

Transitioning from Products to Platforms: Evaluating House Price Sentiment in India with the Role of Digital Payments

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ABSTRACT

House price sentiment, particularly in India, has always been an important factor for the economy. Over the years, the government of India has launched many programs to enhance financial inclusion and reduce poverty. The existing digital divide, driven by multiple factors, has served as a barrier. However, the proliferation of digital payments has led to a shift in financial behaviour. Thus, in our study, we aim to understand whether the transformation in banking and the newly adopted digital transaction mechanisms have a significant impact on Indian households' house price sentiment. We explore house price expectations from the Inflation Expectations Survey of Households (IESH) and use data from RBI's payment system indicator. Our findings strengthen the argument that digital payment diffusion reduces information and transactional frictions, increases optimism in financial systems, and can also foster a behavioural shift towards home-buying decisions rather than being restricted to household adoption. The findings have important implications for policy developers and implementers seeking to understand how to leverage technology to catalyse housing market development in developing countries.

1. INTRODUCTION

Household finances' are the owners of productive corporations of economies. Housing comprises a substantial portion of any household's financial portfolio. Therefore, tracking the variations in house prices can have notable impacts on the behaviour of households (Dong *et al.*, 2024; Gomes *et al.*, 2021), that is responsible for inducing their participation in financial markets, economic consumption of resources, and savings. This is forecasted using house price sentiment as an indicator, *i.e.*, an aggregate of households' expectations towards house prices. This indicator reflects sentiments associated with future developments in households' consumption and saving, according to the Organisation

for Economic Co-operation and Development (OECD) (Girouard & Blöndal, 2001; Broom & Shine, 2023). Given its importance, house price sentiment has been instrumental in helping policymakers understand the fiscal and monetary aspects needed for a nation's development. Households' home-buying decision is said to be induced by how they perceive appreciation in house prices (Armona et al., 2019; Landvoigt, 2017). Perceptions of house prices affect households' mortgage choices and leverage decisions (Bailey *et al.*, 2019; De Stefani, 2021). Additionally, there exists significant heterogeneity across household price expectations (Hjalmarsson & Österholm, 2020). In a similar study, Kuchler *et al.* (2023) show that perceptions of house prices vary over time and across population groups. Other existing evidence on household sentiment includes the OECD Consumer Barometer, developed by the OECD, which studies changes in consumer sentiment across countries (Gamba & Guidetti, 2021).

In line with the OECD, scholars have found that households' attitudes can serve as a crucial predictor of household expenditure in normal times, though they fluctuate during global disturbances (Carroll *et al.*, 1994; Throop, 1992). According to Dua, (2008) houseprice expectations serve as an index of housing markets and influences the aggregate economy. Furthermore, outlook on house prices play a vital role in shaping actual house prices inducing household decisions to transact (sell or buy). Some current studies uses responses like "Now is a good time or a bad time to buy a house?" (Rooj *et al.*, 2026) to estimate home-buying sentiment. For instance, using a good-time-to-buy (GTTB) index in monthly frequency to capture households' expectations about housing market in U.S, Huang, (2014) shows that it can predict real estate cycles. Factors like mortgage choices, affordability, present house prices as well as uncertainty are likely to impact housing sentiment (Rooj *et al.*, 2026). However, D 'acunto *et al.*, (2015) find that such sentiments are induced by unusual fiscal policy announcements. In this chapter, we therefore explore how the use of digital payments, driven by technological growth, affects households' sentiments towards house prices in India.

The current state in India can be said to be the outcome of a sustained, long-term vision and strategy, which has led the government of India (GOI) to launch multiple initiatives over the years that embrace technology-enabled governance. Initially, grassroots issues were addressed for financial inclusion through the induction of a zero balance savings account and the provision of a digital identity to citizens with Aadhaar. These served as stepping stones for the largest financial inclusion program, Pradhan Mantri Jan Dhan Yojana (PMJDY), launched in 2014. It is envisioned to provide banking services to all households in the country. The scheme ensures access to a range of financial services, including basic savings bank accounts, need-based credit, remittance facilities, insurance, and pensions (Pratik *et al.*, 2024). Following this, the Digital India programme in 2015 laid the foundation for digital public infrastructure, which has initiated cashless transactions, i.e., digital payments. It started with the incubation of bank-based applications, a tie-up with a third-party platform, and the introduction of chip-enabled, electronic cards. Though there were a few glitches initially, the increased availability of the internet and

the introduction of interoperability through the National Payments Corporation of India (NPCI)'s launch of the Unified Payment Interface (UPI) catalysed digital payments (Press Information Bureau, 2025). UPI has induced trust, perceived security, and perceived usefulness through features such as the ability to choose the application, ease of use, and by fostering healthy competition among service providers, thereby enhancing security and services (Press Information Bureau, 2025). This has transformed the traditional way of banking services through its strategic changes to five core domains, such as customers, competition, innovation, data, and value (Rogers, 2016).

Continued upgradation in finance technologies is constantly changing the landscape of the owned-house based marketplace. The evolution of FinTech lenders has also resulted in a significant uptick in the global mortgage market. The digital payments system further improves access to and repayment of mortgage payments. Also, customers in well-banked zones tend to use FinTech platforms for swift service with higher transparency (Allen *et al.*, 2021). The global e-mortgage market is expected to be at US\$8.7 billion and is estimated to grow to US\$46.2 billion by 2032, having a CAGR of 18.2¹ per cent. Existing works also argue the role of digital payments system as a crucial factor to trace economic movement as well as growth (Aprigliano *et al.*, 2019; Duarte *et al.*, 2017; Galbraith & Tkacz, 2013; Mura & Donath, 2023; Rooj & Sengupta, 2021). The literature also suggests that data on payment systems can predict consumption expenditure (Rooj *et al.*, 2023). Other sets of studies also show that consumption of durables are mostly financed by either bank transfers and/or through loans (Carlsen & Storgaard, 2010; Rodrigues & Esteves, 2010). Flynn and Kostecki (2023) show that credit card use is positively associated with homeownership. Furthermore, Maalsen *et al.* (2022) explore how the advancement of digital platforms is closely connected with a dynamic environment, other demand drivers, and unfulfilled housing needs to utilize what is often unaccounted for. Increased adoption of electronic payment systems has paved new avenues for policy-makers and practitioners to track macroeconomic activity (Duarte *et al.*, 2017).

Increased purchasing power, sustained growth, and demographic shifts have propelled the development of the Indian housing finance market (National Housing Bank, 2021). Housing continues to be the most important area for investment by Indians (Rooj *et al.*, 2026). Moreover, the mix of Indian household savings at current prices hints about 70% of the total savings accounts for physical assets (Rooj *et al.*, 2026). Likewise, digital payments have also shown a significant uptick since the last decade. It has grown from 1620 Mn. in 2012-13 to 147,260 Mn. in February 2024, clicking a substantial 46%² of the global digital transactions. Besides COVID-19-influenced shifts in digital transactions, the introduction of the Real Estate (Regulation and Development) Act (2016) for India, which targets to protect the interests of buyers (of homes), has induced a significant boost in the use of digital payment systems for housing transactions. We postulate that, similar to

¹ <https://www.globenewswire.com/news-release/2022/06/15/2463245/0/en/Advent-of-Technology-in-Lending-Mortgage-Domain-Will-Increase-Business-Opportunities-for-e-Mortgage-Companies-Evaluates-Fact-MR.html>

² https://www.rbi.org.in/Scripts/BS_SpeechesView.aspx?Id=1422

advanced economies, digital platforms can also impact household sentiments about the future behaviour of house prices.

Therefore, in this book chapter, we aim to understand whether the transformation in banking and the newly adopted digital transaction mechanisms have a significant impact on the house price sentiment of Indian households. For this, we use data on digital payments from the RBI's payment system indicator and that on house price expectations from the Inflation Expectations Survey of Households (IESH), which is publicly released by the RBI on a bi-monthly basis across 19 major Indian cities. We focus on house price sentiment measures based on Indian households' responses to the expectation in house prices at 3 months and 1 year ahead. Figure 1 plots the co-movement in house price expectations (both at 3 months and 1 year ahead) along with digital payments from November 2019 to December 2025. Although both the sentiments and digital payment move in the same direction, it is still not conclusive whether digital payments have a significant impact on the house price sentiments. For this, we empirically try to bridge this gap using a large panel dataset. The results show that the use of digital payments has a positive significance on house price sentiments. Additionally, we run a disaggregated analysis of other survey parameters in the IESH survey and observe some interesting insights. Lastly, our alternative variable as a proxy to digital payments also validates our baseline outcome. This study helps readers enhance their understanding of the phenomenon using Rogers' (2016) framework, which shows that simultaneous transformation across five strategy domains due to the introduction of digital payments leads to improved house price sentiment in India.

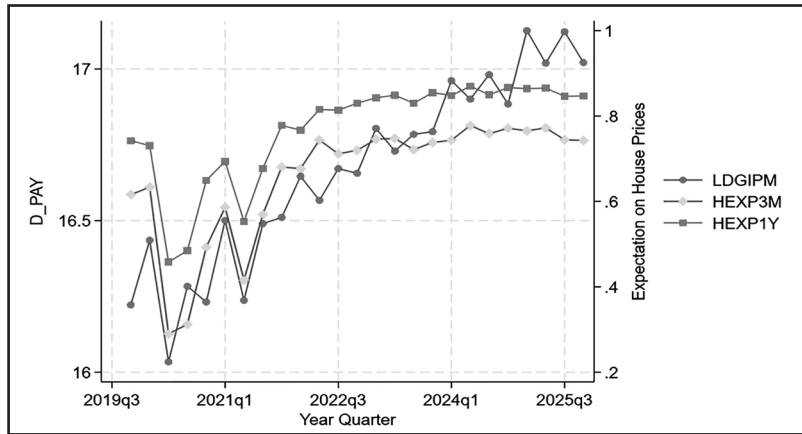


Figure-1: Time Series Plot of HEXP3M, HEXP1Y, and Digital Payments (LDGIPM)

Note: House Price Expectations 3 months ahead (HEXP3M) and House Price Expectations 1 year ahead (HEXP1Y) are from the Inflation Expectation of Household Survey (IESH) released by the Reserve Bank of India (RBI). Data on the Digital Payments at the Indian level (in logs) comes from the Payment System Indicator of the Reserve Bank of India (RBI).

**Source: Author's own calculations*

The following sections include literature on trends over time in banking with technology, Initiatives taken by the Indian GOI, the role of Digital payment in digital transformation, house price sentiments, followed by methodology, results, analysis, conclusion, and Future implications.

2. BACKGROUND LITERATURE

The study in this chapter is at the conjecture of two core domains, i.e., technology and banking. The study's phenomenon is rooted in understanding the unique relation between household price sentiment and digital payments. Literature associated with the house price sentiment, role of technology in banking services, and role of digital payments in digital transformation is reviewed in the following sections. This review and synthesis, based on Rogers' (2016) five domains of digital transformation, strengthens the conceptual foundations.

2.1 Technology in Banking Services

The banking sector has evolved along with technological advancements. Digitization has pushed banks towards IT adoption, which has, in turn, led to digital transformation (DT). DT has erased the borders between the physical and virtual worlds, with changes in organizational culture, customer relations, and restructured business models (Fitzgerald *et al.*, 2014). Today, digital channels are no longer just alternative and cost-effective means for reaching and serving customers, but rather an important and growing share of retail client relationships worldwide (Jünger & Mietzner, 2020). Rather, they are channels in which purchasers, customers, and suppliers are decentralized, making the economy a shared activity (Nian *et al.*, 2023). Scholars have highlighted the criticality of building a sustainable society amid technological influence, as individual household physical ability, digital literacy, and socio-economic factors have an impact beyond revenue. The availability of resources can lead to financial inclusion and bridge the digital divide, while a lack of them can increase existing inequalities in society (Vassilakopoulou & Hustad, 2023). A few scholars have stated that technology can also induce new social stratifications and divisions, loss of privacy, cybersecurity issues, economic diversification, and the threat of digital and information exclusion (Echeverri and Abels, 2008; Ferro *et al.*, 2010; Ziemba, 2019).

In Indian context, scholars have highlighted the importance of digital financial services in helping individuals move out of poverty. For it to happen, 18 barriers have been identified, ranging from the risk of using digital services to bank investment issues, i.e., high-cost investments with low returns. Solutions to these have been suggested to improve digital literacy along with access, security, and trust in digital financial services Rana *et al.*, (2020). Azman Ong *et al.* (2023), in their work on a consumer-level behavioural model aimed at understanding *what drives people to adopt digital payments*, state that consumers' intentions play a major role and that these intentions are dependent on five factors: epistemic value,

facilitating conditions, social influence, habit, and effort expectancy. In recent times, according to the Global Findex 2025 report, digital payments by the government have increased financial inclusion since 2017 by 20 per cent till 2024, The gender gap has reduced as the number of women receiving payments rose from 13 per cent in 2021 to 24 per cent by 2024 (Klapper *et al.*, 2025). From all the studies, one can infer that the studies are in line supporting Rogers' (2016) argument, which emphasizes that digital transformation is not merely a technological upgrade but a strategic rethinking of how organisations create value across five interconnected domains, such as customers, competition, data, innovation, and value. Thus, to keenly understand the role played by digital payment in digital transformation in India we explore literature in the following section.

2.2 Role of Digital Payments in Digital Transformation in India

The associated literature over the years has evolved from studying the adoption of technology by individuals to changing roles, and then to creating value (Sambamurthy *et al.*, 2003; Karimi & Walter, 2015; Li *et al.*, 2018). Kohtamäki *et al.* (2025), based on a bibliometric study, proposed that digital transformation is not a mere technological change but an outcome of changes in digital strategy, digital marketing, and digital business innovation. A report by MIT and Deloitte strengthens the argument, stating that the sole deployment of digital payments without a strategy leads to an early-adopter trap, failing to achieve operational gains or competitive positioning for banks (Kane *et al.*, 2015). Thus, the GOI, with a strategic vision, has launched multiple initiatives through the Reserve Bank of India (RBI), India's federal banking organization, to close the gap between the banked and the unbanked. RBI implemented measures like "priority sector lending requirements for banks, Lead Bank Scheme, establishment of Regional Rural Banks, Service Area Approach (1989), Self-Help Group-Bank Linkage Programme (1989-90), setting up of Local Area Banks etc." while the Government of India (GOI) nationalized banking operations by 1980 which was mainly concerned with ensuring that everyone could profit from banking (Bhole, 2004). Due to the low penetration of banks in rural India, the existing postal network was leveraged through India Post Payment Bank (IPPB) to enhance financial inclusion (Jayaprakash & Pillai, 2018). In parallel, bank-owned digital products like IMPS, NEFT, RTGS, and bank-specific mobile wallets, this phase of digital banking is characterised by low network effects and vertical integration (Piccoli & Ives, 2005). Yet, benefits could not be realized due to issues like coordination, a lack of neutral intermediaries, and interoperability. GOI for the welfare of citizens launched few programmes.

The Indian government has launched four major initiatives, including Aadhaar for citizenship identification, the Pradhan Mantri Jan Dhan Yojana (PMJDY) to enable banking services for the unbanked with zero-balance savings accounts, access to credit, and a RuPay card with accident insurance. The Unified Payments Interface (UPI) payment platform,

introduced by NPCI, provides interoperability and a digital infrastructure guarantee. As of 2025, it has facilitated over 640 million transactions per day, i.e., comparable to Visa's transactions. The Jan Dhan, Aadhaar, and Mobile (JAM) trinity, which has enabled direct bank transfers by encompassing the Stack of foundations responsible for the digital transformation. These projects were launched under 22 milestones from 2004 to 2025 (Press Information Bureau [PIB], 2025).

Among these projects, UPI is a strong example of success, a regulatory framework developed cooperatively by the RBI and NPCI that has enabled its success. It resulted in same-side and indirect network effects in digital transformation, as well as new competition from FinTech services in banking (Thakor, 2020). In summary, the way UPI and mobile banking significantly changed the customer relationship in India can be explained by Rogers' (2016) concept of developing customer networks. The idea of "datafying your business" is closely related to the data architectures developed by RBI and NPCI to enable predictive financial services. The JAM (Jan Dhan–Aadhaar–Mobile) Trinity makes the distinction between disruptive and sustaining innovation particularly pertinent in the Indian setting. Below is Table 1, analysing the core domain changes across digital transformation domains.

Effect of digital payment on core domains and associated consumer sentiment.

Table 1: Inferring the Digital Payment Enablement and Consumer Sentiment Based on Literature

Domain	Feature enabled with digital payment	Influenced consumer sentiment
Customers	Improved accessibility, Eased Interface usage, Enhanced Trust	Increased confidence through financial inclusion
Competition	New entrants (Fintech companies), interoperability	Multiple choices, lowered cost of services, Improved services
Data	Improved privacy and personalisation	Increased reliability
Innovation	UPI, digital wallets, biometrics	Increased habitual use and reduced anxiety
Value	Improved financial inclusion	Increased confidence through financial inclusion

Digital payments have not only impacted individuals but also their sentiments within household portfolios, which include trust, housing, and financial inclusion, according to Findex (2025) and Huang *et al.*, (2023). Therefore, the following section reviews the literature on house price sentiments

2.3 House Price Sentiment

Sentiments in the housing market are more closely tied to its illiquidity and lack of short-selling mechanisms, which limit the ability to correct the pricing (Clayton *et al.*, 2009). Thereby impacting people's buying conditions, as referred to as housing sentiment by Bork *et al.* (2020). Scholars state that financial stress, regulatory forces, and macroeconomic uncertainties are the factors, and the same empirical evidence is supported by Rooj *et al.* (2024a). In this paper, a detailed exploration of how policy uncertainty significantly depresses household consumer confidence, along with global factors, is analysed. In addition, Rooj *et al.* (2025) highlight that financial stress significantly reduces expectations of home prices, especially in the equity and foreign exchange markets. The negative effects of financial stress are asymmetric, with above-average financial stress having a disproportionately greater negative impact. Cong *et al.* (2024) show that the expansion of the digital economy affects housing prices differently across cities, suggesting that digital transformation alters housing market dynamics in diverse spatial ways. This has opened up new avenues for exploring how the digital transformation of financial systems creates new pathways through which household sentiment, including expectations about the housing market, can be influenced. Jünger and Mietzner (2020) report that the adoption of FinTech among households is predominantly seen in younger, urban, and more educated demographic groups—the same groups identified as being most responsive to macroeconomic uncertainty in the housing sector (Rooj *et al.*, 2024a). Digital payment systems lower transaction costs, enhance income smoothing, and produce transaction records that reduce information asymmetry between borrowers and lenders, thereby broadening access to formal credit for previously excluded groups, such as the self-employed and informal-sector workers (Ozili, 2018).

3. DATA AND METHODOLOGY

Our unit-level data on house price sentiments comes from the IESH survey administered by the Reserve Bank of India, on a bi-monthly basis across 19 major Indian cities³. In our study, we include observations from Round 57B (November 2019) to Round 81B (December 2025). In every round, approximately 5,500 respondents are surveyed and asked to give their opinions about their expectations on inflation and house prices for three months and one year ahead from the date of the survey. Following, Goyal and Parab, (2019) and Rooj *et al.*, (2024), we define EXHP3M=+1 if the respondent perceives house prices to rise from the current rate, 0 if respondents expect no change and -1 if they perceive house prices to decline vis-à-vis the current rate three months ahead from the survey date. Similarly, EXHP1Y =+1 +1 if the respondent perceives house prices to rise from the current rate, 0 if respondents expect no change and -1 if they perceive house prices to decline vis-à-vis the current rate a year ahead from the survey date.

³ Andaman & Nicobar Islands, Arunachal Pradesh, Dadra & Nagar Haveli, Diu & Daman, Lakshadweep, Manipur, Meghalaya, Mizoram, Nagaland, and Sikkim.

Our data on digital payments comes from the RBI's Payment System Indicators. RBI defines a digital transaction as a flawless system that does not require physical cash and takes places through an electronic or digital platform, wherein the payer and beneficiary pays/receives money using an electronic platform. Hence, we use the digital payments indicators from the Payment System Indicators published by the RBI, which lists the different forms of digital payments. For instance, financial market instruments (FMI) like Real Time Gross Transfer (RTGS), Aadhaar Payment Bridge System-ABPS, retail-based transfers (Aadhaar Enabled Payment System-AePS), Electronic Clearing System-ECS, Immediate Payment Service-IMPS, Unified Payments Interface-UPI, National Electronic Fund Transfer-NEFT, and National Automated Clearing House-NACH). It also includes card payments (credit, debit, and POS), as well as E-Wallets. This variable on digital payments should be perceived as capturing transmission of digital payments infrastructure and its use at the macroeconomic level rather than household-centred usage. Table 1 presents a detailed explanation of the variables used in this study.

Following the existing works (Binder & Makridis, 2020; Rooj *et al.*, 2024) we also explore the impact of digital payments on house price expectations by estimating the following equation, for Indian households:

$$EXHP_{icmt} = \alpha + \beta LDPAY_{(m-1),t} + \gamma X_{icmt} + \phi_c + \delta_m + \theta_t + \varepsilon_{icmt}$$

In the above equation, the subscript i refer to a household, c indicates the city of domicile of the respondent, m denotes month, t indicates the year. X is the vector of demographic controls at the household level, like gender, age and employment category. Since our dataset is in a panel format, ϕ_c is the set of city fixed effects that is assumed to counter the variations of household sentiments amongst respondents that might be driven by the non-random selection of households over different cities with fluctuating housing market conditions, economic growth rates as well as heterogeneous belief and experiences (own-self, friends, and relatives) influencing the way an information is perceived.

Similar to Case *et al.*, (2005) m is the component for month effects that is ought to control cyclical fluctuations in the housing market. Finally, we also incorporate θ_t as the year-fixed effects, which is likely to account for the unobserved variations across the macro-economic environment in India that might impact the housing market in a particular year. The inclusion of time and city fixed effects allows us to control for the location and time-specific variations in our dataset that would otherwise have remained unaccounted for at the city-level (González-Pampillón, 2022).

$LDPAY_{(m-1),t}$ is our key independent variable in this study, which incorporates the total amount (in ₹) of digital payments (in logs) for the preceding month corresponding to the IESH survey period. We postulate that unobserved shocks in household sentiments about

expectations on house prices are uncorrelated with changes in the LDIPAY, conditional on demographic controls. The variable on house price expectations is captured at the individual level, whereas the amount of digital payments (₹, in logs) is lagged at the national level. Hence, it is highly unlikely that the current level of household sentiment can influence the value of lagged digital payment activities captured at the India level, thereby mitigating chances of reverse causality (Bellemare *et al.*, 2017). Furthermore, the inclusion of city- and time-level fixed effects removes location-specific fluctuations that might otherwise be correlated with unobserved respondent-specific tastes and beliefs, thereby helping to address endogeneity. All standard errors are clustered at the city level and are heteroskedastic and autocorrelation consistent. Our coefficient of interest is β .

4. RESULTS AND DISCUSSIONS

Table 2 shows some interesting observations for the variables used in the study. The results reveal that the house price expectation is, on average, 6% for the sample period considered in the study and about 47% of the households are female-dominated. Tables 3 and 4 present our findings from the baseline regression outcome involving house price expectations at three months and one year ahead, respectively. While Model I considers only the impact of variations of digital payments (in ₹) on house price expectations, Model II includes the household controls from the IESH dataset. The estimated coefficients of LDIPAY for both tenure (three months and one year ahead) and models (Model I and Model II) are statistically significant and positive. However, there has been a marginal change in the coefficient outcome with one-year-ahead expectations. Thus, our results hint that the growth rate in digital payment significantly contributes to increased respondent perception towards house prices. It is interesting to note that the increased use of digital payment platforms is associated with increased optimism towards house prices, which may be due to its contribution to higher overall inflation scenarios that can also transmit towards higher house price expectations (Rooj *et al.*, 2026). Moreover, the literature on FinTech also connects to housing markets and show that technology backed financing options reduces transaction frictions, widens credit access and correlates with house price dynamics (Choi *et al.*, 2019). Furthermore, our baseline results also compliments the TAM (Davis, 1989) stating that adoption of new technologies is dependent on perceived ease of use as well as its usefulness. Therefore, our findings are in line with the proposed idea, that digital payment diffusion results in reduced information and transactional frictions, increases optimism in financial systems, and can also foster a behavioural shift towards home-buying decisions than being only restricted to household adoption.

Table 2: Descriptive Statistics

Variables	Measurement	Mean	S.D.
EXHP3M	=-1 if the respondent expects a decline in 3-months ahead house prices, 0 if the respondent expects no change in 3-months ahead house prices, and 1 if the respondent expects a rise in 3-months ahead house prices.	0.663	0.593
EXHP1Y	=-1 if the respondent expects a decline in 1-year ahead house prices, 0 if the respondent expects no change in 1-year ahead house prices, and 1 if the respondent expects a rise in 1-year ahead house prices.	0.771	0.526
LLDGIP	Lag of digital payments in logs	16.652	0.298
AGE	=1 if the age of the respondent is up to 25 years (reference group), 2 if it is between 25 and 35 years, 3 if it is between 35 and 50 years, 4 if it is between 50 and 60 years, and 5 if it is 60 years or above.	2.619	1.129
FEMALE	=1 if the respondent is female, 0 otherwise.	0.476	0.499
EMPCAT	=1 captures the occupation if the household respondent belongs to other occupational groups; EMPCAT=2 if the household respondent is a retired person; EMPCAT=3 if the household respondent is a housewife/homemaker; EMPCAT=4 if the household respondent daily wage earner; EMPCAT=5 if the household respondent is self-employed; EMPCAT=6 if the household respondent belongs to employed category including employment in the financial sector.	3.903	1.629

Note: This table presents the definitions of the variables used in our empirical analysis and their descriptive statistics.

The sample size is 220983.

*Source: Author's own calculations

Table 3: Baseline Results with 3 Months Ahead Expectations

Variables	EXHP3M	
	Model I	Model II
	Coeff. (Std. Err.)	Coeff. (Std. Err.)
LL1DIPAY	0.822*** (0.085)	0.804*** (0.085)
Household controls	No	Yes
City, Month, and Year Fixed Effects	Yes	Yes
Observations	215178	215178

Note: This table presents the impact of use of digital payments on sentiments towards house prices. HPEXP3M = 1 if the respondent's outlook towards house prices for the next months, increases more than current rate or similar to current rate or less than current rate, 0 if it remains unchanged, and -1 if it declines. LL1DIPAY is the lag of the digital payments (in logs). Standard errors clustered at the city level. Standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1%, respectively.

*Source: Author's own calculations

Table 4: Baseline Results with 1-Year Ahead Expectations

Variables	EXHP1Y	
	Model I	Model II
	Coeff. (Std. Err.)	Coeff. (Std. Err.)
LL1DIPAY	0.620*** (0.078)	0.607*** (0.076)
Household controls	No	Yes
City, Month, and Year Fixed Effects	Yes	Yes
Observations	215178	215178

Note: This table presents the impact of the use of digital payments on sentiments towards house prices. HPEX-P1Y=1 if the respondent's outlook towards house prices for a year ahead, increases more than the current rate or is similar to the current rate or is less than the current rate, 0 if it remains unchanged; and -1 if it declines. LL1DIPAY is the lag of the digital payments (in logs). Standard errors clustered at the city level. Standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1%, respectively.

**Source: Author's own calculations*

Since our data comes from the IESH survey of the RBI that incorporates the different elements of the inflation basket, hence we also extend our analysis by estimating the above equation using a recursive approach to find the probable impacts of the use of digital payments on other elements of the inflation basket, like food prices, non-food prices, prices of household durables, general prices, and service prices. Table 5 to 9 presents our findings from the disaggregated analysis. We find that general prices and food prices show a negative and significant impact for the use of digital payments for the three-month-ahead expectations, while price expectations of household durable show a positive outcome for the same period. However, for the one-year-ahead timeline, almost all the variables reveal a positive and significant impact of the use of digital payments.

Table 5: Disaggregated Analysis with Food Prices

Variables	Expectation on Food prices	
	EFP3M	EFP1Y
	Coeff. (Std. Err.)	Coeff. (Std. Err.)
LL1DIPAY	-0.126** (0.045)	0.205*** (0.042)
Household controls	Yes	Yes
City, Month, and Year Fixed Effects	Yes	Yes
Observations	215178	215178

Note: This table presents the impact of the use of digital payments on sentiments towards food prices. EFP3M =1 if the respondent's outlook towards food prices for the next months, increases more than the current rate or similar to the current rate or less than the current rate; 0 if it remains unchanged; and -1 if it declines. Similarly, EFP1Y=1 if the respondent's outlook towards food prices for a year ahead increases more than

the current rate or is similar to the current rate or is less than the current rate; 0 if it remains unchanged; and -1 if it declines. LL1DIPAY is the lag of the digital payments (in logs). Standard errors clustered at the city level. Standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1%, respectively.

**Source: Author's own calculations*

Table 6: Disaggregated Analysis with Non-Food Prices

Variables	Expectation on Non-Food prices	
	ENFPP3M	ENFPP1Y
	Coeff. (Std. Err.)	Coeff. (Std. Err.)
LL1DIPAY	-0.025 (0.046)	0.194*** (0.031)
Household controls	Yes	Yes
City, Month, and Year Fixed Effects	Yes	Yes
Observations	215178	215178

Note: This table presents the impact of the use of digital payments on sentiments towards non-food prices. ENFPP3M=1 if the respondent's outlook towards non-food prices for the next month's increases more than the current rate or similar to the current rate or less than the current rate, 0 if it remains unchanged, and -1 if it declines. Similarly, ENFPP1Y=1 if the respondent's outlook towards non-food prices for a year ahead increases more than the current rate or is similar to the current rate or is less than the current rate; 0 if it remains unchanged; and -1 if it declines. LL1DIPAY is the lag of the digital payments (in logs). Standard errors clustered at the city level. Standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1%, respectively.

**Source: Author's own calculations*

Table 7: Disaggregated Analysis with General Prices

Variables	Expectation on General Prices	
	EGP3M	EGP1Y
	Coeff. (Std. Err.)	Coeff. (Std. Err.)
LL1DIPAY	-0.063*** (0.021)	0.041* (0.022)
Household controls	Yes	Yes
City, Month, and Year Fixed Effects	Yes	Yes
Observations	215178	215178

Note: This table presents the impact of the use of digital payments on sentiments towards general prices. EGP3M=1 if the respondent's outlook towards general prices for the next month's increases more than the current rate or similar to current rate or less than current rate; 0 if it remains unchanged; and -1 if it declines. Similarly, EGP1Y=1 if the respondent's outlook towards general prices for a year ahead, increases more than the current rate or is similar to the current rate or is less than the current rate, 0 if it remains unchanged, and -1 if it declines. LL1DIPAY is the lag of the digital payments (in logs). Standard errors clustered at the city level. Standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1%, respectively.

**Source: Author's own calculations*

Table 8: Disaggregated Analysis with Household Durables

Variables	Expectation of Household Durables	
	EHDP3M	EHDP1Y
	Coeff. (Std. Err.)	Coeff. (Std. Err.)
LL1DIPAY	0.141*** (0.090)	0.216*** (0.056)
Household controls	Yes	Yes
City, Month, and Year Fixed Effects	Yes	Yes
Observations	215178	215178

Note: This table presents the impact of the use of digital payments on sentiments towards household durable prices. EHDP3M =1 if the respondent's outlook towards household durable prices for the next month's increases more than the current rate or similar to the current rate or is less than the current rate, 0 if it remains unchanged, and -1 if it declines. Similarly, EHDP1Y=1 if the respondent's outlook towards household durable prices for a year ahead, increases more than current rate or similar to current rate or less than current rate, 0 if it remains unchanged, and -1 if it declines. LL1DIPAY is the lag of the digital payments (in logs). Standard errors clustered at the city level. Standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1%, respectively.

**Source: Author's own calculations*

Table 9: Disaggregated Analysis with Service Prices

Variables	Expectation on Service Prices	
	ESP3M	ESP1Y
	Coeff. (Std. Err.)	Coeff. (Std. Err.)
LL1DIPAY	0.056 (0.049)	0.154*** (0.028)
Household controls	Yes	Yes
City, Month, and Year Fixed Effects	Yes	Yes
Observations	215178	215178

Note: This table presents the impact of use of digital payments on sentiments towards service prices. ESP3M =1 if the respondent's outlook towards service prices for the next months, increases more than current rate or similar to current rate or less than current rate, 0 if it remains unchanged, and -1 if it declines. Similarly, ESP1Y=1 if the respondent's outlook towards service prices for a year ahead, increases more than current rate or similar to current rate or less than current rate, 0 if it remains unchanged, and -1 if it declines. LL1DIPAY is the lag of the digital payments (in logs). Standard errors clustered at the city level. Standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1%, respectively.

**Source: Author's own calculations*

Finally, to reinstate our baseline findings we also re-run the baseline regression using an alternative definition of digital payments, that is $LDPAY_{(m-1),t}$ which is our variable of interest for the model's robustness (Table 10). This variable is interpreted in the same

manner as our amount of digital payments (logs in ₹). Our findings from this section further validates our baseline outcomes as to the use of digital payments has a positive and significant impact on house price sentiments of Indian households.

Table 10: Robustness Check with Volume of Digital Payments

Variables	EXHP3M	EXHP1Y
	Coeff. (Std. Err.)	Coeff. (Std. Err.)
LL1DIPV	0.832*** (0.082)	0.681*** (0.081)
Household controls	Yes	Yes
City, Month, and Year Fixed Effects	Yes	Yes
Observations	215178	215178

Note: This table presents the impact of volume of digital payments on sentiments towards house prices. HPEX-P3M=1 if the respondent's outlook towards house prices for the next months, increases more than current rate or similar to current rate or less than current rate, 0 if it remains unchanged, and -1 if it declines. HPEX-P1Y=1 if the respondent's outlook towards house prices for a year ahead, increases more than current rate or similar to current rate or less than current rate, 0 if it remains unchanged, and -1 if it declines. LL1DIPV is the lag of the digital payments (in logs). Standard errors clustered at the city level. Standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1%, respectively.

**Source: Author's own calculations*

5. CONCLUSION

When we set out to explore this question, the intuition was simple: if digital payments were reshaping how Indians transact, save, and access financial services, could they also be quietly shifting how households approach buying a home? The answer, as our findings suggest, is a convincing yes. Using a large panel of Indian households surveyed across 19 major cities between November 2019 and December 2025, we demonstrate that the growth in digital payment transactions, measured in both value and volume, is positively and significantly associated with households' expectations of rising house prices, whether they are looking three months or a year ahead. This holds even after accounting for who the respondents are, i.e., their age, gender, and occupation, and after controlling for the city they live in and the broader macroeconomic environment of any given year. The robustness checks, using an alternative measure of digital payments, only strengthen this story.

What makes this finding particularly intriguing is what the disaggregated analysis reveals. In the short run, digital payment growth tends to temper expectations for general and food prices, reflecting efficiency gains and lower transaction costs that are flowing through to everyday consumption. But for household durables and over a one-year horizon, the association turns decisively positive across nearly all price categories. This suggests that the effect of digital finance on household optimism is not narrow or sector-specific. It builds gradually, and it is broad.

Viewed through Rogers' (2016) lens of digital transformation, this makes considerable sense. India's journey from zero-balance Jan Dhan accounts to Aadhaar-linked identities, from IMPS to a UPI ecosystem processing over 640 million transactions daily, was never just about payments. It was about rebuilding trust in formal financial systems, one transaction at a time. Our results reflect that cumulative shift.

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