The Buy Now Pay Later Divide: Merchant Heterogeneity and Market Structure

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Abstract

We examine who benefits from Buy Now Pay Later (BNPL) and how these services shape market structure. Using novel transaction-level data from a large fintech lender and a shift-share instrumental variable, we find that BNPL adoption increases revenue growth of small, credit-constrained merchants over three times more than that of large ones. Digitization-driven formalization channel contributes to this disparity: BNPL shifts transactions from cash to digital, generating verifiable records that enable previously excluded merchants to access formal credit. BNPL improves not just credit access but credit allocation—despite expanded lending, default rates decline. Spillover effects on non-adopting merchants are negative but an order of magnitude smaller than adopter gains, suggesting BNPL predominantly expands the market rather than only redistributing existing demand. Yet, while BNPL reduces concentration among adopters by disproportionately benefiting small, constrained firms, overall market concentration increases as non-adopters—who are systematically smaller—bear these negative spillovers, highlighting that adoption barriers shape the aggregate distributional impact of fintech payment innovations.

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1 Introduction

Buy Now Pay Later (BNPL) has experienced explosive growth worldwide, with transaction volumes exceeding $560 billion in 2025 and projected to surpass $912 billion by 2030.[1] Regulators across jurisdictions have responded with increasing consumer-protection restrictions.[2] Yet BNPL is fundamentally a two-sided platform that intermediates between consumers and merchants, with potential effects on both sides of the market. Understanding how BNPL affects merchant outcomes and market structure is therefore critical for evaluating both the welfare implications and the regulatory design of these rapidly expanding payment innovations. In this paper, we address two questions. First, which merchants benefit most from BNPL and through what channels? Second, does BNPL expand the overall market or merely redistribute existing demand among merchants—and what does this imply for market concentration?

A priori, it is unclear which merchants benefit most from BNPL adoption. Complementarities between BNPL and existing digital infrastructure (Milgrom and Roberts 1990) and network effects in payment adoption (Rochet and Tirole 2002) suggest that larger, more established merchants may benefit the most, predicting that BNPL reinforces existing scale advantages and increases market concentration. Alternatively, by digitizing transactions and making cash flows observable to lenders, BNPL may disproportionately relax financing constraints for smaller, previously opaque firms lacking pledgeable assets (Townsend 1979; Holmstrom and Tirole 1997), thereby reducing concentration by benefiting smaller constrained firms more.

The aggregate market effect is similarly ambiguous. BNPL provides consumers with a zero-interest installment loan bundled into the purchase. For consumers who already have access to alternative credit—credit cards, microfinance, or informal lending—this acts as

1. The Paypers, "Buy Now, Pay Later Report 2025". Accessed from https://thepaypers.com/payments/reports/buy-now-pay-later-report-2025

2. For example, the U.S. CFPB classified BNPL providers as credit card issuers in 2024; India's RBI brought BNPL under formal lending regulations in 2022–2025; the EU extended its Consumer Credit Directive to cover BNPL in 2023; and Australia introduced BNPL-specific legislation in 2024.

an implicit price discount at adopting merchants relative to non-adopters. Even consumers who are not liquidity-constrained therefore have an incentive to redirect spending toward BNPL-accepting merchants to capture the interest savings, diverting demand away from non-adopters without generating new economic activity in aggregate. The critical condition for this zero-sum outcome is not that consumers face no liquidity constraints, but that those constraints are already being addressed elsewhere—so that BNPL changes the distribution of spending across merchants rather than its level.

Alternatively, BNPL can expand the market through two distinct channels. First, if consumers lack any prior credit access, BNPL enables transactions that would not have occurred at all by bringing previously excluded consumers into the market or increasing purchase frequency for those who could not previously transact on credit. Second, operating independently of consumer-side effects, BNPL's digitization of merchant transactions generates verifiable records that reduce information asymmetries between merchants and lenders, relaxing merchant-side financial constraints and enabling adopters to expand supply to meet previously unserved latent demand. Which force dominates is an empirical question, and the answer has direct implications for market structure and whether BNPL should be treated by regulators as a redistributive payment innovation or as a tool of financial inclusion.

Empirically evaluating the effect of BNPL on merchants faces two fundamental challenges. First, it requires comprehensive merchant-level data combining payment transactions with financial outcomes that is not easily available. Second, even with appropriate data, endogeneity issues remain a concern. Merchant adoption decisions are endogenous—firms that choose to offer BNPL may differ systematically in ways that independently affect their performance. For instance, merchants experiencing declining revenues may adopt BNPL in an attempt to attract new customers, making it difficult to attribute improved outcomes to BNPL specifically.

We address these challenges using novel daily merchant-level data from a large fintech lender in India. Our data provides comprehensive information on transaction volumes, pay-

ment methods, and credit outcomes for thousands of businesses spanning multiple years. For each merchant day, we observe the number and total value of transactions by payment type (cash, card, BNPL, UPI), allowing us to trace how payment composition evolves following BNPL adoption. We further link these transaction records to credit bureau data and loan origination information, enabling us to track merchants' access to formal credit both before and after the entry of BNPL. India's large informal economy—where many small businesses operate predominantly in cash and lack access to formal credit—provides a natural setting for examining how BNPL innovation interacts with financial constraints. Importantly, the BNPL product in our setting carries no fees for either merchants or consumers, ensuring that adoption decisions are not driven by costs.

We begin by evaluating which merchants adopt BNPL. We find that adopters exhibit substantially higher baseline revenues and transaction counts compared to non-adopters, with mean revenues nearly double those of non-adopters. Adopters also show higher transaction count growth but lower average transaction size growth. Interestingly, credit market participation prior to adoption is similar across the two groups—suggesting that differential credit access does not drive the adoption decision.

In our main analysis, we address this selection and other endogeneity concerns by employing a shift-share instrumental variable strategy that exploits spatial variation in pre-existing digital payment infrastructure. Specifically, we interact pincode-level UPI (Unified Payments Interface, India's real-time digital payment system) transaction growth from 2017-2019 with the timing of BNPL market entry in late 2021. For our estimates to have a causal interpretation, the instrument must satisfy two conditions. First, relevance: merchants in areas with higher historical digital payment adoption are more likely to adopt BNPL due to existing infrastructure, digitally familiar customer bases, and complementarity in technology adoption (Higgins 2024). Consistent with this argument, we find that areas with ex-ante higher UPI growth experienced 3.0 percentage points higher BNPL uptake following launch, with a first-stage F-statistic of 20.28.

Second, exclusion restriction: the instrument must affect merchant outcomes only through BNPL adoption, conditional on our controls. This assumption is plausible for several reasons. Because UPI growth is measured years before BNPL entry, it cannot be influenced by merchants' anticipation of or response to BNPL availability. Moreover, the timing of BNPL entry on our data provider's platform is exogenous to an individual merchant's characteristics. We include merchant and time fixed effects that control for time-invariant merchant characteristics and economy-wide trends, respectively, and show robustness to pincode and month fixed effects. A potential concern is that historical UPI growth might directly affect merchant outcomes through continued digital payment trends rather than BNPL adoption specifically. We address this by explicitly controlling for merchants' contemporaneous UPI transaction share, allowing us to separate the effect of BNPL adoption from ongoing digital payment usage. Reassuringly, our results strengthen rather than weaken when including these controls, suggesting our estimates reflect BNPL-specific effects.

We find that BNPL adoption significantly increases merchant revenue growth by 93 percentage points per month. To contextualize this magnitude, the median merchant in our sample has monthly revenues of approximately ₹22,370 (approximately $266 USD).[3] Given these modest baseline revenue levels and the substantial month-to-month volatility typical of small merchants in India's informal economy, large proportional growth rates can emerge from relatively modest absolute changes in sales. This revenue expansion operates through both intensive and extensive margins: transaction volumes increase by 41 percentage points, and average basket sizes grow by 52 percentage points. BNPL adoption also substantially improves merchants' access to formal credit. The probability of having any active loan increases by 18 percentage points following BNPL adoption, while the probability of obtaining a first formal loan increases by 8 percentage points among previously credit-excluded merchants. These effects are economically meaningful: they represent both a deepening of existing credit access and a transition from complete exclusion from formal credit markets

3. ₹to USD conversion is based on the nominal exchange rate of $1= ₹84 as of November 2024, which represents the end of our sample period.

to accessing working capital for the first time.

These baseline effects mask substantial heterogeneity across merchant types, showing that BNPL operates through different channels depending on firm characteristics. We examine heterogeneity along two dimensions that proxy for merchants' financial constraints: firm size and creditworthiness. Specifically, we split merchants based on ex-ante revenue and credit bureau scores into below vs. above median values. Revenue growth effects for small merchants are over three times those for large merchants. This divergence is even more pronounced when examining credit access: small merchants experience substantially larger increases in credit access compared to large merchants. Similarly, merchants with low credit scores experience significantly higher revenue growth in response to BNPL adoption compared to those with high credit scores. Critically, the composition of benefits differs across firm types. For small and low-credit-score merchants, revenue growth coincides with proportionally larger improvements in credit access, consistent with BNPL facilitating formalization and enabling supply-side expansion. For large merchants, revenue gains are substantial but credit access effects are more modest, suggesting that demand expansion plays a relatively larger role for firms that already have some access to formal credit.

To better understand the potential drivers of these differential effects, we examine how BNPL adoption transforms merchants' payment composition. Following the adoption of BNPL, we observe a substantial decline in the shares of cash transactions. Notably, this shift from cash accrues not only to BNPL but also to traditional card payments, as card transaction shares increase significantly. This complementarity between BNPL and card usage contrasts with standard substitution patterns documented in the payments literature, where digital payment methods typically compete for share. Two mechanisms could explain this pattern. First, BNPL adoption may require merchants to invest in digital payment infrastructure (terminals, integration with payment gateways) that simultaneously enables card acceptance, making cards and BNPL complements rather than substitutes (Higgins 2024; Sampaio and Ornelas 2024). Second, BNPL may attract a different customer base

of digitally-savvy consumers who use multiple digital payment methods—thereby increasing both BNPL and card usage. Regardless of the precise mechanism, the key implication is that BNPL acts as a catalyst for comprehensive payment digitization rather than simply adding another payment option. We further evaluate the importance of this digitization channel by examining heterogeneity based on merchants' ex-ante reliance on cash: merchants with above-median cash transaction shares experience effects roughly two to three times as large as those less reliant on cash. The wholesale shift from cash to digital payments generates verifiable transaction records that can reduce information asymmetries between merchants and lenders, with the benefits concentrated among merchants who were previously most opaque to formal financial institutions.

We further investigate the importance of financial constraints in driving the effects of BNPL by examining heterogeneity in our results across neighborhood characteristics. Merchants in economically disadvantaged areas, as measured by nightlight intensity or vehicle registrations, experience substantially larger effects from BNPL adoption, while the effects diminish or disappear entirely in the wealthiest areas. These geographic patterns suggest that BNPL's effect depends critically on the presence of binding financial constraints, whether on the merchant side (credit access and formalization) or the consumer side (liquidity for purchases). The absence of significant effects in affluent areas where neither merchants nor consumers face meaningful constraints indicates that BNPL is a product that addresses specific financial frictions in underserved segments. These patterns are further supported by heterogeneity across business types, with effects concentrated among merchants selling low-ticket and non-discretionary goods. These findings are consistent with the theoretical prediction that the zero-sum reallocation mechanism, which operates through relative price effects among consumers who already have credit alternatives, dominates in affluent areas, while the market-expansion channels dominate where consumers and merchants face binding financial constraints.

We next evaluate whether credit expansion improves or deteriorates credit allocation.

We find that BNPL adoption reduces default rates across all measures of loan delinquency, indicating an increase in not just credit access but credit allocation. Default reductions are similar across the revenue distribution, suggesting this is not driven by cash flows, with larger merchants servicing debt more easily. Instead, the effects are concentrated among merchants with low credit scores—the same population that gains the most from BNPL-facilitated credit access. Combined with our finding that credit access effects operate primarily among previously excluded merchants, this pattern is consistent with the merchant-side formalization channel — BNPL generates verifiable transaction records that enable lenders to assess previously opaque merchants, expanding credit supply and enabling merchants to cater to serve latent demand that previously went unmet due to supply-side constraints rather than lack of consumer interest.

A central concern for policymakers is whether payment innovations like BNPL simply redistribute market share from non-adopting to adopting merchants—a zero-sum game that might exacerbate inequality between digitally-enabled and traditional businesses—or whether they expand overall economic activity. We examine spillover effects on non-adopting merchants and find that while the effects are statistically significant, they are economically small: non-adopters experience revenue declines roughly an order of magnitude smaller than the gains accruing to adopters. This asymmetry suggests that BNPL predominantly expands the market by enabling new transactions—either bringing in previously excluded consumers or increasing purchase frequency for existing ones—rather than merely redistributing existing demand as would be predicted if BNPL simply acts as an implicit price discount drawing consumers away from non-adopters toward adopters.

Finally, we examine the implications of these heterogeneous effects for market structure. BNPL predominantly expands the overall market. Yet, since the negative spillover effects on non-adopting merchants are an order of magnitude smaller than adopter gains, overall market concentration nonetheless increases. This occurs because non-adopters are systematically smaller than adopters, so even modest negative spillovers shift relative market share

toward larger firms. Crucially, however, concentration within the adopter pool moves in the opposite direction: it falls as small, constrained merchants gain disproportionately from BNPL adoption. The aggregate distributional impact of BNPL is therefore shaped by differential adoption. This suggests that policies aimed at reducing adoption barriers for the smallest merchants would simultaneously strengthen BNPL's equalizing effects and mitigate its adverse consequences on market concentration.

Contribution: Our paper makes four main contributions. First, we provide the first evidence on which merchants benefit most from BNPL, documenting that benefits are over three times larger for small, credit-constrained merchants than for large ones. Second, we document a novel formalization channel: while BNPL has been studied primarily as a consumer credit product, we show that it digitizes merchant transactions, generating verifiable records that improve both merchant credit access and credit allocation. Third, we show that BNPL predominantly expands the overall market with negative spillover effects on non-adopters that are an order of magnitude smaller than adopter gains. Fourth, despite this, overall market concentration increases as non-adopters who are systematically smaller bear these spillovers, while concentration falls within the adopter pool.

2 Literature

Our paper contributes to several strands of literature. First, we extend the nascent literature on BNPL, which has focused primarily on consumer outcomes including spending increases (Di Maggio, Williams, and Katz 2022), over-borrowing risks (deHaan et al. 2024), and debt accumulation patterns (Guttman-Kenney, Firth, and Gathergood 2023). Cross-country analyses show that BNPL usage is concentrated among younger, liquidity-constrained consumers (Cornelli, Gambacorta, and Pancotto 2023), with recent evidence suggesting both beneficial flexibility and potential financial vulnerability (Larrimore et al. 2025). Recent work examines BNPL from multiple angles, including cross-market debt accumulation (Boshoff et al. 2022)

and competition with other payment methods (Bian, Cong, and Ji 2023). A notable exception is Berg et al. 2024, which examines a single large e-commerce merchant and finds that BNPL enables price discrimination by bundling products with zero-interest loans.[4]

Second, we contribute to the broader literature on digital payment adoption and formalization. Extant literature has shown that digital payment technologies can reduce informal transactions (Higgins 2024; Bachas et al. 2021), with mobile money in Kenya demonstrating particularly strong effects on household welfare and business growth (Jack and Suri 2014). Our finding that BNPL adoption increases card payment usage contributes to the literature on payment method complementarities (Rochet and Tirole 2002; Higgins 2024; Sampaio and Ornelas 2024). This contrasts with typical substitution patterns documented when new payment technologies are introduced (Alvarez and Argente 2022). Our findings on substitution away from cash also contrast with prior work that documents no impact of debit cards on cash usage (Brown et al. 2022). Taken together, our results suggest that BNPL serves as a gateway for broader payment digitization rather than simply another payment option competing for transaction share.

Third, our findings speak to the literature on information asymmetries in credit markets. Classic work by Petersen and Rajan 1994 and Petersen and Rajan 2002 establishes that lending relationships generate valuable information. Recent studies, however, show that digital footprints can substitute for traditional credit information (Agarwal et al. 2020). The credit access improvements we document build on work showing that transaction account data provides valuable information for lending decisions (Mester, Nakamura, and Renault 2007; Norden and Weber 2010; Puri, Rocholl, and Steffen 2017; Alok et al. 2024). This information generation mechanism is particularly important in emerging markets where traditional credit bureaus have limited coverage and information frictions are severe, significantly limiting firm

4. In a different context, Sharma, Jindal, and Kumar 2025 study the introduction of BNPL on a digital asset platform and find that financing increases transaction volume without affecting prices, with effects concentrated among existing users rather than new ones. While their focus is on platform growth strategy, our paper examines how BNPL affects heterogeneous merchant outcomes and market structure in a physical retail context.

growth (Banerjee and Duflo 2014; Burgess and Pande 2005). More broadly, our paper relates to the literature on FinTech lending and its effects on traditional credit markets (Buchak et al. 2018; Fuster et al. 2019; Tang 2019; De Roure, Pelizzon, and Thakor 2022). While these papers focus on direct lending by FinTech platforms, we demonstrate how a FinTech payment innovation facilitates access to credit indirectly through information generation. Moreover, our finding that default rates decline following BNPL-facilitated credit expansion, particularly among low-score merchants, suggests that BNPL-generated transaction records improve credit allocation.

Fourth, our spillover analysis contributes to the literature on the aggregate market effects of technology adoption. A long-standing question is whether gains from new technologies represent a net creation of economic activity or merely a reallocation from non-adopters to adopters (Aghion and Howitt 1992). In the context of payment technologies specifically, prior work has documented effects on individual firm outcomes but has been largely silent on whether adoption by some firms comes at the expense of others (Higgins 2024; Bachas et al. 2021). We address this directly by estimating spillover effects on non-adopting merchants, finding that negative spillovers are an order of magnitude smaller than adopter gains, showing that BNPL predominantly expands the market rather than redistributing existing demand. Yet overall market concentration increases, as non-adopters who are systematically smaller bear these negative spillovers. Within the adopter pool, however, concentration falls, as small, constrained firms gain disproportionately. These results highlight how adoption barriers shape the aggregate distributional consequences of fintech payment innovations.

3 Institutional Setting

3.1 India's Digital Payment Revolution

India's digital revolution has redefined the nation's economic and social landscape, setting the foundation for profound transformation in the financial sector. Central to this change are

policy-led initiatives such as Digital India, Aadhaar, and the Jan Dhan Yojana, collectively known as the JAM trinity.[5] These programs brought hundreds of millions into the formal banking system and interconnected them via affordable mobile devices and the world's lowest data costs. The creation of a robust digital public infrastructure, use of Aadhar for faster Know your Customer (KYC) check led to the development of early digital rails for payments, such as NEFT and RTGS digitized interbank transfers, while IMPS in 2010 introduced instant mobile-based payments. These developments laid the groundwork for what would become the centrepiece of India's financial digitization — the Unified Payments Interface (UPI). UPI, launched in 2016, enabled seamless, real-time, any bank-to-any bank transfers through mobile phones and was designed as an open, interoperable and low-cost payments protocol. Its impact was unprecedented: retail digital payments in India reached 164.16 billion transactions valued at ₹265 trillion in FY 2023–24, with projections to triple to 481 billion transactions by FY 2028–29, supported by the four-fold rise in the Reserve Bank of India's Digital Payments Index over six years. Digital payments are expected to contribute nearly half of India's target of a USD 1 trillion digital economy by 2030.

The wide-scale behavioural shift toward digital payments created the ideal environment for a second wave of financial innovation and fundamentally reshaped India's small-merchant economy: turning millions of cash-dependent micro-enterprises into active participants in the digital financial ecosystem. Before UPI, most small and micro enterprises were limited to cash transactions, which constrained business growth, prevented transaction tracking, and limited access to working capital. UPI reversed this dynamic. The zero-MDR policy, interoperable QR codes, and low-cost infrastructure meant that even the smallest shop could begin accepting digital payments simply by sticking a printed QR on a counter top. Because the QR system was interoperable, merchants did not need to match the customer's app—whether the customer used PhonePe, Google Pay, Paytm or a banking app, the payment landed directly in the merchant's bank account. Digital payments—once limited to

5. https://www.indiabudget.gov.in/budget2016-2017/es2015-16/echapvol1-03.pdf

organized retail—became routine for kirana stores, salons, tea stalls, pharmacies, food vendors, and home-based micro-entrepreneurs. This was the key catalyst that accelerated adoption across India's fragmented merchant base and helped UPI become the world's largest real-time payment system with more than 19 billion transactions processed every month.

As kirana stores and micro-enterprises began to digitize their sales through QR payments, fintech companies identified a huge opportunity: merchants who were once invisible to formal finance now had transaction histories that could serve as proof of business turnover. As QR-based UPI acceptance proliferated across kirana stores and small businesses, payment platforms increasingly leveraged granular transaction patterns as a proxy for creditworthiness, transforming digital payments from a passive acceptance tool into a foundation for embedded credit delivery. The outcome was a new competitive phase in the Indian fintech ecosystem in which providers built products tailored to the operational realities of small merchants—credit tied to inventory cycles, repayment aligned with revenue inflows, and financing delivered through familiar payment interfaces rather than separate loan journeys. One of the most transformative offerings born from this ecosystem was Buy Now Pay Later (BNPL), which allowed merchants to access small working-capital loans or inventory financing based on their payment flows, and in parallel gave consumers the ability to split payments at checkout.

3.2 BNPL in the Indian Context

India's BNPL landscape has entered a phase of accelerated scale, driven by strong digital payments infrastructure, explosive e-commerce growth, and widening demand for frictionless short-tenure credit across both consumers and merchants. The domestic BNPL market, valued at USD 3.5–4 billion in 2021, is projected to expand ten-fold to USD 35–40 billion by 2026, marking one of the fastest adoption curves globally.[6] Recent industry outlooks estimate that India's BNPL business will grow 13.4% in 2026 to reach USD 21.95 billion, with

6. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4924971

sustained double-digit growth expected until 2029 as checkout financing becomes embedded across digital commerce and offline retail. Structural economic factors support this trend: India has only 69 million credit card users (about 5% of the population), creating a wide base of under-served customers who favour BNPL for instant, low-friction access to credit. The scale of adoption is reflected in customer demographics: over 70% of BNPL users in India are under the age of 35, signaling that BNPL has become a preferred credit instrument among Millennials and Gen Z rather than a niche lending product. Consumer behaviour indicates that usage is distributed across both aspirational and routine consumption, with 71% of BNPL users spending on electronics, 67% on fashion, and 57% on everyday shopping, showing that BNPL is no longer restricted to discretionary categories. [7]

The adoption has also broadened from discretionary spending to routine commerce: BNPL usage is now observed across electronics, fashion, mobile retail and everyday online purchases, demonstrating that it has become an integral component of India's digital consumption behaviour, and the BNPL model has now extended beyond online shoppers to India's vast small-merchant and kirana ecosystem, where retail customers uses BNPL as a mode of payments for goods. As QR-based UPI payments became ubiquitous at small retail stores, BNPL platforms began leveraging merchants' transaction histories as a proxy for business performance, enabling credit decisions without formal collateral or long documentation cycles. This shift unlocked a new revenue opportunity for merchants while simultaneously giving BNPL lenders a low-cost, high-frequency repayment channel through UPI collections embedded within everyday transactions. Adoption patterns demonstrate a strong geographic diffusion effect: 60% of demand now originates from Tier-2 and Tier-3 cities, and a comparable shift is visible in merchant-side pay-later products offered by platforms such as PhonePe, Pine Labs, Paytm, BharatPe and Amazon Pay. Younger urban and semi-urban users, many of whom are thin-file or new-to-credit, form the core customer segment, attracted by instant approval, zero-interest installments, and repayment aligned with cashflow cycles rather than

7. https://benori.com/uploads/insight/1690267046Buy_Now_Pay_Later_Report.pdf

fixed billing. There are an estimated 22-25 million Buy Now, Pay Later (BNPL) retail customer loans in India as of today. This number is expected to grow significantly, with some reports projecting it will reach 90-100 million by 2026. [8]

The overall landscape of BNPL in India can therefore be characterized by three reinforcing dynamics: rapid consumer adoption among young, digitally active cohorts; growing merchant acceptance across online and offline channels; and a macro-level shift toward alternative credit models embedded directly within the digital commerce stack. Regulatory attention is increasing as the Reserve Bank of India evaluates BNPL through responsible lending requirements and reporting standards, yet this has not dampened growth—rather, it is expected to push the sector toward more sustainable risk management. Taken together, BNPL in India has transitioned from an experimental payment feature to a mainstream retail-credit mechanism with a young and expanding customer base, poised for continued scale.

4 Data & Sample

4.1 Data

Our empirical analysis leverages proprietary data from one of India's largest payment-system fintech firms, which has a deep penetration in the small-merchant ecosystem and has built one of the fastest-scaling BNPL (Buy Now Pay Later) portfolios in the country. After establishing itself as the largest offline payments network—with more than 10 million merchants across 300+ cities—the firm entered the BNPL segment in late 2021, offering credit for both online and offline purchases, including QR-based and card-based transactions at physical stores. Within three months of launch, the BNPL product achieved an annualized TPV run-rate of ₹2,400 crore, illustrating rapid adoption driven by seamless consumer credit access, zero-cost EMIs, and flexible repayment structures.

8. https://www.herofincorp.com/blog/buy-now-pay-later

A core feature of the firm's BNPL strategy is its integration with the merchant-acquiring network. QR-based transactions at kirana and small retail stores generate rich, high-frequency transaction histories that feed into underwriting models. This enables two-sided credit provisioning—consumer BNPL at checkout and merchant BNPL/working-capital financing—through the same digital interface. By embedding credit into standard payment flows rather than introducing a separate loan journey, BNPL operates as a natural extension of the firm's existing payments infrastructure. Importantly, the BNPL product carries no transaction fees for either merchants or consumers, ensuring that adoption decisions are driven by operational readiness and demand considerations rather than cost frictions.

We construct our dataset using a random sample of merchants from 2020 to 2024, drawn from this fintech firm. For each merchant, we observe detailed characteristics including merchant category and sub-category (e.g., fuel/petrol pump, retail/footwear), geographic location (pincode), gender of the merchant, and comprehensive credit bureau information such as credit scores and tradelines. High-frequency business activity is recorded at the daily level, including the volume and count of transactions by payment type (UPI, credit card, debit card, and cash) as well as end-of-day revenue balance. For merchants who borrow from the platform, we additionally observe complete loan-level data—loan sanction date, sanctioned amount, tenure, interest rate, repayment history, and default outcomes. In September 2021, the firm launched a Buy Now Pay Later (BNPL) product, and adoption was voluntary. For each merchant, we capture whether and when BNPL was adopted, allowing us to distinguish clearly between the pre-BNPL period (2020–October 2021) and the post-BNPL period (September 2021 onward). The combination of granular merchant characteristics, daily transaction and revenue data, and loan-level credit outcomes—along with quasi-voluntary technology adoption—creates a rich empirical setting to examine the causal impact of BNPL availability on merchant behavior, business performance, and access to credit.

4.2 Sample Construction & Summary Statistics

We construct our analysis sample by applying several filters to ensure data quality and representativeness. First, we restrict attention to merchants on the platform who have taken at least one loan from the firm, ensuring that all merchants in our sample have demonstrated creditworthiness and engagement with the platform's financial services. Second, to ensure statistical power and avoid idiosyncratic effects from niche sectors, we retain only business categories with at least 500 unique merchants. Third, we require merchants to have transaction records from April 2020 onward, providing sufficient pre-period data before the BNPL launch in September 2021.

Figures 1 and 2 illustrate the geographic distribution of merchants and BNPL adopters across Indian districts. Our sample spans the country broadly, with merchant density concentrated in southern and western India. The distribution of BNPL adopters closely mirrors the overall merchant distribution, suggesting that adoption is not confined to particular regions.

Figure 3 illustrates the evolution of our sample over time. Panel A shows the total number of merchants on the platform growing from approximately 50,000 in April 2020 to over 800,000 by late 2023, reflecting both organic platform growth and the broader digitization of India's small merchant economy. Panel B decomposes this growth into BNPL adopters and non-adopters, revealing that adoption accelerated rapidly following the September 2021 launch, with adopters comprising roughly half of active merchants by mid-2023.

Figure 4 presents the distribution of merchants across business categories. Panel A shows that Food & Beverages, Grocery/General Store, and Retail Outlet dominate our sample in roughly equal proportions, each comprising approximately 290,000 merchants. This distribution reflects India's retail landscape, where food-related businesses constitute the backbone of the small merchant economy. Panel B examines BNPL adoption rates by category, revealing meaningful heterogeneity: categories such as Others Miscellaneous, Home Services, and Education show the highest adoption rates (exceeding 60%), while Pan/Cigarette/Tea

stalls and Dairy/Fresh Products show the lowest (below 30%). This variation motivates our heterogeneity analysis by business type in Section 5.5.

Table 1 presents summary statistics for BNPL-adopting merchants. The typical merchant in our sample operates at a modest scale, with a median monthly revenue of ₹22,370 (approximately $266 USD) and a median transaction count of 106 per month.[9] The distribution is highly skewed, as shown by the mean revenue of ₹60,942, reflecting the presence of a few very large merchants in the sample. Transaction count growth rates exhibit substantial volatility typical of small businesses, with standard deviations of 0.95 for transaction count growth and 1.29 for revenue growth. Average transaction sizes vary widely, with a median of ₹163 and a mean of ₹708, indicating diverse business models ranging from small-ticket daily essentials to higher-value discretionary purchases. Notably, 14.3% of merchant months involve new loan origination, indicating active credit market participation.

Table 2 compares BNPL adopters with non-adopters across key pre-adoption characteristics, revealing systematic differences that motivate our instrumental variable approach. Adopters exhibit substantially higher baseline scale, with a mean revenue of ₹26,530 versus ₹14,703 for non-adopters and average transaction counts of 96 versus 31. Interestingly, non-adopters have higher average transaction sizes (₹716 versus ₹522). Growth dynamics also differ significantly: adopters exhibit higher transaction count growth (10.9% versus 5.9% monthly) but lower transaction size growth (4.7% versus 9.3%), consistent with adopters focusing on volume expansion through smaller ticket sizes.

Credit market participation is remarkably similar between groups in the pre-period, with loan take-up rates of 15.6% for adopters versus 15.2% for non-adopters. However, conditional on borrowing, adopters access larger loans (₹121,858 versus ₹97,944). First loan amounts show minimal difference (₹80,525 for adopters versus ₹76,851 for non-adopters), suggesting similar initial credit access conditions.

The sample composition reveals several important patterns for interpreting our results.

9. ₹to USD conversion is based on the nominal exchange rate of $1= ₹84 as of November 2024, which represents the end of our sample period.

First, the dominance of small-scale merchants with median monthly revenues under $300 explains the large proportional effects we document—even modest absolute increases translate to substantial percentage growth from low baselines. Second, the diversity across business categories, from essential fresh products to discretionary retail, enables us to examine heterogeneous effects across merchant types. Third, the presence of both adopters and non-adopters with similar pre-period credit access but different operational characteristics provides variation essential for identifying the causal effects of BNPL adoption on merchant outcomes. These systematic differences also underscore the selection into BNPL adoption: larger, growth-oriented merchants with established digital payment infrastructure are more likely to adopt, highlighting the importance of our instrumental variable strategy in identifying causal effects.

5 Empirical Methodology

Our primary objective is to estimate the association between BNPL adoption and merchant outcomes. A simple OLS approach would regress merchant outcomes on BNPL adoption status to capture this association like in the equation below:

$$Y_{ipt} = \beta \cdot \text{BNPL}_{it} + \alpha_i + \delta_t + \varepsilon_{ipt} \tag{1}$$

where Y_{ipt} represents various outcomes for merchant i in pincode p at year-month t. Our primary outcome variables include: (i) revenue growth, measured as the log difference in monthly transaction values; (ii) transaction patterns, decomposed into log transaction count and average transaction size; (iii) credit access metrics, including the number of loans, total loan amount, and an indicator for first-time loan access; (iv) loan quality measures such as overdue amounts and default rates; and (v) payment composition variables, including the share of cash, card, and digital transactions. The variable BNPL_{it} is an indicator equal to one if merchant i has adopted BNPL by time t, α_i denotes merchant fixed effects, δ_t captures

time fixed effects, and ε_{ipt} is the error term.

While equation (1) controls for time-invariant merchant characteristics and common time trends, the coefficient β is likely to be biased due to several endogeneity concerns. First, selection bias may arise because adopting BNPL is an endogenous choice made by merchants and those who adopt likely differ systematically from non-adopters in both observable and unobservable ways. For example, more innovative or growth-oriented merchants may be more like to adopt new payment technologies, and these same characteristics independently drive merchant outcomes like revenue growth and credit access. Second, reverse causality poses a significant challenge: merchants experiencing declining revenue growth or poor credit conditions may be more likely to adopt BNPL in an attempt to attract new consumers. Third, omitted variables correlated with both BNPL adoption and outcomes could bias our estimates. For instance, local economic shocks or changes in consumer demographics might simultaneously influence merchant performance and the attractiveness of offering BNPL options.

5.1 Instrumental Variable Approach

To address these endogeneity concerns, we employ a shift-share instrumental variable that exploits spatial variation in pre-existing digital payment infrastructure interacted with the exogenous timing of BNPL launch. Our instrument is constructed as:

$$Z_{pt} = \text{UPIGrowth}_{p,2017-2019} \times \text{BNPLLaunch}_t \tag{2}$$

where $\text{UPI_Growth}_{p,2017-2019}$ measures the growth rate of UPI (Unified Payments Interface) transactions at the pincode level between 2017 and 2019, well before BNPL services were launched by our data provider in November of 2021, and BNPLLaunch_t is an indicator equal to one for periods after BNPL launch.

The intuition underlying our instrument is that areas with higher pre-BNPL digital

payment adoption had better infrastructure and consumer familiarity with digital payments, making BNPL adoption more feasible and attractive for merchants in these areas once the service became available. Importantly, the instrument exploits predetermined variation in digital payment infrastructure that predates BNPL availability by several years, addressing concerns about reverse causality. The interaction with the post-BNPL timing ensures that our identification comes from differential changes in outcomes between high and low UPI-growth areas after BNPL becomes available, not from permanent differences between these regions.

We implement our instrumental variable strategy using two-stage least squares (2SLS). The first stage estimates the effect of our instrument on BNPL adoption:

$$\text{BNPL}_{it} = \pi Z_{pt} + \alpha_i + \delta_t + \nu_{it} \tag{3}$$

where all variables are as previously defined, and ν_{it} is the first-stage error term. The coefficient π captures the differential likelihood of BNPL adoption in high versus low UPI-growth areas after BNPL market entry.

The second stage uses the predicted values from the first stage to estimate the causal effect of BNPL adoption on our outcomes of interest:

$$Y_{ipt} = \beta \cdot \widehat{\text{BNPL}}_{it} + \alpha_i + \delta_t + \epsilon_{ipt} \tag{4}$$

We estimate this specification for our full set of outcome variables described above with β being our coefficient of interest.

5.2 Identifying Assumptions

The validity of our instrumental variable strategy relies on two key assumptions. First, the instrument must be relevant—that is, pre-BNPL UPI growth must predict BNPL adoption after the service becomes available. Table 3 presents our first-stage results, where we test

this assumption directly. We estimate two specifications to ensure robustness: column (1) includes pincode and time fixed effects, while column (2) includes merchant and time fixed effects. The coefficient on our instrument is 0.0303 (s.e. = 0.007) with pincode fixed effects and 0.0274 (s.e. = 0.006) with merchant fixed effects, both highly significant at the 1% level. This confirms that areas with higher pre-BNPL digital payment growth experienced greater BNPL adoption once the service became available. The Kleibergen-Paap F-statistic is 20.28 with pincode fixed effects and 17.89 with merchant fixed effects, above the conventional threshold of 10, suggesting our instrument has sufficient power to identify the effect. The consistency of results across both fixed effects structures—whether absorbing time-invariant differences across pincodes or across individual merchants—strengthens our confidence in the instrument's validity.

Second, the exclusion restriction requires that the instrument affects merchant outcomes only through its effect on BNPL adoption, conditional on controls. This assumption would be violated if areas with higher UPI growth between 2017-2019 were on different outcome trajectories for reasons unrelated to BNPL adoption after BNPL launch. We address this concern in several ways. First, the timing of our instrument (2017-2019) predates BNPL availability by over two years, making it unlikely that merchants were anticipating BNPL and adjusting behavior accordingly. Second, we control for merchant fixed effects, which absorb any time-invariant differences between merchants in high versus low UPI-growth areas. Third, and most importantly, we directly test for violations of the exclusion restriction by controlling for contemporaneous UPI transaction shares at the merchant level. If our instrument were simply capturing ongoing digitization trends, we would expect our results to attenuate or disappear when controlling for current UPI usage. Instead, we find that our estimates strengthen with this control, suggesting that the variation we exploit is specifically related to BNPL adoption rather than general digital payment trends.

6 Main Results

We now present our empirical findings on how BNPL adoption affects merchant outcomes. We begin by establishing the main effects of BNPL on revenue growth, transaction patterns, and credit access using our instrumental variable strategy. We then explore heterogeneity across merchant characteristics to understand which types of firms benefit most from BNPL adoption and through what channels. Finally, we examine how BNPL transforms payment composition.

6.1 Baseline Results

Table 4 presents our main results on how BNPL adoption affects merchant revenue and transaction patterns. BNPL adoption increases merchant revenue growth by 93.3 percentage points with pincode fixed effects (column 1) and 85.1 percentage points with merchant fixed effects (column 2), both highly significant at the 1% level. To understand the sources of this revenue growth, we decompose the effect into changes in transaction count versus average transaction size. Transaction count increases by 41.3 percentage points with pincode fixed effects (column 3) and 39.4 percentage points with merchant fixed effects (column 4), both significant at the 1% level. Average transaction size increases by 51.9 percentage points with pincode fixed effects (column 5) and 45.7 percentage points with merchant fixed effects (column 6), both significant at the 1% level. BNPL thus drives revenue growth through both channels — enabling merchants to serve more customers while also increasing basket sizes.

The magnitude of these revenue effects warrants discussion. An 85 percentage point increase may initially appear implausibly large. However, several factors help interpret this effect. First, our instrumental variable identifies a local average treatment effect (LATE) for compliers—merchants whose BNPL adoption is induced by pre-existing digital payment infrastructure. These marginal adopters are likely to experience the greatest transformation from digitization, transitioning from informal, cash-based operations to formal, digitally en-

abled businesses. Second, the baseline revenue levels for many merchants in our sample are relatively small. For a median merchant in our sample with monthly revenue of ₹22,370 (approximately $266 USD), an 85% increase represents an additional ₹19,015 ($226 USD) per month—economically meaningful for the merchant but reasonable given they are gaining access to new customer segments and payment technologies. Third, these effects capture not just direct BNPL transactions but the broader transformation of business operations, including improved inventory management, better cash flow, and access to previously unreachable customers.

Table 5 examines credit market outcomes, revealing BNPL's role in financial inclusion. BNPL adoption significantly increases the probability of having any active loan by 18.4 percentage points with pincode fixed effects and 23.7 percentage points with merchant fixed effects (columns 1-2). Total loan amounts also increase substantially, with the inverse hyperbolic sine of loan amounts rising by 2.385 and 3.063 across specifications (columns 3-4), both statistically significant. The effects extend to first-time credit access: the probability that a previously unbanked merchant obtains their first formal loan increases by 8.4–8.7 percentage points (columns 5-6), significant at the 1% level, while first loan amounts roughly double following BNPL adoption (columns 7-8). These results indicate that BNPL expands credit access along both margins—deepening existing credit access and enabling previously excluded merchants to enter formal credit markets for the first time.

The reduced form estimates presented in Tables IA.1 and IA.2 in the online appendix confirm these patterns. The reduced form coefficients represent the direct effect of our instrument on outcomes without the scaling by first-stage effects. For revenue outcomes, we find positive and significant reduced form effects across all specifications, with coefficients ranging from 0.011 to 0.028 for different outcomes. For credit access, the reduced form effects are positive and significant across both overall lending and first-time credit access. These reduced form results provide additional confidence that our instrument is capturing meaningful variation in outcomes.

Figure 5 presents event study estimates that examine the dynamic relationship between our instrument and key outcomes. We interact pincode-level UPI growth (2017-2019) with quarterly indicators relative to the BNPL launch in September 2021, plotting the coefficients along with 95% confidence intervals. We normalize coefficients to the quarter three periods before BNPL launch and exclude the quarter immediately preceding launch to account for potential anticipation effects as merchants learned about BNPL availability. Panels A through E show results for revenue, transaction count, average transaction size, loan dummy, and loan amount (in inverse hyperbolic sine), respectively. Several patterns emerge. First, for revenue (Panel A) and transaction count (Panel B), the pre-treatment coefficients are generally small and statistically indistinguishable from zero, supporting the parallel trends assumption underlying our identification strategy. Following BNPL launch, both outcomes show sharp positive increases that persist and grow over subsequent quarters. Second, average transaction size (Panel C) shows positive post-treatment effects, consistent with our main results. Third, the credit access variables (Panels D and E) display relatively flat pre-trends with positive post-period increases, with loan amounts exhibiting larger effects and somewhat wider confidence intervals reflecting greater heterogeneity in borrowing amounts.

The absence of systematic pre-trends across most outcomes provides reassurance that high and low UPI-growth areas were not on differential trajectories prior to BNPL availability, supporting our exclusion restriction assumption.

6.2 Heterogeneity by Firm Size and Credit Access

To understand which types of merchants benefit most from BNPL adoption and through what channels, we examine heterogeneous effects based on ex-ante merchant characteristics: revenue and credit bureau score. While the former captures the size and availability of resources, the latter proxies for the merchant's access to credit. These analyses show striking differences in how BNPL affects different types of merchants, providing evidence for distinct mechanisms through which BNPL operates. Table 6 presents these results, with Panel A

splitting by ex-ante revenue and Panel B by credit bureau score.‘

Panel A evaluates heterogeneity by firm size. While both small and large merchants benefit from BNPL adoption, the magnitude of effects differs substantially. For below-median revenue merchants, revenue growth is 172.7 percentage points compared to 52.5 percentage points for above-median merchants—over three times as large—driven by both higher transaction count growth and basket size growth. Credit access also improves for both groups, with small merchants experiencing a 26.3 percentage point increase in the probability of having any active loan compared to 16.5 percentage points for large merchants.

These patterns suggest that while BNPL benefits merchants across the size distribution, the composition of benefits differs. For smaller merchants, BNPL increases both sales and credit access. The proportionally larger credit access effects for small merchants indicate that BNPL's role in generating verifiable transaction records is especially valuable for firms that previously lacked formal financial histories. For larger merchants, revenue gains are substantial but credit access effects are more modest, consistent with demand expansion playing a relatively larger role for firms with existing access to formal credit.

Panel B provides complementary evidence based on credit bureau scores. Merchants with below-median scores experience revenue growth of 327.9 percentage points compared to 118.8 percentage points for above-median merchants—roughly a 3:1 ratio that mirrors the size-based heterogeneity. Transaction count and average transaction size effects follow a similar pattern. Credit access coefficients are directionally positive and larger for merchants with low bureau score but imprecisely estimated. Nonetheless, the consistency of the results across both dimensions—whether we define constraints by size or creditworthiness—supports our interpretation that BNPL's benefits concentrate among the most constrained merchants. For established merchants, BNPL primarily provides demand expansion. For marginal merchants operating informally, BNPL catalyzes a more fundamental transformation of business operations.

6.3 Credit Performance

Our results thus far show that BNPL significantly expands credit access, particularly among small, credit-constrained merchants. A natural question is whether this credit expansion improves or deteriorates credit allocation. Table 7 examines this question by evaluating the effect of BNPL adoption on loan delinquency. Panel A presents baseline results across three measures: an overdue dummy, overdue amount, and the inverse hyperbolic sine of overdue amounts. BNPL adoption reduces default rates across all three measures—the probability of having an overdue loan declines by 2.3 percentage points, while overdue amounts decline significantly on both the level and IHS measures. These results indicate that BNPL-facilitated credit expansion does not come at the cost of deteriorating loan quality.

Panels B and C examine heterogeneity in these effects by revenue and bureau score, respectively. The revenue split reveals similar magnitudes across both groups—coefficients for below-median and above-median revenue merchants are directionally similar, though statistical significance is concentrated among above-median merchants. This pattern suggests that the default reduction is not driven by cash-flow differences, where larger merchants might more easily service debt. In contrast, the bureau score split reveals significant economic heterogeneity. Merchants with below-median credit scores experience default reductions two to three times larger than those with above-median scores across all three measures. Combined with our earlier finding that credit access effects are concentrated among smaller, constrained merchants, this pattern suggests that BNPL-generated transaction records enable lenders to better assess previously unobservable merchant quality—improving not just credit access but also credit allocation.

6.4 Payment Mix and Formalization

A central mechanism through which BNPL affects merchant outcomes is by catalyzing a shift from cash-based to digital transactions, especially for small and credit-constrained merchants. Our data allows us to directly test this hypothesis by evaluating how BNPL

adoption transforms payment composition, and whether merchants who relied more heavily on cash ex-ante experience larger benefits from BNPL adoption.

Table 8 evaluates payment patterns following BNPL adoption. Cash transaction shares decline significantly, confirming that BNPL facilitates a shift away from informal cash-based operations. However, surprisingly, card transaction shares increase alongside the adoption of BNPL. This complementarity between BNPL and card payments runs counter to standard substitution patterns in the payments literature, where new digital payment methods typically compete with existing ones for market share. The simultaneous increase in both BNPL and card usage suggests that BNPL adoption triggers a broader digital transformation rather than simply adding another payment option. Three mechanisms could explain this pattern. First, BNPL adoption may require merchants to upgrade their payment infrastructure in ways that also facilitate card acceptance. Second, BNPL may attract digitally oriented customers who prefer multiple digital payment options. Third, and perhaps most importantly, BNPL may relax liquidity constraints for cash-preferring consumers, inducing them to participate in the digital economy. Regardless of the specific mechanism, the key insight is that BNPL serves as a gateway to comprehensive payment digitization, not just another payment method competing for transaction share.

The importance of this digitization channel is further supported by the heterogeneity analysis in Table 9, which splits the sample by merchants' ex-ante cash reliance. Merchants with above-median cash transaction shares experience effects that are 2-3 times larger across all outcome variables compared to those with below-median cash shares. This dramatic difference provides compelling evidence that BNPL's benefits are concentrated among merchants who are more likely to undergo the largest transformation in payment practices. The merchants who relied most heavily on cash—and were therefore most opaque to formal financial institutions—gain the most from adopting BNPL.

6.5 Heterogeneity by Neighborhood Characteristics

We next examine the role of local economic conditions in influencing the effects of BNPL. To this end, we use two measures of local economic development: nightlight intensity from satellite data and vehicle registration rates at the pincode level. These metrics provide complementary perspectives on area-level affluence and economic activity.

Table 10, panel A, presents results split by nightlight intensity, a widely used proxy for economic development (Henderson, Storeygard, and Weil 2012). We use a global nighttime light dataset provided by Li et al. 2020.[10] Merchants in below-median nightlight areas experience revenue growth of 85.6 percentage points following BNPL adoption, compared to 45.5 percentage points in above-median areas. This pattern extends to credit access: the probability of an outstanding loan increases by 35.4 percentage points in low-nightlight areas versus 3.6 percentage points in high-nightlight areas. Loan amounts show an even starker contrast, increasing by 446.6 percentage points in less developed areas compared to 60.9 percentage points in more developed areas.

In Table 10, panel B, we use four-wheeler registration rates as a proxy for regional economic affluence.[11] We find that BNPL effects are concentrated entirely in less affluent neighborhoods. Merchants in below-median vehicle registration areas experience significant revenue growth of 59.6 percentage points, increased transaction counts of 29.5 percentage points, and higher average transaction sizes of 30.1 percentage points. Consistent with the evidence based on the nightlight intensity measure, the credit access channel is also limited to less affluent pincodes.

In sharp contrast, merchants in high-vehicle-registration areas, the wealthiest neighborhoods, show no significant effects across any outcome variable. This complete absence of effects in affluent areas provides compelling evidence that BNPL's impact depends on the

10. Li et al. 2020 integrates nighttime data from the Defense Meteorological Satellite Program (DMSP) and the Visible Infrared Imaging Radiometer Suite (VIIRS) to create a harmonized time series from 2012 onwards.

11. Vehicle registration data comes from the state website: https://vahan.parivahan.gov.in/nrservices/

presence of binding financial constraints.

These geographic patterns reveal that BNPL addresses financial frictions that are most severe in economically disadvantaged areas. In low-income neighborhoods, both merchants and consumers face substantial financial constraints: merchants struggle with credit access and operate informally, while consumers lack liquidity for purchases. BNPL simultaneously relaxes both constraints, enabling transactions that would not otherwise occur. In wealthy areas where established merchants already have credit access and affluent consumers have multiple payment options, BNPL offers little incremental value.

6.6 Heterogeneity by Business Categories

To further understand the mechanisms driving BNPL adoption and its effects, we examine heterogeneity across business types along two dimensions: average transaction ticket size (low versus high) and consumption type (discretionary versus non-discretionary). Low-ticket categories include merchants in the following sectors: Fresh Products, Food & Beverages, Utilities, Education & Professional Classes, Fuel & Gas, Transportation, and Entertainment. High-ticket categories include Retail Outlet, Automobiles and Vehicles, Beauty and Wellness, Business & Professional Services, Electronics & Durables, and Hospitals & Healthcare. Discretionary category refers to merchants in Food & Beverages, Automobiles and Vehicles, Beauty and Wellness, Electronics & Durables, and Entertainment. Non-discretionary merchants include Fresh Products, Hospitals and Healthcare, Business & Professional Services, Utilities, Education & Professional Classes, and Fuel & Gas.

Table IA.3, panel A, presents results for subsamples split by average ticket size. Merchants in low-ticket categories experience modestly larger effects from BNPL adoption compared to high-ticket businesses. The credit access differential exhibits similar patterns. These results suggest that BNPL is particularly valuable for enabling small, frequent purchases that consumers might otherwise forgo or delay. Low-ticket categories include everyday essentials such as fresh products, utilities, and transportation—purchases where even small liquidity

constraints can prompt consumers to reduce their consumption. For these merchants, BNPL likely enables them to transform marginal customers into regular buyers by smoothing temporary cash flow mismatches. The stronger credit access effects for low-ticket merchants likely reflect that these businesses face working capital constraints, making the formalization and credit access enabled by BNPL particularly transformative.

Panel B examines the effects along the discretionary versus non-discretionary dimension, revealing nuanced patterns. While both categories experience significant revenue growth, the effects are more pronounced for non-discretionary businesses. Transaction count and average transaction size also exhibit similar patterns. The fact that these effects are substantially larger for non-discretionary merchants suggests that BNPL enables more frequent purchases of essential goods and services by relaxing liquidity constraints for the merchant's customer base. This pattern also extends to credit access.

Overall, these business category results reinforce our interpretation that BNPL's effects are strongest where financial constraints bind most tightly. The technology proves most transformative for merchants serving liquidity-constrained consumers, enabling small-ticket, essential, and frequent purchases, thus boosting their revenues.

We further examine whether the business-type and neighborhood heterogeneity patterns reinforce each other by interacting these two dimensions. Table IA.7 presents results for discretionary versus non-discretionary merchants separately within economically disadvantaged areas (below-median nightlight intensity and below-median vehicle registrations). In both cases, effects are concentrated among non-discretionary merchants in less affluent neighborhoods—the segment where both demand-side liquidity constraints and supply-side credit constraints are most binding. For instance, among merchants in low-nightlight areas, non-discretionary businesses experience revenue growth of 120.6 percentage points compared to 51.8 percentage points for discretionary merchants, with a similar divergence in credit access. These patterns confirm that BNPL's transformative effects are strongest at the intersection of financially constrained merchants and liquidity-constrained consumers.

7 Spillover Effects and Market Structure

Our results so far have focused on the direct effects of BNPL adoption on the merchants that adopt it. Two critical questions remain for understanding BNPL's broader welfare implications. First, do the benefits to adopters come at the expense of non-adopting merchants, or does BNPL expand the overall market? Second, what do the heterogeneous effects documented above imply for aggregate market concentration? We address these questions in turn, first examining spillover effects on non-adopters and then analyzing how BNPL adoption reshapes market share structure.

7.1 Spillover Effects on Non-Adopters

A critical question for understanding the welfare implications of BNPL is whether its benefits come at the expense of non-adopting merchants. To examine potential spillover effects, we estimate the impact of local BNPL adoption on merchants who do not themselves adopt BNPL. This analysis helps distinguish between market expansion (where BNPL grows the overall pie) and business stealing (where BNPL merely redistributes existing demand).

We estimate the following specification for non-adopting merchants only:

$$Y_{ipt} = \beta \cdot \text{BNPLAdoptionFraction}_{pt} + \alpha_i + \delta_t + \varepsilon_{ipt} \tag{5}$$

where Y_{it} represents outcomes for non-adopting merchant i at time t, and $\text{BNPLAdoptionFraction}_{pt}$ is the fraction of merchants in pincode p that have adopted BNPL by time t. We include merchant and time fixed effects to control for time-invariant merchant characteristics and common temporal shocks. The coefficient β captures the spillover effect.

Table 12 presents the results. We find statistically significant but economically small negative spillovers on non-adopting merchants. A 10 percentage point increase in local BNPL adoption is associated with a 0.66% decline in non-adopter revenue and a 0.51% decline in transaction counts, while average transaction size shows no significant change. To

put these magnitudes in perspective, the revenue effect on non-adopters is roughly an order of magnitude smaller than the gains accruing to adopters, suggesting that the vast majority of BNPL's revenue impact represents genuine market expansion rather than redistribution.

Table IA.8 examines heterogeneity in these spillover effects by business type. The negative revenue effects on non-adopters are modestly larger for non-discretionary merchants (-7.9 percentage points per 10 percentage point increase in local adoption) than for discretionary merchants (-4.5 percentage points), while average transaction size spillovers remain insignificant across both groups. A similar pattern emerges when splitting by ticket size. These magnitudes remain an order of magnitude smaller than the corresponding adopter gains within each category, reinforcing our conclusion that BNPL predominantly expands the overall market rather than redistributing demand.

These findings indicate that while some demand reallocation from non-adopters to adopters occurs, BNPL predominantly expands the market by enabling new transactions—either by attracting previously inactive consumers (extensive margin) or increasing purchase frequency among existing consumers (intensive margin)—rather than creating winner-take-all dynamics where adopting merchants capture significant market share from non-adopters. This aligns with our earlier evidence that effects are largest in financially constrained areas where latent demand exists but cannot be realized without the liquidity relief that BNPL provides

7.2 Market Concentration

The negative spillovers documented above, while small relative to adopter gains, raise an important question about market structure: does BNPL adoption increase or decrease market concentration? The answer depends on which set of merchants one considers. If BNPL disproportionately benefits small, constrained merchants, as our heterogeneity results indicate, then concentration among adopters should fall. But if non-adopters, who are systematically smaller, bear negative spillovers while larger adopters gain, then overall market concentration could rise even as BNPL equalizes outcomes within the adopter pool.

To test this, we construct Herfindahl-Hirschman Indices (HHI) for both revenue and transaction count at the pincode-month level and regress them on the fraction of merchants in the pincode that have adopted BNPL:

$$HHI_{pt} = \beta \cdot AdopterFraction_{pt} + \alpha_p + \delta_t + \varepsilon_{pt} \tag{6}$$

where HHI_{pt} is the Herfindahl-Hirschman Index of revenue (or transaction count) in pincode p at time t, $AdopterFraction_{pt}$ is the share of merchants in the pincode that have adopted BNPL by time t, and α_p and δ_t are pincode and time fixed effects, respectively. We estimate this specification for two samples: all merchants in the pincode and BNPL adopters only.

Table 13 presents the results. Columns 1–2 examine all merchants in a pincode. A higher BNPL adopter fraction is associated with significantly greater market concentration: a 10 percentage point increase in adopter fraction raises the revenue HHI by 0.72 percentage points, and the transaction count HHI by 0.89 percentage points. This increase in overall concentration is consistent with BNPL adoption shifting market share from smaller non-adopters toward relatively larger adopting merchants, amplifying the modest negative spillover effects documented in Section 7.1 into measurable changes in market structure.

The pattern reverses when we restrict attention to adopters only (Columns 3–4). Within the adopter pool, higher BNPL penetration is associated with significantly *lower* concentration: the revenue HHI declines by 1.89 percentage points and the transaction count HHI by 1.80 percentage points for each 10 percentage point increase in adopter fraction. This decline is consistent with our earlier finding that, within adopters, BNPL disproportionately benefits small, credit-constrained merchants, compressing the revenue distribution among firms.[12]

The juxtaposition of these two results reveals an important tension in BNPL's distributional effects. Within the adopter pool, BNPL is equalizing: small merchants gain the

12. Table IA.9 in the Internet Appendix confirms that these results are robust to explicitly controlling for UPI transaction fraction, ensuring that the concentration effects reflect BNPL-specific dynamics rather than broader trends in digital payment adoption.

most, narrowing the gap with larger competitors. But at the market level, the key margin is the adoption decision itself. Because non-adopters are systematically smaller and less digitally integrated, even modest negative spillovers, when combined with the positive shock to adopters, widen the gap between the two groups, pushing overall concentration upward. The aggregate distributional impact of BNPL is therefore shaped by differential adoption, which determines who benefits and who is left behind.

This finding carries a direct policy implication: reducing barriers to BNPL adoption, particularly for the smallest, most constrained merchants who stand to gain the most but are least likely to adopt, can simultaneously strengthen the equalizing effects while mitigating the adverse concentration effects arising from the adopter/non-adopter divide.

8 Robustness

We subject our main findings to a series of robustness tests that address potential threats to our identification strategy, alternative specifications, and sample composition concerns. We summarize the key results here and present the full tables in the Internet Appendix.

Controlling for UPI usage: A potential concern with our shift-share instrument is that historical UPI growth may directly affect merchant outcomes through ongoing digital payment trends rather than specifically through BNPL adoption. We address this in Table 11 by augmenting our baseline specification with a control for each merchant's contemporaneous UPI transaction share. If our instrument were simply capturing continued digitization, controlling for current UPI usage should attenuate or eliminate our estimates. Instead, the results strengthen: the revenue coefficient increases to 95.4 percentage points (compared to 85.1 in our baseline), and the credit access coefficient rises to 13.7 percentage points. This pattern suggests that our instrument captures variation specifically related to BNPL adoption, distinct from general digital payment trends, and provides direct support for the exclusion restriction.

Alternative fixed effects and sample: We next assess whether our results are sensitive to the composition of the estimation sample and fixed effects structure. Table IA.4 expands the sample to include both BNPL adopters and non-adopters, rather than restricting attention to adopters as in our baseline. The estimated revenue effect is 57.2 percentage points, attenuated relative to our main estimate but highly significant. This attenuation is expected: including non-adopters dilutes the complier population, as non-adopters in high-UPI-growth areas who still do not adopt BNPL are unlikely to exhibit treatment effects. The consistency in sign and significance across this broader sample is reassuring. Table IA.5 replaces time fixed effects with business-category $\times$ time fixed effects, which absorb industry-specific temporal shocks such as seasonal demand patterns or category-level policy changes. The revenue coefficient of 89.8 percentage points remains economically and statistically significant, indicating that our results are not driven by differential trends across merchant types.

Outliers: A further concern specific to shift-share designs is that extreme values of the shift component—pincodes with unusually high or low UPI growth—may unduly influence the estimates. Following the diagnostics recommended by Borusyak, Hull, and Jaravel 2022, Table IA.6 re-estimates our baseline specification after excluding merchants in the top and bottom deciles of pincode-level UPI growth. The results are robust: the revenue coefficient is 97.8 percentage points, and the first-stage F-statistic increases sharply to 117.8, indicating that our findings are not driven by outlier pincodes. The strengthening of instrument relevance after trimming extremes provides additional confidence in the validity of our identification strategy.

9 Conclusion

This paper provides the first evidence on which merchants benefit most from Buy Now Pay Later services and what this implies for market structure. Using a shift-share instrumental variable that exploits the interaction between pre-existing digital payment infrastructure and

BNPL market entry timing, we document that BNPL adoption increases merchant revenue growth, with effects over three times larger for small, credit-constrained firms than for large ones.

For small, credit-constrained merchants, BNPL facilitates a transition from cash-based, informal operations to digitally enabled, formal businesses. The generation of verifiable transaction records through this digitization enables previously excluded merchants to access formal credit, with BNPL adoption significantly increasing both the probability of having an active loan and the amounts borrowed. Crucially, this credit expansion improves not just access but allocation — default rates decline following BNPL adoption, with the largest reductions among merchants with low credit scores, suggesting that BNPL-generated transaction records enable lenders to better assess previously unobservable merchant quality. For larger, established merchants, benefits flow primarily through demand expansion as BNPL attracts liquidity-constrained consumers.

While BNPL predominantly expands the overall market — with negative spillover effects on non-adopters an order of magnitude smaller than adopter gains — overall market concentration nonetheless increases. Non-adopters are systematically smaller than adopters, so even modest negative spillovers shift relative market share toward larger firms. Within the adopter pool, however, concentration falls, as small constrained firms gain disproportionately.

Our findings contribute to ongoing policy debates about BNPL regulation. While regulators have focused primarily on consumer protection concerns, our evidence suggests that BNPL generates substantial benefits for the most financially constrained merchants through formalization and improved credit allocation. Yet our concentration results point to the need of reducing adoption barriers. BNPL reduces concentration within the adopter pool but increases it overall because smaller, more constrained merchants are less likely to adopt. Policies that lower adoption barriers for these merchants would therefore simultaneously improve financial inclusion and mitigate the adverse concentration effects we document.

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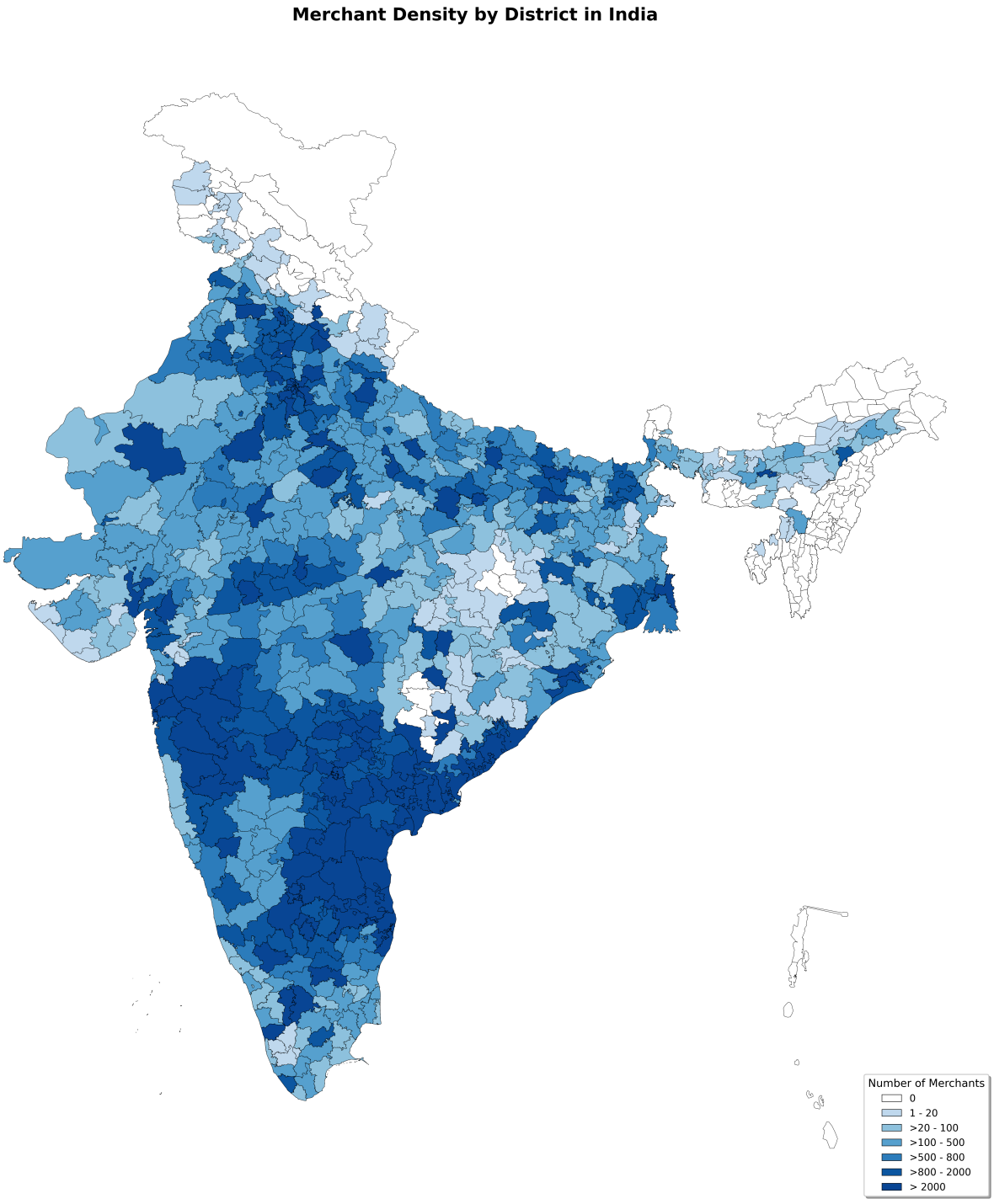


Figure 1: Merchant Distribution at the District Level

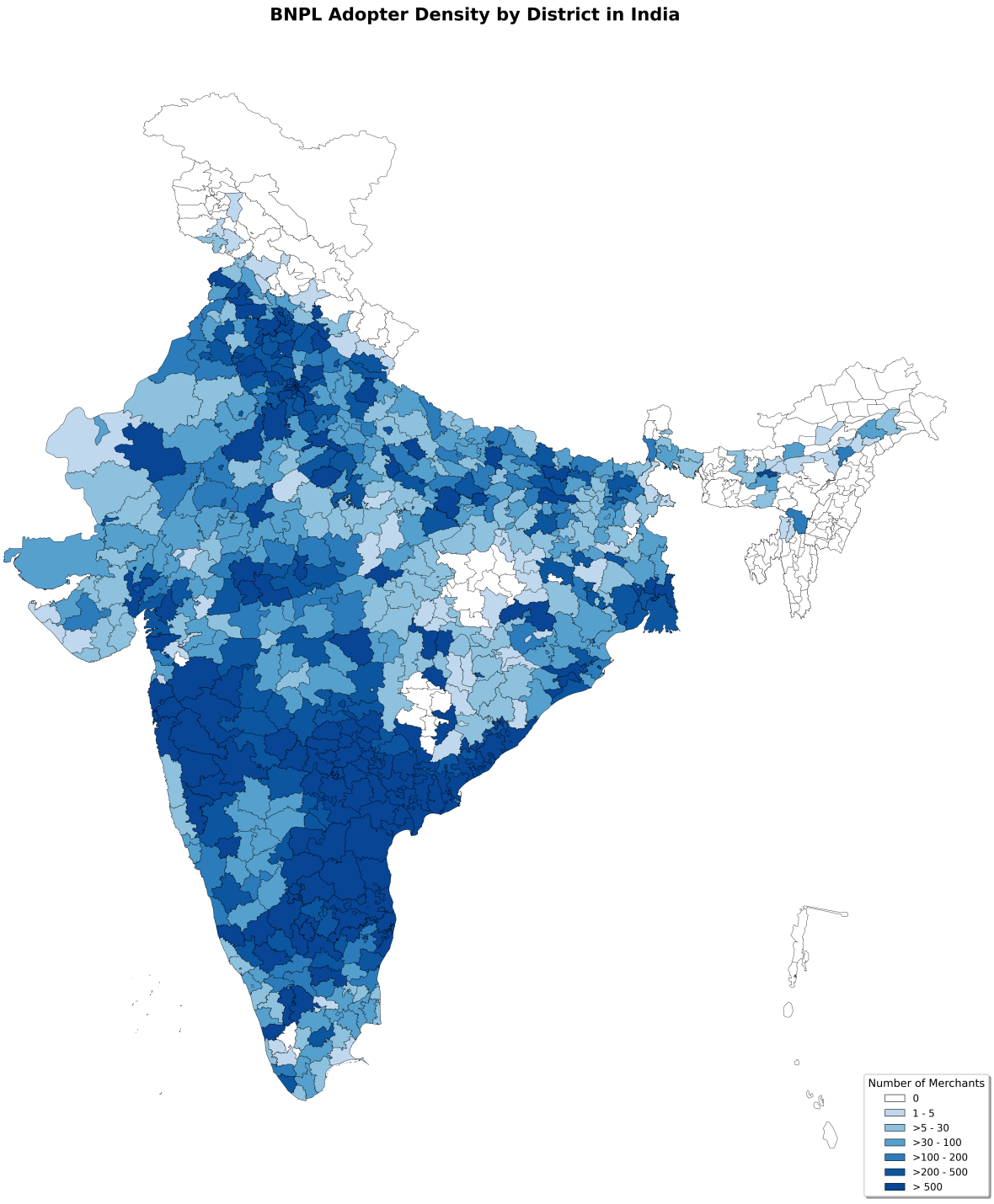
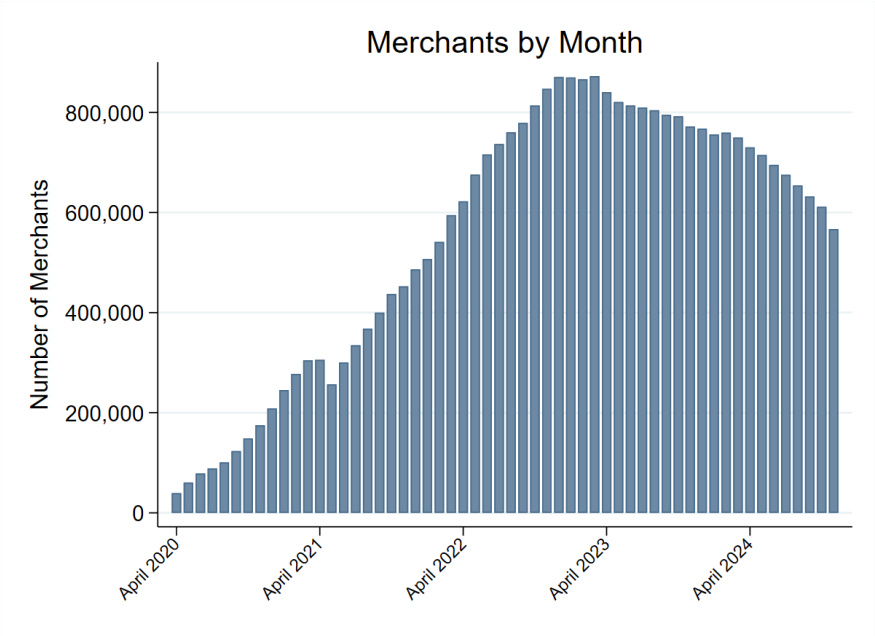
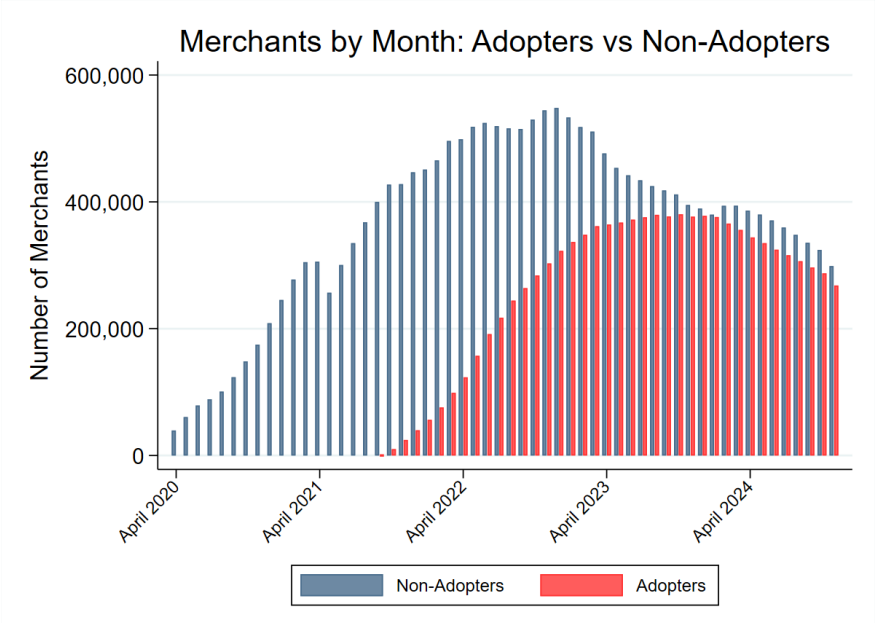


Figure 2: Adopter Distribution at the District Level

Figure 3: Merchants Over Time
This figure plots total number of merchants (panel A) and adopters and non-adopters (panel B) over the sample period.

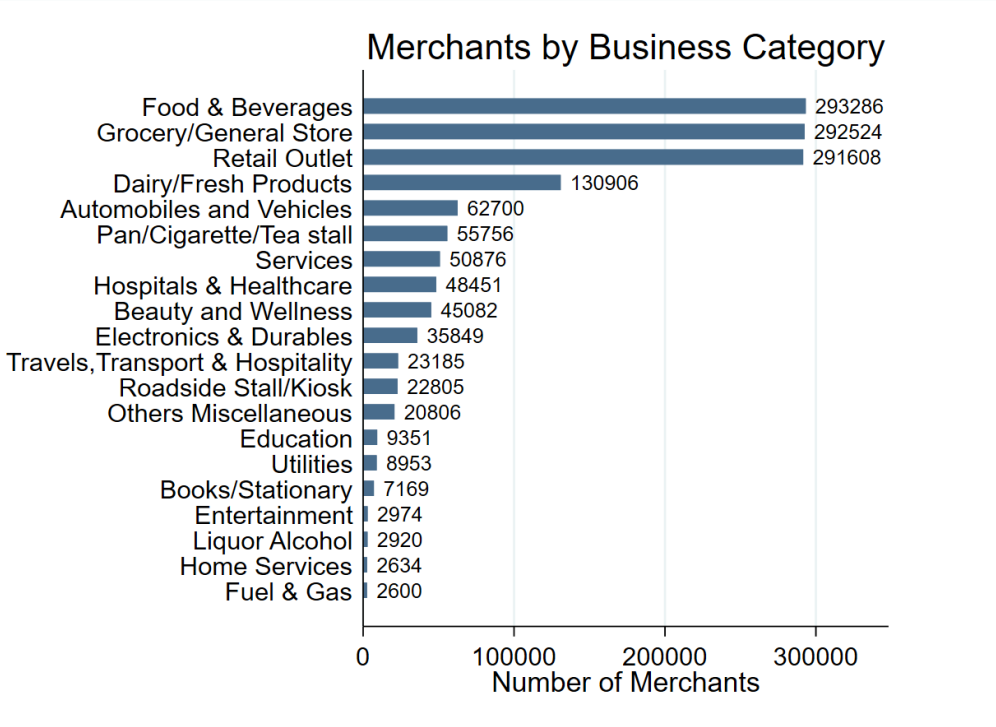


(A) Number of Merchants Over Time

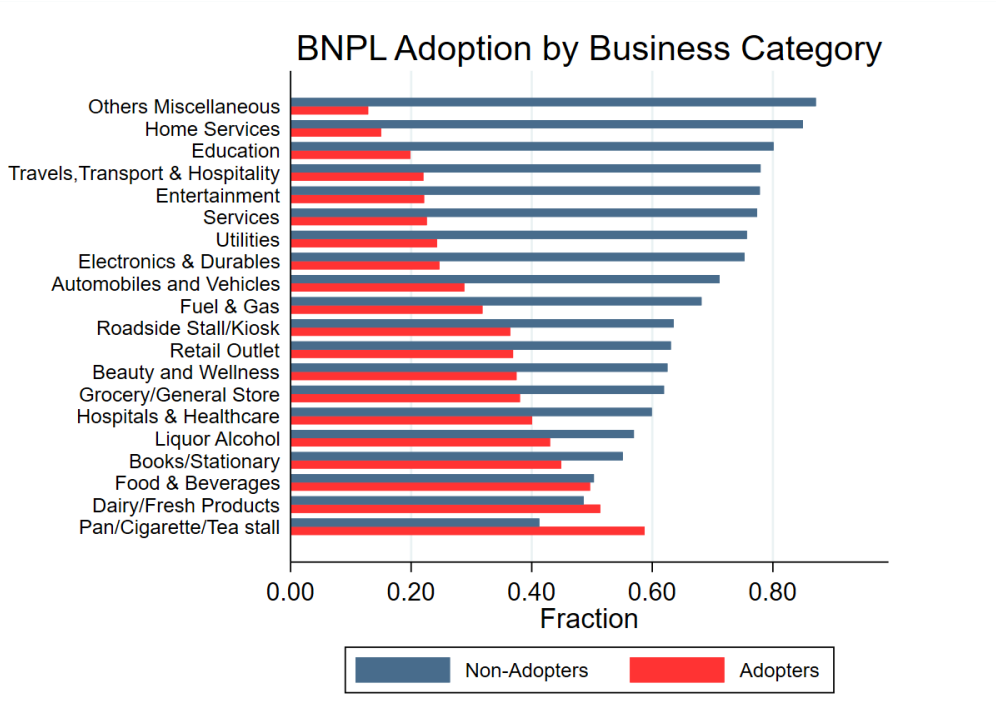


(B) Number of Adopters vs Non-adopters Over Time

Figure 4: Business Categories
This figure presents business categories in our sample. While panel (A) plots these for the entire sample, panel (B) does so for adopters and non-adopters separately.



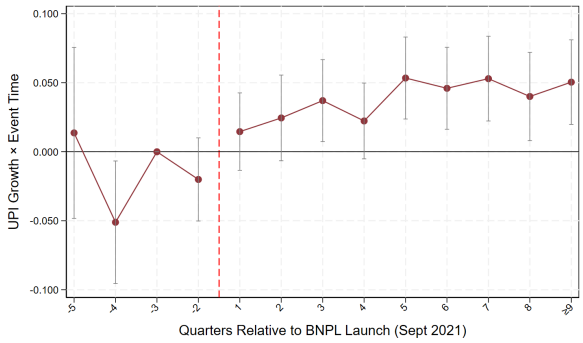
(A) Sample



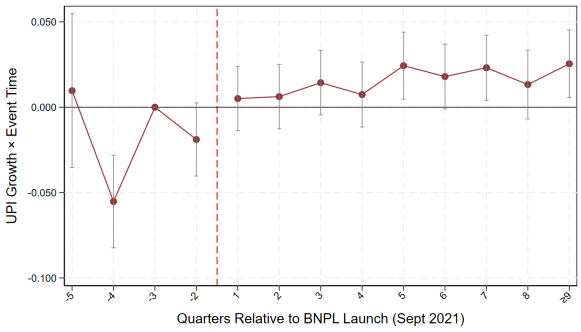
(B) Split by Adopters and Non-Adopters

Figure 5: Event Study Estimates

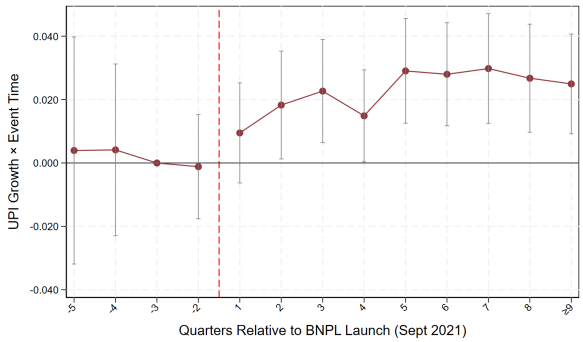
This figure presents event study estimates of the association between the average UPI Growth between 2017 and 2019 and revenue, transaction count, average transaction size, loan dummy and loan amount. The horizontal axis plots quarters relative to the event, with the red vertical line denoting the reference period September, 2021. All the graphs include time and merchant fixed effects. Error bars represent 95 percent confidence intervals.



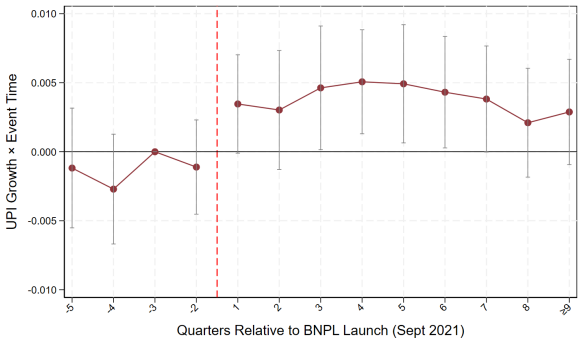
(A): Revenue



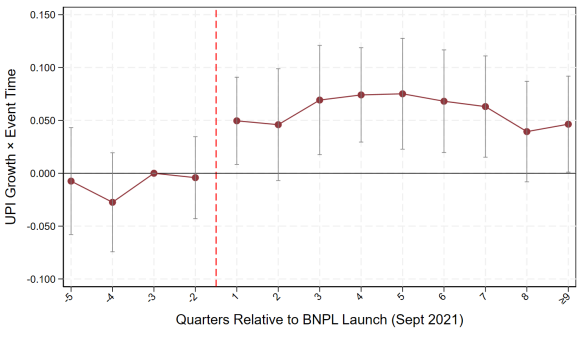
(B): Transaction Count



(C): Average Transaction Size



(D): Loan Dummy



(E): IHS(Loan Amount)

Table 1: Summary Statistics For BNPL Adopters

This table reports summary statistics for the sample of BNPL-adopting merchants. Transaction Count Growth, Avg Transaction Size Growth, and Revenue Growth are computed as month-over-month log differences. Revenue Amount, Transaction Count, and Avg Transaction Size are levels. Post BNPL Adoption is an indicator that takes the value 1 in all months after a merchant adopts BNPL, 0 otherwise. Loan Dummy equals 1 if a merchant has taken any new loan in that month. All monetary values are in ₹.

	Obs	Mean	SD	p25	Median	p75
Transaction Count Growth	14558187	-0.013	0.948	-0.288	0.006	0.289
Avg Transaction Size Growth	14558187	0.009	0.828	-0.198	0.000	0.203
Revenue Growth	14558187	-0.005	1.288	-0.381	0.008	0.384
Revenue Amount	15819707	60942.330	109253.589	6492.000	22370.000	62836.000
Transaction Count	15819707	280.147	460.249	26.000	106.000	318.000
Avg Transaction Size	15819707	707.756	1844.368	70.000	163.443	489.355
Post Bnpl Launch X Avg UPI Growth	10962880	1.074	0.867	0.000	1.543	1.778
Post BNPL Adoption	15819707	0.658	0.474	0.000	1.000	1.000
Loan Dummy	16475262	0.143	0.350	0.000	0.000	0.000
Loan Amount	16475272	28749.628	197222.608	0.000	0.000	0.000
First Loan Dummy	14330692	0.019	0.135	0.000	0.000	0.000
First Loan Amount	257231	17499.806	7173.225	13589.000	21998.000	21998.000

Table 2: Balance Test: Non-adopters vs Adopters

This table compares BNPL adopters and non-adopters on key pre-adoption characteristics. All variables are measured over the pre-period from April 2020 to October 2021. For each variable, the mean for non-adopters, the mean for adopters, the difference in means, and the corresponding two-sample t-statistic are reported. Growth variables are computed as month-over-month log differences. Revenue, transaction count, and average transaction size are level variables. Loan Dummy equals one if a merchant has taken any new loan in that month, zero otherwise. Loan Amount and First Loan Amount are reported in ₹. *, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

	Non-adopters Mean	Adopters Mean	Difference	t-stat
Transaction Count Growth	0.059	0.109	-0.050***	-38.44
Avg Transaction Size Growth	0.093	0.047	0.045***	32.00
Revenue Growth	0.151	0.156	-0.005*	-2.19
Revenue Amount	14702.873	26530.258	-11827.385***	-238.23
Transaction Count	30.751	95.578	-64.827***	-466.75
Avg Transaction Size	715.770	522.319	193.452***	140.26
Loan Dummy	0.152	0.156	-0.004***	-10.56
Loan Amount	97944.173	121857.944	-23913.771***	-39.20
First Loan Dummy	0.011	0.012	-0.000***	-3.95
First Loan Amount	76850.932	80525.159	-3674.227	-1.80

Table 3: 2SLS: First Stage

For each merchant adopting BNPL, the post-adoption dummy equals one in all months on or after its BNPL adoption month and 0 otherwise. The instrument is the interaction of the BNPL Launch dummy and the average UPI growth (2017–2019) for the merchant's pincode. The BNPL Launch period is defined as months on or after November 2021, which corresponds to the earliest BNPL adoption event in the data. It takes value one for one or after Nobvember 2021, 0 otherwise. Standard errors are clustered at the pincode level and reported in parentheses. The Kleibergen–Paap rk Wald F-statistic is reported to assess instrument relevance. *, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

	Post adoption	
UPI Growth × BNPL Launch	0.0303***	0.0274***
	(0.007)	(0.006)
Time FE	Y	Y
Merchant FE	Y	
Pincode FE		Y
Observations	10135610	10136724
Kleibergen–Paap Wald rk F stat	20.28	17.89

Table 4: Revenue variables

This table reports the second-stage coefficients from the 2SLS specification where $\widehat{\text{BNPL}}$ is instrumented using the interaction of the post-adoption dummy and the merchant's pincode-level average UPI growth (2017–2019).The dependent variables are Revenue (Columns 1-2), Transaction Count (Columns 3-4), and Average Transaction Size (Columns 5-6). Odd-numbered columns include merchant and time fixed effects, while even-numbered columns include pincode and time fixed effects. Standard errors are clustered at the pincode level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

	Revenue		Transaction Count		Average transaction size	
$\widehat{\text{BNPL}}$	0.933***	0.851***	0.413***	0.394***	0.519***	0.457***
	(0.199)	(0.197)	(0.119)	(0.121)	(0.105)	(0.099)
Time FE	Y	Y	Y	Y	Y	Y
Merchant FE	Y		Y		Y	
Pincode FE		Y		Y		Y
Observations	10135610	10136724	10135610	10136724	10135610	10136724

Table 5: Credit Outcomes

This table reports the second-stage coefficients from the 2SLS specification where $\widehat{\text{BNPL}}$ is instrumented using the interaction of the post-adoption dummy and the merchant's pincode-level average UPI growth (2017–2019). The dependent variables are Loan Dummy (Columns 1-2), IHS(Loan Amount) (Columns 3-4), First Loan Dummy (Columns 5-6), and IHS(First Loan Amount) (Columns 7-8).Odd-numbered columns include merchant and time fixed effects, while even-numbered columns include pincode and time fixed effects. Standard errors are clustered at the pincode level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

	Loan Dummy		IHS(Loan Amount)		First Loan Dummy		IHS(First Loan Amount)	
$\widehat{\text{BNPL}}$	0.184**	0.237***	2.385**	3.063***	0.084***	0.087***	0.912**	0.971***
	(0.081)	(0.083)	(0.949)	(0.982)	(0.032)	(0.028)	(0.355)	(0.310)
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Merchant FE	Y		Y		Y		Y	
Pincode FE		Y		Y		Y		Y
Observations	11295221	11295292	11295221	11295292	9935014	9935239	9935014	9935239

Table 6: Heterogeneity by Revenue Amount & Bureau Score

This table reports the second-stage coefficients from the 2SLS specification where $\widehat{\text{BNPL}}$ is instrumented using the interaction of the post-adoption dummy and the merchant's pincode-level average UPI growth (2017–2019). The dependent variables are revenue (Columns 1-2), transaction count (Columns 3-4), average transaction size (Columns 5-6), loan dummy (Columns 7-8)and IHS(loan amount) (Columns 9-10). The table presents heterogeneity estimates by splitting merchants into below-median and above-median revenue (panel A) and bureau score (panel B) groups. Standard errors are clustered at the pincode level and reported in parentheses. The Kleibergen–Paap rk Wald F-statistic is reported to assess instrument relevance. *, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A: Revenue Amount

	Revenue		Transaction Count		Avg Transaction Size		Loan Dummy		IHS(Loan Amount)	
	Below	Above	Below	Above	Below	Above	Below	Above	Below	Above
$\widehat{\text{BNPL}}$	1.727***	0.525***	0.587***	0.281***	1.139***	0.243**	0.263**	0.165**	3.382**	2.131**
	(0.433)	(0.172)	(0.216)	(0.108)	(0.270)	(0.097)	(0.121)	(0.075)	(1.409)	(0.887)
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Merchant FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	4597478	5257948	4597478	5257948	4597478	5257948	5199118	5747030	5199118	5747030
Kleibergen-Paap rk Wald F	17.956	17.888	17.956	17.888	17.956	17.888	18.45	17.87	18.45	17.87

Panel B: Bureau Score

	Revenue		Transaction Count		Avg Transaction Size		Loan Dummy		IHS(Loan Amount)	
	Below	Above	Below	Above	Below	Above	Below	Above	Below	Above
$\widehat{\text{BNPL}}$	3.279**	1.188**	2.093**	0.651**	1.186*	0.537	0.249	0.141	4.235	1.406
	(1.460)	(0.511)	(0.855)	(0.300)	(0.708)	(0.344)	(0.434)	(0.192)	(5.242)	(2.245)
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Merchant FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	1519691	1586928	1519691	1586928	1519691	1586928	1753842	1782925	1753844	1782926
Kleibergen-Paap rk Wald F	7.242	17.957	7.242	17.957	7.242	17.957	9.432	16.758	9.432	16.758

Table 7: Overdue Amount

This table reports the second-stage coefficients from the 2SLS specification where $\widehat{\text{BNPL}}$ is instrumented using the interaction of the post-adoption dummy and the merchant's pincode-level average UPI growth (2017–2019). The dependent variables include overdue dummy, overdue amount and ihs(overdue amount). Panel A estimates these for the entire sample while panels B and C report heterogeneity in estimates based on revenue amount and bureau score respectively. All specifications include Time and Merchant fixed effects. Standard errors are clustered at the pincode level and reported in parentheses. The Kleibergen–Paap rk Wald F-statistic is reported to assess instrument relevance. *, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A: Entire Sample

	Overdue Dummy	Overdue Amount	ihs(Overdue Amount)
$\widehat{\text{BNPL}}$	-0.023**	-0.907**	-0.227**
	(0.009)	(0.361)	(0.093)
Time FE	Y	Y	Y
Merchant FE	Y	Y	Y
Observations	2800882	2800882	2800882
Kleibergen-Paap rk Wald F statistic	26.319	26.319	26.319

Panel B: Heterogeneity by Revenue Amount

	Overdue Dummy		Overdue Amount		IHS(Overdue Amount)	
	Below	Above	Below	Above	Below	Above
$\widehat{\text{BNPL}}$	-0.019	-0.024***	-0.775	-0.983***	-0.172	-0.251**
	(0.022)	(0.009)	(0.908)	(0.377)	(0.213)	(0.099)
Time FE	Y	Y	Y	Y	Y	Y
Merchant FE	Y	Y	Y	Y	Y	Y
Observations	1119584	1681298	1119584	1681298	1119584	1681298
Kleibergen-Paap rk Wald F statistic	13.58	25.98	13.58	25.98	13.58	25.98

Panel C: Heterogeneity by Bureau Score

	Overdue Dummy		Overdue Amount		IHS(Overdue Amount)	
	Below	Above	Below	Above	Below	Above
$\widehat{\text{BNPL}}$	-0.086*	-0.039*	-3.313*	-1.636*	-0.922*	-0.352
	(0.048)	(0.024)	(1.956)	(0.978)	(0.494)	(0.214)
Time FE	Y	Y	Y	Y	Y	Y
Merchant FE	Y	Y	Y	Y	Y	Y
Observations	653313	591585	653313	591585	653313	591585
Kleibergen-Paap rk Wald F statistic	6.982	20.806	6.982	20.806	6.982	20.806

Table 8: Payment Mix

This table reports the second-stage coefficients from the 2SLS specification where $\widehat{\text{BNPL}}$ is instrumented using the interaction of the post-adoption dummy and the merchant's pincode-level average UPI growth (2017–2019).The dependent variables are the fractions of transactions made via UPI, card, cash, and payment links respectively. Standard errors are clustered at the pincode level and reported in parentheses. The Kleibergen–Paap rk Wald F-statistic is reported to assess instrument relevance. *, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

	UPI fraction	Card Fraction	Cash fraction	Payment Link fraction
$\widehat{\text{BNPL}}$	-0.071	0.171***	-0.099**	0.0002
	(0.058)	(0.042)	(0.044)	(0.0002)
Time FE	Y	Y	Y	Y
Merchant FE	Y	Y	Y	Y
Observations	10962687	10962687	10962687	10962687
Kleibergen-Paap rk Wald F statistic	21.183	21.183	21.183	21.183

Table 9: Heterogeneity by Cash Fraction

This table reports the second-stage coefficients from the 2SLS specification where $\widehat{\text{BNPL}}$ is instrumented using the interaction of the post-adoption dummy and the merchant's pincode-level average UPI growth (2017–2019).The dependent variables are revenue (Columns 1-2), transaction count (Columns 3-4), average transaction size (Columns 5-6), loan dummy (Columns 7-8)and IHS(loan amount) (Columns 9-10). The table examines heterogeneity by splitting merchants into below-median and above-median cash-fraction groups, defined using their average monthly share of cash transactions in the pre-period. Standard errors are clustered at the pincode level and reported in parentheses. The Kleibergen–Paap rk Wald F-statistic is reported to assess instrument relevance. *, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

	Revenue		Transaction Count		Avg Transaction size		Loan Dummy		ihs(loan amount)	
	Below	Above	Below	Above	Below	Above	Below	Above	Below	Above
$\widehat{\text{BNPL}}$	0.812***	1.964***	0.349**	0.984**	0.463***	0.979***	0.082	0.325*	1.346	3.806*
	(0.248)	(0.658)	(0.157)	(0.381)	(0.140)	(0.331)	(0.102)	(0.191)	(1.193)	(2.26)
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Merchant FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	3033167	2930283	3033167	2930283	3033167	2930283	3343523	3226710	3343524	3226712
Kleibergen-Paap rk Wald F statistic	18.57	21.34	18.57	21.34	18.57	21.34	19.79	21.42	19.79	21.42

Table 10: Heterogeneity by Neighborhood Characteristics

This table reports the second-stage coefficients from the 2SLS specification where $\widehat{\text{BNPL}}$ is instrumented using the interaction of the post-adoption dummy and the merchant's pincode-level average UPI growth (2017–2019). The dependent variables are revenue (Columns 1-2), transaction count (Columns 3-4), average transaction size (Columns 5-6), loan dummy (Columns 7-8)and IHS(loan amount) (Columns 9-10). Panel A examines heterogeneity by splitting merchants into below-median and above-median nightlight intensity at the pincode level. Panel B examines heterogeneity by splitting merchants into below-median and above-median vehicle registration at the pincode level. Standard errors are clustered at the pincode level and reported in parentheses. The Kleibergen–Paap rk Wald F-statistic is reported to assess instrument relevance. *, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A: Nightlight Intensity

	Revenue		Transaction Count		Avg Transaction size		Loan Dummy		ihs(loan amount)	
	Below	Above	Below	Above	Below	Above	Below	Above	Below	Above
$\widehat{\text{BNPL}}$	0.856***	0.455***	0.385**	0.127*	0.472***	0.329***	0.354***	0.036	4.466***	0.609
	(0.281)	(0.109)	(0.173)	(0.074)	(0.145)	(0.072)	(0.127)	(0.071)	(1.499)	(0.835)
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Merchant FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	4933685	5185739	4933685	5185739	4933685	5185739	5477111	5799879	5477111	5799879
Kleibergen-Paap rk Wald F statistic	25.367	8.642	25.367	8.642	25.367	8.642	24.47	8.51	24.47	8.51

Panel B: Vehicle Registrations

	Revenue		Transaction Count		Avg Transaction size		Loan Dummy		ihs(loan amount)	
	Below	Above	Below	Above	Below	Above	Below	Above	Below	Above
$\widehat{\text{BNPL}}$	0.596***	-0.754	0.295**	-1.458**	0.301***	0.704	0.252**	-0.435	3.218**	-3.973
	(0.187)	(0.909)	(0.126)	(0.652)	(0.105)	(0.446)	(0.119)	(0.517)	(1.409)	(5.780)
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Merchant FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	3615842	3929204	3615842	3929204	3615842	3929204	4031151	4388812	4031151	4388812
Kleibergen-Paap rk Wald F statistic	7.225	7.997	7.225	7.997	7.225	7.997	7.474	4.589	7.474	4.589

Table 11: Controlling for UPI fraction

This table reports the second-stage coefficients from the 2SLS specification where $\widehat{\text{BNPL}}$ is instrumented using the interaction of the post-adoption dummy and the merchant's pincode-level average UPI growth (2017–2019). The dependent variables are Revenue, Transaction Count, Average Transaction Size, Loan Dummy, and IHS(Loan Amount). Each regression additionally includes controls for the merchant's monthly UPI transaction share (UPI fraction). All specifications include Time and Merchant fixed effects.Standard errors are clustered at the pincode level and reported in parentheses. The Kleibergen–Paap rk Wald F-statistic is reported to assess instrument relevance. *, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

	Revenue	Transaction Count	Average Transaction Size	Loan Dummy	ihs(Loan Amount)
$\widehat{\text{BNPL}}$	0.954***	0.429***	0.524***	0.137***	1.801***
	(0.201)	(0.120)	(0.105)	(0.040)	(0.493)
Time FE	Y	Y	Y	Y	Y
Merchant FE	Y	Y	Y	Y	Y
UPI Fraction	Y	Y	Y	Y	Y
Observations	10135609	10135609	10135609	10962685	10962687
Kleibergen-Paap rk Wald F statistic	20.48	20.48	20.48	21.30	21.30

Table 12: Spillover on Non-adopters

This table reports the spillover effects of BNPL adoption on merchants that do not adopt BNPL. The dependent variables are merchant-level revenue, transaction count , and average transaction size . The key independent variable is the fraction of merchants adopting BNPL in the same pincode. All specifications include merchant and time fixed effects. Standard errors are clustered at the pincode level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

	Revenue	Transaction Count	Average Transaction Size
BNPL Adoption Fraction	-0.066***	-0.051***	-0.015
	(0.014)	(0.008)	(0.005)
Time FE	Y	Y	Y
Merchant FE	Y	Y	Y
Observations	8,070,090	8,070,090	8,070,090
R^2	0.046	0.048	0.036

Table 13: Market Concentration

This table reports regression results examining the effect of adopter fraction on market concentration measured by the Herfindahl-Hirschman Index (HHI) of Revenue and Transaction Count at the pincode month level. Standard errors are clustered at the pincode level and reported in parentheses.All specifications include pincode and time fixed effects. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	All Merchants		Adopters	
	Revenue HHI	Transaction Count HHI	Revenue HHI	Transaction Count HHI
Adopter fraction	0.072***	0.089***	-0.189***	-0.180***
	(0.007)	(0.007)	(0.008)	(0.008)
Time FE	Y	Y	Y	Y
Pincode FE	Y	Y	Y	Y
Observations	627,392	627,392	310,564	310,564
R^2	0.821	0.837	0.859	0.873

Internet Appendix

Table IA.1: Reduced Form Analysis: Revenue Variables

This table presents reduced form estimates of the effect of BNPL adoption on merchant revenue outcomes. The dependent variables are merchant-level revenue amount (Columns 1–2), transaction count (Columns 3–4), and average transaction size (Columns 5–6). The key independent variable is the interaction between the post-BNPL adoption dummy and the pincode-level average UPI growth rate during 2017–2019. Odd-numbered columns include merchant and time fixed effects, while even-numbered columns include pincode and time fixed effects. Standard errors are clustered at the pincode level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Revenue		Transaction Count		Average Transaction Size	
Post BNPL Adoption × Avg. UPI Growth	0.028***	0.023***	0.013***	0.011***	0.016***	0.013***
	(0.007)	(0.006)	(0.004)	(0.003)	(0.004)	(0.004)
Observations	10,135,610	10,136,724	10,135,610	10,136,724	10,135,610	10,136,724
Time FE	Y	Y	Y	Y	Y	Y
Merchant FE	Y		Y		Y	
Pincode FE		Y		Y		Y

Table IA.2: Reduced Form Analysis: Loan Variables

This table presents reduced form estimates of the effect of BNPL adoption on merchant revenue outcomes. The dependent variables are merchant-level loan dummy (Columns 1–2), IHS(loan amount) (Columns 3–4), first loan dummy (Columns 5–6) and IHS(first loan amount) (Columns 7–8). The key independent variable is the interaction between the post-BNPL adoption dummy and the pincode-level average UPI growth rate during 2017–2019. Odd-numbered columns include merchant and time fixed effects, while even-numbered columns include pincode and time fixed effects. Standard errors are clustered at the pincode level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Loan dummy		ihs(loan amount)		first loan		ihs(First loan amount)	
Post BNPL Adoption × Avg. UPI Growth	0.005**	0.006**	0.067**	0.080**	0.002**	0.002**	0.026**	0.025**
	(0.003)	(0.003)	(0.031)	(0.032)	(0.001)	(0.001)	(0.012)	(0.001)
Observations	11,295,221	11,295,295	11,295,221	11,295,295	9,935,014	9,935,239	9,935,014	9,935,239
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Merchant FE	Y		Y		Y		Y	
Pincode FE		Y		Y		Y		Y

Table IA.3: Heterogeneity by Business Types

This table reports the second-stage coefficients from the 2SLS specification where $\widehat{\text{BNPL}}$ is instrumented using the interaction of the post-adoption dummy and the merchant's pincode-level average UPI growth (2017–2019). The dependent variables are revenue (Columns 1-2), transaction count (Columns 3-4), average transaction size (Columns 5-6), first loan (Columns 7-8)and IHS(first loan amount) (Columns 9-10). Panel A examines heterogeneity by splitting merchants low ticket and high ticket categories.. Panel B examines heterogeneity by splitting merchants into sellers of non-discretionary and discretionary groups. Standard errors are clustered at the pincode level and reported in parentheses. The Kleibergen–Paap rk Wald F-statistic is reported to assess instrument relevance. *, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A: Ticket Size

	Revenue		Transaction Count		Avg Transaction size		Loan Dummy		ihs(loan amount)	
	Low	High	Low	High	Low	High	Low	High	Low	High
$\widehat{\text{BNPL}}$	1.044***	0.734***	0.446***	0.391***	0.598***	0.343**	0.141	0.109*	1.914*	1.409**
	(0.265)	(0.237)	(0.160)	(0.123)	(0.134)	(0.158)	(0.098)	(0.059)	(1.141)	(0.692)
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Merchant FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	6662840	3296442	6662840	3296442	6662840	3296442	7516809	3554652	7516810	3554654
Kleibergen-Paap rk Wald F statistic	16.57	25.12	16.57	25.12	16.57	25.12	16.25	16.38	16.25	16.38

Panel B: Discretionary versus Non-discretionary

	Revenue		Transaction Count		Avg Transaction size		Loan Dummy		ihs(loan amount)	
	Non Disc.	Disc.	Non Disc.	Disc.	Non Disc.	Disc.	Non Disc.	Disc.	Non Disc.	Disc.
$\widehat{\text{BNPL}}$	1.099**	0.733***	0.629***	0.231**	0.471***	0.502***	0.264***	0.068*	3.419***	0.959*
	(0.356)	(0.181)	(0.226)	(0.109)	(0.172)	(0.108)	(0.102)	(0.041)	(1.228)	(0.489)
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Merchant FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	3982828	5957529	3982828	5957529	3982828	5957529	4584650	6444704	4584651	6444706
Kleibergen-Paap rk Wald F statistic	13.14	22.15	13.14	22.15	13.14	22.15	13.89	22.29	13.89	22.29

Table IA.4: Robustness: Including both Adopters and Non-adopters

This table reports the second-stage coefficients from the 2SLS regression where $\widehat{\text{BNPL}}$ is instrumented using the interaction of the post-adoption dummy and the merchant's pincode-level average UPI growth (2017–2019).The dependent variables are revenue, transaction count, average transaction size, first loan dummy and first loan amount.Standard errors are clustered at the pincode level and reported in parentheses.The Kleibergen–Paap rk Wald F-statistic is reported to assess instrument relevance. *, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

	Revenue	Transaction Count	Average Transaction Size	Loan Dummy	ihs(Loan Amount)
$\widehat{\text{BNPL}}$	0.489***	0.133***	0.356***	0.073***	1.110***
	(0.076)	(0.037)	(0.047)	(0.019)	(0.236)
Time FE	Y	Y	Y	Y	Y
Merchant FE	Y	Y	Y	Y	Y
Observations	17377299	17377299	17377299	19198970	19198970
Kleibergen-Paap rk Wald F statistic	25.148	25.148	25.148	26.231	26.231

Table IA.5: BNPL Effects with Business and Time Fixed Effects

This table reports the second-stage coefficients from the 2SLS regression where $\widehat{\text{BNPL}}$ is instrumented using the interaction of the post-adoption dummy and the merchant's pincode-level average UPI growth (2017–2019).The dependent variables are revenue, transaction count, average transaction size, first loan dummy and first loan amount.Standard errors are clustered at the pincode level and reported in parentheses.The Kleibergen–Paap rk Wald F-statistic is reported to assess instrument relevance. *, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

	Revenue	Transaction Count	Average Transaction Size	Loan Dummy	ihs(Loan Amount)
$\widehat{\text{BNPL}}$	0.898***	0.030***	0.514***	0.141***	1.849***
	(0.196)	(0.116)	(0.104)	(0.040)	(0.495)
Time-Business Category FE	Y	Y	Y	Y	Y
Merchant FE	Y	Y	Y	Y	Y
Observations	10135610	10135610	10135610	10962686	10962686
Kleibergen-Paap rk Wald F statistic	21.202	21.202	21.202	22.109	22.109

Table IA.6: BNPL Effects Excluding Top and Bottom Deciles of UPI Growth

This table reports the second-stage coefficients from the 2SLS specification where $\widehat{\text{BNPL}}$ is instrumented using the interaction of the post-adoption dummy and the merchant's pincode-level average UPI growth (2017–2019). The dependent variables are Revenue, Transaction Count, Average Transaction Size, First Loan Dummy, and IHS(First Loan Amount). All specifications include Time and Merchant fixed effects. Standard errors are clustered at the pincode level and reported in parentheses. The Kleibergen–Paap rk Wald F-statistic is reported to assess instrument relevance. *, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

	Revenue	Transaction Count	Average Transaction Size	Loan Dummy	ihs(Loan Amount)
$\widehat{\text{BNPL}}$	0.978***	0.381***	0.596***	0.207***	2.781***
	(0.127)	(0.075)	(0.075)	(0.064)	(0.747)
Time FE	Y	Y	Y	Y	Y
Merchant FE	Y	Y	Y	Y	Y
Observations	9318178	9318178	9318178	10386940	10386943
Kleibergen-Paap rk Wald F statistic	117.83	117.834	117.834	125.252	125.252

Table IA.7: Heterogeneity (Adopters)

This table reports the second-stage coefficients from the 2SLS specification where $\widehat{\text{BNPL}}$ is instrumented using the interaction of the post-adoption dummy and the merchant's pincode-level average UPI growth (2017–2019). The dependent variables are revenue (Columns 1-2), transaction count (Columns 3-4), average transaction size (Columns 5-6), loan dummy (Columns 7-8)and IHS(loan amount) (Columns 9-10). Panel A examines heterogeneity by splitting merchants into discretionary vs non-discretionary at below-median nightlight intensity at the pincode level. Panel B examines heterogeneity by splitting merchants into discretionary vs non-discretionary at below-median vehicle registration at the pincode level. Standard errors are clustered at the pincode level and reported in parentheses. The Kleibergen–Paap rk Wald F-statistic is reported to assess instrument relevance. *, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A: Below Median Nightlight Intensity

	Revenue		Transaction Count		Avg Transaction size		Loan Dummy		ihs(loan amount)	
	Non Disc.	Disc.	Non Disc.	Disc.	Non Disc.	Disc.	Non Disc.	Disc.	Non Disc.	Disc.
$\widehat{\text{BNPL}}$	1.206**	0.518**	0.717**	0.121	0.489*	0.397**	0.438***	0.038	5.643***	0.600
	(0.492)	(0.262)	(0.296)	(0.165)	(0.255)	(0.157)	(0.156)	(0.067)	(1.876)	(0.767)
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Merchant FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	1996272	2847149	1996272	2847149	1996272	2847149	2283508	3070104	2283508	3070106
Kleibergen-Paap rk Wald F statistic	25.367	27.744	25.367	27.744	25.367	27.744	14.653	28.965	14.653	28.965

Panel B: Below Median Vehicle Registrations

	Revenue		Transaction Count		Avg Transaction size		Loan Dummy		ihs(loan amount)	
	Non Disc.	Disc.	Non Disc.	Disc.	Non Disc.	Disc.	Non Disc.	Disc.	Non Disc.	Disc.
$\widehat{\text{BNPL}}$	0.497**	0.567**	0.411**	0.171	0.086	0.396***	0.295**	0.059	3.809**	0.777
	(0.251)	(0.239)	(0.208)	(0.142)	(0.133)	(0.142)	(0.116)	(0.062)	(1.411)	(0.739)
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Merchant FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	1389859	2154628	1389859	2154628	1389859	2154628	1605772	2328126	1605773	2328127
Kleibergen-Paap rk Wald F statistic	5.255	8.479	5.255	8.479	5.255	8.479	5.191	8.554	5.191	8.554

Table IA.8: Heterogeneity: Spillover on Non-adopters

This table reports the spillover effects of BNPL adoption on merchants that do not adopt BNPL. The dependent variables are revenue (Columns 1-2), transaction count (Columns 3-4), average transaction size (Columns 5-6). The key independent variable is the fraction of merchants adopting BNPL in the same pincode. Panel A examines heterogeneity by splitting merchants into discretionary vs non-discretionary. Panel B examines heterogeneity by splitting merchants into high ticket vs low ticket size. Standard errors are clustered at the pincode level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A: Heterogeneity by Discretionary vs Non-Discretionary Goods

	Revenue		Transaction Count		Avg Transaction size	
	Non Disc.	Disc.	Non Disc.	Disc.	Non Disc.	Disc.
$\widehat{\text{BNPL}}$	-0.079***	-0.045**	-0.056***	-0.042***	-0.024*	-0.003
	(0.0196)	(0.018)	(0.012)	(0.009)	(0.013)	(0.012)
Observations	3153834	4609118	3153834	4609118	3153834	4609118
Time FE	Y	Y	Y	Y	Y	Y
Merchant FE	Y	Y	Y	Y	Y	Y

Panel B: Heterogeneity by Ticket Size

	Revenue		Transaction Count		Avg Transaction size	
	Low	High	Low	High	Low	High
$\widehat{\text{BNPL}}$	-0.068***	-0.052**	-0.051***	-0.046***	-0.017	-0.006
	(0.017)	(0.020)	(0.012)	(0.010)	(0.011)	(0.014)
Time FE	Y	Y	Y	Y	Y	Y
Merchant FE	Y	Y	Y	Y	Y	Y
Observations	4331635	3467171	4331635	3467171	4331635	3467171

Table IA.9: Market Concentration: Controlling for UPI fraction

This table reports regression results examining the effect of adopter fraction on market concentration measured by the Herfindahl-Hirschman Index (HHI) of Revenue and Transaction Count at the pincode month level, controlled for UPI fraction. Standard errors are clustered at the pincode level and reported in parentheses.All specifications include pincode and time fixed effects. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	All Merchants		Adopters	
	Revenue HHI	Transaction Count HHI	Revenue HHI	Transaction Count HHI
Adopter fraction	0.072***	0.089***	-0.191***	-0.180***
	(0.007)	(0.007)	(0.008)	(0.008)
Time FE	Y	Y	Y	Y
Pincode FE	Y	Y	Y	Y
UPI Fraction	Y	Y	Y	Y
Observations	627,392	627,392	310,564	310,564
R^2	0.821	0.838	0.860	0.873