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Inflation Expectation and Cryptocurrency Investment

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Abstract

Using proprietary data from a dominant crypto exchange in India and the country's Household Inflation Expectations Survey, we document a significant positive correlation between inflation expectations and individual cryptocurrency purchases. Furthermore, inflation expectations prompt more new investors, particularly male investors, to begin purchasing cryptocurrencies. Token-wise, this effect is predominantly concentrated in Bitcoin (BTC) and Tether (USDT). The effect also has causal interpretations, as confirmed by using idiosyncratic shocks in current perceived inflation as an instrumental variable for long-term inflation expectations. We also discover that the relationship between inflation expectations and cryptocurrency investment is not driven by speculative expected returns from cryptocurrencies. Our findings suggest that certain cryptocurrencies have already been perceived by households as inflation hedges.

Keywords: Inflation Hedge, Expectations, Household Survey, Cryptocurrency, FinTech.

1 Introduction

A fundamental question in cryptocurrency research asks where the global demands for cryptocurrencies originate, as answers to such questions help better understand why cryptocurrencies with fiat backing ever accrue value. Over the years, the literature has provided a myriad of possible explanations for cryptocurrency demands, ranging from financing illicit activities (Foley, Karlsen, and Putniņš (2019), Li, Baldimtsi, Brandao, Kugler, Hulays, Showers, Ali, and Chang (2021), etc.), bypassing capital controls (Makarov and Schoar (2020), Yu and Zhang (2022), etc.), ensuring financial freedom (Choi, Lehar, and Stauffer (2022), Pagnotta (2022), etc.), or supporting platforms (Cong, Li, and Wang (2021), Li and Mann (2018), Sockin and Xiong (2023), etc.). Despite these discourses, there is little theory or empirical evidence for arguably one of the most oft-advocated advantages of cryptocurrencies in that many of them are not "inflationary" and may serve as inflation hedges.[1]

Empirically establishing the relationship between inflation hedging motives and cryptocurrency demand, however, faces many challenges. For example, a naive correlation between cryptocurrency/Bitcoin returns and inflation expectations (or realized inflation) indicates mixed results. Therefore, we still need direct evidence to answer (1) whether households really regard cryptocurrency investment as inflation hedges. In case of a positive answer, there are also many follow-up questions: (2) How much does inflation expectation drive cryptocurrency investment? (3) What cryptocurrency do households view as inflation hedges? (4) Does the result differ across demographic groups? Finally, given that cryptocurrencies are global assets, one may also wonder (5) do households outside of the United States, especially those in emerging economies, view cryptocurrency investment as inflation hedges?

From a theoretical perspective, we also highlight that the answers to the above questions are not necessarily clear ex ante. For example, for question (1), despite what people may discuss or respond to in surveys (Stix, 2021), it is not guaranteed that people do put money where their mouths are. For question (3), it is also not clear whether all coins will be regarded

[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*.

similarly for inflation hedging: Although 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 an increasing supply or non-committed coin issuance schedules (e.g. Ethereum's EIP-1559 significantly changed its coin issuance schedule, changing it from an inflationary asset to a likely deflationary one). In sum, answering the various questions requires access to granular trader-level information to link inflation expectations and cryptocurrency investment decisions.

In this paper, we overcome the data challenges facing researchers and firmly establish direct evidence of the relation between inflation expectation and cryptocurrency investment by exploiting a micro-level dataset from India, one of the largest emerging economies perennially gripped by high inflation. Specifically, our proprietary data come from one of the largest Indian cryptocurrency exchanges with granular individual-level trading records. In addition to having access to the timestamp, size, price, market (the pair of the exchanged asset), 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 the localized, demographic-level data on inflation expectations from the semi-bi-monthly Inflation Expectations Survey of Households (IESH) to explore the relationship between inflation expectations and cryptocurrency trading.

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 survey month. 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). We further investigate the heterogeneity of our findings across different dimensions: 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. Across the demography 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 the response to cryptocurrency investment to inflation expectation. Across the geographic dimension, we find that positive relationships between inflation expectations and crypto investments tend to occur in states with higher historical inflation. Finally, across the time dimension, we find the effect to be more salient during periods with higher aggregate attention to cryptocurrencies.

Overall, our findings suggest that inflation expectations have a significant impact on households' purchase decisions in Bitcoin and Tether (USDT). Therefore, some cryptocurrencies, although not all of them, are perceived as potential inflation hedges by households. Therefore, using granular micro-level evidence, our study highlights the macro-level implications of cryptocurrencies within the broader economy.

Related Literature Our research contributes to multiple streams of the literature.

First, our results 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, and find that they tend to be momentum traders with cryptocurrencies despite being contrarian with stock and gold investments. This paper, however, does not look into inflation expectations. In a parallel work to ours, 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. Aside from the population differences, they measure cryptocurrency investment by fiat transfers to crypto exchanges, so they cannot distinguish what coins are being purchased (nor the potential gap between fiat deposit to exchanges and actual investment), while we directly observe investors' trading decisions on the exchange so that we can identify what coins are being purchased for inflation hedges. We are the first work to match cryptocurrency trading data with household survey data.

Second, our paper contributes to the literature on the economic impact of inflation expectations. Recent examples include Coibion, Gorodnichenko, and Weber (2022) and Coibion, Gorodnichenko, and Ropele (2020), which shed light on the repercussions of inflation expectations on consumer behaviors and corporate decisions, respectively. We further this narrative by soliciting firsthand inflation expectations from households and exploring their impact on cryptocurrency investments. More specific to cryptocurrency investment, Weber, Candia, Coibion, and Gorodnichenko (2023) conduct surveys of U.S. households about their cryptocurrency investment decisions and relate to inflation hedging motives. While their findings resonate with ours, our direct evidence from the actual trading behaviors of the entire crypto investor population on the largest cryptocurrency exchange in India complements their survey from a representative sample of U.S. households.

In a broader sense, our study also 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 (VAR) model to suggest Bitcoin as an inflation hedge but not a safe haven. The interaction among the US dollar, the Indian Rupee, and cryptocurrencies also echoes the theoretical framework of Cong and Mayer (2022). In sum, harnessing granular individual-level trading data allows us to exploit micro-level evidence to provide macro-level implications.

Finally, our findings also contribute to the emerging literature on the cryptocurrency trading market overall. For example, Makarov and Schoar (2020), Choi, Lehar, and Stauffer (2020), and Yu and Zhang (2020) 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. Shams (2020) and Benetton and Compiani (2020) relate crypto-asset returns to investor demands, while Schwenkler and Zheng (2021) relate them to co-mentions in news. Biais, Bisiere, Bouvard, Casamatta, and Menkveld (2018) relate Bitcoin prices with changes in transactional benefits and costs of Bitcoin. Gandal, Hamrick, Moore, and Oberman (2018), Hamrick, Rouhi, Mukherjee, Feder, Gandal, Moore, and Vasek (2018), Griffin and Shams (2020), Li, Shin, and Wang (2019), Xu and Livshits (2019), Dhawan and Putniņš (2021), Cong, Li, Tang, and Yang (2020), Aloosh and Li (2023), Amiram, Lyandres, and Rabetti (2020), and Dyhrberg, Foley, and Svec (2019) document various manipulations in the cryptocurrency market. Augustin, Rubtsov, and Shin (2020) studies the impact of introducing the Bitcoin futures contract on the spot market. Foley et al. (2019) study the illegal usage of cryptocurrencies. Guo, Li, Luo, and Wang (2022) studies the liquidity of Bitcoin options contracts. Our paper also touches upon the regulation of the crypto market in general, as in Li and Mann (2018, 2021).

2 India and Cryptocurrencies

This section provides some institutional background to help appreciate why India has many features that make it a particularly relevant market to study the relationship between inflation expectation and crypto investment.

On the one hand, India holds a significant position in the global cryptocurrency landscape. As evidence, the Chainalysis 2022 Global Crypto Adoption Index[2] places India in the fourth spot for cryptocurrency adoption, leading in numerous categories. This elevated adoption is also witnessing substantial growth. A Statista survey projects that by the end of 2023, over 11% of India's population will have ventured into the cryptocurrency sector. This rate of adoption is poised to surpass that of the United States, the United Kingdom, Japan, and Russia[3]. Additionally, India's prominent role in the global crypto market is underpinned by its demographics. It is the most populous country in the world, with a projected population surpassing 1.39 billion by 2023, and more than half of its residents are under 25, a group more likely to be digitally literate.

On the other hand, India is also particularly relevant for studying the relationship between inflation expectations and cryptocurrency investment for multiple reasons.

[2] https://www.chainalysis.com/blog/2022-global-crypto-adoption-index/
[3] https://cryptopotato.com/india-to-have-over-150-million-crypto-users-by-the-end-of-2023-study/

First, India has historically been plagued with high inflation. Indeed, India's average inflation rate over the past decade hovers over 6.32%, peaking at 10.91% in 2013 and bottoming at 3.59% in 2017. Furthermore, such high inflation in India is largely due to monetary oversupply rather than shortages of goods in the supply chain. As Table 1 presents the inflation, exchange rate, and the differential for INR from 2011 to 2021, we notice that the inflation rate and depreciation rate in USD/INR are both high in India, although their difference is much smaller. Therefore, cryptocurrencies like Bitcoin that does not suffer from oversupply thanks to its fixed quantity by design or the stablecoin Tether that is pegged to USD may enjoy nice properties that make them attractive alternatives for Indian households to preserve the value of their wealth.

Table 1: Inflation, Exchange Rate, and Differential of INR (2011-2021)

Year	**Inflation (%)**	**FX Rate (INR/USD)**	**FX Rate Change (%)**	**Diff. (%)**
2011	8.87	46.67	-	-
2012	9.30	53.44	14.50	-5.20
2013	10.91	58.60	9.66	1.25
2014	6.37	61.03	4.14	2.23
2015	5.87	64.15	5.13	0.74
2016	4.94	67.19	4.75	0.19
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	6.33	-0.13
2021	4.91	73.49	-1.80	6.71
Average	6.15	64.02	4.78	1.37

This table presents the inflation, exchange rate, and the differential for INR from 2011 to 2021. **Year** indicates the year. **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 rate and the depreciation rate of the INR/USD exchange rate.

Second, it is difficult for Indian households to hedge inflation via fiat currencies. Theoretically, other fiat currencies like the US dollar could serve as a hedge against inflations 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 could as a viable alternative.

3 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 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, $y_t^{nominal} - c_t^{nominal}$:

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

The marginal influence of inflation expectations on savings and investments can be represented by $1 + \sigma(\rho - 1)$. When an asset serves as an effective inflation hedge—indicated by a larger ρ value—the impact of inflation expectations on asset acquisitions intensifies.

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.

4 Data

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

Cryptocurrency Exchange Dataset We use proprietary individual-trader-level data from a dominant cryptocurrency exchange in India to gauge investors' crypto trading decisions. This dataset encompasses in total of 85,785,078 transactions, spanning from January 2018 to June 2022. Each transaction contains information such as 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), Pincode, and Date_of_joining as presented in Table 2. The median age of investors is 31 years, with 83.66% identifying as male and 93.79% located in India.

Our data contains many trading pairs with different base currencies (for example, in the trading pair BTC-INR, Indian rupee, or INR, is the base currency). Among all transactions, The dominance of the local fiat currency INR as base currency is evident, accounting for 76.53%. This is succeeded by Tether (USDT) which represents 21.36% of the volume. The exchange's native token contributed to 1.16% of the transactions, and Bitcoin (BTC) constituted a minor proportion, representing 0.95% of the total transactions.

Cryptocurrency adoption and trading trends across different Indian states also show distinct patterns. Figure 1 provides an overview of the raw netbuy volumes of an average investor in each state during our sample period of January 2018 to June 2022. Distinct disparities are evident in the raw netbuy volumes. States like Tamilnadu, Puducherry, and Uttar Pradesh register prominent netbuy volumes, while Delhi, Gujarat, and West Bengal

Table 2: Summary of Indian Cryptocurrency Exhcange 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 × Volume	Num
Bid Fee Paid	Fee Paid by Buyer	Num
Ask Fee Paid	Fee Paid by Seller	Num
Currency for Bid Fee	Currency in which fee is paid by buyer	Char
Currency for Ask Fee	Currency in which fee is paid by Seller	Char

reflect significant net sells, suggesting heightened selling activities.

IESH Dataset We use Indian's Inflation Expectation Survey of Households (IESH) data to evaluate investors' inflation expectations. The IESH dataset was initiated in November 2006 and contains survey periods, city, respondent demographics (age and gender), perceived current inflation rates, and projected three-month-ahead and one-year-ahead inflation rates. Inflation expectations are recorded in intervals (e.g., 1% - 2%), except for those beyond 16%, for which the actual number is recorded. Table 3 lists all the included variables.

Inflation expectations display variance across Indian states according to the IESH dataset. For instance, Delhi projects a one-year inflation rate of 12.83%, while Maharashtra's expectation is 13.87%. In stark contrast, Nagaland anticipates a mere 2.5%. On the higher spectrum, Manipur predicts an inflation of 20.00%. Figure 2 provides a detailed visualization.

Data matching We match the exchange data with the IESH data to carry forward our subsequent analysis. Because the inflation expectation in the IESH dataset comes with an interval rather than a precise number (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. This transformation lets us proxy each investor's inflation expectation

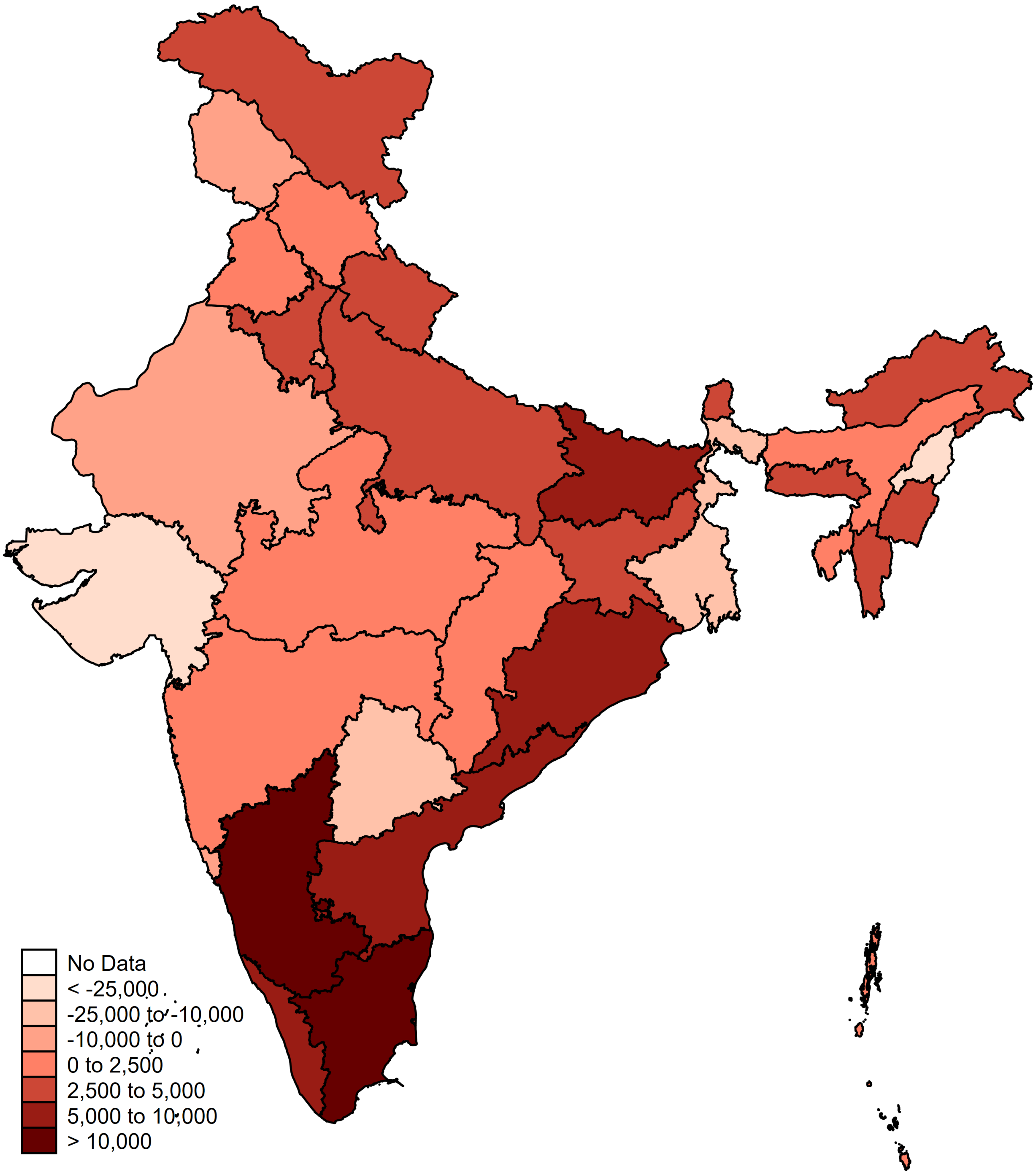

Figure 1: Crypto Netbuy Volume Across States

This figure illustrates the net cryptocurrency purchase volumes of an average investor by state, totalling our sample period from January 2018 to June 2022.

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%

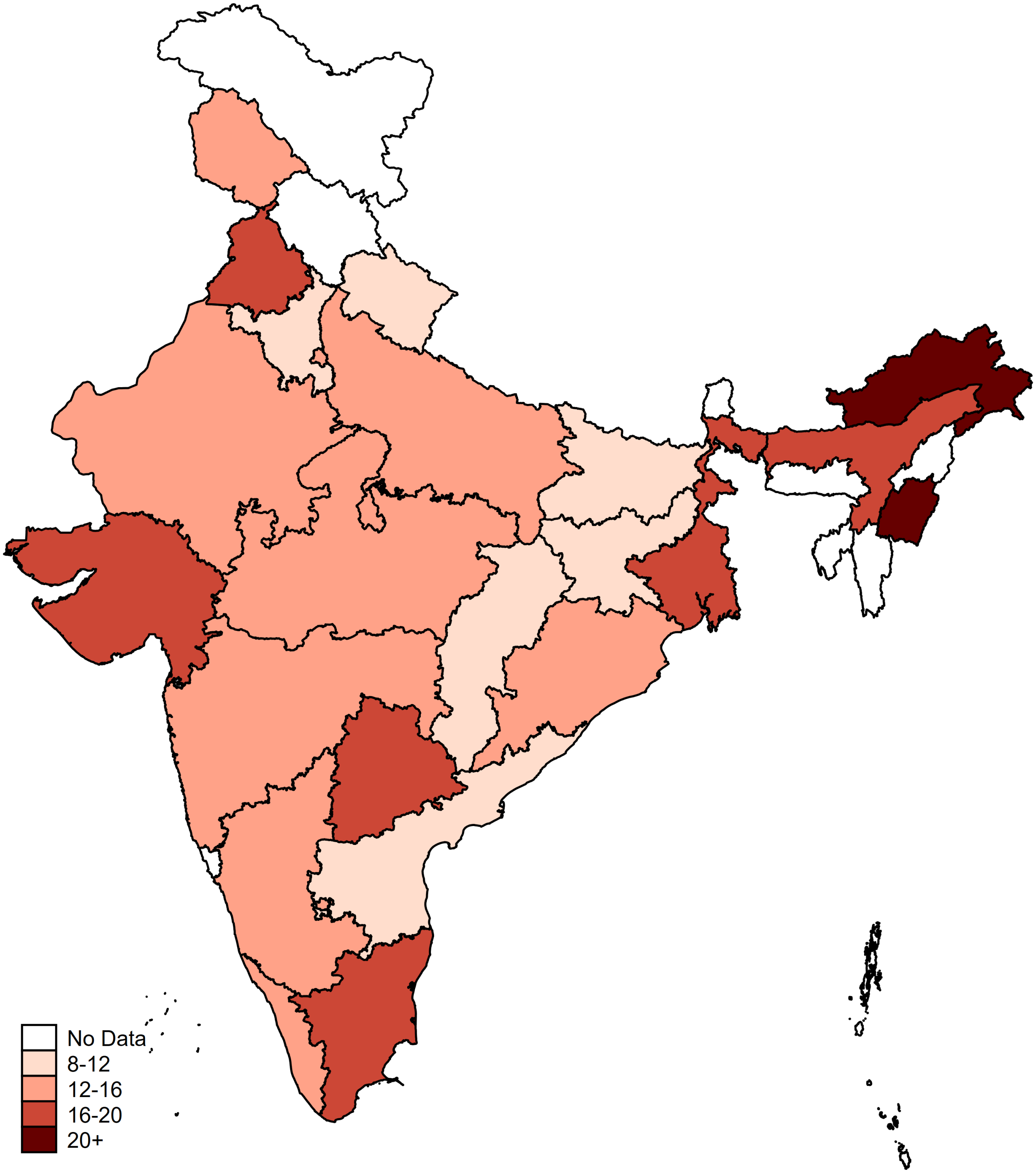

Figure 2: One-year inflation expectation across Indian states using the IESH dataset.

in a specific pincode-period using the average for that pincode-period pair.

Summary Statistics We provide summary statistics of our main variables in Table 4, offering insights into selected financial and demographic indicators of the participants. The average age of the respondents is roughly 32.26 years, with a dispersion of 7.80 years, spanning from a youthful 18 to a mature 87 years.

The gender index, where "1" corresponds to male, denotes that males constitute approximately 85.25% of the sample, with a variance encapsulated by a standard deviation of 0.35.

Shifting focus to inflation expectations, current perceived inflation in the Indian market averages at 13.48%, accompanied by a 6.27% standard deviation. The three-month forward-looking inflation rate stands at an average of 15.94% and has a 7.73% standard deviation. For the one-year horizon, the rate slightly diminishes, averaging at 15.63% with a deviation of 7.94%.

The variable `inr_amount_net` provides a window into the net buy volume in Indian rupees (INR) for individual investors. The mean transaction volume is positioned at -5236.227 INR. However, there is considerable variability among investors, highlighted by a substantial standard deviation of around 2.84 million INR. The spectrum of transactions stretches from a notable negative of nearly -1.58 billion INR to a significant positive peak close to 755 million INR, reflecting the varied trading magnitudes within the dataset.

Table 4: Summary Statistics of the Matched Data

	Obs	**Mean**	**Std. dev.**	**1%**	**25%**	**50%**	**75%**	**99%**
age	650,973	32.26	7.79	20	26	31	38	50
gender_index	650,973	0.86	0.35	0	1	1	1	1
current_inflation	650,973	13.52	6.26	4.57	9.13	12.27	16.57	34.09
three_month_inflation	650,972	15.99	7.72	5.45	10.5	14.4	19.51	42.86
one_year_inflation	650,973	15.69	7.92	3.23	10.17	14.1	19.43	41.97
inr_amount_net	650,973	-5,023.26	2,853,142	-236311.8	-887.8	146.44	3204.72	237311.6

5 Identification and Empirical Results

As our dataset features infrequent transactions over time from a large cross-section of investors, we employ the Fama-MacBeth regression, a popular technique in finance (Fama and MacBeth, 1973). This approach offers several advantages for our analysis. First, it allows us to extract the cross-sectional relationship between households' inflation expectations and their netbuy volume of cryptocurrencies. Second, it enables us to estimate time-varying coefficients, thereby accounting for the dynamic nature of the inflation-crypto relationship. Third, it does not require each individual to have multiple time-series observations, making it well-suited for our data, which features a large number of investors with infrequent trading activities.

In this section, we outline our empirical design. Specifically, our baseline regression includes the netbuy volume in Indian Rupee of investor i at period $t+1$, inflation expectation, age, gender, and individual total volume traded, and 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 denotes the investor and t denotes the period in which the inflation expectation survey is conducted.

To identify the causal effect between inflation expectations and netbuy volumes of cryptocurrency among Indian households, we turn to an instrumental variable (IV) approach. In line with Weber et al. (2023), we employ perceived inflation (current inflation) as the IV for expected inflations, either three months or one year ahead. This IV satisfies the relevance criteria as Table 6 shows significant first-stage regression results. We argue that the IV also satisfies the exogeneity criteria. This is because 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's reasonable to posit that such perceptions are not directly implicated in subsequent cryptocurrency investment decisions. Thus, ensuring the exogeneity of the perceived inflation helps mitigate concerns about omitted variable bias or reverse causality that might confound the relationship between inflation expectations and cryptocurrency investments.

5.1 Empirical Analyses: The Role of Inflation Expectations

Table 5 presents regression results exploring the association between inflation expectations and the net amount (denoted by *inr_amount_net*) in the context of cryptocurrency.

1. **Statistical Significance of Inflation Variables**: The inflation expectation variables, namely current inflation, three months inflation, and one-year inflation, exhibit statistical significance at the 5% level. This significance persists even when demographic controls, such as age and gender, are included in the regression.

2. **Economic Magnitudes**: The regression coefficients also demonstrate the magnitude of the association between the inflation metrics and the dependent variable. Specifically, a one percentage point increase in current inflation is associated with a ₹1,112 increase in netbuy volume of cryptocurrencies in the period before the next inflation expectation survey (typically two or three months), holding other factors constant. Similarly, a one percentage point increase in three-month (one-year) inflation expectation is associated with a ₹819.3 (₹998.5) increase in netbuy volume of cryptocurrencies, respectively. For context, India's net national income per capita (at current prices) for 2022-23 stands at ₹172,000. Therefore, given that IESH typically conducts five to six inflation surveys every year, a one percentage point increase in inflation expectations results in an increase in cryptocurrency investment of about 3% - 4% (annualized) net national income per capita in India.

3. **Instrumental variables and casual interpretation**: The last two columns in Table 5 also show the IV regression results. Specifically, 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 (typically two or three months). The coefficients of IV regressions are slightly larger than the coefficents in the direct regressions of (2) and (3) of Table 5. Specifically, a one percentage point increase in three-month (one-year) inflation expectation leads to a ₹962.3 (₹1,066) increase in netbuy volume of cryptocurrencies, respectively.

4. **Placebo Tests**: In assessing the robustness of our findings, we further extend our analysis to trading pairs with base currency denominations of USDT and BTC, in addition to INR. The outcomes are articulated in Tables 14 and 15. For trading pairs denominated in USDT and BTC, the regression coefficients are negative, albeit statistically insignificant. This contrasts sharply with our findings for pairs denominated in INR, wherein a notable relationship is evident. Such findings suggest that inflation expectations induce investors to pivot from the Indian Rupee (INR) towards other cryptocurrencies. In contrast, such expectations do not manifest a similar behavior with USDT or BTC. This strengthens our primary assertion that cryptocurrencies serve as a hedge against inflation risks inherent in the INR.

The results of first stage of IV regressions are shown in Table 6, in which we regress three-month and one-year inflation expectations on current perceived inflation. The coefficients of current inflation are both significant at 1%. We notice that the R-squard of the three-month inflation expectation is 87.3%, and that for one-year inflation is 67.7%. This makes sence since when households consider the inflation in a longer term, more uncertainties are taken into account. The coefficient of age is positive and significant, indicating that individuals who are older have higher inflation expectations, while the coefficient of gender (Male=1) is negative and significant, which means female individual generally has higher inflation expectations than male.

Table 5: Effects of Inflation Expectations on Cryptocurrency Purchase Behavior: Fama-MacBeth Regression Results (Jan 2018 - June 2022)

VARIABLES	(1) **current** **inr_amount_net**	(2) **three_months** **inr_amount_net**	(3) **one_year** **inr_amount_net**	(4) **three_months_hat** **inr_amount_net**	(5) **one_year_hat** **inr_amount_net**
current_inflation	1,112**				
	(485.0)				
three_months_inflation		819.3**			
		(340.2)			
one_year_inflation			998.5**		
			(419.3)		
three_months_inflation_hat				965.0**	
				(420.8)	
one_year_inflation_hat					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)
gender_index	-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 *three_months_inflation_hat* and *one_year_inflation_hat* are fitted values from the first stage linear regression on current perceived inflation. Standard errors 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 Inflation	1.153***	1.040***
	(0.000544)	(0.000890)
Age	0.00277***	0.00351***
	(0.000438)	(0.000717)
Gender Index	-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

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

5.2 Extensive Margin: Inflation Expectations and New Cryptocurrency Customers

Beyond evaluating the impact of inflation expectations on the investment behavior of existing cryptocurrency participants (the intensive margin), our research extends to investigate the role these expectations play in driving new customer onboarding within the cryptocurrency domain (the extensive margin). The temporal dynamics of new entrant demographics, delineated in Figure 3, shed light on the gender distribution of these 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.

We further calculate the new customer count at each pincode-period combination and match it with the inflation expectation level of the pincode and the period. We find a

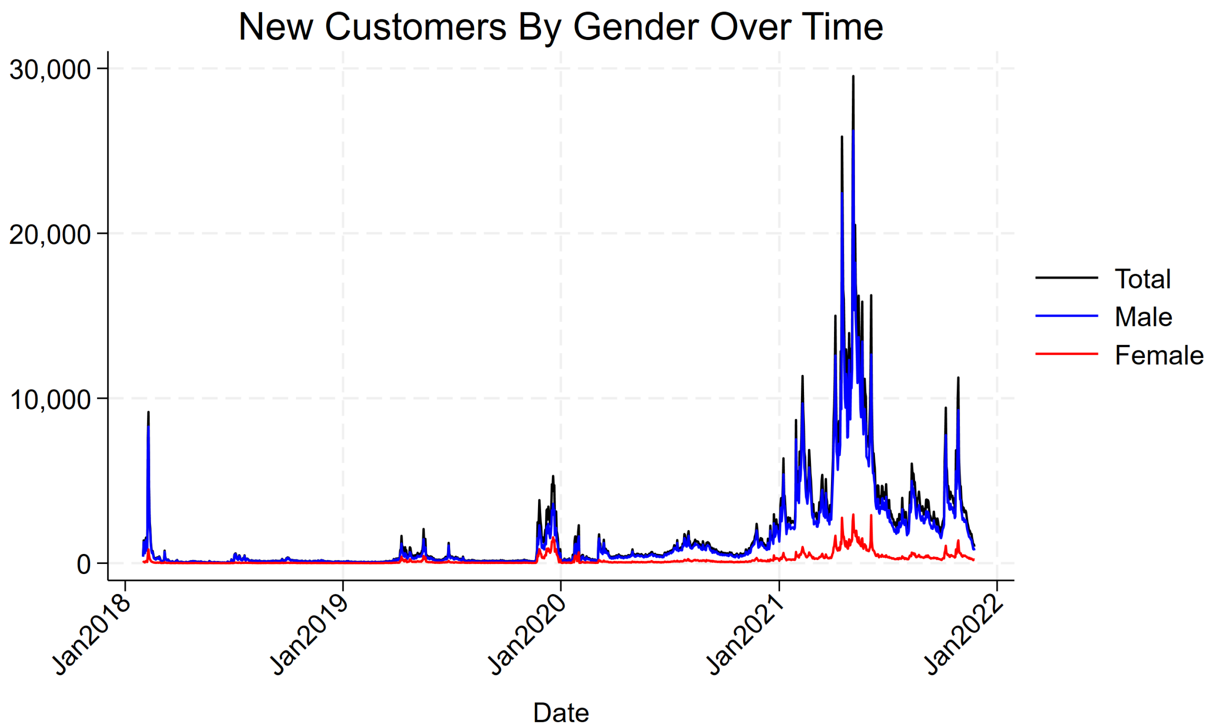

Figure 3: New Customers By Gender Over Time

significant and positive relation at the 1% level between inflation expectation and the number of new customers, as the results shown in Table 7. 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, and standard errors clustered at the pincode level. Thus, we find evidence that inflation expectations increase cryptocurrency investment at the extensive margin, pulling new customers into the space of cryptocurrency investment, in addition to the intensive margin of making customers invest more. This is consistent with our observations that, in our sample, cryptocurrency investors have a significantly higher inflation expectation level of 14% than the national level of 11%.

Does the influence of inflation expectations on cryptocurrency investment vary between genders? Addressing this question, a regression analysis was conducted to examine the differential response of new male and female investors to inflation expectations.

Table 7: Inflation Expectation and New Customers

	Dependent Variable: New_Customer			
	(1)	(2)	(3)	(4)
	Base	Add_Pop	Add_Emp	FE
One_Year_Inflation	0.407***	0.632***	0.623***	1.040***
	(0.113)	(0.114)	(0.114)	(0.151)
Population		1.922***	1.911***	0.606***
		(0.226)	(0.225)	(0.188)
P_Self_Employed			25.56***	20.23***
			(5.124)	(6.536)
Constant	34.47***	2.839	-2.018	12.79***
	(1.908)	(3.590)	(3.840)	(4.321)
Observations	7,735	7,735	7,735	7,733
R-squared	0.001	0.039	0.041	0.010
Number of Pincode_Index				945

Note: The table presents regression analyses exploring the link between inflation expectations and the influx of new customers in the cryptocurrency market. Column (1) shows the basic model results, Columns (2) and (3) incorporate demographic controls such as population and self-employment ratios, and Column (4) introduces fixed effects to account for unobserved heterogeneity. Robust standard errors, clustered at the pincode level, are reported in parentheses below the coefficients. The consistent positive coefficients for One_Year_Inflation across different model specifications suggest a robust association between inflation expectations and the likelihood of new individuals entering the cryptocurrency investment space. *** p<0.01, ** p<0.05, * p<0.1.

The results, detailed in Table 8, indicate a distinct difference in the impact on male and female customers. The regression coefficients suggest a stronger correlation between inflation expectations and the likelihood of male entry into the cryptocurrency market, compared to females.

This finding points to gender-specific variations in the response to economic indicators, highlighting the necessity for nuanced approaches in financial market analysis and policy formulation. Understanding these differences is key to developing effective strategies and policies in the evolving landscape of cryptocurrency investments, ensuring they are responsive to the diverse behaviors of different investor groups.

Table 8: Impact of Inflation Expectations on New Cryptocurrency Customers by Gender

	Dependent Variable: New Customer by Gender			
	(1)	(2)	(3)	(4)
	female_base	male_base	female_fe	male_fe
One_Year_Inflation	0.0524***	0.320***	0.142***	0.857***
	(0.0149)	(0.0950)	(0.0205)	(0.126)
Population			0.0741***	0.517***
			(0.0240)	(0.161)
P_Self_Employed			2.754***	16.97***
			(0.825)	(5.552)
Constant	4.559***	28.91***	1.699***	10.55***
	(0.242)	(1.624)	(0.547)	(3.694)
Observations	7,735	7,735	7,733	7,733
R-squared	0.001	0.001	0.011	0.009
Number of Pincode_Index			945	945

Note: This table presents regression analyses examining the differential impact of inflation expectations on new cryptocurrency customers by gender. Columns (1) and (3) correspond to female customers, while Columns (2) and (4) pertain to male customers. The data indicates a stronger correlation between inflation expectations and the likelihood of males entering the cryptocurrency market compared to females. Robust standard errors are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

5.3 Inflation-Crypto Sensitivity across cryptocurrencies

Table 9 presents the regression results that delineate the relationship between one-year inflation expectations and the net buy volume of specific cryptocurrencies, transacted in INR, USDT, and BTC denominations. In cases where an investor does not trade a specific trading pair, the net buy volume is denoted as zero, rather than excluding these investors from the regression sample. By adopting this approach, our regression analysis considers all traders in our sample across the cross-section.

For BTCINR, we observe a coefficient of 383.7, significant at the 5% level, indicating a strong positive relationship with inflation when denominated in INR. Similarly, USDTINR has a coefficient of 818.6, significant at the 10% level, underscoring a pronounced positive association with inflation when denominated in INR.

Interestingly, when considering the USDT denomination, most cryptocurrencies display either negative coefficients or non-significant results. This actively suggests a lesser inclination among investors to trade these cryptocurrencies against USDT during inflationary periods.

In contrast, for trades against the BTC denomination, the results exhibit varied coefficients. However, the significance level is generally low, indicating that the BTC base might not be as consistently responsive to inflation expectations as the INR base.

These findings underscore the distinctiveness of BTC and USDT, specifically when denominated in INR, as having both statistically significant and economically meaningful relationships with inflationary expectations. In summary, while Bitcoin and Tether appear as potential inflation hedges, other cryptocurrencies demonstrate varied responses, underscoring the necessity for investor diligence. Our result also holds when the dependent variable is the amount of cryptocurrencies instead of trade volume, as shown in Table 16.

Table 9: Regression results for the impact of one-year inflation on crypto netbuy volume (Jan 2018 - June 2022) across various base currencies

Token	**INR**		**USDT**		**BTC**	
	Coefficient	Std. Error	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)	-11.34	(29.58)
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)	-14.04	(18.85)
ETH	-56.61	(34.94)	-66.36	(62.44)	-36.25	(21.92)
BTT	-10.02**	(4.580)	5.444	(3.653)	-17.26	(18.26)
ADA	1.232	(2.337)	-5.127**	(2.453)	1.913	(4.819)
MATIC	-3.469	(6.445)	0.628	(2.580)	-10.42	(9.643)
WRX	-20.64	(16.29)	15.38	(11.27)	9.310	(17.34)
BNB	-2.797	(2.540)	2.378	(2.489)	-2.036	(3.206)

Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. This table showcases the regression results assessing the relationship between the one-year inflation rate and the net-buy volume of various cryptocurrencies in INR, USDT, and BTC denominations for the period Jan 2018 to June 2022. The coefficients indicate the change in net-buy volume (in respective base currency denomination) 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.

5.4 Inflation Expectation and Cryptocurrencies Expected Return

We utilize survey data that an exchange collects from investors in November 2021, focusing on their expected returns on cryptocurrency investments. This dataset is matched with inflation survey data from September 30, 2021, and cryptocurrency purchase records spanning from September 30 to November 30, 2021. After matching, the dataset comprises 898 unique email addresses, which form the basis for the regression analysis.

The survey classifies investors into various annual income categories. These categories are defined as follows: Category 1 for annual incomes less than 2.5 Lakh; Category 2 for incomes between 2.5 Lakh and 5 Lakh; Category 3 for 5 Lakh to 7.5 Lakh; Category 4 for 7.5 Lakh to 10 Lakh; Category 5 for 10 Lakh to 50 Lakh; and Category 6 for incomes exceeding 50 Lakh.

Moreover, the survey probes investors' expectations for returns over the following 12 months. The responses exhibit a wide variance, indicative of potentially speculative expectations. The observed mean for expected returns is 1.97e+09, with a standard deviation of 1.40e+11, ranging from -18,000 to a maximum of 1.00e+13.

The regression analyses reveal insightful patterns. Initially, the base regression (Table 10) indicates that inflation expectations have a positive and significant impact on cryptocurrency investments. When income categories are controlled in the subsequent regression, the impact of inflation expectations persists. Further incorporation of expected return into the analysis does not materially alter the influence of inflation expectations, as their coefficient remains positive and significant. The final regression, which examines the relationship between expected returns and inflation expectations while controlling for other covariates, shows that inflation expectations are not statistically significant. This outcome suggests that the expected returns of cryptocurrencies do not correlate with regional inflation expectations. Consequently, it can be inferred that the effects of inflation expectations on cryptocurrency purchases are not primarily driven by speculative demands stemming from high expectations of cryptocurrency returns.

Table 10: Inflation Expectation and Cryptocurrencies Expected Return

VARIABLES	(1) base **inr_amount_net**	(2) add_income **inr_amount_net**	(3) add_exp_ret **inr_amount_net**	(4) exp_ret_inf **expected_return**
One_Year_Inflation	1,386**	1,594*	1,605*	-2,185
	(693.0)	(828.9)	(833.7)	(2,420)
Expected_Return			0.00472*	
			(0.00256)	
2.Income_Category		-14,877	-15,254	80,017
		(21,168)	(21,282)	(73,287)
3.Income_Category		26,173	26,122	10,893
		(25,372)	(25,387)	(8,950)
4.Income_Category		-31,459	-31,562	21,901
		(37,417)	(37,473)	(15,363)
5.Income_Category		-35,436	-35,414	-4,669
		(31,092)	(31,118)	(9,363)
6.Income_Category		-14,910	-15,018	22,744
		(18,745)	(18,776)	(21,233)
Age	-649.0	-2,699*	-2,714*	3,239
	(1,574)	(1,406)	(1,413)	(3,270)
Male	10,293	9,988	9,880	22,960
	(12,375)	(13,616)	(13,646)	(18,817)
Constant	-15,414	54,107	54,557	-95,458
	(48,582)	(45,675)	(45,843)	(89,164)
Observations	898	681	681	681
R-squared	0.004	0.025	0.025	0.010

Note: The table presents regression analyses on the effect of inflation expectation on cryptocurrency investment, using data from a survey conducted in November 2021, matched with inflation survey data as of September 30, 2021, and cryptocurrency purchases between September 30 and November 30, 2021. The survey data include investor's annual income categories and their expected returns, which show extremely high variance, suggesting speculative expectations. The base regression indicates a positive and significant effect of inflation expectation on cryptocurrency investment. The subsequent regressions control for income categories and expected returns, maintaining the significance of inflation expectation. The final regression examines the relationship between expected returns and inflation expectations, indicating no significant correlation, suggesting that the impact of inflation expectations on cryptocurrency purchases is not driven by speculative demands for high crypto returns.

5.5 Inflation-Cryptocurrency Purchase Sensitivity Across States

Table 11 presents coefficients quantifying the relation between inflation and cryptocurrency adoption for various Indian states.

1. **State Variation:** The coefficients vary substantially across states. For instance, Chhattisgarh and Karnataka show the highest positive coefficients of 3902.098 and 3913.18 respectively, whereas Punjab reveals a negative coefficient of -77.50698.

2. **Statistical Significance:** Several states including Madhya Pradesh, Rajasthan, Gujarat, Uttar Pradesh, Bihar, Jharkhand, Assam, and Chandigarh have coefficients significant at the 5% level, confirming a robust inflation-cryptocurrency relationship in these regions.

3. **Directional Insights:** Most states display positive coefficients, suggesting a general positive association between inflation and cryptocurrency acquisitions. Punjab is an exception with its negative value.

4. **Standard Errors:** States such as Karnataka and Chhattisgarh warrant cautious interpretation due to their elevated standard error values relative to their coefficients.

5. **Highlighted States:** Gujarat, Uttar Pradesh, and Chhattisgarh, significant at the 1% level, indicate a pronounced sensitivity to inflationary movements within the cryptocurrency domain.

In conclusion, Table 11 and Figure 4 jointly emphasize the varied state-specific reactions to inflation in the context of cryptocurrency adoption in India.

Table 12 presents state-specific coefficients (labeled as Coef), derived from Fama-MacBeth regressions, representing the sensitivity of cryptocurrency purchases to inflation expectations. A preliminary analysis of the coefficients reveals diverse sensitivities across states. We note that states with a history of elevated inflation tend to experience a more pronounced impact of inflation expectations on cryptocurrency investment.

Table 11: Regression Results Across States

State	Coefficient	Std. Error	t-statistic	p-value
Maharashtra	1140.87	700.7756	1.63	0.116
Madhya Pradesh	2217.921**	921.388	2.41	0.024
West Bengal	865.9692*	431.3894	2.01	0.056
Karnataka	3913.18*	1943.078	2.01	0.055
Rajasthan	2143.499**	929.3368	2.31	0.030
Gujarat	1106.283***	387.7458	2.85	0.009
Andhra Pradesh	485.7024	363.9414	1.33	0.194
Bihar	2726.756**	1167.349	2.34	0.028
Tamilnadu	864.8581	761.8373	1.14	0.267
Uttar Pradesh	1761.203***	632.1912	2.79	0.010
Odisha	1448.737*	844.1981	1.72	0.099
Jharkhand	2893.437**	1391.728	2.08	0.048
Haryana	-	-	-	-
Punjab	-77.50698	77.50698	-1.00	0.327
Himachal Pradesh	-	-	-	-
Jammu and Kashmir	237.3018	353.252	0.67	0.508
Ladakh	-	-	-	-
Chhattishgarh	3902.098***	1299.675	3.00	0.006
Telengana	828.0243*	474.5956	1.74	0.093
Kerala	1418.143*	822.6213	1.72	0.097
Assam	3037.706**	1144.54	2.65	0.014
Daman and Diu & Dadra & Nagar Haveli	-	-	-	-
Delhi	682.7665	780.962	0.87	0.390
Meghalaya & others	-	-	-	-
Chandigarh	2830.037**	1032.14	2.74	0.011

This table presents the regression results of $inr\_amount\_net_{i,t+1} = \alpha + \beta \times \text{inflation\_expectation}_{i,t} + \gamma \times \text{age}_{i,t} + \lambda \times \text{male}_{i,t} + \epsilon_{i,t+1}$, and the coefficient of inflation expectation is changeable across states. 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. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The hyphen (-) indicates omitted states.

Table 12: State-wise Inflation Expectation to Cryptocurrency Investment Sensitivity and Economic Variables in India

State	Coef	Gdp	Pcgdp	Pop	Inf	Unemp	Lit	Pov	Exp	Imp	Fdi	Hist_Inf	Age
Maharashtra	1140.87	430	7200	60	4.5	7.8	82.3	17.4	60	80	18	6.3%	26
Madhya Pradesh	2217.921**	120	1100	73	5.2	3.5	70.6	31.7	10	15	2	5.9%	23
West Bengal	865.9692*	240	2100	91	4.8	5.2	77.1	20.1	16	25	4	6.2%	29
Karnataka	3913.18*	270	3600	61	5.1	6.5	75.6	20.9	35	45	10	5.7%	26
Rajasthan	2143.499**	130	1600	68	4.3	4.2	67.1	14.7	15	18	3	4.3%	24
Gujarat	1106.283***	290	4500	64	4.9	3.1	79.3	16.6	42	60	12	5.8%	25
Andhra Pradesh	485.7024	170	2200	49	5.0	6.2	67.4	9.2	18	28	5	5.4%	26
Bihar	2726.756**	100	750	104	4.7	5.6	63.8	33.7	5	10	1	9.4%	22
Tamil Nadu	864.8581	380	5900	64	4.8	2.8	80.3	11.3	30	45	7	5.0%	28
Uttar Pradesh	1761.203***	330	800	199	5.0	4.3	69.7	29.4	15	35	5	5.8%	24
Odisha	1448.737*	95	1100	42	4.6	5.3	73.5	32.6	10	15	2	8.1%	24
Jharkhand	2893.437**	45	750	32	5.1	5.2	67.6	42.0	5	10	1	9.7%	22
Haryana	-	130	4600	28	4.7	8.4	76.6	11.2	25	30	5	5.2%	26
Punjab	-77.50698	110	3800	29	4.5	6.1	76.7	8.3	15	25	3	4.1%	27
Himachal Pradesh	-	30	2100	14	4.3	7.2	83.8	8.1	1	5	0.5	5.0%	24
Jammu and Kashmir	237.3018	28	1100	13	4.7	15.4	68.7	10.4	1	5	0.2	5.7%	22
Ladakh	-	2	1500	0.3	4.5	10.0	74.0	12.0	0.1	0.5	0.05	4.6%	22
Chhattisgarh	3902.098***	45	1300	32	5.0	2.1	71.0	39.9	10	15	1	6.2%	23
Telangana	828.0243*	130	3100	35	5.2	7.6	72.8	9.9	15	25	3	4.5%	25
Kerala	1418.143*	160	4500	35	4.8	7.4	94.0	7.1	10	30	1	4.9%	29
Assam	3037.706**	40	1000	31	5.1	7.8	73.2	31.9	2	8	0.5	5.5%	24
Sikkim	-	2	2000	0.7	4.6	6.7	82.0	8.2	0.1	0.5	0.02	7.1%	25
Goa	-	10	4500	1.5	4.9	9.6	87.4	5.4	1	2	0.2	4.5%	29
Manipur	-	3	1100	2.9	5.0	18.0	79.8	36.9	0.1	0.5	0.01	5.7%	22
Tripura	-	3	1200	3.7	4.8	15.7	87.8	14.7	0.1	0.5	0.02	5.5%	25
Mizoram	-	1	1300	1.2	4.7	6.1	91.6	21.1	0.05	0.2	0.005	5.7%	23
Meghalaya	-	3	1800	3.3	4.6	5.4	75.5	11.9	0.1	0.5	0.01	5.6%	24
Nagaland	-	2	1300	2.2	4.8	16.5	80.1	19.9	0.05	0.3	0.005	5.4%	23
Arunachal Pradesh	-	2	1600	1.4	5.0	6.7	66.0	32.7	0.1	0.4	0.01	7.5%	22
Uttarakhand	-	30	2200	11	4.5	5.8	78.8	11.3	1	5	0.5	7.6%	24
Andaman and Nicobar	-	0.5	6000	0.4	4.9	6.0	86.0	10.0	0.02	0.5	0.0005	4.2%	28
Chandigarh	2830.037**	3	17000	0.1	4.8	7.6	86.0	7.1	0.2	1	0.02	4.7%	28

Notes: Coef - The State-dependent Fama-MacBeth Coefficient of inflation expectation on cryptocurrency investment, Gdp - Gross Domestic Product (in billion USD), Pcgdp - Per Capita GDP (in USD), Pop - Population (in millions), Inf - Inflation Rate (in %), Unemp - Unemployment Rate (in %), Lit - Literacy Rate (in %), Pov - Poverty Rate (in %), Exp - Exports (in billion USD), Imp - Imports (in billion USD), Fdi - Foreign Direct Investment (in billion USD), Hist_Inf - Historical Inflation Rate (2012-2017 average, in %), Age - Average Age of Population.

For instance, Maharashtra exhibits a coefficient of 1140.87, suggesting a pronounced sensitivity of cryptocurrency purchases to inflation expectations in this state. Comparatively, Madhya Pradesh, with a coefficient of 2217.921, indicates even stronger reactivity in cryptocurrency investment behavior in response to changing inflation expectations.

It is also intriguing to note certain outliers such as Haryana, Punjab, Himachal Pradesh, and several others that do not display any coefficients, implying that in these states, the relationship between inflation expectations and cryptocurrency purchases might be non-significant or requires further investigation.

Furthermore, the significance levels associated with the coefficients, denoted by asterisks, provide additional insights. States like Madhya Pradesh, Rajasthan, and Jharkhand, to name a few, manifest coefficients with double asterisks, emphasizing the robustness of the relationship in these regions. Conversely, states like West Bengal, Karnataka, and Kerala with a single asterisk imply a moderate level of significance in the relationship.

In summary, the presented coefficients offer a comprehensive landscape of how varying inflation expectations across states influence cryptocurrency purchasing behaviors, underscoring the heterogeneous nature of this relationship across the Indian states.

5.6 Temporal Dynamics of Inflation Expectations and Cryptocurrency Netbuys

Table 13 presents coefficients of one-year ahead inflation expectations for BTC, USDT, and the broader cryptocurrency market from December 2017 to March 2022. The coefficients are juxtaposed with the INR-USD exchange rate and its sequential percentage variations. Figure 5 serves as a visual complement.

1. **BTC Dynamics**: Prior to 2020, BTC's coefficients demonstrate minimal influence from inflation expectations. From January to November 2020, a noticeable increase in the coefficients is evident, potentially resulting from global financial disruptions in the wake of COVID-19.

2. **USDT's Role**: USDT's coefficients exhibit significant fluctuations over the observed periods. During phases when BTC's coefficients amplify, USDT's coefficients often diverge, suggesting its potential role as a stabilizing asset given its stablecoin properties.

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4. **Crypto Market Dynamics**: The broader cryptocurrency market's coefficients largely follow BTC's trajectory. A surge is identifiable from January to November 2020. Post-2020, the coefficients display increased volatility.

5. **Regulatory Impacts**: The start of 2022 sees a downturn in coefficients. This shift may align with the introduction of India's crypto tax in April 2022, highlighting potential regulatory impacts on market behavior.

   Furthermore, there exists a correlation between the presented coefficients and the INR-USD exchange rate. Periods of INR depreciation often correspond with heightened coefficients for BTC and the broader cryptocurrency market.

6. **Attention Channel**: Amid the major sporting event in India, the IPL cricket matches from September 19 to October 15, 2021—equivalent to the NBA's significance—several leading cryptocurrency exchanges spearheaded an unprecedented advertising campaign. This novel approach clearly delineates the channel of attention. Referring to Table 13, a discernible surge in the coefficient is evident for November 2021. The interplay between inflation expectations and cryptocurrency investments is further illuminated by the correlation with the Google Search Index for cryptocurrencies within the Indian context, as depicted in Figure 6. Such findings reinforce the attention-driven interpretation of our empirical outcomes.

In conclusion, Table 13 emphasizes the interplay between inflation expectations, cryptocurrency purchase patterns, and macroeconomic indicators, such as the INR-USD exchange rate and attention of investors.

Table 13: By-Period Coefficients of One-Year Ahead Inflation Expectation

Period	BTC	USDT	All-Cryptos	INR-USD	% Change	BTC Attention
Dec 2017	115.63	0.00	253.23	64.24	-	100
Mar 2018	2165.22	0.00	2839.46	65.05	1.24	17
May 2018	-516.41	0.00	-1325.64	67.51	3.78	10
Jun 2018	94.95	127.51	178.28	67.79	0.41	8
Sep 2018	-0.88	23.68	33.74	72.28	6.63	7
Nov 2018	-12.50	-13.38	-12.70	71.74	-0.74	7
Dec 2018	-21.22	48.28	6.33	70.83	-1.26	7
Mar 2019	18.67	-11.77	13.73	69.49	-1.89	4
May 2019	5.26	2.97	14.52	69.78	0.42	8
Jul 2019	-42.65	42.00	9.41	68.74	-1.49	8
Sep 2019	-5.18	-10.33	-20.03	71.31	3.73	6
Nov 2019	6.09	14.83	18.91	71.49	0.26	5
Jan 2020	253.21	1239.21	1415.44	71.28	-0.30	6
Mar 2020	3557.58	-1181.63	1904.22	74.55	4.57	11
May 2020	1659.62	1486.87	2112.05	75.66	1.49	10
Jul 2020	917.97	5029.00	3526.71	74.93	-0.96	9
Sep 2020	546.16	3823.66	3739.96	73.52	-1.88	7
Nov 2020	864.72	8451.29	8926.02	74.23	0.96	12
Jan 2021	760.07	543.11	1250.26	73.11	-1.51	33
Mar 2021	-607.57	271.80	-623.03	72.82	-0.40	23
May 2021	-30.55	160.77	201.83	73.21	0.53	50
Jul 2021	56.30	-342.60	-108.96	74.54	1.82	20
Sep 2021	53.25	394.26	410.29	73.64	-1.21	17
Nov 2021	107.06	2943.04	3096.51	74.48	1.14	27
Jan 2022	-1.58	-1074.68	-1455.95	74.41	-0.09	26
Mar 2022	33.07	-683.93	-443.78	76.07	2.23	17
Average	383.70	818.61	998.49	71.55	0.58	-

This table displays the coefficients of one-year-ahead inflation expectation for different periods. The data includes the coefficients for BTC, USDT, and All-Cryptos, the INR-USD exchange rate, and the percentage change in the exchange rate compared to the previous period, as well as the Google Search Index of Bitcoin in India. Coefficients are calculated based on the model of inflation expectation.

6 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. We also investigate the heterogeneity of such a relationship across cryptocurrency, geographic location, demography, and time. Our findings highlight that the pursuit of inflation hedges is an important source of the demand for certain cryptocurrencies.

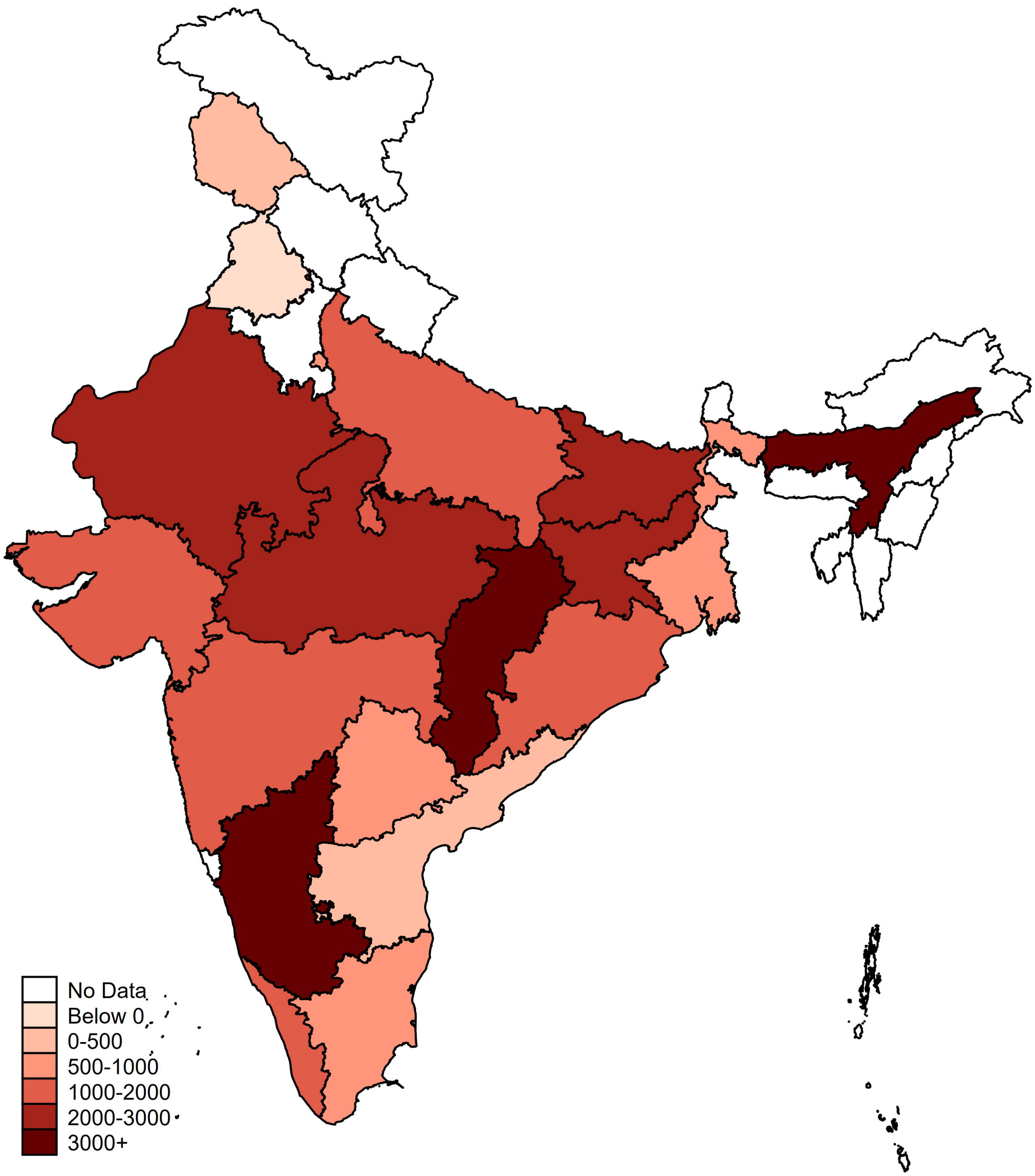

Figure 4: Cryptocurrency Purchases in Response to Inflation Expectations by States

The coefficients presented capture the correlation between inflation expectations and cryptocurrency purchase tendencies of individual investors across various states in India during the observed sample timeframe.

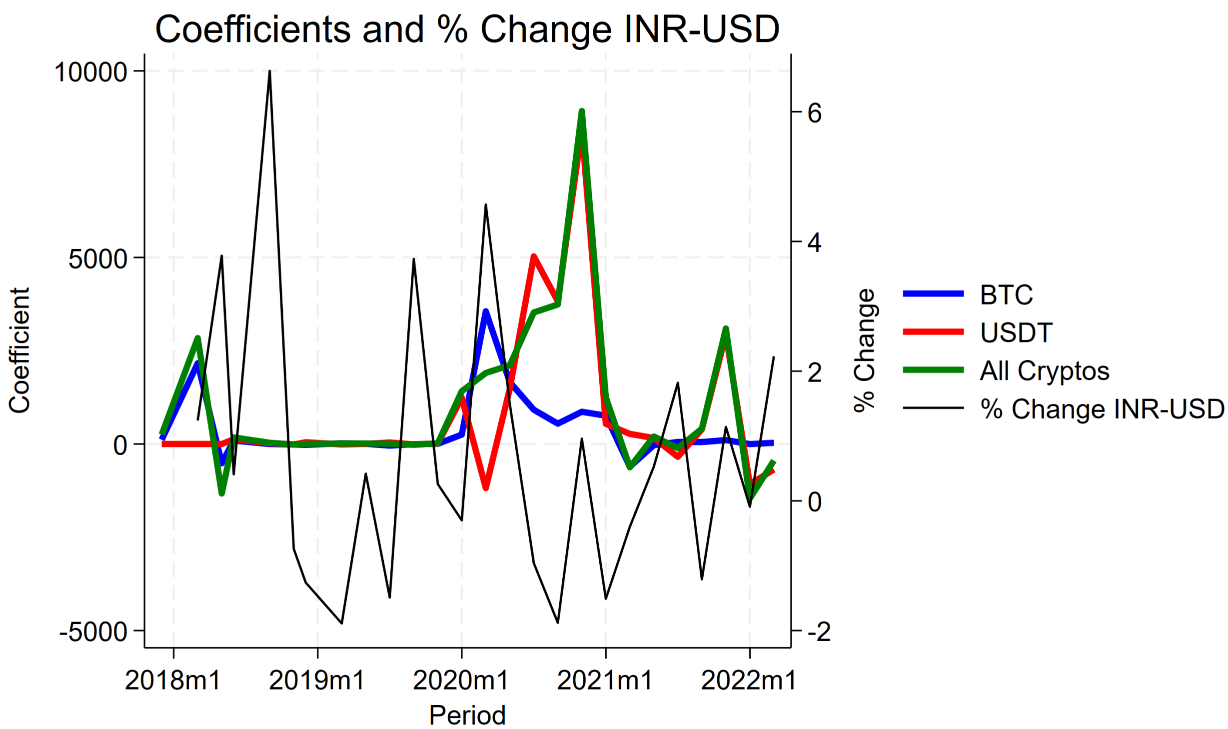

Figure 5: Inflation-Crypto Index Over Time

This figure showcases the evolving relationship between one-year ahead inflation expectations and the netbuy 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.

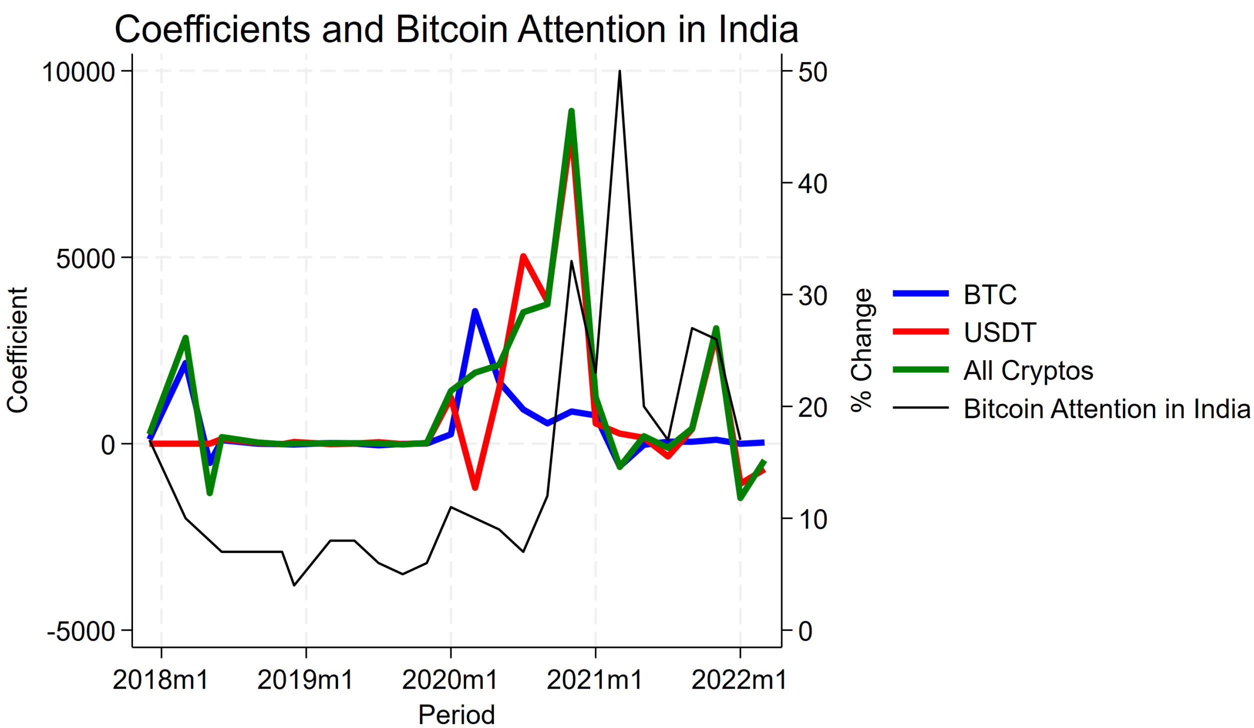

Figure 6: Inflation-Crypto Index Over Time

This figure showcases the evolving relationship between one-year ahead inflation expectations and the netbuy volume in Indian Rupee of BTC, USDT, and the broader cryptocurrency market from December 2017 to March 2022, as well as the Google Search Index of Bitcoin in India.

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A First Appendix Section

Figures 7-11 illustrate how inflation expectations 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).

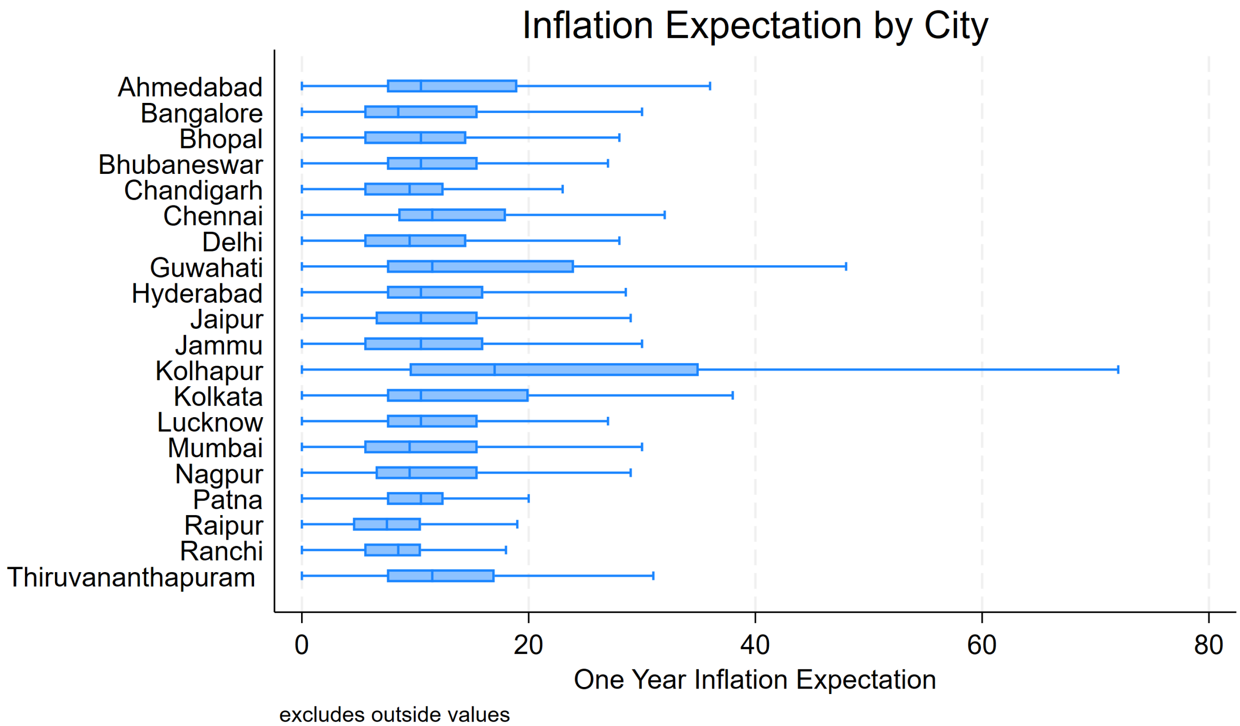

Figure 7: Inflation Expectation Across Cities

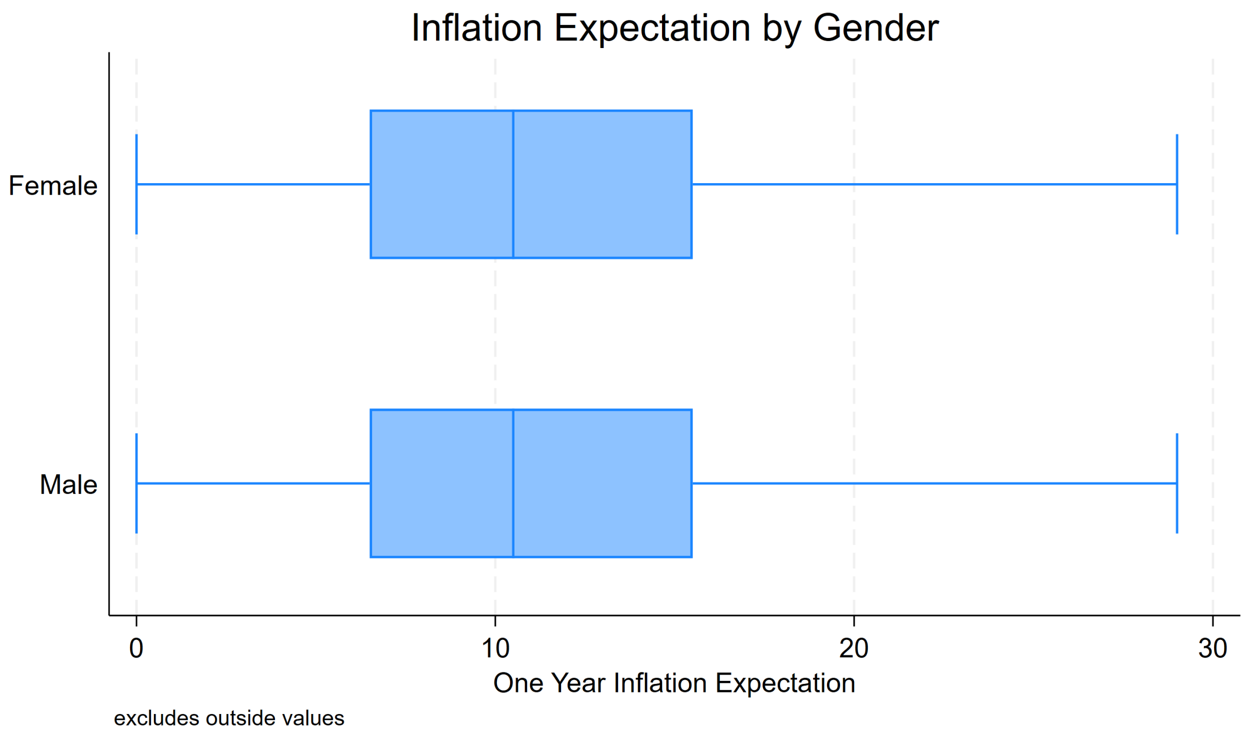

Figure 8: Inflation Expectation Across Gender

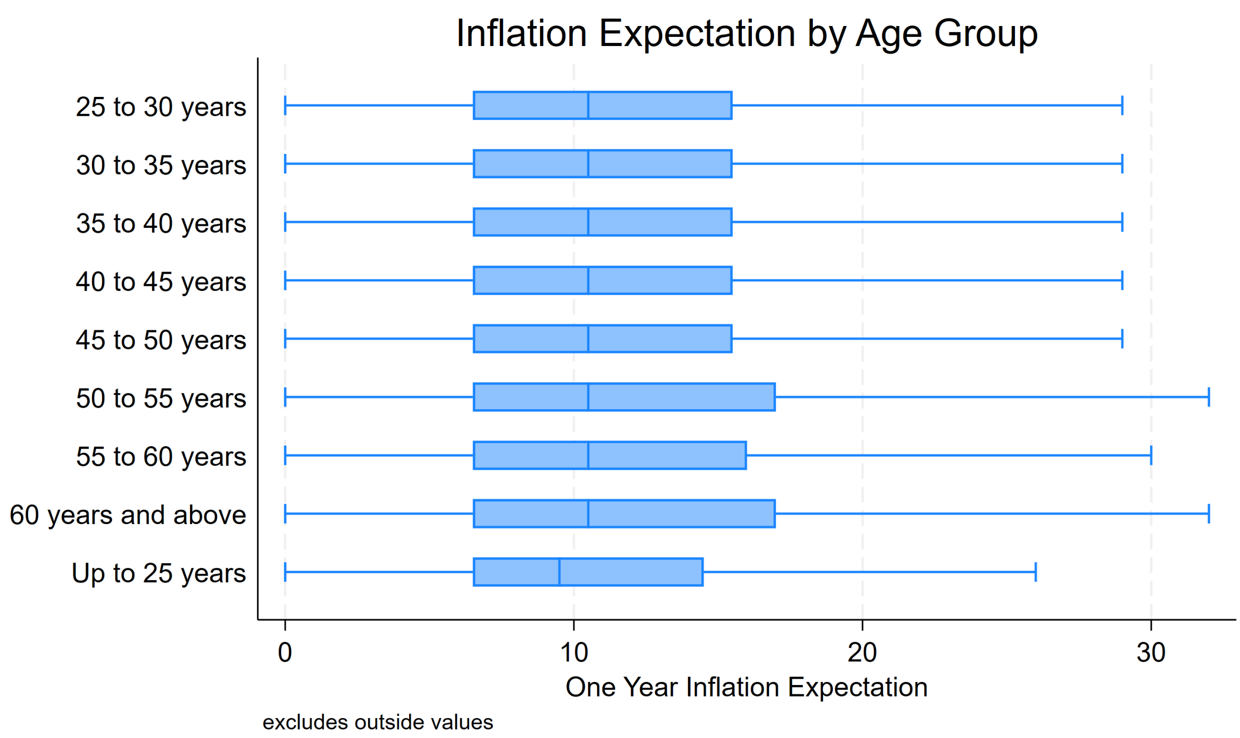

Figure 9: Inflation Expectation Across Ages

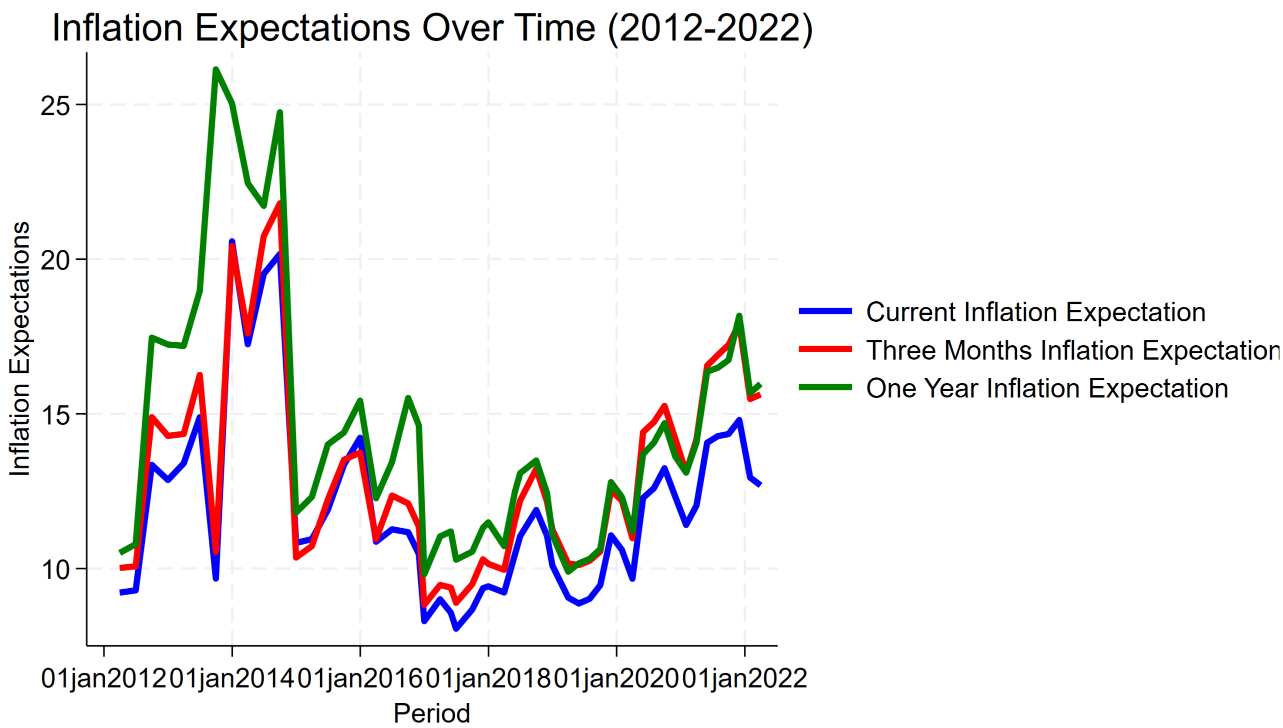

Figure 10: Inflation Expectation Over Periods

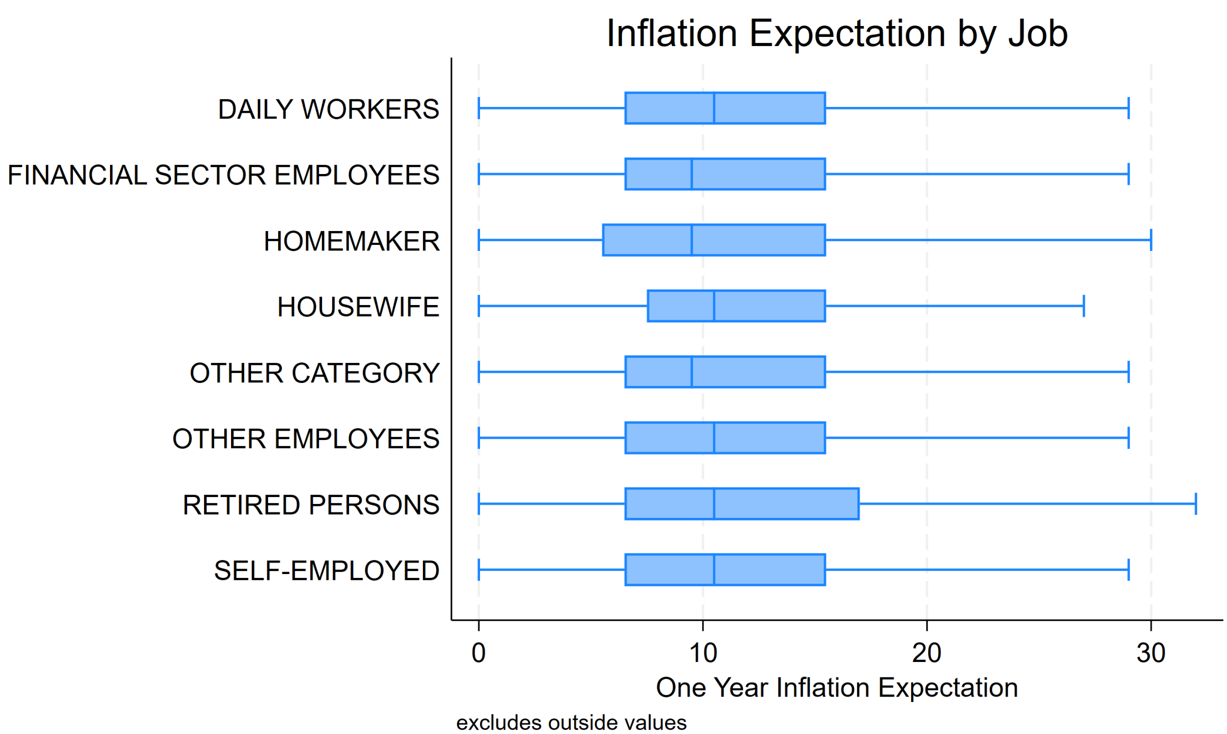

Figure 11: Inflation Expectation Across Job Types

B Second Appendix Section

Table 14: Effects of Inflation Expectations on Cryptocurrency Purchase Behavior: Fama-MacBeth Regression Results (Jan 2018 - June 2022) with USDT as Base Currency

VARIABLES	(1) **current** **inr_amount_net**	(2) **three_months** **inr_amount_net**	(3) **one_year** **inr_amount_net**	(4) **three_months_hat** **inr_amount_net**	(5) **one_year_hat** **inr_amount_net**
current_inflation	-247.9				
	(235.4)				
three_months_inflation		-257.3			
		(224.0)			
one_year_inflation			-231.6		
			(225.0)		
three_months_inflation_hat				-215.1	
				(204.2)	
one_year_inflation_hat					-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)
gender_index	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

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The regression is given by: $usdt\_amount\_net_{i,t+1} = \alpha + \beta \times \text{inflation\_expectation}_{i,t} + \gamma \times \text{age}_{i,t} + \lambda \times \text{male}_{i,t} + \epsilon_{i,t+1}$. 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 *three_months_inflation_hat* and *one_year_inflation_hat* are fitted values from the first stage linear regression on current perceived inflation.

Table 15: Effects of Inflation Expectations on Cryptocurrency Purchase Behavior: Fama-MacBeth Regression Results (Jan 2018 - June 2022) with BTC as Base Currency

VARIABLES	(1) **current** **inr_amount_net**	(2) **three_months** **inr_amount_net**	(3) **one_year** **inr_amount_net**	(4) **three_months_hat** **inr_amount_net**	(5) **one_year_hat** **inr_amount_net**
current_inflation	-128.0				
	(109.1)				
three_months_inflation		-119.3			
		(99.49)			
one_year_inflation			-101.9		
			(81.71)		
three_months_inflation_hat				-111.0	
				(94.65)	
one_year_inflation_hat					-123.0
					(104.9)
age	101.7	102.8	101.6	102.0	102.1
	(68.10)	(68.40)	(67.68)	(68.15)	(68.17)
gender_index	5,953**	5,950**	5,875**	5,946**	5,941**
	(2,603)	(2,607)	(2,590)	(2,601)	(2,599)
Constant	-6,130	-6,095	-6,182	-6,090	-5,935
	(3,911)	(3,865)	(3,944)	(3,909)	(3,903)
Observations	652,168	652,164	652,152	652,168	652,168
R-squared	0.003	0.003	0.002	0.003	0.003
Number of groups	26	26	26	26	26

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The regression is given by: $btc\_amount\_net_{i,t+1} = \alpha + \beta \times \text{inflation\_expectation}_{i,t} + \gamma \times \text{age}_{i,t} + \lambda \times \text{male}_{i,t} + \epsilon_{i,t+1}$. 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 *three_months_inflation_hat* and *one_year_inflation_hat* are fitted values from the first stage linear regression on current perceived inflation.

Table 16: Regression results for the impact of one-year inflation on crypto netbuy amount (Jan 2018 - June 2022) across various base currencies

Token	**INR**		**USDT**		**BTC**	
	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error
USDT	10.49*	(5.238)	0	(0)	0	(0)
BTC	0.000502*	(0.000260)	-0.000239	(0.000307)	0	(0)
XRP	-1.182	(0.898)	-3.087*	(1.641)	-0.0776	-0.101
DOGE	0.0763	(0.453)	-0.110	(0.942)	0	(0)
SHIB	1,041	(1,291)	531.0	(660.4)	0	(0)
WIN	7.310	(13.44)	9.119	(23.29)	0	(0)
TRX	-12.78	(12.54)	13.26	(12.09)	-2.040	(1.785)
ETH	-0.00224	(0.00148)	-0.00314	(0.00411)	-0.000304	(0.000187)
BTT	-1,088	(914.4)	5,675	(5,219)	-10.66	(16.56)
ADA	0.101	(0.150)	-0.350	(0.302)	0.147	(0.173)
MATIC	-4.776	(3.324)	0.985	(2.078)	-1.175	(1.131)
WRX	-2.064	(1.671)	1.552	(1.025)	-0.0414	(0.128)
BNB	-0.000710	(0.000670)	0.000719	(0.00133)	-0.000192	(0.000421)

Standard errors are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. This table showcases the regression results assessing the relationship between the one-year inflation rate and the net-buy amount of various cryptocurrencies in INR, USDT, and BTC denominations for the period Jan 2018 to June 2022. The coefficients indicate the change in net-buy amount (in respective base currency denomination) 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.