Demographics and Technology Diffusion: Evidence from Mobile Payments*

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Abstract

We show that the age composition of the population can shape the speed at which businesses adopt new technologies, using evidence from mobile payments in India. Consumers' propensity to use new payment technologies declines with age, creating stronger incentives for businesses serving younger customers to accept these technologies. We document this pattern in the rollout of a mobile payment option by a major fintech company. A model where consumer attitudes toward technology vary by age implies that business adoption is inefficiently low, with the young bearing disproportionate welfare losses from network externalities. Jointly subsidizing transaction and adoption costs restores efficiency.

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1 Introduction

The progressive aging of the population in developed economies has recently spurred renewed research on the economic consequences of large demographic shifts. This research has shown that population aging can impact the rate or direction of innovation and, ultimately, productivity growth. Among others, Derrien et al. (2023) show that young workers are often key drivers of innovation within firms, while Acemoglu and Restrepo (2022) and Abeliansky and Prettner (2023) argue that a shrinking working-age population should spur innovation in labor-saving technologies.[1]

In this paper, we study a complementary channel through which demographics and aging may impact productivity growth: the rate of *diffusion* of new technologies, as opposed to the rate of innovation itself. A large literature has argued that the adoption of new technologies is a key component of the link from innovation to growth, but also one that is subject to a number of frictions, ranging from information, to coordination, to financial frictions (Hall and Khan 2003). We provide evidence that, in the case of consumer-facing technologies, heterogeneous preferences across demographic groups, and particularly across age cohorts, play a central role in shaping diffusion rates. These effects are both direct and *indirect*: age accounts for a substantial part of the variation in consumers' propensity to use technology; and heterogeneous propensities across age groups shape business decisions around the adoption of new technologies. We show that these effects lead to inefficiently low equilibrium diffusion, and that restoring efficiency requires subsidies whose optimal design depends on the demographic composition of consumers.

The context of our analysis is the diffusion of mobile payment technologies in India. We define mobile payment technologies as electronic systems allowing consumers to settle transactions using a phone or other digital device. Among electronic payment technologies, mobile payment is the main alternative to traditional bank-issued credit or debit cards. Since 2016, the rapid diffusion of mobile payment technology has dramatically altered the payment landscape in India. Prior to 2016, India's electronic payments were predominantly facilitated by cards, similar to many developed countries. However, the Demonetization gave momentum to mobile payment options. While the initial surge was driven by the adoption of mobile wallets (Chodorow-Reich et al. 2019; Crouzet et al. 2023), the Unified Payments Interface (UPI) has been the main driver of the continued diffusion of this technology in more recent years.[2]

Overall, the speed of diffusion of mobile payments in India stands out: between 2016 and 2020, mobile payment technologies essentially replaced cards as the main means of electronic payments, with their share in total electronic payments increasing from less than 10% to approximately 80%, as illustrated in Figure 1. Given the potential effects of mobile payment usage on financial inclusion

[1]Other work highlighting the link between aging and innovation, both theoretically and empirically, include Ludwig et al. (2012), Hashimoto and Tabata (2016), Costinot et al. (2019), Cheng and Weinberg (2024), and Aksoy et al. (2019). Relatedly, Lewis (2011) and Anelli et al. (2019) study the impact of immigration on technology choice in the manufacturing sector and on innovation, respectively. Aging populations have numerous other economic consequences beyond innovation, including labor market shortages, increased pressure on pension systems, and higher healthcare costs, potentially slowing economic growth; see Bloom et al. (2003) and Gordon (2017) for overviews.

[2]Section 2 explains the distinctions between mobile wallets and the UPI.

and economic activity (Yermack 2018; Das et al. 2022; Dubey and Purnanandam 2023; Alok et al. 2024), understanding the mechanisms behind this transition, and its effects on consumer welfare, is an important question, with potential relevance to other environments beyond India.

Our analysis proceeds in four steps. First, we show that in our context the propensity to use mobile payment technology is strongly (and negatively) related to age, even after controlling for other potential observable determinants of technology choice. Second, we develop a simple model of technology adoption by businesses, where, consistent with the data, consumers of different ages value access to mobile payment technologies differently. Third, we test empirically the main implication of the model, namely that businesses are more likely to adopt mobile payments if they operate in markets where their potential customer base is younger. Our test uses merchant-level technology adoption data from a leading Indian fintech provider of payment services, and leverages the introduction of new payment modalities in 2019. Our evidence strongly supports the model prediction that the technology we study diffused faster in districts where the customer base was younger. Fourth, we use the model to study whether heterogeneity in consumer preferences toward technology leads to inefficient adoption decisions by businesses in competitive equilibrium, relative to what a planner would choose. We show that the competitive equilibrium of the model features inefficiently low technology diffusion, and characterize the subsidies required to restore efficiency, highlighting how their optimal design depends on demographic composition.

The first step in our analysis is to document the strong empirical relationship between customer age and the propensity to use mobile payments. We use a dataset comprising approximately 200,000 customers from one of India's largest banks. The data includes comprehensive bank account activity and demographic information for a subset of customers.[3] It allows us to measure the proportion of electronic payments made using mobile technologies. We establish two main stylized facts. First, we show that age is a primary factor explaining the variation in mobile payment use among consumers: it accounts for about 38% of total cross-sectional variance in mobile payment use, much more than wealth (7%) or occupation (5%).[4] Second, we show that younger customers strongly favor mobile payments relative to older consumers. The relationship with age is largely monotonic, robust to controlling for a host of factors, including occupation, marital status, assets, location, or even access to credit cards. It is also quantitatively large: the share of mobile payments is half as large in the oldest age bracket (60 and older) than in the youngest one (30 and younger). Interestingly, this gap persists even years after the technology has reached full maturity: using an alternative data set, we find that the difference in the use of mobile payments between young and old appeared in the data already in the early phase of mobile payments (e.g., 2016), and has persisted at least until 2022, when our data ends.[5]

[3]The dataset we used is described in detail by Agarwal et al. (2022). Although our sample generally represents individuals who are wealthier than the average Indian citizen, the age distribution within our sample closely aligns with the national demographic distribution.

[4]The other primary contributor is geographic location (i.e., six-digit pincode), which accounts for approximately the same amount of variation in the payments share as age.

[5]While quantifying the mechanisms explaining this relationship is outside the scope of the paper, Section 2 provides some discussion of this issue.

In the second step, we develop a simple model to work out the implications of these differences in propensity to use technology across age demographics for the adoption decisions of businesses. In the model, businesses must decide whether to invest in a new technology to process sales, which we interpret as mobile payments. They face customers of two potential types, young and old. We assume that these two groups only differ in one dimension: young consumers' preferences are sensitive to the technology choice of the businesses from whom they purchase, while old consumers are not. In addition, we allow the technology to feature a simple form of network externalities, by assuming that young consumers' preferences also depend on the average level of technology adoption across all businesses.[6] For an individual firm, adoption of the technology raises their market share of young consumers' purchases. This creates a stronger incentive to adopt when the customer base is younger; conversely, an older consumer base results in a lower equilibrium rate of technology adoption by businesses.

In the third step of our analysis, we provide direct empirical evidence consistent with business technology adoption decisions being influenced by the demographics of their customer base, as predicted by the simple model. We study the introduction of QR code-enabled terminals by a prominent fintech company in India in 2019. This company offers payment processing services to merchants, providing them in particular with point-of-sale (POS) machines. Until 2019, the functionality of these terminals was limited to traditional card payments. However, in May 2019, the company expanded its offerings to include terminals capable of processing payments via QR codes, thus accommodating mobile payment applications. This shift allows us to assess whether — consistent with the model — merchants' propensity to adopt mobile payments is influenced by the demographic structure of potential customers. In particular, we study how the adoption of our company's services changes after the May 2019 policy in relationship with the share of young adults in the area, which we define as the share of the population less than 30 years of age.

In our baseline results, we find that, on average, a one-standard-deviation higher share of young adults is associated with a 25% higher adoption response to the introduction of the QR code option. Importantly, this increase does not materialize until two months after the announcement of the new option and is not explained by differential adoption patterns before the announcement. The findings are robust to controlling for a rich set of demographic and economic characteristics, helping to account for observable differences across districts. Our interpretation is that merchants face stronger incentives to adopt mobile payments in younger districts due to intrinsic preferences of young consumers for the technology.

We present two tests to address the endogeneity of local demographic structure to the propensity to adopt. First, we find similar results when we instrument our main treatment variable using historical determinants of fertility. Specifically, we leverage the simple observation that the presence of a skewed sex ratio in a region, should predict — all else equal — lower birthrates going forward (Guilmoto 2012; Dyson 2012; Angrist 2000). We then use a quadratic function of the sex ratio

[6] Individual businesses behave atomistically and thus fail to internalize this in their private technology adoption decision.

in 1991 to instrument the share of young adults two decades later.[7] This approach allows us to isolate variation in the youth share that is driven by historical demographic features and should be orthogonal to migration trends or recent changes in local conditions.

Second, we leverage the distribution of universities *within* districts as an alternative way to generate differences in demand by younger customers. The idea is that businesses near universities naturally cater to a younger clientele (i.e., students), yet should be otherwise similar to businesses in other neighborhoods within the same district. Using university presence at the pincode level—the most granular location identifier in our data—and controlling for district-by-month fixed effects, we show that post-May 2019 adoption rates rose more sharply in university pincodes than in other pincodes within the same district. Apart from allowing us to control for time-varying district-level confounders, this approach has the added benefit of clearly identifying the consumer group driving demand for the technology: university students. This specificity enables us to predict which types of businesses are most affected. Indeed, we find that the results are driven mainly by businesses serving university students. In contrast, merchants less likely to cater to students show no significant effects, effectively functioning as a placebo group and helping to rule out explanations driven by broad merchant-side differences across neighborhoods.[8]

Having validated the basic predictions of the model, in the final step of our analysis, we use it to assess whether equilibrium adoption decisions are efficient. A simple prior might be that, absent network externalities, adoption should be efficient. We show this is not the case: monopolistically competitive firms restrict quantities, and because technology adoption and output are complements, this leads to under-investment. Importantly, this distortion does not interact meaningfully with demographics: monopoly pricing alone reduces adoption and welfare by similar amounts regardless of age composition.

Network externalities introduce a richer interaction with demographics. Aggregate welfare losses relative to first-best are largest when the population is young, since that is when uninternalized network externalities would benefit the most consumers. However, each individual young consumer faces larger welfare losses as the population ages: in an older society, the young not only constitute a smaller share of the population, but also bear a larger per-capita efficiency cost from the failure of businesses to internalize adoption externalities. Thus, although an older population may not lower aggregate welfare, it amplifies welfare differences across age groups for technologies with network externalities.

We conclude by studying optimal subsidy design, motivated by financial incentive schemes targeting adoption and use of electronic payment systems in India and elsewhere. We first consider a subsidy to adoption costs. Used in isolation, this subsidy raises adoption but cannot restore the

[7]The quadratic function allows us to flexibly exploit the effects of skewed sex ratio (Hesketh and Xing 2006; Hesketh and Min 2012), without imposing any structural assumption about the optimal level of sex ratio or the slope of this relationships.

[8]For instance, this approach allows us to assuage concerns about the role of differences in managers' demographics in explaining our results. First, while areas with universities should have a younger clientele, the composition of business owners should be similar. Second, if differences in manager demographics did drive our findings, this alternative mechanism should be detected by our placebo test.

first best.[9] We then consider an electronic transaction subsidy, which likewise improves adoption but fails to restore efficiency on its own. Restoring first-best requires combining both instruments. The jointly optimal scheme has a simple structure: the transaction subsidy eliminates markup distortions and increases with population age, while the adoption subsidy corrects the wedge between private and social returns to the technology and decreases with population age. As discussed in Section 5, this result is consistent with the common practice of providing this type of joint subsidy in many contexts (e.g., India and Italy).

Our evidence supports the view that demographics may be an important driver of the diffusion of new technologies. Population aging may slow both the pace of innovation and the adoption of new technologies. Our setting allows us to isolate this demographic channel cleanly: the regulatory framework across Indian districts is homogeneous and the technology identical, separating demographic effects from institutional differences that confound cross-country comparisons. The welfare analysis suggests that policy can help: optimal subsidies to correct under-adoption should themselves vary with demographic composition.

Section 2 reports the stylized facts on the relationship between age and the propensity to use mobile payments. Section 3 outlines a model connecting this propensity to business adoption decisions. Section 4 describes the evidence on the effect of population age on merchants' decision to adopt mobile payments. Section 5 studies sources of inefficiency in the competitive equilibrium of the model and draws policy implications for how to subsidize technology adoption when consumers of different age groups display different preferences towards the technology. Section 6 concludes by discussing the broader implications of our evidence.

Contribution to the literature Our findings contribute to three bodies of literature. First, they relate to the literature on the adoption and diffusion of new technology. While previous studies have documented that age differences can affect customers' decision to adopt a new product (Klee 2008; Wang and Wolman 2016), our key contribution is to extend this analysis and demonstrate that these differences can have a significant economic impact on merchants' decisions to adopt. In other words, our results underscore how heterogeneity in consumer technology preferences can influence firms' adoption decisions. We also examine the welfare implications of this distortion.

Existing work has predominantly focused on the agricultural or farming sectors, where the preferences of end consumers regarding the technology used in production are less relevant, provided they do not affect the final product's quality or price.[10] By contrast, consumer preferences may be more important determinants of adoption decisions in the service sector, since the technology used to deliver services can be an integral part of value creation, making consumer preferences crucial. Importantly, our results highlight that differences in preferences will not only affect adoption due

[9] We also show that, surprisingly, the optimal subsidy within this class is independent of both the shape of adoption costs and the fraction of consumers who value the technology (i.e., the young), so long as at least some of them do.

[10] For instance, Atkin et al. (2017) studies the role of organizational constraints in the manufacturing of soccer balls; work by Munshi (2004), Conley and Udry (2010), and Gupta et al. (2022) examine from these perspectives the role of information frictions and learning in agriculture. Our findings also relate to Goehring et al. (2023), which studies the role of career concerns in technology adoption.

to demand differences among final consumers, but will also reduce technology adoption on the business side. An implication is that differences in diffusion rates could derive from differences in consumer preferences, including those driven by demographic characteristics, which are the focus of our analysis. Thus our evidence adds more broadly to the literature on why new technology diffuses slowly, even when financial, regulatory, or informational hurdles are not obvious (Hall and Khan 2003; Comin and Hobijn 2010; Foster and Rosenzweig 2010; Manuelli and Seshadri 2014). Furthermore, we also highlight that, unlike frictions studied in existing work, which tend to both slow down diffusion and reduce welfare, the welfare implications of slow diffusion driven by heterogeneous preferences across consumers are more nuanced.[11]

Second, our research contributes to the fintech literature, which has seen a surge of interest in analyzing the drivers and impacts of new payment technologies. A significant body of recent research has focused on understanding the expansion of various payment methods, including traditional cards (Higgins 2023; Aggarwal et al. 2023), crypto (Hu et al. 2019), mobile wallets (Chodorow-Reich et al. 2019; Crouzet et al. 2023; Ghosh et al. 2024), and instant payment systems like UPI in India (Dubey and Purnanandam 2023; Alok et al. 2024) and Pix in Brazil (Sarkisyan 2023).[12] Despite the wealth of insights, a common characteristic of these studies is that they focus on a specific electronic payment method (relative to cash). Our study diverges from most of the previous literature by examining the decision-making process between different electronic payment options. Our results suggest that the simultaneous presence of multiple technologies (i.e., multi-homing) could partially arise from heterogeneous consumer preferences for distinct products.[13]

Finally, our paper is connected to work on the productivity implications of large demographic transitions (Feyrer 2007, 2008; Acemoglu and Restrepo 2017; Maestas et al. 2023; Acemoglu and Restrepo 2022). A related literature has connected aging to declining rates of entrepreneurship and firm entry (Liang et al. 2018; Peters and Walsh 2019; Azoulay et al. 2020; Bornstein 2021). Our paper complements this work by providing empirical support for a new channel through which aging could affect productivity growth, distinct from entrepreneurial innovation, the diffusion of new technologies to businesses.

[11]For instance, as noted earlier, while population aging lowers mobile adoption and hurts the young in our setting, it does not necessarily lead to a decline in aggregate welfare.

[12]This paper also complements the literature studying the real impact of electronic payments. For instance, several papers have examined the impact of digital payments on households' behavior (Jack and Suri 2014; Suri and Jack 2016; Bachas et al. 2021; Agarwal et al. 2024; Bian et al. 2023) and businesses (Agarwal et al. 2019).

[13]Our paper also relates to Jiang et al. (2024), which studies the disparate impact of digital banking among U.S. consumers, showing that older and poorer consumers are, on average, net losers in the shift from branch banking to mobile. While our papers differ in many important dimensions, a fundamental distinction is that Jiang et al. (2024) take a supply-side approach, focusing on how banks' strategic decisions (i.e., branch closure) drive the differential impact of digital transformation across groups. In contrast, our paper adopts a demand-side perspective, emphasizing how consumers' inherent preferences and characteristics, particularly age, shape technology adoption among the businesses in the market.

2 Age and the propensity to use mobile payments

This section provides stylized facts on the relationship between consumer age and the propensity to use mobile payments. Our data focus on the Indian market, so we start with a brief institutional background on mobile payments in India.

2.1 Institutional background: mobile payments in India

The Indian mobile payment landscape offers a captivating example of rapid adoption of new financial technologies within a short timeframe. This section reviews these recent changes, highlighting the difference between mobile payment technologies and traditional card-based transactions.

Mobile payment modalities In the Indian context, mobile payment can refer to two key technologies: mobile wallets and the Unified Payments Interface (UPI). Mobile wallets function as preloaded payment technologies, allowing users to deposit funds in their mobile wallets for use in future transactions. Similarly, businesses can utilize digital wallets to receive payments. The contents of the wallets can then be transferred to the traditional bank deposit accounts of consumers and businesses. These services, often free for consumers, have attracted numerous providers competing based on security, convenience, and integration with traditional payment methods. Initially introduced in the early 2010s with platforms like Paytm and MobiKwik, their popularity surged after India's 2016 demonetization, with mobile payment volumes nearly tripling from April 2016 to April 2017 (Chodorow-Reich et al. 2019; Crouzet et al. 2023).

Mobile payments can also refer to the UPI. Introduced by the National Payments Corporation of India (NPCI) in 2016, the UPI facilitates immediate, real-time bank-to-bank transfers, enabling transactions via a mobile interface without requiring physical cards or certificates (Dubey and Purnanandam 2023). Managed by the NPCI, the UPI is accessible through various popular apps, including those offering mobile wallet services. Like mobile wallets, UPI services are free for consumers. Competing apps distinguish themselves through additional services or a differentiated user experience. The UPI offers two primary advantages over mobile wallets. First, it provides direct connectivity to a funding source (e.g., a bank account), eliminating the need to preload funds into a digital wallet. Second, the UPI guarantees interoperability across different banks and financial service companies (Copestake et al. 2025).[14] While the UPI was formally introduced in 2016, UPI transactions remained small, compared to mobile wallet transactions, until the end of 2017.[15] However, the UPI's growth trajectory surpassed that of mobile wallets post-2017, reaching approximately 80% of mobile transactions by the end of 2021.

[14] In other words, a traditional mobile wallet managed by a fintech company A can only send money to other wallets managed by A. Instead, with UPI, you can pay any UPI holders, irrespective of the application that the firm uses to manage the UPI account.

[15] https://www.npci.org.in/what-we-do/upi/product-statistics

Mobile payments versus traditional card-based payments In addition to mobile payments, Indian households have long had access to traditional card-based electronic payment methods. Much like in the United States, Indian consumers enjoy a range of options including debit, credit, and prepaid cards. The Indian market is served by major international card companies, reflecting a level of accessibility comparable to that seen in the United States.[16] Since the bulk of our analysis is concerned with comparing adoption of mobile payment technology with traditional card-based electronic payment methods, it is important to clarify the differences between these technologies. We highlight three main differences.

First, mobile payment options generally involve lower adoption costs for consumers. Typically, there are no financial expenses associated with opening a mobile wallet or registering with UPI. Moreover, the non-monetary costs involved in setting up these accounts are often less burdensome than those required for obtaining a card. Second, while the fees associated with processing mobile payment through UPI may vary depending on the payment company handling the transaction, they are generally lower than those associated with card payments.

The third significant distinction between mobile payments and cards pertains to the transaction process itself. As the term suggests, mobile transactions are executed using an app on a phone or similar digital device.[17] In consumer-to-business transactions, QR code technology is the primary payment method, allowing consumers to swiftly complete purchases by scanning a QR code provided by the merchant, and facilitating rapid and contactless payments.[18] Additionally, the digital interfaces of applications hosting the UPI or mobile can offer a customized consumer experience, with additional options to monitor payments made or transfers received in real-time, for instance.

The expansion of mobile payments Aggregate data from the Reserve Bank of India (RBI) underscores the remarkable surge in mobile payments that occurred from 2016 onward (Figure 1). Prior to 2016, India's electronic payment landscape was largely dominated by card-based transactions. However, this landscape underwent a significant transformation following the Demonetization at the end of 2016. Not only did this event spur a general increase in electronic payments, but it also notably bolstered mobile payments, primarily through mobile wallets. The momentum towards mobile payment dominance persisted beyond 2017, with UPI transactions gradually capturing a larger share of mobile payment volumes. By 2019, mobile payments equaled the volume of card transactions and have since continued to grow at a rapid pace. As of the end of 2021, mobile payments represented the predominant form of electronic payment in the Indian market.

[16]For instance, the major card providers (i.e., Visa, AMEX, and Mastercard) all operate in the Indian market. One notable difference with the United States market is that the Indian government has entered indirectly the offering of card services through Rupay.

[17]In theory, both mobile wallets and UPI have options that do not require a smartphone, allowing payment validation through a phone call or text, but this option appears relatively uncommon (albeit exact statistics are hard to find).

[18]While credit cards theoretically can be integrated into a digital interface for use via QR code scanning, akin to how ApplePay operates in the US, this digital card option appears relatively rare within our context. For instance, in the dataset provided by our fintech company used later for the analyses, we found that a small percentage (3% of volume) of QR code transactions were conducted using cards in 2019.

The Indian transition of electronic payments from card-based technologies to mobile technologies is particularly striking when contrasted with the recent evolution of electronic payments in many developed countries, including the United States. Recent market research shows that in 2023, Apple Pay, the most popular mobile payment option in the US, only accounted for 3.1% of all in-store purchases in the United States by volume, indicating a comparatively low rate of adoption of the technology by consumers.[19] Additionally, it is crucial to recognize that most mobile payment options in the United States are still fundamentally linked to credit cards, and therefore represent a smaller step in innovation than mobile payments in India.[20]

2.2 Consumer age and the propensity to use mobile payments

Many economic, technological, and institutional factors could explain the recent surge in mobile payments in India. Our focus in this paper is on the role of age. Our key premise is that young consumers tend to be more predisposed to use mobile payment technologies. In a country with a younger population, this predisposition could not only directly generate more mobile payment usage, but also, *indirectly*, encourage greater adoption among businesses. The remainder of this section presents evidence consistent with our argument's foundation: namely, that younger consumers tend to prefer mobile payments to traditional cards.

1. Data sources

Our primary dataset comes from one of the top four banks in India, encompassing approximately 200,000 customers. This bank operates an extensive network of over 18,000 branches and ATMs, offering a comprehensive suite of financial products and services.[21] The dataset used in this study contains transactions from January and February 2020 and provides insight into the usage of traditional cards versus mobile payments, with the latter measured solely through UPI transactions.[22] Additionally, the data provides basic demographic information about the clients. As our focus is on understanding how age effects impact payment preferences, we compare the age distribution of the dataset with the national demographic profile of household heads.[23] As illustrated in panel (a) of Figure A-1, the age profiles of bank account owners and household heads closely align. Lastly, we note that our data are mechanically skewed toward wealthier households, since households must

[19] See https://capitaloneshopping.com/research/apple-pay-statistics. A 2021 survey by PYMNTS confirms this qualitative fact: this survey adopts a wider definition of mobile wallet (i.e., not only Apple Pay but also other providers) and finds that only about 10% of US respondents had recently utilized this payment option; see https://www.pymnts.com/apple-pay-tracker/2021/7-years-later-6pct-people-with-iphones-in-us-use-apple-pay-in-store/.

[20] In other words, services like Apple Pay build on the the pre-existing card network, rather than replacing it. If anything, this feature should make scaling easier.

[21] To maintain confidentiality, we refrain from disclosing the bank's identity, although its data has been utilized in other academic studies, such as Agarwal et al. (2022).

[22] Card payments include transactions made with both debit and credit cards, while mobile payments are determined by UPI transactions.

[23] Throughout our analysis, we only consider bank customers aged between 18 and 65. This selection is motivated by the presence of few accounts held by people outside this group. Given the non-parametric nature of our exercise, this choice does not affect our main results presented.

maintain a bank deposit account to be in our sample (panel b of Figure A-1). However, the data have relatively broad coverage of wealth levels, allowing us to disentangle the effects of age from those of wealth. Appendix A.1.1 provides a more extensive comparison of our data with the Indian population at large.

2. Results

Age as a source of variation in mobile payment usage We start by documenting the degree to which age accounts for variations in payment preferences when contrasted with other factors, such as gender, occupation, marital status, wealth, or geographical location. To do this, we employ a Shapley R-squared decomposition method (Huettner and Sunder 2012; Israeli 2007).[24]

The findings are presented in Table 1. These results highlight age as the primary economic or demographic factor explaining the largest share of variance in payment methods.[25] The precise contribution of age to variation in mobile payment share of depends on the other factors included in the decomposition. Nevertheless, we can use the most conservative estimates, obtained by including all factors simultaneously, as a benchmark. In this scenario, age accounts for approximately 38% of the explained variance, making it the most significant factor alongside location (i.e., six-digit pincode), which explains roughly 42% of the variation. Marital status follows as the next significant factor (8%), trailed by wealth (7%) and occupation (5%). The depositor's gender proves to be essentially inconsequential. Thus age emerges as a key characteristic accounting for the cross-sectional variation in payment preferences between cards and mobile payment.

Mobile vs. Card across the Age Distribution We now analyze the relationship between payment preferences and the age of the account holder using the data. To start, Figure 2, panel (a), reports a non-parametric scatter plot of the relationship between the share of mobile payment amounts and age. We observe a negative, monotonic, and approximately linear relationship between age and mobile payment usage: older individuals consistently utilize mobile payments less frequently than cards. These differences are substantial, with consumers in the oldest category conducting approximately 25% of their electronic payments using mobile, compared to 55% for younger consumers.[26]

The same relationship holds if we incorporate individual-level controls. In Figure 2, panel (b), we incorporate demographic controls for gender, marital status, and occupation, finding that this inclusion has virtually no impact. In Figure 2, panel (c), we further introduce controls for the wealth of the individual — proxied using the individuals' total balance in current, savings and

[24] Several applied papers have used this method in recent years, including Biasi and Ma (2022) and Mezzanotti and Simcoe (2023). Drawing on the concept of the Shapley value in cooperative game theory, this method calculates the average marginal contribution of a predictor (in our case, age) to the total R-squared of regressions including all possible subsets of predictors, thus offering a breakdown of the total R-squared among all combinations of the predictors considered. In our case, the additional predictors beyond age include gender, marital status, occupation, wealth (proxied by total deposits), and location, defined by a (6-digit) pincode.

[25] Age is defined non-parametrically using age groups, with 48 dummies classifying all ages between 18 and 65.

[26] Appendix Figure A-2 replicates the same result with fixed age groups (i.e., 18-25, and then at 5-year intervals) and providing confidence intervals relative to zero. More discussion on this in Appendix A.2.1.

fixed deposit accounts at the bank — to mitigate the possibility that age-related differences are merely reflections of wealth disparities across cohorts. Once again, the inclusion of this control has a relatively modest impact.[27] Another issue is that different age groups may reside in different areas. For instance, the younger population may locate in areas where stores are less inclined to accept credit cards, potentially increasing their reliance on mobile payments. In that case our results would reflect lack of access to credit card payments, as opposed to a preference for mobile payments. To address this concern, Figure 2, panel (d), replicates the previous analysis but includes controls for pincode (6-digit)-by-wealth group fixed effects, alongside standard demographic controls. While the magnitude is somewhat reduced, the evidence still strongly supports a significant relationship between age and mobile payment usage.

A final concern is that age is a proxy for differences in the ability to obtain a card across different age groups. Older individuals might be more likely to be approved for debit or credit cards, potentially underpinning the observed relationship.[28] To address this issue, Figure 2, panel (e), conducts a similar analysis as before — incorporating individual controls and pincode-by-wealth fixed effects — but focuses only on customers who possessed cards during the analyzed period. Even after conditioning on ownership of a card, we find that younger consumers consistently allocate a significantly higher proportion of their expenditures to mobile payments. Specifically, the share of mobile payments is approximately twice as large for the youngest cohort as for the oldest one. The linear fit of this relationship remains quantitatively identical to the one estimated in panel (a).

Discussion After highlighting the surge of mobile payments in India in recent years, this section showed that consumers of different ages exhibit distinct propensities to use mobile payments. The relationship between age and mobile payment usage is both economically significant and broadly monotonic. This relationship persists even after controlling for differences in occupation, wealth, geographic location, and electronic payment card ownership.

We interpret this evidence as suggesting that younger consumers have a stronger preference for mobile payments than their older counterparts. A natural question is what factors may explain this difference. On the one hand, the behavior could reflect cohort-specific preferences for certain features of new technologies. For instance, younger cohorts may naturally be more inclined to adopt and use digital technologies (Prensky 2001a,b). On the other hand, the preference for mobile payments could stem from differences in life experiences across cohorts. Older adults, having been more exposed to older payment technologies (i.e., cards), may have developed habits that create a preference for continuing with these options, even when newer ones are available (Dynan 2000).

Although this paper does not aim to fully explain the source of heterogeneity, a few clarifications are in order. In general, the importance of identifying the exact mechanism arises primarily when

[27] We then control for wealth by creating 20 equal bins each month and then using fixed effects for each of the 20 bins.

[28] It is important to note that differences in card ownership among cohorts may also stem from varying preferences. For instance, if a young person strongly prefers mobile payments, they may choose not to apply for a credit card. This suggests that the test conducted here may, in part, underestimate the role of preferences, as defined in this study.

making predictions about the long-run dynamics and is less crucial for explaining adoption patterns in the cross-section or during the early stages of the technology's life. In fact, the main distinctive difference between the two explanations is in the time-series: in particular, differences in behavior due to habits are likely to diminish over time, leading the gap between the two demographic groups to shrink in the future. In a static framework, this feature is clearly not critical, and more broadly, it becomes important only as sufficient time passes for the role of habits to wane.

In this context, we introduce two new tests that aim to better assess the extent to which habit formation may play a role in explaining our findings. Our key takeaway is that while habit formation may partly explain the choice between payment forms, we also find that differences in habit do not dissipate quickly: the gap between the young and old has persisted for several years and shows no significant reversal in recent years. To make these claims, we use panel data from the same bank.[29] While this sample focuses on a more limited set of clients in a few large districts in India, it tracks their monthly spending behavior from 2012 to 2022, and therefore allows us to explore the dynamics of the preference.

We conduct two complementary exercises with this sample. First, we provide evidence consistent with habit formation by examining whether early use of a credit card is associated with a lower likelihood of using mobile payments in the later part of the sample. In Figure A-3, we plot the month-by-month difference in the probability of using mobile payments across individuals with and without a credit card in 2015. After mobile payments gained significant traction (i.e., post-2017), we observe a lower likelihood of using mobile payments among individuals who already had credit cards, and this effect persists at least until 2021.

Next, we examine how young clients' preference for mobile payments has evolved over time. In the panels of Figure A-4, we plot the monthly difference in the average use of mobile payments between younger and older clients starting in 2016. Throughout the sample period, younger clients consistently used mobile payments more than their older counterparts. This gap widened during the boom period for mobile payments and stabilized around 2020 for this sample. While mobile payments grew significantly during the analysis period (Figure 1), the level of penetration remains different across cohorts. To the extent that habits may have explained in part the difference between cohorts, this evidence suggests that this mechanism does not dissipate quickly, since we find large differences in behavior six years after the boom in mobile payments.[30]

Altogether, our evidence suggests that the preference for mobile payments may partly stem from differences in habits between groups.[31] However, we also find that—to the extent habits contribute

[29] While the data carries the advantage of providing transactional details over a long panel of customers, including providing details before 2016, it is nevertheless not well-suited for our main analysis for few reasons. First, the data comes only from nine biggest metropolitan Indian cities and, therefore, is not representative of less urban regions. Second, because the data keeps the panel of customers fixed beginning in 2012, we are unable to capture a large share of younger population in the year 2020 with this data. The test discussed below use the sample of customers that entered the data before 2015 and kept using the account until at least 2021.

[30] Importantly, we find that the persistence of the age gap is stronger than the persistence in the difference in behavior found between early card-users and consumers without a card in 2015. Arguably, this comparison is a more direct test of habits. This suggests that the age-induced preference appears to persistent longer than what induced by a direct early use of cards.

[31] This idea is consistent with experimental evidence studying possible interventions—such as direct exposure (Breza

to the age gap—their importance does not appear to dissipate even after several years.

3 Model

In this section, we outline a simple model of the interaction between demographics and the adoption of new technologies by businesses. The model shows how differences in preferences across consumer demographics — as documented in Section 2 — can shape technology adoption by businesses. In Section 5, we will come back to the model to evaluate the effects of different subsidy schemes targeting adoption of the technology.

3.1 Description

Consumers There is a unit mass of consumers, indexed by $i \in [0,1]$. Each consumer has preferences over an outside good, $O(i)$, and an aggregate of varieties produced by businesses in the economy, $C(i)$, described by:

$$W(i) = \log\left(O(i)^{1-\alpha} C(i)^{\alpha}\right), \tag{1}$$

where $\alpha \in [0,1]$ governs the elasticity of substitution between $O(i)$ and $C(i)$. The outside good serves as the numéraire, and each household is endowed with E units of it. Households each own an equal number of shares in the businesses and receive the profits they earn in the form of dividends.

There are two types of consumers: young and old. Let $\mathcal{I}_O \in [0,1]$ denote the set of old consumers, and $\mathcal{I}_Y = [0,1] \setminus \mathcal{I}_O$ denote the set of young consumers. Our first key assumption is that young and old consumers only differ in their sensitivity to the technology choices of businesses.

Assumption 1 (Preferences for technology)**.** *For old consumers, the consumption aggregate over varieties produced by businesses is:*

$$C(i) = \left(\int_0^J c(i,j)^{\rho} dj\right)^{\frac{1}{\rho}} \qquad \text{if } i \in \mathcal{I}_O.$$

Instead, for young consumers, the consumption aggregate over varieties is given by:

$$C(i) = \left(\int_0^J b(j)^{1-\rho} c(i,j)^{\rho} dj\right)^{\frac{1}{\rho}} \qquad \text{if } i \in \mathcal{I}_Y,$$

where $b(j) \geq 1$ depends on the technology adoption decision of business j.

Here, J is the number of varieties produced, which we index by j.[32] Moreover, $c(i,j)$ is the consumption of variety j by household i, and $\rho \in [0,1]$ determines the elasticity of substitution

et al. 2020) or training (Hartinger et al. 2025)—aimed at inducing adoption of financial technologies. Our paper is particularly related to Hartinger et al. (2025), which focused on an intervention aimed at increasing the use of digital banking among older consumers.

[32] Each business produces a unique variety so we also use j to index businesses.

between varieties. The budget constraint of each household is:

$$\int_0^J p(j)c(i,j)dj + O(i) \leq E + \int_0^J \pi(j)dj. \tag{2}$$

where $p(j)$ is the price of variety j.[33] Maximization of (1) subject to (2) yields the usual demand curves:

$$\forall i \in \mathcal{I}_O, \quad c(i,j) \;=\; \left(\frac{p(j)}{P_o}\right)^{-\frac{1}{1-\rho}} C(i), \quad P_o \equiv \left(\int_0^J p(j)^{-\frac{\rho}{1-\rho}} dj\right)^{-\frac{1-\rho}{\rho}}, \tag{3}$$

$$\forall i \in \mathcal{I}_Y, \quad c(i,j) \;=\; b(j)\left(\frac{p(j)}{P_y}\right)^{-\frac{1}{1-\rho}} C(i), \quad P_y \equiv \left(\int_0^J b(j)p(j)^{-\frac{\rho}{1-\rho}} dj\right)^{-\frac{1-\rho}{\rho}}. \tag{4}$$

Because all young consumers and all old consumers make identical choices, we will omit the index i and refer instead to the consumption choices of old households by O_o, C_o and c_o, and to those of young households by O_y, C_y and c_y.

Businesses Each business is the monopolistic producer of its corresponding variety. Businesses all have the same unit cost of sales ξ and the same fixed operating cost ν. Finally, they face a cost of adopting technology level $\tilde{b}(j)$, which we model as follows.

Assumption 2 (Technology adoption costs)**.** *Choosing technology adoption level* $\tilde{b} \geq 1$ *requires* $\gamma(\tilde{b})$ *units of the numéraire good, where* $\gamma : [1, +\infty) \to \mathbb{R}^+$ *is a twice-differentiable, strictly increasing, and strictly convex function satisfying* $\gamma(1) = \gamma'(1) = 0$*.*

Because of externalities across businesses, the level of technology adoption $\tilde{b}(j)$ chosen by business j need not be the same as the effective impact of the technology on young households, $b(j)$. This is our third assumption.

Assumption 3 (Externalities in technology adoption)**.** *The technology adoption choice of business* j *affects young consumers' preferences as follows:*

$$\forall j \in [0, J], \quad b(j) = \bar{b}^{\theta}\, \tilde{b}(j), \quad \bar{b} \equiv \prod_{k \neq j} \tilde{b}(k)^{\frac{1}{J}}, \quad \theta \geq 0. \tag{5}$$

As we explain in more detail below, the parameter θ captures the strength of *network externalities* associated with the technology, with $\theta = 0$ corresponding to the case of no network externalities. Profits for business j are given by:

$$\pi(j) = (p(j) - \xi)(\eta c_o(j) + (1-\eta)c_y(j)) - \gamma(\tilde{b}(j)) - \nu, \tag{6}$$

where $c_o(j)$ and $c_y(j)$ are given by the demand curves (3)-(4), and business j takes $\bar{b}$, the average level of technology adoption, as given.

[33] We assume that businesses cannot price-discriminate between young and old.

Competitive equilibrium Given the number of businesses J, a competitive equilibrium is a set of prices and quantities such that (a) each household i maximizes utility (1) subject to their budget constraint (2); (b) each business j maximizes profits (6) subject to the demand curves (3)-(4) and taking $\bar{b}$ in Equation (5) as given. Appendix A.3 provides an analytical characterization of the equilibrium.[34]

3.2 Discussion

Assumptions We make three important assumptions. First, assumption 1 is meant to capture the idea that young consumers are more sensitive to businesses' technology offerings than old consumers. For the particular case of mobile payments, the focus of this paper, this assumption is consistent with the evidence presented in Section 2, which highlighted the quantitative importance of the negative relationship between age and the propensity to use the technology in India. As a consequence of this assumption, business j has the following market share of young consumers:

$$s_y(j) = b(j) \left(\frac{p(j)}{P_y} \right)^{-\frac{\rho}{1-\rho}}, \quad b(j) = \bar{b}^{\theta} \tilde{b}(j).$$

which has unit elasticity with respect to the technology choice $\tilde{b}(j)$ of business j. Thus, business j's technology adoption choice raises their market share of the young all else equal.[35]

Second, assumption 2 says that adopting the technology generates costs to individual businesses. One interpretation is that the technology may require workforce training to be deployed. Businesses may also be uncertain that the technology is reliable. This cost limits the scale of adoption by individual firms.[36] The assumption that the cost function $\gamma(.)$ is strictly convex furthermore guarantees that, given aggregate variables, the optimal scale of adoption is unique.[37]

Finally, with assumption 3, we embed the idea that the particular technology we study may have positive externalities across firms (when $\theta > 0$). We do this because our object of study is the adoption of a digital payments interface. Network externalities associated with digital payment systems have been recently documented in Parlour et al. (2022) (for banking payment infrastructure), Crouzet et al. (2023) (for retail payment interfaces), and Higgins (2024) (for debit cards and point of sales terminals). We keep the modeling of these externalities deliberately simple: in particular, they are one-sided in that consumers make no explicit technology adoption choice. The benefit of this simplicity is that it makes the model tractable while preserving the fundamental intuition

[34] Appendix A.3 also discusses the model with free entry, that is, endogenous J, and provides proofs of all the results to follow in that case. We keep the main discussion on the case of a fixed number of businesses because our empirical analysis is focused on the short- and medium-term effects of the introduction of the technology.

[35] The Cobb-Douglas form $b(j)^{1-\rho} c(j)^{\rho}$ in the aggregator for young households is a normalization chosen to ensure that the market share $s_y(j)$ has unit elasticity with respect to $\tilde{b}(j)$.

[36] Note that, consistent with the features of the UPI described in Section 2 (for which, if anything, transaction costs are lower than traditional card payments), we do not assume that the firm incurs differential transaction costs from using the technology.

[37] By contrast, an S-shaped adoption cost curve (where $\gamma''(.) \leq 0$ over some range) could generate multiplicity even without externalities ($\theta = 0$). This multiplicity would arise from the cost structure alone, as the equilibrium condition in Equation (10) could have multiple solutions when the left-hand side is non-monotone.

that business decisions to adopt the payment technology, the object of our analysis, have positive spillovers that each business may fail to fully internalize.[38]

Sources of inefficiency In this model, there are two potential reasons why the competitive equilibrium level of adoption might differ from what a planner would choose.[39] The first are the adoption externalities discussed above (when $\theta > 0$). Higher adoption by businesses benefits the young consumers, but businesses cannot fully internalize this benefit through higher prices, as their efforts to gain market share cancel each other out in the (symmetric) equilibrium. This has a direct effect on adoption, and generically implies that it will be too low relative to the planner's preferred level. Second, as is usual with Dixit and Stiglitz (1977) demand systems, monopolistically competitive firms charge a markup, thereby reducing equilibrium quantities relative to the socially optimal level. As in standard innovation or diffusion models, markups are a necessary condition for positive technology adoption in the competitive equilibrium. But they have an indirect effect on adoption: because adoption $b(j)$ and quantities $c(j)$ are complements, restricting quantities will also lead to lower levels of adoption. This latter distortion will also depress adoption relative to first-best.[40] We come back to these sources of inefficiency, and to the question of whether a planner can address them with targeted subsidies, in Section 5.

Some caveats Finally, we note two restrictions in the scope of our analysis. First, consumers' attitudes toward technology are treated as exogenous and determined by age. This restriction is significant. We make it deliberately so as to focus the analysis on how businesses adapt to consumer preferences (as implied by demographics), separate from how these preferences might evolve endogenously as a result of exposure to new technologies. However, we note that this assumption is consistent with the evidence, discussed in Section 2, that consumers preferences appear to be relatively rigid over the period we study, with limited evidence that adoption rates increase among the old over the period of time we study. Second, the model has a single period. This rules out, in particular, businesses adapting to forecasted changes in demographic structure over time. This restriction could be relaxed, at the cost of more complicated exposition. The

[38] Despite the adoption externalities ($\theta > 0$ in Assumption 3), equilibrium in this model is unique. The economic intuition is that while higher aggregate adoption $\bar{b}$ makes the technology more valuable to consumers, this benefit is fully dissipated in equilibrium through relative price adjustments. When all firms adopt symmetrically, relative prices adjust so that no individual firm gains from the higher aggregate adoption level. The externality therefore affects welfare—creating a wedge between private and social returns—but not the equilibrium allocation itself. Each firm's adoption decision is pinned down by the trade-off between its marginal cost $\gamma'(\tilde{b})$ and the scale of the young consumer base $1 - \eta$, independent of what other firms do in equilibrium.

[39] Under free-entry, another source of inefficiency is the "love-for-variety" effect (Spence 1976; Dixit and Stiglitz 1977; Dhingra and Morrow 2019). The constant elasticity of substitution aggregator implies that consumer welfare is increasing in the number of varieties whenever $\rho < 1$, but the monopoly markup does not allow firms to fully internalize these welfare benefits of greater variety, leading to insufficient entry relative to first-best. We discuss welfare implications of the model under free-entry in Appendix A.3.

[40] Monopolistic competition is a key and necessary feature of this environment because we model the technology as affecting the preferences of young households. Absent monopolistic competition, individual firms would not have private incentives to adopt the technology, and there would be zero adoption in equilibrium; imperfect competition ensures there are positive profits associated with adoption. Formally, the only solution to the first-order condition (7) when $\rho = 1$ and firms do not charge a markup is $\tilde{b}(j) = 0$ for all j.

main benefit of these restrictions is that we can compare the competitive equilibrium with efficient benchmarks and study optimal policy, which we do in Section 5.[41]

3.3 Model implications

The necessary first-order conditions for profit maximization are:

$$\begin{aligned} p(j) &= \frac{\xi}{\rho}, \\ (1-\rho)(1-\eta)P_y C_y \frac{\partial s_y(j)}{\partial \tilde{b}(j)} &= \gamma'(\tilde{b}(j)). \end{aligned} \tag{7}$$

The markup is set equal to the price elasticity of demand of the consumer base of each business. Because businesses are identical ex-ante, and because old and young consumers have the same, constant price elasticity, the markup is constant and equal to $\frac{1}{\rho}$. The first-order condition for technology adoption equates its marginal benefit with its marginal cost. Aggregate spending by young households is $(1-\eta)P_y C_y$, and the business earns profits $(1-\rho)$ per dollar of sales to young consumers. Technology adoption serves to increase the business's market share of young consumers, all else equal, which is captured by the term $\partial s_y(j)/\partial \tilde{b}(j)$ on the left-hand side of Equation (7). Combining the two first-order conditions yields an alternative formulation for the optimal choice of technology:

$$(1-\eta)\frac{1-\rho}{\rho}\frac{c_y(j)}{\tilde{b}(j)} = \frac{\gamma'(\tilde{b}(j))}{\xi}. \tag{8}$$

The left-hand side can be interpreted as a private marginal rate of transformation between technology, $\tilde{b}(j)$, and quantity choice, $c_y(j)$, while the right-hand side is the relative marginal cost.

Because all businesses charge the same markup, the equilibrium is symmetric. As all businesses make identical choices, despite the fact that each of them attempts to attract more young customers by adopting the technology, their efforts cancel out. However, in this model technology adoption has general equilibrium effects. Appendix A.3 shows that, for any number of active businesses J, equilibrium household income is given by:

$$I = \frac{1}{1-(1-\rho)\alpha}\left(E - J\left(\gamma(\tilde{b}) + \nu\right)\right). \tag{9}$$

where $\tilde{b}$ is the equilibrium (private) technology adoption choice of each business. In particular, all else equal, more adoption lowers household income (by increasing overhead costs of businesses). Thus condition (8), on its own, is insufficient to characterize how adoption varies with demographics. Nevertheless, we can show that the following result always holds.

[41] However, we note that the free entry equilibrium sheds light on how the number of businesses might adjust over time in response to the introduction of the technology, given a particular demographic structure; we analyze the free entry equilibrium in Appendix A.3.

Result 1 (Demographics and technology adoption). *In the competitive equilibrium, technology adoption $\tilde{b}$ is decreasing in the share of old consumers, η:*

$$\frac{\partial \tilde{b}}{\partial \eta} < 0.$$

Proof. See Appendix A.3. ■

To see why this is true, note that we can re-arrange condition (8) using the fact that demand from the young is $c_y = \alpha I/(pJ) = \alpha\rho I/(\xi J)$, to obtain:

$$\tilde{b}\gamma'(\tilde{b}) = (1-\eta)(1-\rho)\alpha\ \frac{I}{J}. \tag{10}$$

Differentiating both sides of Equation (10) with respect to η gives:

$$\frac{d}{d\tilde{b}}\left[\tilde{b}\gamma'(\tilde{b})\right]\frac{\partial \tilde{b}}{\partial \eta} = \underbrace{-(1-\rho)\alpha\frac{I}{J}}_{\text{effect on size of young consumer base}} + \underbrace{(1-\eta)(1-\rho)\frac{\alpha}{J}\frac{\partial I}{\partial \eta}}_{\text{income effect}}$$

The function on the left-hand side is strictly increasing, because of Assumption 1. On the right-hand side, the first term is a direct effect of the change in demographics on the marginal benefit from technology adoption for each business. The second term is an indirect general equilibrium effect — all else equal, a demographic shift changes technology adoption choices, which in turns affect firm profits and household income. Using Equation (9) and re-arranging, we obtain:

$$\overbrace{\left\{\frac{d}{d\tilde{b}}\left[\tilde{b}\gamma'(\tilde{b})\right] + (1-\eta)\frac{(1-\rho)\alpha}{1-(1-\rho)\alpha}\gamma'(\tilde{b})\right\}}^{>0}\frac{\partial \tilde{b}}{\partial \eta} = \underbrace{-(1-\rho)\frac{\alpha I}{J}}_{<0},$$

establishing the result.[42] Thus the model implies that, when the share of old consumers is higher (that is, when η increases), there is a weaker incentive for individual businesses to invest in technology, in order to gain market share.[43] In the following section, we will test this prediction by contrasting the technology adoption choices of businesses that face consumer bases with different demographics.

[42] Note that there are no countervailing effects on demand, because the markup is constant across demographic groups. If, instead, young consumers were also more price-elastic than old consumers, businesses might have a weaker incentive to adopt the technology, as this would increase their market share of the most price-elastic consumers. We do not include this heterogeneity in order to focus on the effects of differences in attitudes toward technology.

[43] Result 1 also holds under free-entry; see Appendix A.3. In the Appendix, we also establish that a uniform increase in $\gamma(.)$, the cost of technology adoption, lowers equilibrium adoption rates by businesses.

4 Evidence

This section uses business-level data on mobile payment adoption to test whether a merchant's decision to adopt mobile payments is indeed influenced by the composition of its customer base (Result 1, Section 3).

4.1 Data

The data for our analysis comes from a prominent fintech company in India that caters to small and medium-sized businesses. This company provides businesses with physical terminals and digital payment management systems to facilitate the receipt and processing of payments across various networks. For our study, the dataset enables us to observe the decision of new stores to adopt one of the firm's terminals and their subsequent usage patterns.[44] Our analysis will focus on examining how the adoption of the fintech company's terminals by stores has evolved over time.[45]

In particular, our study focuses on a shift in the types of payment services provided by the fintech company that occurred in 2019. Historically, the company had only offered traditional point-of-sale (POS) terminals, which required a consumer to use a physical card to conduct a transaction. Starting in May 2019, the company expanded its offerings to include mobile payment options through QR codes. This strategic shift was motivated by the increasing prevalence of mobile payments documented in Section 2. A merchant could still obtain a regular POS terminal after 2019: however, starting in May 2019, the fintech company started to also offer QR-enabled terminals, that would allow individuals to directly use mobile payment options, for instance paying using UPI through any supporting apps.[46] Lastly, although our fintech company is sizable, it represents just one among various entities providing mobile payment solutions to merchants in India. Consequently, the decision to adopt QR-code payments is unlikely to significantly enhance consumer benefits from using UPI through network effects.[47]

Aside from the data provided by our fintech company, we also use public data on demographic

[44] In the data, a store is defined as a combination of one or more terminals owned by the same firm within a six-digit pincode. In other words, the assumption is that, if a firm owns multiple terminals in the same narrowly defined location, they are assumed to operate as part of the same store. To be clear, this assumption is unlikely to have any impact on our analysis, because most firms in the data own only one terminal and operate in only one pincode.

[45] We determine store adoption based on the date of first-time terminal usage provided by our fintech company. For a significant subset of the data, we also have information about the terminal installation date, enabling us to validate our primary adoption measure. Upon comparing our adoption time with the terminal installation month for the sample of terminals adopted in the sample period, we find that the two measures coincide exactly for almost 86% of the terminals (and this increases to over 94% when we allow for one period delay). This evidence validates our baseline approach.

[46] In particular, the company offered both terminals that are enabled for both traditional cards and QR combined, as well as QR-code only terminals, that could be used only for mobile payments. Note that, in principle, a QR code could also be connected to a credit card. However, this option appears to be used very infrequently in our data, as most of QR transactions are UPI. Appendix A.1.2 contains more details on the data provided by our fintech partner and on the different POS offerings.

[47] Therefore, our context diverges from Agarwal et al. (2020)'s study on Singapore's largest bank introducing mobile payments and reducing cash usage. There, the involvement of the country's largest bank meant the shift prompted a significant change in the payment ecosystem.

and economic outcomes at the district level from the 2011 Census of India. Among other things, we use these data to construct measures of age structure for specific district, as well as other location-specific characteristics that allow us to adjust for other differences across areas in India (such as population, measures of economic activity, literacy, and others).[48] Finally, for our analysis in Section 4.5, we manually collected a list of universities in the country as of 2019, and mapped each university to its official pincode (see Appendix A.1.3).

4.2 Identification strategy

The model laid out in Section 3 shows that when consumers have different attitudes toward technologies, the distribution of these preferences should influence technology adoption by businesses. The prediction in the context of mobile payments is the following: merchants are likely to show greater interest in mobile payment technologies in areas with a higher concentration of young adults. In this section, we leverage data from our fintech payment company to test this prediction empirically.

To more accurately frame the empirical predictions of our model, we introduce the following ideal experiment. To start, we consider different groups of merchants and randomly allocate customer groups to each merchant group, with each customer group having a different age structure. This step aims to introduce exogenous variation in customer age, independent of merchants' characteristics. After this initial step, we would propose a dual offering where half of the merchant groups are presented with a traditional POS system exclusively for card transactions, while the other half are provided with terminals capable of mobile payments. We would then study how the adoption of the mobile-enabled terminal varies across groups as a function of the age of the consumer base. This experiment would allow us to estimate the extent to which variation in customer age could influence merchants' technology adoption decisions.

In our study, we emulate the experiment by using two sources of variation: technology availability and client age demographics. The first source of variation comes from our company's May 2019 launch of mobile payment options; this allows us to observe adoption rates at the same locations before and after the mobile payment option became available. The second source of variation comes from differing age demographics across Indian districts, enabling us to assess if an increase in adoption is related to the age of the potential customer base. Unlike the ideal experiment described above, however, age structure is not randomly assigned across Indian districts. Therefore, we will also need to convincingly show that our findings are attributable to age rather than other confounding factors that might influence adoption decisions.

The estimation of our empirical model would allow us to test the key prediction of the model: merchants facing more young consumers see a larger value in using mobile payments. This interpretation does not hinge on whether merchants that newly started a payment terminal from the

[48] A district is an administrative unit in India. There are 640 districts in the 2011 Census, with an average of 23 districts per state. There are about 2 million residents per district, which is close to the average population of a county in the United States.

fintech company were entirely new adopters of mobile payments, or transitioned from other mobile payment providers. In either case, observing higher adoption rates in younger districts would still be consistent with mobile payments being more valuable for these merchants.[49]

We implement this strategy by estimating a difference-in-differences model measuring how overall adoption of terminals of the fintech company increased after May 2019 across districts characterized by different age structures. The reduced-form model is:

$$y_{dt} = \alpha_d + \alpha_t + \beta\ (\text{AgeStructure}_d \times 1_{\{t \geq t_0\}}) + \Gamma_t^{'}\mathbf{X}_d + \epsilon_{dt}, \tag{11}$$

where y_{dt} is a measure of adoption of the fintech company's terminals in district d and in month t; α_t and α_d are respectively time and district fixed-effects; and t_0 is May 2019. AgeStructure$_d$ in our baseline model is the share of adults (i.e., 15-74 years old) that are less than 30 years of age, according to the 2011 Census — the most recent Census before the technology rollout, but we consider also alternative treatment definitions below. To facilitate the comparison across variables, we always standardize the treatment variable by subtracting mean and dividing by its standard deviation.[50] $\mathbf{X}_d$ is a vector of district characteristics, measured before the policy, and is allowed to have time-varying effects on the outcome, Γ_t. In all our analyses, we use six months of data before May 2019 (i.e., pre-period) and six months after. When plotting the dynamic effects, we normalize the last month of the pre-period (i.e., April 2019) to zero in the following specification:

$$y_{dt} = \alpha_d + \alpha_t + \sum_{k=-6, k\neq -1}^{k=+6} \beta_k\ (\text{AgeStructure}_d \times 1_{\{t = t_0 + k\}}) + \Gamma_t^{'}\mathbf{X}_d + \epsilon_{dt}. \tag{12}$$

In our baseline specification, we measure the level of adoption y_{dt} with the number of new stores that obtained a terminal from the fintech company in that month, scaled by the number (in hundreds) of firms in the district from the Census.[51] However, as robustness, we also consider alternative ways to measure the same outcome, which we discuss below. Standard errors are clustered at the district level.

[49] If anything, the availability of other mobile-enabled payment systems in the district, and the awareness with merchants regarding these systems, should bias us toward documenting weaker adoption responses.

[50] Unlike our previous analyses, which are largely non-parametric, the tests in this section require us to take a stand on the specific definition of the young population. However, we generally find that the exact definition of "young" or "adult" has little bearing on the final results. We also highlight that the choice of age bucket is influenced by the available age aggregates in the Census.

[51] To clarify, our analysis covers the overall adoption of fintech company's products, not just QR-enabled ones. This method is justified for several reasons. Firstly, our empirical approach focused solely on QR-enabled terminals would be impossible, as their presence was nonexistent before the period in question (though we will later conduct a post-period test on this variable, Appendix Table A-1). Secondly, as explained in the thought experiment, the examination of how overall adoption evolves over time provides insights into how the addition of a mobile payment option changed the demand for merchants. In fact, our approach uses the information on adoption before May 2019 as a benchmark for the district demand for the company's product. Lastly, it is also useful to note that (as expected) the majority of adoption growth in the post-period is attributed to QR-enabled terminals: in fact, about 80% of the increase in new platform users is due to stores opting for QR-enabled terminals.

4.3 Main Results

Table 2 presents the results from the baseline specification 11. On average, the fintech company experienced a larger increase in new businesses joining the platform in areas with a younger population, consistent with our initial hypothesis (column 1). Specifically, we find that one standard deviation increase in the share of young population led to almost 0.05 new businesses joining the platform per hundred firms in the district. This corresponds to roughly a 25% increase relative to the adoption rate right before the policy change (i.e., April 2019). Panel (a) of Figure 3 reproduces the same finding using the dynamic specification, which allows us to identify changes in adoption month-by-month. Consistent with the validity of our design, we find that the share of young adults is not connected in a significant way with adoption during the pre-period. Furthermore, after May 2019, we see a significant increase in adoption. The effect increases over time, with the effect size peaking at more than 0.1 new stores per hundred firms in the district. The same results are confirmed using the inverse hyperbolic sine transformation of the number of new businesses joining the platform as the outcome variable (Panel (a) of Appendix Figure A-5 and Table 2, column 3)

A key concern with our analysis is that age differences are likely to correlate with other district characteristics and these factors may also potentially influence the impact of the policy change on adoption. This issue is evident in Table 3, where we observe that districts with a higher proportion of young adults differ significantly across various dimensions. For example, these areas are generally smaller, exhibit lower literacy rates, have fewer schools, have a reduced percentage of the working population, and are less densely populated, among other traits. Notably, districts with a younger population also tend to feature fewer stores using our partner company's services and record fewer transactions on their platform.[52]

Before addressing this issue empirically, it is critical to highlight that the direction of most relationships observed is in fact *opposite* of what one might anticipate if an omitted variable were explaining the positive link between age structure and adoption. The prevailing literature on technology adoption usually indicates that newer technologies are more readily adopted in areas with higher education levels and greater wealth (Caselli and Coleman 2001). Contrary to this, our findings imply that, if anything, regions with a younger population tend to be less educated and exhibit lower economic activity (Jones et al. 2010). If this observation is correct, we expect to find that including these controls increases the size of the effect.

To directly mitigate this concern, we incorporate a wide set of district-level controls in our empirical model. In particular, our analysis controls for population, number of firms, the share of agricultural workers, the share of literate individuals, the share of the working population, and the average amount of night light in 2018, as a proxy of overall economic activity.[53] As we show in Table

[52] In principle, this stylized fact is consistent with our theory: before May 2019, our partner company did not offer mobile options and therefore this company was less attractive in areas where a larger share of the population has a preference for mobile payments.

[53] Variables that are aggregates (e.g., population) are included after being log-transformed. We selected controls in a parsimonious way, and we discuss below (Appendix Figure A-6) how our result is robust to alternative ways to select the set of controls included in this analysis.

3, we find that once we control for these variables, districts with different demographic structures do not differ across other observed characteristics. Consistent with our earlier intuition, the magnitude of the effects increases slightly when controls are included (Table 2, columns 2 and 4), and estimates in the dynamic analysis generally becomes more precise (panel (b) of Figure 3).[54] Importantly, our results are not driven by any single controls, therefore assuaging any concern on the robustness of the control selection. In Appendix Figure A-6, we plot the dynamic effects including one control at the time. Although the precise magnitude varies slightly across specifications, both the sign and the general scale of the estimates remain stable across models.

The age structure not only predicts the increase in adoption for our fintech company following the introduction of QR-enabled terminals but also explains the share of stores that opted for QR-enabled terminals in the post-period. Indeed, stores could continue to adopt our fintech company's services and request card-only POS terminals after May 2019.[55] In Table A-1, we explore whether the district-level share of adopting stores with QR-enabled terminals in the post-period is associated with the age structure. It is important to note that this analysis is strictly cross-sectional, as QR-enabled terminals were only available in the post-period. We find that districts with a younger population showed a higher preference for QR-enabled terminals among adopters, and this result holds both with and without our standard set of controls. This result aligns well with our model's prediction, supporting the notion that the increase in adoption documented earlier was driven by the introduction of QR-enabled terminals.

Appendix A.2.2 discusses some ancillary results. Among others, we show that the findings do not depend on how we construct the share of young individuals in a district (Appendix Figures A-7 and A-8) or on the definition of outcomes (Appendix Figure A-9). We also document that the increase in adoptions is associated with a broader rise in the number of stores active on the platform (Appendix Figure A-10).

4.4 Age and historical fertility: a 2SLS application

As previously mentioned, one possible concern with our findings is that omitted variables influence both the age distribution and adoption rates. One such omitted variable bias could stem out if younger individuals gravitate towards areas of greater economic dynamism, which could independently drive the uptake of new digital payment methods, regardless of demographic disparities. Although this hypothesis seems at odds with the summary statistics presented earlier (Table 3), we cannot categorically dismiss the possibility that such a mechanism might operate through factors not observable in our data.

To address the concern regarding the selection of younger individuals into more economically dynamic areas, we introduce a test designed to isolate variation in the age distribution at the time

[54] The same holds when we use the inverse hyperbolic sine transformation of the number of new stores joining the platform as the outcome variable (Appendix Figure A-5).

[55] As we mentioned before, while some firms continue adopting card-only POS, we also see in aggregate that about 80% of the increase in new platform members is due to stores opting for QR-enabled terminals.

of our study that is independent of migration patterns from previous decades and only captures the historical characteristics of the districts. The underlying idea is as follows: the proportion of young adults in a given region is influenced by both migration trends and the fertility rates within districts several decades earlier. All else equal, it is reasonable to expect that districts that exhibited higher fertility rates in the 1990s will have a greater proportion of young adults by 2010. Hence, by leveraging only the variation in the current age structure attributable to differences in historical fertility rates, our findings should be shielded from critiques pertaining to migration effects.

The sex ratio from the past represents a good candidate for the current age structure. A skewed sex ratio can affect the marriage market and consequently fertility (Guilmoto 2012; Dyson 2012; Angrist 2000). Therefore, we should expect that regions with a more skewed sex ratio in the early 1990s may end up with fewer kids, and therefore a smaller share of young adults in the early 2010s. This idea seems to be supported by the data: in Appendix Figure A-11, we plot the share of young adults (i.e., adults less than thirty) in 2010 against the district-level sex ratio in 1991, measured as the ratio of male to female.[56] Consistent with this idea, we find that districts that are at either tail of the distribution tend to have a smaller share of young adults twenty years later. This relationship can be confirmed formally: in Table 4, we predict the share of young adults used in this paper with the quadratic function of the sex ratio in 1991. The analysis finds that the historical sex ratio strongly predicts the future share of young adults, with the largest share of the young population present in districts with a sex ratio slightly above one.[57] The Sanderson and Windmeijer (2016) multivariate first-stage F-statistics for the validity of the instruments is 43.46. As the Stock–Yogo 10 percent and 15 percent critical values for a perfectly identified model with two excluded instruments are, respectively, 19.93 and 11.59, we can reject that the instruments are weak.

Building on this result, we implement a 2SLS estimator, where we instrument the share of young adults in 2011 – our main treatment variable in the analyses above – with a quadratic function of the sex ratio in 1991. Before showing the result, we want to clarify what the purpose of this 2SLS is. Our goal is to replicate our main findings with a historical measure that is less likely to be affected by the level of dynamism in the district in 2019. We implement this approach as a 2SLS (rather than in reduced form) because this allows us to generate estimates that are directly comparable to the OLS presented before, while using historical information about the district. However, we recognize that an exclusion restriction is unlikely to hold, since the historical sex ratio may affect other aspects of the local economy beyond the age distribution.

With these caveats in mind, the results are presented in Figure 4: as usual, we present the results dynamically around May 2019. The estimates using the 2SLS are qualitatively close to our baseline estimates in terms of dynamics and magnitude (panel a): we find that the age structure

[56] We source this information from the 2011 Census which provides the number of males and females across Indian districts by each decade since 1901. Importantly, the Census data provides this information using the definition of districts in 2011.

[57] Our analysis suggests that the sex ratio maximizing the share of young adults in our context is between 1.1 and 1.2, with lower natality at the tail. This evidence appears consistent with the previous literature on the topic (Hesketh and Xing 2006; Hesketh and Min 2012).

does not systematically predict differential adoption before May 2019, and we confirm that districts with more young individuals saw a larger increase in adoption afterwards. However, the magnitude of the effect is larger. The same result also holds when we include all controls that were employed in our main specification, as considered before (panel b). Columns 2 and 3 of Table 4 confirms the same result when comparing the average behavior pre- and post-May 2019.

This evidence confirms that our results do not simply reflect the sorting of young people towards more dynamic areas. Instead, this evidence is consistent with the idea that structural demographic characteristics may be important to understand the diffusion of technologies from the business side. In fact, locations that were expected to have a higher share of young people based on historical demographic structure saw larger adoption after the QR code was available.

4.5 An alternative approach: the location of universities

The findings detailed above validate the key prediction of the model: merchants in regions populated by younger individuals tend to be more interested in adopting the new technology, mobile payment. As a way to further bolster our result, we present a new test that does not rely on district-level measures of demographic structure, but exploits variation of consumer demand *within* a district. In particular, we leverage the presence of universities in the country as a way to create differences in demand from young adults across neighborhoods within the same district. The premise is that neighborhoods with a university tend to receive a daily influx of young adults, who could constitute a significant share of customers. Concurrently, these areas are experiencing similar general economic and social conditions to those of businesses located in the same district but in a different neighborhood. If this assumption holds, then a comparative analysis of adoption rates within a district, between areas with and without a university, could provide supplementary evidence to the discussion above and help address the issue raised.

Among the others, this test allows us to address specific concerns about the importance of the heterogeneity in business owners' characteristics in explaining our findings. In fact, a possible alternative interpretation is that regions with a younger demographic could also have a higher share of younger entrepreneurs who may be more inclined to adopt mobile payment methods, regardless of customer demand. The proposed test outlined here addresses this issue because neighborhoods with a university should face stronger demand from young adults, because of the daily influx of students. However, there is no basis to believe that business owners in these areas are systematically younger than those living in other areas of the same districts. Furthermore, this setting allows us to directly rule out this alternative interpretation by exploiting merchant-level variation. For instance, as we discuss below, we can use the set of businesses that do not normally cater to university students as a placebo test.

To test this hypothesis, we manually compiled a list of universities in India and linked each to its official location, identified by a (six-digit) pincode.[58] With this data, we are able to identify the list of pincodes in India that host at least one university. Then, we estimate a differences-in-differences

[58]See Data Appendix A.1 for more info on the methodology employed to gather this information.

estimator of the following form:

$$y_{pt} = \alpha_{dt} + \alpha_p + \sum_{k=-6,k\neq-1}^{k=+6} \gamma_k \, \left(1\{Univ = 1\}_p \times 1_{\{t=t_0+k\}}\right) + \nu_{pt} \tag{13}$$

where y_{pt} is a measure of adoption of terminals provided by our fintech company at the pincode p and month t level; α_{dt} and α_p are, respectively, district-by-month and pincode fixed-effects; $1\{Univ = 1\}_p$ is a dummy variable equal to one if the pincode has at least one university.[59] Given the absence of information on the number of firms that operate in a pincode, we cannot utilize the rate of adoption relative to firms as our primary outcome y_{pt}. Nonetheless, in line with the findings presented earlier, we will employ both the raw number of adoptions and the inverse hyperbolic sine (IHS) transformation of the adoption numbers as alternative measures. Standard errors are clustered at the pincode level to accommodate this approach.

The findings are detailed in Figure 5: in line with our initial hypothesis, we observe that pincodes hosting a university experienced a more substantial increase in the number of stores adopting our fintech services compared to other pincodes within the same district. The magnitude of the effects is significant: pincodes with a university witnessed approximately a 20% greater increase in adoption over a few months, with this disparity enduring throughout most of the post-intervention period. Appendix Figure A-12 corroborates this result by utilizing the raw count of new stores adopting the fintech company's terminals each month as the outcome.[60] Table 5 confirms the same result when comparing the average behavior pre- and post-May 2019.

Therefore, the presence of university plays a significant economic role in explaining the increased demand for mobile payment options in our sample. We interpret these findings as evidence that young adult customers—who tend to prefer mobile payments over cards, as documented earlier—affect local businesses' adoption of mobile payment technology. Consistent with this interpretation, we show that our results are driven by merchants likely to interact with students.[61] As detailed in Appendix A.2.2, we identify student-serving businesses as those in the non-tradable sector that rely on highly localized consumer demand (e.g., restaurants, retailers). We also consider a broader definition that encompasses financial services, healthcare providers (e.g., pharmacies), and educational services. For these merchants, we find an increase in adoption consistent with our earlier findings (Table A-2 and panels (a) and (b) in Figure A-14). Conversely, as shown in panel (c) of Figure A-14, we find no difference in adoption in university pincodes for businesses that are unlikely to cater to local students (e.g., manufacturing, wholesale, professional services, ...).[62]

[59] Similar to before, we use six months of data before May 2019 (i.e., pre-period) and six months after. Therefore, the last month of data used in this analysis is November 2019. When plotting the dynamic effects, we normalize the last month of the pre-period (i.e., April 2019) to zero.

[60] As expected, in Appendix Figure A-13 we replicate the findings discussed above by manually dropping districts without any university and find identical results.

[61] In fact, one advantage of the university analysis is that it assumes the increase in demand originates specifically from university students. This feature allows us to generate predictions about the heterogeneity of the effects at store level.

[62] A more detailed discussion of these tests is provided in Appendix A.2.2. We also find a positive and significant

Taken together, these results support a demand-driven interpretation of the university effect: proximity to universities increases adoption primarily in sectors serving students, while leaving other merchants unaffected. This pattern is difficult to reconcile with explanations based on merchant characteristics and is consistent with differences in consumer age composition shaping technology adoption incentives.

5 Policy implications

The evidence presented in Section 4 is consistent with the key implication of the model (Section 3): the presence of an older population leads to lower adoption by businesses. In this section, we use the same model to understand the possible welfare implications of demographic differences. Furthermore, we examine how various commonly used policy tools can help limit these welfare costs.

Whether and how to subsidize electronic payments adoption is a question of practical relevance. In recent years, governments in a number of countries have put in place incentive schemes aimed at fostering adoption of these technologies by small businesses. In India, starting in 2018, the government reimburses all Merchant Discount Rate (MDR) fees on electronic transactions, including UPI, to small merchants.[63] In 2025, the government took the additional step to provide subsidies proportional to the cost of transactions for small merchants processing payments through the UPI.[64] Subsidies proportional to the revenue generated through electronic payments platforms exist in other countries as well.[65] An alternative approach, sometimes used in tandem with subsidies that vary with electronic payment volume, is to subsidize the cost of adopting payment terminals themselves.[66] Motivated by these examples, in what follows we analyze the effects of the two types of incentive schemes, those designed as subsidies proportional to the value of sales, and those offsetting part of or the totality of adoption costs for merchants.[67] Proofs are in Appendix A.4.[68]

effect for those merchants that could not be categorized into any of the discussed groups due to missing merchant codes or classification under the miscellaneous category (column 4 of Table A-2). We interpret this result as consistent with our interpretation, as this group likely consists of small establishments broadly in the retail sector but not cleanly fitting into a specific sub-category (e.g., a street cart serving prepared food while also selling produce).

[63] See here for the government announcement.

[64] The subsidy is 0.15% of transaction value up to a fixed notional amount; details are discussed here.

[65] Italy adopted a scheme similar to India, involving tax credits that offset fees charged by payments providers; see details here). Other countries, like Uruguay (see here as well as Brockmeyer and Sáenz Somarriba 2025) and Japan (see here), opted instead for reductions in VAT for consumers paying electronically.

[66] The Italian, Uruguayan, and Japanese incentive schemes also involves tax credits offsetting the cost of purchasing or leasing the point of sales (POS) terminal. Singapore adopted a similar scheme during COVID, aimed at very small businesses, while Greece more recently also introduced a program aimed at subsidizing the cost of purchasing the terminal; for Singapore, see here, and for Greece, see here.

[67] Our analysis focuses on the case where the number of businesses is fixed, but Appendix A.4 discusses the need for and optimal design of subsidies in the case of free-entry.

[68] In this section, we use the words "technology adoption" to refer to $\tilde{b}$, the level of technology chosen by firms. The impact on household welfare is either $b = \tilde{b}$ without externalities, or $b = \tilde{b}^{1+\theta}$ with externalities.

5.1 Distortions relative to first-best

As a benchmark for evaluating policies, we use the first-best allocation. Deriving this allocation also helps clarify the inefficiencies at work in the competitive equilibrium (CE).[69]

Definition 1. *The first-best (FB) allocation consists of values for* $\left\{O_o, O_y, c_o, c_y, \tilde{b}\right\}$ *that maximize the welfare criterion:*

$$W = \eta W_o + (1-\eta)W_y = \eta \log\left(O_o^{1-\alpha} C_o^{\alpha}\right) + (1-\eta)\log\left(O_y^{1-\alpha} C_y^{\alpha}\right), \tag{14}$$

subject to the resource constraint:

$$\eta O_o + (1-\eta)O_y + J\xi\left(\eta c_o + (1-\eta)c_y\right) + J\left(\gamma(\tilde{b}) + \nu\right) \leq E,$$

where $C_o = J^{\frac{1}{\rho}} c_o$ *and* $C_y = J^{\frac{1}{\rho}} \tilde{b}^{(1+\theta)\frac{1-\rho}{\rho}} c_y$.

Result 2 (First-best allocation)**.** *In the first-best allocation, the planner chooses* $(c_y, \tilde{b})$ *so that:*

$$(1+\theta)(1-\eta)\frac{1-\rho}{\rho}\frac{c_y}{\tilde{b}} = \frac{\gamma'(\tilde{b})}{\xi}. \tag{15}$$

Moreover, the first-best allocation is consistent with utility maximization of consumers if prices are equal to the marginal cost of production, $p = \xi$, *so that business profits are strictly negative. Finally, in the first-best allocation, so long as* $\eta < 1$, *technology adoption is higher than in the competitive equilibrium (CE):*

$$\tilde{b}_{FB} > \tilde{b}_{CE} \quad \textit{iff} \quad \eta < 1.$$

This is true even in the absence of adoption externalities ($\theta = 0$)*.*

To interpret this result, recall that in the competitive equilibrium, the first-order condition relating output and technology adoption is:

$$(1-\eta)\frac{1-\rho}{\rho}\frac{c_y}{\tilde{b}} = \frac{\gamma'(\tilde{b})}{\xi}. \tag{16}$$

In order to clarify the sources of inefficient adoption at work in the model, we discuss Result 2 separately for the case without externalities ($\theta = 0$) and with externalities ($\theta > 0$).

[69] In Appendix A.4, we also compare the CE allocation to another benchmark, the "constrained optimal" (CO) allocation (Dixit and Stiglitz 1977; Dhingra and Morrow 2019). This allocation maximizes welfare subject to businesses breaking even. The comparison between the CO and the CE is largely similar to our comparison of the FB and the CE, with one notable exception: under free-entry, in the absence of externalities ($\theta = 0$), the CE and the CO exactly coincide. This is a version of the classic Dixit and Stiglitz (1977) constrained efficiency result applied to our framework, which includes heterogeneous consumers and a technology choice. Our focus is on optimal adoption subsidies. With adoption subsidies, the set of feasible allocations in the CE contains some that would violate the positive profit condition without subsidies, and are therefore not feasible in the CO. Because our subsidies are financed from lump-sum taxation of the household, they are within the feasible set of the FB planning problem. This motivates us to use the FB as our benchmark.

1. No externalities ($\theta = 0$)

When $\theta = 0$, the only difference between the CE and FB is monopoly pricing. We establish three findings. First, monopoly distortions alone cause under-investment in technology. Second, and perhaps surprisingly, the magnitude of this under-investment does not vary substantially with demographics. Third, while young consumers are worse off when they coexist with many old consumers, this is true in both CE and FB, and the *incremental* welfare loss from monopoly distortions is largely independent of demographic composition.

Monopoly distortions alone reduce technology adoption. When $\theta = 0$, Equations (15) and (16) are identical. The social and private marginal rates of substitution between output and technology coincide: for a given level of output c_y, the corresponding adoption choice in the CE is first-best efficient. Yet Result 2 states that technology adoption is too low in the CE relative to FB, so long as some consumers value the technology ($\eta < 1$).

The reason is that output itself is distorted. Monopolistically competitive firms restrict quantities to charge higher prices. The top left panel of Figure 6 confirms that the ratio $c_{y,CE}/c_{y,FB}$ is below one. Because output and technology adoption are complements, the quantity restriction causes under-investment in technology. The top right panel of Figure 6 shows that the ratio $\tilde{b}_{CE}/\tilde{b}_{FB}$ is also below one. Thus monopoly distortions alone reduce technology adoption relative to FB, creating a potential role for policy even absent externalities.

Demographics have a limited effect on the adoption gap. A natural conjecture is that under-investment might be more severe in younger markets, where more consumers value the technology. The top right panel of Figure 6 shows that this is not the case: when $\theta = 0$, the ratio $\tilde{b}_{CE}/\tilde{b}_{FB}$ is nearly constant across values of η, except as $\eta \to 1$.

The intuition is as follows. Monopoly pricing reduces output by a factor that depends on the price elasticity ρ and income share α, but not on η, as we have assumed that both ρ and α are homogeneous across consumers. To a first approximation, the output gap $c_{y,CE}/c_{y,FB}$ is therefore independent of demographics.[70] Now consider the adoption gap. Equations (15) and (16) are identical when $\theta = 0$, so in both CE and FB, the product $\tilde{b}\gamma'(\tilde{b})$ is proportional to $(1-\eta)c_y$:

$$\tilde{b}\gamma'(\tilde{b}) = (1-\eta)\frac{1-\rho}{\rho}\xi\, c_y.$$

The term $(1-\eta)$ appears identically on both sides of the CE-FB comparison and therefore cancels

[70] Appendix A.4 shows that the output ratio can be written as:

$$\frac{c_{y,CE}}{c_{y,FB}} = \frac{\rho}{1-(1-\rho)\alpha} \cdot \frac{1-\Phi_{CE}}{1-\Phi_{FB}},$$

where Φ_{CE} and Φ_{FB} are the shares of overhead costs in total resources under the CE and FB allocations, respectively. The leading term $\rho/[1-(1-\rho)\alpha]$ combines the direct markup effect (ρ) with general equilibrium income feedback ($1/[1-(1-\rho)\alpha]$); neither depends on η. When overhead costs are small, the second factor is approximately one, and demographic variation in the output gap is negligible.

when taking ratios. If the output gap is independent of η, so is the adoption gap.[71]

Welfare consequences Appendix A.4 shows that the aggregate welfare gap between CE and FB can be decomposed as:

$$\begin{aligned} W_{CE} - W_{FB} &= \underbrace{\log(\rho^{\alpha}(1-(1-\rho)\alpha))}_{\text{(i) markup distortion}} \\ &+ \underbrace{\log\left(\frac{E - J(\gamma(\tilde{b}_{CE})+\nu)}{E - J(\gamma(\tilde{b}_{FB})+\nu)}\right)}_{\text{(ii) overhead costs}} \\ &+ \underbrace{(1-\eta)\alpha(1+\theta)\frac{1-\rho}{\rho}\log\left(\frac{\tilde{b}_{CE}}{\tilde{b}_{FB}}\right)}_{\text{(iii) technology benefits}} \end{aligned} \tag{17}$$

Term (i) captures the direct welfare effect of markups: higher prices reduce consumer surplus, independent of both technology and demographics. Terms (ii) and (iii) capture opposing effects of the adoption gap: lower adoption in the CE reduces overhead costs (raising income and welfare), but also reduces the technology benefits enjoyed by young consumers. When $\theta = 0$, both terms depend on the adoption gap $\tilde{b}_{CE}/\tilde{b}_{FB}$, which we have argued is largely invariant to η. The middle left panel of Figure 6 confirms that aggregate welfare losses are approximately constant across demographic compositions.

The middle right panel examines the welfare of individual consumers. For old consumers, technology adoption is irrelevant; their welfare gap between CE and FB reflects only the markup distortion, which is constant in η. For young consumers, the picture is more nuanced. The figure plots W_y in both CE and FB, normalized by its FB value when $\eta = 0$. Both lines decline sharply as η increases: as the population ages, firms adopt less technology, directly harming young consumers. However, because the adoption *gap* between CE and FB is stable across η, the distance between the two lines, which is the incremental welfare loss to young consumers from monopoly distortions, does not vary substantially with demographics.

Summary When $\theta = 0$, monopoly distortions cause under-investment in technology relative to first-best. However, the magnitude of this distortion is largely independent of demographics: markups reduce output proportionally regardless of the age composition, and the adoption gap inherits this invariance. Young consumers are worse off in older populations because firms adopt less technology, but this is equally true in CE and FB. The welfare losses from monopoly pricing

[71]This argument is exact in a version of the model where household income is exogenous. There, markups reduce output by exactly the factor ρ, so that $c_{y,CE}/c_{y,FB} = \rho$ regardless of η. With endogenous income from profit rebates, general equilibrium effects introduce mild demographic variation in the output gap, as visible in the top left panel of Figure 6. However, these effects are quantitatively small, and the dominant force remains the direct, demographic-invariant effect of markups.

do not fall disproportionately on markets with particular demographic structures.

2. Externalities ($\theta > 0$)

When $\theta > 0$, a second distortion arises: firms fail to internalize that their adoption decisions benefit young consumers economy-wide. We highlight two changes relative to the case $\theta = 0$. First, the adoption gap between CE and FB is larger. Second, this gap now varies with demographics.

The adoption gap is larger and varies with demographics. Comparing Equations (15) and (16), the wedge between the social and private marginal rate of substitution is now $(1 + \theta)$ rather than one. Firms in the CE equate the marginal cost of adoption to its private benefit (their own market share gains) while the planner accounts for the additional benefit that higher aggregate adoption confers on young consumers through the externality. The top right panel of Figure 6 shows that, when $\theta > 0$, the ratio $\tilde{b}_{CE}/\tilde{b}_{FB}$ is lower than when $\theta = 0$.

Unlike the case $\theta = 0$, the adoption gap now varies with demographics. Two considerations help interpret this pattern. First, as $\eta \to 1$, both CE and FB lead to minimal adoption ($\tilde{b} \to 1$) since few consumers value the technology. Second, when η is low, the FB planner chooses high adoption to capture externality benefits for the many young consumers; the CE fails to do so because firms do not internalize these spillovers. Near $\eta = 0$, high adoption in the FB incurs substantial overhead costs $\gamma(\tilde{b}_{FB})$, which constrain the planner's choice and moderate the gap relative to CE. As η rises and FB adoption falls, this resource constraint loosens, first widening the gap, before both regimes converge to minimal adoption as $\eta \to 1$.

A perhaps surprising feature of the top left panel of Figure 6 is that, when θ is large and η is small, output in the CE can exceed its FB level. The planner, facing strong externalities, chooses high adoption to capture the associated welfare benefits. But high adoption requires high overhead costs $\gamma(\tilde{b}) + \nu$ per firm. These costs lower profits and therefore household income. In the CE, by contrast, firms under-invest in the technology, but their lower overhead costs lead to higher household income. The result is higher consumption and output relative to FB.

Welfare losses are larger and concentrated among the young. The bottom left panel of Figure 6 shows that, when $\theta > 0$, the aggregate welfare gap between CE and FB is larger than when $\theta = 0$. Moreover, unlike the case without externalities, this gap varies with demographics: welfare losses are largest when η is small. This reflects term (17) in the welfare decomposition: the welfare benefits of adoption are weighted by $(1 - \eta)(1 + \theta)$, so under-adoption is most costly when many consumers value the technology and externalities amplify the gains.

The bottom right panel shows that young consumers bear the burden of this inefficiency. Compared to the case $\theta = 0$, the gap between W_y in FB and CE is larger, and this gap widens as η falls. In young populations, the planner would choose high adoption, generating large welfare gains for young consumers through both direct preferences and externalities; the CE fails to deliver these gains. Old consumers, by contrast, do not benefit from adoption; their welfare gap between CE and FB reflects only the markup distortion and is unaffected by θ.

Summary With externalities, the CE features two distortions: monopoly pricing and failure to internalize adoption spillovers. The resulting under-investment in technology is more severe than when $\theta = 0$, and, unlike that case, varies with demographics. Output can be higher in the CE than in the FB, because under-adoption in the CE conserves resources that the planner would devote to technology investment. However, this comes at the cost of foregone adoption benefits, and welfare losses are concentrated precisely where the potential gains from adoption are largest: in young populations.

5.2 Subsidizing adoption costs

Consider encouraging the adoption of the technology by using a constant marginal subsidy rate τ to the adoption cost.[72] Firm profits become:

$$\pi = (p - \xi)(\eta c_o + (1-\eta)c_y) - ((1-\tau)\gamma(\tilde{b}) + \nu).$$

Moreover, assume that the subsidy is financed via lump-sum taxation so that incomes become:

$$I = E + J\left(\pi - \tau\gamma(\tilde{b})\right).$$

Appendix A.3 characterizes the competitive equilibrium with an adoption subsidy. We ask the following question: what value of the subsidy maximizes the welfare criterion (14)?

Result 3 (Optimal adoption subsidy)**.** *The optimal adoption subsidy is given by:*

$$\tau^* = \begin{cases} 0 & \text{if} \quad \eta = 1 \\ 1 - \dfrac{1}{1+\theta}\dfrac{\rho}{1-(1-\rho)\alpha} & \text{if} \quad 0 \leq \eta < 1 \end{cases}$$

In particular, (a) so long as $\eta < 1$, τ^* is strictly positive even in the absence of externalities; (b) it increases with the strength of externalities, θ; (c) it is independent of η so long as $\eta < 1$; (d) it is independent of the features of technology adoption costs, $\gamma(.)$. Under the optimal adoption subsidy, adoption reaches its first-best level, but output does not:

$$\tilde{b}_{CE}(\tau^*) = \tilde{b}_{FB}, \quad c_{y,CE}(\tau^*) < c_{y,FB}.$$

This result has several interesting features. First, the optimal subsidy is positive even without externalities ($\theta = 0$). This is because monopoly distortions alone lead to under-adoption, highlighting that externalities are not necessary to justify technology adoption subsidies.

[72] In a model with business taxes, this could capture a rate of deductibility of expenses related to technology adoption from taxable business income.

Second, the optimal adoption subsidy is independent of the share of young consumers, so long as that share is non-zero (that is, so long as $\eta < 1$). To understand why, consider the two first-order conditions characterizing the optimal ratio of technology adoption to output in the CE with a subsidy and in the FB:

$$
\begin{aligned}
(1-\eta)\frac{1-\rho}{\rho}\frac{c_{y,CE}}{\tilde{b}_{CE}} &= (1-\tau)\gamma'(\tilde{b}_{CE}) \\
(1+\theta)(1-\eta)\frac{1-\rho}{\rho}\frac{c_{y,FB}}{\tilde{b}_{FB}} &= \gamma'(\tilde{b}_{FB})
\end{aligned}
$$

Both the planner and the market weigh the benefits of the technology by the fraction of young consumers, $1-\eta$; and both agree on the marginal cost of adoption. Suppose that there were a subsidy level that equalized adoption between the CE and FB; then taking ratios of the first-order conditions above, one obtains:

$$
\frac{c_{y,CE}}{c_{y,FB}} = (1-\tau)(1+\theta). \tag{18}
$$

Furthermore, because markups are constant, both income and prices in the CE are simple multiplicative function of those corresponding to the FB.[73] As a result, under identical technology adoption choices:

$$
\frac{c_{y,CE}}{c_{y,FB}} = \frac{\rho}{1-(1-\rho)\alpha}, \tag{19}
$$

which is independent of demographics or of the shape of the technology adoption costs. Comparing (18) and (19), we see that the subsidy consistent with raising the CE adoption level to its FB counterpart must be independent of demographics or the shape of technology adoption costs.[74]

The reason why the planner setting the subsidy uses it to restore adoption to its first-best level is that the subsidy itself does not affect the markup chosen by businesses, which remains equal to $1/\rho$ even with the subsidy. Thus the planner cannot target directly the monopoly distortion, but it can mitigate its effects on technology adoption. This is also the reason why the subsidy fails to restore the first-best allocation and consumption remains distorted downward.

Finally, note that a lower bound on the optimal adoption subsidy is given by:

$$
\tau^* \geq \underline{\tau}^* = 1 - \frac{\rho}{1-(1-\rho)\alpha}.
$$

This lower bound (which coincides with the optimal subsidy when $\theta = 0$) can be viewed as the Pigouvian subsidy that exactly offsets the effects of the monopoly distortion on adoption; network externalities then further add subsidy incentives beyond that lower bound.[75]

[73] This property would hold even without technology choice in the model, and only depends on CES preferences.

[74] Appendix A.4 further discusses the intuition for why the optimal adoption subsidy is invariant to demographic composition, so long as $\eta < 1$.

[75] See Appendix A.4 for a further discussion.

5.3 Subsidizing electronic transactions

We next study the effects of a differentiated subsidy, which, similar to those recently implemented in some countries and discussed at the start of this section, targets specifically transactions conducted using electronic payment technologies. We assume that the revenue earned by firm j from its sales to young consumers (who use electronic payments) and old consumers (who do not) are given, respectively, by:

$$R_y(j) = (1-\eta)(1+\varepsilon)p(j)c_y(j), \quad R_o(j) = \eta p(j)c_o(j),$$

where ε represents the subsidy (or tax, if $\varepsilon > 0$) on electronic transactions. Subsidies are financed via lump-sum taxation of households.

Appendix A.4 shows that with a transaction subsidy, the two first-order conditions for adoption and prices can be written as:

$$\begin{aligned}
(1-\eta)\frac{1+\varepsilon-\tilde{\rho}(\varepsilon)}{\tilde{\rho}(\varepsilon)}\frac{c_y}{\tilde{b}} &= \frac{\gamma'(\tilde{b})}{\xi} \\
p &= \frac{\xi}{\tilde{\rho}(\varepsilon)} \\
\tilde{\rho}(\varepsilon) &\equiv (1+(1-\eta)\varepsilon)\rho
\end{aligned}$$

Similar to the adoption subsidy, the transaction subsidy affects the marginal rate of substitution between output and the level of technology adoption, and thus impacts adoption for a given level of output. Specifically, for a given output level, a higher subsidy (a higher value of ε) increases the marginal rate of substitution between consumption and adoption, without changing the marginal rate of transformation. All else equal this increases adoption.

However, different from the adoption subsidy, the transaction subsidy also affects markups. Specifically, firms charge lower markups when $\varepsilon > 0$ than they would otherwise. Moreover, this effect is stronger, the higher the share of young households.

Using the expressions derived above, one sees that the first-order condition governing the optimal transaction subsidy is:

$$0 = \underbrace{\frac{1}{I}\frac{\partial I}{\partial \varepsilon} - \frac{\alpha}{p}\frac{\partial p}{\partial \varepsilon}}_{\text{Effect on markups}} + \left(\underbrace{\alpha(1-\eta)(1+\theta)\frac{1-\rho}{\rho} + \frac{\tilde{b}}{I}\frac{\partial I}{\partial \tilde{b}}}_{\text{Effect on adoption}}\right)\frac{1}{\tilde{b}}\frac{\partial \tilde{b}}{\partial \varepsilon}.$$

The first part of this equation captures the direct effect of the subsidy on equilibrium markups, and therefore incomes and quantities. In a model with no adoption but with a subsidy to sales, this is the only term that would feature in the first-order condition governing the optimal choice of the transaction subsidy. The transaction subsidy for which this term is equal to zero is simply the one that neutralizes markups, i.e. $\tilde{\rho}(\varepsilon_1) = 1$, or:

$$\varepsilon_1 = \frac{1}{1-\eta}\frac{1-\rho}{\rho}.$$

This term is increasing with respect to the share of old consumers, η. This is because only sales to the young are affected by the subsidy; a planner wanting to neutralize markups must subsidize sales to the young more if their overall market share is lower.

The term highlighted in the second part of the equation represents the indirect effect of the subsidy on the rate of adoption. It captures a trade-off between the utility benefits from higher adoption (which accrue to the young), and the lower income associated with the overhead costs of adoption. This second term is equal to zero if the subsidy is given by:

$$\varepsilon_2 = \frac{(1+\theta)(1-\alpha(1-\rho))-\rho}{1-(1-\eta)(\rho+(1+\theta)(1-\rho)\alpha)}\frac{1-\rho}{\rho}.$$

Because the numerator in this expression is positive, the subsidy ε_2 is strictly decreasing with respect to the share of old consumers, η. For a given subsidy level, ε, an older population leads to higher markups; in turn, higher markups reduce the elasticity of income to adoption. On the other hand, the utility benefits of higher adoption for each young household do not depend on the share of old consumers, η. The net effect is that, as η increases, the subsidy level that equates the elasticity of income to adoption, to the marginal utility benefits from higher adoption, declines.

Thus there are two forces at play shaping the optimal transaction subsidy: the effect of the monopoly distortion on quantities, and the wedges in the marginal rate of substitution between output and adoption. As a result, while the optimal transaction subsidy depends on the demographic share (unlike the optimal transaction subsidy), it need not be, in general, a monotonic function of it. The right panel of Figure 7 illustrates this in a numerical example, by reporting the optimal transaction subsidy as a function of the demographic share, as well as comparing the resulting levels of output and adoption in both the CE with $\varepsilon = 0$ and the CE with the optimal transaction tax.

The optimal stand-alone transaction subsidy is an decreasing function of the demographic share η in an intermediate range of values for η, the share of old consumers; in this case, the adoption effect dominates, and the planner subsidizes the technology less if the population is older. For η closer 1, on the other hand, the markup effect dominates, and the planner subsidizes the technology more if the population is older. Finally, when η is very close to 1, the subsidy becomes very large. At this stage, the only reason for the planner to subsidize transactions is to eliminate markups, so that $\varepsilon^{**} \approx \varepsilon_1$. This requires applying a very large subsidy because the consumer base whose demand is sensitive to the subsidy becomes vanishingly small. This effect is also present in the optimal joint subsidy scheme discussed in Section 5.4 below.

The middle panel of Figure 7 shows that the subsidy always increases adoption relative to the CE with no subsidy. With the transaction subsidy, on the other hand, output can decline, as shown in the left panel of Figure 7; this is because the higher levels of adoption induced by the subsidy increase overhead costs and lower pre-tax firm profits, and therefore household income, thus resulting in lower overall demand (but higher welfare, becuase of the higher adoption rate).

Thus a transaction subsidy alone has generally positive welfare effects, and always increases adoption relative to the competitive equilibrium, though it need not have a monotonic relationship to the share of young consumers.

5.4 Jointly optimal subsidy scheme

Neither subsidy scheme, on a stand-alone basis, is sufficient to jointly address the distortions associated with monopoly pricing and network externalities, so it is natural to ask whether a joint subsidy scheme targeting both adoption costs and transactions could be. As noted above, many subsidy schemes implemented in recent years have that structure. In the context of our model, the optimal joint subsidy scheme within this class can be characterized as follows.

Result 4 (Optimal joint subsidy)**.** *The optimal joint subsidy scheme is:*

$$\tau^{**}\begin{cases} \in [0,1[& \textit{if} \quad \eta = 1 \\ = 1 - \dfrac{1}{1+\theta}\dfrac{1}{1-\eta} & \textit{if} \quad 0 \leq \eta < 1 \end{cases}$$

$$\varepsilon^{**}\begin{cases} \in [0,+\infty[& \textit{if} \quad \eta = 1 \\ = \dfrac{1}{1-\eta}\dfrac{\rho}{1-\rho} & \textit{if} \quad 0 \leq \eta < 1 \end{cases}$$

This subsidy scheme neutralizes equilibrium markups, so that $p = \xi$ in the CE. Furthermore, the resulting levels of output and technology adoption coincide with the first-best.

There are two main things to note about this result. First, the optimal subsidy scheme yields the first-best allocation. The two policy tools (the adoption subsidy and the transaction subsidy) can be used to target separately the two externalities in the model. Second, the instruments play distinct roles, and therefore vary differently with demographics. The optimal subsidy scheme uses the transaction subsidy to target the markup directly, undoing the monopoly distortion on quantities sold. For the reasons described above, this requires a transaction subsidy that is increasing with the age of the population. On the other hand, the adoption subsidy adjusts the private marginal rate of substitution between output and adoption so as to match its social value. This requires an adoption subsidy that declines with the age of consumers.[76]

[76] When θ is small, τ^{**} is negative, implying a tax on adoption rather than a subsidy. This reflects an interaction between the two instruments. The transaction subsidy ε^{**} amplifies the returns to selling to young consumers: even with $p = \xi$, firms earn a margin of $\varepsilon^{**}\xi$ on each unit sold to the young. This creates an incentive to over-invest in adoption to capture market share. The adoption instrument must offset this effect. When $\theta = 0$, there is no externality to correct, so τ^{**} is purely a corrective tax. When $\theta > 0$, the externality pushes toward subsidizing adoption, and τ^{**} reflects the net effect of these two forces.

5.5 Key take-aways

This section highlighted the basic forces at play in the model when designing an optimal subsidy scheme. Both the monopoly distortion and, when $\theta > 0$, network externalities created wedges between the CE and FB. Moreove, absent externalities, these wedges are largely independent of demographics, and while young consumers are worse off in older populations, the welfare losses from monopoly pricing alone do not fall disproportionately on them. With externalities, wedges in adoption, output and welfare depend more sharply on demographics, and the welfare losses from the combined effects of monopoly pricing and externalities fall disproportionately on the young, and more sharply so when the population is older.

Subsidies to the adoption costs or to the volume of transactions help reduce these wedges, but neither subsidy alone eliminates them. Moreover, the relationship of optimal subsidies to the age of the consumer base is nuanced: the optimal stand-alone adoption subsidy does not vary with demographics; the optimal stand-alone transaction tax would vary non-monotonically with demographics. However, joint optimal subsidies to adoption and transactions yield the first-best allocation and have simple comparative statics, with the former falling as the population ages, and the latter rising. This finding is encouraging from a practical standpoint, as many of the subsidy schemes recently adopted, such as those in India and Italy, combine elements of both transaction and adoption subsidies, suggesting that policymakers are targeting the correct margins. None of these schemes, however, varies with demographics or consumer attitudes toward technology more generally, which our model suggests is crucial for efficiency.

6 Conclusion

This paper examines whether demographics influence the diffusion of new technologies. We focus on mobile payment adoption in India, where age is a key determinant of individuals' propensity to use such technology. In a simple model of technology adoption, we show that this empirical fact implies businesses are more likely to adopt when serving a younger customer base. Using data from a leading Indian fintech, we document that areas with younger populations are more likely to adopt mobile-enabled payment terminals after introduction. Finally, we study the welfare and policy implications of our model. Our welfare analysis shows that monopoly pricing alone causes under-investment in technology relative to the first-best, even in the absence of network externalities, justifying policy intervention. However, the presence of network externalities makes the welfare loss more severe and generates a significant reduction in welfare for the younger population. Restoring efficiency requires combining transaction subsidies with adoption subsidies; moreover, these instruments should vary with demographics in opposite directions, with transaction subsidies increasing in population age and adoption subsidies decreasing.

Thus the core message of our analysis is that younger consumers exhibit markedly different preferences for mobile payments in India, and that these customer preferences shaped merchants' decisions to adopt the mobile payment technology we analyzed. While our paper focuses specifically on mobile payments in India, we believe that some of the implications may be broader. The idea that younger individuals may be more responsive to new technologies is likely to hold across different countries and technologies. For instance, Figure A-16 examines the use of Pix in Brazil. Pix is a form of payment that shares many similarities to UPI (Sarkisyan 2023). Consistent with our evidence, we find that areas with a younger population show stronger penetration of this technology.[77]

In this context, we believe that there are two broad conclusions from this paper. First, in the context of mobile payments, an interesting question is whether the dramatic speed of diffusion in India is tied to the particular demographic structure of the country. India has a significantly younger population than developed nations, with a median age of 28, compared to 40 in OECD countries.[78] Our analysis suggests that this peculiarity may indeed have played a role. Second, our results speak to the broader question of what determines the rate of diffusion of new technologies. We highlight that for consumer-facing technologies, demographics appear to play a large quantitative role, both directly and indirectly, through their impact on business incentives. This result raises the possibility that population aging leads to slower rates of technology diffusion, and that demographic-dependent policy interventions may be warranted.

[77]We thank Sergey Sarkisyan for this point, providing the first version of this analysis when discussing our paper. We partially modified the initial version he created to make this test closer to our own approach.

[78]http://www.oecd-ilibrary.org/sites/d56a2fbc-en/index.html?itemId=/content/component/d56a2fbc-en

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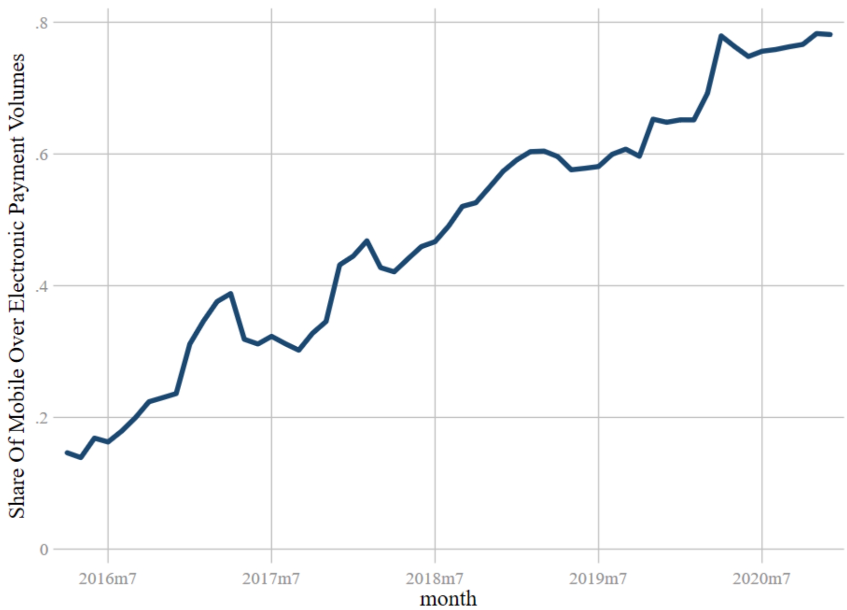
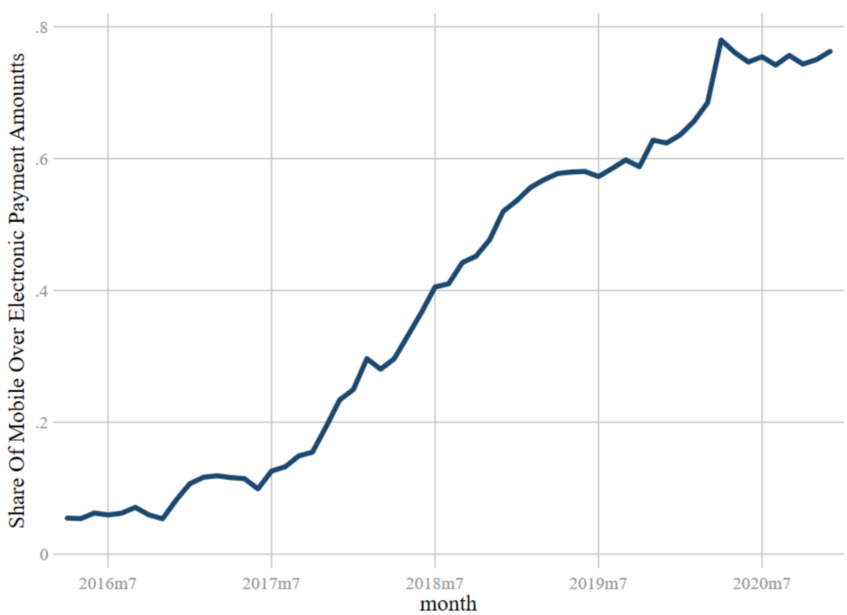
Figures and Tables

Figure 1: Share of electronic payments done using a mobile option

(a) Volume of transactions

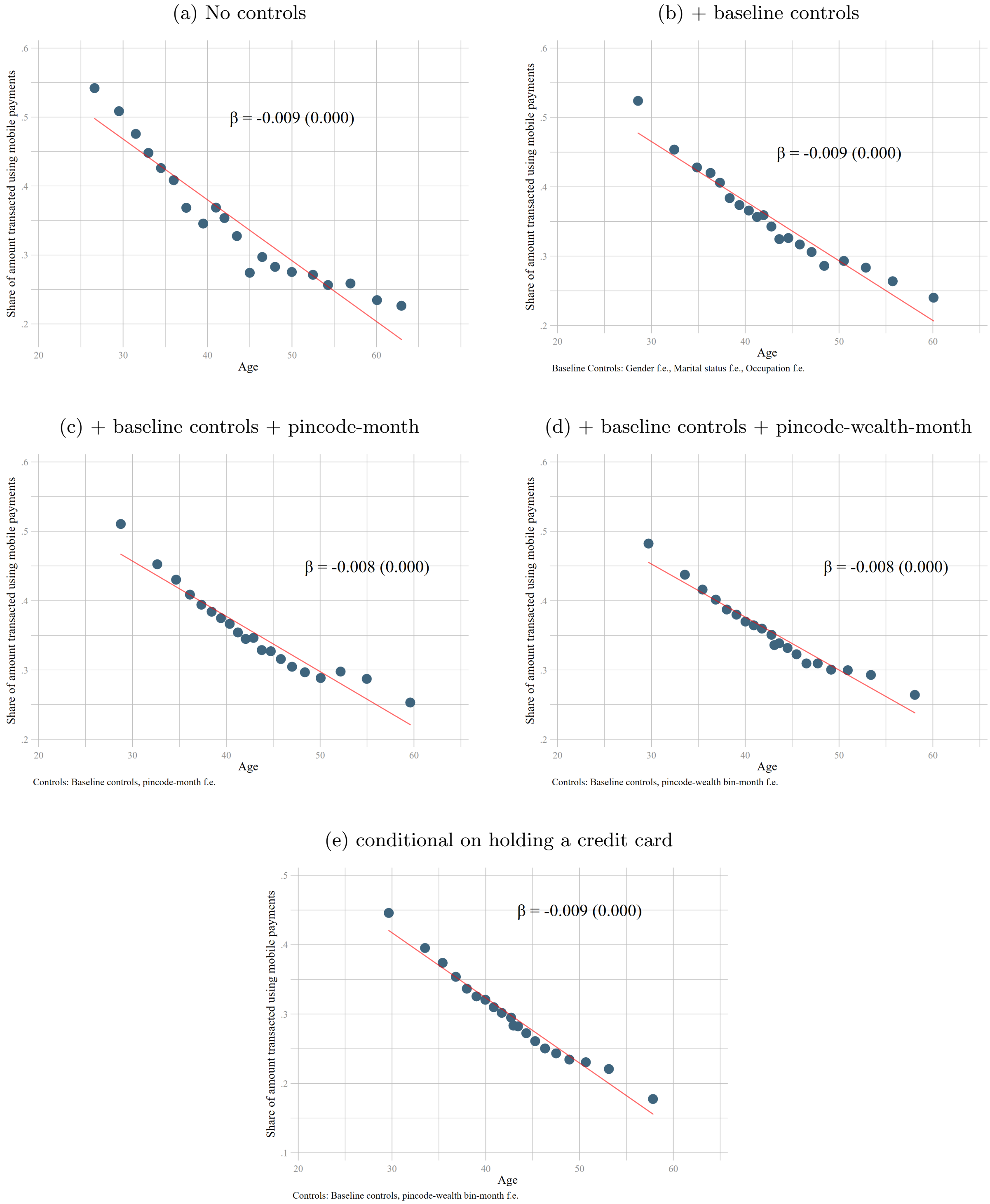


(b) Value of transactions



Notes: These two figures plot the share of electronic transactions that are done using mobile (at monthly level). Panel (a) reports the measure based on volume of transactions, while panel (b) examines the value of transaction. Electronic transactions are defined as the sum of UPI, mobile wallets, and cards (debit, credit, and prepaid), excluding the use of cards at the ATM. Mobile transactions are defined as the sum of UPI and mobile wallets. The data to construct these figures come from the Reserve Bank of India Payment Data.

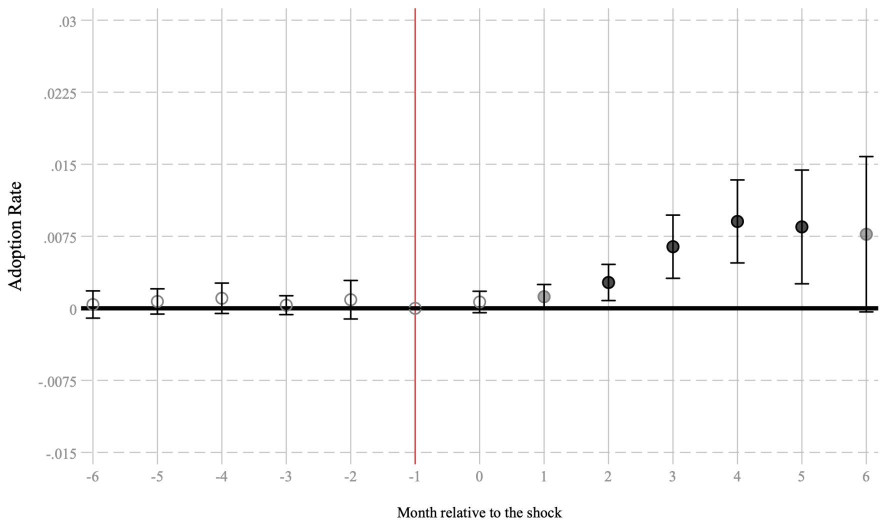
Figure 2: Share of amount transacted using mobile payments by households



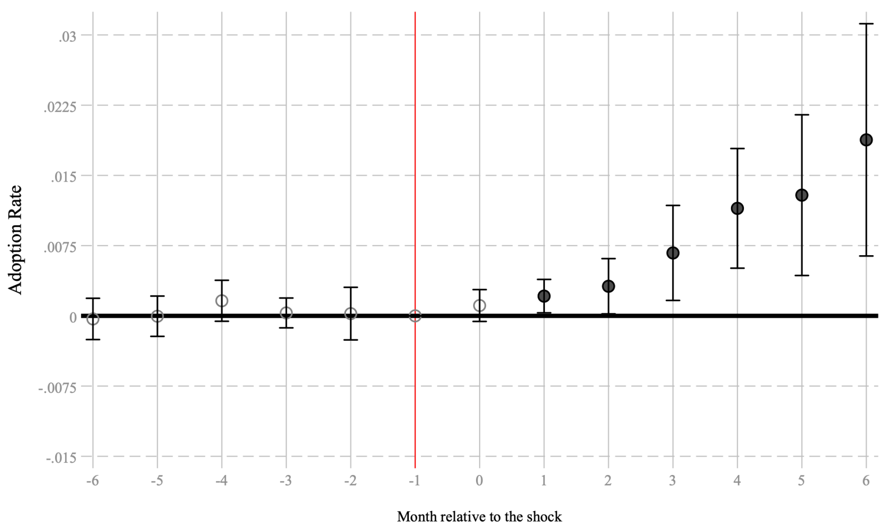
Notes: The figure plots the share of the amount transacted by households using mobile payments in the bank-level transaction data. All figures report the average of the share across 20 age bins and the slope of the line is reported in each panel. Panel (a) reports the mean with no controls. Panel (b) reports the means with baseline demographic controls for gender, marital status, and occupation. Panel (c) reports the means with baseline controls as well as pincode-month controls. Panel (d) reports the means with baseline controls as well as pincode-wealth bins-month controls. Panel (e) reports the means based on Panel (d) but is conditional on the sample of households that also hold a credit card. Each figure also reports the estimated coefficient β from the regression of the share of mobile payments on age with the controls based on the corresponding figure.

Figure 3: District Adoption Dynamics
(New Store Adopting/Total firms per district ('100))

(a) baseline specification



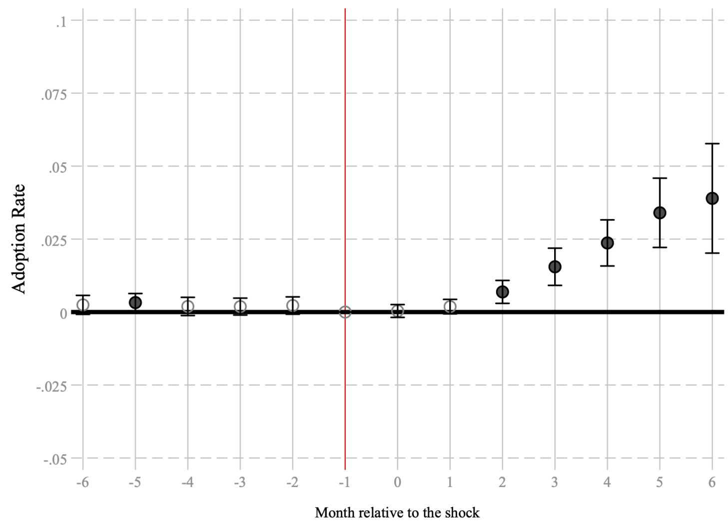
(b) all controls



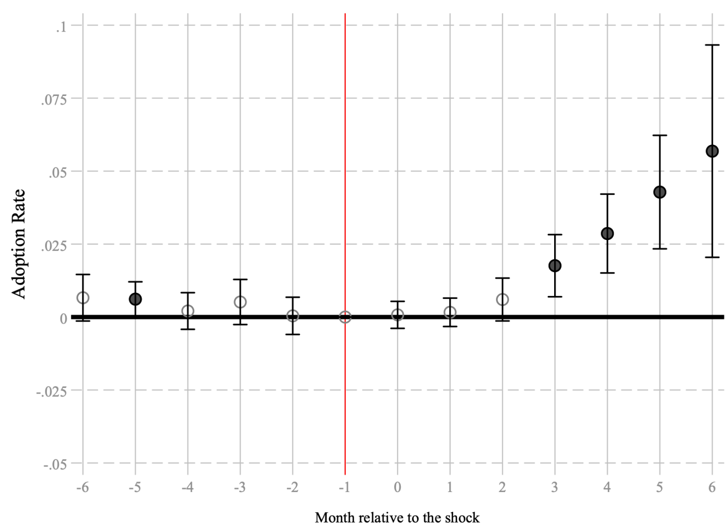
Notes: The figure plots the dynamic treatment effects of age structure on adoption. The dependent variable is the number of stores that adopted our fintech company in month t and district d, scaled by the total number of firms in the districts (in hundreds) measured by the Census. The period considered is the six months before and after May 2019 (i.e., zero in the graph), which is the month when the company introduced the mobile payment option. The graphs report the coefficients β_k from specification 12. Panel (a) reports the effects from baseline specification without any baseline district-level controls; panel (b) reports the effects from the specification that includes the district controls interacted with month fixed effects. Baseline district controls include the population (IHS), the share of agricultural workers, the number of firms (IHS), literacy rate, the share of working population, and the log of average night lights in 2018 in the district. Vertical lines indicate 95% confidence intervals. Black dots represent significance at 95% significance levels, gray dots represent significance at 90% significance levels, and hollow dots represent insignificant levels. Standard errors are clustered at the district level.

Figure 4: District Adoption Dynamics: IV results

(a) baseline specification

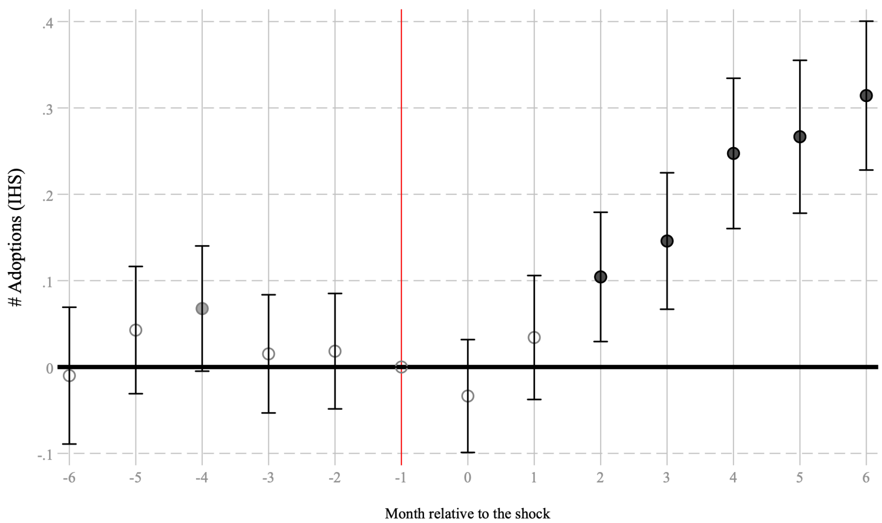


(b) all controls



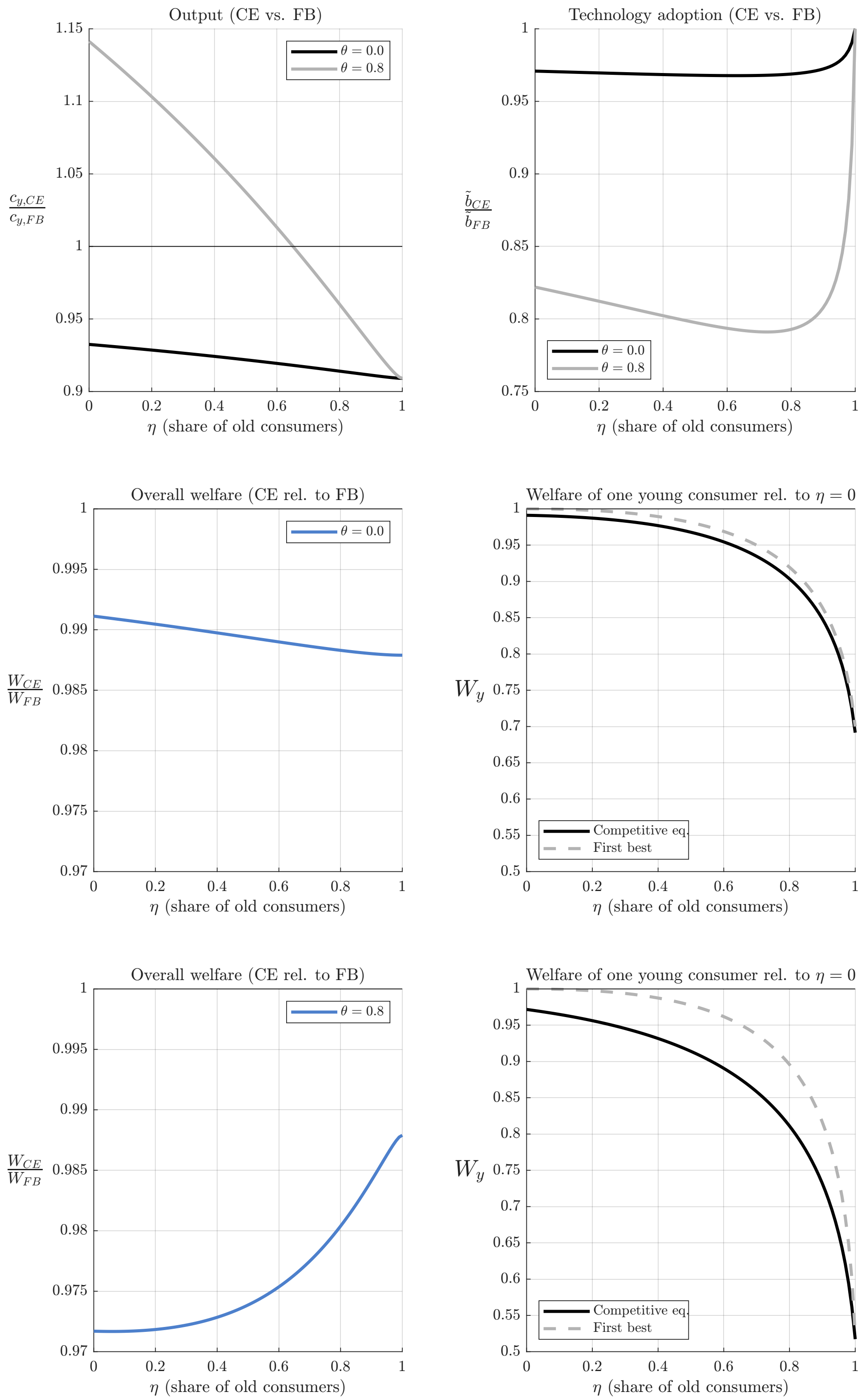
Notes: The figure plots the dynamic treatment effects of age structure on adoption, where the share of young adults is instrumented by a function of the historical sex-ratio, as described in the paper. The dependent variable is the number of stores that adopted our fintech company in month t and district d, scaled by the total number of firms in the districts (in hundreds) measured by the Census. The period considered is the six months before and after May 2019 (i.e., zero in the graph), which is the month when the company introduced the mobile payment option. The graphs report the coefficients β_k from specification 12. Panel (a) reports the effects from baseline specification without any baseline district-level controls; panel (b) reports the effects from the specification that includes the district controls interacted with month fixed effects. Baseline district controls include the population (IHS), the share of agricultural workers, the number of firms (IHS), literacy rate, the share of working population, and the log of average night lights in 2018 in the district. Vertical lines indicate 95% confidence intervals. Black dots represent significance at 95% significance levels, gray dots represent significance at 90% significance levels, and hollow dots represent insignificant levels. Standard errors are clustered at the district level.

Figure 5: Adoption across pincodes: university areas



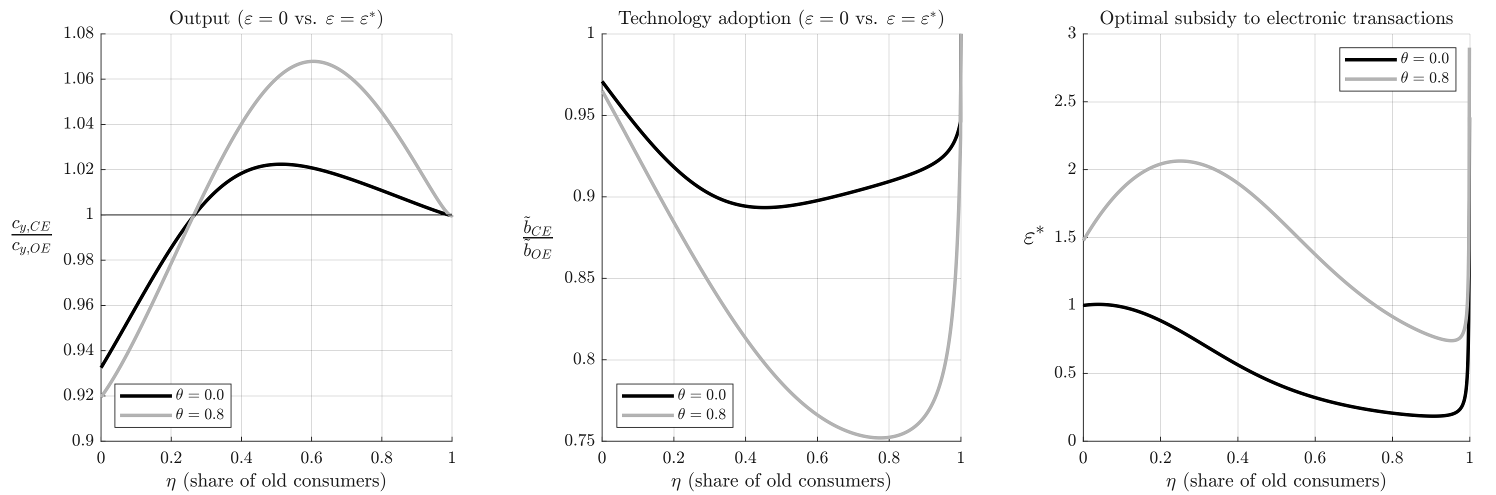
Notes: The figure plots the dynamic treatment effects of the presence of a university on the adoption of our fintech company. The dependent variable is the (inverse hyperbolic sine transformation of) the number of stores that adopted our fintech company at pincode-level in a month. The graphs report the coefficients γ_k from specification 13, and always include district-by-month fixed effects as well as pincode fixed-effects. The period considered is the six months before and after May 2019 (i.e., zero in the graph), which is the month when the company introduced the mobile payment option. Vertical lines indicate 95% confidence intervals. Black dots represent significance at 95% significance levels, gray dots represent significance at 90% significance levels, and hollow dots represent insignificance at 90% levels. Standard errors are reported in parentheses and are clustered at the pincode level.

Figure 6: Comparison between competitive equilibrium (CE) and first best allocation (FB).



Notes: The top two panels compare allocations in the CE and FB. The middle two panels compare welfare in the CE and FB without externalities ($\theta = 0$), and the bottom two panels compare welfare with externalities ($\theta = 0$). Welfare for the young in the middle and bottom right panels is normalized by the welfare of a young household in the FB with $\eta = 0$. The calibration used is $E = 1$, $J = 2$, $\alpha = 0.9$, $\rho = 0.5$, $\nu = 0.1$, $\xi = 0.1$, and $\gamma(b) = \frac{1}{2}\omega(b-1)^2$ with $\omega = 0.025$. Results are reported for the case of no externalities ($\theta = 0$) and externalities ($\theta = 0.8$).

Figure 7: Optimal transaction tax.



Notes: The left panel shows the ratio of output in the competitive equilibrium with the optimal transaction tax (OE) $\varepsilon = \varepsilon^*$, relative to the competitive equilibrium (CE) with no transaction tax ($\varepsilon = 0$). The middle panel shows the ratio of adoption in the OE, relative to CE with no transaction tax. The right panel shows the optimal transaction tax ε^*. In all three panels the horizontal axis is the share of old consumers. The calibration used is $E = 1$, $J = 2$, $\alpha = 0.9$, $\rho = 0.5$, $\nu = 0.1$, $\xi = 0.1$, and $\gamma(b) = \frac{1}{2}\omega(b-1)^2$ with $\omega = 0.025$. Results are reported for the case of no externalities ($\theta = 0$) and externalities ($\theta = 0.8$).

Table 1: Variance composition

	Share of amount transacted with mobile money				
	(1)	(2)	(3)	(4)	(5)
Age	99%	81%	74%	65%	38%
Gender	1%	1%	1%	1%	0%
1(Married)		18%	16%	14%	8%
Industry			9%	8%	5%
Wealth				12%	7%
Pincode					42%

Notes: The table reports the variance decomposition generated using the Shapley Value approach as in (Huettner and Sunder 2012). Each column reports the share of the outcome's explained variance that is due to each of the characteristics reported across rows. Each characteristic is classified as a group rather than a continuous variable (for e.g., variable Age represents 48 bins, each corresponding to one age group between integer age 18 to 65), and the number reported represents the share explained by the whole group. Each column should sum to 100.

Table 2: Age Structure and Mobile Demand

	Adoption Rate		# Adoptions (IHS)	
	(1)	(2)	(3)	(4)
$\text{AgeStructure}_d \times \text{Post}_t$	0.005*** [0.002]	0.008*** [0.002]	0.083*** [0.028]	0.162*** [0.036]
Observations	7,722	7,722	7,722	7,722
R-squared	0.559	0.602	0.839	0.849
District f.e.	✓	✓	✓	✓
Month f.e.	✓	✓	✓	✓
District Controls × Month f.e.	✗	✓	✗	✓

Notes: The table reports the difference-in-differences estimates of the effect of the age structure on adoption. The estimated specification is equation 11. Columns 1 - 2 report the estimate, where the outcome is expressed as the number of stores that adopted our fintech company in month t and district d, scaled by the total number of firms in the districts (in hundreds) measured by the Census. Columns 3 - 4 report the estimate on the IHS of the number of stores that adopted our fintech company district d during month t. Odd columns have no controls while even columns incorporate district controls interacted with month dummies. The district controls include the population (IHS), the share of agricultural workers, the number of firms (IHS), literacy rate, the share of working population, and the log of average night lights in 2018 in the district. Standard errors are reported in parentheses and are clustered at the district level. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 3: Age Structure: Balance Table

	Univariate OLS		Baseline Controls	
	Coefficient	R^2	Coefficient	R^2
	(1)	(2)	(3)	(4)
Population (IHS)	-0.192***	0.042		
	(0.045)			
Share of agricultural workers	-0.023***	0.048		
	(0.005)			
Number of firms (IHS)	-0.360***	0.116		
	(0.047)			
Literacy Rate	-0.049***	0.222		
	(0.004)			
Share of working population	-0.015***	0.051		
	(0.003)			
Night lights (IHS)	-0.069	0.003		
	(0.063)			
Total stores (IHS)	-0.610***	0.077	-0.056	0.612
	(0.080)		(0.082)	
Total new stores (IHS)	-0.512***	0.065	-0.118	0.562
	(0.070)		(0.072)	
Total transaction volumne (IHS)	-0.784***	0.081	-0.055	0.548
	(0.105)		(0.121)	
Total transaction amount (IHS)	-0.859***	0.055	-0.018	0.417
	(0.144)		(0.189)	
Total rural population (IHS)	0.003	0.000	0.046	0.270
	(0.105)		(0.119)	
Number of schools (IHS)	-0.120***	0.023	0.039	0.781
	(0.044)		(0.035)	
Population density	-0.127***	0.017	-0.075	0.488
	(0.048)		(0.066)	
Bank Branch Density	-0.113*	0.005	-0.010	0.044
	(0.059)		(0.064)	
Share of manufacturing workers	-0.005	0.002	-0.003	0.221
	(0.005)		(0.008)	
Share of small firms	-0.000	0.000	-0.000	0.257
	(0.000)		(0.001)	
Share of primary education	-0.049***	0.112	-0.005	0.808
	(0.007)		(0.004)	
% of urban HH with mobile phones	-0.005	0.001	-0.013	0.053
	(0.006)		(0.009)	
% of urban HH with computers	0.002	0.001	0.006	0.356
	(0.004)		(0.004)	

Notes: The table tests for differences in observable district characteristics and age structure of the districts. Column 1 reports the mean of the district characteristics. The treatment variable is our measure of AgeStructure_d, as described Section 4. Columns 2 and 3 report the coefficient of the univariate OLS regression of each variable on the treatment variable. Columns 4 and 5 report the coefficients after controlling for the districts' population (IHS), the share of agricultural workers, the number of firms (IHS), literacy rate, the share of working population, and the log of average night lights in 2018 in the district. The district characteristics come from the 2011 Census, with the exception of the night light (which comes from the VIIRS Night light data) and information about the number of stores and transactions, which are measured using the data from our fintech company in the standard pre-period of the analysis. Robust standard errors are in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Age Structure and Adoption: IV analysis

	First Stage	2SLS	
	$\text{AgeStructure}_d \times \text{Post}_t$	Adoption rate	# Adoptions (IHS)
	(1)	(2)	(3)
$(\text{Sex Ratio})_{d,1991} \times \text{Post}_t$	61.04***		
	(11.71)		
$(\text{Sex Ratio})^2{}_{d,1991} \times \text{Post}_t$	-25.70***		
	(5.332)		
$\text{AgeStructure}_d \times \text{Post}_t$		0.020***	0.256***
		(0.0046)	(0.085)
Observations	7,722	7,722	7,722
SW F-statistic	43.46		
District f.e.	✓	✓	✓
Month f.e.	✓	✓	✓
Controls × Month f.e.	✓	✓	✓

Notes: The table reports the instrumental variables (IV) estimates of the effect of the age structure on adoption. The estimated specification is equation 11, where we instrument the age structure of the district using a quadratic polynomial of sex ratio. Column 1 reports the first stage estimates. Column 2 reports the IV-2SLS estimate on our standard outcome (i.e., number of new stores adopting in month t and district d, divided by the number of firms in the district, in hundreds). Column 3 reports the IV-2SLS estimate on the IHS of the number of new firms that obtained a terminal from the firm. District controls include the population (IHS), the share of agricultural workers, the number of firms (IHS), literacy rate, the share of working population, and the log of average night lights in 2018 in the district. Standard errors are reported in parentheses and are clustered at the district level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Adoption and University

	# Adoptions (IHS)		# Adoptions	
	(1)	(2)	(3)	(4)
$\mathbf{1}(\text{has university})_p \times \text{Post}_t$	0.217***	0.132***	3.344***	2.828***
	[0.024]	[0.024]	[0.529]	[0.599]
Observations	196,547	109,599	196,547	109,599
R-squared	0.706	0.761	0.511	0.606
Pincode f.e.	✓	✓	✓	✓
Month f.e.	✓	✓	✓	✓
District f.e. × Month f.e.	✗	✓	✗	✓

Notes: The table reports the difference-in-differences estimates of the effect of the presence of a university on the demand for mobile payments by retailers. The estimated specification is equation 13. Columns 1 - 2 report the estimate on the IHS of the number of new stores that adopted a terminal from our fintech company in pincode p during month t. Columns 3 - 4 report the estimate of the (raw) number of new stores that adopted a terminal from our fintech company in pincode p during month t. All columns include pincode fixed effects, month fixed effects and district-month fixed effects. Standard errors are reported in parentheses and are clustered at the pincode level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Internet Appendix for “Demographics and Technology Diffusion: Evidence from Mobile Payments”

A.1 Data Appendix

In this section, we discuss more in details some aspects of our data construction.

A.1.1 Bank Data

The first data used in the paper is a data set provided by one of the leading banks in India. As explained in Section 2, the data is a sample of about 200,000 customers from this bank, which is active across the whole country and several business areas. In this Appendix, we aim to expand a bit on some of the tests presented in the draft.

As part of the data validation conducted in the data section, we compare how our measure of age and total deposits in our bank data compares with representative data sets about Indian households. These analyses are conducted on the subset of individuals 18 to 65 years old, since this is the population later used in the analysis. In the bank data, the age of the account owner is provided as of January 2020. Furthermore, we estimate deposits from the bank data as the total deposit available in January 2020. The analyses use data from January and February 2020, the closest months to the fintech experiment that we were able to obtain from the bank.

To benchmark age, we use the NFHS survey conducted from 2019-2021, a nationally representative household level survey on household level demographics and health outcomes. The data set provides directly the age of household's head at the time of the survey, and this variable is used directly to construct our age distribution. To make the data representative, we employ the weights provided in the data set.[79] We focus on household head because we want something that is comparable to the bank data. As illustrated in panel (a) of Figure A-1, the age profiles of bank account owners and household heads closely align, with a minor under-representation of individuals aged 60 to 65 offset by a higher presence of middle-aged individuals (30-50 years).

Despite a similar age profile, we expect our data to over-represent wealthier individuals. Mechanically, individuals in our data have a positive bank deposit balance. To benchmark the deposit distribution, we utilize the AIDIS survey, part of the 77th round of the NSS survey, using data conducted for the first visit in 2019.[80] This is a nationally representative survey on households, reporting information about families' assets and liabilities. From this data, we obtain the value of deposits as of 06/30/2018 of households from the table called Visit1 Level - 12 (Block 11a) - Financial assets including receivables (other than shares and related instruments) owned by the household using assets with serial numbers 3-9 based on AIDIS survey 2019 documentation. In particular, these categories are: (a) 3 - deposit in savings bank account (excl. Post Office Savings Bank POSB); (b) 4 - fixed deposit/term deposit/ RD / flexi-RD in banks (excl. POSB); (c) 5 - savings and/or fixed deposits in post office savings bank; (d) 6 - other fixed income deposits (NSC, KVP, saving bonds, other small savings schemes, etc.); (e) 7 - deposits in cooperative banks; (f) 8 - deposits with non-banking finance companies; (g) 9 - deposits with Co-op credit society/micro-

[79] https://dhsprogram.com/data/dataset/India_Standard-DHS_2020.cfm?flag=0
[80] See https://microdata.gov.in/nada43/index.php/catalog/156/overview

finance institutions/self-help groups. If households do not report assets with such serial numbers, we assume that they have 0 deposits.

Based on this, we obtain that 52% of the population does not have deposits. The final figure is then constructed conditional on the household having non-zero deposits, so that we can make this more directly comparable to the bank data. Also in this case, we use the internally provided survey weights to make the data representative. Appendix Figure A-1, panel (b), then confirms that our data over-sample households with higher deposit account balances.

While we recognize the difference in wealth between our sample and the population at large, we do not think that this difference hinders us to conduct a insightful study of payment behavior. First, in general, wealthier individuals are more inclined towards electronic payments. Therefore, although the data may not perfectly represent the entire Indian population, it offers a useful snapshot of the subset more engaged with electronic payments. Second, even if the data set is skewed towards wealthier individuals, our dataset has a broad coverage across all wealth levels. This feature allows us to directly control for differences in wealth, and therefore isolate the effect of age from wealth differences.

A.1.2 Fintech Payment Data

We now describe in detail the way we construct the district panel measuring the growth of our fintech payment provider in India. The raw data is provided to us in the form of a transaction panel identified by a terminal and firm ID as well as a master file for the terminals that provides us with the pincode where the terminal operates, and some firm demographic information for each terminal. To have a sense of the data set, we have about 473M transactions, covering the payment activity of more than 900K firms. We want to note here that the data from the fintech company is completely orthogonal to the data from the bank, discussed in Section 2.

The data cleaning for the store panel involves a few key steps. First, we consolidate the terminal transaction panel and identify payment processor and transaction types. This data at the timestamp level is aggregated to a month-transaction category-payment processor panel. The second step is to clean the terminal IDs and the terminal–pincode link. This step enables us to match the transaction file to the master file and attach location information such as pincodes. We want to note here that our data does not allow us to identify the name of the firm and therefore we cannot match this data to any external data set at the firm level. To assign consistent terminal IDs to the transaction panel, we need to deal with changing terminal IDs over time. We solved this issue with the help of additional datasets provided by the fintech company that provides information on how the IDs change. Another issue with the master file is that pincode information is available for only around 90% of terminals. For the rest, we have a location ID variable, which is an internal ID variable constructed by the company. The good news is that this location ID uniquely identifies pincodes except for a handful of terminals. We then use this variable to fill in remaining pincodes. When there are more than one location IDs across the files provided by the company, we use the one in the most recent file.

In the last step, we match the two data sets. In a few cases, we do not find all terminals in the constructed master file (about 10% of the sample), which implies we cannot directly connect the pincode. However, since both datasets have a firm identifier, we can infer the location for some of these unmatched terminals. In particular, a sizable subset of these firms only operates terminals in one pincode, and therefore we infer that the unmatched terminal is likely also in the same pincode. We discard terminals with more irregular patterns. However, as it will be clear below, this choice is not going to affect our analysis unless the specific discard terminal is the first terminal adopted by the firm.

Once we have connected to each terminal the firm ID and the location, we construct our store ID: as we mentioned in the paper, we define a store as a combination of terminals belonging to the same firm within the same (6-digit) pincode. In general, the largest majority of firms only have one terminal. The construction of the store ID allows us to normalize for the fact that certain stores may have more than one terminal, and in some cases firms have more than one location. However, it is important to point out that this adjustment is likely second order here, since the majority of firms have only one terminal, and only a few thousand firms have more than one location. This is a relatively small number given that the total size of the data.

We then use the information about transactions to understand the adoption time, which we infer by looking at the time of the first transactions done in a store. Notice that for a subset of the sample, we also have information about the time of installation of the terminal, which can be used as an alternative way to measure the exact time of adoption. Comparing adoption month using the first transaction and installation for the sample of terminals adopted during the sample period, we find that the two measures coincide exactly almost 86% of the sample, and the gap is limited to a few days for most others (for instance, if we allow the first transaction to be a month delay, the measures are the same for over 94%). We therefore use the first day of adoption as our main measure because this version is available for our full sample, rather than a portion of it.

The last step is straightforward: once the data is organized, we aggregate the data at district by month level, measuring the number of stores active in a district as well as the number of new stores adopting our company's payment that specific district. We particularly focus our analysis on the period around the May 2019 policy shift, which is what we use in our model.

A.1.3 Data on University Location

This section outlines details regarding the presence of universities at the pincode level, as discussed in the main text. The goal of utilizing this data is to pinpoint locations with an unusually high concentration of young adults. Specifically, the aim is to compile an exhaustive list of higher education institutions operational in 2019, the year under scrutiny in our analysis. Collecting this data presented three main challenges, which are outlined below. Firstly, we needed to secure a reliable list of higher education institutions. Secondly, it was important to verify "to the best of our ability" that these institutions were indeed active in 2019. Lastly, identifying the pincode for each institute was necessary.

To determine the list of universities in India, we utilize the classification of universities provided by the University Grants Commission of India, an organization that provides recognition to universities in India. We utilize four groups of universities provided by the UGC:

1. Central Universities: established by an act of parliament and are under the purview of the Department of Higher Education in the Ministry of Education;

2. State Universities: established by an act of parliament and are under the purview of the Department of Higher Education in the Ministry of Education;

3. Deemed Universities: status of autonomy granted by the Department of Higher Education on the advice of the UGC, under Section 3 of the UGC Act;

4. Private Universities: approved by the UGC. They can grant degrees, but they are not allowed to have off-campus affiliated colleges.

In addition to this list, we also use the list of Institutions of National Importance, which are not universities but considered important by the Indian Ministry of Education.

We now provide a bit more detail about each of these lists, in particular describing how we make sure that these centers were active in 2019. Regarding Central Universities, the list was provided by UGC, with a document that appeared to be released in April 2023.[81] One concern is that some Central Universities may have been added after 2020: we then manually check if there was any law passed in 2020 about this and we could not find any. For State Universities, the list was also provided by UGC.[82] In this case, the last was provided as of March 31st 2019, therefore matching perfectly our time of interest. For Deemed Universities, the list was provided on the UGC website,[83] updated at the day close to the download (i.e., January 2024). In this case, it could therefore be possible that some universities in the list were opened after 2020: we manually checked a sub-sample of the data and could not find any cases. Therefore, even if we cannot exclude this issue entirely, we do not expect this problem to be significant. The list of private Universities was also found on an external website (i.e., Boston University) but appeared to come from UGC, and the list was updated November 12th 2018, therefore fitting well our needs.[84] Lastly, the list of Institutions of National Importance was found on the Government website updated at least until 2022.[85] A manual check of the list seems to exclude any recent additions.

We then combine the list of universities, cleaned the data, also removing a few duplicates that are found in the process. We then connect each university with a (six-digit) pincode: for entries coming from UGC files, the pincode can be generally extracted from the address that is provided.

[81] https://web.archive.org/web/20230404082827/https://www.ugc.gov.in/oldpdf/Consolidated_CENTRAL_UNIVERSITIES_List.pdf

[82] https://web.archive.org/web/20190805020657if_/https://www.ugc.ac.in/oldpdf/State%20University/Consolidated%20State%20%20University%20List.pdf

[83] https://deemed.ugc.ac.in/Home/ListOfDeemedToBeUniversity

[84] https://www.bu.edu/globalprograms/files/2019/02/Private-University-Consolidated-List-Private-Universities.pdf

[85] https://www.education.gov.in/institutions-national-importance

For Institutions of National Importance, the address is not provided and we had to manually add the pincode. In general, we add pincode manually using Google, specifically searching"<university name> pincode". Two points related to this analysis are worth highlighting. First, it is important to point out that the pincode identified through this data collection is likely to capture the location of the headquarters or main building of the University. For Universities that are very large, it is possible that some buildings are located outside the original pincode. Given the impossibility to find a complete list of all Universities' buildings in India, we thought that this issue was generally acceptable. Furthermore, we expect that, if anything, this issue would bias us towards finding no difference in the data. This is particularly the case given that this analysis will only exploit within-district variation.

Second, the higher education sector in India is characterized by the presence of both universities and colleges. Universities, which we consider above, are educational institutions that are authorized to award degree under a Central or a state Legislature. In other words, these intuitions are close to what is traditionally referred to as a university or 4-year college in the U.S.. However, India is also characterized by another type of higher education institution, generally referred to as Colleges. These institutions are not authorized to award an educational degree in their own name and may be affiliated with some university. However, colleges are much smaller than universities in their enrollment size: two-third of colleges have less than 500 students and only 8% colleges have greater than 2000 students.[86] Moreover, 60% of the colleges are located in rural areas. Thus, unlike universities, we do not expect the presence of colleges to be a large enough force to have significant impact on local demand coming from younger customers (i.e. college graduates). Furthermore, their presence is likely to also bias our findings towards zero.

A.2 Appendix Empirical

This appendix provides additional detail on several tests referenced in the main text and, in some cases, includes supplementary robustness checks and ancillary analyses.

A.2.1 Age and Mobile

In Section 2.2, we analyze the relationship between payment preferences and the age of the account holder using the data. This sub-section presents the same tests discussed in the body of the paper, providing more details around the analyses presented.

To start, Figure 2, panel (a), reports a non-parametric scatter plot of the relationship between the share of mobile payment amounts and age. We observe a negative, monotonic, and approximately linear relationship between age and mobile payment usage: older individuals consistently utilize mobile payments less frequently than cards. These differences are substantial, with consumers in the oldest category conducting approximately 25% of their electronic payments using

[86] See the All India Survey of Higher Education (2018) from the Ministry of Education India: https://cdnbbsr.s3waas.gov.in/s392049debbe566ca5782a3045cf300a3c/uploads/2024/02/2024021480881112.pdf

mobile, compared to 55% for younger consumers. In Appendix Figure A-2, we replicate the same analysis using age groups (i.e., 18-25, and then at 5-year intervals) and present the results with confidence intervals relative to zero. This confirms that mobile payment usage significantly differs from the youngest group for every age group, with each subsequent age group exhibiting lower mobile usage than the preceding one.

Next, we introduce individual-level controls. As discussed in the draft, the objective is to disentangle the effect of age from other observable characteristics that may influence electronic payment preferences and could be correlated with age. In Figure 2, panel (b), we incorporate demographic controls for gender, marital status, and occupation. These controls are applied by residualizing them against both the proportion of payments made via mobile and age, and then plotting the residuals against age. This adjustment has minimal impact on the observed relationship: indeed, the coefficient in the linear fit of the relationship (reported in the figure) remains virtually unchanged from panel (a). In Figure 2, panel (c), we further introduce controls for the wealth of the bank customer to mitigate the possibility that age-related differences are merely reflections of wealth disparities across cohorts. Once again, the inclusion of this control has a relatively modest impact.[87]

We then introduce controls for location. Different age groups may reside in distinct parts of the country or in different neighborhoods within the same districts. For instance, the younger population may locate in areas where stores are less inclined to accept credit cards, potentially increasing their reliance on mobile payments. In that case our results would reflect lack of access to credit card payments, as opposed to a preference for mobile payments. To address this concern, Figure 2, panel (d), replicates the previous analysis but includes controls for pincode-by-wealth group fixed effects, alongside standard demographic controls.[88] Although the magnitude of the relationship between age and mobile payment usage is somewhat diminished, consistent evidence of a significant of relationship between age and mobile payment usage remains compelling.[89]

A final concern is that age is a proxy for differences in the ability to obtain a card across different age groups. Older individuals might be more likely to be approved for debit or credit cards, potentially underpinning the observed relationship. To address this issue, Figure 2, panel (e), conducts a similar analysis as before — incorporating individual controls and pincode-by-wealth fixed effects — but focuses only on customers who possessed cards during the analyzed period. Even after conditioning on ownership of a card, we find that younger consumers consistently allocate a significantly higher proportion of their expenditures to mobile payments. Specifically, the share of mobile payments is approximately 30% higher for the youngest cohort than for the oldest one. The

[87]We total account balances (including savings in fixed deposits, mutual funds investments, public provident funds accounts, recurring deposits accounts, and savings accounts) held by the customers with the bank as an empirical proxy for their wealth. We then control for wealth by creating 20 equal bins each month and then using fixed effects for each of the 20 bins.

[88]Pincodes are at the 6-digit level, so the fixed effects are expected to significantly mitigate variation in business types encountered by individuals.

[89]Additionally, with the full set of controls, we repeat the analysis using constructed age bins rather than equal-sized bins and find similar results.

linear fit of this relationship remains quantitatively identical to the one estimated in panel (a). Due to the smaller sample size and the large number of controls, the relationship between payment and age is slightly noisier, particularly at higher age levels.

A.2.2 Age and Technology Adoption

Section 4 analyzes how demographic age structure shapes demand for mobile payments, using the rollout of QR payments by our fintech partner as a natural experiment. This appendix complements that discussion by providing additional detail on several results briefly referenced in the main text.

Ancillary Result to the Baseline. To start, we present some ancillary results to the baseline findings. First, our results are generally robust to our definition of the treatment variable. In particular, Appendix Figure A-7 reproduces our main analysis with controls using the share of the total population less than 30 years old as treatment. In other words, our age structure index now includes also very young individuals (i.e., less than 15 years old), which were excluded from the baseline to allow for the possibility that this group is less likely to capture potential shopping customers and use electronic payments. Appendix Figure A-8 repeats the same exercise but defines the share of young adults focusing on those below 40 years old. In both cases, we standardize the treatment variable to have a mean of zero and a standard deviation of one, thus facilitating comparison across figures. In general, the results we obtain are almost identical: if anything, the magnitude of the effects is slightly larger.

Second, we examine the robustness to the construction of the outcome variable. In Appendix Figure A-9, we show our main results when the outcome is the number of new stores joining the platform scaled by the population size (in 100,000s) rather than the number of firms. The scale of the coefficient is different, but the message remains unchanged. In this context, we also remind the reader that the paper also highlights how results are similar when using the inverse hyperbolic sine transformation of the number of new stores joining the platform as the outcome variable (Appendix Figure A-5).

Third, we examine whether the increase in adoptions leads to an overall surge in the number of stores active on the platform. In other words, rather than looking at new adoptions in a month, our outcome is now the total number of stores that have a terminal with our company, irrespective of whether they joined that month or earlier. Appendix Figure A-10 presents the result: indeed, the relatively larger increase in adoption in younger districts also translated into more stores active in the platform. The effect is sizable, as a one-standard-deviation increase in the treatment variable leads to about two extra stores per hundred firms in the district. This evidence confirms that the effect of adoption led to an overall increase in the business managed by the fintech company.

Heterogeneity by Merchant-University Results. In the last part of Section **??**, we provide an alternative test focused on changes in adoption across areas with universities. The main finding is that the introduction of a QR-code option led to a within-district increase in adoption, particularly concentrated in pincodes with universities.

We interpret these findings as evidence that young adult customers—who tend to prefer mobile payments over cards, as documented earlier—affect local businesses' adoption of mobile payment technology. To reinforce this interpretation, we also conducted a set of tests exploiting variation in merchant types. One advantage of the university analysis is that it assumes the increase in demand originates specifically from university students. This feature allows us to generate predictions about the heterogeneity of the effects at store level. In particular, we expect an increase in mobile payment adoption, specifically among merchants who are likely to interact with students.

To identify businesses that typically serve students, we first look at those businesses in the non-tradable sector that would generally depend on very localized demand from consumers. In our data, these are made up of retailers, gas stations, restaurants, leisure facilities, personal services, and transportation. Additionally, we also consider an alternative approach which broadens this category to also include financial services, healthcare (e.g., pharmacies), and educational services.[90] We then replicate our main results using only stores that belong to these categories. The findings, presented in columns 1 and 2 of the two panels of Table A-2, support our hypothesis: the increase in mobile payment adoption in university areas is predominantly from businesses within these sectors that are likely serving students on a regular basis. Indeed, the results from these sub-samples are positive and qualitatively similar to our main findings. Moreover, as before, the surge in adoption is solely attributed to changes post-May 2019 (panels (a) and (b) in Figure A-14).

To validate this idea, we provide complementary analysis on a set of businesses likely indifferent to local consumer demands in their decision to adopt mobile payment methods. These include government and regulated sectors, manufacturing, wholesale, warehouse operations, and professional services. This test serves as a placebo; if our model accurately captures how business technology decisions reflect student demand, we should observe no significant effects in these sectors. Conversely, finding an impact here could indicate that our results are influenced by other business owner characteristics that vary by university presence. The results confirmed our hypothesis: university presence did not affect mobile adoption in these sectors, with the effects being not only statistically insignificant but also small in magnitude and precisely estimated (panel (c) in Figure A-14).

In columns 4 of the panels of Table A-2, we also look at those merchants that could not be categorized in any of the groups discussed. In this sub-sample, we find a positive effect, consistent with the main findings. This result is not surprising for us, because the sample of stores that are not categorized is mostly made-up businesses that belong to a "miscellaneous" category in our data (91%). We expect this category to be mostly made up by very small establishment that belong broadly to the retail sector, while failing to fit clearly in one of its sub-categories (e.g., street cart serving prepared food but also selling produces).

[90] To be precise, we define consumer facing merchants as merchants categorized as clothing and accessories, consumer durable, retail consumer goods, restaurants and hotels, gas station, personal services (e.g., hair salons), telecom services, transportation. We incorporate professional services by adding businesses that are categorized as health, financial, and education.

A.3 Appendix to Section 3

In what follows, anticipating our analysis of optimal subsidies, we assume that businesses face a constant adoption subsidy τ per unit of numéraire spent on technology adoption costs $\gamma(\tilde{b}(j))$, as well as a subsidy ε per unit of revenue generated by transactions with young households (that is, those relying on the electronic payment technology). Our baseline competitive equilibrium is the one corresponding to $\tau = \varepsilon = 0$.

A.3.1 Competitive equilibrium with fixed number of businesses

Utility maximization for each type of household is equivalent to the following demand system:

$$c_o(j) = \left(\frac{p(j)}{P_o}\right)^{-\frac{1}{1-\rho}} C_o \tag{A1}$$

$$C_o = \alpha \frac{I}{P_o} \tag{A2}$$

$$O_o = (1-\alpha)I \tag{A3}$$

whereas for young consumers, the demand system is:

$$c_y(j) = b(j)\left(\frac{p(j)}{P_y}\right)^{-\frac{1}{1-\rho}} C_y \tag{A4}$$

$$C_y = \alpha \frac{I}{P_y} \tag{A5}$$

$$O_y = (1-\alpha)I \tag{A6}$$

Here, I is income, which is identical across households:

$$I = E + \int_0^J \pi(j)dj - \tau \int_0^J \gamma(\tilde{b}(j))dj - \varepsilon \int_0^J p(j)c_y(j)dj, \tag{A7}$$

where note that households are taxed lump-sum in order to fund the subsidies. The two prices indices P_o and P_y are given by:

$$P_o = \left(\int_0^J p(j)^{-\frac{\rho}{1-\rho}} dj\right)^{-\frac{1-\rho}{\rho}}, \quad P_y = \left(\int_0^J b(j)p(j)^{-\frac{\rho}{1-\rho}} dj\right)^{-\frac{1-\rho}{\rho}} \tag{A8}$$

Profits for each business can be expressed as:

$$\pi(j) = \eta(p(j)-\xi)c_o(j) + (1-\eta)((1+\varepsilon)p(j)-\xi)c_y(j) - (1-\tau)\gamma(\tilde{b}(j)) - \nu \tag{A9}$$

Profit maximization for each business leads to the following first-order conditions:

$$p(j) = \frac{\xi}{\rho}\left(1 - \varepsilon\frac{(1-\eta)c_y(j)}{\eta c_o(j) + (1-\eta)(1+\varepsilon)c_y(j)}\right), \tag{A10}$$

$$\left(1+\varepsilon-\frac{\xi}{p(j)}\right)(1-\eta)\frac{p(j)c_y(j)}{\tilde{b}(j)} = (1-\tau)\gamma'(\tilde{b}(j)). \tag{A11}$$

Equations (A10)-(A11) imply that any competitive equilibrium is symmetric because the markup is the same across businesses. Thus we omit the index j in what follows.

The two first-order conditions can be rewritten as:

$$p = \frac{\xi}{\rho}\left(1-\varepsilon\frac{(1-\eta)c_y}{\eta c_o+(1-\eta)(1+\varepsilon)c_y}\right), \tag{A12}$$

$$\left(1+\varepsilon-\frac{\xi}{p}\right)(1-\eta)\frac{pc_y}{\tilde{b}} = (1-\tau)\gamma'(\tilde{b}). \tag{A13}$$

Household demand systems imply:

$$P_o = J^{-\frac{1-\rho}{\rho}}p \tag{A14}$$

$$c_o = \alpha\left(\frac{p}{P_o}\right)^{-\frac{1}{1-\rho}}\frac{I}{P_o} = \frac{\alpha I}{Jp} \tag{A15}$$

$$P_y = \tilde{b}^{-(1+\theta)\frac{1-\rho}{\rho}}J^{-\frac{1-\rho}{\rho}}p \tag{A16}$$

$$c_y = \alpha\tilde{b}^{1+\theta}\left(\frac{p}{P_y}\right)^{-\frac{1}{1-\rho}}\frac{I}{P_y} = \alpha\tilde{b}^{-(1+\theta)\frac{1-\rho}{\rho}}J^{-\frac{1}{\rho}}\tilde{b}^{(1+\theta)\frac{1-\rho}{\rho}}J^{\frac{1-\rho}{\rho}}\frac{I}{p} = \frac{\alpha I}{Jp} \tag{A17}$$

Thus $c_o = c_y$. Therefore the price set by businesses is:

$$p = \frac{1}{1+(1-\eta)\varepsilon}\frac{\xi}{\rho} \tag{A18}$$

Thus profits per business are:

$$\pi = \eta(p-\xi)c_o + (1-\eta)((1+\varepsilon)p-\xi)c_y - (1-\tau)\gamma(\tilde{b}) - \nu \tag{A19}$$

Substituting this into the definition of household income we obtain:

$$\begin{aligned} I &= E + J\pi - \tau J\gamma(\tilde{b}) - \varepsilon J(1-\eta)pc_y \\ &= E + (p-\xi)\frac{\alpha I}{p} - J\left(\gamma(\tilde{b})+\nu\right) \end{aligned}$$

Solving for income,

$$I = \frac{1}{1-\frac{p-\xi}{p}\alpha}\left(E - J\left(\gamma(\tilde{b})+\nu\right)\right) = \frac{1}{1-(1-(1+(1-\eta)\varepsilon)\rho)\alpha}\left(E - J\left(\gamma(\tilde{b})+\nu\right)\right) \tag{A20}$$

This gives the rest of the allocation:

$$\tilde{\rho}(\varepsilon) = (1+(1-\eta)\varepsilon)\rho \tag{A21}$$

$$p = \frac{1}{1+(1-\eta)\varepsilon}\frac{\xi}{\rho} \tag{A22}$$

$$(1-\tau)\gamma'(\tilde{b})\tilde{b} = (1-\eta)\frac{(1+\varepsilon-\tilde{\rho}(\varepsilon))\alpha}{1-(1-\tilde{\rho}(\varepsilon))\alpha}\left(\frac{E}{J}-\left(\gamma(\tilde{b})+\nu\right)\right) \tag{A23}$$

$$I = \frac{1}{1-(1-\tilde{\rho}(\varepsilon))\alpha}\left(E-J(\gamma(\tilde{b})+\nu)\right) \tag{A24}$$

$$c_y = \frac{\tilde{\rho}}{1+\varepsilon-\tilde{\rho}(\varepsilon)}\frac{1-\tau}{1-\eta}\frac{\gamma'(\tilde{b})\tilde{b}}{\xi} \tag{A25}$$

$$= \frac{\alpha\tilde{\rho}(\varepsilon)}{1-(1-\tilde{\rho}(\varepsilon))\alpha}\left(\frac{E}{J}-(\gamma(\tilde{b})+\nu)\right)\frac{1}{\xi} \tag{A26}$$

$$= \frac{\alpha I}{Jp} \tag{A27}$$

$$\pi = \frac{1}{1-(1-\tilde{\rho}(\varepsilon))\alpha}\Bigg(\tag{A28}$$

$$(1-\tilde{\rho}(\varepsilon)+(1-\eta)\varepsilon)\alpha\frac{E}{J} \tag{A29}$$

$$-\ ((1-\tilde{\rho}(\varepsilon)+(1-\eta)\varepsilon)\alpha+(1-\tau)(1-(1-\tilde{\rho}(\varepsilon))\alpha))\gamma(\tilde{b}) \tag{A30}$$

$$-\ (1+\alpha\varepsilon(1-\eta))\nu \quad \Bigg) \tag{A31}$$

$$c_y = \frac{\alpha I}{Jp} \tag{A32}$$

$$P_y = \tilde{b}^{-(1+\theta)\frac{1-\rho}{\rho}}J^{-\frac{1-\rho}{\rho}}p \tag{A33}$$

$$C_y = \frac{\alpha I}{P_y} \tag{A34}$$

$$O_y = (1-\alpha)I \tag{A35}$$

$$c_o = \frac{\alpha I}{Jp} = c_y \tag{A36}$$

$$P_o = J^{-\frac{1-\rho}{\rho}}p \tag{A37}$$

$$O_o = (1-\alpha)I = O_y \tag{A38}$$

In particular, solving for the allocation requires solving for the unique value of $\tilde{b}$ such that:

$$(1-\tau)\gamma'(\tilde{b})\tilde{b} = (1-\eta)\frac{(1+\varepsilon-(1+(1-\eta)\varepsilon)\rho)\alpha}{1-(1-(1+(1-\eta)\varepsilon)\rho)\alpha}\left(\frac{E}{J}-(\gamma(\tilde{b})+\nu)\right). \tag{A39}$$

When $\tau = \varepsilon = 0$, these conditions are:

$$\gamma'(\tilde{b})\tilde{b} = (1-\eta)\frac{(1-\rho)\alpha}{1-(1-\rho)\alpha}\left(\frac{E}{J} - (\gamma(\tilde{b}) + \nu)\right) \tag{A40}$$

$$(1-\eta)\frac{1-\rho}{\rho}\frac{c_y}{\tilde{b}} = \frac{\gamma'(\tilde{b})}{\xi} \tag{A41}$$

$$p = \frac{\xi}{\rho} \tag{A42}$$

$$\pi = \frac{1}{1-(1-\rho)\alpha}\left((1-\rho)\alpha\frac{E}{J} - (\gamma(\tilde{b}) + \nu)\right) \tag{A43}$$

$$I = \frac{1}{1-(1-\rho)\alpha}\left(E - J\left(\gamma(\tilde{b}) + \nu\right)\right) \tag{A44}$$

$$c_y = \frac{\alpha I}{Jp} \tag{A45}$$

$$P_y = \tilde{b}^{-(1+\theta)\frac{1-\rho}{\rho}} J^{-\frac{1-\rho}{\rho}} p \tag{A46}$$

$$C_y = \frac{\alpha I}{P_y} \tag{A47}$$

$$O_y = (1-\alpha)I \tag{A48}$$

$$c_o = \frac{\alpha I}{Jp} = c_y \tag{A49}$$

$$P_o = J^{-\frac{1-\rho}{\rho}}\frac{\xi}{\rho} \tag{A50}$$

$$O_o = (1-\alpha)I = O_y \tag{A51}$$

Finally, welfare in the competitive equilibrium with a fixed number of businesses is given by:

$$W = \eta\log(O_o^{1-\alpha}C_o^{\alpha}) + (1-\eta)\log(O_y^{1-\alpha}C_y^{\alpha}) \tag{A52}$$

$$= \log((1-\alpha)^{1-\alpha}\alpha^{\alpha}) + \log(I) - \alpha(\eta\log(P_o) + (1-\eta)\log(P_y)) \tag{A53}$$

$$= \log((1-\alpha)^{1-\alpha}\alpha^{\alpha}) + \alpha\frac{1-\rho}{\rho}\log(J) \tag{A54}$$

$$+ \log(I) - \alpha\log(p) + \alpha(1-\eta)(1+\theta)\frac{1-\rho}{\rho}\log(\tilde{b}). \tag{A55}$$

Proof of Prediction 1 with fixed number of businesses. Suppose $\tau = 0$ and $\varepsilon = 0$. When $\eta < 1$, the condition characterizing $\tilde{b}$ when the number of businesses is fixed can be written as:

$$g(\tilde{b};\eta) \quad = \quad \frac{E}{J} - \nu \tag{A56}$$

$$g(\tilde{b};\eta) \quad \equiv \quad \frac{1}{1-\eta}\frac{1-(1-\rho)\alpha}{(1-\rho)\alpha}\gamma'(\tilde{b})\tilde{b} + \gamma(\tilde{b}) \tag{A57}$$

Differentiating with respect to η,

$$\frac{\partial \tilde{b}}{\partial \eta} = -\frac{\partial g/\partial \eta}{\partial g/\partial \tilde{b}} \tag{A58}$$

Because γ is increasing and convex, $\partial g/\partial \tilde{b} > 0$. Moreover,

$$\frac{\partial g}{\partial \eta} = \frac{1}{(1-\eta)^2}\frac{1-(1-\rho)\alpha}{(1-\rho)\alpha}\gamma'(\tilde{b})\tilde{b} > 0, \tag{A59}$$

establishing the result. ■

A.3.2 Competitive equilibrium with free-entry

In what follows we focus the analysis on the case of $\varepsilon = 0$ (no transaction subsidy), as the main policy we will analyze in Appendix A.4 for the case of free-entry is an adoption subsidy.

Definition 2 (Competitive equilibrium with free-entry)**.** *A competitive equilibrium with free-entry is a number of varieties J and a set of prices and quantities such that (a) each household i maximizes utility (1) subject to their budget constraint (2); (b) each business j maximizes profits (6) subject to (3)-(4) and (5); (c) the number of businesses J adjusts such that $\inf_{j\in[0,J]} \pi(j) = 0$.*

The value of J such that profits are zero in the competitive equilibrium characterized above is:

$$J = \frac{(1-\tilde{\rho})\alpha}{(1+\alpha(1-\eta)\varepsilon - [1-(1-\tilde{\rho})\alpha]\,\tau)\gamma(\tilde{b}) + (1+\alpha(1-\eta)\varepsilon)\nu}E, \tag{A60}$$

where $\tilde{\rho} = (1+(1-\eta)\varepsilon)\rho$. Substituting we find:

$$\begin{aligned} I \quad = \quad & \frac{1}{(1+\alpha(1-\eta)\varepsilon - [1-(1-\tilde{\rho})\alpha]\,\tau)\gamma(\tilde{b}) + (1+\alpha(1-\eta)\varepsilon)\nu} \times \\ & \left(\nu + (1-\tau)\gamma(\tilde{b}) + \frac{\alpha(1-\eta)\varepsilon}{1-(1-\tilde{\rho})\alpha}\left(\nu+\gamma(\tilde{b})\right)\right)E \end{aligned} \tag{A61}$$

Solving for the allocation requires finding $\tilde{b}$ such that:

$$(1-\tau)\gamma'(\tilde{b})\tilde{b} = (1-\eta)\frac{1+\varepsilon-\tilde{\rho}}{1-\tilde{\rho}}\left((1-\tau)\gamma(\tilde{b}) + \nu + \frac{\alpha(1-\eta)\varepsilon}{1-(1-\tilde{\rho})\alpha}(\gamma(\tilde{b})+\nu)\right) \tag{A62}$$

The rest of the allocation is given by:

$$\tilde{\rho} = (1 + (1-\eta)\varepsilon)\rho \tag{A63}$$

$$p = \frac{\xi}{\tilde{\rho}} \tag{A64}$$

$$\pi = 0 \tag{A65}$$

$$I = \frac{1}{(1 + \alpha(1-\eta)\varepsilon - [1-(1-\tilde{\rho})\alpha]\,\tau)\gamma(\tilde{b}) + (1+\alpha(1-\eta)\varepsilon)\nu} \times$$
$$\left(\nu + (1-\tau)\gamma(\tilde{b}) + \frac{\alpha(1-\eta)\varepsilon}{1-(1-\tilde{\rho})\alpha}\left(\nu + \gamma(\tilde{b})\right)\right) E \tag{A66}$$

$$J = \frac{(1-\tilde{\rho})\alpha}{(1 + \alpha(1-\eta)\varepsilon - [1-(1-\tilde{\rho})\alpha]\,\tau)\gamma(\tilde{b}) + (1+\alpha(1-\eta)\varepsilon)\nu} E \tag{A67}$$

$$\frac{I}{J} = \frac{1}{(1-\tilde{\rho})\alpha}\left(\nu + (1-\tau)\gamma(\tilde{b}) + \frac{\alpha(1-\eta)\varepsilon}{1-(1-\tilde{\rho})\alpha}\left(\nu + \gamma(\tilde{b})\right)\right) \tag{A68}$$

$$c_y = \frac{\alpha I}{pJ} = \frac{\tilde{\rho}}{1-\tilde{\rho}}\frac{1}{\xi}\left(\nu + (1-\tau)\gamma(\tilde{b}) + \frac{\alpha(1-\eta)\varepsilon}{1-(1-\tilde{\rho})\alpha}\left(\nu + \gamma(\tilde{b})\right)\right) \tag{A69}$$

$$P_y = \tilde{b}^{-(1+\theta)\frac{1-\rho}{\rho}} J^{-\frac{1-\rho}{\rho}} p \tag{A70}$$

$$C_y = \frac{\alpha I}{P_y} \tag{A71}$$

$$O_y = (1-\alpha)I \tag{A72}$$

$$c_o = \frac{\alpha I}{Jp} = c_y \tag{A73}$$

$$P_o = J^{-\frac{1-\rho}{\rho}} p \tag{A74}$$

$$O_o = (1-\alpha)I = O_y \tag{A75}$$

In particular, when $\tau = \varepsilon = 0$, we have:

$$\gamma'(\tilde{b})\tilde{b} = (1-\eta)\left(\nu + \gamma(\tilde{b})\right) \tag{A76}$$

$$p = \frac{\xi}{\rho} \tag{A77}$$

$$\pi = 0 \tag{A78}$$

$$I = E \tag{A79}$$

$$J = \frac{(1-\rho)\alpha E}{\gamma(\tilde{b})+\nu} \tag{A80}$$

$$\frac{I}{J} = \frac{\gamma(\tilde{b})+\nu}{(1-\rho)\alpha} \tag{A81}$$

$$c_y = \frac{\rho}{1-\rho}\frac{\gamma(\tilde{b})+\nu}{\xi} \tag{A82}$$

Finally, welfare in the competitive equilibrium with free-entry is given by:

$$W = \log((1-\alpha)^{1-\alpha}\alpha^{\alpha}) + \alpha\frac{1-\rho}{\rho}\log(J) \tag{A83}$$

$$+ \log(I) - \alpha\log(p) + \alpha(1-\eta)(1+\theta)\frac{1-\rho}{\rho}\log(\tilde{b}). \tag{A84}$$

Proof of Result 1 with free-entry. When $\eta < 1$, and $\varepsilon = \tau = 0$, the condition characterizing $\tilde{b}$ when there is free-entry can be written as:

$$g(\tilde{b};\eta) = \nu \tag{A85}$$

$$g(\tilde{b};\eta) \equiv \frac{1}{1-\eta}\gamma'(\tilde{b})\tilde{b} - \gamma(\tilde{b}) \tag{A86}$$

Differentiating with respect to η,

$$\frac{\partial\tilde{b}}{\partial\eta} = -\frac{\partial g/\partial\eta}{\partial g/\partial\tilde{b}} \tag{A87}$$

We have:

$$\frac{\partial g}{\partial\eta} = \frac{1}{(1-\eta)^2}\gamma'(\tilde{b})\tilde{b} > 0. \tag{A88}$$

Moreover,

$$\frac{\partial g}{\partial\tilde{b}} = \left(\frac{1}{1-\eta} - 1\right)\gamma'(\tilde{b}) + \frac{1}{1-\eta}\tilde{b}\gamma''(\tilde{b}). \tag{A89}$$

Or equivalently:

$$\frac{\partial g}{\partial\tilde{b}} = \left(\frac{1}{1-\eta} - 1\right)\gamma'(\tilde{b}) + \frac{1}{1-\eta}\tilde{b}\gamma''(\tilde{b}) > 0 \tag{A90}$$

because $\gamma(.)$ is increasing and convex, establishing the result. ■

A.4 Appendix to Section 5

A.4.1 Fixed number of businesses

Proof of Result 2. The first-best allocation is the solution to:

$$W = \max_{O_o,O_y,c_o,c_y,\tilde{b}} \eta \log(O_o^{1-\alpha} C_o^{\alpha}) + (1-\eta)\log(O_y^{1-\alpha} C_y^{\alpha}) \tag{A91}$$

$$\text{s.t.} \quad \eta O_o + (1-\eta)O_y + J\xi\left(\eta c_o + (1-\eta)c_y\right) + J(\gamma(\tilde{b})+\nu) \le E \qquad [\lambda]$$

$$C_O = J^{\frac{1}{\rho}} c_o \tag{A92}$$

$$C_y = J^{\frac{1}{\rho}} \tilde{b}^{(1+\theta)\frac{1-\rho}{\rho}} c_y \tag{A93}$$

The solution is:

$$\tilde{b}\gamma'(\tilde{b}) = \alpha(1-\eta)(1+\theta)\frac{(1-\rho)}{\rho}\left(\frac{E}{J} - (\gamma(\tilde{b})+\nu)\right) \tag{A94}$$

$$\lambda^{-1} = E - J(\gamma(\tilde{b})+\nu)$$

$$O_y = (1-\alpha)\lambda^{-1}$$

$$O_o = O_y$$

$$c_y = \alpha\frac{\lambda^{-1}}{J\xi}$$

$$c_o = c_y \tag{A95}$$

Note that in particular, $(c_y, \tilde{b})$ satisfy:

$$(1-\eta)(1+\theta)\frac{1-\rho}{\rho}\frac{c_y}{\tilde{b}} = \frac{\gamma'(\tilde{b})}{\xi}. \tag{A96}$$

Any price system consistent with utility maximization of either young or old household must yield an equilibrium level of income I that satisfies $O_o = O_y = (1-\alpha)I$. Thus:

$$I = \lambda^{-1} = E - J(\gamma(\tilde{b})+\nu). \tag{A97}$$

Moreover, the budget constraint of young (and old) households must hold with equality. Letting p be the price of each variety we must have:

$$I = \lambda^{-1} = O_y + Jpc_y = \lambda^{-1}\left(1-\alpha+\alpha\frac{p}{\xi}\right), \tag{A98}$$

so that:

$$p = \xi. \tag{A99}$$

Thus there is a unique price such that the allocation above is consistent with household utility maximization. Either Equation (A97) or (A99) imply that under this price, business profits are:

$$\pi = -(\gamma(\tilde{b}) + \nu). \tag{A100}$$

Finally, like in the competitive equilibrium, welfare can be written as:

$$W = \log((1-\alpha)^{1-\alpha}\alpha^{\alpha}) + \alpha\frac{1-\rho}{\rho}\log(J) \tag{A101}$$

$$+ \log(I) - \alpha\log(p) + \alpha(1-\eta)(1+\theta)\frac{1-\rho}{\rho}\log(\tilde{b}) \tag{A102}$$

for the income I, price p and technology adoption $\tilde{b}$ derived above.

The two conditions determining the optimal level of technology adoption in the competitive equilibrium (when $\tau = 0$) and the first-best can be written as:

$$\tilde{b}\gamma'(\tilde{b}) = Z_{FB}\left(\frac{E}{J} - (\gamma(\tilde{b}) + \nu)\right), \qquad Z_{FB} = \alpha(1-\eta)(1+\theta)\frac{(1-\rho)}{\rho} \tag{A103}$$

$$\tilde{b}\gamma'(\tilde{b}) = Z_{CE}\left(\frac{E}{J} - (\gamma(\tilde{b}) + \nu)\right), \qquad Z_{CE} = (1-\eta)\frac{(1-\rho)\alpha}{1-(1-\rho)\alpha} \tag{A104}$$

Thus a sufficient condition for $\tilde{b}_{CE} < \tilde{b}_{FB}$ is that:

$$Z_{CE} < Z_{FB}, \tag{A105}$$

which is equivalent to:

$$1 + \theta(1-(1-\rho)\alpha) < (1-\rho)\alpha + \rho. \tag{A106}$$

The latter condition is true for any $\theta \geq 0$. ■

Approximate Demographic Invariance of the Output Gap Next, we provide an analytical foundation for the claim that the output gap between CE and FB is approximately independent of demographics when $\theta = 0$.

From the discussion above, equilibrium income and output in the CE (with no subsidies) are:

$$I_{CE} = \frac{E - J(\gamma(\tilde{b}_{CE}) + \nu)}{1-(1-\rho)\alpha}, \quad c_{y,CE} = \frac{\alpha\rho I_{CE}}{J\xi}. \tag{A107}$$

In the FB:

$$I_{FB} = E - J(\gamma(\tilde{b}_{FB}) + \nu), \quad c_{y,FB} = \frac{\alpha I_{FB}}{J\xi}. \tag{A108}$$

The output ratio is therefore:

$$\frac{c_{y,CE}}{c_{y,FB}} = \rho \cdot \frac{I_{CE}}{I_{FB}} = \frac{\rho}{1-(1-\rho)\alpha} \cdot \frac{E - J(\gamma(\tilde{b}_{CE}) + \nu)}{E - J(\gamma(\tilde{b}_{FB}) + \nu)}. \tag{A109}$$

Define the overhead cost shares in the CE and FB as:

$$\Phi_{CE} \equiv \frac{J(\gamma(\tilde{b}_{CE}) + \nu)}{E}, \quad \Phi_{FB} \equiv \frac{J(\gamma(\tilde{b}_{FB}) + \nu)}{E}. \tag{A110}$$

The output ratio can then be written as:

$$\frac{c_{y,CE}}{c_{y,FB}} = \frac{\rho}{1-(1-\rho)\alpha} \cdot \frac{1-\Phi_{CE}}{1-\Phi_{FB}}. \tag{A111}$$

The leading term, $\rho/[1-(1-\rho)\alpha]$, has two components. The factor ρ reflects the direct effect of markups: monopoly pricing raises prices by $1/\rho$, reducing quantities by a factor of ρ. The factor $1/[1-(1-\rho)\alpha]$ captures general equilibrium feedback: markup revenue becomes profit income for households, partially offsetting the quantity reduction. Crucially, neither component depends on η.

When overhead costs are small relative to the endowment ($\Phi_{CE}, \Phi_{FB} \ll 1$), a first-order Taylor expansion yields:

$$\frac{1-\Phi_{CE}}{1-\Phi_{FB}} \approx 1 + (\Phi_{FB} - \Phi_{CE}). \tag{A112}$$

Thus:

$$\frac{c_{y,CE}}{c_{y,FB}} \approx \frac{\rho}{1-(1-\rho)\alpha} \left(1 + \Phi_{FB} - \Phi_{CE}\right). \tag{A113}$$

The correction term $(\Phi_{FB} - \Phi_{CE})$ is positive, since $\tilde{b}_{FB} > \tilde{b}_{CE}$ implies higher overhead costs in the FB. This term does depend on η: as η increases, both $\tilde{b}_{FB}$ and $\tilde{b}_{CE}$ fall, reducing both Φ_{FB} and Φ_{CE}, and shrinking the difference between them. However, since the correction term is already second-order in overhead costs, its variation with η has a negligible effect on the output ratio.

To summarize, defining $\Phi \equiv \max\{\Phi_{CE}, \Phi_{FB}\}$:

$$\frac{c_{y,CE}}{c_{y,FB}} = \frac{\rho}{1-(1-\rho)\alpha} + O(\Phi). \tag{A114}$$

The leading term is independent of η. Demographic variation enters only through the $O(\Phi)$ correction, which is quantitatively small when overhead costs are a modest share of total resources.

Proof of Result 3. Suppose $\varepsilon = 0$. Recall that welfare in the competitive equilibrium can be written as:

$$W \quad = \quad \log((1-\alpha)^{1-\alpha}\alpha^{\alpha}) + \alpha\frac{1-\rho}{\rho}\log(J) \tag{A115}$$

$$+ \quad \log(I) - \alpha\log(p) + \alpha(1-\eta)(1+\theta)\frac{1-\rho}{\rho}\log(\tilde{b}). \tag{A116}$$

where:

$$(1-\tau)\gamma'(\tilde{b})\tilde{b} \;=\; (1-\eta)\frac{(1-\rho)\alpha}{1-(1-\rho)\alpha}\left(\frac{E}{J}-(\gamma(\tilde{b})+\nu)\right) \tag{A117}$$

$$p \;=\; \frac{\xi}{\rho} \tag{A118}$$

$$I \;=\; \frac{1}{1-(1-\rho)\alpha}\left(E - J\left(\gamma(\tilde{b})+\nu\right)\right) \tag{A119}$$

The optimal adoption subsidy is the solution to:

$$\tau^* \;=\; \arg\max_{\tau} \quad \log(I) - \alpha\log(p) + \alpha(1-\eta)(1+\theta)\frac{1-\rho}{\rho}\log(\tilde{b}) \tag{A120}$$

subject to Equations (A117)-(A119). The first-order condition is:

$$\frac{\partial\tilde{b}}{\partial\tau}\left(\frac{1}{I}\frac{\partial I}{\partial\tilde{b}} + \alpha(1-\eta)(1+\theta)\frac{1-\rho}{\rho}\frac{1}{\tilde{b}}\right) = 0. \tag{A121}$$

From equation (A117) we see that $\frac{\partial\tilde{b}}{\partial\tau} > 0$. Then, from Equation (A119) we have:

$$\frac{1}{I}\frac{\partial I}{\partial\tilde{b}} = \frac{-J\gamma'(\tilde{b})}{E - J(\gamma(\tilde{b})+\nu)}. \tag{A122}$$

Thus the optimal tax rate must be such that $\tilde{b}$ satisfies:

$$\tilde{b}\gamma'(\tilde{b}) = \alpha(1-\eta)(1+\theta)\frac{1-\rho}{\rho}\left(\frac{E}{J}-(\gamma(\tilde{b})+\nu)\right), \tag{A123}$$

which implies the same level of adoption as in the first-best (Equation A94). Taking ratios of (A123) and (A118), we see that τ must satisfy:

$$1-\tau^* = \frac{1}{\alpha(1+\theta)}\frac{(1-\rho)\alpha}{1-(1-\rho)\alpha}\frac{\rho}{1-\rho} = \frac{1}{1+\theta}\frac{\rho}{1-(1-\rho)\alpha} \in (0,1)\,. \tag{A124}$$

The corresponding level of consumption (under the optimal tax rate) satisfies:

$$(1-\eta)\frac{1-\rho}{\rho}\frac{c_{y,CE}}{\tilde{b}} = \frac{(1-\tau^*)\gamma'(\tilde{b})}{\xi}. \tag{A125}$$

Substituting the expression for τ^* above,

$$(1+\theta)(1-\eta)\frac{1-\rho}{\rho}\frac{c_{y,CE}}{\tilde{b}} = \frac{\rho}{1-(1-\rho)\alpha}\frac{\gamma'(\tilde{b})}{\xi}. \tag{A126}$$

Comparing this with the expression for the first-best level of consumption:

$$(1+\theta)(1-\eta)\frac{1-\rho}{\rho}\frac{c_{y,FB}}{\tilde{b}} = \frac{\gamma'(\tilde{b})}{\xi}, \tag{A127}$$

we see that:

$$\frac{c_{y,CE}}{c_{y,FB}} = \frac{\rho}{1-(1-\rho)\alpha} < 1. \tag{A128}$$

Thus the optimal subsidy does not achieve the first-best level of consumption or output. ■

Intuition for the structure of the optimal adoption subsidy Another intuition for why the optimal adoption subsidy is independent of demographic structure is the following. Recall that, up to a constant, welfare is given by:

$$\begin{aligned} W \quad &\propto \quad (1-\eta)\left(\log(I) - \alpha\log(p) + \alpha(1+\theta)\tfrac{1-\rho}{\rho}\log(\tilde{b})\right) && \text{(Welfare of young consumers)} \\ &+ \quad \eta\left(\log(I) - \alpha\log(p)\right) && \text{(Welfare of old consumers)} \end{aligned}$$

In each of the components of welfare, the common term $\log(I/p^{\alpha})$ appears, and represents the utility associated with the household's real equilibrium income. Moreover, young consumers benefits from the technology adoption choices of businesses directly, as captured by the term $\alpha(1+\theta)\frac{1-\rho}{\rho}\log(\tilde{b})$.

The relative price p is fixed and independent of the adoption subsidy, which, as highlighted above, does not affect markups. Aggregate income does not depends directly on the subsidy τ (since its proceeds to businesses are taxed lumpsum), but only indirectly, through its effect on adoption. Specifically, equilibrium income is:

$$I = \frac{1}{1-(1-\rho)\alpha}\left(E - J(\gamma(\tilde{b}) + \nu)\right). \tag{A129}$$

In choosing the optimal subsidy, the planner trades off two effects. The first is that a higher subsidy drives up adoption, which increases overhead costs of businesses and therefore lowers household income. This represents a welfare cost affecting equally the young and the old; it does not directly depend on the share of young households. The welfare benefit accrues entirely to the young households, who enjoy a higher level of adoption. Formally, the first-order condition characterizing the optimal subsidy is:

$$(1-\eta)\alpha(1+\theta)\frac{1-\rho}{\rho} + \frac{\tilde{b}}{I}\frac{\partial I}{\partial \tilde{b}} = 0. \tag{A130}$$

From Equation (A129), one can see that the elasticity of income to adoption depends on the marginal cost of adoption, $\gamma'(\tilde{b})$. But, in turn, the optimal adoption decision of businesses equates this (private) marginal cost of adoption to the (private) marginal benefit, through Equation (18). The latter private marginal benefit to individual businesses is directly proportional to $(1-\eta)$, the share of young households, which captures the fraction of their sales that are sensitive to the adoption choice. Thus in the planner's first-order condition, both the social benefit (the utility gains from adoption to the young) and the social cost (the decline in income, shared by all) are both proportional to $(1-\eta)$. The impact of demographics on the social costs and benefits of greater adoption exactly cancel out, leaving an optimal subsidy that is independent of demographics.

Letting $L = 1-\rho$, on can write $\underline{\tau}^* = \frac{L(1-\alpha)}{1-\alpha L}$. The Lerner index L captures the "tax" that markups place on the output of businesses on the model, and the term $(1-\alpha)L$ reflects the ability of consumers to substitute into the outside good as a result of that tax. The denominator $1-\alpha L$ reflects higher income from profits rebated to households, which partially offsets the "tax" in the numerator. The resulting optimal subsidy exactly offsets the effect of this mix of two distortions coming from monopoly pricing on adoption.

Optimal transaction subsidy. Suppose $\tau = 0$. Again welfare can be written as:

$$W = \log((1-\alpha)^{1-\alpha}\alpha^{\alpha}) + \alpha\frac{1-\rho}{\rho}\log(J) \tag{A131}$$

$$+ \log(I) - \alpha\log(p) + \alpha(1-\eta)(1+\theta)\frac{1-\rho}{\rho}\log(\tilde{b}), \tag{A132}$$

where:

$$\gamma'(\tilde{b})\tilde{b} = (1-\eta)\frac{(1+\varepsilon-(1+(1-\eta)\varepsilon)\rho)\alpha}{1-(1-(1+(1-\eta)\varepsilon)\rho)\alpha}\left(\frac{E}{J}-(\gamma(\tilde{b})+\nu)\right) \tag{A133}$$

$$p = \frac{1}{1+(1-\eta)\varepsilon}\frac{\xi}{\rho} \tag{A134}$$

$$I = \frac{1}{1-(1-(1+(1-\eta)\varepsilon)\rho)\alpha}\left(E - J\left(\gamma(\tilde{b})+\nu\right)\right) \tag{A135}$$

The optimal transaction subsidy is the solution to:

$$\varepsilon^* = \arg\max_{\varepsilon} \quad \log(I) - \alpha\log(p) + \alpha(1-\eta)(1+\theta)\frac{1-\rho}{\rho}\log(\tilde{b}) \tag{A136}$$

subject to Equations (A133)-(A135). The first-order condition is:

$$0 = \frac{1}{I}\frac{\partial I}{\partial\varepsilon} - \frac{\alpha}{p}\frac{\partial p}{\partial\varepsilon}$$

$$+ \left(\alpha(1-\eta)(1+\theta)\frac{1-\rho}{\rho} + \frac{\tilde{b}}{I}\frac{\partial I}{\partial\tilde{b}}\right)\frac{1}{\tilde{b}}\frac{\partial\tilde{b}}{\partial\varepsilon}.$$

We have:

$$\frac{1}{I}\frac{\partial I}{\partial\varepsilon} = -\frac{\rho}{1-(1-(1+(1-\eta)\varepsilon)\rho)\alpha}(1-\eta)\alpha$$

$$
\begin{aligned}
\frac{\tilde{b}}{I}\frac{\partial I}{\partial \tilde{b}} &= -\frac{\gamma'(\tilde{b})\tilde{b}}{\frac{E}{J} - (\gamma(\tilde{b}) + \nu)} \\
&= -\frac{1 + \varepsilon - (1 + (1-\eta)\varepsilon)\rho}{1 - (1 - (1 + (1-\eta)\varepsilon)\rho)\alpha}\alpha(1-\eta) \\
\frac{1}{p}\frac{\partial p}{\partial \varepsilon} &= -\frac{1}{1 + (1-\eta)\varepsilon}(1-\eta)
\end{aligned}
$$

If $\eta < 1$, the first-order condition can then be rewritten as:

$$
\begin{aligned}
0 &= (1-\alpha)\left(1 - (1 + (1-\eta)\varepsilon)\rho\right) \\
&+ (1 + (1-\eta)\varepsilon)\left((1+\theta)\frac{1-\rho}{\rho}\left(1 - (1 - (1 + (1-\eta)\varepsilon\rho)\alpha\right) - (1 + \varepsilon - (1 + (1-\eta)\varepsilon)\rho)\right)\frac{1}{\tilde{b}}\frac{\partial \tilde{b}}{\partial \varepsilon}.
\end{aligned}
$$

This equation characterizes the optimal value of ε, noting that:

$$
\frac{1}{\tilde{b}}\frac{\partial \tilde{b}}{\partial \varepsilon} = \frac{h'(\varepsilon)}{h(\varepsilon)}\frac{\gamma'(\tilde{b})}{(1 + h(\varepsilon))\gamma'(\tilde{b}) + \tilde{b}\gamma''(\tilde{b})} \tag{A137}
$$

where:

$$
\begin{aligned}
h(\varepsilon) &= (1-\eta)\frac{(1 + \varepsilon - (1 + (1-\eta)\varepsilon)\rho)\alpha}{1 - (1 - (1 + (1-\eta)\varepsilon)\rho)\alpha} \\
h'(\varepsilon) &= \frac{(1-\eta)\alpha[1 - (1-\eta)\rho][1 - (1 - (1 + (1-\eta)\varepsilon)\rho)\alpha] - (1-\eta)(1 + \varepsilon - (1 + (1-\eta)\varepsilon)\rho)\alpha\rho\alpha}{[1 - (1 - (1 + (1-\eta)\varepsilon)\rho)\alpha]^2} \\
\frac{h'(\varepsilon)}{h(\varepsilon)} &= \frac{1 - (1-\eta)\rho}{1 + \varepsilon - (1 + (1-\eta)\varepsilon)\rho} - \frac{(1-\eta)\rho\alpha}{1 - (1 - (1 + (1-\eta)\varepsilon)\rho)\alpha}.
\end{aligned}
$$

■

Proof of result 4. When $\varepsilon > 0$ and $\tau > 0$, welfare can still be written as:

$$
\begin{aligned}
W &= \log((1-\alpha)^{1-\alpha}\alpha^{\alpha}) + \alpha\frac{1-\rho}{\rho}\log(J) && \text{(A138)} \\
&+ \log(I) - \alpha\log(p) + \alpha(1-\eta)(1+\theta)\frac{1-\rho}{\rho}\log(\tilde{b}), && \text{(A139)}
\end{aligned}
$$

where:

$$
\begin{aligned}
(1-\tau)\gamma'(\tilde{b})\tilde{b} &= (1-\eta)\frac{(1 + \varepsilon - (1 + (1-\eta)\varepsilon)\rho)\alpha}{1 - (1 - (1 + (1-\eta)\varepsilon)\rho)\alpha}\left(\frac{E}{J} - (\gamma(\tilde{b}) + \nu)\right) && \text{(A140)} \\
p &= \frac{1}{1 + (1-\eta)\varepsilon}\frac{\xi}{\rho} && \text{(A141)}
\end{aligned}
$$

$$I = \frac{1}{1-(1-(1+(1-\eta)\varepsilon)\rho)\alpha}\left(E - J\left(\gamma(\tilde{b})+\nu\right)\right) \tag{A142}$$

The optimal transaction and adoption subsidies are the solution to:

$$\{\varepsilon^{**},\tau^{**}\} \in \arg\max_{\varepsilon,\tau} \quad \log(I) - \alpha\log(p) + \alpha(1-\eta)(1+\theta)\frac{1-\rho}{\rho}\log(\tilde{b}) \tag{A143}$$

subject to Equations (A140)-(A142).

Suppose first that $\eta < 1$. The first-order conditions are:

$$\begin{aligned} 0 &= \frac{1}{I}\frac{\partial I}{\partial \varepsilon} - \frac{\alpha}{p}\frac{\partial p}{\partial \varepsilon} \\ &+ \left(\alpha(1-\eta)(1+\theta)\frac{1-\rho}{\rho} + \frac{\tilde{b}}{I}\frac{\partial I}{\partial \tilde{b}}\right)\frac{1}{\tilde{b}}\frac{\partial \tilde{b}}{\partial \varepsilon} \\ 0 &= \left(\alpha(1-\eta)(1+\theta)\frac{1-\rho}{\rho} + \frac{\tilde{b}}{I}\frac{\partial I}{\partial \tilde{b}}\right)\frac{1}{\tilde{b}}\frac{\partial \tilde{b}}{\partial \tau} \end{aligned}$$

We will later check that, at the optimum, $\frac{\partial \tilde{b}}{\partial \tau} > 0$. Therefore the optimality conditions simplify to:

$$0 = \frac{1}{I}\frac{\partial I}{\partial \varepsilon} - \frac{\alpha}{p}\frac{\partial p}{\partial \varepsilon} \tag{A144}$$

$$0 = \alpha(1-\eta)(1+\theta)\frac{1-\rho}{\rho} + \frac{\tilde{b}}{I}\frac{\partial I}{\partial \tilde{b}} \tag{A145}$$

From Equation (A141) and (A142), since income I and prices p do not depend directly on adoption subsidies τ, we have that:

$$\begin{aligned} \frac{1}{I}\frac{\partial I}{\partial \varepsilon} &= -\frac{\rho}{1-(1-(1+(1-\eta)\varepsilon)\rho)\alpha}(1-\eta)\alpha \\ \frac{1}{p}\frac{\partial p}{\partial \varepsilon} &= -\frac{1}{1+(1-\eta)\varepsilon}(1-\eta) \end{aligned}$$

From Equation (A144) we see that ε^{**} must satisfy:

$$(1+(1-\eta)\varepsilon^{**})\rho = 1 \tag{A146}$$

$$\varepsilon^{**} = \frac{1}{1-\eta}\frac{1-\rho}{\rho} \tag{A147}$$

Note that this is the subsidy that neutralizes the markup, so that $p = \xi$ when $\varepsilon = \varepsilon^{**}$. Next, from

Equation (A142) again, we have that:

$$\frac{\tilde{b}}{I}\frac{\partial I}{\partial \tilde{b}} \quad = \quad -\frac{\gamma'(\tilde{b})\tilde{b}}{\frac{E}{J}-(\gamma(\tilde{b})+\nu)}$$

Thus at the optimum, the adoption rate will satisfy:

$$\gamma'(\tilde{b})\tilde{b} = \alpha(1-\eta)(1+\theta)\frac{1-\rho}{\rho}\left(\frac{E}{J}-(\gamma(\tilde{b})+\nu)\right) \tag{A148}$$

which is the same as Equation (A103), which characterizes the first-best level of adoption. Thus adoption will equal the first-best level. When $\varepsilon = \varepsilon^{**}$, Equation (A140) becomes:

$$(1-\tau)\gamma'(\tilde{b})\tilde{b} \quad = \quad (1-\eta)\varepsilon^{**}\alpha\left(\frac{E}{J}-(\gamma(\tilde{b})+\nu)\right) \tag{A149}$$

$$= \quad \alpha\frac{1-\rho}{\rho}\left(\frac{E}{J}-(\gamma(\tilde{b})+\nu)\right) \tag{A150}$$

Taking ratios of Equation (A149) and (A148), we obtain:

$$1-\tau^{**} \quad = \quad \frac{1}{(1-\eta)(1+\theta)}, \tag{A151}$$

or equivalently:

$$\tau^{**} \quad = \quad 1-\frac{1}{1+\theta}\frac{1}{1-\eta}. \tag{A152}$$

To conclude the proof we need to show that $\frac{\partial\tilde{b}}{\partial\tau} > 0$. From Equation (A140), we have:

$$\frac{\partial\tilde{b}}{\partial\tau} \quad = \quad \frac{\gamma'(\tilde{b})\tilde{b}}{\Xi(\varepsilon)\gamma'(\tilde{b})+(1-\tau)\frac{\partial}{\partial\tilde{b}}(\gamma'(\tilde{b})\tilde{b})} \tag{A153}$$

$$\Xi(\varepsilon) \quad \equiv \quad (1-\eta)\frac{(1+\varepsilon-(1+(1-\eta)\varepsilon)\rho)\alpha}{1-(1-(1+(1-\eta)\varepsilon)\rho)\alpha} \tag{A154}$$

Since γ is strictly increasing and weakly convex, this equation implies that $\frac{\partial\tilde{b}}{\partial\tau} > 0$. Thus when $\eta < 1$, the optimal subsidies are:

$$\tau^{**} \quad = \quad 1-\frac{1}{1+\theta}\frac{1}{1-\eta}$$

$$\varepsilon^{**} \quad = \quad \frac{1}{1-\eta}\frac{1-\rho}{\rho}$$

We have already shown that when $\tau = \tau^{**}$, adoption is equal to its first-best level. Moreover when

$\varepsilon = \varepsilon^{**}$, prices are equal to marginal cost. Income is given by:

$$I = E - J\left(\gamma(\tilde{b}) + \nu\right), \tag{A155}$$

also as in the first-best. Thus welfare is at its first-best level. Finally output is:

$$c_y = \frac{\alpha}{\xi}\left(\frac{E}{J} - \left(\gamma(\tilde{b}) + \nu\right)\right), \tag{A156}$$

also as in the first-best.

To conclude, we now consider the case when $\eta = 1$. In this case the optimal subsidy scheme solves:

$$\{\varepsilon^{**}, \tau^{**}\} \in \arg\max_{\varepsilon,\tau} \quad \log(I) - \alpha \log(p) \tag{A157}$$

subject to:

$$(1-\tau)\gamma'(\tilde{b})\tilde{b} = 0 \tag{A158}$$

$$p = \frac{\xi}{\rho} \tag{A159}$$

$$I = \frac{1}{1-(1-\rho)\alpha}\left(E - J\left(\gamma(\tilde{b}) + \nu\right)\right) \tag{A160}$$

From this we can see that the subsidies have no effect on the allocation so long as $\tau < 1$. Thus any $\tau^{**} \in [0, 1)$ and any $\varepsilon^{**} > 0$ is optimal, but the allocation remains identical to the competitive equilibrium, and therefore not first-best efficient. ■

A.4.2 The case of free-entry

1. Discussion of main results

With free entry, an additional inefficiency arises in the competitive equilibrium: businesses cannot perfectly internalize the consumer surplus associated with the greater variety that their entry creates. As we will show, this demand externality can also interact with adoption decisions.

First-best benchmark

Definition 3. *The first-best (FB) allocation are quantities* $\left\{O_o, O_y, c_o, c_y, \tilde{b}\right\}$ *and a number of businesses* J *that maximize the welfare criterion (14) subject to the resource constraint (1).*

Result 5 (First-best allocation)**.** *In the first-best allocation, the planner chooses an adoption rate that satisfies:*

$$(1-\eta)(1+\theta)(\gamma(\tilde{b}) + \nu) = \gamma'(\tilde{b})\tilde{b}. \tag{A161}$$

If there are no externalities ($\theta = 0$), technology adoption and consumption are equal to their competitive equilibrium level, though entry is higher in the first-best than in the competitive equilibrium.

With externalities ($\theta > 0$), the first-best allocation features more technology adoption and production than the competitive equilibrium:

$$\tilde{b}_{FB} > \tilde{b}_{CE}, \quad c_{y,FB} > c_{y,CE}. \tag{A162}$$

The first-best allocation can also feature less entry than the competitive equilibrium for a sufficiently large value of the externality parameter θ.

To understand this result, note that the competitive equilibrium level of adoption with free-entry is given by:

$$(1 - \eta)(\gamma(\tilde{b}) + \nu) = \gamma'(\tilde{b})\tilde{b}. \tag{A163}$$

Equation (A163) can be thought of as follows. With free-entry, the markup revenue from production of each variety must be equal to the total overhead costs $\gamma(\tilde{b}) + \nu$. As explained in Section 3, the elasticity of markup revenue to adoption is constant equal to $1 - \eta$, so that the equilibrium marginal benefit of technology adoption will equal $(1 - \eta)(\gamma(\tilde{b}) + \nu)/\tilde{b}$. Thus the equation above equates the marginal benefits from technology adoption to their marginal cost. In the absence of network externalities ($\theta = 0$), this equation coincides with the planner's first-order condition, (A161), leading to an efficient outcome for adoption. Because the planner and the market also have the same marginal rate of substitution between output and technology when $\theta = 0$, an efficient level of adoption also coincides with an efficient level of production.

Note, however, that even without externalities ($\theta = 0$), the competitive equilibrium allocation does not lead to the first-best level of entry. This is because of the love-for-variety effect: the planner would value more consumer surplus from additional varieties, but businesses cannot capture that surplus once the break-even condition binds.[91] Appendix Figure A-15, right panel, illustrates this — when $\theta = 0$, entry remains inefficiently low.

Finally, Result 5 states that entry might be inefficiently *high* in the CE when adoption externalities are strong enough. This is shown, numerically, in the right panel of Appendix Figure A-15. With positive network externalities, the first-best planner would want to adopt the technology more broadly. This increases the overhead resource costs $\gamma(\tilde{b}) + \nu$ associated with the creation of each variety. Despite the love-for-variety effect, the first-best planner is willing to tolerate somewhat lower entry in order to reduce these welfare costs, effectively substituting variety for broader technology adoption.

Optimal adoption subsidy Let $W(\tau; \theta, \eta)$ be the welfare criterion from Equation (14) under the allocation corresponding to the competitive equilibrium with free entry and with an adoption subsidy equal to $\tau \geq 0$. We denote by $\tau^{**}(\eta, \theta)$ the subsidy that maximizes $W(\tau; \theta, \eta)$.

[91] As mentioned above, we show in Appendix A.4 that the CE level of entry is constrained-efficient, that is, coincides with the level of entry chosen by a planner bound to meet a zero-profit condition.

Result 6 (Optimal adoption subsidy with free-entry)**.** *For all $\eta < 1$, a small adoption subsidy improves welfare:*

$$\frac{\partial W}{\partial \tau}(0; \eta, \theta) > 0 \quad \forall \eta \in [0, 1), \quad \forall \theta \geq 0, \tag{A164}$$

even in the absence of externalities. The optimal adoption subsidy in the competitive equilibrium with free-entry is therefore strictly positive: $\tau^{**}(\eta, \theta) > 0$.

Moreover, absent externalities, the marginal welfare gain from a small adoption subsidy is smaller, the larger the share of old consumers:

$$\frac{\partial}{\partial \eta}\left(\frac{\partial W}{\partial \tau}(0; \eta, \theta)\right) < 0 \quad \text{when } \theta = 0. \tag{A165}$$

To understand this result, the key is to note that With free entry, an adoption subsidy is a second-best tool: it raises adoption b, but also increases overhead costs $\gamma(\tilde{b}) + \nu$ for each business, thus potentially lowering entry J, even when externalities are absent ($\theta = 0$).

First consider the case $\theta = 0$. An adoption subsidy is always desirable, *even though* adoption in the CE without subsidy is already at its first-best level, as indicated by Result 5. Since adoption increases with the subsidy, it will therefore be *above* its first-best level. This is illustrated in the bottom middle panel of Appendix Figure A-15, which reports the level of adoption under the optimal subsidy $\tau = \tau^{**}$ relative to the CE without subsidy.[92] The bottom right panel of Appendix Figure A-15 also reports the entry rate under the optimal subsidy, and shows that it is *lower than* the entry rate in the CE without subsidy, and therefore also lower than in FB.

Lower entry under the optimal subsidy might be surprising. In the CE, entrants cannot appropriate the surplus from more varieties once the zero-profit condition binds; one might have expected policy to aim at relaxing that constraint. However, with an adoption subsidy the planner cannot directly increase the number of varieties. Instead, an adoption subsidy raises overhead costs $\gamma(b) + \nu$, and tightens free entry, lowering the number of businesses. At the optimum, the gains from higher adoption outweigh the loss from fewer varieties. This is a second-best outcome: with an entry subsidy, the planner could instead target entry directly, and leave adoption unchanged.

Result 5 also shows that, even when $\theta = 0$, a small subsidy has a larger effect on welfare when the share of old consumers is smaller. A direct implication of this second point is that even with free-entry, a planner should subsidize adoption everywhere, but more aggressively in places where consumers are younger. This stands in contrast with the optimal adoption subsidy with a fixed number of businesses, which is entirely independent of demographics. Underscoring this point, the bottom left panel of Appendix Figure A-15 shows that the optimal subsidy $\tau^{**}(\eta)$ is decreasing with respect to η even without externalities. As discussed above, the effect of the adoption subsidy is primarily to increase adoption (the welfare effects of which are limited to the young), at the expense of reducing variety (the welfare effects of which are shared by the young and the old).

In the case $\theta > 0$, the optimal subsidy is also positive. But in that case, adoption in the CE

[92] The optimal subisdy rate τ^{**} does not admit an analytical characterization, so we use the numerical example in Appendix Figure A-15 to discuss the properties of the CE under the optimal subsidy rate.

without subsidy is too low relative to first-best, as businesses cannot fully internalize the consumer surplus that network externalities create. The resulting optimal subsidy is naturally higher, as shown in the bottom left panel of Appendix Figure A-15. Because the social returns to higher adoption are larger, the planner is also willing to tolerate a larger reduction in entry relative to the CE; that is, with only an adoption subsidy, the planner substitutes lower variety with a higher rate of technology adoption. That effect is stronger, the larger the share of young consumers, as indicated by the bottom right panel of Appendix Figure (A-15).

In summary, with free-entry, subsidizing adoption is always optimal, but comes at the expense of reduced entry relative to the competitive equilibrium level. Moreover, because the benefits of higher adoption entirely fall on the young, the subsidy is increasing in the share of young consumers.

2. Proofs for the case of free-entry

Proof of Result 5. Using Result 2, the first-best is the solution to:

$$W = \max_J \quad \log((1-\alpha)^{1-\alpha}\alpha^{\alpha}) + \alpha\frac{1-\rho}{\rho}\log(J) \tag{A166}$$

$$+ \quad \log(I) - \alpha\log(p) + \alpha(1-\eta)(1+\theta)\frac{1-\rho}{\rho}\log(\tilde{b}) \tag{A167}$$

where:

$$\begin{aligned}
\tilde{b}\gamma'(\tilde{b}) &= \alpha(1-\eta)(1+\theta)\frac{(1-\rho)}{\rho}\left(\frac{E}{J} - (\gamma(\tilde{b})+\nu)\right) \\
I &= E - J(\gamma(\tilde{b})+\nu) \\
p &= \xi
\end{aligned}$$

The first-order condition is:

$$\alpha\frac{1-\rho}{\rho}\frac{1}{J} + \frac{1}{I}\frac{\partial I}{\partial J} + \frac{\partial\tilde{b}}{\partial J}\left(\frac{1}{I}\frac{\partial I}{\partial\tilde{b}} + \alpha(1-\eta)(1+\theta)\frac{1-\rho}{\rho}\frac{1}{\tilde{b}}\right) = 0. \tag{A168}$$

But note that:

$$\frac{1}{I}\frac{\partial I}{\partial\tilde{b}} = -\alpha\frac{\gamma'(\tilde{b})}{\xi}\frac{1}{c_y}. \tag{A169}$$

Moreover, from result 2, we have that:

$$(1-\eta)(1+\theta)\frac{1-\rho}{\rho}\frac{1}{\tilde{b}} = \frac{\gamma'(\tilde{b})}{\xi}\frac{1}{c_y}. \tag{A170}$$

Thus in Equation (A168), the term in parentheses is equal to zero at any optimal allocation (for fixed J). Thus the first-order condition simplifies to:

$$\alpha\frac{1-\rho}{\rho}\frac{1}{J}+\frac{1}{I}\frac{\partial I}{\partial J}=\alpha\frac{1-\rho}{\rho}\frac{1}{J}-\frac{\gamma(\tilde{b})+\nu}{E-J(\gamma(\tilde{b})+\nu)}=0. \tag{A171}$$

Thus the optimal $(J,\tilde{b})$ are the unique solution to the system:

$$\alpha\frac{1-\rho}{\rho}\left(\frac{E}{J}-(\gamma(\tilde{b})+\nu)\right) = \gamma(\tilde{b})+\nu \tag{A172}$$

$$\alpha\frac{1-\rho}{\rho}\left(\frac{E}{J}-(\gamma(\tilde{b})+\nu)\right) = \frac{1}{(1-\eta)(1+\theta)}\tilde{b}\gamma'(\tilde{b}) \tag{A173}$$

implying:

$$(1-\eta)(1+\theta)(\gamma(\tilde{b})+\nu) = \tilde{b}\gamma'(\tilde{b}) \tag{A174}$$

$$J = \frac{\alpha(1-\rho)}{\rho+\alpha(1-\rho)}\frac{E}{\gamma(\tilde{b})+\nu} \tag{A175}$$

$$I = \frac{\rho}{\rho+\alpha(1-\rho)}E \tag{A176}$$

$$p = \xi \tag{A177}$$

$$\pi = -(\gamma(\tilde{b})+\nu) \tag{A178}$$

$$O_y = (1-\alpha)\frac{\alpha(1-\rho)}{\rho+\alpha(1-\rho)}E \tag{A179}$$

$$O_o = O_y \tag{A180}$$

$$c_y = \frac{1}{\xi}\frac{\rho}{1-\rho}(\gamma(\tilde{b})+\nu) \tag{A181}$$

Recall that the competitive equilibrium with free-entry is described by:

$$(1-\eta)(\nu+\gamma(\tilde{b}_{CE})) = \tilde{b}_{CE}\gamma'(\tilde{b}_{CE}) \tag{A182}$$

$$J_{CE} = \frac{\alpha(1-\rho)}{\gamma(\tilde{b}_{CE})+\nu}E \tag{A183}$$

$$c_{y,CE} = \frac{1}{\xi}\frac{\rho}{1-\rho}\left(\gamma(\tilde{b}_{CE})+\nu\right) \tag{A184}$$

First consider the case with no externalities: $\theta = 0$. Then we see that $\tilde{b}_{CE} = \tilde{b}_{FB}$, and so $c_{y,CE} = c_{y,FB}$. However, there is still too little entry relative to first-best: $J_{CE} < J_{FB}$.

Now consider the case with externalities: $\theta > 0$. Because $(1-\eta)(1+\theta)(\gamma(\tilde{b})+\nu) > (1-\eta)(\gamma(\tilde{b})+\nu)$, there is too little adoption in the competitive equilibrium:

$$\tilde{b}_{CE} < \tilde{b}_{FB}. \tag{A185}$$

This also implies that output is too low in the equilibrium with free-entry, $c_{y,CE} < c_{y,FB}$. Finally, whether entry is higher in CE or FB is ambiguous, and depends on whether:

$$(\alpha(1-\rho)+\rho)(\gamma(\tilde{b}_{FB})+\nu) > \gamma(\tilde{b}_{CE})+\nu. \tag{A186}$$

From Equation (A174), one sees that $\lim_{\theta\to+\infty} b_{FB}(\theta) = +\infty$, while $\tilde{b}_{CE}$ is independent of θ; thus for sufficiently large θ the condition above will hold and entry in the competitive equilibrium will be too high relative to that required by the planner. ■

proof of Result 6. Recall that welfare in the competitive equilibrium can be written as:

$$W = \log((1-\alpha)^{1-\alpha}\alpha^{\alpha}) + \alpha\frac{1-\rho}{\rho}\log(J) \tag{A187}$$

$$+ \log(I) - \alpha\log(p) + \alpha(1-\eta)(1+\theta)\frac{1-\rho}{\rho}\log(\tilde{b}). \tag{A188}$$

where:

$$(1-\tau)\gamma'(\tilde{b})\tilde{b} = (1-\eta)\left(\nu+(1-\tau)\gamma(\tilde{b})\right) \tag{A189}$$

$$p = \frac{\xi}{\rho} \tag{A190}$$

$$I = \frac{\nu+(1-\tau)\gamma(\tilde{b})}{\nu+(1-[1-(1-\rho)\alpha]\,\tau)\gamma(\tilde{b})}E \tag{A191}$$

$$J = \frac{(1-\rho)\alpha E}{\nu+(1-[1-(1-\rho)\alpha]\,\tau)\gamma(\tilde{b})} \tag{A192}$$

The optimal subsidy is the solution to:

$$\tau^{**} = \arg\max_{\tau} \quad \alpha\frac{1-\rho}{\rho}\log(J) + \log(I) + \alpha(1-\eta)(1+\theta)\frac{1-\rho}{\rho}\log(\tilde{b}) \tag{A193}$$

subject to Equations (A189), (A191) and (A192).

We first rewrite the objective as:

$$W(\tau;\eta,\theta) = \left(1+\alpha\frac{1-\rho}{\rho}\right)\log(J) + \log(\Omega) + \alpha(1-\eta)(1+\theta)\frac{1-\rho}{\rho}\log(\tilde{b}) \tag{A194}$$

where:

$$(1-\tau)\gamma'(\tilde{b})\tilde{b} = (1-\eta)\left(\nu+(1-\tau)\gamma(\tilde{b})\right) \tag{A195}$$

$$\frac{I}{J} \equiv \Omega = \frac{\nu+(1-\tau)\gamma(\tilde{b})}{(1-\rho)\alpha} \tag{A196}$$

$$J = \frac{(1-\rho)\alpha E}{\nu+(1-[1-(1-\rho)\alpha]\,\tau)\gamma(\tilde{b})} \tag{A197}$$

Next, we have the following relationships:

$$\frac{\partial J}{\partial \tau} = (1-(1-\rho)\alpha)\gamma(\tilde{b})\frac{J^2}{(1-\rho)\alpha E} \tag{A198}$$

$$\frac{\partial J}{\partial \tilde{b}} = -(1-[1-(1-\rho)\alpha]\,\tau)\gamma'(\tilde{b})\frac{J^2}{(1-\rho)\alpha E} \tag{A199}$$

$$\frac{\partial \Omega}{\partial \tau} = \frac{-\gamma(\tilde{b})}{\nu+(1-\tau)\gamma(\tilde{b})}\Omega \tag{A200}$$

$$\frac{\partial \Omega}{\partial \tilde{b}} = \frac{-\gamma(\tilde{b})}{\nu+(1-\tau)\gamma'(\tilde{b})}\Omega \tag{A201}$$

The necessary first-order condition characterizing τ^{**} can be written as:

$$\begin{aligned} 0 = \frac{\partial W}{\partial \tau}(\tau;\eta,\theta) &= \left(1+\alpha\frac{1-\rho}{\rho}\right)\frac{1}{J}\left(\frac{\partial J}{\partial \tau}+\frac{\partial J}{\partial \tilde{b}}\frac{\partial \tilde{b}}{\partial \tau}\right) \\ &+ \frac{1}{\Omega}\left(\frac{\partial \Omega}{\partial \tau}+\frac{\partial \Omega}{\partial \tilde{b}}\frac{\partial \tilde{b}}{\partial \tau}\right) \\ &+ \alpha(1-\eta)(1+\theta)\frac{1-\rho}{\rho}\frac{1}{\tilde{b}}\frac{\partial \tilde{b}}{\partial \tau} \end{aligned}$$

Using the equations above, we can reorganize the expression for the derivative of the objective function as:

$$\begin{aligned} \frac{\partial W}{\partial \tau}(\tau;\eta,\theta) &= \frac{\gamma(\tilde{b})}{\nu+(1-\tau)\gamma(\tilde{b})}\left[\left(1+\alpha\frac{1-\rho}{\rho}\right)(1-(1-\rho)\alpha)\frac{\nu+(1-\tau)\gamma(\tilde{b})}{\nu+(1-(1-(1-\rho)\alpha)\,\tau)\gamma(\tilde{b})}-1\right] \\ &+ (1-\eta)\frac{1}{\tilde{b}}\frac{\partial \tilde{b}}{\partial \tau}\left[1+(1+\theta)\alpha\frac{1-\rho}{\rho}-\left(1+\alpha\frac{1-\rho}{\rho}\right)\frac{1-(1-(1-\rho)\alpha)\tau}{1-\tau}\frac{\nu+(1-\tau)\gamma(\tilde{b})}{\nu+(1-(1-(1-\rho)\alpha)\,\tau)\gamma(\tilde{b})}\right] \end{aligned}$$

Finally, note that:

$$\frac{\nu+(1-\tau)\gamma(\tilde{b})}{\nu+(1-(1-(1-\rho)\alpha)\,\tau)\gamma(\tilde{b})}=\frac{I}{E},\quad \geq 1,\quad >1\quad \text{iff } \tau>0.$$

So we write the derivative of the objective function in more condensed form as:

$$\begin{aligned}\frac{\partial W}{\partial \tau}(\tau;\eta,\theta) &= \frac{\gamma(\tilde{b})}{\nu+(1-\tau)\gamma(\tilde{b})}\left[\left(1+\alpha\frac{1-\rho}{\rho}\right)(1-(1-\rho)\alpha)\frac{I}{E}-1\right] \\ &+ (1-\eta)\frac{1}{\tilde{b}}\frac{\partial \tilde{b}}{\partial \tau}\left[1+(1+\theta)\alpha\frac{1-\rho}{\rho}-\left(1+\alpha\frac{1-\rho}{\rho}\right)\frac{1-(1-(1-\rho)\alpha)\tau}{1-\tau}\frac{I}{E}\right]\end{aligned}$$

Next, note that:

$$\begin{aligned}\frac{\partial \tilde{b}}{\partial \tau} &= \frac{1}{(1-\tau)^2}\frac{(1-\eta)\nu}{\gamma''(\tilde{b})\tilde{b}+\eta\gamma'(\tilde{b})}>0 \\ \frac{\partial \tilde{b}}{\partial \eta} &= \frac{1}{1-\tau}\frac{-(\nu+(1-\tau)\gamma(\tilde{b}))}{\gamma''(\tilde{b})\tilde{b}+\eta\gamma'(\tilde{b})}<0\end{aligned}$$

Now we prove that $\tau^{**}>0$, even when $\theta=0$. We have:

$$\begin{aligned}\frac{\partial W}{\partial \tau}(0;\eta,\theta) &= \frac{\gamma(\tilde{b})}{\nu+\gamma(\tilde{b})}\left[\left(1+\alpha\frac{1-\rho}{\rho}\right)(1-(1-\rho)\alpha)-1\right] \\ &+ (1-\eta)\frac{1}{\tilde{b}}\frac{\partial \tilde{b}}{\partial \tau}\theta\alpha\frac{1-\rho}{\rho}\end{aligned}$$

Note that:

$$\left(1+\alpha\frac{1-\rho}{\rho}\right)(1-(1-\rho)\alpha)=1+(1-\alpha)(1-\rho)\alpha\frac{1-\rho}{\rho}$$

So:

$$\begin{aligned}\frac{\partial W}{\partial \tau}(0;\eta,\theta) &= \alpha\frac{1-\rho}{\rho}\left(\frac{\gamma(\tilde{b})}{\nu+\gamma(\tilde{b})}(1-\alpha)(1-\rho)+(1-\eta)\frac{1}{\tilde{b}}\frac{\partial \tilde{b}}{\partial \tau}\theta\right) \\ &> 0,\end{aligned}$$

so that it must be that $\tau^{**}>0$. This is true even when $\theta=0$.

Next we prove that when $\theta=0$, the welfare gain from a small adoption subsidy is lower, the higher the share of old consumers. We have:

$$\frac{\partial}{\partial \eta}\frac{\partial W}{\partial \tau}(0;\eta,\theta) \quad \propto \quad -\frac{\theta}{\tilde{b}}\frac{\partial \tilde{b}}{\partial \tau}$$

$$+ \quad (1-\eta)\theta \frac{\partial}{\partial \eta}\left(\frac{1}{\tilde{b}}\frac{\partial \tilde{b}}{\partial \tau}\right)$$

$$+ \quad (1-\alpha)(1-\rho)\frac{\partial}{\partial \eta}\left(1 - \frac{\nu}{\nu+\gamma(\tilde{b})}\right)$$

The last term is always negative because $\partial\tilde{b}/\partial\eta < 0$. Additionally, when $\theta = 0$, the first two terms are equal to zero, establishing the result. ■

A.4.3 Comparing the CE and the constrained optimal (CO) allocation

We use "CO" to denote the planner's problem that maximizes welfare *subject to* the same technological and market constraints as the competitive equilibrium, most importantly, positive profits. This benchmark is distinct from the first best (FB), which can set $p = \xi$ and transfer business losses to the household. Under free entry, with $\theta = 0$, CO and CE coincide (the classic constrained-efficiency result), whereas with a fixed number of businesses CO can differ from CE.

1. Fixed number of businesses

Definition 4. *A constrained optimal (CO) allocation is a price p for intermediate varieties and a set of quantities* $\left\{O_o, O_y, c_o, c_y, \tilde{b}\right\}$ *that maximizes the welfare criterion (14) subject to the constraints that (a) the quantities* $\{O_o, O_y, c_o, c_y\}$ *are consistent with utility maximization of young and old consumers given* $(p, \tilde{b})$*; (b) resulting business profits are weakly positive,* $\pi \geq 0$*; and (c) the resource constraint (1) holds.*

Result 7 (Constrained-optimal allocation)**.** *In the constrained optimal allocation, the planner also chooses* $(c_y, \tilde{b})$ *such that (15) holds. Price is equal to average cost and businesses make zero profits. Finally, when profits in the competitive equilibrium are strictly positive, technology adoption and consumption are strictly higher than in the CE, even without externalities* ($\theta = 0$)*:*

$$\tilde{b}_{CO} > \tilde{b}_{CE}, \quad c_{y,CO} > c_{y,CE} \quad \text{if} \quad \pi_{CE} > 0. \tag{A202}$$

Proof of result 7. The constrained optimal allocation is the solution to:

$$W \quad = \quad \max_{O_o, O_y, c_o, c_y, \tilde{b}, p} \eta \log(O_o^{1-\alpha} C_o^{\alpha}) + (1-\eta)\log(O_y^{1-\alpha} C_y^{\alpha}) \tag{A203}$$

$$\text{s.t.} \quad \eta O_o + (1-\eta)O_y + J\xi\left(\eta c_o + (1-\eta)c_y\right) + J(\gamma(\tilde{b}) + \nu) \leq E \qquad [\lambda]$$

$$C_O = J^{\frac{1}{\rho}} c_o \tag{A204}$$

$$C_y = J^{\frac{1}{\rho}} \tilde{b}^{(1+\theta)\frac{1-\rho}{\rho}} c_y \tag{A205}$$

$$\pi = (p - \xi)c_y - (\gamma(\tilde{b}) + \nu) \geq 0 \tag{A206}$$

$$c_y = \frac{\alpha(E + J\pi)}{Jp} \tag{A207}$$

Note here that implementability (that is, maximization of utility by consumers given p) requires $O_o = O_y = (1-\alpha)(E + J\pi)$ and $c_o = c_y$, but we have omitted these conditions for brevity, though they are implicit in the expression of business profits.

Ignoring the constraint (A206), we see that the price p only appears in the implementability condition (A207). So we can solve for the optimal allocation ignoring (A207), and use that condition to back out the resulting equilibrium price. But in this case, the problem is identical to the first-best allocation problem discussed above. And this problem, along with the implementability condition (A207), leads to $\pi = -(\gamma(\tilde{b}) + \nu) < 0$, violating the zero-profit condition (A206). Thus, that condition must bind. As a result, at the constrained optimal allocation businesses make zero profits and therefore:

$$I = E, \quad c_o = c_y = \alpha \frac{E}{Jp}, \quad O_o = O_y = (1-\alpha)E. \tag{A208}$$

Substituting these expressions in the definition of profits implies that, for any level of $\tilde{b}$ we must have:

$$\begin{aligned} p &= \xi \left(1 + \frac{\gamma(\tilde{b}) + \nu}{\alpha \frac{E}{J} - (\gamma(\tilde{b}) + \nu)} \right) \\ c_y &= \frac{1}{\xi} \left(\alpha \frac{E}{J} - (\gamma(\tilde{b}) + \nu) \right) \end{aligned}$$

Finally, substituting the expression for c_y in the objective function and optimizing with respect to $\tilde{b}$ gives the following solution:

$$\begin{aligned} \tilde{b}\gamma'(\tilde{b}) &= (1-\eta)(1+\theta)\frac{(1-\rho)}{\rho} \left(\alpha \frac{E}{J} - (\gamma(\tilde{b}) + \nu) \right) \\ \lambda^{-1} &= E \\ O_y &= (1-\alpha)E \\ O_o &= O_y \\ c_y &= \frac{1}{\xi} \left(\alpha \frac{E}{J} - (\gamma(\tilde{b}) + \nu) \right) \\ c_o &= c_y \\ I &= E \\ \pi &= 0 \end{aligned}$$

$$p = \xi\left(1+\frac{\gamma(\tilde{b})+\nu}{\alpha\frac{E}{J}-(\gamma(\tilde{b})+\nu)}\right)$$

Note that in particular, $(c_y, \tilde{b})$ satisfy:

$$(1-\eta)(1+\theta)\frac{1-\rho}{\rho}\frac{c_y}{\tilde{b}} = \frac{\gamma'(\tilde{b})}{\xi}. \tag{A209}$$

Finally, like in the competitive equilibrium, welfare can be written as:

$$W = \log((1-\alpha)^{1-\alpha}\alpha^{\alpha}) + \alpha\frac{1-\rho}{\rho}\log(J) \tag{A210}$$

$$+ \log(I) - \alpha\log(p) + \alpha(1-\eta)(1+\theta)\frac{1-\rho}{\rho}\log(\tilde{b}) \tag{A211}$$

for the income I, adoption $\tilde{b}$ and price p derived above.

The two conditions determining the optimal level of technology adoption in the constrained optimal allocation and the first-best can be written as:

$$\tilde{b}\gamma'(\tilde{b}) = Z_{FB}\left(\frac{E}{J}-(\gamma(\tilde{b})+\nu)\right) \qquad (FB) \tag{A212}$$

$$\tilde{b}\gamma'(\tilde{b}) = Z_{FB}\left(\frac{E}{J}-\frac{1}{\alpha}(\gamma(\tilde{b})+\nu)\right) \qquad (CO) \tag{A213}$$

The right-hand sides of these equations satisfy $Z_{FB}\left(\frac{E}{J}-\frac{1}{\alpha}(\gamma(\tilde{b})+\nu)\right) \leq Z_{FB}\left(\frac{E}{J}-(\gamma(\tilde{b})+\nu)\right)$ for all $\tilde{b}$, implying that $\tilde{b}_{FB} > \tilde{b}_{CE}$, and therefore (from Equation (A209), which also holds in the first-best allocation), that $c_{y,FB} > c_{y,CO}$.

Next, we prove that for all $\theta \geq 0$, if profits strictly positive in the CE:

$$(1-\rho)\alpha\frac{E}{J} - (\gamma(\tilde{b}_{CE})+\nu) > 0, \tag{A214}$$

then $\tilde{b}_{CO} > \tilde{b}_{CE}$. To establish this we proceed in two steps. First we establish it for the case $\theta = 0$. Then we deal with the case $\theta = 0$.

In the case $\theta = 0$, note that both in the CO and CE the following condition links consumption and technology adoption:

$$(1-\eta)\frac{1-\rho}{\rho}\frac{c_y}{\tilde{b}} = \frac{\gamma'(\tilde{b})}{\xi}. \tag{A215}$$

From the solutions derived above, we can write:

$$c_{y,CO} - c_{y,CE} = \frac{1}{\xi}\alpha\left(1-\frac{\rho}{1-\alpha(1-\rho)}\right)\frac{E}{J} + \frac{1}{\xi}\left(\frac{\alpha\rho}{1-\alpha(1-\rho)}\left(\nu+\gamma(\tilde{b}_{CE})\right) - \left(\nu+\gamma(\tilde{b}_{CO})\right)\right)$$

$$= \frac{1}{\xi}\frac{1-\alpha}{1-\alpha(1-\rho)}\left(\alpha(1-\rho)\frac{E}{J}-\left(\nu+\gamma(\tilde{b}_{CE})\right)\right)+\frac{1}{\xi}\left(\gamma(\tilde{b}_{CE})-\gamma(\tilde{b}_{CO})\right) \quad \text{(A216)}$$

Preparing for a contradiction, assume that:

$$c_{y,CO} \leq c_{y,CE}.$$

Then Equation (A216) implies that we must have $\gamma(\tilde{b}_{CE}) < \gamma(\tilde{b}_{CO})$, since profits are positive in the CE. Therefore, we must also have $\tilde{b}_{CE} < \tilde{b}_{CO}$. But by convexity of γ, Equation (A215 implies that $c_{y,CE} < c_{y,CO}$, a contradiction. Therefore, it must be that:

$$c_{y,CO} > c_{y,CE}.$$

From the first-order conditions with respect to $\tilde{b}$, we then also must have:

$$\tilde{b}_{CO} > \tilde{b}_{CE}.$$

Next, turn to the case $\theta > 0$. Note that $\tilde{b}_{CE}$ is independent of θ. Moreover from the condition determining $\tilde{b}_{CO}$,

$$\tilde{b}\gamma'(\tilde{b}) = (1-\eta)(1+\theta)\frac{(1-\rho)}{\rho}\left(\alpha\frac{E}{J}-(\gamma(\tilde{b})+\nu)\right),$$

it follows that $\frac{\partial \tilde{b}_{CE}}{\partial \theta} > 0$. Thus for any $\theta > 0$,

$$\tilde{b}_{CO}(\theta) > \tilde{b}_{CO}(0) \geq \tilde{b}_{CE}, \quad \text{(A217)}$$

establishing the result. ■

2. Free-entry

Definition 5. *A constrained optimal (CO) allocation with free-entry is a number of businesses J, a price p for intermediate varieties and a set of quantities $\left\{O_o, O_y, c_o, c_y, \tilde{b}\right\}$ that maximizes the welfare criterion (14) subject to the constraints that (a) the quantities $\{O_o, O_y, c_o, c_y\}$ are consistent with utility maximization of young and old consumers given $(p, \tilde{b})$; (b) resulting business profits are weakly positive, $\pi \geq 0$; and (c) the resource constraint (1) holds.*

Result 8 (Constrained optimal allocation with free-entry)**.** *In the constrained-optimal allocation, the planner chooses a level of adoption that coincides with the first-best and is given by Equation (A161). Moreover, the planner chooses prices that are equal to a constant markup over marginal costs, as in the competitive equilibrium. If there are no externalities ($\theta = 0$), technology adoption, consumption and entry coincide with their competitive equilibrium level. With externalities ($\theta > 0$), the constrained-optimal allocation features more technology adoption, more production, and less* *entry than the competitive equilibrium:*

$$\tilde{b}_{CO} > \tilde{b}_{CE}, \quad c_{y,CO} = c_{o,CO} > c_{y,CE} = c_{o,FB}, \quad J_{CO} < J_{CE}. \tag{A218}$$

Proof of result 8. Using Result 7, the constrained optimum is the solution to:

$$W = \max_{J} \quad \log((1-\alpha)^{1-\alpha}\alpha^{\alpha}) + \alpha\frac{1-\rho}{\rho}\log(J) \tag{A219}$$

$$+ \quad \log(I) - \alpha\log(p) + \alpha(1-\eta)(1+\theta)\frac{1-\rho}{\rho}\log(\tilde{b}) \tag{A220}$$

where:

$$\begin{aligned}
\tilde{b}\gamma'(\tilde{b}) &= (1-\eta)(1+\theta)\frac{(1-\rho)}{\rho}\left(\alpha\frac{E}{J} - (\gamma(\tilde{b})+\nu)\right) \\
I &= E \\
p &= \xi\left(1 + \frac{\gamma(\tilde{b})+\nu}{\alpha\frac{E}{J} - (\gamma(\tilde{b})+\nu)}\right)
\end{aligned}$$

$$\begin{aligned}
\tilde{b}\gamma'(\tilde{b}) &= (1-\eta)(1+\theta)\frac{(1-\rho)}{\rho}\left(\alpha\frac{E}{J} - (\gamma(\tilde{b})+\nu)\right) \\
I &= E \\
p &= \xi\left(1 + \frac{\gamma(\tilde{b})+\nu}{\alpha\frac{E}{J} - (\gamma(\tilde{b})+\nu)}\right)
\end{aligned}$$

The first-order condition is:

$$\alpha\frac{1-\rho}{\rho}\frac{1}{J} - \alpha\frac{1}{p}\frac{\partial p}{\partial J} + \frac{\partial\tilde{b}}{\partial J}\left(-\alpha\frac{1}{p}\frac{\partial p}{\partial\tilde{b}} + \alpha(1-\eta)(1+\theta)\frac{1-\rho}{\rho}\frac{1}{\tilde{b}}\right) = 0. \tag{A221}$$

But note that:

$$\frac{1}{p}\frac{\partial p}{\partial\tilde{b}} = \frac{\gamma'(\tilde{b})}{\xi}\frac{1}{c_y}. \tag{A222}$$

Moreover, from result 7, we have that:

$$(1-\eta)(1+\theta)\frac{1-\rho}{\rho}\frac{1}{\tilde{b}} = \frac{\gamma'(\tilde{b})}{\xi}\frac{1}{c_y}. \tag{A223}$$

Thus in Equation (A221), the term in parentheses is equal to zero at any optimal allocation (for fixed J). Thus the first-order condition simplifies to:

$$\frac{1-\rho}{\rho}\frac{1}{J} - \frac{1}{p}\frac{\partial p}{\partial J} = 0. \tag{A224}$$

We have:

$$\frac{1}{p}\frac{\partial p}{\partial J} = \frac{1}{\xi}\frac{\gamma(\tilde{b})+\nu}{J}\frac{1}{c_y} \tag{A225}$$

Thus the optimal $(J, \tilde{b})$ are the unique solution to the system:

$$\frac{1-\rho}{\rho}\left(\alpha\frac{E}{J} - (\gamma(\tilde{b})+\nu)\right) = \gamma(\tilde{b})+\nu \tag{A226}$$

$$\frac{1-\rho}{\rho}\left(\alpha\frac{E}{J} - (\gamma(\tilde{b})+\nu)\right) = \frac{1}{(1-\eta)(1+\theta)}\tilde{b}\gamma'(\tilde{b}) \tag{A227}$$

implying:

$$(1-\eta)(1+\theta)(\gamma(\tilde{b})+\nu) = \tilde{b}\gamma'(\tilde{b}) \tag{A228}$$

$$J = \alpha(1-\rho)\frac{E}{\gamma(\tilde{b})+\nu} \tag{A229}$$

$$I = E \tag{A230}$$

$$p = \frac{\xi}{\rho} \tag{A231}$$

$$\pi = 0 \tag{A232}$$

$$O_y = (1-\alpha)E \tag{A233}$$

$$O_o = O_y \tag{A234}$$

$$c_y = \frac{1}{\xi}\frac{\rho}{1-\rho}(\gamma(\tilde{b})+\nu) \tag{A235}$$

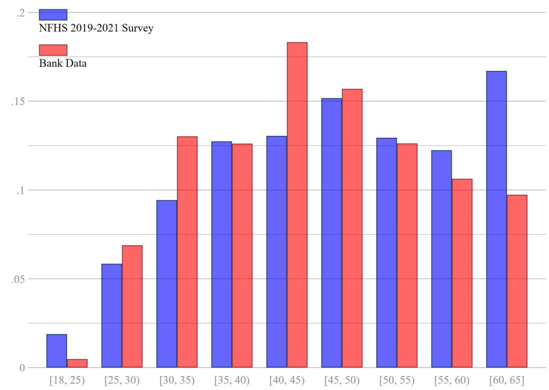
To compare with the competitive equilibrium with free-entry, note that when $\theta = 0$, the two coincide exactly, so the competitive equilibrium is constrained-efficient. On the other hand, when $\theta > 0$, the constrained optimum features a higher rate of adoption. Thus it also features fewer businesses and a higher rate of output.

Finally, note that when $\theta = 0$, adoption and output are the same in the CO and in the FB, though entry is higher in the FB. When $\theta > 0$, adoption and output are also the same in the CO and in the FB, but entry is strictly lower in the CO than in the FB. ■

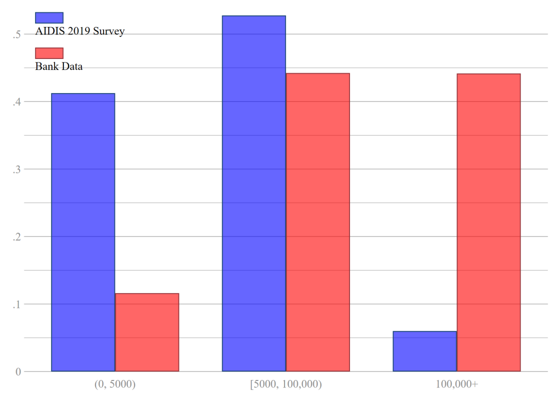
Appendix Figures and Tables

Figure A-1: Comparison of distributions across datasets

(a) Distribution across Age

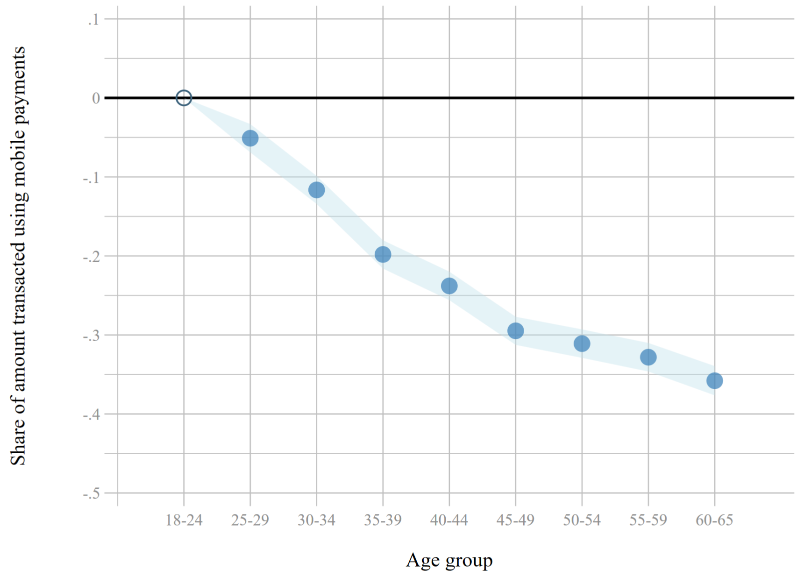


(b) Distribution across income levels



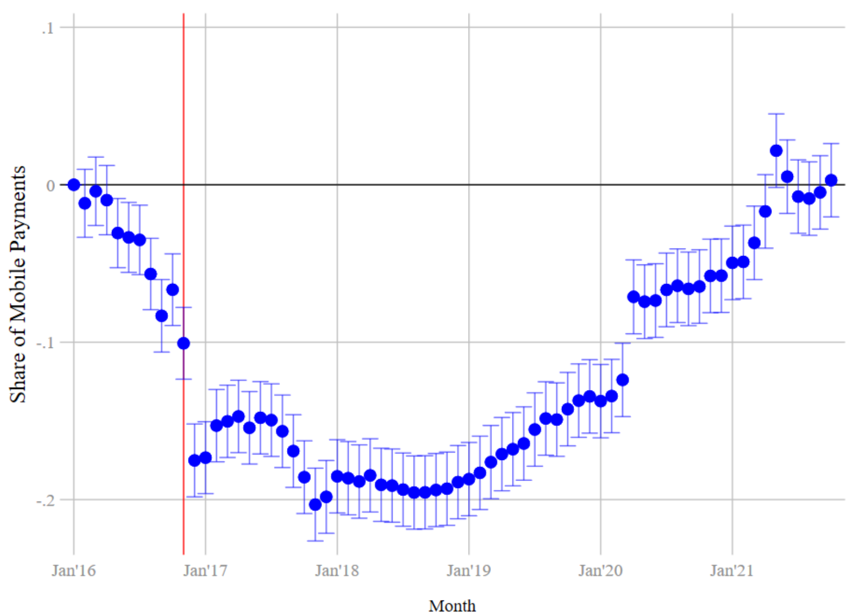
Notes: This figure compares the age and income distribution in our bank level data to the same information provided in nationally representative surveys. Panel (a) reports the age distribution, dividing the sample in 5-year intervals (with the exception of the youngest group that goes from 18 to 25). For each group, the first bar reports the share of head of the household in that age group from the NFHS 2019-2021 survey, as described in the paper; the second bar reports the same statistic for our bank data. Panel (b) reports the wealth distribution, across three broad category (i.e., less than 5,000 Rp., between 5,000 and 100,000, and above 100,000). For each group, the first bar reports the share of individuals that have that level of deposit in the AIDIS 2019, as described in the paper; the second bar reports the same statistic for our bank data. Notice that, as explained in the paper, the share from the AIDIS is conditional on having any deposit.

Figure A-2: Share of amount transacted using mobile payments by households



Notes: The figure plots the estimates of the share of the amount transacted using mobile payments by households across different age-groups. We normalize the age groups of 18 to 24 to be zero. 95% confidence intervals are denoted using the blue shaded region.

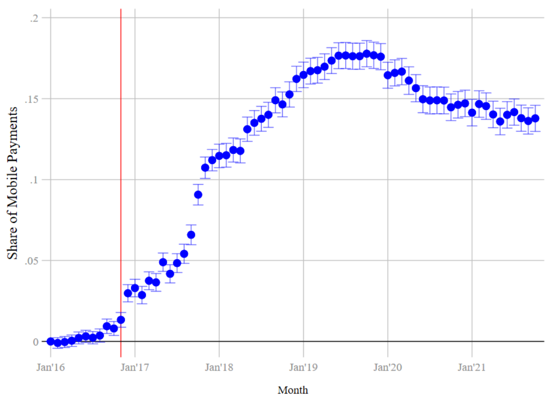
Figure A-3: Difference in Mobile Penetration and Card Early-Users



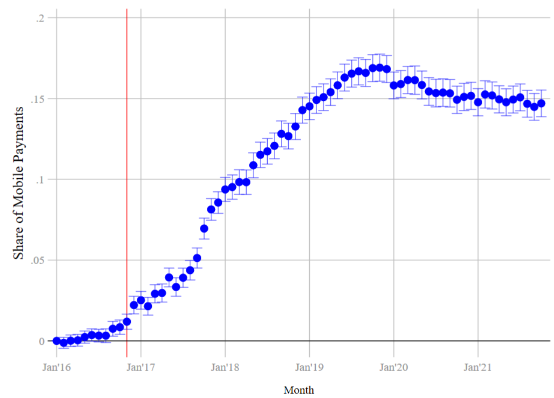
Notes: The figure plots month-by-month the difference in the share of mobile transactions between consumers that were early users of credit cards (i.e., had credit card in 2015) and not early users. The share of mobile is defined as usual. The vertical red-line identifies November 2016 — the month of Indian Demonetization. The sample uses the set of customers active between (at least) 2015 and 2021. The point estimate is also reported together with the 95% confidence interval.

Figure A-4: Difference in Mobile Penetration across Young and Old

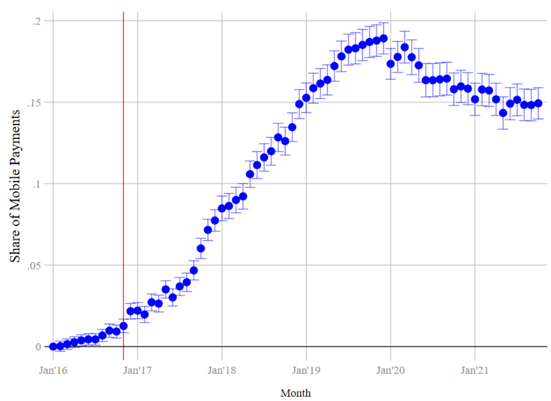
(a) No controls



(b) card ownership-month f.e.+ pincode-month f.e.



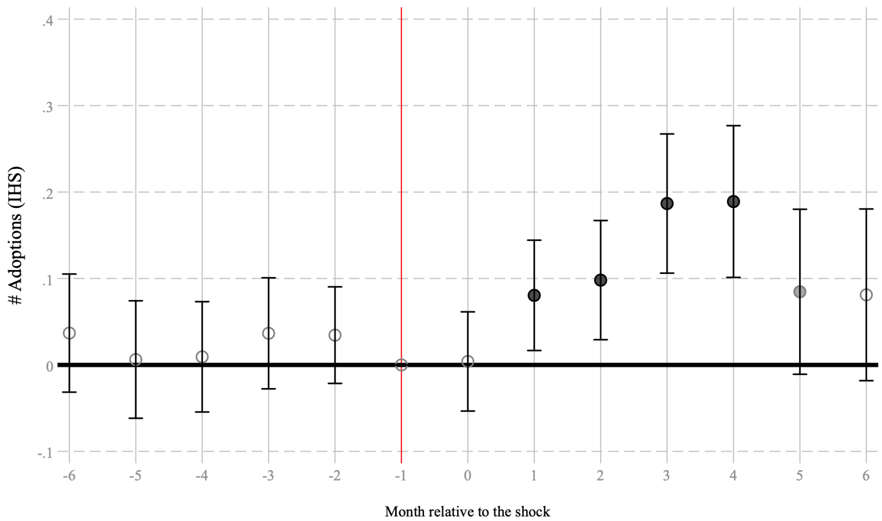
(c) Only card holders



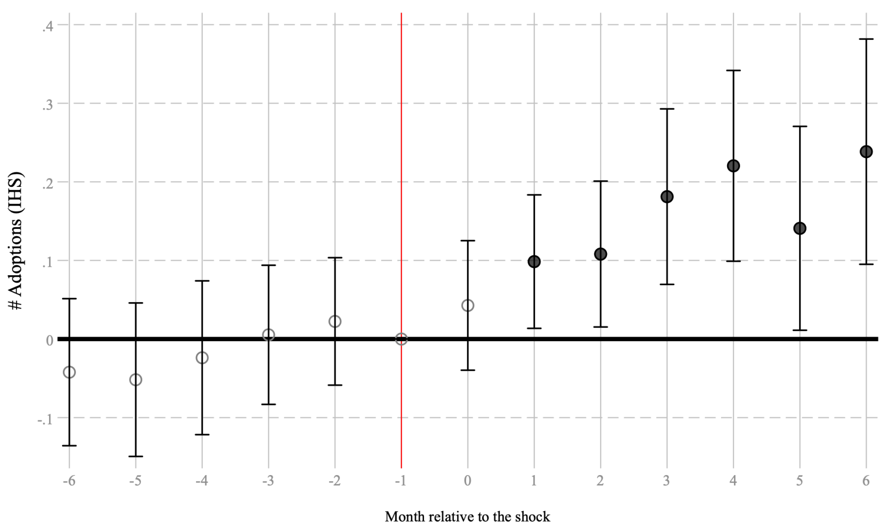
Notes: The figure plots month-by-month the difference in the share of mobile transactions between young and old consumers using the panel from the bank-level transaction data. We divide the sample across young and old splitting around age 40, defined in 2015. The share of mobile is defined as usual. Panel (a) reports the difference with no controls. Panel (b) reports the difference while also controlling for card ownership-month fixed-effects and pincode-month fixed-effects. Panel (c) reports the difference using only the sample of those borrowers that have used any card in the sample period. The vertical red-line identifies November 2016 — the month of Indian Demonetization. The sample uses the set of customers active between (at least) 2015 and 2021. The point estimate is also reported together with the 95% confidence interval.

Figure A-5: District Adoption Dynamics: IHS of New Stores Adoption per district

(a) baseline specification

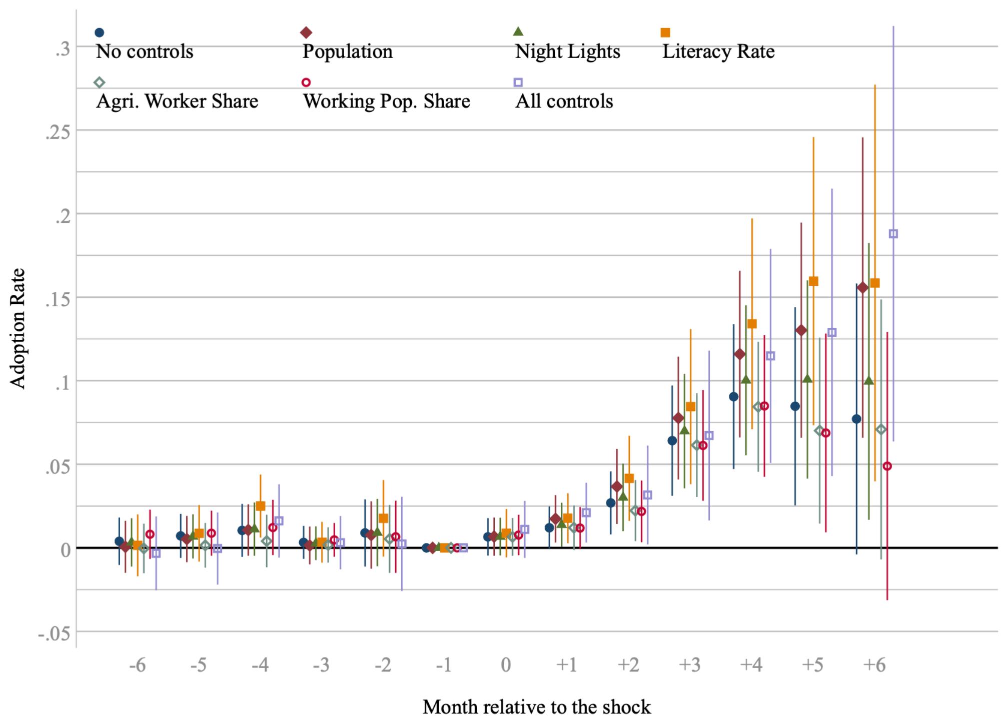


(b) all controls



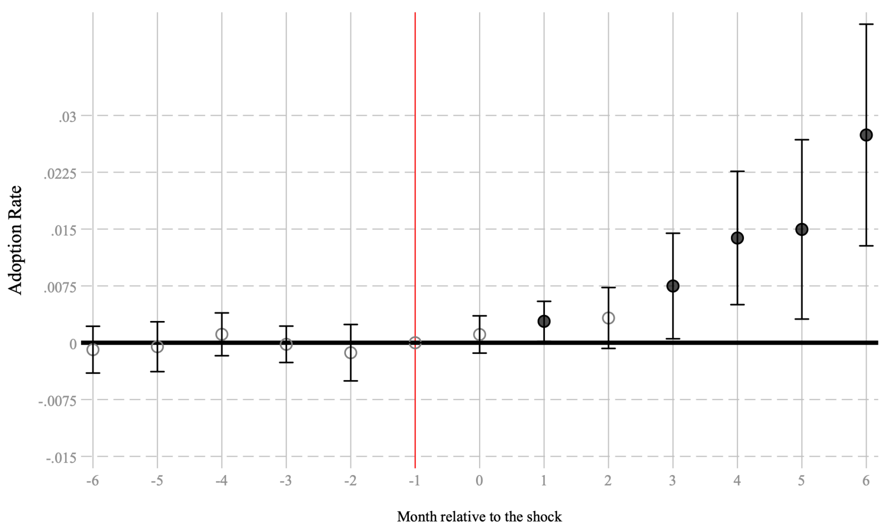
Notes: The figure plots the dynamic treatment effects of age structure on adoption. The dependent variable is the inverse hyperbolic sine (IHS) transformation of number of stores that adopted our fintech company in month t and district d. The period considered is the six months before and after May 2019 (i.e., zero in the graph), which is the month when the company introduced the mobile payment option. The graphs report the coefficients β_k from specification 12. Panel (a) reports the effects from baseline specification without any baseline district-level controls; panel (b) reports the effects from the specification that includes the district controls interacted with month fixed effects. Baseline district controls include the population (IHS), the share of agricultural workers, the number of firms (IHS), literacy rate, the share of working population, and the log of average night lights in 2018 in the district. Vertical lines indicate 95% confidence intervals. Black dots represent significance at 95% significance levels, gray dots represent significance at 90% significance levels, and hollow dots represent insignificant levels. Standard errors are clustered at the district level.

Figure A-6: District Adoption Dynamics
Sensitivity to Controls



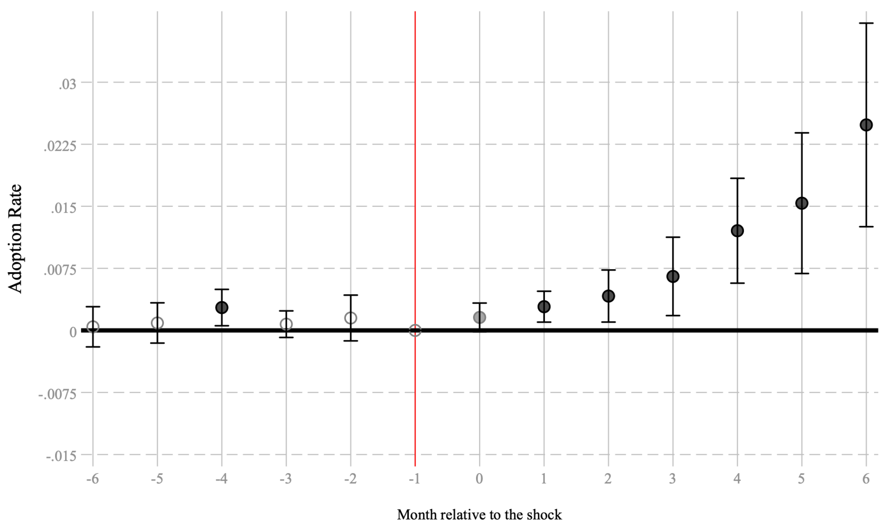
Notes: This figure reports a robustness of our main specification to the inclusion of controls. In particular, we reproduce the same Figure 3 with different level of controls. As in the main figure, the dependent variable is the number of stores that adopted our fintech company in month t and district d, scaled by the total number of firms in the districts (in hundreds) measured by the Census. The period considered is the six months before and after May 2019 (i.e., zero in the graph), which is the month when the company introduced the mobile payment option. However, each set of coefficient differs in the controls used: in particular, we consider the specification without any control (as in panel a of Figure 3) as well as with each control included alone. As a benchmark, we also report the specification with all the controls (as in panel b of Figure 3) Vertical lines indicate 95% confidence intervals. Standard errors are clustered at the district level.

**Figure A-7: District Adoption Dynamics:
no adult adjustment**



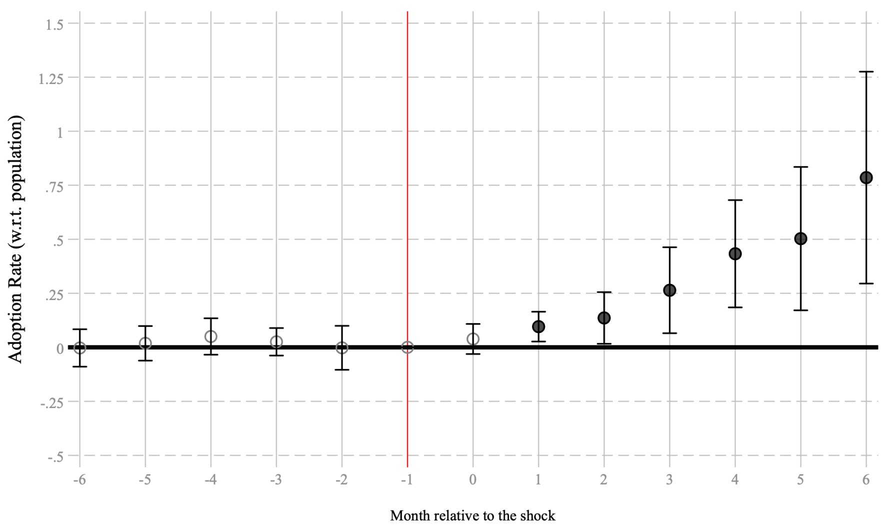
Notes: This figure provides a robustness test for the main dynamic specification. Everything is identical to the main figure (i.e., Figure 3), but for the treatment variable. In the main analysis, the treatment variable is the number of individuals between 15 and 29, scaled by the number of adults, defined as individuals between 15 and 74. This robustness figure instead uses as treatment a measures that scales number of individuals between 15 and 29 by total population, without any adjustment for children or elderly. Apart from this change, everything is equivalent to the specification with controls. In particular, the dependent variable is the number of stores that adopted our fintech company in month t and district d, scaled by the total number of firms in the districts (in hundreds) measured by the Census. The period considered is the six months before and after May 2019 (i.e., zero in the graph), which is the month when the company introduced the mobile payment option. The graphs report the coefficients β_k from specification 12. Baseline district controls include the population (IHS), the share of agricultural workers, the number of firms (IHS), literacy rate, the share of working population, and the log of average night lights in 2018 in the district. Vertical lines indicate 95% confidence intervals. Black dots represent significance at 95% significance levels, gray dots represent significance at 90% significance levels, and hollow dots represent insignificant levels. Standard errors are clustered at the district level.

Figure A-8: District Adoption Dynamics: alternative treatment



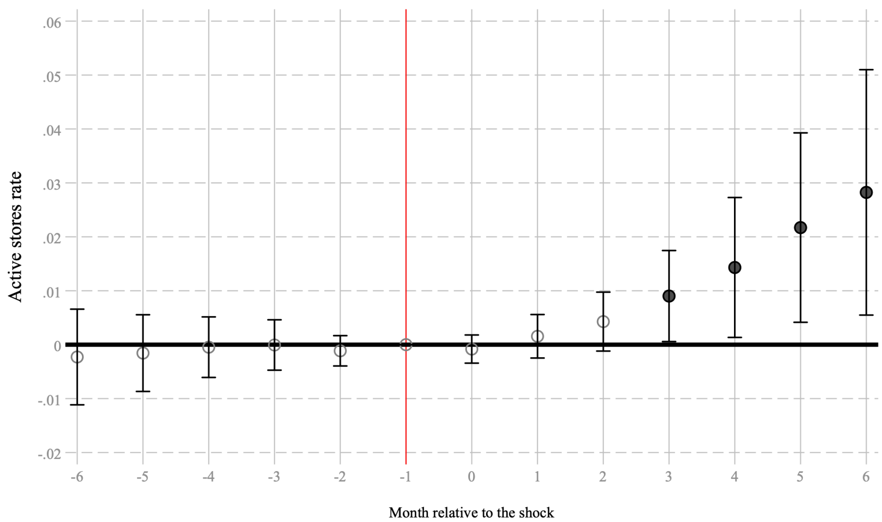
Notes: This figure provides a robustness test for the main dynamic specification. Everything is identical to the main figure (i.e., Figure 3), but for the treatment variable. In the main analysis, the treatment variable is the number of individuals between 15 and 29, scaled by the number of adults. This robustness figure instead uses as a treatment the share of individual that are less than 40. Apart from this change, everything is equivalent to the specification with controls. In particular, the dependent variable is the number of stores that adopted our fintech company in month t and district d, scaled by the total number of firms in the districts (in hundreds) measured by the Census. The period considered is the six months before and after May 2019 (i.e., zero in the graph), which is the month when the company introduced the mobile payment option. The graphs report the coefficients β_k from specification 12. Baseline district controls include the population (IHS), the share of agricultural workers, the number of firms (IHS), literacy rate, the share of working population, and the log of average night lights in 2018 in the district. Vertical lines indicate 95% confidence intervals. Black dots represent significance at 95% significance levels, gray dots represent significance at 90% significance levels, and hollow dots represent insignificant levels. Standard errors are clustered at the district level.

**Figure A-9: District Adoption Dynamics
(New Adopters/Population per district ('100,000))**



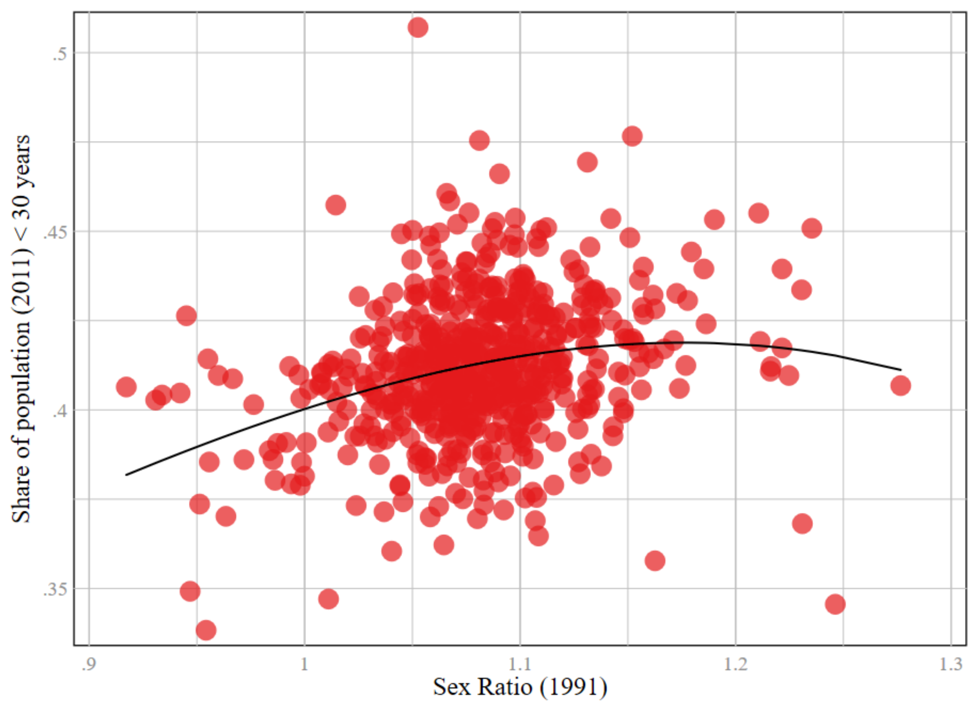
Notes: This figure provides a robustness test for the main dynamic specification. Everything is identical to the main figure (i.e., Figure 3), but for the way the outcome is constructed. In particular, the dependent variable is the number of stores that adopted our fintech company in month t and district d, scaled by the total population (in hundred of thousands) measured by the Census. The period considered is the six months before and after May 2019 (i.e., zero in the graph), which is the month when the company introduced the mobile payment option. The graphs report the coefficients β_k from specification 12. Baseline district controls include the population (IHS), the share of agricultural workers, the number of firms (IHS), literacy rate, the share of working population, and the log of average night lights in 2018 in the district. Vertical lines indicate 95% confidence intervals. Black dots represent significance at 95% significance levels, gray dots represent significance at 90% significance levels, and hollow dots represent insignificant levels. Standard errors are clustered at the district level.

Figure A-10: Effect on Platform Size
(# firms on platform /# firms per district ('100))



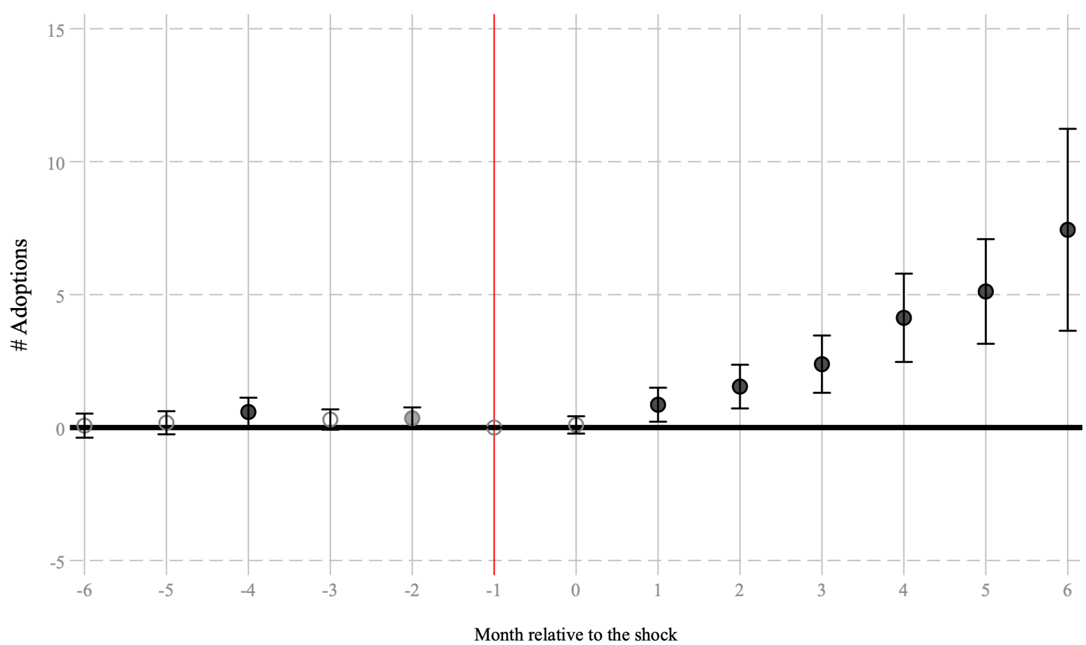
Notes: The figure plots the dynamic treatment effects of age structure on the total number of firms that are in our fintech platform. Apart from the outcome, everything is identical to the main figure (i.e., Figure 3). The dependent variable is the number of stores are in the platform in month t and district d, scaled by the total number of firms in the districts (in hundreds) measured by the Census. The period considered is the six months before and after May 2019 (i.e., zero in the graph), which is the month when the company introduced the mobile payment option. The graphs report the coefficients β_k from specification 12. Panel (a) reports the effects from baseline specification without any baseline district-level controls; panel (b) reports the effects from the specification that includes the district controls interacted with month fixed effects. Baseline district controls include the population (IHS), the share of agricultural workers, the number of firms (IHS), literacy rate, the share of working population, and the log of average night lights in 2018 in the district. Vertical lines indicate 95% confidence intervals. Black dots represent significance at 95% significance levels, gray dots represent significance at 90% significance levels, and hollow dots represent insignificant levels. Standard errors are clustered at the district level.

Figure A-11: Correlation: Sex Ratio (1991) and Age Structure (2011)



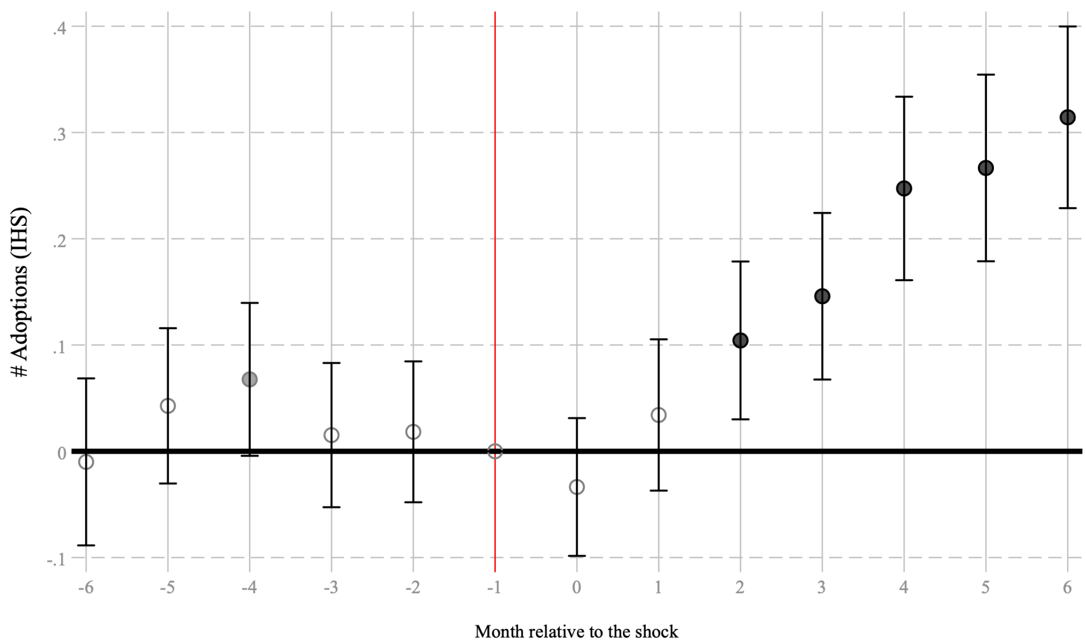
Notes: The figure documents the relationship between district sex ratios, defined as the number of males per female, in 1991 and the share of 2011 population in districts that is below 30 years. Each dot represents a district in the 2011 Census. The black line represents a quadratic polynomial fit.

Figure A-12: Adoption across pincodes:
University areas, in levels



Notes: The figure provides a robustness to the main university result (Figure 5). In particular, we change the way the outcome is measure. The dependent variable is the (raw, without any transformation) the number of stores that adopted our fintech company at pincode-level in a month. The graphs report the coefficients γ_k from specification 13, and always include district-by-month fixed effects as well as pincode fixed-effects. The period considered is the six months before and after May 2019 (i.e., zero in the graph), which is the month when the company introduced the mobile payment option. Vertical lines indicate 95% confidence intervals. Black dots represent significance at 95% significance levels, gray dots represent significance at 90% significance levels, and hollow dots represent insignificance at 90% levels. Standard errors are reported in parentheses and are clustered at the pincode level.

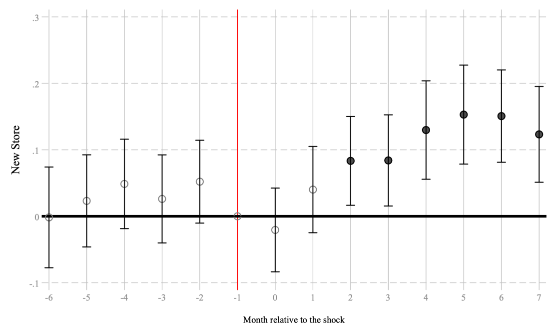
Figure A-13: Adoption across pincodes:
University areas, only districts w. university



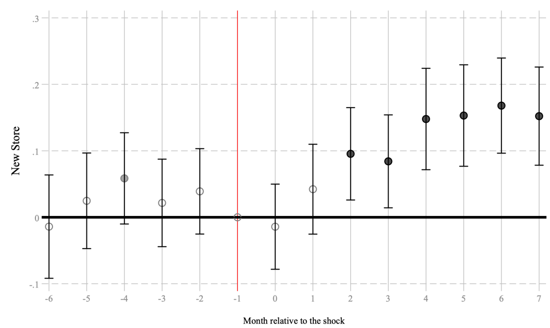
Notes: The figure provides a robustness to the main university result (Figure 5). In particular, everything is identical to the main analysis, with the exception that here we only use the sample of districts that have at least one university in their terriroty. The dependent variable is the (inverse hyperbolic sine transformation of) the number of stores that adopted our fintech company at pincode-level in a month. The graphs report the coefficients γ_k from specification 13, and always include district-by-month fixed effects as well as pincode fixed-effects. The period considered is the six months before and after May 2019 (i.e., zero in the graph), which is the month when the company introduced the mobile payment option. Vertical lines indicate 95% confidence intervals. Black dots represent significance at 95% significance levels, gray dots represent significance at 90% significance levels, and hollow dots represent insignificance at 90% levels. Standard errors are reported in parentheses and are clustered at the pincode level.

Figure A-14: Adoption across pincodes: University areas, merchant-level variation

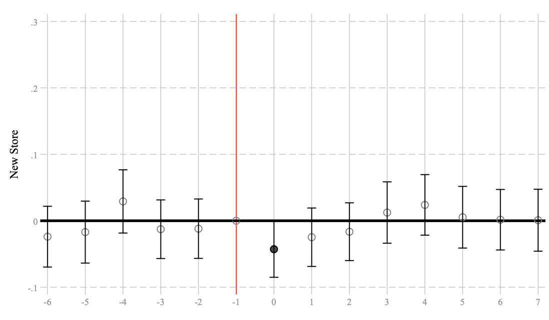
Panel (a): Student-consumer businesses



Panel (b): Student-consumer businesses, broader

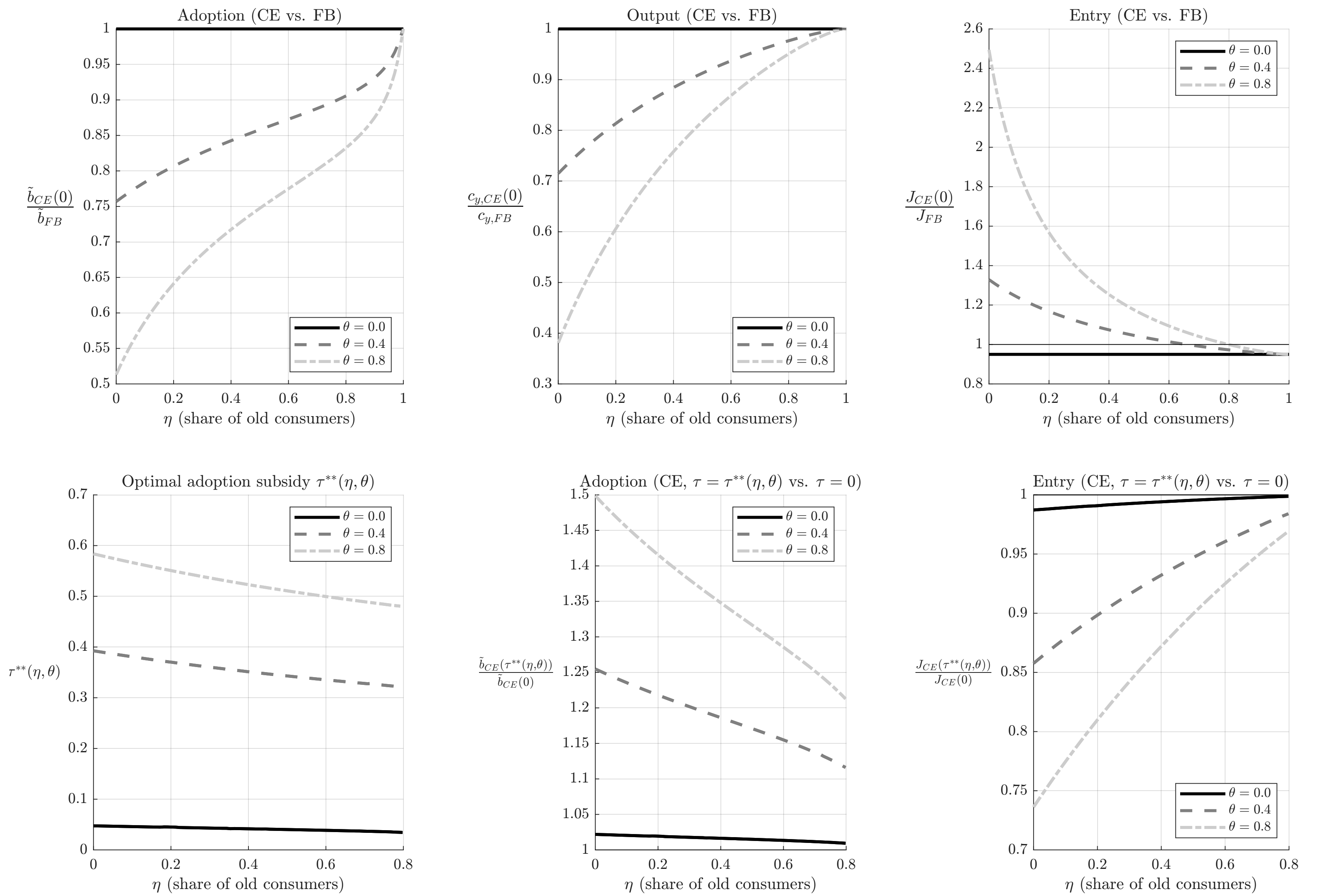


Panel (c): Placebo Merchants



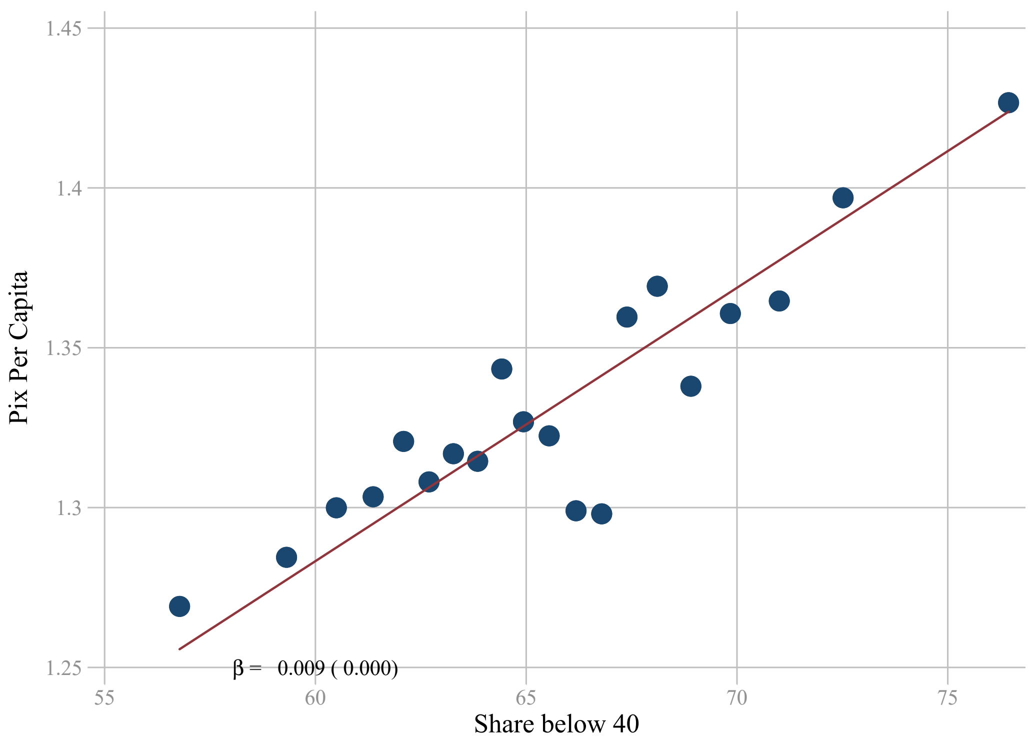
Notes: The figure provides a robustness to the main university result (Figure 5). Across the three panels, we replicate our main analyses using only a sub-sample of merchants. In panel (a), we identify businesses that are mostly depending on local demand by students (i.e., retailers, gas stations, restaurants, leisure facilities, personal services, and transportation). Panel (b) modifies this definition to include also financial services, healthcare (e.g., pharmacies), and educational services. Panel (c) instead runs the analyses on businesses that should not be affected by the local demand by students, such as government and regulated sectors, manufacturing, wholesale, warehouse operations, and professional services. Across the panels, the dependent variable is the (inverse hyperbolic sine transformation of) the number of stores that adopted our fintech company at pincode-level in a month for the subset of merchants considered. The graphs report the coefficients γ_k from specification 13, and always include district-by-month fixed effects as well as pincode fixed-effects. The period considered is the six months before and after May 2019 (i.e., zero in the graph), which is the month when the company introduced the mobile payment option. Vertical lines indicate 95% confidence intervals. Black dots represent significance at 95% significance levels, gray dots represent significance at 90% significance levels, and hollow dots represent insignificance at 90% levels. Standard errors are reported in parentheses and are clustered at the pincode level.

Figure A-15: Competitive equilibrium (CE) and first-best (FB) with free entry.



Notes: Competitive equilibrium (CE) and first-best (FB) allocation with free entry. In all figures the horizontal axis is the share η of old consumers. The top row reports comparisons of adoption, production and entry in the CE with no subsidy ($\tau = 0$) and in the FB. The bottom row reports the optimal adoption subsidy (left panel) and a comparison of the CE with optimal subsidy ($\tau = \tau^{**}(\eta, \theta)$) vs. the CE with no subsidy ($\tau = 0$). The calibration used is $E = 1$, $\alpha = 0.9$, $\rho = 0.5$, $\nu = 0.1$, $\xi = 0.1$, and $\gamma(b) = \frac{1}{2}\omega(b-1)^2$ with $\omega = 0.025$. Results are reported for different degrees of network externalities.

Figure A-16: Pix Adoption in Brazil and Share of Young Individuals



Notes: The figure examines the relationship between the use of Pix in Brazilian municipalities and the age structure of the municipalities, following a similar graphical representation presented before. The use of Pix is measured as the average Pix used (in value) per unit of population in Brazil. Pix is measured using monthly data between November 2020 and July 2024. The age structure is measured using the share of population that is below forty years old, from the 2010 Census. The figure reports the scatterplot of the two quantities after controls and the linear fit. The slope coefficient of the linear fit is also reported. We control for (log) population, average income, literacy rate, and share of rural population.

Table A-1: Age Structure and share of new stores that adopted QR code

	% new stores that adopted QR code	
	(1)	(2)
$AgeStructure_d$	0.033***	0.048***
	(0.012)	(0.015)
Observations	580	580
R-squared	0.012	0.139
District Controls	✗	✓

Notes: The table reports the estimates of the effect of the age structure in the district on the share of new adopters that adopted QR code with the company. The outcome is the share between the total number of stores that have adopted the product of our fintech company with at least one terminal enabled to use QR code, and the total number of adopters (without any requirement to have a QR code enabled terminal). The share is constructed over the full period May 2019 and November 2019. Column 1 reports the estimate without any controls and Column 2 reports the estimate after controlling for baseline district controls of the population (IHS), the share of agricultural workers, the number of firms (IHS), literacy rate, the share of working population, and the log of average night lights in 2018 in the district. Standard errors are reported in parentheses and are clustered at the district level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table A-2: University Analyses: merchant-level

	Panel A: # Adoption (IHS)			
	(1)	**(2)**	**(3)**	**(4)**
1(has university)$_p$× Post$_t$	0.065***	0.076***	0.000	0.172***
	(3.33)	(3.76)	(0.00)	(6.99)
Pincode FE	Y	Y	Y	Y
District × Month FE	Y	Y	Y	Y
Outcome	Student businesses	Student businesses (expanded)	Placebo	Others
Adj R-Sq	0.674	0.693	0.310	0.628
Obs	109,599	109,599	109,599	109,599
	Panel B: # Adoption			
	(1)	**(2)**	**(3)**	**(4)**
1(has university)$_p$× Post$_t$	0.292***	0.332***	-0.004	2.505***
	(2.64)	(2.65)	(-0.24)	(4.43)
Pincode FE	Y	Y	Y	Y
District × Month FE	Y	Y	Y	Y
Outcome	Student businesses	Student businesses (expanded)	Placebo	Others
Adj R-Sq	0.776	0.800	0.342	0.318
Obs	109,599	109,599	109,599	109,599

Notes:The table reports the results of the university analysis, where we focus only on a sub-set of businesses across the various columns. In column (1), we focus on businesses that are mostly depending on local demand by students (i.e., retailers, gas stations, restaurants, leisure facilities, personal services, and transportation). In column (2) we expand this definition to include also financial services, healthcare (e.g., pharmacies), and educational services. In column (3) we run the analyses on businesses that should not be affected by the local demand by students, such as government and regulated sectors, manufacturing, wholesale, warehouse operations, and professional services. Column (4) focuses instead on the residual merchants, that do not belong to either the group defined in column (2) or (3) (this is mostly businesses categorized as "miscellaneous".) The dependent variable is the number of adoptions of our fintech solution: panel (a) uses this outcome after applying the inverse-hyperbolic transformation; panel (b) instead looks at the value in level. The specifications include fixed effects for pincode and district-by-month. The coefficients for the interaction between the presence of a university and the post period are reported. Standard errors are clustered at the pincode level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.