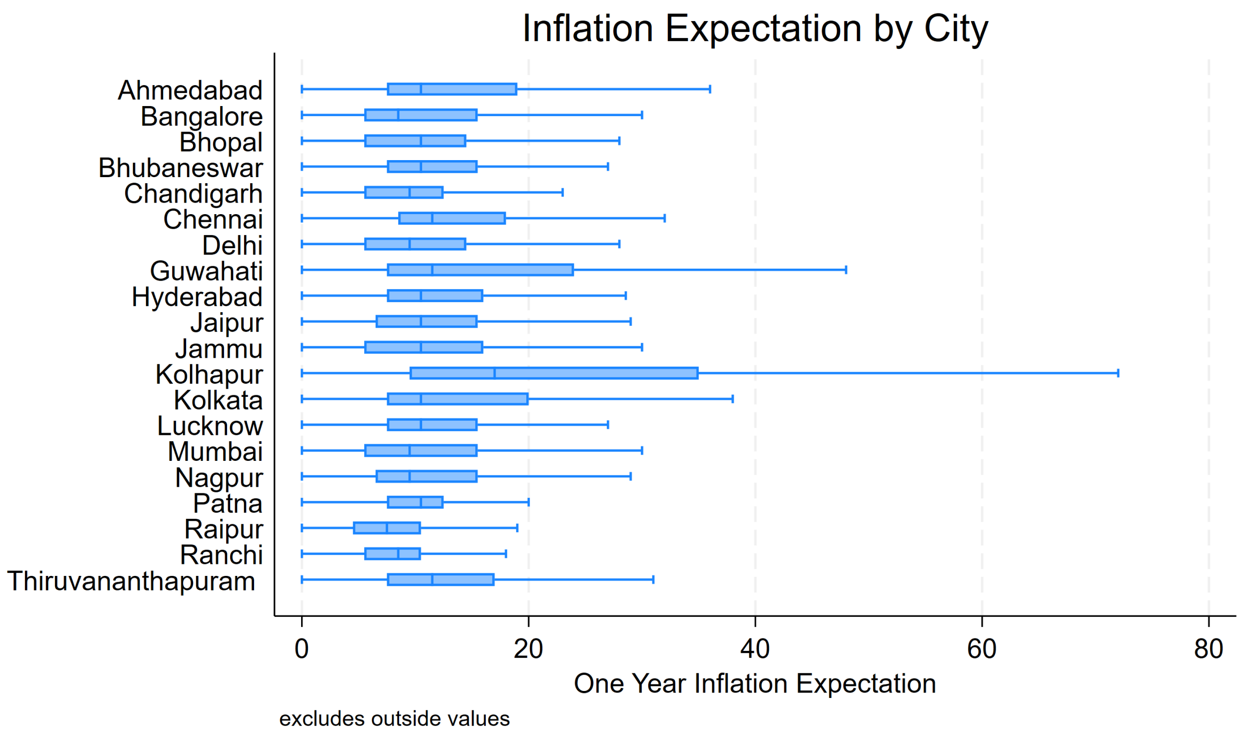


Figure A1: Inflation Expectations across Different Dimensions (Continued)

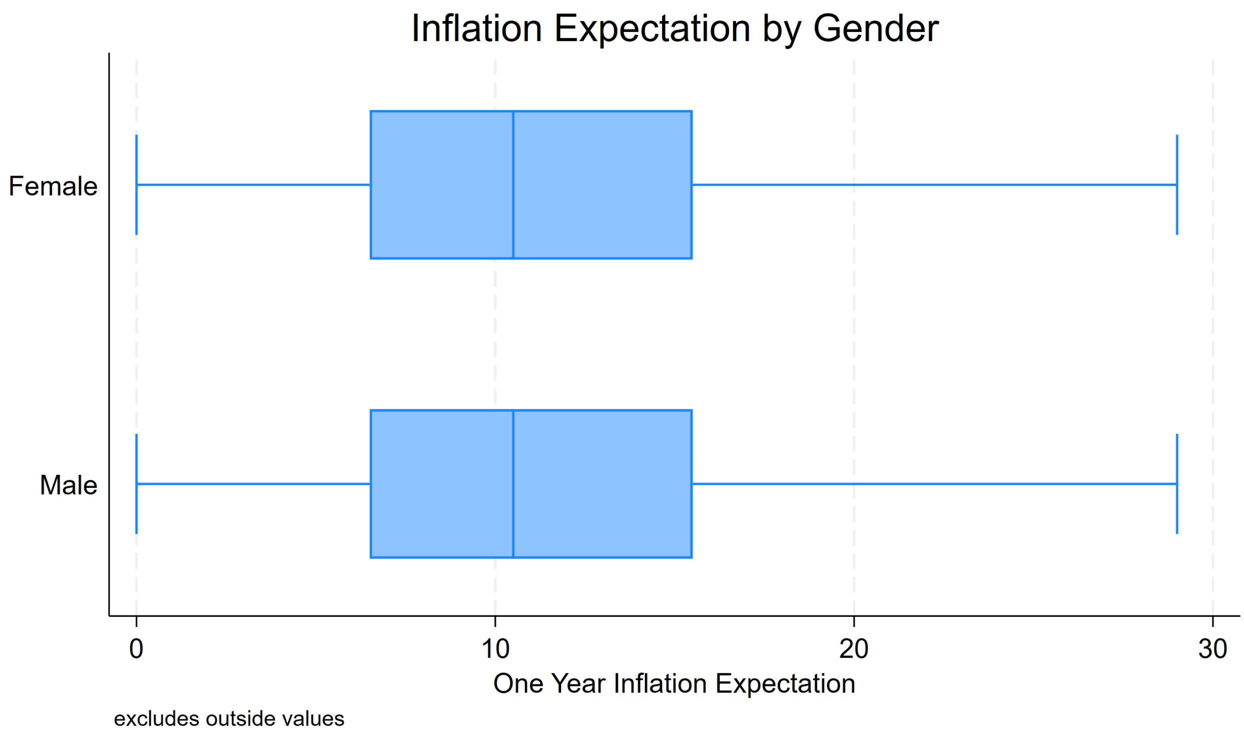


Figure A1: Inflation Expectations across Different Dimensions (Continued)

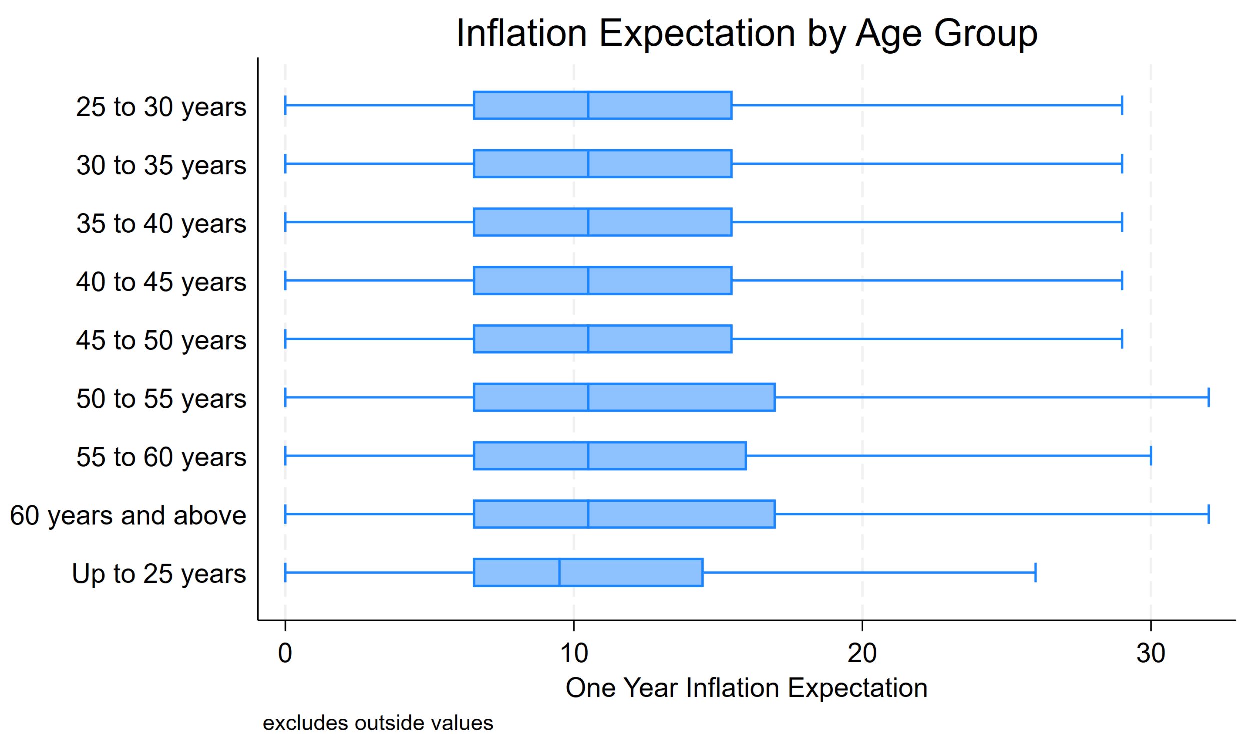


Figure A1: Inflation Expectations across Different Dimensions (Continued)

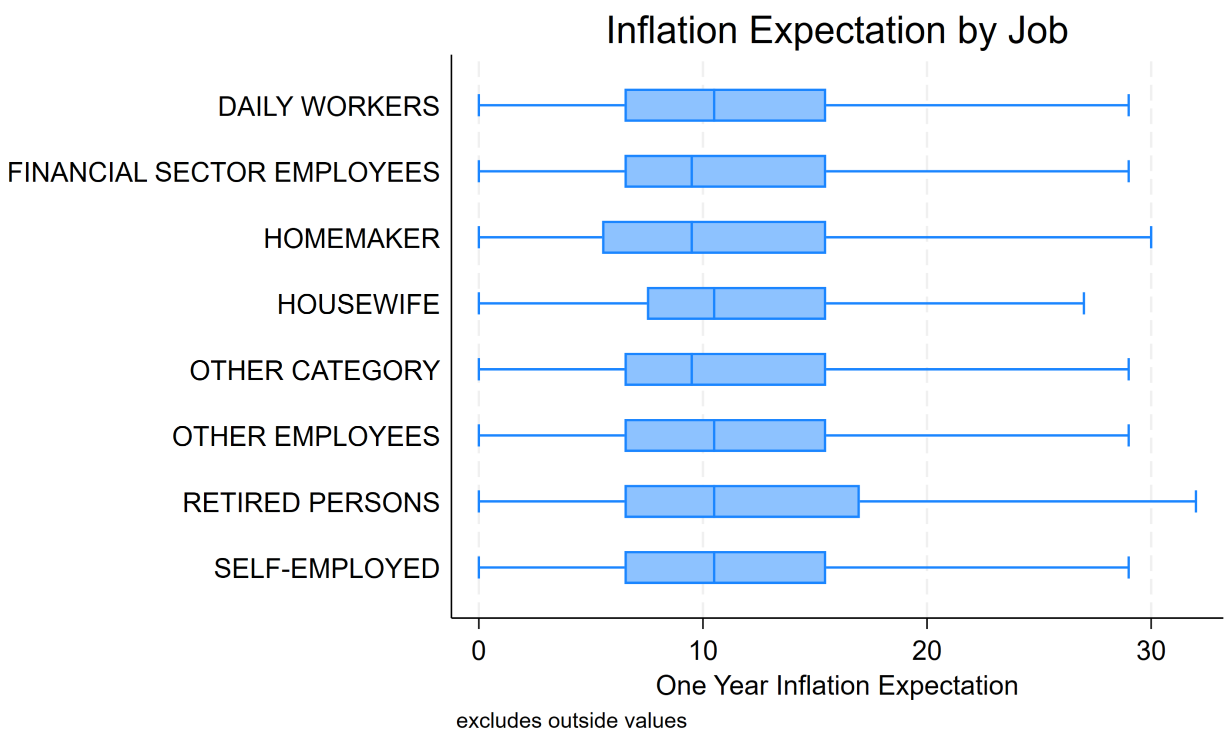
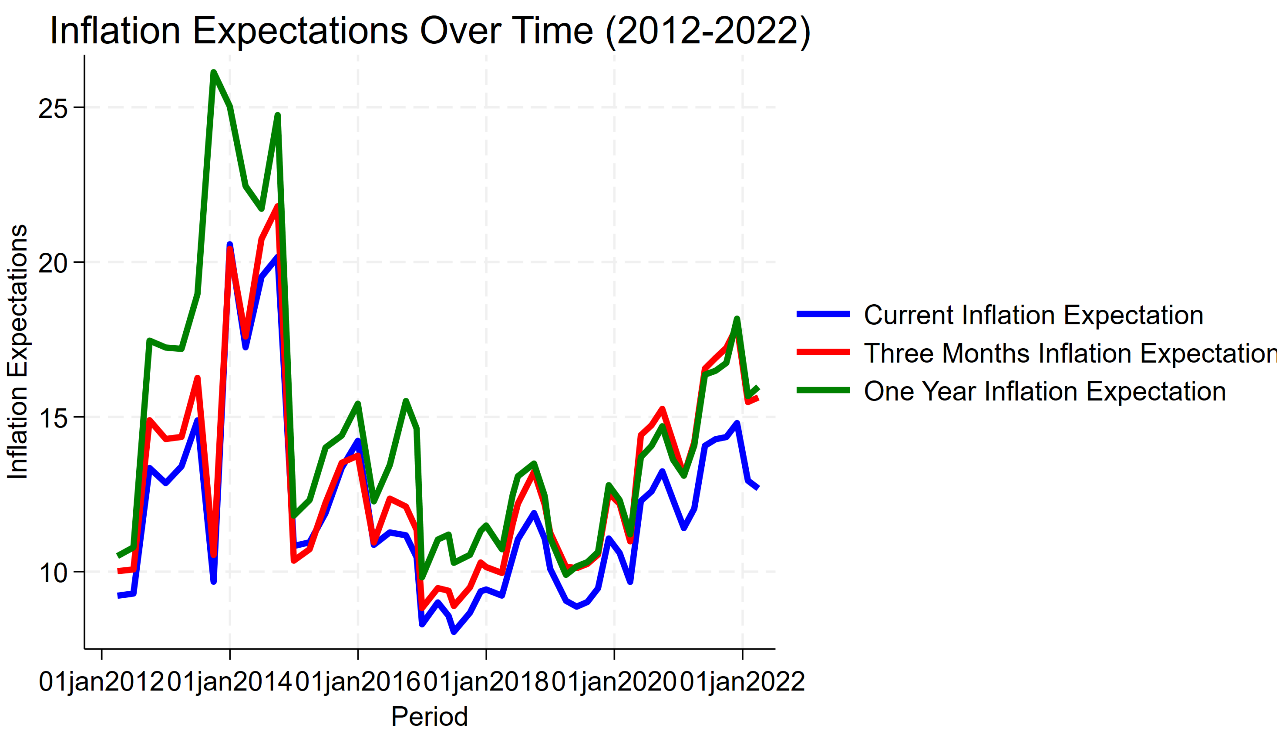


Figure A1: Inflation Expectations across Different Dimensions (Continued)



B Multiple Instrumental Variables Approach

To evaluate the robustness of our causal interpretation and address potential endogeneity concerns, we employ two additional instrumental variables (IVs) alongside our primary instrument of current inflation. These additional IVs are: (1) a weighted average of inflation expectations based on phone call networks connecting pincodes, and (2) an interaction term between the log of gas station density (normalized by nighttime light intensity) and state-level gasoline price changes. Both additional IVs follow the shift-share approach, originally developed by Bartik (1991) and further refined and applied in recent literature (Goldsmith-Pinkham, Sorkin, and Swift, 2020; Cong, Gao, Ponticelli, and Yang, 2019).

B.1 Social Network Shift-Share IV

Our first additional IV captures the impact of information diffusion through social networks on individual expectations. We construct this IV using detailed call data from 2019 to measure the strength of social connections between pincodes. Following Bailey, Cao, Kuchler, Stroebel, and Wong (2018) and Büchel, Puga, Viladecans-Marsal, and von Ehrlich (2020), we calculate call concentration as:

$$\text{Call Concentration}_{ij} = \frac{\text{Call Minutes}_{ij}}{\text{Total Call Minutes}_i},$$

where Call Minutes_{ij} is the total duration of calls between pincodes i and j, and $\text{Total Call Minutes}_i$ is the total duration of calls from pincode i.

For each pincode, we then calculate the weighted average inflation expectation of connected pincodes:

$$\text{Social Network IV}_i = \sum_{j \neq i} \text{Call Concentration}_{ij} \times \text{Inflation Expectation}_j,$$

where $\text{Inflation Expectation}_j$ is the average inflation expectation in pincode j.

B.2 Bartik Shift-Share IV

Our second additional IV follows the modified Bartik shift-share approach, using exposure to gasoline and exogenous gasoline price changes. We measure a region's exposure to gasoline prices as:

$$\text{Gas Exposure}_i = \log\left(\frac{\text{Number of Gas Stations}_i}{\text{Nightlight Intensity}_i}\right),$$

where Number of Gas Stations_i is the count of gas stations in pincode i, and Nightlight Intensity_i serves as a proxy for economic activity in the same pincode.

The shift component uses state-level gasoline price changes. The Bartik IV is then constructed as:

$$\text{Bartik IV}_i = \text{Gas Exposure}_i \times \Delta\text{State Gas Price}_s,$$

where s denotes the state in which pincode i is located. We use gas station counts from early 2018 and nightlight data from 2017 to ensure exogeneity.

B.3 Validation Tests

Following Cong et al. (2019), we conduct rigorous validation tests for both IVs. To examine the persistence of shares, we estimate the stability of both call concentrations and gas station densities over time using the equation $\text{Share}_{i,t} = \alpha + \beta\text{Share}_{i,t-1} + \epsilon_{i,t}$. A β close to 1 indicates high persistence, supporting the exogeneity assumption. We then test the exogeneity of shifts by examining whether inflation expectations for the social network IV and gas price changes for the Bartik IV are correlated with pre-existing pincode characteristics. This involves estimating $\text{Shift}_{i,t} = \alpha + \beta X_{i,t-1} + \epsilon_{i,t}$, where $X_{i,t-1}$ includes pre-period economic indicators and demographic characteristics. Insignificant β coefficients support the exogeneity of shifts.

B.4 Econometric Specification

Our first-stage regression equation is:

$$\text{Inflation Expectation}_{i,t} = \alpha + \beta_1 \text{Current Inflation}_{i,t} + \beta_2 \text{Social Network IV}_{i,t} + \beta_3 \text{Bartik IV}_{i,t} + \gamma X_{i,t} + \epsilon_{i,t},$$

where $X_{i,t}$ represents a vector of control variables including age, gender, and urban/rural classification.

The second-stage equation remains consistent with our main specification:

$$\text{INR Amount Net}_{i,t+1} = \alpha + \beta \widehat{\text{Inflation Expectation}}_{i,t} + \gamma X_{i,t} + \epsilon_{i,t+1},$$

where $\widehat{\text{Inflation Expectation}}_{i,t}$ is the fitted value from the first-stage regression.

B.5 Results and Discussion

Table A1 presents the first-stage IV estimation results. All three IVs exhibit positive and statistically significant coefficients, confirming their relevance in explaining inflation expectations. Specifically, a 1% increase in current inflation is associated with 1.148 and 1.044 percentage point increases in three-month and one-year ahead inflation expectations, respectively. The social network IV demonstrates positive effects, with coefficients of 0.0845 and 0.0544 for the three-month and one-year horizons. The Bartik shift-share IV yields coefficients of 0.639 and 2.375 for three-month and one-year inflation expectations, respectively.

Table A2 reports the second-stage results. The coefficient on current inflation is 1,162, statistically significant at the 5% level. The coefficients on three-month and one-year inflation expectations are 855.9 and 1,038, respectively, both statistically significant at the 5% level. When using fitted values from first-stage regressions as IVs, we obtain slightly larger coefficient estimates of 1,075 and 1,187 for three-month and one-year inflation expectations, significant at the 10% level.

While our sample size decreases from over 630,000 to approximately 460,000 observations due to the requirement of overlapping coverage for all three IVs, the coefficient estimates of the impact of inflation expectations on cryptocurrency investment remain consistent with our main results. The robustness of our analyses is further confirmed by the consistency of

Table A1: First-stage Regressions of Instrumental Variables

	Dependent Variable:	
	3-Month Inflation (1)	**1-Year Inflation** (2)
Current Inflation	1.148***	1.044***
	(0.000688)	(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***	2.375***
	(0.0340)	(0.0545)
Age	0.00304***	0.00530***
	(0.000546)	(0.000876)
Male	-0.0682***	-0.144***
	(0.0120)	(0.0193)
Semi-Urban	1.247***	0.714***
	(0.0382)	(0.0613)
Rural	-0.113***	-0.766***
	(0.0304)	(0.0488)
Constant	-0.805***	0.926***
	(0.0416)	(0.0683)
Observations	459,969	459,956
R^2	0.864	0.672

Note: This table presents the first-stage regression results for the IV estimations. The dependent variables are three-month and one-year ahead inflation expectations. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A2: 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	348.0	341.1	663.0	659.6
	(412.1)	(413.0)	(414.2)	(518.5)	(519.1)
Male	-20,370	-20,379	-20,347	-22,945	-22,848
	(12,928)	(12,910)	(12,886)	(16,755)	(16,713)
Semi-Urban	16,672***	15,960***	15,863***	10,983*	11,426*
	(5,319)	(4,903)	(4,837)	(5,462)	(5,687)
Rural	3,258	3,127	2,773	2,725	3,472
	(2,918)	(2,901)	(2,902)	(2,846)	(2,917)
Constant	-12,993	-10,766	-12,750	-21,500	-22,876
	(23,010)	(23,331)	(22,535)	(27,225)	(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

Note: This table presents the second-stage regression results. The dependent variable is the net amount of cryptocurrency purchased in Indian Rupees. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

results across different IV combinations.

C Temporal Dynamics of New Entrants

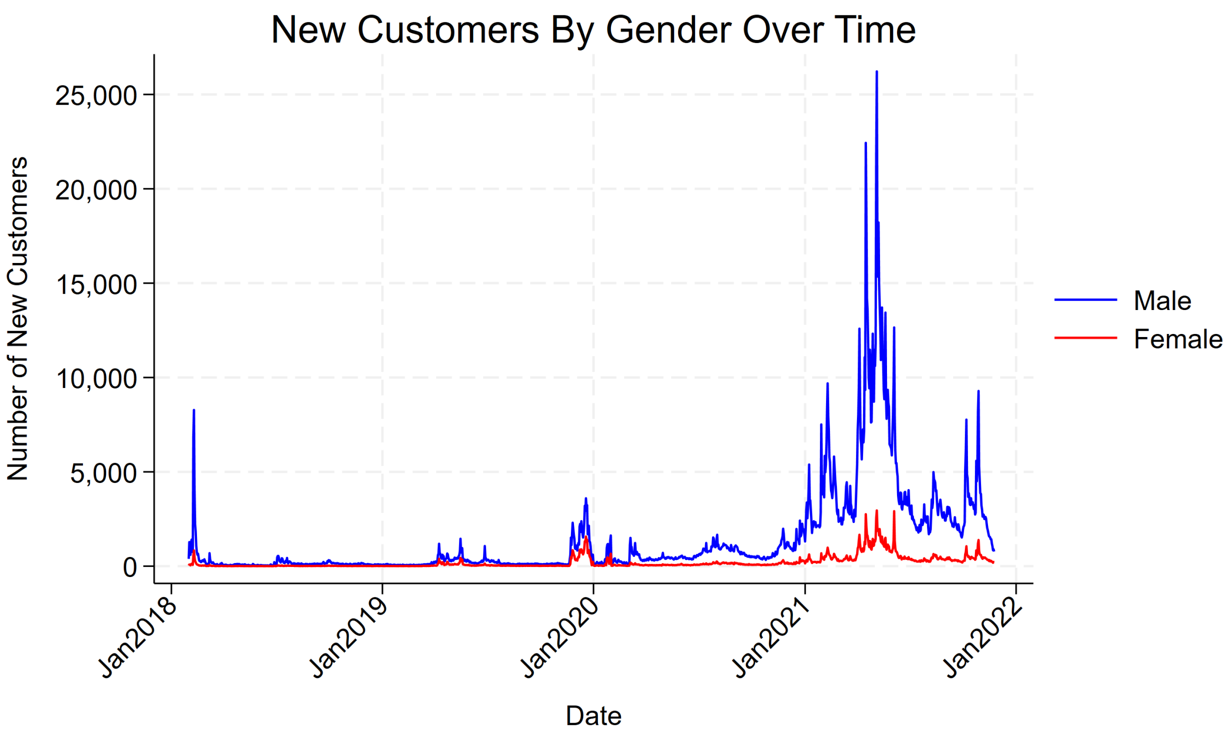
This section presents additional results on the temporal dynamics of new entrants to the exchange based on different entrant demographics.

The first panel of Figure A2 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 A3 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 A4 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 A2: New Customers By Gender Over Time



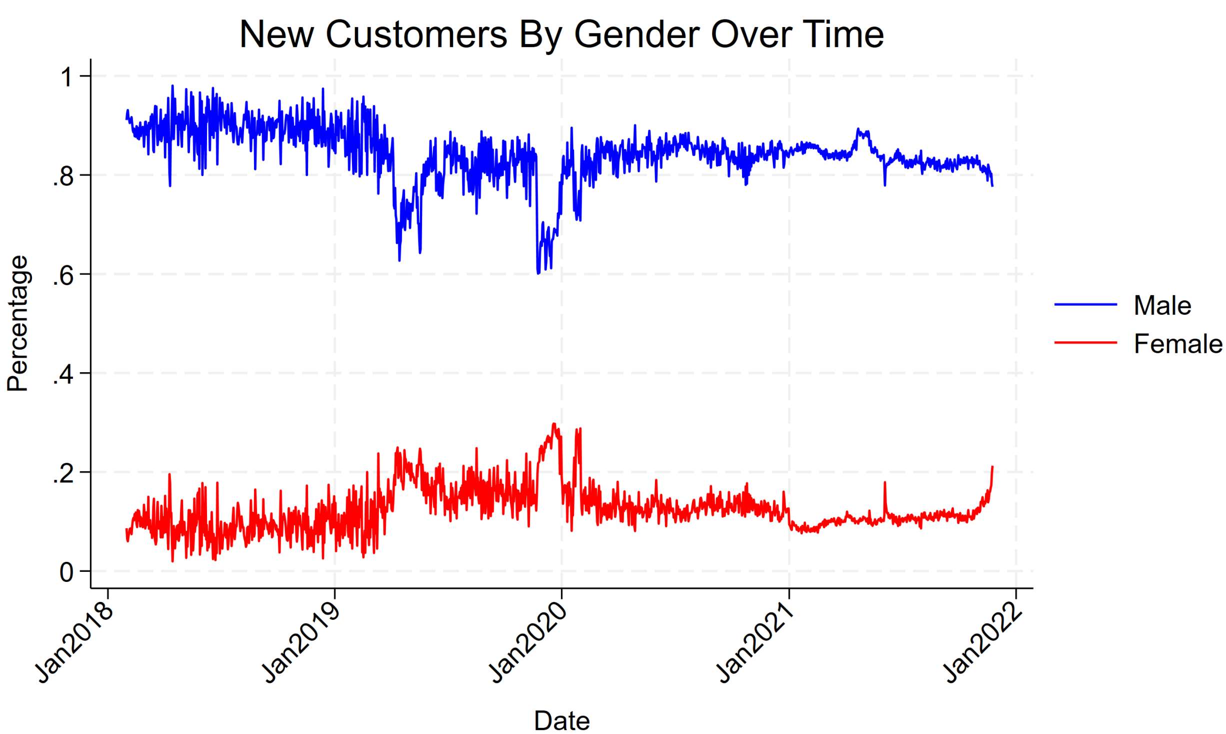
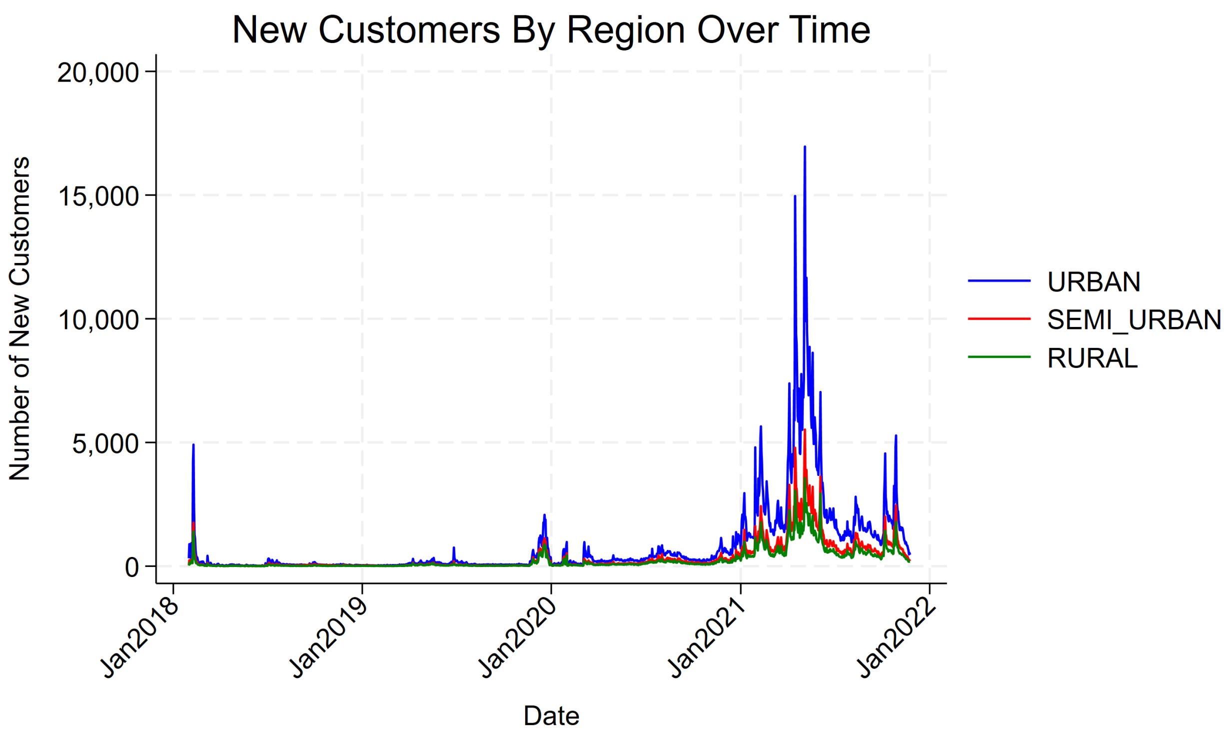
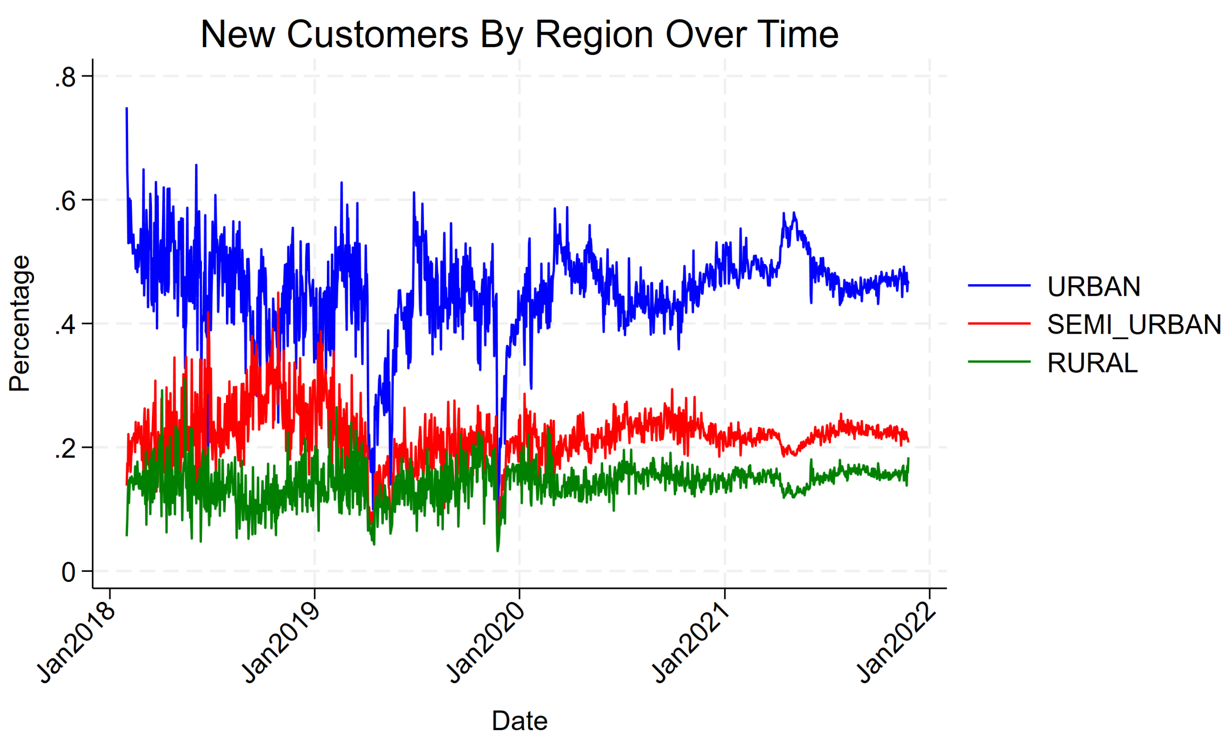


Figure A3: New Customers By Gender Over Time

Figure A4: New Customers By Region Over Time





D Theoretical Framework

As complement to our empirical analysis, this section further 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 intertemperal 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, our empirical analysis will help test the hypothesis that an increase in inflation expectations will prompt a surge in net purchases of US dollars and Bitcoin.