Consumption Response to Permanent Income Shocks: Evidence from India's Mobile Internet Rollout*

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Abstract

We provide novel empirical evidence on the Permanent Income Hypothesis (PIH) by exploiting plausibly exogenous, unanticipated and persistent income shocks generated by the arrival of mobile internet in India. A key challenge in testing the PIH is the scarcity of plausibly exogenous, persistent income shocks; we argue that the staggered arrival of 3G mobile internet—driven by the staggered legal resolution of a major telecom corruption scandal—offers such a shock, and identify its pass through effects on consumption. Using detailed transaction-level data from two of India's largest banks, we estimate the consumption response to income gains driven by mobile internet access. We find that two years after 3G rollout, average household incomes rose by 4.7–5.6%, translating into a consumption increase of 90–93 paise per rupee of income. These marginal propensities to consume (MPCs) are some of the highest documented, and especially significant as they closely approach the benchmark of unity predicted by the PIH. We further identify two internet-enabled mechanisms that drive this high consumption response: (i) expanded access to consumption goods via e-commerce, especially for wealthier rural households; (ii) increased use of digital payment systems. Finally, we show that the arrival of mobile internet led to greater adoption of insurance products, which reduced precautionary savings, and therefore allowed the substantial pass-through to consumption. Overall, our findings not only provide new evidence for the validity of the PIH, but also highlight how digital infrastructure can generate durable economic transformations.

Keywords: Mobile internet, Indian economy, Income growth, Consumption growth
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1 Introduction

Testing the Permanent Income Hypothesis (PIH) (Friedman, 1957) has long posed a foundational challenge in the consumption literature (Jappelli and Pistaferri, 2010). The PIH predicts that households smooth consumption over time, saving the majority of unanticipated transitory income shocks while adjusting consumption one-for-one in response to permanent income changes. However, most empirical tests of this hypothesis have focused on temporary income shocks, primarily due to the difficulty of isolating income changes that are both exogenous and persistent. These studies typically exploit variation from tax rebates, stimulus payments, and other short-term transfers—shocks that are unlikely to be perceived by households as permanent—and have found mixed evidence regarding the PIH's central prediction of limited consumption responses to transitory income. In contrast, direct evidence from micro data on how consumption responds to a dollar increase in *permanent* income remains limited, despite its central importance for both macroeconomics and household finance. Such an estimate is critical for calculating the fiscal multiplier associated with policy-induced income changes, and thus for assessing the long-run growth and output effects of economic interventions.

In this paper, we provide rare empirical evidence on the PIH by studying a shock that plausibly and unexpectedly altered households' permanent income trajectories: the staggered introduction of 3G mobile internet across districts in India. Unlike many income shocks previously studied, the arrival of 3G networks triggered a structural and durable transformation in household economic activity. While the internet could be accessed before using 2G connections, speed limitations implied that it was primarily for voice and basic text; 3G enabled faster internet, video streaming, and allowed popular apps like WhatsApp, Facebook and Youtube to function properly, helping boost overall mobile internet usage.[1] Moreover, its rollout was both unpredictable and unrelated to pre-existing local economic conditions, offering a unique opportunity to identify the causal effect of permanent income shocks on consumption.

The staggered rollout of 3G mobile internet was the result of an exogenous institutional shock: the cancellation of telecom licenses following a major corruption scandal at the central government level in 2012. The Supreme Court of India revoked 122 spectrum licenses held by

[1] We compare the the impact of 3G internet with that of 2G and 4G in Section 4.3.

18 telecom operators, many of which had assets spanning multiple districts. Since over 90% of 3G infrastructure in India was installed on pre-existing 2G towers (see Figure 1), legal uncertainty surrounding the status of these towers directly impeded 3G deployment in affected areas. In 2017, however, a special court of the Central Bureau of Investigation acquitted all accused parties, resolving the legal bottleneck. This led to a rapid acceleration of 3G rollout in previously stalled districts, as assets were acquired by untainted firms and regulatory approvals were finalized. The result was a surge in mobile internet access that unlocked higher incomes through increased productivity, entrepreneurship, and firm creation.

Crucially, the timing of 3G expansion across districts was driven by legal and bureaucratic processes—such as regulatory clearance and network restructuring—rather than local economic fundamentals. Following Gopalan et al. (2016), we use a hazard model to validate this key identifying assumption: that the variation in the timing of scam resolution and subsequent 3G rollout across districts was unrelated to pre-existing economic activity. This quasi-experimental setting allows us to credibly estimate the marginal propensity to consume out of permanent income, shedding new light on a central question in the consumption literature.

To implement our empirical strategy, we construct two panel datasets based on two proprietary sources of financial transaction data: (i) individual-level account and spending data a large private-sector bank serving primarily middle- and upper-income households, and (ii) similar data from a large public-sector bank, which serves a broader demographic including rural and lower-income customers. Together, these datasets cover more than 500,000 households and over 75 million transactions between 2013 and 2021. The data include detailed measures of income inflows, consumption outflows, payment methods, and insurance purchases, enabling a granular analysis of household economic behavior over time.

Our first main result is that mobile internet access leads to significant and lasting income growth (Figure 3). In the two years following the resolution of legal uncertainty—and hence, the arrival of 3G connectivity—average household income rises by 4.7% to 5.6%, depending on the dataset and specification. These estimates are robust to a range of controls and alternative specifications, and they are not driven by pre-trends or compositional changes. Using firm-level data from the Ministry of Corporate Affairs, we show that this income growth is accompanied by in-

creases in both total factor productivity (TFP) and the number of registered firms. Specifically, we find a 4.7% increase in TFP and a 48% increase in firm registrations two years after 3G access. These findings suggest that mobile internet enhances both the intensive (productivity) and extensive (entry) margins of local economic activity.

Second, we examine our key question: how do these permanent income gains translate into consumption? We find a remarkably high marginal propensity to consume (MPC): households spend between 90 and 93 paise for every additional rupee of income gained from internet access. These MPC estimates are significantly higher than those typically observed for transitory income shocks, such as tax rebates or stimulus payments (Johnson et al., 2006; Parker et al., 2013; Chetty et al., 2024). The high MPC suggests that households view income gains from mobile internet as persistent, consistent with the predictions of the Permanent Income Hypothesis (Friedman, 1957). In event study analyses, we observe a gradual but sustained increase in consumption following 3G rollout, with no evidence of reversion, further supporting the interpretation that internet access represents a durable shift in household economic opportunities.

Third, we explore the mechanisms underlying this elevated consumption response. We identify two distinct channels through which mobile internet influences consumer behavior:

(i) The expansion of consumption sets via e-commerce. Mobile internet allows households—particularly in rural and semi-urban areas—to access a broader range of goods and services through online platforms. We find that e-commerce spending increases by 9–19% depending on the sample and time horizon, with stronger effects among wealthier rural households. This growth in online consumption accounts for up to 20% of the overall increase in consumption, despite e-commerce constituting a relatively small share of total spending.

(ii) Growth in digital payment infrastructure. Mobile internet facilitates the spread of electronic payment systems, including card-based point-of-sale (POS) terminals and mobile wallets. Using a shift-share instrument based on pre-existing terminal penetration, we estimate that expansion in digital payments infrastructure explains up to 23% of the observed rise in consumption, primarily through increased debit card usage. This channel reflects both convenience and reduced liquidity constraints associated with cashless transactions, and is consistent with evidence in Alok et al. (2024).

Finally, we examine changes in precautionary savings around the arrival of 3G. Precautionary saving provides a challenge to empirical tests of the PIH by causing individuals, especially in countries like India with high income uncertainty and limited social safety nets, to save—even out of permanent income shocks—for a future rainy day. Therefore, if precautionary savings motives are quantitatively important, then households might show a muted consumption response. We find that insurance purchases rise by 17–49% following 3G rollout, alleviating concerns that precautionary savings motives would dampen the pass-through from income to consumption. This could be due to supply side effects—i.e., internet access enabling insurance providers to reach a more diversified customer base at a lower cost, and/or demand-side effects—i.e., lower search costs for the insured; overall, 3G arrival increased the uptake of financial protection products and reduced precautionary saving motives. Conditional on income, insured households spend significantly more than uninsured households, suggesting that risk mitigation leads to lower precautionary saving and higher consumption. This effect was particularly strong for the private bank sample with wealthier households.

From a policy perspective, our results have important implications. First, they suggest that investments in digital infrastructure can yield substantial economic returns—not just through aggregate productivity gains but also via a large consumption multiplier. Second, the heterogeneity we observe across income groups and regions highlights the potential for digital technologies to reduce spatial inequality by expanding access to markets and financial services. Third, the complementarities between internet access and financial products such as insurance and digital payments point to the value of coordinated policies that integrate infrastructure development with financial inclusion initiatives.

These results contribute to several strands of literature. First, we contribute to the literature on consumption and the marginal propensity to consume (MPC). Most empirical work has focused on transitory income shocks (e.g., stimulus payments, tax rebates). Quasi-natural experiments of such transitory income shocks include tax rebates (Shapiro and Slemrod, 1995; Souleles, 1999; Shapiro and Slemrod, 2003; Johnson et al., 2006; Agarwal et al., 2007; Baugh et al., 2021), social security payments (Parker, 1999), lottery prizes (Fagereng et al., 2021), stimulus payments (Baker et al., 2023; Parker et al., 2013; Chetty et al., 2024), dividends (Agarwal and Qian, 2014; Kueng,

2018; Bräuer et al., 2022), mortgage refinancing (Agarwal et al., 2023), and interest rate shocks (Agarwal et al., 2022). Most papers in literature find that consumption responds to plausibly temporary, and even anticipated, shocks to income.

There are fewer empirical studies estimating MPC out of persistent and unpredictable income changes, possibly due to the difficulty in identifying such income shocks, although households are shown to be capable of distinguishing between persistent and transitory income shocks (Druedahl and Jørgensen, 2020). Early literature on tests of the PIH found mixed evidence Hall (1978); Nelson (1987); Campbell (1987); Hsieh (2003). A common empirical setting for many following tests has been tax reforms presumed to be persistent. For example, Souleles (2002) documents a high MPC between 0.6 and 0.9 for a pre-announced tax cut. Other authors document lower MPC estimates in different contexts; e.g., Johnson et al. (2006) finds that the 2001 U.S. income tax cut only had an MPC of 0.2–0.4, although some economists consider it as a permanent tax cut and therefore is expected to have an immediate one-for-one effect on consumption (Carroll, 2009). Finally, using an innovative approach based on an unexpected change in gas price in the U.S., Gelman et al. (2023) find that the MPC out of permanent income is approximately one. Our findings extend this literature by estimating MPCs from a unique setting with a plausibly persistent yet unpredictable technology-driven income shock, unrelated to local economic conditions. The high MPCs we observe are consistent with theoretical predictions for permanent shocks and suggest that digital infrastructure may shift household expectations about future income in a durable way.

Second, the income shock we study arises from corruption-induced differences in exposure to technology, as opposed to fiscal or monetary policies. Policies typically respond to economic conditions, and even in the rare instances they do not, they are unlikely to bring forth as large and permanent income shocks as information technology changes can provide. A large body of academic research on the relation between internet connectivity and various macroeconomic outcomes in the developed world (see, e.g., Autor et al. (1998); Datta and Agarwal (2004); Bartel et al. (2007); Beaudry et al. (2010); Czernich et al. (2011); Atasoy (2013); Akerman et al. (2015); Bhuller et al. (2023); Jiang et al. (2023); or the survey by Goldfarb and Tucker (2019)), and a few papers on developing economies (Hjort and Tian, 2021) attest to information technology advances having substantial effects. Among the papers that have studied the effects of the internet in devel-

oping countries are Hjort and Poulsen (2019), who use the arrival of submarine cables in Africa to show large positive effects of the internet on employment rates, arising from increased firm entry, productivity and exports; this evidence shows that permanent income changes in response to the internet are not an artifact of the Indian setting. In India, Goyal (2010), Parker et al. (2016) both find information technology-driven improvements in rural agricultural markets. More generally, Manacorda and Tesei (2020), Guriev et al. (2021), Jensen (2007), Lewis-Faupel et al. (2016), Jack and Suri (2014), Bahia et al. (2020), Bahia et al. (2021) Fan et al. (2018), Couture et al. (2021) and D'Andrea and Limodio (2023), among iothers, have studied various effects of internet access in developing countries. The key difference in our paper is our ability to use detailed bank transaction-level data to test the PIH using permanent incomes changes arising from the arrival of mobile internet, something that is missing in this literature.

Third, we provide novel evidence on the mechanisms through which internet access affects consumption, highlighting the roles of market access (e-commerce), financial technology (digital payments), and risk mitigation (insurance). These mechanisms are likely to become increasingly salient as digital financial services expand in developing economies. Our findings underscore the importance of viewing internet access not merely as a communication tool, but as a foundational platform for broader economic integration and modernization.

This paper proceeds as follows. Section 2 describes the empirical strategy and identification framework. Section 3 outlines the data sources and construction of key variables. Section 4 presents the main results on income and consumption. Section 5 explores the mechanisms underlying consumption responses. Section 7 concludes.

2 Empirical Methodology

The rollout of 3G across India, even though staggered, could be endogenous. For example, if the rollout was in response to local economic growth, with faster-growing areas getting 3G connectivity sooner, then we might suffer from reverse causality. That is, we might misattribute to mobile internet the underlying effects of stickiness in growth rates. Therefore, we need to consider an instrument here—an underlying variable that would predict 3G rollout, but would not directly

correlate with our variables of interest, like incomes or consumption. In other words, if we find that the instrument has any effect on income/consumption, it must be through its effect on the 3G rollout.

We utilize an earlier corruption scandal involving the allocation of 2G spectrum licenses by the government as the instrument. Due to allegations of irregularity in allocation, a few companies were put under the scanner, and subsequent court rulings created substantial uncertainty over their assets. For example, the Supreme Court canceled 122 affected 2G spectrum licenses granted to 18 different telecom companies in 2012. The 122 licenses involved in the scam covered all 22 telecom zones in India, with about 4–7 licenses in each telecom zone. After a few years of further investigations and legal proceedings, a special Central Bureau of Investigation (CBI) Court finally acquitted all accused in 2017 citing a lack of clear proof. Many of the accused 2G-license holders were severely affected by this uncertainty, affecting their operations. Even after the acquittal, it was unclear whether and how each company would continue operations. Most of them were eventually acquired by larger, untainted companies, resolving this uncertainty.

For example, Idea Cellular Limited, a scam-affected company, was based in Mumbai, and it owned nine 2G licenses that were canceled by the Supreme Court. Idea was also the major shareholder of another telecom company, Spice Communications, which held another three licenses that were cancelled. After the CBI Special Court acquittal, a merger between Idea Cellular and Vodafone India was announced as early as March 2017. However, it was not until July 2018 that the Department of Telecommunications finally approved the merger due to the large size of the deal. The merger was finally completed in August 2018, which created India's largest mobile phone company with the most subscribers and revenue share.

As a result of such delays in the merger process, acquisitions of scam-affected companies were staggered over time; and we exploit this stagger in our identification strategy. Key to this strategy is the fact that the resolution of 2G spectrum uncertainty was intimately linked to 3G growth in India. This was because 93% of 3G infrastructure was installed on telecom towers that had 2G systems installed in them from before. As a result, uncertainty regarding ownership and operation of the 2G infrastructure spilled over onto the 3G domain—3G growth was slower in districts where 2G-scam-affected companies owned assets and occupied tower space; it sped up

once the uncertainty about these assets and their operations got resolved through these affected companies being acquired.

Therefore, we use the differential timing of these acquisitions, often caused by regulatory approval delays, as our instrument for speeding up the 3G rollout. Out of the 720 districts, 129 districts had ever been covered by at least one scam firm, implying there is substantial variation in our instrument in the cross-section.

In the first-stage analysis, we regress the 3G growth rates at the district-quarter level on a dummy variable denoting the resolve of the uncertainty associated with the 2G scam, and the model is specified as follows:

$$\Delta \log (3G)_{d,q} = \beta_1 Resolve_{d,q} + X'_{d,q}\gamma_X + \phi_d + \omega_q + \epsilon_{d,q}, \tag{1}$$

where $\Delta \log (3G)_{d,q}$ is the growth rate of 3G tenancy in district d in quarter q, calculated as the quarterly changes in the log number of 3G tenancies. $Resolve_{d,q}$ is a dummy variable indicating whether the uncertainty due to the 2G scam was resolved in district d in quarter q. Specifically, for districts that were ever affected by the 2G scam, $Resolve_{d,q}$ is set to zero if at least one telecom company involved in the scam was operating in district d in quarter q and had not been acquired; otherwise, it is set to one. For districts that were never affected by the 2G scam, $Resolve_{d,q}$ is always set to one. $X_{d,q}$ is a vector of macroeconomic control variables, including the annual GDP and quarterly commercial bank credit of the districts (both in logarithmic forms). ϕ_d and ω_q represent district and year-quarter fixed effects, respectively. $\epsilon_{d,q}$ is the error term. We cluster the standard errors at the district level.

To test our hypothesis that individual income and consumption spending increase in response to the arrival of 3G Internet, we run the second-stage reduced-form regressions of the following type:

$$Y_{i,q+k} = \beta_1 Resolve_{d,q} + X'_{d,q}\gamma_X + \varphi_i + \omega_{q+k} + \varepsilon_{i,q+k}, \tag{2}$$

where the independent variable of interest ($Resolve_{d,q}$) is the same as in Equation (1). $Y_{i,q+k}$ is the quarterly outcome variable (e.g., consumption or income) for account holder i in quarter $t+k$ (i.e., k quarters later). $X_{d,q}$ is the same vector of macroeconomic control variables as in the first stage.

φ_i are individual fixed effects, and ω_{q+k} are year-quarter fixed effects. Standard errors are clustered at the district level.

Given the presence of district fixed effects, our identification will come from quarters with a change in the $Resolve_{d,q}$ variable. Since our bank sample started in 2013, which is after the 2G scam affected all suspects, any change in $Resolve_{d,q}$ will come from the resolution of uncertainty, i.e., the acquisition of affected companies, in a district-specific quarter Q_d. Effectively, our design compares how the average account holder's income/consumption changes in districts where 3G rollout speeds up following an acquisition, relative to other districts where there were no scam-affected companies (or, if there were scam-affected companies, these were not acquired at the same time).[2]

3 Data

The data on 3G mobile internet used in this study is obtained from the Telecom and Regulatory Authority of India, which covers all telecom cellular towers in the nation. Information contained in the data includes the location coordinates of the towers, operator and start operation time of each tenant (i.e., a base transceiver station) on a telecom tower, and service type of the tenant (2G or 3G). In Figure 1a, we plot the by-year number of 3G telecom tenancies between 2005 and 2021. It shows that most of the country received 3G coverage during our study period (i.e., from 2010 onward). Also, more than 90% of the new 3G tenancies are installed on existing telecom towers that provide 2G services, as shown in Figure 1b.

[Insert Figure 1 Here]

In each telecom zone, we identify the cellular towers that were leased to a telecom company involved in the 2G scam, using the names of the operators. If a district has such cellular towers, we deem that the implicated telecom company operated in this district, so the 3G development

[2]We focus on the changes in quarterly income and consumption in 1 year or 2 years after the 2G scam uncertainty in district d was resolved in quarter Q_d, so k in Equation (2) was set to 4 or 8 in separate regression models. When k equals 4, our model effectively compares the average of Y from $Q_d + 4$ onward with the average of Y up to $Q_d + 3$. To achieve comparable estimates across models, we exclude the observations in quarters $Q_d + 4$ to $Q_d + 7$ when we set k to 8; that is, we compare the average of Y from $Q_d + 8$ onward with the average of Y up to $Q_d + 3$. We confirm that our results remain robust if these observations are included in regressions with k equal to 8.

in the district was affected due to the 2G scam uncertainty. Further, we collect the dates that the scam-affected telecom companies were eventually acquired by other untainted firms through a comprehensive manual search on the Internet. We define that the uncertainty was resolved when all scam-affected telecom companies in a district were acquired. Among the 129 districts that were affected, the uncertainty was resolved in 4 waves: 8 in May 2016, 1 in October 2017, 81 in May 2018, and 39 in August 2018. Figure 2 plots the corresponding staggered resolutions of the uncertainty in the Indian districts.

[Insert Figure 2 Here]

The first proprietary banking transaction data used in this study is provided by one of the top 2 largest private banks in India and targets at the higher-income segments of customers. We have information on their (1) bank account and debit card transactions; (2) credit card transactions and monthly credit card outstanding debt; (3) ATM deposits and withdrawals; and (4) insurance and home loan information. The bank data also includes the cross-sectional information on an account holder's birth year, occupation, pin-code of residency, and self-reported income collected at the time of opening the account. Our sample includes 349,911 account holders, who are between 18 and 80 years old and live in 629 out of the 720 districts in India.[3] The sample period is from April 2013 to October 2021.

With the private bank data, we construct income as the sum of all cash inflows into the account, excluding inflows due to reversals of charges/fees, claims of insurance, maturity of investments and disbursal of loans. Consumption is measured as the sum of debit card spending, credit card spending, ATM withdrawals, and other payments directly debited from the bank account. Loan repayments, insurance premiums, and transfers to other individual accounts made by account holders are excluded from our measurement of consumption. We also measure e-commerce consumption based on the corresponding debit and/or credit card transactions, and denote the remaining proportion of total consumption as non-e-commerce consumption. We winsorize these measures of consumption and income at the top and bottom 1% levels.

[3]The Indian government has adjusted the boundaries of districts several times during our sample period. To minimize measurement error, we collect the spatial coordinates of the pin-codes that the account holders live in from India's Department of Posts (https://www.indiapost.gov.in/VAS/Pages/findpincode.aspx) and map the pin-code locations to the boundaries of Indian districts in 2020.

The second proprietary banking transaction data is provided by one of India's top two public sector banks. Compared with the private bank, this public bank serves clients with broader demographics, including the lower to middle-income groups. The data provides information on account holders' monthly ending balances and the aggregated monthly spending through POS machines, ATM withdrawals, and e-commerce platforms. Similar to the private bank data, the public bank data also has information on account holders' birth year, pin-code of residency, and self-reported annual income at account opening time. Finally, it also provides information on when account holders purchased insurance products from the public bank, if any. The data contains 36,358 account holders who are between the ages of 22 and 65 and live in 683 out of the 720 Indian districts. The sample period is from April 2016 to December 2020.

To be comparable with the private bank data, we adopted a similar approach to compute the quarterly income and consumption in the public bank data. The total consumption is measured as the sum of debit card spending and ATM withdrawals, while the e-commerce spending equals the subset of debit card spending on e-commerce platforms. The total income is computed as the sum of total consumption and the change in ending account balances. All these measures are winsorized at the top and bottom 1% levels.

Table 1 presents the summary statistics of the quarterly income and consumption of our sampled bank account holders. Panel A reports the summary statistics of the private bank data. On average, a private bank account holder has a quarterly income of 296.24 thousand INR (around 3,600 USD) and a quarterly consumption of 188.63 thousand INR (around 2,300 USD). Within consumption, the average spending by debit card, credit card, and cash withdrawal equal 11.87 thousand, 158.52 thousand, and 12.27 thousand IND, respectively. Around 6.98 thousand IND is spent via e-commerce per quarter, using either debit or credit cards.

[Insert Table 1 Here]

Panel B reports the summary statistics of the quarterly income and consumption of the public bank account holders. On average, they earn 105.93 thousand INR (around 1,300 USD) and spend 82.97 thousand INR (around 1,000 USD) per quarter, lower than the average income and consumption of the private bank account holders. 17.38 thousand INR are withdrawn from ATMs,

and 64.66 thousand INR are spent through debit cards, of which 3.19 thousand INR are spent on e-commerce platforms.

To investigate the channels of internet-led income growth, we also use the annual firm performance data from India's Ministry of Corporate Affairs (MCA), which collects the financial reports of all companies registered with the Registrar of Companies (RoC). Based on the performances of 894,722 firms between 2012 and 2021, we calculate the total factor productivity (TFP) of these firms using the method in Wooldridge (2009). Panel C of Table 1 summarizes the estimated TFP, together with other fundamental variables including total assets, debt ratio, and liquidity.

Apart from these key data sets, we also collect the macroeconomic control variables from the administrative data sources. The annual GDP of the Indian districts is obtained from Indicus Analytics, and the information on quarterly commercial bank credits is collected from the Reserve Bank of India. Further, we combine additional data sets to conduct our channel analyses on consumption growth. The data of POS terminals is obtained from one of India's top-2 largest payment terminal suppliers, and the data of digital wallet facilities is sourced from one of India's largest payment service providers.

4 Results

4.1 Impact of 3G Connection on Income

Table 2 presents the first-stage results on the impact of the 2G scam on 3G growth rates at the district-quarter level, obtained using Equation (1). We find that the scam instrument is strong. Resolution of uncertainty resulting from acquisitions increases the speed of 3G rollout in the affected districts by 2.9% in a quarter. The first-stage F-statistic is over 20, indicating that we do not have a weak instrument problem. Further, the exclusion restriction is likely to be satisfied in our context, because the stagger in acquisitions was produced mainly by delays in regulatory and court approvals due to considerations of monopoly power and other legal issues. In fact, in the acquisition of the largest scam-affected company, there was a 15-month delay in obtaining regulatory approval from the government's Department of Telecommunications, followed by another two months before the National Company Law Tribunal gave its final verdict.

Another possible instrument in our setting is the propensity of lightning strikes, as in Andersen et al. (2012), Manacorda and Tesei (2020), Guriev et al. (2021), or Jiang et al. (2023). The idea here is that a higher frequency of lightning strikes leads to higher installation costs due to the need to have surge protectors, as well as higher maintenance costs. As a result, telecom towers are set up later in areas with a higher propensity of strikes. To construct the lightning instrument, one can take a time-trend variable and multiply it with an indicator for high lightning-propensity regions, similar to Manacorda and Tesei (2020). Nevertheless, we follow this method and find that in our setting, the instrument of lightning strikes is only strong for the rollout of 2G service but not for the rollout of 3G service (Appendix Table A1). The plausible reason is that the rollout of 2G service involves the construction of new telecom towers, which are affected by the propensity of lightning strikes. In contrast, over 90% of the new 3G tenancies are installed on existing towers that provide 2G services, as shown in Figure 1b, so the rollout of 3G is less affected by lightning strikes than the rollout of 2G.

[Insert Table 2 Here]

To further verify that the timing of staggered acquisitions of scam-affected 2G telecom companies is exogenous to individual income and consumption, we follow Gopalan et al. (2016) and relate district characteristics to the timing of acquisition using a hazard model. The results are reported in Table 3. We find that the 1-year lagged macroeconomic variables of a district (e.g., the level or growth of GDP and bank credit, the ratio of bank credit to GDP, and the share of bank credit in the nation) do not predict the timing of acquisitions. The average income or consumption in the preceding year does not relate to the timing of acquisitions, either. Therefore, these results lend support for the assumption of exclusion restrictions of our instrument.

[Insert Table 3 Here]

Given the strong 2G scam instrument, we proceed to estimate the impacts of 3G connection on individual income, using the reduced-form regressions (Equation (2)). Table 4 reports the corresponding regression results, using the quarterly income of the account holders as the outcome variables. Panel A presents the results estimated using the private bank data. We find that the

average quarterly income of the private bank account holders increased mildly by 3,929 to 5,151 INR in one year after the resolution of uncertainty (Columns (1) and (2)), and the estimates are not statistically significant. In two years after the acquisitions, the quarterly income of the account holders increased by 16,058–16,622 INR (Columns (3) and (4)), which translates to a 4.7–4.9% increase from the average quarterly income (340.13 thousand INR). The estimates are statistically significant at the 1% and 5% level, respectively.

[Insert Table 4 Here]

In Panel B, we replicate the analysis using the quarterly income imputed from the public bank data. In one year after resolving the 2G scam uncertainty, the quarterly income of the public bank account holders increased by 5,711 INR (Column (1)), and the estimate is statistically significant at the 1% level. Considering the average quarterly income of 106.86 thousand INR, this estimate translates to a 5.3% increase in quarterly income. The result is consistent if we add the controls for the GDP and bank credit at the district level, as reported in Column (2). Further, results reported in Columns (3) and (4) reveal that the magnitude of the impact is slightly enlarged in 2 years, equal to a higher income of 5,912–6,116 INR per quarter. These estimates translate to a 5.5–5.6% increase from the average income level and are statistically significant at the 1% level.

To investigate the gradual changes in income following the resolution of the 2G scam uncertainty, we proceed to conduct an event-study analysis. Specifically, for districts affected by the 2G scam, we construct a set of dummy variables indicating quarters within the event window. Since the last resolution event occurred in 2018 and our private bank dataset ends in 2021, we focus on a window of [-4, +12] quarters around each event for the private bank data. The public bank data ends in 2020, so we use a narrower window of [-4, +8] quarters for that analysis. Further, for each affected district, we identify a matched unaffected district based on the closest propensity score, considering their state and macroeconomic factors (GDP and bank credit). We then assign the corresponding quarter dummies to the matched unaffected districts based on the same time frame. Last, we replace $Resolve_{d,y}$ by this set of dummy variables in Equation (2) and estimate their coefficients, using observations from the affected and unaffected districts, respectively. Figure 3 plots our event-study analysis results on income growth. It shows that, in both the private and public

bank datasets, the income of account holders in affected districts gradually increases following the resolution, whereas no such incremental pattern is observed in the matched unaffected districts over the same period.

[Insert Figure 3 Here]

We further investigate the channels of the internet-led income growth. The first channel is that 3G internet contributes to improving the TFP of local firms, resulting in higher income for employees. To examine the impact of 3G internet on the TFP of the local firms, we adopt the following empirical model, which is modified from Equation (2):

$$TFP_{f,y+k} = \beta_1 Resolve_{d,y} + Z'_{f,y+k}\gamma_Z + X'_{d,y}\gamma_X + \varphi_f + \omega_{y+k} + \varepsilon_{f,y+k}. \quad (3)$$

Specifically, since the MCA firm data is only available on an annual basis, we modify the independent variable of interest to the district-year level ($Resolve_{d,y}$), indicating whether the 2G scam uncertainty was resolved in district d in year y. The outcome variable, $TFP_{f,y+k}$, refers to the TFP of firm f in year $y + k$, and we set k as 1 or 2 in separate regressions. We control for the firm fixed effects (φ_f) and a set of yearly firm fundamental variables ($Z_{f,y+k}$), including total asset, leverage, and liquidity. Similar to Equation (2), $X_{d,y}$ refers to the macroeconomic control variables at the district-year level, and ω_{y+k} are year fixed effects. Standard errors are clustered at the district level.

Panel A of Table 5 reports the corresponding estimation results of Equation (3). We find a modest increase of approximately 2% in TPF one year after the uncertainty is resolved, as shown in Columns (1) and (2). Column (3) reveals that the increase in TFP enlarges to 4.65% two years after the resolution, and the estimate is statistically significant at the 1% level. This result is robust after we control for the macroeconomic variables, as reported in Column (4). These findings indicate that, with the arrival of 3G internet, the productivity of the local firms gradually improves.

[Insert Table 5 Here]

The second channel we explore relates to the extensive margin of the local outputs, approximated by the number of firms registered in a district. To investigate this channel, we adopt the

following district-year level regression model, modified from Equation (1):

$$FirmNum_{d,q+k} = \beta_1 Resolve_{d,q} + X'_{d,q}\gamma_X + \varphi_d + \omega_{q+k} + \varepsilon_{d,q+k}. \quad (4)$$

$FirmNum_{d,q+k}$ denotes the number of firms registered in district d in quarter $q + k$. Definitions of other variables are the same as in Equation (1), and we cluster the standard errors at the district level.

We present the regression results of Equation (4) in Panel B of Table 5. On average, the number of firms registered in a district increases by over 880 within one year following the resolution of the 2G scam uncertainty (Columns (1) and (2)), representing approximately a 54% increase relative to the average level. Consistent increases are also evident two years following the resolution, as reported in Columns (3) and (4), equalling around 48% of the average level. These findings suggest a strong effect of mobile internet connectivity on stimulating local business activities.

In summary, our reduced-form results support our hypothesis that individual income increases in response to the arrival of 3G mobile internet. We provide evidence that enhanced mobile internet connectivity improves the productivity of local firms and increases the number of registered firms, which contributes to income growth.

4.2 Impact of 3G Connection on Consumption

Table 6 reports the results of the impact of resolving 2G uncertainty on quarterly consumption, estimated using Equation (2). Panel A reports the estimation results based on the private bank data. Within one year following the resolution of uncertainty, the average quarterly consumption of the private bank account holders increased by 7,212 to 7,976 INR (Columns (1) and (2)), translating to a 3.4–3.8% increase from the average consumption level. Notably, this increase exceeds the corresponding rise in income during the same period (3,929 to 5,151 INR, as reported in Table 4), suggesting that users of the private bank, who are likely in the higher-income group, tend to spend more than their additional earnings after the 2G uncertainty had been resolved for one year.

[Insert Table 6 Here]

Results in Columns (3) and (4) reveal that two years after the resolution, the quarterly consumption of private bank users increased by 14,778 to 15,446 INR, corresponding to a 6.7–7% increase relative to the average quarterly consumption of 221.35 thousand INR. These estimates are statistically significant at the 1% level. Compared to the corresponding increase of 16,058 to 16,622 INR in income over the same period, our findings suggest that private bank account holders spent around 92–93% of their income growth after the 2G uncertainty had been resolved for two years.

Further, we use the public bank data to repeat the same analysis and report the corresponding results in Panel B. We find that the quarterly consumption of the public bank users increased by 2,786–2,797 IND after one year, and by 5,292–5,508 IND after two years. All these estimates are statistically significant at the 1% level, and they translate to approximately a 3.3% increase after one year and a 6.3–6.5% increase after two years, relative to the average consumption level. Given the corresponding income increases equal to 5,704–5,711 IND after one year and 5,912–6,116 IND after two years, we estimate that the public bank account holders spent about 49% of their income growth after one year, and around 90% of that after two years.

Similar to our analysis of income growth, we also perform an event study on consumption patterns in districts impacted by the 2G uncertainty, along with their matched unaffected counterparts. Figure 4 illustrates the findings, revealing a steady rise in the quarterly consumption of both private and public bank users from affected districts after the resolution. In contrast, in either dataset, this upward trend is not observed among the matched unaffected districts during the corresponding time frame.

[Insert Figure 4 Here]

In summary, we find consistent evidence across the two datasets that quarterly consumption increases significantly following the enhanced 3G mobile internet connection.[4] Private bank users,

[4]In Appendix Table A4, we further examine the heterogeneity in consumption growth across different payment methods: debit card transactions, ATM withdrawals (cash), and credit card spending. For both the private and public bank users, the majority of the consumption growth is driven by increased debit card spending. Among the private bank users, cash withdrawals decline, suggesting a shift from cash-based transactions to debit card payments following the introduction of 3G mobile internet. However, this shift is less evident among the public bank users, as we do not observe statistically significant changes in cash withdrawals. Lastly, the private bank data also provides information on credit card spending, and we find it slightly decreased following the 3G internet connection, plausibly because the private bank users, whose earnings have increased, tend to reduce their reliance on credit.

who belong to a higher-income group, exhibit a stronger response after one year than public bank users, who represent a broader demographic. After two years, both groups of users exhibit a high pass-through rate, spending at least 90% of the increase in their quarterly income.

4.3 Comparing 3G Connectivity to 2G and 4G

Here we seek to understand whether 3G rollout—which allowed people to access various internet services at sufficient speed on their mobile devices—provided the strongest boost to incomes (and hence consumption) or would it be equally useful to study other improvements to telecom networks in India. We study both the 2G rollout immediately preceding 3G (which mostly provided better voice and message services) and the 4G rollout following it (which increased internet speed beyond 3G networks).

First, using the lightning instrument described before (recall that it is a strong instrument for 2G but not for 3G), we find no statistically significant impact of 2G communication networks on income or consumption in our sample period (Appendix Table A2). This is true both for the private bank sample and the public bank sample.

This is not surprising, given that 3G's higher bandwidth capacity enabled applications that fundamentally transformed user behavior. Nokia's analysis revealed that 60% of mobile data traffic in 2015 involved multimedia services, with video streaming and social networking accounting for the majority of usage (see, e.g., https://www.medianama.com/2016/03/223-3g-usage-india-nokia/). This represented a qualitative shift from 2G-era usage patterns dominated by basic messaging. The availability of 3G speeds facilitated critical digital behaviors including Mobile video consumption at scale, social media interactions (with 43% of mobile internet users accessing Facebook monthly), and messaging app dominance (users spending 20-25 minutes daily on platforms like WhatsApp), alongside e-commerce transactions requiring secure connections. These behavioral changes were technologically impossible under 2G constraints, underscoring 3G's role as an enabler rather than merely an incremental improvement.

Second, in Appendix Table A3, we further investigate the impact of 4G internet connectivity and confirm that the more significant effect comes from the arrival of 3G. We follow Alok et al. (2024) and exploit the launching of 4G services by Reliance Jio Inforcomm Limited—popularly

known as Jio—as a source of exogenous variation in 4G access. Specifically, Jio entered the market with a unique strategy, focusing on reliable and high-speed 4G data services only, rather than traditional voice and message services. We find that among the private bank users, 4G connection also results in higher income and a large MPC, but the increases in income are smaller than those resulting from the arrival of 3G. Further, for the public bank users, who are less wealthy, the incremental impacts of 4G connection on income and consumption are small. Higher speed internet, therefore, seems to matter more for the wealthier who possibly have more use for the increment in speed (watching video streams, etc.)

Overall, our evidence indicates that the initial mobile internet access brought by 3G services brought about more significant change in the Indian context than other improvements in networks.

5 Channels of Internet-led Consumption Growth

Our estimates suggest that the average pass-through rate from internet-driven income growth exceeds 0.9, surpassing even the pass-through rates associated with permanent income shocks documented in the existing literature. In this section, we explore distinct channels underlying this unusually high consumption response to 3G internet expansion.

5.1 Expanded Reach of Products via E-commerce

The first unique channel through which mobile internet drives consumption growth is the expansion of accessible goods via e-commerce. Enhanced internet connectivity reduces geographic constraints, enabling consumers to access a wider variety of products that were previously inaccessible in local markets. This expanded consumption set matters more for wealthier households in rural areas, who are less restricted by budget constraints but did not have easy access to urban products prior to internet access. We therefore hypothesise that consumption through e-commerce increases more than consumption through traditional non-e-commerce channels, with this effect being stronger among the wealthier rural population.

To test this hypothesis, we first examine the heterogeneous impacts of 3G mobile connection on consumption via e-commerce and non-e-commerce, separately using the consumption through

these channels as outcome variables in Equation (2). Table 7 presents corresponding estimation results. In Panels A and B, we report the estimated effects on e-commerce and non-e-commerce consumption, respectively, based on the private bank data. Columns (1) and (2) in Panel A show that 1 year after the resolution, the quarterly e-commerce spending of the private bank users increased by 739–845 INR, translating to a 9–10.3% increase from the average e-commerce consumption level (8,200 INR). While the e-commerce consumption constitutes only around 3.9% of the total quarterly consumption on average, this internet-led consumption growth from e-commerce contributes to more than 10% of the total internet-led consumption after one year (7,212–7,976 IND). Similarly, we find large relative e-commerce consumption growth from the average level by 8.7–9.4% after two years (Columns (3) and (4)), which constitutes 5.3–5.5% of the total consumption growth. All these estimates are statistically significant at the 1% level. In contrast, while Panel B shows consistent growth in non-e-commerce consumption after both one and two years, the relative increases to the average level——around 3.2–3.5% after one year and 5.2–5.5% after two years——are lower than the corresponding relative growth observed in e-commerce consumption.

[Insert Table 7 Here]

In Panels C and D, we repeat the analysis using the public bank data. We find that e-commerce spending of the public bank users increased by 569–576 INR and 670–681 INR in one and two years after the resolution, respectively, as presented in Panel C. Relative to their average level of e-commerce spending, these estimates are equivalent to approximately a 16.7–16.9% increase in one year and a 18.4–18.7% increase in two years. The relative growth in non-e-commerce consumption, in contrast, equals around 2.8% after one year and 5.7–6% after two years, as shown in Panel D. The internet-led consumption growth from e-commerce contributes to around 20% of the total consumption growth in one year and 12% of that in two years, although the average share of e-commerce spending in total quarterly spending equals only around 4%. All these results support our hypothesis that the substantial growth in e-commerce spending following the 3G internet connection contributes significantly to the observed strong consumption responses.

Next, we examine the heterogeneous responses of e-commerce spending to mobile internet based on the urbanisation of the areas considered and the wealth of the account users. For the

analysis of the private bank data, we consider that most users are in a higher-income group and thus modify Equation (2) as follows:

$$\widehat{Y}_{i,q+k} = \beta_1 Resolve_{d,q} + \beta_2 Resolve_{d,q} \times Rural_d + X'_{d,q}\gamma_X + \varphi_i + \omega_{q+k} + \varepsilon_{i,q+k}. \tag{5}$$

Specifically, we use a dummy variable $Rural_d$ to indicate the rural districts, which are classified based on the definitions from the Indian Space Research Organisation, and interact it with $Resolve_{d,q}$. The isolated item of $Rural_d$ is absorbed by the district fixed effects. Since the average consumption levels in rural and urban districts are largely different, we scale the quarterly e-commerce consumption ($Y_{i,q+k}$) of an account holder i living in a rural (urban) district by the average quarterly e-commerce consumption in rural (urban) districts and denote the scaled outcome variable as $\widehat{Y}_{i,q+k}$. Therefore, the coefficient β_1 denotes the impact of the 2G scam on the percentage change in e-commerce spending of account holders in urban districts, relative to the average level in the subgroup. $\beta_1 + \beta_2$ represents the corresponding impact on account holders in rural districts. Definitions of other variables are the same as in Equation (2), and we cluster the standard errors at the district level.

For the public bank data, which represents a broader demographic across various income levels, we further categorise the account holders into higher-income and lower-income groups. Specifically, we use a dummy variable $HighIncome_i$ to denote the users whose reported annual income is the highest quantile (i.e., higher than 1.5 million INR). Then, we conduct a triple interact among $HighIncome_i$, $Resolve_{d,q}$ and $Rural_d$, and the empirical specification is modified as follows:

$$\begin{aligned}\widehat{Y}_{i,q+k} = \beta_1 Resolve_{d,q} + \beta_2 Resolve_{d,q} \times Rural_d + \beta_3 Resolve_{d,q} \times HighIncome_i + \\ \beta_4 Resolve_{d,q} \times Rural_d \times HighIncome_i + X'_{d,q}\gamma_X + \varphi_i + \omega_{q+k} + \varepsilon_{i,q+k}.\end{aligned} \tag{6}$$

Similar to Equation (5), we scale the outcome variable by the mean of each subgroup (e.g., high-income urban, high-income rural, low-income urban, and low-income rural users). Definitions of other variables are the same as in Equation (5). Standard errors are clustered at the district level.

Panel A of Table 8 reports the estimation results of Equation (5), based on the private bank data. Columns (1) and (2) show that in one year after the resolution, the e-commerce spending of

private bank users in urban districts increased by 6.6–7.7%, while that of users in rural districts increased by 10.7–12.7%. The differences between the estimates of different groups, represented by the coefficients of the interaction term, are statistically significant at the 10% level. The results are consistent if we use the e-commerce spending after two years as the outcome variables, as shown in Columns (3) and (4).

[Insert Table 8 Here]

Panel B reports the estimation results of Equation (6), based on the public bank data. In one year after resolving the 2G uncertainty, the e-commerce spending of lower-income users in urban districts increases by 16.9–17.2%, as reported in Columns (1) and (2). The corresponding growth equals 18.8–19.5% in two years, as shown in Columns (3) and (4). Compared with them, we do not find statistically significant differences in the relative growth among rural lower-income users and urban higher-income users, indicated by the coefficients of $Resolve_{d,q} \times Rural_d$ and $Resolve_{d,q} \times High\ Income_i$ in all columns. In contrast, we find a larger relative increase in e-commerce spending among the rural higher-income users after one year, reflected by the positive and statistically significant coefficients of the triple interaction terms in Columns (1) and (2). After two years, this difference remains positive, but the magnitude becomes smaller and statistically insignificant, as reported in Columns (3) and (4).

Our findings indicate that the introduction of 3G mobile internet led to a greater increase in e-commerce spending compared to traditional consumption channels. This effect is more pronounced in rural districts than in urban areas, particularly among higher-income users. A likely explanation is that wealthier rural residents, who previously had limited access to urban products, were able to broaden their consumption choices once connected to mobile internet services.

5.2 Convenience and Electronic Payments

The second unique channel through which 3G mobile internet boosts consumption is the increased convenience enabled by electronic payment technologies. The introduction of 3G internet facilitates the rapid adoption of digital payment platforms in India, such as POS terminals and mobile wallets: Replacing the outcome variable by the numbers of payment terminals at the district-

quarter level in Equation (4), we show in Appendix Table A5 that the terminal numbers increased significantly after the 3G internet connectivity was enhanced in the district. The expansion of these payment infrastructures is expected to improve consumer convenience and enable more frequent and seamless purchases. As a result, we hypothesise that areas experiencing greater growth in digital payment terminals also exhibit significantly higher levels of consumption.

To address the potential endogeneity concern regarding unobserved variables that correlate with increases in both digital payment terminals and consumption, we adopt a Bartik-style shift-share instrument as the identification strategy. More concretely, we calculate the product of the dummy variable $Resolve_{d,q}$ and the historical number of terminals in the first available period in our data ($TerminalNum_{d,q0}$) as the instrument variable (IV) for the number of terminals in district d in quarter q. Accordingly, the empirical models of the first and second stage estimations are specified as Equations (7) and (8) below:

$$TerminalNum_{i,q} = \beta_1 Resolve_{d,q} \times TerminalNum_{d,q0} + X_{d,q}^{'}\gamma_X + \varphi_i + \omega_q + \varepsilon_{i,q}. \tag{7}$$

$$Y_{i,q+k} = \beta_2 Resolve_{d,q} \times TerminalNum_{d,q0} + X_{d,q}^{'}\gamma_X + \varphi_i + \omega_{q+k} + \varepsilon_{i,q+k}. \tag{8}$$

Since cash spending is unlikely to be affected by the convenience of payment terminals, we use the debit card spending as the outcome variable ($Y_{i,q+k}$) in the second stage. Definitions of other variables are the same as in Equations (1) and (2). Standard errors are clustered at the district level.

Table 9 reports the estimation results based on the POS terminal numbers. Panel A presents the first-stage results estimated from Equation (7). We find a strong positive correlation between our IV and the number of POS terminals in districts, and the F-statistic is larger than 10, confirming that we do not have the weak instrument issue.

[Insert Table 9 Here]

Panel B reports the second-stage results estimated from Equation (8), based on the private bank data. The correlations between the IV and the debit card spending after 1 year or 2 years are positive and statistically significant at the conventional levels. Combining the estimates from the first and second stages, we find that an increase in a district's POS terminals by 1,000 will result

in a higher quarterly debit card spending by 142–157 INR after one year and 279–293 INR after two years. Since we estimate that resolving the 2G scam uncertainty leads to around 6.9 thousand more POS terminals per district after one year and 8.1 thousand more after two years (Appendix Table A5), the associated increases in quarterly debit card spending are estimated to be 977–1,081 INR after one year and 2,265–2,385 INR after two years. These increases are equivalent to 13.6% and 15.4% of the total consumption growth in the corresponding periods, respectively.

Similar to the analysis of the private bank data, we conduct the second-stage regressions with the public bank data and report the results in Panel B. We find that if the number of POS terminals in a district increases by 1,000, the debit card spending of public bank users rises by 55–69 INR after one year and by 59–66 INR after two years. All these estimates are statistically significant at the 1% level. These magnitudes translate to a higher quarterly debit card spending by 380–476 INR after one year and 480–537 INR after two years of resolving the 2G uncertainty, constituting approximately 13.6–17.1% of the total consumption growth in one year and 8.7–10.1% of that in two years.

In Table 10, we replicate the analysis using the number of mobile wallet payment facilities in the Indian districts, for which the information is available between 2015 and 2020. Again, we find supporting evidence that our IV is strong, as shown by the first-stage results in Panel A. The second-stage results of the private bank and public bank data are reported in Panels B and C, respectively. Following a 1,000 increase in the district's mobile wallet facilities, the private bank users spend an additional 116–136 INR with debit cards after one year and 189–198 INR after two years, while the corresponding growth among the public bank users equals 18–23 INR and 19–21 INR, respectively. Given that the number of mobile wallet facilities per district increases by 13.3–13.6 thousand in one year and 8.5–8.7 thousand in two years after the resolution, we estimate that the associated rises in private bank users' debit card spending equal 1,552–1,862 INR after one year and 1,612–1,727 INR after two years, contributing to 21.5–23.3% and 10.9–11.2% of their total consumption growth in corresponding periods. For the public bank account holders, the associated increases in debit card spending are 239–313 INR after one year and 164–182 INR after two years, equivalent to 8.6–11.2% and 3–3.4% of the corresponding total consumption growth.

[Insert Table 10 Here]

To conclude, our results reveal that, with the connection to 3G mobile internet, more digital payment terminals that require an internet connection to operate were introduced, making it more convenient for debit card users to consume. As a result, the debit card spending of residents in the connected districts substantially increased, which constitutes a significant proportion of their total consumption growth.

6 Insurance and Precautionary Savings

One challenge often faced by empirical studies of the PIH comes from the precautionary saving motives of households. Precautionary saving introduces the issue that individuals do not base their consumption solely on their expected lifetime income, as assumed by the Permanent Income Hypothesis, but instead save more than necessary due to uncertainty about future income, health expenses, or employment stability. This behavior becomes particularly important in a country like India, where many people work in the informal sector without job security, social insurance, or access to formal credit. In such environments, households often face significant income volatility and lack reliable safety nets, prompting them to save excessively as a form of self-insurance. This undermines the assumption that consumption remains stable over time and instead might make it both more sensitive to short-term income changes, and less sensitive to permanent income changes which get saved up for the rainy day.

One way we make progress on this issue is by studying insurance behavior around the 3G rollout. The idea is that if insurance uptake improves as a result of mobile internet, then precautionary savings motives can even be dampened at the same time as the income increase in this setting. Of course, there is a good reason to hypothesize that such an expansion in insurance uptake might have occurred in response to the arrival of mobile internet– mobile platforms allow insurers to sell to a broader swath of customers, across a more varied demographic, e.g., spread out over different states and hitherto unreached areas. Such a more diverse base of clients provides risk diversification benefits on the supply side. Coupled with lower costs of reaching consumers, this can lower premiums. On the demand side, mobile internet can lower search costs for insurance-seekers, again leading to an overall increase in uptake.

We empirically examine this channel by analysing growth in insurance purchases and subsequent consumption behaviour following the arrival of 3G mobile internet.

First, we examine whether the number of insured bank account holders increases in districts with enhanced 3G connectivity. We modify the empirical specification in Equation (4), replacing the outcome variable by the number of insured account holders at the district-quarter level.[5] Other control variables and fixed effects remain unchanged, and we cluster the standard errors at the district level.

Panels A and B of Table 11 report the corresponding regression results based on the private bank and public bank data, respectively. With both datasets, we observe consistent growth in the number of insurance users after one year and two years of the resolution. Specifically, compared with the average number at the district level, there is approximately a 49% increase in one year and a 47% increase in two years among the private bank account holders. These estimates are statistically significant at the 1% level. Among the public bank users, the corresponding growth relative to the average level equals 19% in one year and 17% in two years, statistically significant at the 10% level.

[Insert Table 11 Here]

Further, we investigate whether account holders covered by insurance are more likely to increase spending in the following periods. Specifically, we estimate the correlation between the behaviour of purchasing insurance and the subsequent levels of consumption, using the following empirical model:

$$Y_{i,q} = \beta_1 Purchase_{i,q-4,q-1} + \beta_2 Income_{i,q} + X'_{d,q}\gamma_X + \varphi_i + \omega_{q+k} + \varepsilon_{i,q+k}. \tag{9}$$

To address the concern for any long-term changes in life status, we focus on the short-term impact of insurance on consumption over one year. Accordingly, we construct an independent variable $Purchase_{i,q-4,q-1}$ that denotes whether bank user i has paid insurance premiums in the past year

[5]Since our data does not provide detailed information on the actual type and coverage duration of each insurance product that an account holder purchased, we assume that an account holder became insured after the first payment of insurance premiums.

(from $q-4$ to $q-1$).[6] Similar to our baseline models on consumption growth, we also control for the macroeconomic factors, as well as the individual and year-quarter fixed effects. Moreover, to alleviate the concern that both insurance purchases and consumption growth may be driven by higher earnings, we also include the control of the user's income at quarter q, presented by $Income_{i,q}$.[7] Standard errors are clustered at the district level.

We present the estimation results of Equation (9) based on the private bank and public bank data in Panels A and B of Table 12, respectively. In each panel, we report the results without any control variables in Column (1), and Columns (2) to (4) sequentially incorporate additional controls, including macroeconomic factors and individual income. We observe positive and statistically significant correlations between insurance purchases and subsequent consumption level across all models and with both datasets. In other words, conditional on the same income, people who are covered by insurance are found to have higher spending. Based on the results with the full set of controls in Columns (4) of each panel, we estimate that insurance purchases correlate with a 14.2% increase from the average consumption among private bank users and a 9.1% increase among the public bank users, both of which are statistically significant at the 1% level.

[Insert Table 12 Here]

Considering both the growth in insurance uptake and the subsequent increase in consumption following insurance purchases, our back-of-the-envelope calculation suggests that the insurance channel accounts for about 30% of the total consumption growth among private bank users.[8] In contrast, it only accounts for around 2% of the consumption growth among the public bank users, due to both a modest increase in the number of insurance users following the 3G rollout and a smaller relative rise in consumption after insurance purchases. This weaker effect may be caused

[6] Since we only observe insurance premium payments and not the actual coverage duration, we assume that account holders who made payments within the past year are likely to be currently covered.

[7] We confirm that our results are robust to alternative income measures, such as the average income from $q-4$ to $q-1$.

[8] Prior to the resolution of the 2G uncertainty, the average probability of private bank account holders in the affected districts being insured was 34.7%, while the corresponding probability for public bank users was 7.3%. Considering the estimates in Table 11, we assume that the probability of private (or public) bank account holders purchasing insurance increased by 49% (or 19%) one year after the resolution. According to Table 12, new insurance purchasers in the private (or public) bank increase their quarterly spending by 26,869 INR (or 7,606 INR) in the year following their insurance purchase. Based on these figures, the insurance channel contributes to an average increase in quarterly spending of 4,569 INR (or 105 INR) among all private (or public) bank users two years after the resolution.

by factors like limited financial literacy among the lower-income group, which represents a larger share of public bank users.

In summary, our empirical results show that insurance coverage expanded following the rollout of 3G mobile internet, thereby reducing the need for precautionary savings. As a result, regular consumption rises, particularly among the private bank users, who are mainly from a higher-income group and exhibit a more substantial uptake of insurance products with enhanced 3G service.

7 Conclusion

This paper provides a rare empirical test of the Permanent Income Hypothesis (PIH) by exploiting a plausibly exogenous, persistent income shock arising from the staggered rollout of 3G mobile internet in India. We show that this technological shift led to sustained income gains and a marginal propensity to consume of 90–93 paise per rupee—among the highest estimates in the literature, and consistent with the PIH's predictions.

The high consumption response is driven by mechanisms uniquely enabled by mobile internet: improved access to goods through e-commerce, reduced frictions via digital payments, and arise also from lower precautionary saving due to increased insurance adoption.

These findings demonstrate that technology-driven income shocks can meaningfully shift household expectations and consumption behavior. They also suggest that structural investments in digital infrastructure may yield larger and more durable economic effects than previously expected. Our results highlight the importance of viewing internet access not simply as a communications upgrade, but as a long-term investment in economic capacity with broad and persistent effects.

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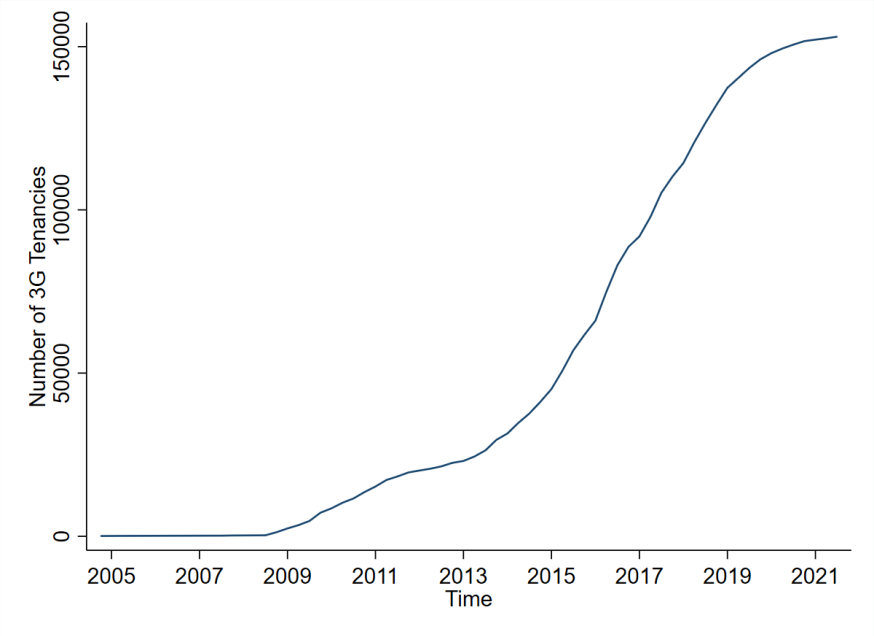
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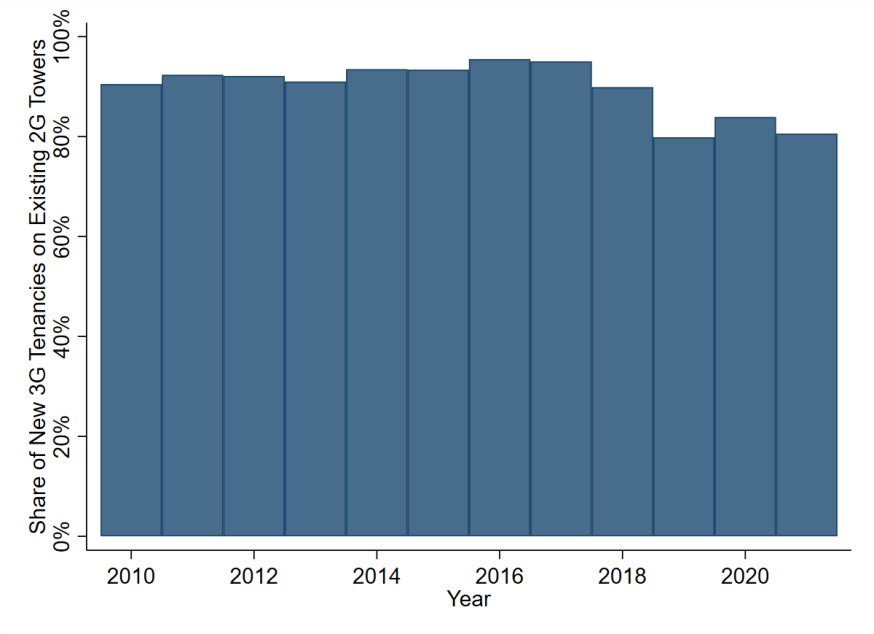
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Figure 1: 3G Development in India

Figure 1a plots the by-year number of 3G telecom tenancies (base transceiver stations) operated in India between 2005 and 2021. Figure 1b plots the by-year shares of new 3G tenancies that are installed on existing 2G towers in all new 3G tenancies between 2010 and 2021.



(a) Total Number of 3G Tenancies



(b) Share of New 3G Tenancies Installed on Existing 2G Towers

Figure 2: Staggered Resolutions of 3G Development Uncertainty

This figure plots the staggered resolutions of the 3G development uncertainty due to complete acquisitions of all scam-affected 2G telecom firms at the district level.

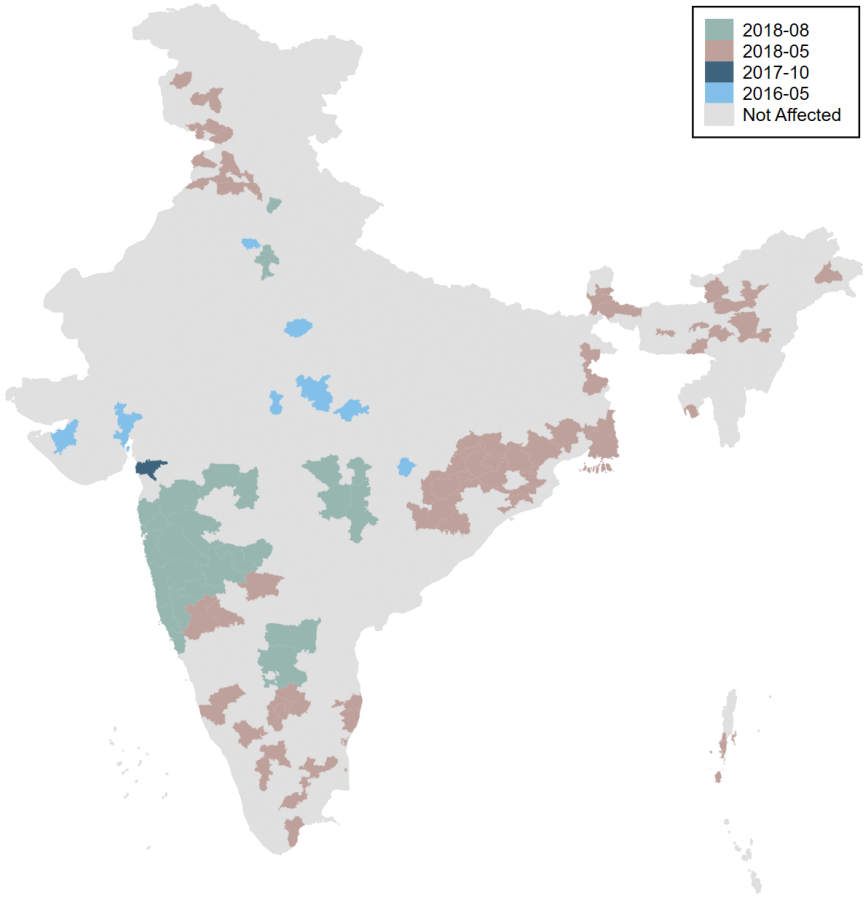
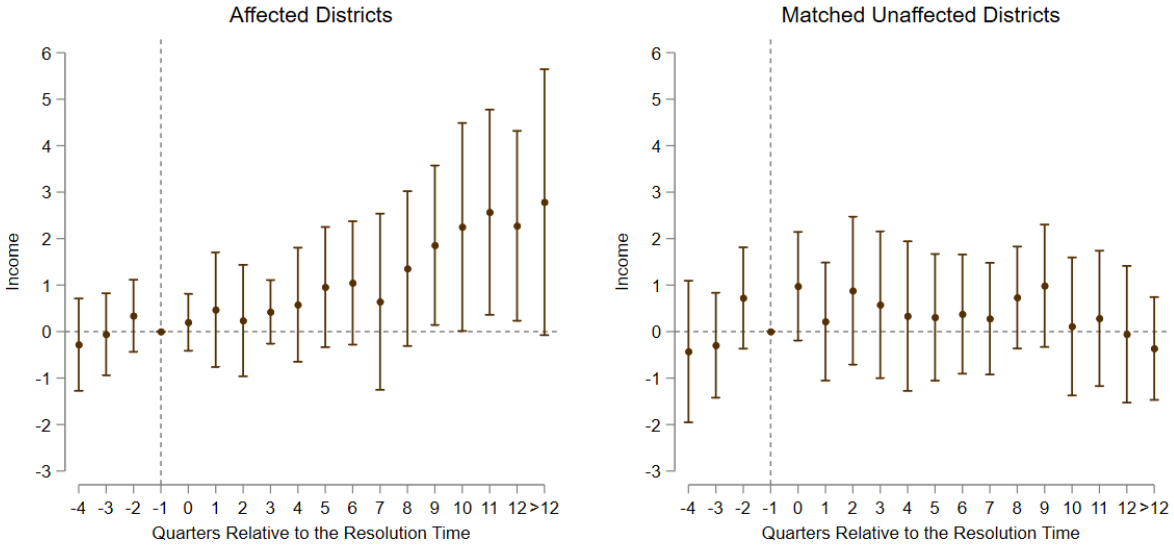
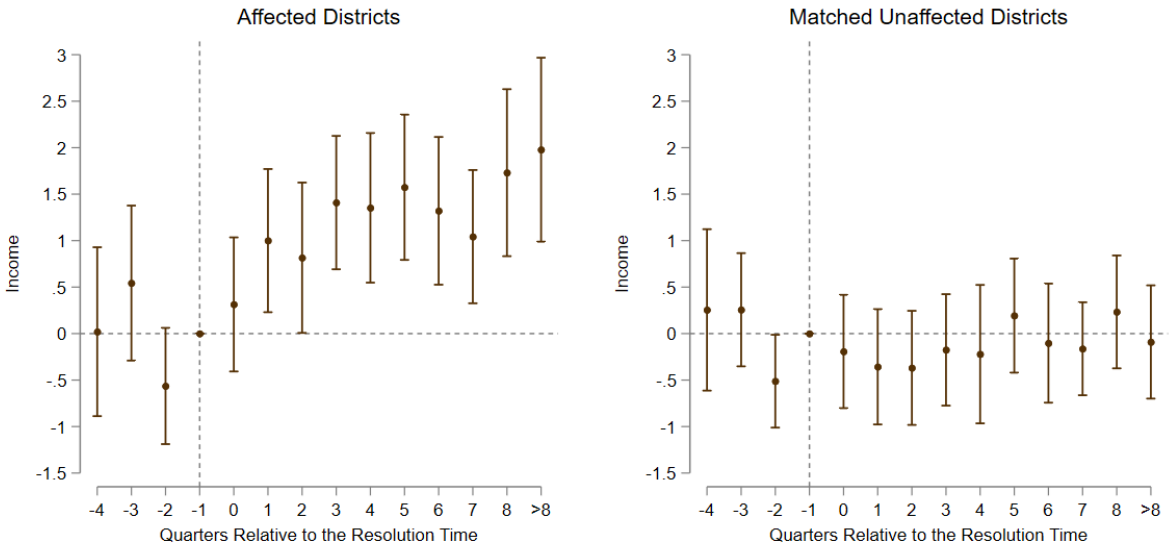


Figure 3: Event-Study Analysis of Income Growth

This figure plots the event-study analysis results of income growth, based on the private bank data (Panel A) and public bank data (Panel B). For affected districts in a resolution event, we identify the matched unaffected districts using a propensity score matching method, considering their state and macroeconomic factors (GDP and bank credit) before the event. In each panel, the left figure shows the results based on the observations in districts affected by the 2G scam, and the right one shows the results based on the observations in matched unaffected districts. The error bars indicate the 95% confidence intervals.



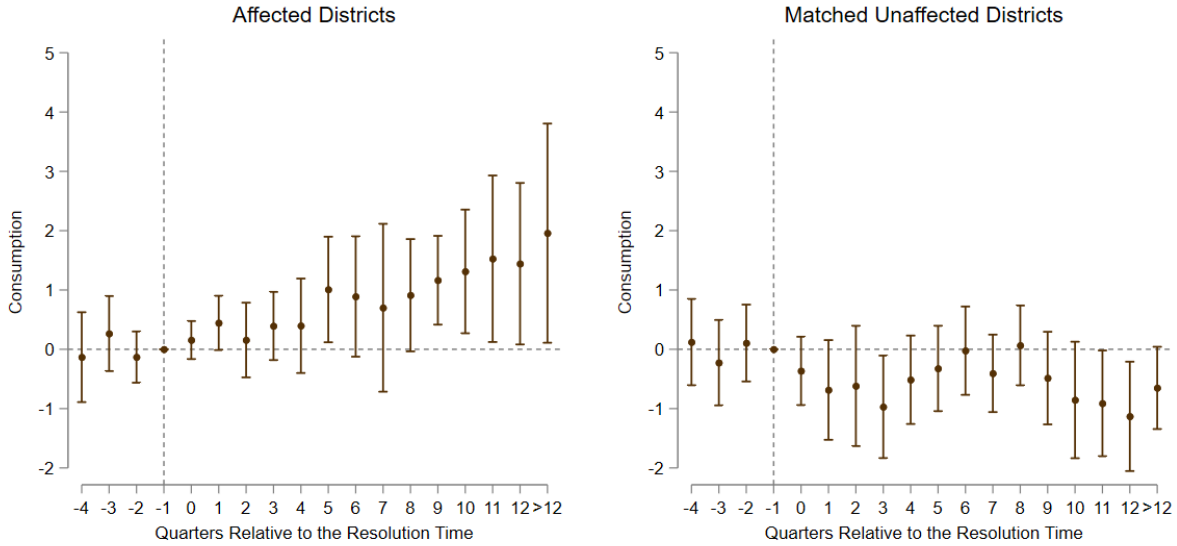
(a) Private Bank Data



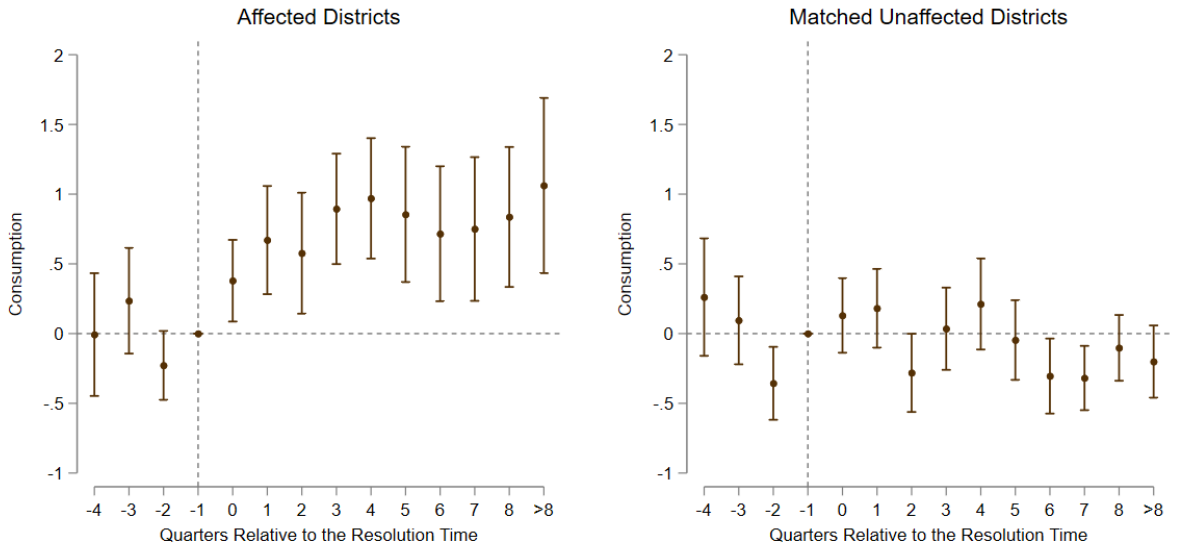
(b) Public Bank Data

Figure 4: Event-Study Analysis of Consumption Growth

This figure plots the event-study analysis results of consumption growth, based on the private bank data (Panel A) and public bank data (Panel B). For affected districts in a resolution event, we identify the matched unaffected districts using a propensity score matching method, considering their state and macroeconomic factors (GDP and bank credit) before the event. In each panel, the left figure shows the results based on the observations in districts affected by the 2G scam, and the right one shows the results based on the observations in matched unaffected districts. The error bars indicate the 95% confidence intervals.



(a) Private Bank Data



(b) Public Bank Data

Table 1: Summary Statistics

This table presents the summary statistics of (a) the quarterly income and consumption imputed from the private bank data, (b) the quarterly income and consumption imputed from the public bank data, and (c) the annual firm performance data from the Ministry of Corporate Affairs (MCA) of India. In Panels A and B, the amounts are in units of 10,000 INR. In Panel C, the TFP is estimated using the method in Wooldridge (2009). Total assets are reported in millions of IND. Debt ratio is defined as total liabilities divided by total assets, and liquidity is defined as cash and cash equivalents divided by total liabilities. All variables are winsorized at the top and bottom 1% levels.

Panel A. Private Bank Data

Variable	Obs	Mean	SD
Income	8,951,950	29.624	74.902
Consumption	8,951,950	18.863	45.751
- Debit Card Spending	8,951,950	15.852	42.357
- ATM Withdrawal	8,951,950	1.227	3.041
- Credit Card Spending	8,951,950	1.187	4.239

Panel B. Public Bank Data

Variable	Obs	Mean	SD
Income	435,834	10.593	11.267
Consumption	435,834	8.297	6.843
- Debit Card Spending	435,834	6.466	6.036
- ATM Withdrawal	435,834	1.738	2.611

Panel C. MCA Firm-level Data

Variable	Obs	Mean	SD
log(TFP)	3,536,154	0.829	1.39
Total Assets	3,536,154	77.023	227.984
Debit Ratio	3,536,154	0.494	0.356
Liquidity	3,536,154	6.474	23.136

Table 2: First-stage Results: Impact of Resolving 2G Scam Uncertainty on 3G Development

This table presents the results of the impact of resolving the 2G scam uncertainty on the quarterly growth of 3G tenancies at the district level. The dependent variable is the change in the logarithm form the 3G tenancy number in district d in quarter q. The independent variable of interest is a dummy variable ($Resolve_{d,q}$) denoting whether the 2G scam uncertainty was resolved in district d in quarter q. Standard errors are clustered at the district level and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	(1) $\Delta\log(3G)_{d,q}$	(2) $\Delta\log(3G)_{d,q}$
$\text{Resolve}_{d,q}$	0.0289***	0.0287***
	(0.0063)	(0.0063)
$\log(\text{GDP})_{d,q}$		0.1037***
		(0.0387)
$\log(\text{Bank Credit})_{d,q}$		0.0141***
		(0.0038)
Mean Dep. Var.	0.069	0.069
District FE	Y	Y
Year-quarter FE	Y	Y
F-statistics	21.04	20.50
Observations	20,754	20,754
Adjusted R^2	0.093	0.095

Table 3: Timing of Resolving 2G Scam Uncertainty in Indian Districts: Cox Survival Regressions

This table reports results from Cox survival regressions that investigate the timing of resolving the 2G scam uncertainty (i.e., the acquisitions of scam-affected telecom companies) in different Indian districts. The sample includes Indian districts affected by the 2G scam, and the explanatory variables include a set of covariates of the districts in the previous year. Standard errors are clustered at the district level and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(\text{GDP})_{d,y-1}$	-0.0578								-0.1436
	(0.0530)								(0.2145)
$\text{GDP Growth}_{d,y-1}$		-0.9659							-0.3968
		(1.4594)							(1.5947)
$\log(\text{Bank Credit})_{d,y-1}$			-0.0256						0.0743
			(0.0316)						(0.1632)
$\text{Bank Credit Growth}_{d,y-1}$				0.5955					0.7254
				(0.5129)					(0.4982)
$\text{Bank Credit/GDP}_{d,y-1}$					-0.3903				1.3194
					(1.0623)				(2.8044)
$\text{Share of Bank Credit}_{d,y-1}$						-4.7548			-7.5807
						(3.6561)			(7.0813)
$\text{Average Income}_{d,y-1}$							0.0002		0.0006
							(0.0019)		(0.0020)
$\text{Average Consumption}_{d,y-1}$								-0.0004	0.0000
								(0.0028)	(0.0035)
Observations	1,473	1,473	1,473	1,473	1,473	1,473	1,473	1,473	1,473

Table 4: Second-Stage Results: Impact of Resolving 2G Scam Uncertainty on Income

This table presents the results of the impact of resolving the 2G scam uncertainty on the quarterly income at the individual level. Panel A reports the results estimated using the private bank data, and Panel B reports the results estimated using the public bank data. Standard errors are clustered at the district level and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Panel A. Private Bank Data

	(1) After 1 Year $Income_{i,q+4}$	(2) After 1 Year $Income_{i,q+4}$	(3) After 2 Years $Income_{i,q+8}$	(4) After 2 Years $Income_{i,q+8}$
$Resolve_{d,q}$	0.5151	0.3929	1.6622***	1.6058**
	(0.4380)	(0.3981)	(0.6382)	(0.6377)
$log(GDP)_{d,q}$		15.2149***		15.6600***
		(4.6632)		(4.8838)
$log(Bank\ Credit)_{d,q}$		0.5126*		0.1325
		(0.3018)		(0.2813)
Mean Dep. Var.	32.418	32.418	34.130	34.130
Individual FE	Y	Y	Y	Y
Year-quarter FE	Y	Y	Y	Y
Observations	7,573,414	7,573,414	5,426,553	5,426,553
Adjusted R^2	0.473	0.473	0.486	0.486

Panel B. Public Bank Data

	(1) After 1 Year $Income_{i,q+4}$	(2) After 1 Year $Income_{i,q+4}$	(3) After 2 Years $Income_{i,q+8}$	(4) After 2 Years $Income_{i,q+8}$
$Resolve_{d,q}$	0.5711***	0.5704***	0.6116***	0.5912***
	(0.1191)	(0.1200)	(0.1997)	(0.2032)
$log(GDP)_{d,q}$		-1.7461		2.4857*
		(1.0869)		(1.3550)
$log(Bank\ Credit)_{d,q}$		-0.0023		0.0899
		(0.0806)		(0.0648)
Mean Dep. Var.	10.686	10.686	10.840	10.840
Individual FE	Y	Y	Y	Y
Year-quarter FE	Y	Y	Y	Y
Observations	391,680	391,680	274,156	274,156
Adjusted R^2	0.258	0.258	0.272	0.272

Table 5: Channels of Internet-led Income Growth

This table presents the results of the channels of Internet-led income growth. Panel A reports the results on the impact of resolving the 2G scam uncertainty on the total factor productivity (TFP) at the firm-year level. The independent variable of interest is a dummy variable ($Resolve_{d,y}$) denoting whether the 2G scam uncertainty was resolved in district d in year y. The dependent variables are the TFP of firm i located in district d after 1 year (y + 1) or 2 years (y + 2). Unreported fundamental control variables include log(total assets), debt ratio, and liquidity. Panel B reports the results on the impact of resolving the 2G scam uncertainty on the number of registered firms at the district-quarter level. The independent variable of interest is a dummy variable ($Resolve_{d,q}$) denoting whether the 2G scam uncertainty was resolved in district d in quarter q. The dependent variables are the number of registered firms in district d after 1 year (q + 4) or 2 years (q + 8), in units of 1,000. Standard errors are clustered at the district level and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Panel A. Total Factor Productivity

	(1) After 1 Year $\log(TFP)_{i,y+1}$	(2) After 1 Year $\log(TFP)_{i,y+1}$	(3) After 2 Years $\log(TFP)_{i,y+2}$	(4) After 2 Years $\log(TFP)_{i,y+2}$
$Resolve_{d,y}$	0.0241	0.0197	0.0465***	0.0418***
	(0.0177)	(0.0128)	(0.0171)	(0.0133)
$\log(GDP)_{d,y}$		-0.3104***		-0.3427***
		(0.1091)		(0.1166)
$\log(\text{Bank Credit})_{d,y}$		-0.0265***		-0.0055
		(0.0092)		(0.0070)
Mean Dep. Var.	0.900	0.900	0.913	0.913
Fundamental Controls	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	2,184,697	2,184,697	1,411,179	1,411,179
Adjusted R^2	0.818	0.818	0.840	0.840

Panel B. Number of Registered Firms

	(1) After 1 Year $\text{Firm Number}_{d,q+4}$	(2) After 1 Year $\text{Firm Number}_{d,q+4}$	(3) After 2 Years $\text{Firm Number}_{d,q+8}$	(4) After 2 Years $\text{Firm Number}_{d,q+8}$
$Resolve_{d,q}$	0.8873***	0.8919***	0.7492***	0.7553***
	(0.2453)	(0.2395)	(0.2228)	(0.2186)
$\log(GDP)_{d,q}$		1.6293**		1.2397**
		(0.6700)		(0.5077)
$\log(\text{Bank Credit})_{d,q}$		0.1385		0.0788
		(0.1163)		(0.0751)
Mean Dep. Var.	1.643	1.643	1.551	1.551
District FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	21,917	21,917	18,389	18,389
Adjusted R^2	0.987	0.987	0.991	0.991

Table 6: Second-Stage Results: Impact of Resolving 2G Scam Uncertainty on Consumption

This table presents the results of the impact of resolving the 2G scam uncertainty on the quarterly consumption at the individual level. Panel A reports the results estimated using the private bank data, and Panel B reports the results estimated using the public bank data. Standard errors are clustered at the district level and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Panel A. Private Bank Data

	(1) After 1 Year $\text{Consumption}_{i,q+4}$	(2) After 1 Year $\text{Consumption}_{i,q+4}$	(3) After 2 Years $\text{Consumption}_{i,q+8}$	(4) After 2 Years $\text{Consumption}_{i,q+8}$
$\text{Resolve}_{d,q}$	0.7976**	0.7212**	1.5446***	1.4778***
	(0.3852)	(0.3507)	(0.5236)	(0.5153)
$\log(\text{GDP})_{d,q}$		11.1817***		11.7188***
		(2.9160)		(2.8772)
$\log(\text{Bank Credit})_{d,q}$		0.3060		0.1877
		(0.3007)		(0.2955)
Mean Dep. Var.	20.940	20.940	22.135	22.135
Individual FE	Y	Y	Y	Y
Year-quarter FE	Y	Y	Y	Y
Observations	7,573,414	7,573,414	5,426,553	5,426,553
Adjusted R^2	0.481	0.481	0.494	0.494

Panel B. Public Bank Data

	(1) After 1 Year $\text{Consumption}_{i,q+4}$	(2) After 1 Year $\text{Consumption}_{i,q+4}$	(3) After 2 Years $\text{Consumption}_{i,q+8}$	(4) After 2 Years $\text{Consumption}_{i,q+8}$
$\text{Resolve}_{d,q}$	0.2797***	0.2786***	0.5508***	0.5292***
	(0.0770)	(0.0790)	(0.1165)	(0.1220)
$\log(\text{GDP})_{d,q}$		-3.0357***		0.2790
		(0.7352)		(0.9117)
$\log(\text{Bank Credit})_{d,q}$		-0.0068		0.0944**
		(0.0571)		(0.0476)
Mean Dep. Var.	8.365	8.365	8.411	8.411
Individual FE	Y	Y	Y	Y
Year-quarter FE	Y	Y	Y	Y
Observations	391,680	391,680	274,156	274,156
Adjusted R^2	0.453	0.453	0.474	0.474

Table 7: Heterogeneous Impacts of Resolving 2G Scam Uncertainty on E-Commerce and Non-E-Commerce Consumption

This table presents the results of the heterogeneous impacts of resolving the 2G scam uncertainty on e-commerce and non-e-commerce consumption at the individual level. Panels A and B reported the impacts on e-commerce and non-e-commerce consumption estimated using the private bank data, and Panels C and D reported the impacts estimated using the public bank data. Standard errors are clustered at the district level and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Panel A. E-Commerce Consumption – Private Bank Data

	(1) After 1 Year $ECOM_{i,q+4}$	(2) After 1 Year $ECOM_{i,q+4}$	(3) After 2 Years $ECOM_{i,q+8}$	(4) After 2 Years $ECOM_{i,q+8}$
$Resolve_{d,q}$	0.0845***	0.0739***	0.0845***	0.0778***
	(0.0229)	(0.0191)	(0.0189)	(0.0167)
$log(GDP)_{d,q}$		0.8812***		0.8365***
		(0.2535)		(0.2253)
$log(Bank\ Credit)_{d,q}$		0.0487***		0.0251*
		(0.0162)		(0.0140)
Mean Dep. Var.	0.820	0.820	0.898	0.898
Individual FE	Y	Y	Y	Y
Year-quarter FE	Y	Y	Y	Y
Observations	7,573,414	7,573,414	5,426,553	5,426,553
Adjusted R^2	0.483	0.483	0.502	0.502

Panel B. Non-E-Commerce Consumption – Private Bank Data

	(1) After 1 Year $Non\text{-}ECOM_{i,q+4}$	(2) After 1 Year $Non\text{-}ECOM_{i,q+4}$	(3) After 2 Years $Non\text{-}ECOM_{i,q+8}$	(4) After 2 Years $Non\text{-}ECOM_{i,q+8}$
$Resolve_{d,q}$	0.7131*	0.6473*	1.1780***	1.1099***
	(0.3653)	(0.3350)	(0.4037)	(0.3945)
$log(GDP)_{d,q}$		10.3005***		10.2612***
		(2.7214)		(2.7575)
$log(Bank\ Credit)_{d,q}$		0.2573		0.2318
		(0.2883)		(0.2427)
Mean Dep. Var.	20.119	20.119	21.236	21.236
Individual FE	Y	Y	Y	Y
Year-quarter FE	Y	Y	Y	Y
Observations	7,573,414	7,573,414	5,426,553	5,426,553
Adjusted R^2	0.471	0.471	0.484	0.484

Panel C. E-Commerce Consumption – Public Bank Data

	(1) After 1 Year $ECOM_{i,q+4}$	(2) After 1 Year $ECOM_{i,q+4}$	(3) After 2 Years $ECOM_{i,q+8}$	(4) After 2 Years $ECOM_{i,q+8}$
$Resolve_{d,q}$	0.0576***	0.0569***	0.0670***	0.0681***
	(0.0134)	(0.0135)	(0.0214)	(0.0217)
$\log(GDP)_{d,q}$		0.1523*		0.1377
		(0.0910)		(0.1014)
$\log(\text{Bank Credit})_{d,q}$		0.0083*		-0.0047
		(0.0044)		(0.0057)
Mean Dep. Var.	0.340	0.340	0.365	0.365
Individual FE	Y	Y	Y	Y
Year-quarter FE	Y	Y	Y	Y
Observations	391,680	391,680	274,156	274,156
Adjusted R^2	0.410	0.410	0.439	0.439

Panel D. Non-E-Commerce Consumption – Public Bank Data

	(1) After 1 Year Non-$ECOM_{i,q+4}$	(2) After 1 Year Non-$ECOM_{i,q+4}$	(3) After 2 Years Non-$ECOM_{i,q+8}$	(4) After 2 Years Non-$ECOM_{i,q+8}$
$Resolve_{d,q}$	0.2221***	0.2217***	0.4839***	0.4611***
	(0.0751)	(0.0772)	(0.1113)	(0.1159)
$\log(GDP)_{d,q}$		-3.1880***		0.1412
		(0.7254)		(0.8855)
$\log(\text{Bank Credit})_{d,q}$		-0.0151		0.0991**
		(0.0573)		(0.0477)
Mean Dep. Var.	8.025	8.025	8.046	8.046
Individual FE	Y	Y	Y	Y
Year-quarter FE	Y	Y	Y	Y
Observations	391,680	391,680	274,156	274,156
Adjusted R^2	0.454	0.455	0.475	0.475

Table 8: Heterogeneous Impacts of Resolving 2G Scam Uncertainty on E-Commerce Consumption across Urban and Rural Population

This table presents the results of the heterogeneous impacts of resolving the 2G scam uncertainty on the quarterly e-commerce consumption across urban and rural population. Panels A and B report the results estimated using the private bank data and the public bank data, respectively. In both panels, $Rural_i$ is a dummy variable denoting account holders living in rural districts. In Panel B, $HighIncome_i$ is a dummy variable denoting account holders with annual income in the highest quantile (>1,500,000 INR). The outcome variable, quarterly e-commerce consumption, is scaled by the mean of each subgroup (i.e., urban and rural population in Panel A, and high-income urban, low-income urban, high-income rural, and low-income rural population in Panel B). Standard errors are clustered at the district level and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Panel A. Private Bank Data

	(1) After 1 Year Scaled $ECOM_{i,q+4}$	(2) After 1 Year Scaled $ECOM_{i,q+4}$	(3) After 2 Years Scaled $ECOM_{i,q+8}$	(4) After 2 Years Scaled $ECOM_{i,q+8}$
$Resolve_{d,q}$	0.0766***	0.0661***	0.0958***	0.0897***
	(0.0284)	(0.0252)	(0.0311)	(0.0292)
$Resolve_{d,q} \times Rural_i$	0.0499*	0.0408*	0.0583*	0.0486*
	(0.0269)	(0.0232)	(0.0327)	(0.0280)
$log(GDP)_{d,q}$		1.0920***		1.0019***
		(0.3325)		(0.2704)
$log(Bank\ Credit)_{d,q}$		0.0567***		0.0256*
		(0.0196)		(0.0151)
Individual FE	Y	Y	Y	Y
Year-quarter FE	Y	Y	Y	Y
Observations	7,573,414	7,573,414	5,426,553	5,426,553
Adjusted R^2	0.483	0.484	0.502	0.502

Panel B. Public Bank Data

	(1) After 1 Year Scaled $ECOM_{i,q+4}$	(2) After 1 Year Scaled $ECOM_{i,q+4}$	(3) After 2 Years Scaled $ECOM_{i,q+8}$	(4) After 2 Years Scaled $ECOM_{i,q+8}$
$Resolve_{d,q}$	0.1721***	0.1689***	0.1883**	0.1947**
	(0.0608)	(0.0616)	(0.0795)	(0.0802)
$Resolve_{d,q} \times Rural_i$	-0.0044	-0.0061	0.0326	0.0321
	(0.0663)	(0.0661)	(0.0906)	(0.0905)
$Resolve_{d,q} \times High\ Income_i$	-0.1083	-0.1036	-0.0976	-0.1006
	(0.0665)	(0.0667)	(0.0746)	(0.0749)
$Resolve_{d,q} \times Rural_i \times High\ Income_i$	0.2293**	0.2294**	0.0819	0.0825
	(0.1065)	(0.1065)	(0.1411)	(0.1412)
$log(GDP)_{d,q}$		0.3933		0.3681
		(0.2688)		(0.2763)
$log(Bank\ Credit)_{d,q}$		0.0166		-0.0201
		(0.0128)		(0.0158)
Individual FE	Y	Y	Y	Y
Year-quarter FE	Y	Y	Y	Y
Observations	391,680	391,680	274,156	274,156
Adjusted R^2	0.405	0.405	0.435	0.435

Table 9: Impact of POS Terminals on Consumption

This table presents the results of the impacts of POS terminals on quarterly consumption at the individual level, estimated using an instrumental variable (IV) approach. *Initial POS Terminal*$_{d,q0}$ refers to the number of POS terminals in district d in the first period available in the sample (2013Q2). *Resolve*$_{d,q}$ is a dummy variable denoting whether the 2G scam uncertainty was resolved in district d in quarter q. We use the interaction of *Initial POS Terminal*$_{d,q0}$ and *Resolve*$_{d,q}$ as the instrument for the number of POS terminals in district d in quarter q (*POS Terminal*$_{d,q}$). Both *Initial POS Terminal*$_{d,q0}$ and *POS Terminal*$_{d,q}$ are in units of 1,000. Panel A reports the first-stage results, estimated using district-quarter observations from 2013Q3 onwards. Panels B and C report the corresponding second-stage results, estimated using the private bank data and the public bank data, respectively. Standard errors are clustered at the district level and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Panel A. First Stage Results

	(1) POS Terminal$_{d,q}$	(2) POS Terminal$_{d,q}$
Initial POS Terminal$_{d,q0}$ × Resolve$_{d,q}$	300.1020***	298.4105***
	(64.6503)	(63.7678)
log(GDP)$_{d,q}$		4.7856***
		(1.7636)
log(Bank Credit)$_{d,q}$		0.2535
		(0.1823)
Mean Dep. Var.	1.049	1.049
District FE	Y	Y
Year-quarter FE	Y	Y
F-statistics	21.55	21.90
Observations	20,179	20,179
Adjusted R^2	0.632	0.633

Panel B. Second Stage Results – Private Bank Data

	(1) After 1 Year Debit Card$_{i,q+4}$	(2) After 1 Year Debit Card$_{i,q+4}$	(3) After 2 Years Debit Card$_{i,q+8}$	(4) After 2 Years Debit Card$_{i,q+8}$
Initial POS Terminal$_{d,q0}$ × Resolve$_{d,q}$	4.7046**	4.2394***	8.7843***	8.3201***
	(2.2436)	(1.4122)	(2.6436)	(1.9476)
log(GDP)$_{d,q}$		11.1367***		11.3904***
		(2.6789)		(2.6652)
log(Bank Credit)$_{d,q}$		0.1971		0.1189
		(0.3338)		(0.3581)
Mean Dep. Var.	17.821	17.821	18.964	18.964
Individual FE	Y	Y	Y	Y
Year-quarter FE	Y	Y	Y	Y
Observations	7,408,886	7,408,886	5,262,025	5,262,025
Adjusted R^2	0.450	0.450	0.464	0.464

Panel C. Second Stage Results – Public Bank Data

	(1) After 1 Year Debit Card$_{i,q+4}$	(2) After 1 Year Debit Card$_{i,q+4}$	(3) After 2 Years Debit Card$_{i,q+8}$	(4) After 2 Years Debit Card$_{i,q+8}$
Initial POS Terminal$_{d,q0}$ × Resolve$_{d,q}$	1.6542***	2.0632***	1.7663***	1.9709***
	(0.3325)	(0.3641)	(0.3213)	(0.4594)
log(GDP)$_{d,q}$		-1.9777***		0.4261
		(0.7274)		(0.8912)
log(Bank Credit)$_{d,q}$		-0.0789		-0.0383
		(0.0761)		(0.0522)
Mean Dep. Var.	6.495	6.495	6.520	6.520
Individual FE	Y	Y	Y	Y
Year-quarter FE	Y	Y	Y	Y
Observations	391,680	391,680	274,156	274,156
Adjusted R^2	0.457	0.457	0.480	0.480

Table 10: Impact of Mobile Wallet Payment Facilities on Consumption

This table presents the results of the impacts of mobile wallet payment facilities on quarterly consumption at the individual level, estimated using an instrumental variable (IV) approach. *Mobile Wallet*$_{d,q0}$ refers to the number of mobile wallet facilities in district d in the first period available in the sample (2015Q1). *Resolve*$_{d,q}$ is a dummy variable denoting whether the 2G scam uncertainty was resolved in district d in quarter q. We use the interaction of *Initial Mobile Wallet*$_{d,q0}$ and *Resolve*$_{d,q}$ as the instrument for the number of mobile wallet facilities in district d in quarter q (*Mobile Wallet*$_{d,q}$). Both *Initial Mobile Wallet*$_{d,q0}$ and *Mobile Wallet*$_{d,q}$ are in units of 1,000. Panel A reports the first-stage results, estimated using district-quarter observations from 2015Q2 onwards. Panels B and C report the corresponding second-stage results, estimated using the private bank data and the public bank data, respectively. Standard errors are clustered at the district level and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Panel A. First Stage Results

	(1) Mobile Wallet$_{d,q}$	(2) Mobile Wallet$_{d,q}$
Initial Mobile Wallet$_{d,q0}$ × Resolve$_{d,q}$	6350.5207***	6316.7784***
	(1394.1283)	(1407.1826)
log(GDP)$_{d,q}$		7.7517
		(5.8723)
log(Bank Credit)$_{d,q}$		1.1503**
		(0.4540)
Mean Dep. Var.	2.070	2.070
District FE	Y	Y
Year-quarter FE	Y	Y
F-statistics	20.75	20.15
Observations	16,054	16,054
Adjusted R^2	0.405	0.406

Panel B. Second Stage Results – Private Bank Data

	(1) After 1 Year Debit Card$_{i,q+4}$	(2) After 1 Year Debit Card$_{i,q+4}$	(3) After 2 Years Debit Card$_{i,q+8}$	(4) After 2 Years Debit Card$_{i,q+8}$
Initial Mobile Wallet$_{d,q0}$ × Resolve$_{d,q}$	86.6821***	73.8409***	125.0746***	119.3831***
	(12.3910)	(14.9581)	(24.4624)	(25.8306)
log(GDP)$_{d,q}$		8.6735**		8.4654**
		(4.1210)		(4.1198)
log(Bank Credit)$_{d,q}$		0.0891		-0.1151
		(0.2991)		(0.3895)
Mean Dep. Var.	17.845	17.845	19.022	19.022
Individual FE	Y	Y	Y	Y
Year-quarter FE	Y	Y	Y	Y
Observations	6,108,192	6,108,192	3,961,291	3,961,291
Adjusted R^2	0.472	0.472	0.488	0.488

Panel C. Second Stage Results – Public Bank Data

	(1) After 1 Year Debit Card$_{i,q+4}$	(2) After 1 Year Debit Card$_{i,q+4}$	(3) After 2 Years Debit Card$_{i,q+8}$	(4) After 2 Years Debit Card$_{i,q+8}$
Initial Mobile Wallet$_{d,q0}$ × Resolve$_{d,q}$	11.1390**	14.8969***	11.8942***	13.4499***
	(4.4577)	(4.8308)	(3.7146)	(4.2170)
log(GDP)$_{d,q}$		-1.9633***		0.4315
		(0.7293)		(0.8916)
log(Bank Credit)$_{d,q}$		-0.0760		-0.0354
		(0.0761)		(0.0523)
Mean Dep. Var.	6.495	6.495	6.520	6.520
Individual FE	Y	Y	Y	Y
Year-quarter FE	Y	Y	Y	Y
Observations	391,680	391,680	274,156	274,156
Adjusted R^2	0.457	0.457	0.480	0.480

Table 11: Impact of Resolving 2G Scam Uncertainty on Number of Insurance Users

This table presents the results on the impact of resolving the 2G scam uncertainty on the number of insurance users at the district level. Panels A and B report the results estimated using the private bank data and the public bank data, respectively. Standard errors are clustered at the district level and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Panel A. Private Bank Data

	(1) After 1 Year Insurance $User_{d,q+4}$	(2) After 1 Year Insurance $User_{d,q+4}$	(3) After 2 Years Insurance $User_{d,q+8}$	(4) After 2 Years Insurance $User_{d,q+8}$
$Resolve_{d,q}$	76.9098***	78.2224***	72.2148***	73.8105***
	(19.9045)	(19.8358)	(20.0344)	(20.0154)
$log(GDP)_{d,q}$		209.1338***		182.3877***
		(74.0607)		(66.8869)
$log(Bank\ Credit)_{d,q}$		5.7991		3.1118
		(5.9248)		(4.1484)
Mean Dep. Var.	157.885	157.885	155.384	155.384
Individual FE	Y	Y	Y	Y
Year-quarter FE	Y	Y	Y	Y
Observations	18,238	18,238	15,069	15,069
Adjusted R^2	0.976	0.976	0.981	0.982

Panel B. Public Bank Data

	(1) After 1 Year Insurance $User_{d,q+4}$	(2) After 1 Year Insurance $User_{d,q+4}$	(3) After 2 Years Insurance $User_{d,q+8}$	(4) After 2 Years Insurance $User_{d,q+8}$
$Resolve_{d,q}$	1.2069*	1.2603*	1.3295*	1.3931*
	(0.6656)	(0.6608)	(0.7757)	(0.7758)
$log(GDP)_{d,q}$		7.3805		-0.1935
		(5.3748)		(4.4399)
$log(Bank\ Credit)_{d,q}$		-0.0809		-0.3955
		(0.3514)		(0.2828)
Mean Dep. Var.	6.502	6.502	7.825	7.825
Individual FE	Y	Y	Y	Y
Year-quarter FE	Y	Y	Y	Y
Observations	10,245	10,245	6,911	6,911
Adjusted R^2	0.813	0.814	0.895	0.896

Table 12: Correlation between Purchasing Insurance and Subsequent Consumption

This table reports the correlation between the behaviours of purchasing insurance and subsequent consumption. The dependent variable ($Consumption_{i,q}$) is the consumption of account holder i in quarter q, and the independent variable of interest ($Purchase\ Insurance_{i,q-4,q-1}$) is a dummy variable denoting whether the account holder i purchased insurance in the preceding year (from $q-4$ to $q-1$). Standard errors are clustered at the district level and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Panel A. Private Bank Data

	(1) $Consumption_{i,q}$	(2) $Consumption_{i,q}$	(3) $Consumption_{i,q}$	(4) $Consumption_{i,q}$
$Purchase\ Insurance_{i,q-4,q-1}$	5.0153***	5.0250***	2.6808***	2.6869***
	(0.1698)	(0.1670)	(0.1174)	(0.1155)
$\log(GDP)_{d,q}$		12.3686***		7.5831***
		(2.8714)		(1.8554)
$\log(Bank\ Credit)_{d,q}$		0.4102		0.1912
		(0.3090)		(0.2446)
$Income_{i,q}$			0.2749***	0.2748***
			(0.0032)	(0.0032)
Mean Dep. Var.	18.863	18.863	18.863	18.863
Individual FE	Y	Y	Y	Y
Year-quarter FE	Y	Y	Y	Y
Observations	8,951,912	8,951,912	8,951,912	8,951,912
Adjusted $R2$	0.480	0.480	0.587	0.587

Panel B. Public Bank Data

	(1) $Consumption_{i,q}$	(2) $Consumption_{i,q}$	(3) $Consumption_{i,q}$	(4) $Consumption_{i,q}$
$Purchase\ Insurance_{i,q-4,q-1}$	1.5146***	1.5169***	0.7586***	0.7606***
	(0.1805)	(0.1806)	(0.1349)	(0.1350)
$\log(GDP)_{d,q}$		-4.0070***		-3.1468***
		(0.7690)		(0.6231)
$\log(Bank\ Credit)_{d,q}$		-0.0536		-0.0401
		(0.1187)		(0.1006)
$Income_{i,q}$			0.2330***	0.2330***
			(0.0026)	(0.0026)
Mean Dep. Var.	8.313	8.313	8.313	8.313
Individual FE	Y	Y	Y	Y
Year-quarter FE	Y	Y	Y	Y
Observations	434,778	434,778	434,778	434,778
Adjusted $R2$	0.439	0.439	0.549	0.549

Internet Appendix A: Supplementary Tables

Table A1: Impact of 2G Internet on Income and Consumption: First-stage Results Using Lightning Strike Propensity as Instrument Variable

This table reports the first-stage results for the impacts of 2G tenancy growth on quarterly income and consumption, using lightning strike propensity as the instrument variable. The data on lightning strike intensity is provided by the National Aeronautics and Space Administration (NASA) (https://dx.doi.org/10.5067/LIS/LIS-OTD/DATA302), which measures average lightning strikes per square kilometre per year in each 0.5°×0.5° grid cell between 1995 and 2010. We calculate the average lighting strict intensity within each Indian district over this period, weighted by population density based on the 2011 Population Census, and multiply it with a linear time trend (year-quarter t) that captures the generalized increase in 2G adoption across the country, following Manacorda and Tesei (2020) and Guriev et al. (2021). This instrument variable is denoted as $Lightning_{d,t}$. Standard errors are clustered at the district level and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	(1) $\Delta\log(2G)_{d,q}$	(2) $\Delta\log(2G)_{d,q}$
$\text{Lightning}_{d,q}$	-0.0063***	-0.0065***
	(0.0011)	(0.0011)
$\log(\text{GDP})_{d,q}$		0.0182***
		(0.0053)
$\log(\text{Bank Credit})_{d,q}$		0.0012***
		(0.0004)
Mean Dep. Var.	0.016	0.016
F-statistics	32.414	18.229
District FE	Y	Y
Year-quarter FE	Y	Y
Observations	19,332	19,332
Adjusted R^2	0.160	0.162

Table A2: Impact of 2G Internet on Income and Consumption: Second-stage Results Using Lightning Strike Propensity as Instrument Variable

This table reports the second-stage results for the impacts of 2G tenancy growth on quarterly income and consumption, using lightning strike propensity as the instrument variable. The definition of the lightning strict propensity ($Lightning_{d,t}$) remains the same as in Appendix Table A1. Panels A and B report the results estimated using the private bank data, and Panels C and D report the results estimated using the public bank data. Standard errors are clustered at the district level and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

A. Quarterly Consumption – Private Bank Data

	(1) After 1 Year $Consumption_{i,q+4}$	(2) After 1 Year $Consumption_{i,q+4}$	(3) After 2 Years $Consumption_{i,q+8}$	(4) After 2 Years $Consumption_{i,q+4}$
$Lightning_{d,q}$	0.5801	0.8341	0.8484	1.1379
	(0.6602)	(0.6537)	(0.7593)	(0.7579)
$log(GDP)_{d,q}$		11.1235***		11.5447***
		(2.7412)		(2.7455)
$log(Bank\ Credit)_{d,q}$		0.4412		0.4392
		(0.3569)		(0.3780)
Mean Dep. Var.	21.097	21.097	22.256	22.256
District FE	Y	Y	Y	Y
Year-quarter FE	Y	Y	Y	Y
Observations	7,429,238	7,429,238	5,326,993	5,326,993
Adjusted R^2	0.481	0.481	0.494	0.494

B. Quarterly Income – Private Bank Data

	(1) After 1 Year $Income_{i,q+4}$	(2) After 1 Year $Income_{i,q+4}$	(3) After 2 Years $Income_{i,q+8}$	(4) After 2 Years $Income_{i,q+8}$
$Lightning_{d,q}$	0.3120	0.6762	0.6085	0.9586
	(0.5059)	(0.5017)	(0.6707)	(0.6525)
$log(GDP)_{d,q}$		15.2082***		15.4367***
		(4.6811)		(5.0659)
$log(Bank\ Credit)_{d,q}$		0.6803*		0.4185
		(0.3637)		(0.3710)
Mean Dep. Var.	32.662	32.662	34.378	34.378
District FE	Y	Y	Y	Y
Year-quarter FE	Y	Y	Y	Y
Observations	7,429,238	7,429,238	5,326,993	5,326,993
Adjusted R^2	0.472	0.473	0.486	0.486

C. Quarterly Consumption – Public Bank Data

	(1) After 1 Year $\text{Consumption}_{i,q+4}$	(2) After 1 Year $\text{Consumption}_{i,q+4}$	(3) After 2 Years $\text{Consumption}_{i,q+8}$	(4) After 2 Years $\text{Consumption}_{i,q+4}$
$\text{Lightning}_{d,q}$	-0.1861	-0.1608	0.1642	0.1069
	(0.3747)	(0.3770)	(0.5312)	(0.5542)
$\log(\text{GDP})_{d,q}$		-3.0702***		0.3026
		(0.7748)		(0.9349)
$\log(\text{Bank Credit})_{d,q}$		0.0037		0.1238***
		(0.0607)		(0.0455)
Mean Dep. Var.	8.355	8.355	8.400	8.400
District FE	Y	Y	Y	Y
Year-quarter FE	Y	Y	Y	Y
Observations	384,079	384,079	268,861	268,861
Adjusted R^2	0.453	0.453	0.474	0.474

D. Quarterly Income – Public Bank Data

	(1) After 1 Year $\text{Income}_{i,q+4}$	(2) After 1 Year $\text{Income}_{i,q+4}$	(3) After 2 Years $\text{Income}_{i,q+8}$	(4) After 2 Years $\text{Income}_{i,q+8}$
$\text{Lightning}_{d,q}$	0.0231	0.0316	-0.4564	-0.5105
	(0.3273)	(0.3281)	(0.5382)	(0.5396)
$\log(\text{GDP})_{d,q}$		-1.8254		2.5285*
		(1.1779)		(1.3789)
$\log(\text{Bank Credit})_{d,q}$		0.0419		0.1136*
		(0.0843)		(0.0648)
Mean Dep. Var.	10.677	10.677	10.826	10.826
District FE	Y	Y	Y	Y
Year-quarter FE	Y	Y	Y	Y
Observations	384,079	384,079	268,861	268,861
Adjusted R^2	0.258	0.258	0.273	0.273

Table A3: Impact of 4G Internet on Income and Consumption

This table reports the results of the impacts of 4G connection on quarterly income and consumption. Following Alok et al. (2024), we use the entry of Reliance Jio's telecom tower into a district as a source of exogenous variation in access to 4G internet. *Jio 4G Entry*$_{d,q}$ is a dummy variable denoting whether Reliance Jio had 4G telecom towers in district d in quarter q. *Resolve*$_{d,q}$ is a dummy variable denoting whether the 2G scam uncertainty was resolved in district d in quarter q. Panels A and B report the results estimated using the private bank data, and Panels C and D report the results estimated using the public bank data. Standard errors are clustered at the district level and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

A. Quarterly Consumption – Private Bank Data

	(1) After 1 Year Consumption$_{i,q+4}$	(2) After 1 Year Consumption$_{i,q+4}$	(3) After 2 Years Consumption$_{i,q+8}$	(4) After 2 Years Consumption$_{i,q+4}$
Resolve$_{d,q}$	0.6918*	0.6272*	1.4748***	1.4725***
	(0.3816)	(0.3434)	(0.5530)	(0.5623)
Jio 4G Entry$_{d,q}$	0.4442***	0.3726**	0.4449***	0.3952***
	(0.1645)	(0.1820)	(0.1482)	(0.1419)
Resolve$_{d,q}$ × Jio 4G Entry$_{d,q}$	0.0498	0.0604	-0.0113	-0.0688
	(0.1738)	(0.1602)	(0.2469)	(0.2486)
log(GDP)$_{d,q}$		10.9813***		11.4661***
		(2.8228)		(2.7838)
log(Bank Credit)$_{d,q}$		0.2658		0.1429
		(0.3004)		(0.2971)
Mean Dep. Var.	20.940	20.940	22.096	22.096
District FE	Y	Y	Y	Y
Year-quarter FE	Y	Y	Y	Y
Observations	7,573,414	7,573,414	5,426,553	5,426,553
Adjusted R^2	0.481	0.481	0.494	0.494

B. Quarterly Income – Private Bank Data

	(1) After 1 Year Income$_{i,q+4}$	(2) After 1 Year Income$_{i,q+4}$	(3) After 2 Years Income$_{i,q+8}$	(4) After 2 Years Income$_{i,q+8}$
Resolve$_{d,q}$	0.3433	0.2283	1.5984**	1.6245**
	(0.5077)	(0.4533)	(0.7675)	(0.7736)
Jio 4G Entry$_{d,q}$	0.4266**	0.3130	0.4681**	0.4131**
	(0.1955)	(0.2175)	(0.2053)	(0.1694)
Resolve$_{d,q}$ × Jio 4G Entry$_{d,q}$	0.1474	0.1731	-0.0248	-0.1051
	(0.2610)	(0.2321)	(0.3492)	(0.3547)
log(GDP)$_{d,q}$		14.9833***		15.4208***
		(4.5394)		(4.6932)
log(Bank Credit)$_{d,q}$		0.4763		0.0873
		(0.3001)		(0.2875)
Mean Dep. Var.	32.418	32.418	34.130	34.130
District FE	Y	Y	Y	Y
Year-quarter FE	Y	Y	Y	Y
Observations	7,573,414	7,573,414	5,426,553	5,426,553
Adjusted R^2	0.473	0.473	0.486	0.486

C. Quarterly Consumption – Public Bank Data

	(1) After 1 Year $\text{Consumption}_{i,q+4}$	(2) After 1 Year $\text{Consumption}_{i,q+4}$	(3) After 2 Years $\text{Consumption}_{i,q+8}$	(4) After 2 Years $\text{Consumption}_{i,q+4}$
$\text{Resolve}_{d,q}$	0.2489***	0.2461***	0.4835***	0.4577***
	(0.0931)	(0.0936)	(0.1255)	(0.1313)
Jio 4G $\text{Entry}_{d,q}$	-0.0794	-0.0719	-0.0934	-0.0992
	(0.0650)	(0.0658)	(0.0700)	(0.0701)
$\text{Resolve}_{d,q} \times$ Jio 4G $\text{Entry}_{d,q}$	0.0532	0.0559	0.1019	0.1078
	(0.0700)	(0.0707)	(0.0747)	(0.0747)
$\log(\text{GDP})_{d,q}$		-3.0026***		0.2690
		(0.7351)		(0.9146)
$\log(\text{Bank Credit})_{d,q}$		-0.0074		0.0954**
		(0.0571)		(0.0474)
Mean Dep. Var.	8.365	8.365	8.411	8.411
District FE	Y	Y	Y	Y
Year-quarter FE	Y	Y	Y	Y
Observations	391680	391680	274156	274156
Adjusted R^2	0.453	0.453	0.474	0.474

D. Quarterly Income – Public Bank Data

	(1) After 1 Year $\text{Income}_{i,q+4}$	(2) After 1 Year $\text{Income}_{i,q+4}$	(3) After 2 Years $\text{Income}_{i,q+8}$	(4) After 2 Years $\text{Income}_{i,q+8}$
$\text{Resolve}_{d,q}$	0.6151***	0.6136***	0.6729***	0.6531***
	(0.1479)	(0.1483)	(0.2122)	(0.2167)
Jio 4G $\text{Entry}_{d,q}$	-0.0016	0.0024	0.0649	0.0611
	(0.1279)	(0.1281)	(0.1906)	(0.1912)
$\text{Resolve}_{d,q} \times$ Jio 4G $\text{Entry}_{d,q}$	-0.0726	-0.0711	-0.0884	-0.0880
	(0.1364)	(0.1364)	(0.1976)	(0.1979)
$\log(\text{GDP})_{d,q}$		-1.6378		2.5097*
		(1.0882)		(1.3533)
$\log(\text{Bank Credit})_{d,q}$		-0.0041		0.0891
		(0.0811)		(0.0650)
Mean Dep. Var.	10.686	10.686	10.840	10.840
District FE	Y	Y	Y	Y
Year-quarter FE	Y	Y	Y	Y
Observations	391680	391680	274156	274156
Adjusted R^2	0.258	0.258	0.272	0.272

Table A4: Heterogeneous Impacts of Resolving 2G Scam Uncertainty by Payment Methods

This table presents the results of the heterogeneous impacts of resolving the 2G scam uncertainty on consumption across different payment methods: debit card spending, ATM withdrawals, and credit card spending. Panels A to C report the impacts on debit card spending, ATM withdrawals, and credit card spending, estimated using the private bank data. Panels D and E report the impacts on debit card spending and ATM withdrawals, estimated using the public bank data. Standard errors are clustered at the district level and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Panel A. Debit Card Spending – Private Bank Data

	(1) After 1 Year Debit Card$_{i,q+4}$	(2) After 1 Year Debit Card$_{i,q+4}$	(3) After 2 Years Debit Card$_{i,q+8}$	(4) After 2 Years Debit Card$_{i,q+8}$
Resolve$_{d,q}$	0.9824**	0.9154***	1.8317***	1.7458***
	(0.3831)	(0.3490)	(0.5503)	(0.5311)
log(GDP)$_{d,q}$		10.9198***		11.2496***
		(2.7724)		(2.8002)
log(Bank Credit)$_{d,q}$		0.2580		0.2587
		(0.2924)		(0.2726)
Mean Dep. Var.	17.842	17.842	18.899	18.899
Individual FE	Y	Y	Y	Y
Year-quarter FE	Y	Y	Y	Y
Observations	7,573,414	7,573,414	5,426,553	5,426,553
Adjusted R^2	0.447	0.447	0.460	0.460

Panel B. ATM Withdrawals – Private Bank Data

	(1) After 1 Year ATM$_{i,q+4}$	(2) After 1 Year ATM$_{i,q+4}$	(3) After 2 Years ATM$_{i,q+8}$	(4) After 2 Years ATM$_{i,q+8}$
Resolve$_{d,q}$	-0.1699***	-0.1599***	-0.2276***	-0.2058***
	(0.0517)	(0.0468)	(0.0722)	(0.0598)
log(GDP)$_{d,q}$		-1.2367***		-1.0140***
		(0.4636)		(0.3873)
log(Bank Credit)$_{d,q}$		-0.0421*		-0.0738**
		(0.0248)		(0.0318)
Mean Dep. Var.	1.201	1.201	1.166	1.166
Individual FE	Y	Y	Y	Y
Year-quarter FE	Y	Y	Y	Y
Observations	7,573,414	7,573,414	5,426,553	5,426,553
Adjusted R^2	0.533	0.533	0.559	0.559

Panel C. Credit Card Spending - Private Bank Data

	(1) After 1 Year Credit Card$_{i,q+4}$	(2) After 1 Year Credit Card$_{i,q+4}$	(3) After 2 Years Credit Card$_{i,q+8}$	(4) After 2 Years Credit Card$_{i,q+8}$
Resolve$_{d,q}$	-0.0411	-0.0476*	-0.0591*	-0.0561*
	(0.0270)	(0.0244)	(0.0307)	(0.0293)
log(GDP)$_{d,q}$		1.0307***		0.9802***
		(0.2774)		(0.2371)
log(Bank Credit)$_{d,q}$		0.0250		-0.0149
		(0.0158)		(0.0178)
Mean Dep. Var.	1.375	1.375	1.480	1.480
Individual FE	Y	Y	Y	Y
Year-quarter FE	Y	Y	Y	Y
Observations	7,573,414	7,573,414	5,426,553	5,426,553
Adjusted R^2	0.614	0.614	0.632	0.632

Panel D. Debit Card Spending – Public Bank Data

	(1) After 1 Year Debit Card$_{i,q+4}$	(2) After 1 Year Debit Card$_{i,q+4}$	(3) After 2 Years Debit Card$_{i,q+8}$	(4) After 2 Years Debit Card$_{i,q+8}$
Resolve$_{d,q}$	0.1823**	0.1871**	0.4591***	0.4685***
	(0.0730)	(0.0755)	(0.0979)	(0.0995)
log(GDP)$_{d,q}$		-1.8066**		0.4607
		(0.7532)		(0.8804)
log(Bank Credit)$_{d,q}$		-0.0684		-0.0407
		(0.0788)		(0.0510)
Mean Dep. Var.	6.495	6.495	6.520	6.520
Individual FE	Y	Y	Y	Y
Year-quarter FE	Y	Y	Y	Y
Observations	391,680	391,680	274,156	274,156
Adjusted R^2	0.457	0.457	0.480	0.480

Panel E. ATM Withdrawals – Public Bank Data

	(1) After 1 Year ATM$_{i,q+4}$	(2) After 1 Year ATM$_{i,q+4}$	(3) After 2 Years ATM$_{i,q+8}$	(4) After 2 Years ATM$_{i,q+8}$
Resolve$_{d,q}$	0.0729*	0.0672	0.0610	0.0294
	(0.0429)	(0.0422)	(0.0592)	(0.0664)
log(GDP)$_{d,q}$		-1.2541***		-0.1656
		(0.4350)		(0.4496)
log(Bank Credit)$_{d,q}$		0.0599		0.1376***
		(0.0416)		(0.0421)
Mean Dep. Var.	1.771	1.771	1.785	1.785
Individual FE	Y	Y	Y	Y
Year-quarter FE	Y	Y	Y	Y
Observations	391,680	391,680	274,156	274,156
Adjusted R^2	0.470	0.470	0.492	0.493

Table A5: Impact of Resolving 2G Scam Uncertainty on Number of Payment Terminals

This table presents the results of the impacts of resolving the 2G scam uncertainty on the numbers of payment facilities (POS terminals and mobile wallet payment facilities) at the district-quarter level. In Panels A and B, the outcome variables are the numbers of POS terminals and mobile wallet payment facilities, respectively, in units of 1,000. In Panel A, the sample period is between 2013 and 2021, and in Panel B, the sample period is between 2015 and 2020. Standard errors are clustered at the district level and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Panel A. POS Terminals

	(1) After 1 Year POS Terminal$_{d,q+4}$	(2) After 1 Year POS Terminal$_{d,q+4}$	(3) After 2 Years POS Terminal$_{d,q+8}$	(4) After 2 Years POS Terminal$_{d,q+8}$
Resolve$_{d,q}$	6.8957***	6.9183***	8.1016***	8.1250***
	(1.7439)	(1.7161)	(2.0523)	(2.0130)
log(GDP)$_{d,q}$		9.9211**		10.0319**
		(4.3282)		(4.2460)
log(Bank Credit)$_{d,q}$		0.7815		0.7888
		(0.6460)		(0.6387)
Mean Dep. Var.	1.258	1.258	1.273	1.273
District FE	Y	Y	Y	Y
Year-quarter FE	Y	Y	Y	Y
Observations	18,863	18,863	15,695	15,695
Adjusted R^2	0.510	0.516	0.512	0.519

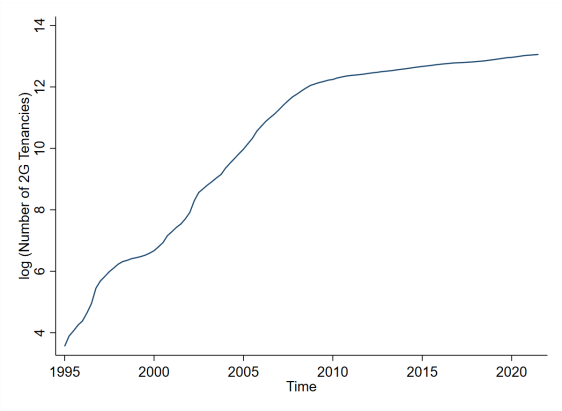
Panel B. Mobile Wallet Payment Facilities

	(1) After 1 Year Mobile Wallet$_{d,q+4}$	(2) After 1 Year Mobile Wallet$_{d,q+4}$	(3) After 2 Years Mobile Wallet$_{d,q+8}$	(4) After 2 Years Mobile Wallet$_{d,q+8}$
Resolve$_{d,q}$	13.6433***	13.3496***	8.7210***	8.5304***
	(4.6498)	(4.4857)	(2.9701)	(2.9646)
log(GDP)$_{d,q}$		30.1103*		29.6519**
		(15.7614)		(13.5583)
log(Bank Credit)$_{d,q}$		4.0931		1.6957
		(2.8868)		(1.5633)
Mean Dep. Var.	3.201	3.201	3.488	3.488
District FE	Y	Y	Y	Y
Year-quarter FE	Y	Y	Y	Y
Observations	10,380	10,380	7,401	7,401
Adjusted R^2	0.495	0.499	0.620	0.621

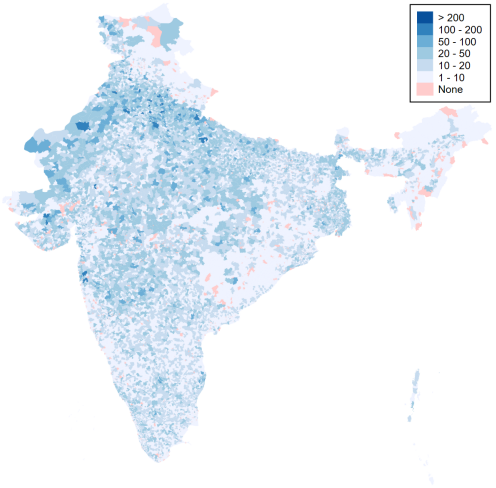
Internet Appendix B: Supplementary Figures

Figure B1: The Rollout of 2G Service in India

This figure plots (a) by-year number of 2G tenancies (base transceiver stations) in India between 1995 and 2021, and (5) the numbers of 2G telecom tenancies in India at the pin-code level in 2010.



(a) By-year Number of 2G Tenancy in 1995–2021



(b) By-pincode Number of 2G Tenancy in 2010