The Digital Divide and Refinancing Inequality

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Abstract

Low-income households derive significantly less savings from mortgage refinancing than their wealthy counterparts. I document that the rise of refinancing inequality in the United States can be partially explained by access to information and communications technology. Using granular spatial variation from a large-scale broadband subsidy program, I show that high-speed internet facilitates refinancing and reduces monthly mortgage payments. These effects are large and persistent, corresponding to a 5 percent increase in disposable income and up to $18,000 in total savings. The impact is pronounced in areas with limited bank branch access and among populations with low financial and digital literacy.

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1 Introduction

Homeownership is an important mechanism for household wealth accumulation in the United States; however, many Americans fail to refinance their mortgages when interest rates fall due to frictions such as search costs and limited financial sophistication (Campbell, 2006). This phenomenon is particularly pronounced among low-income households, implying an imbalance in monetary policy transmission that can exacerbate wealth inequality in the long run. In this paper, I address whether modern information and communications technology can mitigate frictions associated with mortgage refinancing. Specifically, I demonstrate that access to high-speed internet increases refinancing activity and reduces housing costs for low-income borrowers.

While ubiquitous in the modern era, high-speed internet is still inaccessible to millions of American households living without a broadband connection. The persistent gap in access to information technology, known as the "digital divide," has become a prominent policy issue in recent decades due to its overall impact on household well-being (White House, 2024). In 2022, more than a quarter of the U.S. population lacked a broadband internet connection at home, with low-income households reporting significantly lower subscription rates (Figure 1). This trend cannot be fully explained by disparities in physical access to a broadband provider; of the low-income households living in urban areas with near-complete broadband coverage, only 67 percent had a broadband subscription due to high costs.

Technology can significantly reduce the shadow costs associated with financial transactions, especially for mortgages that require more resources and sophistication than regular banking services. Using the internet, an applicant can easily exchange paperwork by e-mail, link financial accounts online to expedite credit verification, and spend less time meeting with a loan officer or visiting a bank branch. Indeed, processing times for mortgage applications at online lenders are estimated to be 15 to 30 percent shorter than at their physical counterparts, with a larger effect for refinance loans (Fuster, Plosser, Schnabl and Vickery, 2019). To the extent that the internet can provide information on the value of refinancing and connect people through social media, it can also reduce the incidence of suboptimal refinancing driven by behavioral mistakes. Despite the tangible advantages, however, the impact of high-speed internet on mortgage refinancing for marginal households are a priori unclear; the proliferation of online resources without clear guidance may have no effect on financial decision-making or even lead to worse outcomes such as increased search costs, overspending, and speculative investment behavior (Agarwal, Grigsby, Hortaçsu, Matvos, Seru and Yao, 2024b; Agarwal, Ghosh, Li and Ruan, 2024a; Brookings Institution, 2022).

Studying the effects of internet access on refinancing inequality is challenging for several reasons. First, the spatial distribution of broadband internet providers is correlated with local subscriber characteristics such as employment and educational attainment. As these characteristics are also linked to refinancing demand, estimates of refinancing outcomes driven by differences in broadband availability will most likely be biased. Second, it is difficult to directly observe exogenous changes in broadband adoption by households, especially for low-income homeowners that tend to refinance suboptimally. As a result, little is known about the extent to which broadband access can reduce refinancing frictions.

To address these empirical challenges, I analyze the Internet Essentials program by Comcast — one of the largest broadband providers in the United States. Introduced in 2012 to receive regulatory support for a merger, Internet Essentials heavily subsidized broadband subscription fees to qualifying low-income households. The monthly cost of $9.95 was up to 75 percent lower than that of a comparable regular plan, and all activation fees and recurring equipment charges were waived. The program became highly successful, connecting 750,000 American families (or 3 million individuals) nationwide in the first five years (Comcast Corporation, 2016). Internet Essentials is a suitable setting to study refinancing behavior due to its unique properties. First, it was immediately available in all of Comcast's existing service areas. This method of rollout is important for identification because physical infrastructure expansions not only take time but also can increase local house prices, confounding the estimated impact of broadband access on refinancing (Wall Street Journal, 2015). Second, Internet Essentials was directly aimed at increasing broadband take-up by low-income households making less than around $40,000 per year — the group that fails to refinance most prominently. Third, internet usage at broadband speeds would have been a binding constraint for households to access various banking services, especially for mortgages. Lastly, the program coincides with the prolonged low-interest rate period following the Great Recession, during which refinancing incentives would have been high throughout the economy.

This paper exploits geographic, temporal, and household-level variation in Internet Essentials eligibility to estimate broadband's impact on reducing refinancing frictions. Specifically, I compare the outcomes of low-income households that were eligible and ineligible for the program, across census tracts with and without Comcast service, before and after 2012. The identifying assumption is that within-census tract differences in refinancing outcomes between eligible and ineligible households are uncorrelated with Comcast coverage except through the introduction of Internet

Essentials. Indeed, I do not find any violation of the common trends assumption under this empirical setting. I construct a unique data set that matches Comcast availability at the census tract level to the universe of refinance originations by eligibility group between 2008 and 2015. I also enhance my analysis using prepayment outcomes for a panel of mortgages originated between 2004 and 2008, as well as Census survey microdata on mortgage cost burdens.

I find that improved broadband access leads to a strongly positive impact on refinancing outcomes. In particular, both the number of submitted applications and originated loans increased by 6 percent as a result of Internet Essentials. Importantly, household financial gains are driven by behavioral changes along the extensive margin (increased likelihood of refinancing) and not through differential outcomes along the intensive margin (lower interest rates). Using household-level survey data, I corroborate the findings of increased refinancing probability with evidence of decreased mortgage payments. In addition, I show that the results are in large part driven by census tracts with limited access to physical bank branches, implying that broadband internet promotes access to financial services for the underbanked. Treatment effects are also stronger for households with low educational attainment, which suggests a digital and financial literacy channel for refinancing.

The economic magnitudes of these results are significant: the average low-income household that refinanced its mortgage between 2012 and 2015 would have saved up to $100 per month on mortgage payments even after accounting for the nominal cost of subscribing to Internet Essentials. This translates to a 5 percent increase in monthly disposable income and total household wealth gains of up to $18,000 in present value terms, which accounts for about 10 percent of the average net worth of homeowners in this income bracket. Rough estimates imply that the program generated up to $100 million in additional refinance savings for Comcast area households and reduced refinancing inequality between the top and bottom income deciles by up to 30 percent.

These empirical findings are robust to several validation and falsification tests. To start, I verify that the results hold when using mortgage prepayment as an alternative measure of refinancing. Second, I assign placebo treatment indicators for AT&T and Charter coverage (the next two largest broadband providers by subscriber count) and find no effects on refinancing outcomes. Third, the results disappear when I use alternative eligibility thresholds. Fourth, treatment effects tend to be concentrated in census tracts with a high likelihood of being affected by Internet Essentials. Fifth, I show that better access to broadband internet improved refinance outcomes under a different setting: the Coronavirus (COVID-19) pandemic of 2020.

Related Literature. This paper is principally related to the literature on frictions in consumer credit markets. Campbell (2006) and Badarinza, Campbell and Ramadorai (2016) document the rise of financial mistakes both in the U.S. and internationally. Recent works have directed special attention to mortgage refinancing in the U.S. and the incidence of low participation among disadvantaged populations; Agarwal, Driscoll and Laibson (2013), Goodstein (2013), Agarwal, Rosen and Yao (2016), Keys, Pope and Pope (2016), Johnson, Meier and Toubia (2018), Andersen, Campbell, Nielsen and Ramadorai (2020), Defusco and Mondragon (2020), Gerardi, Lambie-Hanson and Willen (2021), Agarwal, Chomsisengphet, Kiefer, Kiefer and Medina (2023), and Gerardi, Willen and Zhang (2023) all find evidence of suboptimal refinancing behavior driven by income, race, and educational attainment, particularly during the aftermath of the Great Recession and the recent COVID-19 pandemic. Several papers identify specific behavioral channels such as financial illiteracy (Agarwal, Ben-David and Yao, 2017b; Bajo and Barbi, 2018), inattention (Andersen, Campbell, Nielsen and Ramadorai, 2020; Byrne, Decine, King, McCarthy and Palmer, 2023; Berger, Milbradt, Vavra and Tourre, 2024), distrust of financial institutions (Johnson, Meier and Toubia, 2018; Yang, 2021), and peer effects (Maturana and Nickerson, 2018), while another strand of research uses observed transactions to uncover search frictions arising from lender market power (Woodward and Hall, 2012; Allen, Clark and Houde, 2014; Gurun, Matvos and Seru, 2016; Coen, Kashyap and Rostom, 2023; Agarwal, Grigsby, Hortaçsu, Matvos, Seru and Yao, 2024b). To the best of my knowledge, this paper is the first to analyze the role of a relatively understudied but influential aspect of everyday life — access to high-speed internet — that can significantly reduce search costs and other frictions associated with mortgage refinancing. I also use a unique empirical framework to quantify the incremental effect of technology while taking the prevailing explicit and implicit transaction costs as given.

This paper also contributes to the growing literature on the distributional effects of refinancing and their implications for optimal mortgage market design. Using an equilibrium model, Berger, Milbradt, Tourre and Vavra (2023) and Fisher, Gavazza, Liu, Ramadorai and Tripathy (2024) propose that the failure to refinance among a subset of households can result in negative distributional outcomes. Zhang (2024) additionally documents inefficiencies created by cross-subsidization due to distortions in upfront closing cost choices. Other works study the implications of different mortgage designs (Campbell, 2012; Piskorski and Seru, 2018; Allen and Li, 2020) and the refinancing channel of monetary policy transmission (Hurst, Keys, Seru and Vavra, 2016; Beraja, Fuster, Hurst and Vavra, 2018). In light of the outsized representation of mortgages on U.S. households' balance sheets, this paper studies whether financial inclusion via access to technology, an area in which the U.S. lags behind other developed economies, can partially mitigate the welfare effects of cross-subsidization due to refinancing inequality.

The literature on the role of financial technology in household finance has highlighted technology's large impact on mortgage market composition and consumer lending practices overall (Philippon, 2016; Buchak, Matvos, Piskorski and Seru, 2018; Fuster, Goldsmith-Pinkham, Ramadorai and Walther, 2021; Bartlett, Morse, Stanton and Wallace, 2022; Berg, Fuster and Puri, 2022; Basten and Ongena, 2024; Di Maggio and Ratnadiwakara, 2024). This paper serves as a complement to Fuster, Plosser, Schnabl and Vickery (2019), who document the large role fintech lenders play in reducing processing times for mortgage applications submitted online. Importantly, the authors find no effect of broadband access on mortgage outcomes using the rollout of Google Fiber as an instrument. By studying a national program that did not require low-income customers to pay large upfront costs, I provide suggestive evidence that better access to high-speed internet can indeed reduce refinancing frictions for marginal households. In addition, recent works on financial inclusion highlight the continued importance of bank branches in the modern era (Brown, Cookson and Heimer, 2019; Célerier and Matray, 2019; Nguyen, 2019; Cespedes, Jiang, Parra and Zhang, 2024; Fonseca and Matray, 2024; Jung and Zentefis, 2024) and the implications of digital disruption on financial inclusion (Erel and Liebersohn, 2022; Haendler, 2022; Koont, 2023; Jiang, Yu and Zhang, 2024). Yogo, Whitten and Cox (2024) also find that financial participation depends on household income rather than race or access to financial services. My paper contributes to this series of works by showing that the digital divide can be a significant impediment to financial inclusion in the rapidly transforming financial landscape.

Lastly, this paper adds to the literature on the economic importance of broadband internet — a key infrastructure in the modern era. Kolko (2012), Akerman, Gaarder and Mogstad (2015), Dettling (2016), Hjort and Poulsen (2019), Bhuller, Kostol and Vigtel (2020), and Gürtzgen, Diegmann (né Nolte), Pohlan and van den Berg (2021) study the effect of broadband on labor market outcomes. Importantly, all of these papers instrument broadband access with geographic expansions of broadband infrastructure, which can in turn impact the employment setting of treated areas and confound the results. Zuo (2021) overcomes this empirical challenge by using Internet Essentials to document positive labor market outcomes. My paper makes substantial contributions relative to that study in terms of both the subject matter and empirical framework. By focusing on an important household financial decision — mortgage refinancing — that is conditional on stable employment, I analyze whether broadband induces a reduction of costly financial mistakes that leave money on the table. This paper also exploits more granular geographic variation associated with the program. In general, the two works are highly complementary and document two distinct benefits of broadband access. In terms of the literature on broadband's effect on stock market participation in the U.S. and abroad (Bogan, 2008; Wang, Niu, Zhou and Lu, 2023; Hvide, Meling, Mogstad and Vestad, 2024), I provide an alternative channel for wealth accumulation among low-income homeowners that comprise half of the U.S. low-income population and have most of their wealth stored in housing. Unlike financial market participation that requires recurring contributions and management, timely refinancing around interest rate changes leads to long-term increases in disposable income itself. Overall, the evidence from this paper suggests that refinancing driven by reduced transaction costs can further contribute to household portfolio diversification.

Outline. The remainder of the paper is structured as follows. Section 2 describes background information on mortgage refinancing, broadband access, and the Internet Essentials program. Section 3 outlines the data and empirical methodology. Section 4 discusses the main results and analyzes relevant mechanisms. Section 5 provides robustness and falsification tests. Section 6 concludes.

2 Background

2.1 Mortgage Refinancing Inequality

Households use mortgages to purchase a new property or refinance an existing mortgage on a previously purchased property. Since most mortgages in the United States are fixed-rate loans without prepayment penalties, a refinance allows households to reduce their cost of credit when interest rates fall. In essence, the refinance decision is a call option that should be exercised when the original loan is "in the money" after adjusting for interest rate differentials and closing costs. Refinancing constitutes a large segment of residential real estate markets, accounting for more than half of all mortgage originations by volume between 2005 and 2015 (Haughwout, Lee, Scally and van der Klaauw, 2021).

Homeownership is the primary source of wealth creation among American families, with about 65 percent of the population residing in owner-occupied units as of 2019. Understanding what drives households to refinance their mortgage is important in light of the weight placed on homeownership in their portfolios, representing between 30 and 40 percent of household net worth (Current Population Reports, 2019). As such, refinancing to lower mortgage payments is one of the most consequential decisions a household makes throughout its lifetime. Housing is particularly important for low-income households, whose homes account for over 80 percent of their total wealth. I first document the prevalence of homeownership among low-income households. According to the National Association of Realtors, around 38 percent of low-income households resided in owner-occupied units in 2010. This group's contribution to the housing market is not trivial; households with annual income less than $35,000 took out home mortgages worth $780 billion between 2001 and 2008, with an average home value at origination of $120,000 and monthly payments of $700 over 30 years. Housing cost burdens are also disproportionately large for this income group, with more than half of homeowners paying 30 percent or more of their monthly disposable income on housing. Reducing mortgage payments through refinancing, therefore, is an important way to increase household net worth in the long run.

Prior research has documented that many households fail to refinance their mortgages when it is optimal to do so (Agarwal, Rosen and Yao, 2016; Keys, Pope and Pope, 2016; Johnson, Meier and Toubia, 2018; Andersen, Campbell, Nielsen and Ramadorai, 2020; Agarwal, Chomsisengphet, Kiefer, Kiefer and Medina, 2023). These financial mistakes are pronounced among low-income households; of the mortgages originated between 2004 and 2008 for households making less than $35,000 annually, only around 65 percent were refinanced at any point between 2009 and 2015, the period during which mortgage interest rates fell by an average of 1.5 to 2 percent. This stands in stark contrast to the refinance likelihood of loans originated for households making more than $75,000 (80 percent). The negative relationship between income and refinancing is monotonic and also prevalent in metropolitan areas, which tend to have more resilient banking systems (Figure 2). The pronounced errors at the lower end of the income distribution persists even after controlling for standard predictors of financial distress during the Great Recession, such as debt-to-income ratio (DTI), loan-to-value ratio (LTV), and credit score. This paper shows that borrower frictions relating to transaction costs play an important role in explaining these disparities.

2.2 Broadband Internet in the United States

Broadband technology, which grew in prevalence since the early 2000s, allows households to use the internet for all aspects of life including work, education, and entertainment. In this paper, I define broadband as a residential, high-speed, wireline internet service available in a given geographic area. I focus on residential (as opposed to commercial) service as it is relevant to at-home household financial decisions. High-speed status is determined by whether a service meets the standards for broadband set by the Federal Communications Commission (FCC). The minimum download speed for broadband was 4 megabits per second (Mbps) during the study period, which is adequate for general web browsing, e-mail communication, and some video streaming at low bandwidths.[1] The predecessor technology of dial-up internet, on the other hand, typically has a maximum download speed of 56 kilobytes per second (Kbps), or 1.4 percent of the speed of broadband internet. Dial-up internet is not considered in this paper as the technology has failed to keep up with the increasingly complex needs of everyday internet usage. Lastly, I only consider wireline service provided through physical broadband infrastructure and not cellular plan subscriptions. This is because wireless networks accessed through mobile devices were not reliable or advanced enough to replace broadband during the late 2000s and early 2010s.

The lack of broadband internet at home, particularly in urban areas, can largely be attributed to low affordability. Figure 3 shows a clear negative relationship between census tract poverty rates and broadband subscription rates. This trend is not driven by limited access to a broadband provider. In fact, more than 90 percent of the urban population in the United States lived in areas with broadband service by 2015, while only 70 percent (60 percent for low-income groups) reported actually having a broadband subscription.[2] Survey results confirm that the price of subscription (59 percent) and cost of computer equipment (45 percent) are the top two reasons for not subscribing to broadband (Pew Research Center, 2015). While the urban-rural disparity in broadband coverage is an important access-driven cause for the digital divide, I focus on cost-driven disparities in subscription conditional on having access to infrastructure. This framework is useful for identification because it is invariant to unobservable differences in broadband service quality and customer demand across urban and rural areas.

2.3 Broadband and Mortgage Transaction Costs

At-home internet access is relevant for refinancing inequality due to the unique properties of a refinance mortgage. First, refinancing is largely standardized and thus compatible with technological innovation. In most interest rate refinances, the housing asset in question is already determined and the prospective borrower is in good standing on the existing mortgage.[3] Borrower uncertainty

[1]The 4 Mbps minimum speed standard for broadband was set in 2010 and then revised up to 25 Mbps in 2015.

[2]Statistics are compiled from the 2015 FCC Broadband Progress Report and author's calculations using ACS 2017 5-year estimates. Figure A.1 in the Internet Appendix also shows that subscription rates are low and not readily substituted by cellular data plans in low-income urban areas.

[3]Since a refinance requires current homeownership, it is not determined by exogenous motives to move into or out of a dwelling. This is important as it allows the borrower pool to be invariant from significant income shocks or migrational incentives.

is thus low, allowing the refinance process to be streamlined and automated. Recent innovations in online approval and underwriting technology have led to a notable decrease (up to 30 percent from an average of 51 days) in processing time for refinance applications (Fuster, Plosser, Schnabl and Vickery, 2019). The internet has also enabled both bank and non-bank lenders to reach populations outside their immediate geographic markets, improving the access to mortgage credit for underbanked households.

Second, refinancing involves large shadow costs that can be significantly reduced through internet usage. A refinance typically takes several months to complete, primarily due to stringent documentation requirements that include recent pay stubs, tax returns, W-2s, homeowners insurance policies, asset statements (e.g., checking, savings and investment) and debt statements (e.g., credit card and automobile).[4] For households with a computer and broadband connection, these materials can be conveniently accessed and transmitted online. Furthermore, applicants with internet access can use e-mail to communicate with a loan officer and sign documents electronically, reducing the number of required branch visits. To the extent that the internet can also increase awareness, mitigate bias, and provide access to more lenders, it is an important tool to minimize the various financial and shadow transaction costs associated with refinancing. Figure 4 provides supporting evidence that broadband access is highly correlated with online search activity for information about refinancing and current mortgage rates.

In this paper, I empirically show that reducing transaction costs via broadband internet can improve refinancing outcomes for low-income households. These households typically face volatile employment prospects and work longer hours, finding it particularly difficult to fulfill the verification and qualification requirements for a refinance without at-home internet. Moreover, these households tend to be underbanked and are less confident in their ability to get approved for other types of credit, suggesting that both access to and demand for financial services is limited.[5] Lastly, information frictions regarding upfront costs (which can be waived via low-income programs or rolled into payments) can further hinder refinancing activity for households with low savings.[6]

[4]These are not trivial frictions: in a 2021 survey, 23 percent of homeowners cited "too much paperwork" as a reason for not refinancing their mortgage. This is the third most cited reason after "wouldn't save enough (32 percent)" and "closing costs too high (27 percent)," which additionally signals lack of financial sophistication and cognitive bias. See survey here: `https://www.bankrate.com/mortgages/mortgage-rate-refinancing-survey-august-2021/`.

[5]27 percent of households with less than $40,000 in annual income were underbanked, compared to 11 percent for households with income above $100,000. 32 percent of low-income respondents reported not being confident in their ability to be approved for a credit card loan, compared to 7.2 percent for high-income respondents (Report on the Economic Well-Being of U.S. Households in 2015).

[6]Bhutta and Dettling (2018) find that only 51 percent of households in the bottom income quartile had at least $400 in savings for an unexpected expense, and 17 percent reported having savings worth 3 months of expenses.

Figure 5 confirms that broadband access is correlated with disparities in realized refinancing outcomes: voluntary prepayment probabilities for households with high refinance likelihood are generally lower in census tracts with limited broadband access, with a notably large gap separating the bottom income decile.

2.4 Internet Essentials Program by Comcast

Internet Essentials by Comcast provides a useful quasi-experimental setting to study the digital divide in mortgage refinancing. Comcast is one of the nation's largest internet service providers (ISPs), operating in 39 states and the District of Columbia and covering 48 million households at the time of the study. Internet Essentials was originally conceived to garner the FCC's support for a proposed merger with NBC Universal, a media and entertainment conglomerate corporation. The FCC ultimately approved the merger and enforced Comcast's commitment to institute the low-income subsidy program to promote public interest (FCC, 2012). In the beginning of 2012, Internet Essentials was made available in all Comcast coverage areas nationwide and became the first comprehensive program of its kind by a major ISP.

In an effort to achieve the FCC's mandate of fostering competition and benefiting consumers through reasonably priced broadband offerings, Internet Essentials significantly reduced the cost of broadband subscription. Enrolled households received high-speed broadband (15 Mbps download and 2 Mbps upload) for a $9.95 monthly fee plus applicable taxes, which is about 75 percent lower than the average cost of a comparable unsubsidized broadband plan (Hussain, Russo, Kehl and Lucey, 2013). Moreover, all one-time installation and activation fees (up to $100) as well as modem and router rental fees (up to $20 per month) were waived. Fee savings over a three year period would have exceeded $1,720, which is sizeable for eligible households with an average annual income of $30,000. Internet Essentials also offered subsidized computers for $149.99 and provided digital literacy training resources through online offerings as well as an extensive network of over 9,000 community organizations, libraries, and elected officials.

Eligibility requirements for Internet Essentials were carefully designed to maximize impact and administrative convenience. First, a household must reside in an area that is served by Comcast at the time of application. Second, a household qualifies if it has a child receiving free or reduced-price lunch under the National School Lunch Program (NSLP). These meal benefits in turn depend on household size and income. Specifically, eligibility is restricted to households with annual income below 185 percent of the federal poverty limit (FPL), which translates to around $35,000 for a three-person family and $42,000 for a four-person family during the study period.[7] Third, an applicant must not have any past-due debt to Comcast and cannot have been a Comcast subscriber in the preceding 90 days. This restriction, along with the high concentration and visibility of Comcast as the major ISP in most of its coverage areas, makes it likely that new subscribers did not have an existing broadband subscription. Indeed, 80 percent of Internet Essentials customers reported not having any broadband internet service at some point in the past (Comcast Corporation, 2016). Internet Essentials was principally rolled out through extensive public service announcement campaigns as well as partnerships with thousands of school districts, non-profit organizations, and city councils. Comcast also streamlined the application process in the early years by auto-approving households with children attending majority low-income schools.

Internet Essentials was highly successful, connecting more than 750,000 low-income families (or 3 million individuals) between 2012 and 2016. Importantly, the program grew in urban areas more quickly due to the strong emphasis on community partnerships; 75 percent of the subscribers in the first five years came from 10 of the 40 states and the top 10 cities accounted for 25 percent of subscriptions in this period (Comcast Corporation, 2016). Internet Essentials rapidly became an integral part of everyday life for low-income households, with 89 percent of subscribers reporting using the internet almost every day. Table 1 reports the average characteristics of subscribers and statistics on internet usage. A large fraction of Internet Essentials subscribers are represented by racial minorities (black or hispanic) with low income and low educational attainment. In terms of common internet usage other than children's schoolwork, a majority of subscribers reported using the internet to find general information (92 percent), access e-mail (80 percent), and connect with others on social media (71 percent). Importantly, 65 percent of subscribers said that banks or other financial institutions expect them to have internet access at home. In a subsequent survey, 42 percent reported using the internet to access banking and financial services (Horrigan, 2014, 2019).

3 Methods and Data Description

3.1 Empirical Design

A standard difference-in-differences design cannot cleanly identify the causal effect of Internet Essentials on refinancing. First, studying the refinance behavior of eligible and ineligible households in Comcast areas suffers from non-parallel trends. As income is positively correlated with factors

[7] In 2010, 31.8 million children participated in the NSLP nationwide (U.S. Department of Agriculture, 2019).

such as mortgage principal, creditworthiness, and financial literacy, ineligible households with marginally higher income are generally more likely to refinance (Figure 2). Importantly, households rarely refinance multiple times in succession due to various transaction costs (e.g. closing fees, processing time, credit checks) associated with mortgage origination. This feature leads to faster attrition of the ineligible group's potential refinance pool when interest rates fall. Thus, any positive effects of Internet Essentials' introduction in 2012 – three years after the zero lower bound was established – will be biased upwards by the late refinancing activity by eligible low-income households.

Second, comparing refinance outcomes of eligible households across treated (Comcast) and control (no Comcast) areas results in omitted variable bias. Comcast has near-complete coverage in select cities (e.g., Chicago, Sacramento, Miami, Houston) and is entirely absent in others (e.g., Los Angeles, New York, Dallas), making it difficult to identify two areas within a small geographic footprint with varying levels of Comcast availability. As a result, comparing changes in refinancing behavior between Los Angeles and Sacramento (or between Chicago and New York) is likely to be driven by unobserved confounders. Even after controlling for time-varying economic and financial measures that motivate a household's refinance decision (for instance, house prices and interest rates), I cannot rule out the possibility of bias arising from factors such as industry-by-census tract employment outcomes, migration patterns, or changes in mortgage lending standards.

To overcome these limitations, I study both the variation in geographic coverage and income eligibility, in conjunction with temporal variation pre- and post-program launch. In particular, I use a difference in difference in differences ("triple differences") design from Gruber (1994) to compare changes in the *gap* of refinancing outcomes between eligible and ineligible groups across treated and control census tracts. Under this empirical setting, any confounders at the census tract level that impact both eligible and ineligible groups concurrently are absorbed. Identification relies on the assumption that the difference in outcomes between the two eligibility groups within a census tract will not vary with Comcast availability before and after 2012, except through the impact of Internet Essentials.

Figure A.2 illustrates the intuition behind the triple differences design. All three panels plot the residualized number of annual refinance originations – one of the main outcome variables of interest – by eligibility group at the census tract level. The top panel shows that eligible and ineligible groups in treated areas have divergent refinancing trends prior to the program's launch in 2012. This is broadly consistent with ineligible homeowners refinancing early in the sample and eligible homeowners catching up after 2010, implying that a positive coefficient from a standard differences-in-differences test will be biased upwards. The middle panel confirms that these trends also exist in control census tracts. In fact, eligible groups in control areas exhibit higher refinancing growth (solid line, middle panel) after 2012 than their counterparts in treated areas (solid line, top panel), which may be driven by unobserved differences in local conditions during the recovery period. I address these endogeneity concerns by comparing the gap in outcomes between eligibility groups in control areas with the corresponding gap in treated areas, which are parallel leading up to 2012 (bottom panel).

3.2 Data Sources

Comcast Coverage Rates. I compute coverage rates for Comcast and other major ISPs using service availability data obtained from the National Telecommunications and Information Administration (NTIA)'s State Broadband Initiative. As required by law, each ISP reports whether it offered any type of internet service in a given census block on a biannual basis. I restrict the provider responses to those that can be classified as broadband (high-speed, wireline, residential service) and aggregate the information up to the census tract.

Mortgage Applications and Originations. Data from the Home Mortgage Disclosure Act (HMDA) provides loan-level information on the near-universe of mortgage applications in the United States. To standardize the borrower pool and minimize the effect of refinancing incentives driven by exogenous factors, I restrict the sample to owner-occupied, one- to four-family, conventional refinance mortgages.[8] HMDA data reports the census tract of the property and applicant income, which allows me to assign treatment to Internet Essentials by Comcast availability and income eligibility. The main dependent variables in my analysis capture changes in refinancing demand and outcomes over time. For each year between 2008 and 2015, I count the number of refinance applications submitted by eligible and ineligible households in each census tract. I additionally tally the number of originated mortgages and compute denial rates for each eligibility group by taking the ratio of denials to total applications. I also collect loan-level demographic characteristics such as race and sex.

Prepayment Activity and Loan-Level Covariates. Prepayment refers to the payment of a mortgage's principal before maturity. While there may be many reasons for prepayment including foreclosure, I focus on voluntary prepayment of first-time purchase mortgages between 2004 and

[8]Conventional mortgages are loans that are not insured or guaranteed by the Federal Housing Administration (FHA), Veterans Administration (VA), Farm Service Agency (FSA) and Rural Housing Service (RHS).

2008 as an additional proxy for refinancing activity.[9] By matching loan performance data supplied by two major government sponsored enterprises (GSEs) to HMDA, I construct a panel data set on whether a given household prepaid its mortgage between 2008 and 2011 (pre-Internet Essentials), and between 2012 and 2015 (post-Internet Essentials). The matched data additionally contain information on interest rates, debt-to-income ratios (DTI), combined loan-to-value ratios (CLTV), and credit scores, which can be used to directly control for known refinancing incentives and frictions.[10]

Interest Rates. I test whether broadband access improves refinance outcomes conditional on origination using interest rates. As detailed above, loan-level interest rates are available in the GSE performance data while borrower income is only reported in HMDA. I employ the same matching process to merge the two data sources, this time for refinance mortgages originated between 2008 and 2015. Specifically, I obtain interest rates for a representative subset of owner-occupied, one- to four-family, conventional 30-year mortgages that were originated and sold to Fannie Mae or Freddie Mac.

Mortgage and Rental Costs. I collect information on households' mortgage and rental payments from the Integrated Public Use Microdata Series (IPUMS) of the American Community Survey (ACS) 1-year estimates. De-identified microdata are published for all survey respondents each year. The survey reports mortgage or rental payments made by each household in dollar amounts as well as relevant data on home characteristics and demographic information (age, gender, race, educational attainment, etc.). Importantly, the questionnaire contains details about income and household composition that help refine the assignment to Internet Essentials eligibility. Household location is identified at the PUMA level (average population above 100,000), which is larger than a census tract (average population of 4,000) but still small in geographic footprint for larger cities.

House Prices and Average Income. In my main empirical analysis, census tract-level trends in house prices and homeowner income are absorbed by year fixed effects. While low-income eligible and ineligible groups are likely to experience shocks in these factors concurrently, I additionally incorporate controls for within-census tract changes in economic outcomes for each group using HMDA data. In particular, I construct a time-varying proxy for house prices as the logarithm of

[9]The vast majority of voluntary prepayments are as a result of refinancing, and prior research has studied prepayment speeds as a measure of refinancing activity (Richard and Roll, 1989; Schwartz and Torous, 1989; Stanton, 1995; Longstaff, 2005; Deng and Quigley, 2012).

[10]Further details on the matching process can be found in the Internet Appendix.

average originated loan amounts by eligibility group. Similarly, the logarithm of average income measures changes in income levels among borrowers in each group. For specifications that do not rely on within-tract variation in house prices over time, I use annual house price index (HPI) data published by the Federal Housing Finance Agency (FHFA). The data is available at the census tract level and capture the evolution of overall refinancing incentives for homeowners.

Bank Branch Access. I compile location information for bank branches using data from the Federal Deposit Insurance Corporation (FDIC)'s Summary of Deposits. The data includes precise geographic coordinates for all FDIC-insured financial institutions each year. For each census tract, I compute the number of full service ("Brick and Mortar" or "Retail") bank branches that are within a 1-mile radius of the population centroid as of 2010.[11] Latitude and longitude information for population centroids is obtained from the Census Bureau.

Fintech Lenders. Banks and financial institutions that allow a customer to complete the entire mortgage origination process online are classified as fintech lenders. I use the definition of fintech lenders introduced by Buchak, Matvos, Piskorski and Seru (2018) and Fuster, Plosser, Schnabl and Vickery (2019). I then match these fintech classifications to HMDA data using the respondent identifier associated with each mortgage application.

Other Demographics. Broadband and refinancing inequality are also driven by disparities across urban and rural areas. To address this, I classify census tracts into urban and rural areas using the scheme provided by the National Center for Health Statistics (NCHS).[12] In particular, I use the 2006 delineation of county-level urbanicity and match it to each census tract. Demographic characteristics such as unemployment, broadband usage, and educational attainment, are obtained from the ACS summary and microdata files.

3.3 Comcast Coverage Rates and Income Eligibility

Assignment to treatment in my empirical setting relies on two sources of variation: Comcast availability and income eligibility. To calculate Comcast coverage rates, I first restrict the NTIA's block-level provider data to connection types that qualify as broadband according to the definition used in this paper. As census blocks are a clean subset of a census tract, I then aggregate the

[11] Most studies on "banking deserts" measure branch access within a 10-mile radius of the population centroid, which likely overstates branch access in cities. In fact, the average distance to a branch for low-income urban communities has been stable at 1 mile since 2000 (Covas, 2019; Fee and Tiersten-Nyman, 2021).

[12] https://www.cdc.gov/nchs/data_access/urban_rural.htm.

census block data as of December 2011 (the year prior to Internet Essentials) by calculating:

$$Comcast_{c,2011} = \frac{\sum_{b=1}^{c} Population_{b,2010} \times \mathbf{1}(Comcast_{b,2011})}{Population_{b,2010}}, \tag{1}$$

where $Population_{b,2010}$ refers to the 2010 population of census block b and $\mathbf{1}(Comcast_{b,2011})$ is an indicator for whether Comcast offers broadband service in census block b as of 2011. $Comcast_{c,2011}$ captures the fraction of census tract c's population that has access to Comcast broadband.[13] Although ISP operations are highly persistent, I address possible time-varying changes in coverage by using the same method to calculate $Comcast_{c,2014}$ and taking the average to compute $Comcast_c$. Panel (a) in Figure 6 presents a histogram of $Comcast_c$ in large central metropolitan counties, which exhibits a clear bimodal distribution with peaks at 0 and 100 percent. This distribution enables clean identification of treated census tracts that have near-complete Comcast coverage and control census tracts with no Comcast presence. For placebo tests, I use the same methodology to construct coverage rates for AT&T and Charter, the next two largest ISPs by subscriber count.

Eligibility for Internet Essentials also depends on whether a household has at least one child that receives free or reduced-price lunch at school. The baseline criteria for lunch benefits is in turn determined by low-income status, defined as earning an annual income that less than 185 percent of the federal poverty limit. The poverty limit is defined separately for households of different sizes and increases slightly each year to account for inflation.

A key challenge is that I cannot observe household size or the age of children (if any) from the HMDA or GSE data. To overcome this, I first assume that all homeowners have at least one school-aged child between ages 6 and 18. Next, I assign low-income status based on a four-person household, which is the average household size of Internet Essentials subscribers. The income threshold for a four-person household is around $42,000 by 2012. Instead of using dollar amount cutoffs, I classify all households with income less than 185 percent of the FPL for a three-person household ($35,000) as eligible and households with income more than 185 percent of the FPL for a five-person household ($49,000) as ineligible. Households with income between the three- and five-person household thresholds are excluded from the analysis to account for measurement error and the possibility of strategic bunching behavior around the 4-person cutoff. This classification allows me to compute an intent-to-treat effect that is plausible as long as I can rule out imbalances

[13] Under NTIA's reporting requirements, a provider can report an entire census block as "served" if a single household can be connected to service on demand. As blocks cover a small geographic footprint in urban metropolitan areas, the study's setting is less likely to suffer from overestimation of actual broadband access.

in Internet Essentials eligibility across geographic areas that correlate with Comcast availability. Finally, I further restrict the control group to households with income below 185 percent of the FPL for a six-person family ($57,000). This upper bound ensures that both eligible and ineligible groups can be classified as low to moderate income and share similar characteristics.[14] The resulting annual thresholds for Internet Essentials eligibility are tabulated in Table A.1.

For analyses using ACS data, I directly observe income, family size, and the existence and age of children at the household level. The data thus allows for a cleaner assignment to Internet Essentials eligibility. For these tests, I classify treated households as those with at least one school-aged child and with income less than 170 percent of the FPL based on actual household size. Control households either have incomes between 200 and 270 percent of the FPL, do not have a school-aged child, or both. Again, I drop all households making more than 270 percent of the FPL for comparability as well as households with income between 170 and 200 percent of the threshold to address measurement error. In addition, I construct an alternative control group with the same income levels as the treated group (below 170 percent of FPL) but without a school-aged child. This final classification enables the most direct analysis of households that share similar economic characteristics but differ in program eligibility.

3.4 Final Sample

I restrict my sample to census tracts in large central metropolitan counties as defined by the NCHS. This step is important because Internet Essentials' initial success was primarily led by Comcast's partnerships with local governments and school districts in urban areas. Limiting the geography thus guarantees the highest likelihood of broadband subscription by eligible low-income households in the years following the program's launch. I also drop census tracts without any refinance applications (regardless of income) between 2008 and 2015.

The final sample consists of 5,256 census tracts covering 57 metropolitan statistical areas (MSAs). 2,430 tracts have higher than 50 percent Comcast coverage and 2,826 have less than 50 percent coverage. For easier interpretation, I recast $Comcast_c$ as an indicator for whether census tract c has higher than 50 percent Comcast coverage.[15] Table 2 reports the top 15 Comcast (treated) and no Comcast (control) MSAs ranked by population served. The lack of overlap implies that

[14]For reference, the median income level in the U.S. was around $51,000 in 2012.

[15]This is largely inconsequential because the distribution of coverage rates, as shown in Figure 6, is highly concentrated at 0 and 100 percent. In unreported tests, I use the continuous measure of Comcast coverage as the treatment indicator and find the same results.

Comcast does not operate alongside other major ISPs in cities and rules out potential spillover effects across adjacent census tracts with opposite coverage status. Additionally, the large number of census tracts in each MSA – which comprised of diverse neighborhoods and housing markets – provide support for an empirical strategy that controls for census tract-specific trends.

In Figure 6, panel (b), I map all census tracts in my sample and show that Comcast availability does not exhibit any patterns of regional clustering. Moreover, most of the urban census tracts without Comcast have permanent presence of either AT&T or Charter. This means that broadband environments in treated and control areas are mostly similar; both areas will have comparable access to a major ISP, plan options, network quality and customer service, with the only difference being that eligible households in treated areas could save up to 75% on their subscription costs starting in 2012.

Table 3 presents descriptive statistics for select demographic variables in treated and control census tracts. While treated census tracts are slightly less populated on average, the two groups exhibit economically similar characteristics in terms of income distribution, urbanicity, median age, average household size, owner-occupancy rates, mortgage cost burdens, employment rates, and education levels. Treated census tracts also tend to have a higher concentration of bank branches near the population center and higher ex-ante broadband subscription rates.

In terms of the mortgage sample, this paper focuses on conforming loans only and abstracts away from any indirect effects of targeted government programs that assisted borrowers following the Great Recession (Agarwal, Amromin, Ben-David, Chomsisengphet, Piskorski and Seru, 2017a; Agarwal, Amromin, Chomsisengphet, Landvoigt, Piskorski, Seru and Yao, 2022). Studying conforming loans also allows for better measurement of eligibility status, as special mortgage types held by disadvantaged populations (e.g., Federal Housing Administration (FHA) loans) were mechanically more likely to have negative home equity or be distressed in other unobserved dimensions (e.g., job loss) during the program's operation. I thus study the refinancing choice of relatively stable borrowers in terms of creditworthiness and housing equity but constrained along the income dimension.

In Table 4, I report descriptive statistics for mortgages and homeowners in treated and control areas by eligibility group. Columns 2, 3, 5 and 6 show that across all areas, ineligible households tend to have higher income and credit scores, purchase higher-valued homes, and receive more favorable interest rates than their eligible counterparts. For the average low-income mortgage originated between 2004 and 2008, the interest rate differential for refinancing between 2008 and 2011 is between 1.2 and 1.3 percentage points, which exceeds the standard threshold for optimal refinancing used in the literature (Agarwal, Driscoll and Laibson, 2013). Treated census tracts also tend to have a larger fraction of black homeowners and smaller fraction of hispanic homeowners than control census tracts. In general, the difference in mortgage-related outcomes between eligible and ineligible groups are consistent across regions, both for homes purchased before the Great Recession and for homes refinanced in the early recovery period of 2008 to 2011. Importantly, while the sample households have significantly lower income relative to the rest of the population, their interest rates and credit quality are economically similar to the population average in all periods. This provides further support for studying conventional mortgages, which isolates refinancing frictions from confounding effects driven by the most marginal borrowers or targeted government programs.

3.5 Effects of Internet Essentials on Refinancing

Refinance Outcomes and Interest Rates. I first study the effect of Internet Essentials on the number of refinance applications and originations. Specifically, I estimate the following equation:

$$\begin{aligned} y_{i,c,t} = \alpha + \beta(Eligible_{i,c,t} \times Comcast_c \times Post_t) + X'_{i,c,t}\Phi \\ + \rho_1(\lambda_t \times \gamma_c) + \rho_2(Eligible_{i,c,t} \times \lambda_t) + \rho_3(Eligible_{i,c,t} \times \gamma_c) + \epsilon_{i,c,t}, \end{aligned} \tag{2}$$

where $y_{i,c,t}$ is the number of refinance mortgages originated by households in eligibility group i in census tract c in year t. I also replace the dependent variable with the number of refinance applications submitted and denial rates to study refinancing demand and lender credit standards, respectively. $Eligible_{i,c,t}$ is a binary indicator for group i's Internet Essentials program eligibility, $Comcast_c$ is an indicator for Comcast availability in census tract c and $Post_t$ is an indicator for post-Internet Essentials in 2012. $X_{i,c,t}$ is a vector of eligibility group by census tract by year covariates, which include proxies for house price and income. Census tract by year fixed effects, $\lambda_t \times \gamma_c$, absorb all census tract-specific trends that are invariant to Internet Essentials eligibility. Similarly, the interaction $Eligible_{i,c,t} \times \lambda_t$ controls for aggregate time-varying differences between eligible and ineligible groups and $Eligible_{i,c,t} \times \gamma_c$ controls for permanent differences between eligible and ineligible groups in each census tract. The parameter of interest, β, captures the remaining variation in $y_{i,c,t}$ which only involves time-varying, within-census tract differences between eligible and ineligible groups. The identifying assumption under this setting, therefore, is that within-census tract differences in refinancing activity between the two groups in treated and control areas would have trended the same in the absence of Internet Essentials, conditional on observable covariates.

In the next step, I test whether households with broadband internet are better able to shop around for refinance mortgages and obtain lower interest rates. I replace $y_{i,c,t}$ in equation (2) with loan-level interest rates for originated refinance loans between 2008 and 2015. $X'_{i,c,t}$ now includes loan-level covariates such as income, loan amount, race, sex, number of applicants, combined LTV, DTI, credit score, and loan term. The structure of fixed effects are the same as in equation (2), and the data comprises a subset of HMDA entries that can be matched to GSE performance filings.

For specifications that involve a count measure as the dependent variable, I use Poisson pseudo maximum likelihood (PPML) regressions to model the data (Gourieroux, Monfort and Trognon, 1984; Silva and Tenreyro, 2006; Correia, Guimarães and Zylkin, 2020). In this case, the coefficient β can be interpreted as percentage change in the expected count of the outcome variable, holding all other variables constant. Standard errors are conservatively clustered at the PUMA level to address the possibility that Internet Essentials was rolled out in geographic units larger than individual census tracts (e.g., school districts, neighborhoods). All analyses cover the time period between 2009 and 2015 as other major ISPs and government initiatives introduced similar broadband subsidy programs in 2016. Moreover, the target federal funds rate started rising from the zero lower bound at the end of 2015, which would have reduced refinance incentives for marginal households.

Housing Costs. An important testable prediction of my setting is that mortgage payments should decrease following a refinance. This is not a trivial result as low-income households might refinance at the wrong time (Agarwal, Driscoll and Laibson, 2013) or receive bad interest rates especially when using fintech lenders (Buchak, Matvos, Piskorski and Seru, 2018). It is also useful to quantify the total savings relative to transaction costs and broadband subscription fees. However, it is difficult to directly measure changes in households' payments using HMDA data as the previous mortgage cannot be linked to the refinanced mortgage. To overcome this, I use microdata from the ACS to quantify Internet Essentials' effect on housing costs for both homeowners and renters. I estimate the following equation using survey responses geographically identified at the PUMA level:

$$\begin{aligned} m_{i,p,t} = \alpha &+ \beta(Eligible_{i,p,t} \times Comcast_p \times Post_t) + Z'_{i,p,t}\Phi \\ &+ \rho_1(\lambda_t \times \gamma_p) + \rho_2(Eligible_{i,p,t} \times \lambda_t) + \rho_3(Eligible_{i,p,t} \times \gamma_p) + \epsilon_{i,p,t}, \end{aligned} \tag{3}$$

where $m_{i,p,t}$ is either the natural logarithm of monthly mortgage payments (rent payments) or the mortgage to income ratio (rent-to-income ratio) for household i in PUMA p in year t. $Eligible_{i,p,t}$ is an eligibility indicator that now varies for each household i following the definition outlined in 3.3. In an alternative specification, I restrict the ineligible group further to households with income below 170 percent of the FPL but without a school-aged child. This step aligns the treatment and control groups in terms of observable characteristics while maintaining variation in program eligibility. $Comcast_p$ indicates whether more than 90 percent of PUMA p's population is served by Comcast (control group with less than 10 percent coverage). The redefinition of $Comcast_p$ enables clean identification because PUMAs are on average 10 times larger than census tracts in terms of size and population; PUMAs with medium levels of coverage may lack key broadband infrastructure (e.g. industrial districts) or have neighborhoods with different providers.[16] $Z_{i,p,t}$ is a vector of household-specific covariates obtained from relevant sections of the ACS. To mitigate the effect of new homeowners that may have obtained their first mortgage at lower rates, I restrict the sample to households that moved into their current residence more than three years prior to the response period. Lastly, I relax the urbanicity requirement to address the increased demand on the data arising from PUMA level variation. Concerns of confounding trends as a result of this adjustment are low because I can cleanly identify household-level eligibility status and control for demographic and economic characteristics. Multi-way fixed effects absorb any variation that might threaten the validity of the identification strategy. Standard errors are clustered at the PUMA level.

4 Results

4.1 Main Results

Refinance Outcomes. I first estimate the effect of Internet Essentials on refinance outcomes (applications, originations, and denial rates). Column 1 in Table 5 presents triple differences estimates on refinance originations. I find that the availability of Internet Essentials increased the number of new mortgages originated to eligible households by 6 percent per year, relative to a census tract average of 6 mortgages. These results are statistically significant at the 5 percent level. Given that the average size of the refinance pool is around 60 households per census tract, these are sizeable effects.[17] Figure 7 shows time-varying triple difference estimates of treatment

[16] The majority of PUMAs survive this filtering stpe. In unreported analysis, I verify that the economic results do not change when using the continuous measure of Comcast coverage as in equation (2).

[17] An urban census tract has an average population of 5,000. The lowest income decile for homeowners in these census tracts roughly captures the income group analyzed in this study (Figure 2), while their average owner-occupancy rate is around 50 percent (Table 3). Under the conservative assumption that all such households

effects. I find no evidence of non-parallel trends in the pre-treatment period, confirming the validity of a granular identification strategy that absorbs variation between eligibility groups and across census tracts. Importantly, the coefficient estimates on refinance originations steadily grow throughout the early years of the program and become statistically significant in 2013 and 2014. This gradually increasing trend also mirrors the subscriber growth pattern between 2012 and 2015 (Comcast Corporation, 2016).[18] The treatment effect falls slightly and becomes insignificant in 2015, corresponding to the eventual slowdown in aggregate refinancing demand.

I also do not find evidence that the increase in refinance originations is associated with suboptimal application behavior. As low-income households are more likely to have marginal credit quality, it is possible that the growth in refinance originations masks an increase in costly denials. This is particularly important in the context of search frictions that marginal households face (Agarwal, Grigsby, Hortaçsu, Matvos, Seru and Yao, 2024b). Using application and denial data from HMDA, I test the hypothesis that access to the internet can have the unintended consequence of disseminating misinformation or inflating the perceived likelihood of an approval. In column 2 of Table 5, I show that the number of applications also increases by 6 percent and that the coefficient is statistically significant at the 1 percent level. Column 3 confirms that there are no effects on denial rates relative to a pre-treatment average of 31 and 41 percent for eligible and ineligible groups, respectively. These results imply that internet access does not induce an increase in misguided application behavior or costly search. Moreover, banks and mortgage lenders do not seem to adjust lending standards or reallocate credit in response to the increase in applications.

Internet Essentials also did not induce borrowers to obtain more favorable interest rates conditional on approval. Column 4 of Table 5 shows no effect of treatment on interest rates controlling for a rich set of loan-level covariates. This can be explained by the relative uniformity of terms and requirements for conventional mortgages. In addition, online (fintech) lenders did not have a large market share during this period, which may have limited online rate-shopping activities especially for low-income homeowners (Figure 8). Online lenders also tend to charge higher interest rates than traditional lenders in exchange for improved convenience, dampening any monetary benefits of refinancing along the intensive margin (Buchak, Matvos, Piskorski and Seru, 2018).

The savings from refinancing are economically substantial, especially for low-income households

have mortgages and have four occupants, there are about 62.5 active mortgages held by low-income households for each census tract.

[18]The positive (but not significant) treatment effect in the treatment year of 2012 can largely be attributed to the pilot program in Chicago, IL that began in fall 2011. Chicago is one of the largest cities served by Comcast.

that have most of their wealth tied to home equity. Between 2004 and 2008, the average first-time homebuyer in my sample obtained a fixed-rate mortgage with principal around $120,000 and an interest rate of 6.2 percent. Applying the prevailing average interest rate of 4 percent for comparable loans between 2012 and 2015, each marginal household that refinanced during this period would have saved $110 dollars per month before any adjustments. These households still come out ahead by around $100 after accounting for the cost of Internet Essentials, which corresponds to a 14 percent reduction in mortgage payments and 5 percent increase in monthly disposable income ($2,000 after federal and average state taxes). More importantly, the lifetime savings for an average refinance loan can be up to $29,000, or $18,000 after discounting over time and adjusting for possible closing costs.[19] These lifetime savings account for around one-third of the median net worth of all low-income households and 10 percent of the net worth of low-income homeowners residing in owner-occupied units (Survey of Consumer Finances, 2013; Wolff, 2016).

I also estimate the aggregate economic impact of Internet Essentials to be large and persistent. A 6 percent increase in the number of refinance originations, off a base of 13,000 annual originations for the treated group prior to 2012, corresponds to 780 additional refinancings per year (total origination volume of $100 million per year). Based on the aforementioned conservative measure of household wealth gains ($18,000), Internet Essentials generated $55 million in aggregate household savings through refinancing between 2012 and 2015. These results importantly ignore the effect on non-urban households, so the the upper bound of national savings attributable to Internet Essentials is around $100 million.[20] Taking stock, these aggregate savings almost directly offset the $110 million that Comcast invested into public service announcements to advertise the program during this period. Even if we assume that Comcast breaks even on each subsidized broadband line, the mortgage payment savings combined with other documented economic benefits such as increased employment outcomes (Zuo, 2021) imply that the program was generally successful in reducing inequality.

Mortgage Payments. In this section, I directly test whether Internet Essentials indeed led to lower mortgage payments. This is an important empirical exercise given the incidence of

[19] To calculate the present value, I use a discount rate of 4 percent and adjust the savings downward by an additional 15 percent to account for marginal taxes, closing costs and the probability of moving. Note that closing costs can often be waived for low-income borrowers through federal and state grant programs. Using a more conservative set of parameters from Agarwal, Driscoll and Laibson (2013) and Keys, Pope and Pope (2016) would further reduce the estimated savings to $15,000.

[20] Urban census tracts account for around 54 percent of Comcast's coverage area by population. Assuming that the treatment effect of the program would have been the same (or half as effective) in non-urban census tracts, the upper (lower) bound of mortgage payment savings is $100 million ($78 million).

suboptimal refinancing behavior particularly among low-income households; the true effect of actual savings may be lower than the 14 percent derived from average interest rate differences due to origination costs, taxes, or fluctuations in appraisal value. Table 6 shows the results from estimating equation (3). Panel A uses a control group of all eligibles (higher income, no school-aged child, or both). I find that Internet Essentials decreased mortgage payments in treated areas by 2.5 percent and the mortgage to income ratio by 1.5 percent. The results are statistically significant and are robust to the inclusion of control variables for demographics (e.g., age, race, gender, educational attainment) and economic characteristics (income, home value). Panel B refines the assignment to treatment by comparing mortgage payment outcomes between low-income households with at least one school-aged child and low-income households without a school-aged child. This specification yields similar coefficients for mortgage to income ratio and an even larger effect on mortgage payments (3.8 percent). In Figure 9, I verify that the point estimates on log mortgage payments, the cost measure of choice, are not statistically significant prior to 2012. The point estimates generally decrease over time after Internet Essentials is introduced and becomes statistically significant in 2014 for panel (a). However, I do not find a statistically significant effect in any other year under either specification. This fact, in conjunction with the negative and statistically significant effect on the baseline triple-differences analysis, can be explained by the relative infrequency of refinancing events among low-income homeowners as well as data limitations.

The magnitude of treatment effects in Table 6 provides important baseline estimates for the monetary savings from refinancing. The average existing mortgage payment for eligible households is around \$700, which is consistent with the statistics obtained from HMDA. A 4 percent decrease in costs corresponds to \$30 in monthly savings or \$5,500 in adjusted present value terms. This serves as the lower bound estimate for the treatment effect of Internet Essentials as the ACS does not directly collect information about mortgage refinancing activity. I argue that saving \$30 a month can still have a large impact on financial health when accumulated over several decades due to the low disposable income and discretionary savings of these households. In fact, more than 30 percent of households in this income group reported to be "food insecure," which means they did not have access to enough food for an active, healthy life for all members (Coleman-Jensen, Rabbitt, Gregory and Singh, 2016).

4.2 Mechanisms

I analyze the mechanisms through which expanding broadband access improves refinancing outcomes for low-income households. Internet Essentials' unique empirical setting provides testable predictions for whether the positive effect of broadband internet on refinancing is a result of the rise in online lending or improved access to traditional mortgage services. Moreover, I study two competing explanations for higher refinancing demand — the income effect of broadband connectivity and reduced information frictions.

Lending Channels and Financial Inclusion. Obtaining access to financial services is particularly challenging for the 20 percent of American households that are classified as underbanked (Federal Deposit Insurance Corporation, 2013).[21] I posit that refinancing transaction costs are higher for less digitally connected households as banks transition to a technology-first business model primarily in expensive urban areas (Jiang, Yu and Zhang, 2024). In fact, Comcast cities such as Chicago (13 percent), Philadelphia (18 percent), and Detroit (16 percent), as well as no Comcast cities such as New York (11 percent), Dallas (8 percent), and Las Vegas (17 percent), experienced significant branch closures during this period.

Given the consolidation of bank branches, a key supply-side prediction is that refinancing growth due to broadband is driven by an increased share of online (fintech) lender transactions. Table 7 empirically tests this hypothesis. In column 1, I estimate equation (2) by setting the fraction of fintech lender originations to all refinance originations as the dependent variable. I do not find any effect of Internet Essentials on fintech relationships, which can partially be explained by the relatively low market share of fintech mortgage lenders during this period (4.3 percent and 7.2 percent for eligible and ineligible refinance mortgages, respectively). This fact is also supported by Figure 8, which shows that Google search activity for the top fintech lenders remained muted until 2015.

Figure 8 also provides suggestive evidence that online search activity for large traditional banks increased with broadband adoption through 2014. In columns 2 to 4 of Table 7, I estimate equation (2) for refinance originations after dividing the sample of census tracts into three groups based on the number of physical bank branches within 1 mile of the population center. This measure captures both the quantity and quality of local banking services offered to customers. I

[21] A household is underbanked if it used alternative financial services (money orders, check cashing, remittances, payday loans, refund anticipation loans, rent-to-own services, pawn shops loans, or auto title loans) from non-bank providers in the preceding 12 months. Between 2008 and 2016, more than 6 percent of bank branches closed nationwide (National Community Reinvestment Coalition, 2017).

find that the treatment effect is large (8.9 percent) and statistically significant when comparing Comcast and no Comcast census tracts with low bank branch density (average of 0.55 branches). Conversely, the treatment effect is weaker and not statistically significant for medium and high branch access census tracts. These results imply that refinancing growth is concentrated in areas where households face high non-monetary transaction costs to borrowing. These costs are particularly salient for marginal low-income homeowners; they tend to be constrained in their ability to make long-distance branch visits due to being in service, natural resources, maintenance, and construction occupations with limited flexibility (Bureau of Labor Statistics, 2014). The last-mile problem of credit access is well documented in Argyle, Nadauld and Palmer (2023), which associates low bank branch access with higher search costs and worse financial outcomes. I provide suggestive evidence that broadband improves refinancing outcomes primarily by connecting households to traditional financial institutions — the main source of credit for disadvantaged populations.

Determinants of Refinancing Demand. In this section, I address whether the increased refinancing activity due to Internet Essentials was driven by demand-side factors. First, it is possible that marginal households recognize the value of refinancing but are discouraged by closing costs or their own creditworthiness. If broadband allowed such households to directly increase their income via training and job search, refinancing growth would be a mechanical outcome and not caused by changes in preferences. I test whether the income for eligible homeowners with a mortgage, who comprise close to half of households in this income group, indeed increased as a result of the program. Specifically, I replace the dependent variable in equation (3) with the log of income conditional on having a mortgage and being employed (refinancing is generally available to employed borrowers only). I use the preferred specification that assigns the control group as low-income households that are ineligible due to the absence of a school-aged child. Column 1 of Table 8 shows that Internet Essentials did not have any direct effect on income for employed households with a mortgage, which is also consistent with findings from Zuo (2021) that Internet Essentials benefited households along the extensive margin (finding jobs) but not the intensive margin (income conditional on employment). While reduced opportunity costs does not seem to have played an important role, I do not make a conclusive statement on its relevance; it is possible that households used the internet to free up non-monetary resources (e.g. finding less time-consuming jobs, streamlining errands), which are dimensions I cannot observe in the data.

An alternative explanation for increased refinancing demand is that Internet Essentials bridged existing gaps in digital and financial literacy. Survey results show that households with high digital skills are much more likely to access banking and financial services online (60 percent) than households with low digital skills (39 percent) (Horrigan, 2019). Recognizing the importance of training, Comcast designed various digital literacy initiatives that were readily accessible to subscribers. These programs, which were offered free of charge through multiple outlets both online and offline, covered a wide range of topics on digital readiness (e.g., internet security and e-mail) as well as general well-being (e.g., job search, social services, and personal finance).[22]

I test whether the refinancing growth between 2012 and 2015 stems from an increase in financial sophistication among borrowers. I hypothesize that borrowers with lower financial literacy (measured by educational attainment) are likely to exhibit stronger refinancing patterns post-Internet Essentials than their sophisticated counterparts, who may have internalized the processes and benefits of refinancing already. Columns 2 to 4 of Table 8 estimate regression (2) with refinance originations as the dependent variable. To assess heterogeneous effects, I split the census tracts into three groups based on the fraction of the population with a high school degree or higher as of 2011.[23] Column 2, which compares the refinancing gap between eligible and ineligible households in urban census tracts with low levels of educational attainment, reveals a positive and statistically significant coefficient of 12.3 percent. I find no treatment effect in the middle group of census tracts (column 3), and a significant but lower coefficient of 5.6 percent for high education census tracts (column 4).

In order to identify this channel more directly, I also estimate equation (3) using log mortgage payment as the dependent variable and dividing the sample of ACS respondents into low (less than high school degree) and high (at least high school degree) digital and financial literacy groups. Instead of focusing on overall education levels at each census tract, I study household-level variation in educational attainment in this specification. Columns 5 to 8 of Table 8 provide further support of a financial literacy channel: Internet Essentials reduced mortgage payments by 5.4 to 8.3 percent among low-literacy groups, but had no effect on payments for high-literacy groups. Taken together, these results suggest that Internet Essentials helped improve financial sophistication; low-income households with higher ex-ante financial sophistication were not differentially impacted by Internet Essentials, implying that if desired, they would have managed to refinance even without an at-home broadband connection.

[22]See, for example, Figures A.3 and A.4.

[23]51 percent of Internet Essentials subscribers in my sample report having a high school diploma or less (Comcast Corporation, 2016).

It is difficult to assess the relative contributions of the financial sophistication and transaction cost channels due to data limitations. In principle, financial sophistication may take some time to achieve whereas transaction costs can fall quickly with an internet connection. The nearly immediate effect of Internet Essentials on refinancing growth in the early period (Figure 7) suggests that the reduction of transaction costs likely played a first-order role. While the channels are complementary, I reserve judgment on optimal policy design to future work.

5 Robustness and Falsification Tests

Mortgage Prepayment Probability. While loan counts provide the most direct and comprehensive measure of refinancing activity, it cannot shed light on how refinancing inequality evolves relative to a stock of existing, current mortgages. To address this, I analyze the evolution of prepayment behavior for home purchase mortgages originated between 2004 and 2008 in a two-period model. I estimate the following equation:

$$\begin{aligned} prepay_{i,c,t} = \alpha + \beta(Eligible_{i,c,t} \times Comcast_c \times Post_t) + Y'_{i,c,t}\Phi \\ + \rho_1(\lambda_t \times \gamma_c) + \rho_2(Eligible_{i,c,t} \times \lambda_t) + \rho_3(Eligible_{i,c,t} \times \gamma_c) + \epsilon_{i,c,t}, \end{aligned} \tag{4}$$

where $prepay_{i,c,t}$ is a binary indicator for whether loan i in census tract c has prepaid by year $t \in \{2011, 2015\}$. $Eligible_{i,c,t}$ now indicates whether loan i qualifies for Internet Essentials at the time of origination, with the assumption that eligibility status stays constant through 2015. I mitigate the confounding effects of households switching eligibility status between 2008 and 2012 by constructing a new control group with annual income higher than the threshold for six-person households (average of $50,000) and drop high-income households at twice the lower bound. To focus on financially sound households with a low probability of falling into distress during the Great Recession, I restrict my sample further to loans with origination credit scores above the unconditional mean (around 750). $Y'_{i,c,t}$ is a vector of loan-specific covariates, which includes income, race, sex, number of applicants, interest rate at origination, loan-to-value ratio, debt-to-income ratio, credit score, loan amount, and mortgage tenure. $\lambda_t \times \gamma_c$ absorbs all census tract-specific trends that are invariant to Internet Essentials eligibility and $Eligible_{i,c,t} \times \lambda_t$ controls for aggregate time-varying differences between eligible and ineligible groups. Similarly, $Eligible_{i,c,t} \times \gamma_c$ controls for permanent within-census tract differences between eligible and ineligible groups.

Column 1 of Table 9 shows that the prepayment probability for low-income households increased by 2.8 percentage points, or 6.7 percent, as a result of Internet Essentials. The effect is economically large given the average pre-treatment prepayment probability of 42 percent, and is statistically significant at the 5 percent level. Direct measurement of prepayment status also allows me to compute how much of the observed reduction in refinancing inequality between the top and bottom income deciles can be attributed to Internet Essentials. First, the effect on prepayment activity estimated in Table 9 implies that Internet Essentials can explain up to 20 percent of the growth in prepayment for marginal households in the lowest income decile.[24] In addition, back of the envelope calculations suggest that the program reduced the gap in refinancing activity between the top and bottom income deciles by up to 31 percent. These estimates reflect an upper bound as the reduction in refinancing gap is largely a result of mechanical convergence over time.[25] Note that these are intent-to-treat effects as I cannot observe program take-up; treatment-on-the treated effects will be even larger with imperfect adoption, but a detailed estimation is beyond the scope of this paper.[26] The dynamics of treatment effects over time (Figure A.5) follow a similar pattern to those using loan counts and mortgage payments as the outcome variable; it takes two to three years for the full effect to take hold, which can be attributed to the gradual adoption of Internet Essentials. Overall, the prepayment findings are broadly consistent with my baseline results, albeit limited in its ability to identify eligible and ineligible households at the time of the program's launch.

Alternative Eligibility Thresholds. Internet Essentials eligibility is importantly based on household income and family composition, the latter of which I cannot directly measure from the HMDA or GSE Data. The fact that income conditional on homeownership does not increase helps rule out the possibility of an eligible household becoming ineligible again; still, my analysis still suffers from the concern that the choice of income thresholds does not precisely identify truly eligible households. As such, the validity of my findings would be undermined if I find positive treatment effects on refinancing activity when using comparable groups of households (one with higher income than the other) that are both unlikely to be impacted by Internet Essentials. In column 2 of Table 9, I show that assigning a placebo treated group at the 5-6 person family income threshold and control group at the 7-8 person family income threshold does not yield statistically

[24] A 6.7 percent increase off a base of 65 percent implies a 4.4 percentage point increase in prepayment. I then divide this number by total prepayment growth by this group between 2012 and 2015 (23 percent). Note that the slight difference in base prepayment propensities compared to the regression results is due to the use of static income deciles for illustrative purposes.

[25] At the end of 2011, there was a 23 percent gap in the fraction of pre-crisis mortgages refinanced between the bottom and top income deciles in urban census tracts with high Comcast coverage (65 vs. 88 percent). The same gap was reduced to 9 percent (89 vs. 98 percent) by the end of 2015. I take the ratio of the aforementioned prepayment growth and the reduction of the gap (14 percent).

[26] Zuo (2021) estimates an average take-up rate of 10.6 percent between 2012 and 2015, but those rates were likely higher in urban areas.

significant effects on mortgage refinancing. The absence of a treatment effect confirms that my criteria coincides with actual eligibility and that income-based differences in refinancing trends alone cannot explain the findings. In unreported analysis, I also verify that expanding the original control group to households within the 5-7 person income threshold does not materially change the results.

Placebo ISPs. Internet Essentials was the only broadband subsidy program of its kind until 2016. After that, other major ISPs as well as federal and state governments introduced similar initiatives to bridge the digital divide. These multilateral efforts were made more prominent and permanent following the COVID-19 pandemic. Because of the uniqueness of Internet Essentials between 2012 and 2015, the causal estimates on refinancing should disappear when I assign AT&T or Charter as placebo program providers. To tes this, I compute coverage rates $AT\&T_c$ and $Charter_c$ at the census tract level and re-estimate equation 2. Columns 4 and 5 of Table 9 report the results. Indeed, instituting a placebo broadband program in high AT&T and high Charter areas do not yield any effect on refinance originations.

Rental Costs. Rentals are a prominent alternative housing tenure choice. Unlike mortgages, however, rent payments are typically contractual and regulated by local housing authorities. Renting also does not allow households to build wealth through home equity, meaning that long-term gains from reducing rent payments are less likely to be consequential for low-income households. As such, outcomes on rental payments should not change meaningfully as a result of Internet Essentials. I test this prediction using ACS data on renters and confirm that households do not take advantage of Internet Essentials to reduce their rent payments (Table 9, column 6).

Census Tract Characteristics. Despite reports of Internet Essentials' rapid growth nationwide, I cannot directly observe program take-up at the household, loan, or geographic area level. As an additional falsification test, I analyze whether the treatment effects on refinancing activity are concentrated among census tracts that are likely to have a large pool of new program subscribers. First, in columns 2 to 4 of Table 10, I show that census tracts with a higher fraction of owner-occupied households with children between ages 6 and 18 — one of the main criteria for program eligibility — contribute to the entirety of treatment effects. Second, it is plausible that refinancing demand is correlated with housing cost burdens as the impact of payment savings are largest. I measure census tract-level housing cost burdens as the fraction of homeowners who pay more than 30 percent of income on mortgages as of 2011. Since this measure is calculated regardless of income, it also partially captures differences in local house prices. Columns 5 to 7 report the results: only the treatment effect of refinance originations at the top quartile (16.5 percent) is statistically significant. Lastly, I test for heterogeneous effects across census tracts within PUMAs with varying levels of broadband subscription rates as of 2013, the first year this question was asked in the ACS. Again, a statistically significant treatment effect of 9.2 percent is only present when comparing census tracts in the top quartile of broadband subscription rates. This result provides suggestive evidence that areas with resilient existing broadband infrastructure (such as stronger advertising campaigns, better equipment efficiency, or resilient social networks) benefited the most from the program. Conversely, the finding also implies a relative inefficiency in less connected areas that can be addressed through increased targeting efforts.

Evidence from the COVID-19 Pandemic. In Internet Appendix B, I assess the external validity of my main results using COVID-19 as an alternative quasi-experimental setting. Although interest rates fell to historic lows and led to a refinancing boom, many low-income and minority homeowners failed to refinance during this period (Agarwal, Chomsisengphet, Kiefer, Kiefer and Medina, 2023). I hypothesize that stay-at-home orders led to a sharp increase in refinancing transaction costs because in-person mortgage services became severely limited. I first assign treatment status to census tracts based on ex-ante levels of broadband access. Using a difference-in-differences framework with propensity score matching, I show that refinance originations grew more in high broadband census tracts after March 2020. These results independently confirm that reducing transaction costs via broadband internet can help mitigate refinancing inequality.

6 Conclusion

Failing to refinance a mortgage when it becomes profitable to do so leads to large welfare losses. This phenomenon is prominent among low-income households and has contributed to the growing wealth inequality in recent decades. In this paper, I study whether reducing disparities in access to high-speed internet can mitigate known refinancing frictions by exploiting a natural experiment that brought broadband to over 750,000 low-income households between 2012 and 2015. Using an identification strategy that accounts for geographic, temporal, and household-level variation in access to the program, I find a strong and positive effect on refinancing that leads to a decrease in mortgage cost burdens. The economic significance of the results are large and persistent, resulting in total savings that correspond to 10 percent of average net worth for these households. The treatment effects are concentrated in areas that are underbanked as well as areas with low levels of digital and financial literacy.

This paper provides important implications for monetary policy, mortgage contract design, and infrastructure policy. First, the pass-through of monetary policy may be hindered by refinancing transaction costs that differentially affect households with or without internet access. Since the digital divide persists along the income dimension as well as in less developed areas, the consequences of failing to refinance for disadvantaged groups will be amplified during economic downturns. Moreover, a housing market that is dominated by fixed-rate mortgages places the burden of refinancing solely on households and can lead to more inequality (Berger, Milbradt, Tourre and Vavra, 2023). Over the past several decades, socioeconomically disadvantaged populations have been stymied by the mismatch between the path to homeownership and the lack of ability or resources to refinance when it becomes optimal to do so. To address this, the government, in conjunction with financial institutions, might consider developing mortgage products that target these populations and dynamically induce refinancing behavior. Lastly, large-scale efforts to get Americans connected to broadband internet should continue through subsidy programs and breakthroughs in physical infrastructure expansion.

Access to high-speed internet is one of the most prominent equalizing forces in the modern era. As technology continues to evolve, the new front of financial inclusion will depend less on introducing branches and ATMs to neighborhoods but more on connecting people via devices and applications. While this paper addresses the internet's key role bridging the wealth gap in the context of mortgages, additional consideration should be given to other aspects of household finance such as savings and budgeting decisions.

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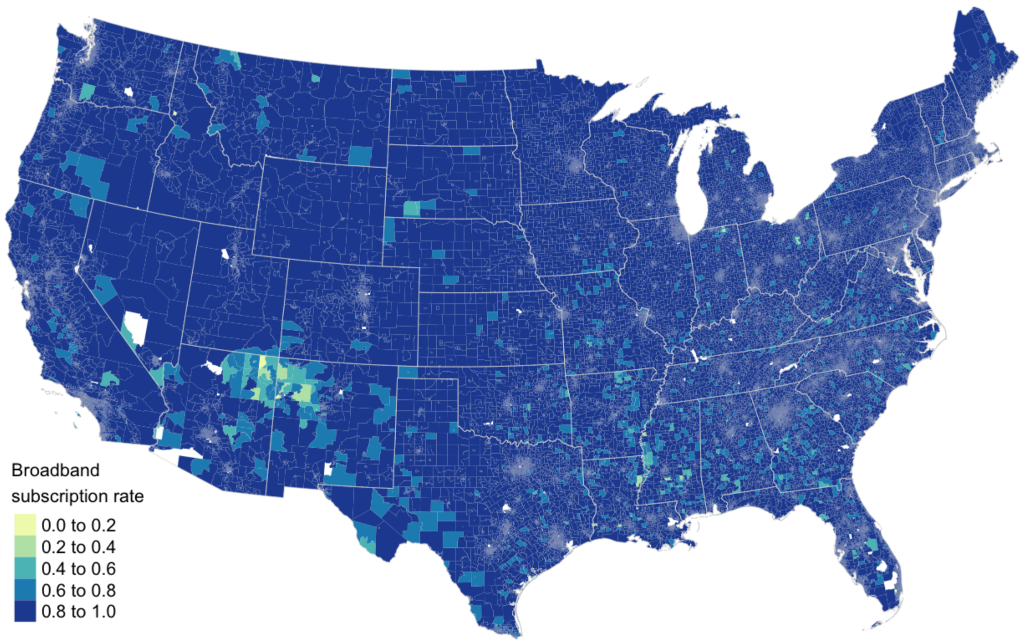
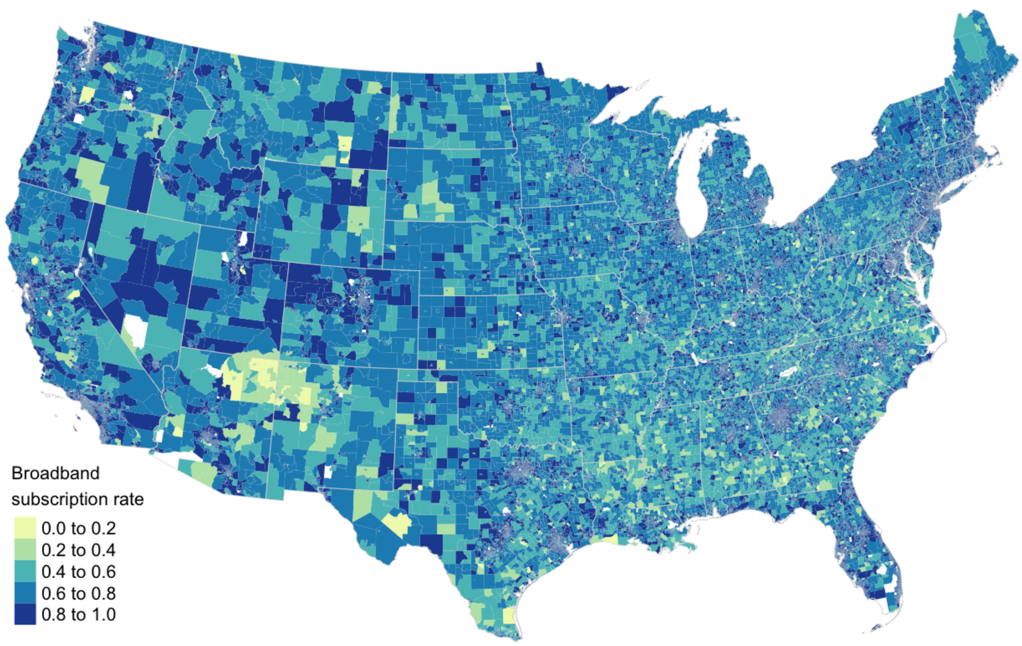
Figures and Tables



(a) Household income above $75,000



(b) Household income below $35,000

Figure 1: Broadband Access in the United States

Note: This figure plots the fraction of high- and low-income households with a broadband internet subscription at the census tract level. Annual household income is in 2022 inflation-adjusted dollars.
Source: 2022 ACS 5-year estimates.

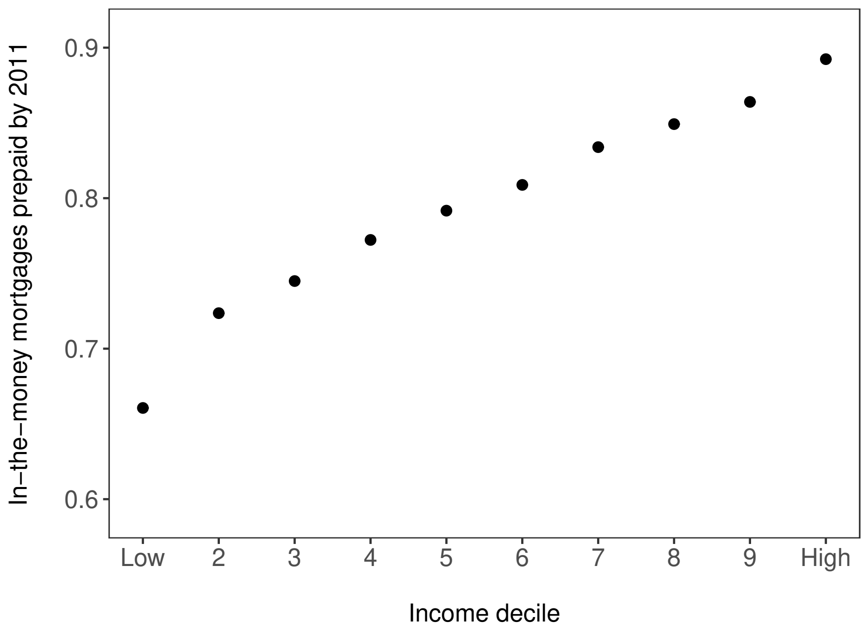


Figure 2: Household Income and Refinancing Inequality

Note: This figure plots the relationship between household income and mortgage prepayment. For each income decile of households that originated a conventional mortgage sold to Fannie Mae or Freddie Mac between 2004 and 2008, I calculate the total volume of "in-the-money" mortgages as those with above-median interest rates and credit quality metrics (combined LTV, DTI, and credit score). Then, I compute the fraction of these mortgages that were voluntarily prepaid (by volume) on or before 2011. The sample consists of loans in urban central metro areas.
Source: HMDA, Fannie Mae and Freddie Mac loan performance files, and author's calculations.

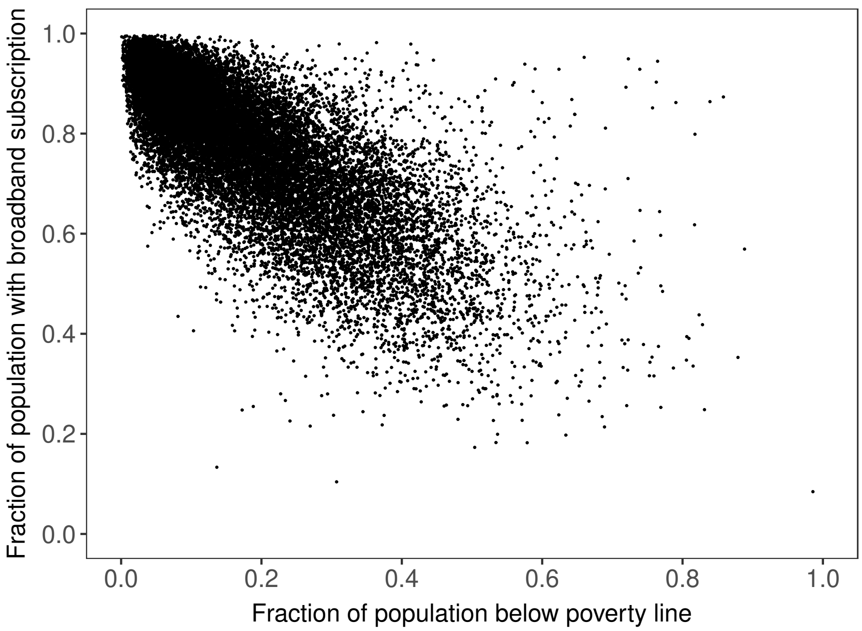


Figure 3: Broadband Affordability and the Digital Divide

Note: This figure shows broadband inequality in large central metro census tracts with high levels of ISP coverage. The x-axis is the fraction of a census tract's population living below the poverty line, and the y-axis is the fraction of the population with a high-speed broadband subscription at home.
Source: NCHS, 2017 ACS 5-year estimates.

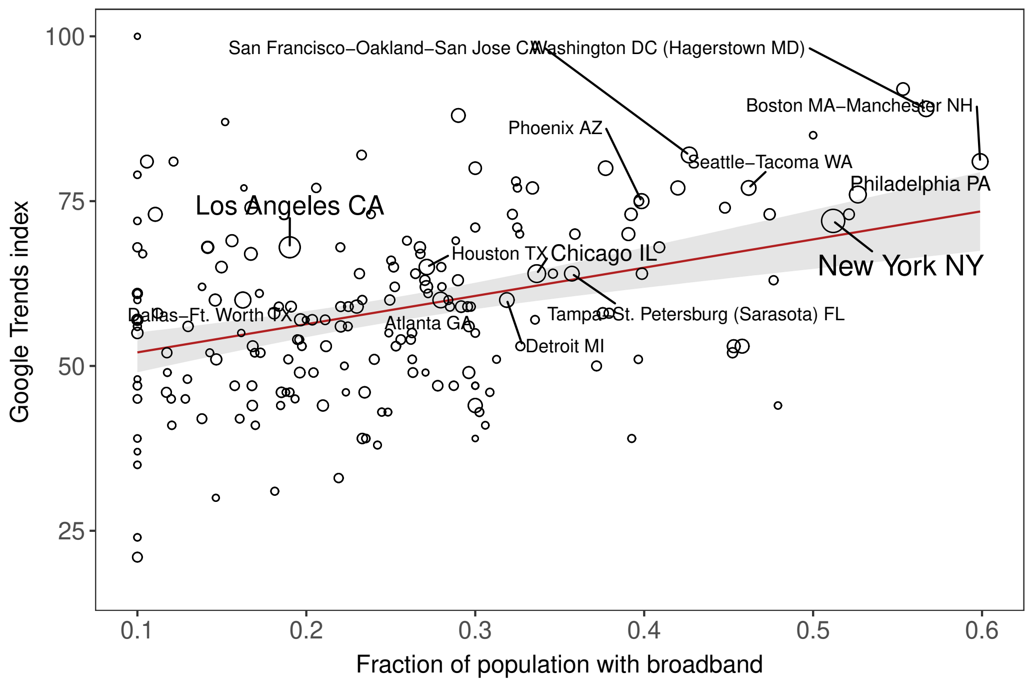


Figure 4: Broadband Access and Refinancing Demand

Note: This figure plots the relationship between broadband connectivity and refinancing demand. Google Trends search data for relevant keywords ("refinance," "refinance rates," "mortgage refinance," and "mortgage rates") are compiled for each metropolitan area between 2012 and 2015. Broadband subscription data (at least 10 Mbps download speed) is compiled at the county level as of December 2011. I match these two data sources and calculate a weighted broadband index at the metropolitan area level. The shaded region represents 95 percent confidence intervals for the linear fitted line. The size of each observation indicates the size of each area, and locations with more than 2 million housing units are labeled.
Source: Google, FCC Form 477, geography crosswalk file from Jacob Schneider.

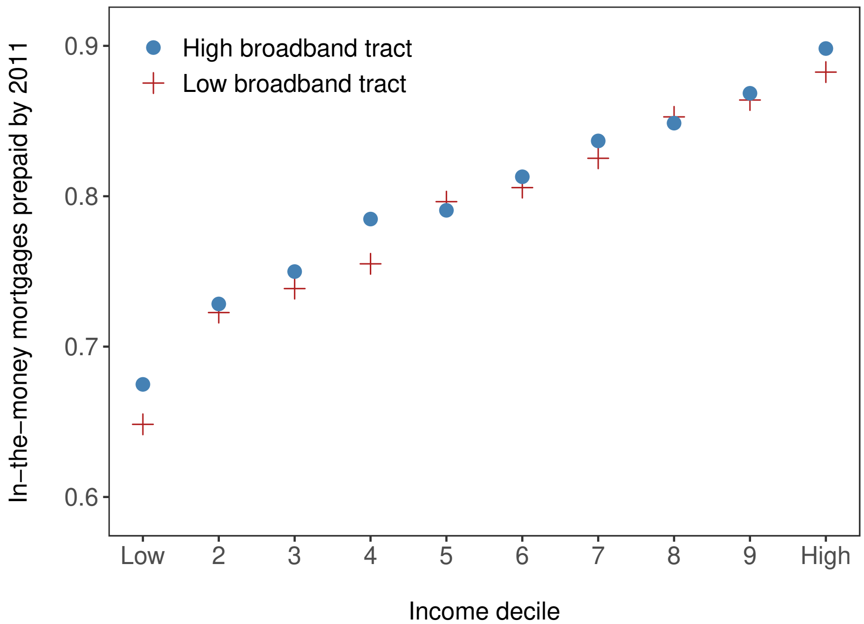
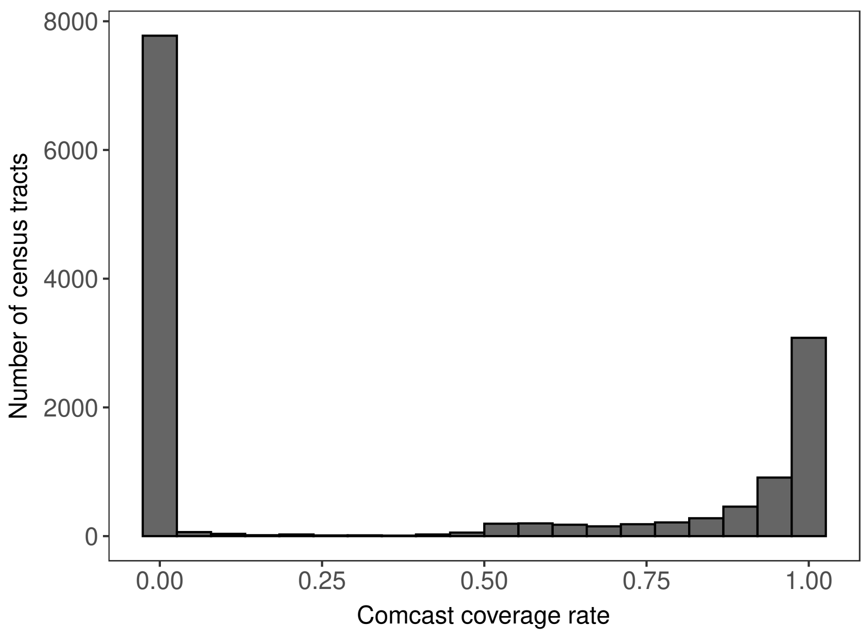
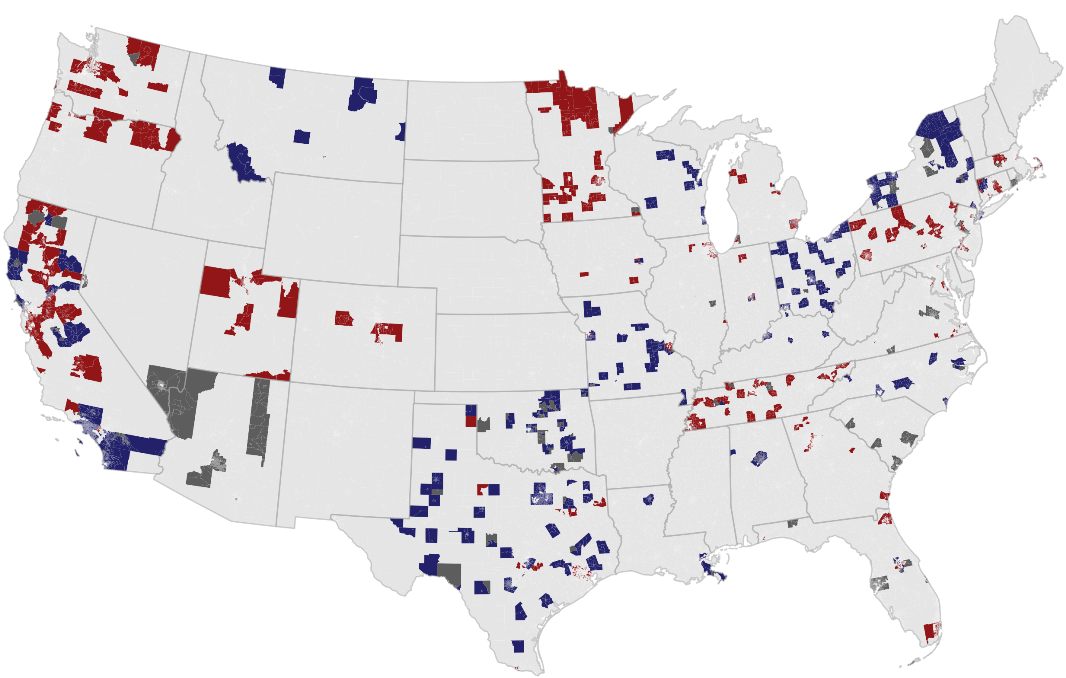


Figure 5: Refinancing Inequality and Access to Broadband

Note: This figure separately plots the relationship between household income and mortgage prepayment in high- and low-broadband census tracts. “High broadband tract” and “low broadband tract” are defined as census tracts that had below 40 percent and above 60 percent coverage of broadband subscription rates as of December 2011, respectively. Income deciles are constructed using conventional mortgages originated and sold to Fannie Mae and Freddie Mac between 2004 and 2008. I restrict the sample to “in-the-money” mortgages, defined as those with above-median interest rates and credit quality metrics (combined LTV, DTI, and credit score) at time of origination. I plot the fraction of these mortgages that were voluntarily prepaid (by volume) on or before 2011. The sample consists of loans in urban central metro areas.
Source: HMDA, Fannie Mae and Freddie Mac loan performance files, FCC Form 477, and author’s calculations.



(a) Histogram of Comcast Coverage Rates



(b) Geography of Comcast Coverage

Figure 6: Comcast Coverage

Note: This figure plots the statistical and geographical distributions of Comcast coverage rates in large central metro census tracts. For each census tract, I first calculate the fraction of the population with Comcast access. The final coverage rate takes the average of coverage rates in December 2011 and December 2014. The top panel shows the distribution of comcast coverage rates. The bottom panel illustrates Comcast (red), no Comcast with AT&T and Charter (blue), and other no Comcast census tracts (dark grey).
Source: NTIA State Broadband Initiative, NCHS.

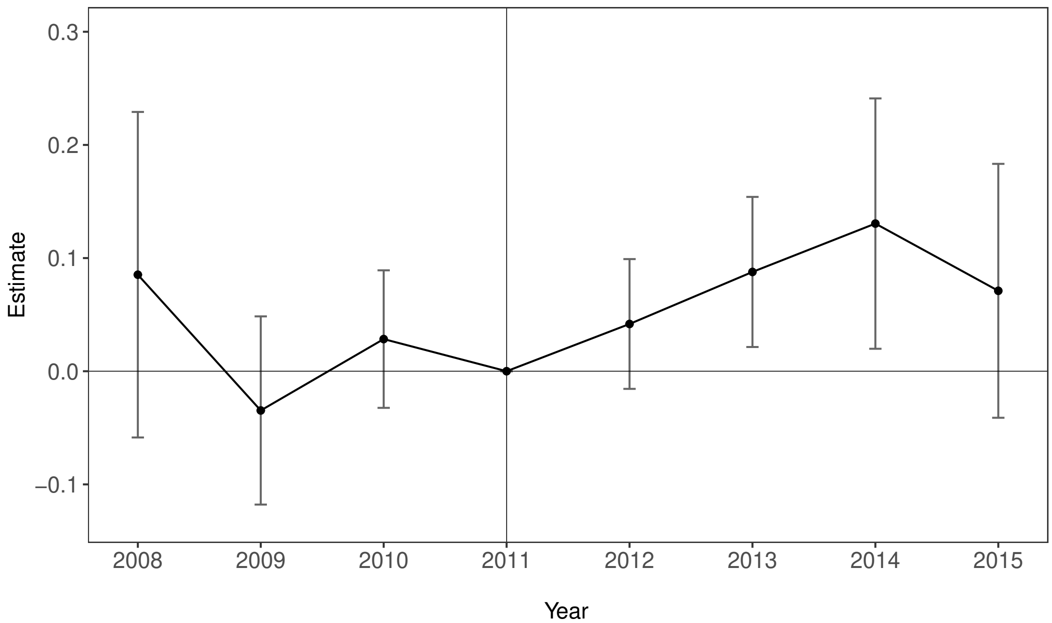


Figure 7: Event Study Estimates for Refinance Originations

Note: This figure plots dynamic triple difference estimates (β_t) and 95 percent confidence intervals for the number of refinance originations. The estimating equation is:

$$\begin{aligned} y_{i,c,t} =& \alpha + \sum_t \beta_t (Eligible_{i,c,t} \times Comcast_c \times Year_t) + X'_{i,c,t}\Phi + \rho_1(\lambda_t \times \gamma_c) + \rho_2(Eligible_{i,c,t} \times \lambda_t) \\ &+ \rho_3(Eligible_{i,c,t} \times \gamma_c) + \epsilon_{i,c,t}, \quad t \in \{2008, 2009, 2010, 2011, 2012, 2013, 2014, 2015\}. \end{aligned}$$

The sample spans the period between 2008 and 2015. The interaction term in the final pre-treatment period (2011) is omitted. Robust standard errors are clustered at the PUMA level.
Source: HMDA.

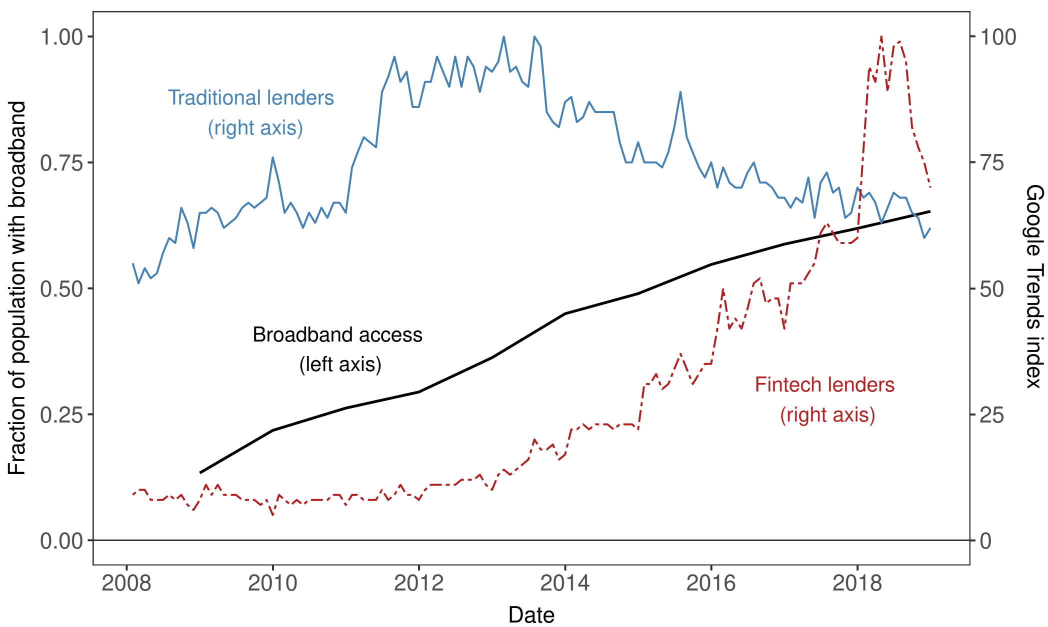
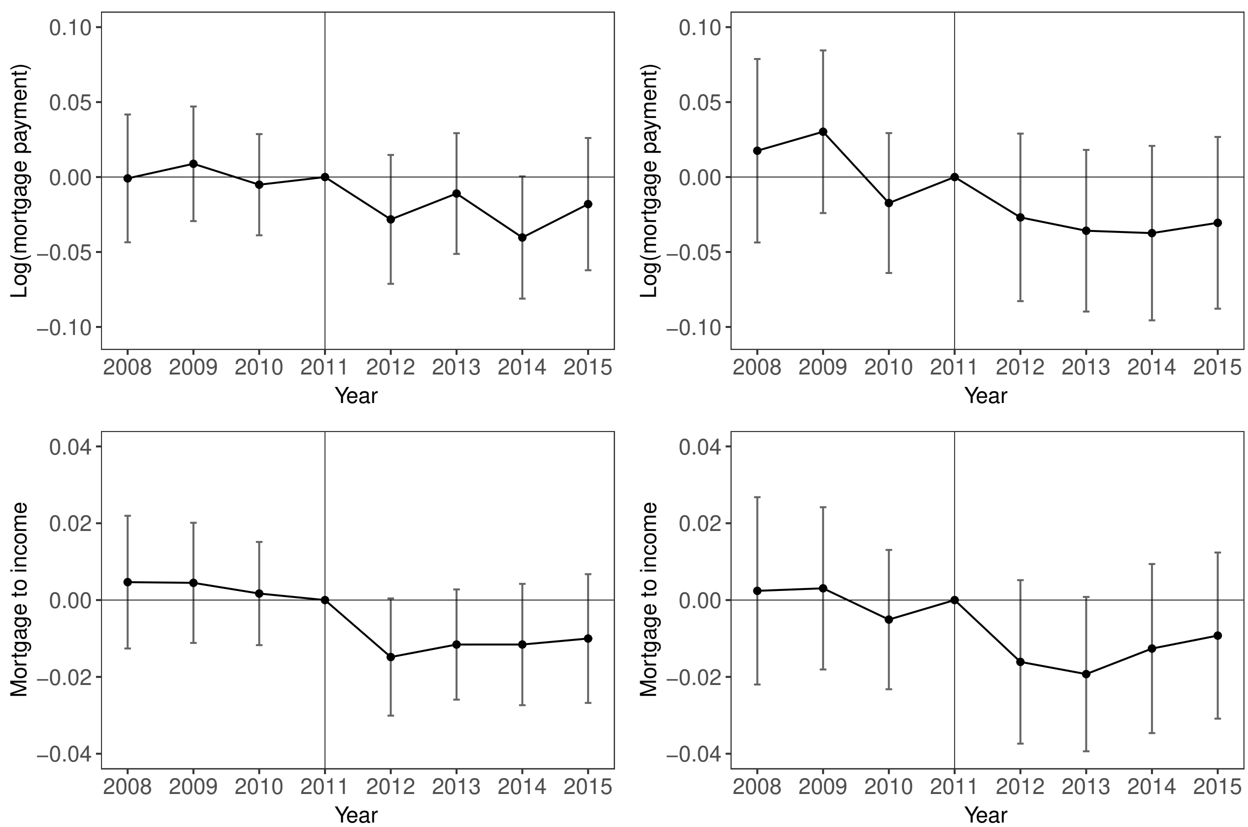


Figure 8: Online Search Trends for Refinancing

Note: This figure plots the evolution of online search trends for traditional and fintech mortgage lenders. Google Trends search data for the top 10 traditional lenders and top 10 fintech lenders by origination volume are plotted each month from 2008 to 2018. The search indices are normalized relative to a maximum of 100 during the study period. Fintech lender classification follows Buchak, Matvos, Piskorski and Seru (2018) and Fuster, Plosser, Schnabl and Vickery (2019). National broadband subscription data are computed using county level annual subscription estimates and housing unit counts. Broadband is defined as wireline connections with a minimum download speed of 10 Mbps.
Source: Google, FCC Form 477.



(a) All ineligibles (b) Low-income ineligibles

Figure 9: Event Study Estimates for Mortgage Costs

Note: This figure plots dynamic triple difference estimates (β_t) and 95 percent confidence intervals for log mortgage payment (top row) and mortgage to income ratio (bottom row). Panel (a) includes all ineligibles as the control group, while panel (b) focuses on low-income ineligibles as the control group. The estimating equation is:

$$
\begin{aligned}
m_{i,p,t} =& \alpha + \sum_t \beta_t(Eligible_{i,p,t} \times Comcast_p \times Year_t) + Z'_{i,p,t}\Phi + \rho_1(\lambda_t \times \gamma_p) + \rho_2(Eligible_{i,p,t} \times \lambda_t) \\
&+ \rho_3(Eligible_{i,p,t} \times \gamma_p) + \epsilon_{i,p,t}, \quad t \in \{2008, 2009, 2010, 2011, 2012, 2013, 2014, 2015\}.
\end{aligned}
$$

The sample spans the period between 2008 and 2015. The interaction term in the final pre-treatment period (2011) is omitted. Robust standard errors are clustered at the PUMA level.
Source: ACS IPUMS microdata.

Table 1

Internet Essentials and Home Internet Use

This table provides summary statistics on demographic characteristics of Internet Essentials subscribers and information on internet usage. The data are collected from anonymous surveys administered by the Comcast Technology Research & Development Fund between 2012 and 2014. (Comcast Corporation, 2016; Horrigan, 2014). All estimates are based on survey respondents and may not necessarily represent the head of household.

	Estimate
Subscriber household characteristics	
Average age	39
Average household size	4
Female (%)	74
Married (%)	46
High school diploma or less (%)	51
Income less than $40,000 (%)	78
Race/ethnicity	
White (%)	44
Hispanic (%)	43
Black or African-American (%)	33
Demand factors and usage	
Children's schoolwork (%)	98
Finding general information (%)	92
E-mail (%)	80
Social networking (%)	71
Paying bills (%)	63
Access to banks and financial institutions (%)	65
Access to government services (%)	52
Access to employment/job search (%)	49

Table 2

Urban Metropolitan Statistical Areas by Comcast Coverage

This table lists the top 15 Comcast and no Comcast MSAs by population served. I classify census tracts with more than 50 percent coverage between 2011 and 2014 as Comcast and less than 50 percent coverage as no Comcast. For each MSA, I tally the number of Comcast and no Comcast census tracts and aggregate their respective populations using 2010 Census data. The resulting MSAs are then ranked by population size.

		Census tracts	2010 population (millions)
Comcast			
1	Chicago–Naperville–Joliet, IL	184	1.935
2	Minneapolis–St. Paul-Bloomington, MN-WI	237	1.446
3	San Jose–Sunnyvale–Santa Clara, CA	113	1.340
4	Oakland-Fremont–Hayward, CA	231	1.312
5	Sacramento–Arden-Arcade–Roseville, CA	111	1.193
6	Miami–Miami Beach–Kendall, FL	91	1.182
7	Houston–Sugar Land–Baytown, TX	94	0.994
8	Philadelphia, PA	55	0.941
9	Seattle–Bellevue–Everett, WA	166	0.927
10	Pittsburgh, PA	227	0.918
11	Salt Lake City, UT	82	0.850
12	San Francisco–San Mateo–Redwood City, CA	129	0.730
13	Portland–Vancouver–Beaverton, OR–WA	93	0.678
14	Washington–Arlington–Alexandria, DC–VA–MD–WV	100	0.658
15	Detroit–Livonia–Dearborn, MI	165	0.653
No Comcast			
1	Los Angeles–Long Beach–Glendale, CA	1,233	9.200
2	New York–White Plains–Wayne, NY–NJ	939	4.154
3	Santa Ana–Anaheim–Irvine, CA	144	3.007
4	San Diego–Carlsbad–San Marcos, CA	216	2.926
5	Phoenix–Mesa–Scottsdale, AZ	178	2.041
6	Dallas–Plano–Irving, TX	160	1.976
7	Tampa–St. Petersburg–Clearwater, FL	144	1.556
8	Fort Worth–Arlington, TX	87	1.507
9	Riverside–San Bernardino–Ontario, CA	83	1.371
10	Las Vegas–Paradise, NV	61	1.170
11	San Antonio, TX	94	1.127
12	Columbus, OH	139	0.980
13	Cleveland–Elyria–Mentor, OH	143	0.933
14	Austin–Round Rock, TX	39	0.875
15	Cincinnati–Middletown, OH–KY–IN	127	0.731

Table 3

Descriptive Statistics

This table provides averages and standard deviations of demographic indicators in urban Comcast and no Comcast census tracts. Population, percent living in urban areas, median age, and average household size are obtained from the 2010 Decennial Census. All other demographic variables are calculated using 2007-2011 ACS 5-year estimates. Cost-burdened homeownership captures the fraction of homeowners paying 30 percent or more of income on housing-related payments, as defined by the U.S. Department of Housing and Urban Development (HUD). Bank branch access is measured as the number of full-service bank branches located within 2 miles of a census tract's population centroid as of 2010 using data from the FDIC. Data on broadband connections are obtained from the FCC's Form 477 as of December 2011. Broadband is defined as fixed internet connections with minimum download speeds of 4 Mbps. Means and standard deviations are weighted by each census tract's 2010 population. Statistics for variables other than population, median age, average household size, and number of bank branches are reported in percent. Column 5 reports t-statistics from the Welch two sample test of difference in means.

	Comcast ($N = 2,430$)		**No Comcast** ($N = 2,826$)		
	Mean (1)	SD (2)	Mean (3)	SD (4)	Diff. (5)
Population (2010)	8845.55	7372.68	11487.21	9674.52	11.21
Annual income under $35,000	29.82	12.73	30.03	12.01	0.61
Annual income $35,000 - $50,000	13.42	4.28	13.83	4.04	3.52
Living in urban areas (2010)	98.80	6.49	97.44	10.33	-5.78
Median age (2010)	36.61	5.15	36.68	5.89	0.42
Average household size (2010)	2.70	0.49	2.82	0.61	7.66
Owner-occupancy					
Annual income under $35,000	44.70	20.16	44.08	19.08	-1.13
Annual income $35,000 - $50,000	56.86	20.90	55.18	19.93	-2.98
With school-aged child	30.65	11.06	30.42	11.24	-0.76
Cost-burdened homeowners	42.41	11.56	43.56	11.81	3.55
Employment rate	90.44	4.62	90.98	3.71	4.59
High school diploma or higher	89.91	9.33	89.31	9.80	-2.26
Number of bank branches	18.71	24.37	11.72	11.19	-13.01
Broadband connections	47.33	15.81	36.90	18.90	-21.77

Table 4

Mortgage Characteristics by Comcast Coverage

This table provides average levels of key variables relating to home ownership for urban Comcast and no Comcast census tracts. *'04-'08 purchase* refers to statistics for home purchase mortgages originated between 2004 and 2008, while *'08-'11 refinance* reports the same averages for refinance mortgages originated between 2008 and 2011. All households refer to the universe of purchase and refinance originations for the respective periods. Eligible households have income below 185 percent of the FPL for a three-person family, and ineligible households have income between 185 percent of the FPL for five- and six-person families. All variables, with the exception of interest rates, debt-to-income, combined loan-to-value, and credit scores, are calculated using the universe of HMDA entries for conventional, one- to four-family, owner-occupied fixed rate mortgages. The remaining variables are computed using a matched data set of HMDA and GSE loan performance files, and comprise a subset of originated loans that were sold to Fannie Mae and Freddie Mac. ***, **, and * represent statistical significance of the Welch two sample t-test between means of each group across Comcast and No Comcast census tracts, at the 1%, 5%, and 10% level.

	Comcast ($N = 2,430$)			**No Comcast** ($N = 2,826$)		
	All	Eligible	Ineligible	All	Eligible	Ineligible
	(1)	(2)	(3)	(4)	(5)	(6)
HH income ($ thousands)						
'04-'08 purchase	98.75	24.00	45.71	113.41***	23.90	45.65
'08-'11 refinance	99.94	24.77	50.21	104.21***	24.81	50.21
Loan count						
'04-'08 purchase	646.16	30.15	49.34	661.30	38.49***	51.84***
'08-'11 refinance	389.01	20.09	21.51	324.44***	21.55***	21.17
Loan amount ($ thousands)						
'04-'08 purchase	233.50	114.08	135.74	291.05***	117.84**	139.00***
'08-'11 refinance	203.13	122.83	148.46	245.20***	136.01***	166.76***
Interest rate (percent)						
'04-'08 purchase	6.06	6.18	6.09	6.06	6.18	6.09
'08-'11 refinance	4.98	4.88	4.89	4.98	4.84***	4.88
Debt-to-income						
'04-'08 purchase	36.49	36.46	37.54	37.37***	36.44	37.50
'08-'11 refinance	31.81	31.92	32.47	33.46***	33.03***	33.00**
Combined loan-to-value						
'04-'08 purchase	80.32	77.37	80.68	78.19***	76.65	77.71***
'08-'11 refinance	67.05	58.97	63.60	63.76***	57.67**	61.93***
Credit score						
'04-'08 purchase	734.61	726.86	732.75	735.59**	726.63	733.93
'08-'11 refinance	753.31	756.39	756.67	752.94	756.80	757.57
Male (percent)						
'04-'08 purchase	59.29	45.46	53.26	60.09***	46.52**	54.39***
'08-'11 refinance	57.17	40.42	50.54	58.50***	43.21***	53.52***
Black (percent)						
'04-'08 purchase	19.05	20.10	20.89	14.87***	15.41***	15.53***
'08-'11 refinance	18.63	18.93	18.67	14.82***	14.56***	14.40***
Hispanic (percent)						
'04-'08 purchase	12.88	14.45	13.23	20.27***	20.39***	18.60***
'08-'11 refinance	9.61	11.53	11.00	17.12***	19.94***	18.87***

Table 5

Broadband Access and Refinancing Activity

This table reports the effect of Internet Essentials on refinancing outcomes. I estimate the following triple differences regression at the eligibility group level (columns 1 to 3) and loan level (column 4):

$$\begin{aligned} y_{i,c,t} =& \alpha + \beta(Eligible_{i,c,t} \times Comcast_c \times Post_t) + X'_{i,c,t}\Phi + \rho_1(\lambda_t \times \gamma_c) + \rho_2(Eligible_{i,c,t} \times \lambda_t) \\ &+ \rho_3(Eligible_{i,c,t} \times \gamma_c) + \epsilon_{i,c,t}. \end{aligned}$$

Dependent variables in columns 1 and 2 are the annual number of refinance mortgage originations and applications for each eligibility group, respectively. In column 3, denial rates are measured as the ratio of refinance applications denied by financial institutions to total applications. The dependent variable in column 4 is the interest rate for an originated refinance loan. The sample consists of all loan applications from 2008 to 2015 in urban central metro counties. $Eligible_{i,c,t}$ is an indicator for whether a refinance mortgage is associated with a household that qualifies for Internet Essentials based on annual income. $Comcast_c$ is an indicator for Comcast availability in census tract c and $Post_t$ is an indicator for post-Internet Essentials launch in 2012. Columns 1 and 2 report PPML results and columns 3 and 4 report OLS results. Group means are reported as of 2011, the last pre-treatment year. I include average income and loan amount as eligibility group controls, and income, loan amount, race, sex, number of applicants, combined LTV, DTI, credit score, and maturity as loan characteristics controls. All specifications incorporate eligibility-year, eligibility-census tract, and census tract-year fixed effects. Robust standard errors reported in parentheses are clustered by Public Use Microdata Area (PUMA). ***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

Dependent variable	Number of originations (1)	Number of applications (2)	Denial rate (3)	Interest rate (4)
$Eligible_{i,c,t} \times Comcast_c \times Post_t$	0.061**	0.062***	0.036	0.003
	(0.024)	(0.019)	(0.045)	(0.014)
Mean of dependent variable				
Eligible	6.48	14.02	40.86	4.35
Ineligible	6.09	10.96	30.95	4.28
Controls				
Eligibility group	✓	✓	✓	
Loan characteristics				✓
Fixed effects	✓	✓	✓	✓
Observations	81,782	82,768	82,768	115,662
Adjusted R^2	0.64	0.72	0.22	0.86

Table 6

Broadband Access and Mortgage Costs

This table reports the effect of Internet Essentials on mortgage costs. I estimate the following triple differences regression at the household level:

$$
\begin{aligned}
m_{i,p,t} =& \alpha + \beta(Eligible_{i,p,t} \times Comcast_p \times Post_t) + Z'_{i,p,t}\Phi + \rho_1(\lambda_t \times \gamma_p) + \rho_2(Eligible_{i,p,t} \times \lambda_t) \\
&+ \rho_3(Eligible_{i,p,t} \times \gamma_p) + \epsilon_{i,p,t}.
\end{aligned}
$$

Dependent variables $m_{i,p,t}$ are the natural logarithm of monthly mortgage payments (column 1) and the mortgage to income ratio (column 2). The sample consists of all ACS respondents from 2008 to 2015. I restrict the sample to households that have a mortgage and lived in the current home for at least three years. $Eligible_{i,p,t}$ is an indicator for Internet Essentials eligibility. $Comcast_p$ is an indicator for Comcast access (over 90 percent coverage is treated, less than 10 percent coverage is control). $Post_t$ is an indicator for post-Internet Essentials launch in 2012. Panel A employs the full control group of ineligibles. Panel B only uses low-income ineligibles as the control group. All specifications report OLS results and group means ($ thousands and percent) are reported as of 2011, the last pre-treatment year. Household controls include age, age-squared, sex, marriage status, number of children, employment status, value of house (log), income (log), years lived in home, indicator for taxes reported in mortgage payments, poverty status, and the Hauser and Warren Socioeconomic Index. All specifications incorporate group-year, group-PUMA, and PUMA-year fixed effects. Robust standard errors reported in parentheses are clustered by PUMA. ***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

Dependent variable	Log(mortgage payment)	Mortgage to income
	(1)	(2)
A. All ineligible control group		
$Eligible_{i,p,t} \times Comcast_p \times Post_t$	−0.025**	−0.015***
	(0.011)	(0.004)
Mean of dependent variable		
Eligible	0.82	36.98
Ineligible	0.83	28.29
Household controls	✓	✓
Fixed effects	✓	✓
Observations	385,122	385,122
Adjusted R^2	0.51	0.57
B. Low-income ineligible control group		
$Eligible_{i,p,t} \times Comcast_p \times Post_t$	−0.038**	−0.014***
	(0.015)	(0.005)
Mean of dependent variable		
Eligible	0.82	36.98
Ineligible	0.66	37.99
Household controls	✓	✓
Fixed effects	✓	✓
Observations	182,900	182,900
Adjusted R^2	0.49	0.52

Table 7

Fintech Mortgages and Bank Branch Access

This table examines fintech substitution and the heterogeneous effects of Internet Essentials based on bank branch access. I estimate the following triple differences regression:

$$\begin{aligned} y_{i,c,t} =& \alpha + \beta(Eligible_{i,c,t} \times Comcast_c \times Post_t) + X'_{i,c,t}\Phi + \rho_1(\lambda_t \times \gamma_c) + \rho_2(Eligible_{i,c,t} \times \lambda_t) \\ &+ \rho_3(Eligible_{i,c,t} \times \gamma_c) + \epsilon_{i,c,t}. \end{aligned}$$

Dependent variables $y_{i,c,t}$ are the fraction of refinances mortgages originated by fintech lenders (column 1) and the number of originations (columns 2 to 4). The sample consists of all originated mortgages from 2008 to 2015 in urban central metro counties. $Eligible_{i,c,t}$ is an indicator for whether a refinance mortgage is associated with a household that qualifies for Internet Essentials based on annual income. $Comcast_c$ is an indicator for Comcast availability and $Post_t$ is an indicator for post-Internet Essentials launch in 2012. Bank branch access is defined as the number of full-service branch locations within a 1-mile radius of a census tract's population center. I divide census tracts into terciles based on the number of branches (low, mid, and high). Group means (percent and loan count) are reported as of 2011, the last pre-treatment year. Column 1 reports OLS regression estimates and columns 2 through 3 report PPML regression estimates. All specifications include controls for average income and loan amount as well as group-year, group-census tract, and census tract-year fixed effects. Robust standard errors reported in parentheses are clustered by Public Use Microdata Area (PUMA). ***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

		Originations		
Dependent variable	% Fintech	Low	Mid	High
	(1)	(2)	(3)	(4)
$Eligible_{i,c,t} \times Comcast_c \times Post_t$	-0.010	0.089***	0.0451	0.026
	(0.009)	(0.027)	(0.031)	(0.047)
Number of bank branches $<$ 1 mi		0.55	3.89	10.05
Mean of dependent variable				
Eligible	4.30	6.52	7.03	5.10
Ineligible	7.16	6.14	6.63	4.78
Eligibility group controls	✓	✓	✓	✓
Fixed effects	✓	✓	✓	✓
Observations	72,578	33,230	33,726	14,826
Adjusted R^2	0.17	0.65	0.66	0.53

Table 8

Heterogeneous Effects by Educational Attainment

This table reports heterogeneous effects of Internet Essentials driven by income and educational attainment. Dependent variables are log annual household income (column 1), number of refinance originations by group (columns 2, 3, and 4), and log monthly mortgage payments (columns 5, 6, 7, and 8). $Eligible_{i,c,t}$ ($Eligible_{i,p,t}$) indicates Internet Essentials eligibility. $Comcast_c$ and $Comcast_p$ are binary indicators for Comcast availability in census tract c and PUMA p. $Post_t$ is an indicator for post-Internet Essentials launch in 2012. In columns 2, 3, and 4, I subset census tracts by educational attainment using the fraction of the population with at least a high school diploma. Low and high census tracts refer to the bottom and top terciles, respectively. In columns 5, 6, 7, and 8, I compare outcomes based on the head of households' educational attainment: low refers to high school diploma or less and high refers to at least some college education. Columns 5 and 6 incorporate all ineligibles as the control group and columns 7 and 8 only use low-income ineligibles as the control group. Group means of dependent variables ($ thousands and loan counts) are reported as of 2011, the last pre-treatment year. All specifications include controls for average income and loan amount (columns 2, 3, and 4) or household characteristics (columns 1, 5, 6, 7, 8). Group-year, group-census tract/PUMA, and census tract/PUMA-year fixed effects are used depending on the level of geography. Robust standard errors reported in parentheses are clustered by PUMA. ***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

Dependent variable		Originations			Log(mortgage payment) All ineligibles		Log(mortgage payment) Low-income ineligibles	
	Log(income)	Low	Mid	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Eligible_{i,p,t} \times Comcast_p \times Post_t$	0.004				-0.054***	0.006	-0.083***	0.012
	(0.012)				(0.015)	(0.013)	(0.020)	(0.020)
$Eligible_{i,c,t} \times Comcast_c \times Post_t$		0.123***	0.046	0.056**				
		(0.048)	(0.030)	(0.027)				
High school diploma or higher		0.72	0.90	0.97				
Mean of dependent variable								
Eligible	29.91	5.20	6.81	6.99	0.78	0.86	0.78	0.86
Ineligible	24.35	3.51	6.23	7.82	0.74	0.91	0.61	0.73
Controls								
Eligibility group		✓	✓	✓				
Household	✓				✓	✓	✓	✓
Fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Observations	102,868	19,958	34,550	27,274	184,172	200,739	98,774	83,484
Adjusted R^2	0.61	0.56	0.65	0.66	0.51	0.50	0.50	0.49

Table 9

Robustness Measures and Sensitivity Analyses

This table provides sensitivity analyses for the effect of Internet Essentials on refinancing. Dependent variables are prepayment indicator (column 1), number of refinance originations by group (columns 2, 3, 4, and 5), and log monthly rent payments (column 6). The sample is restricted to urban metropolitan census tracts except in column 6. $Eligible_{i,c,t}$ ($Eligible_{i,p,t}$) is an indicator for whether a loan or eligibility group (household) qualifies for Internet Essentials. $Comcast_c$, $AT\&T_c$, and $Charter_c$ indicators for Comcast, AT&T, and Charter availability in census tract c, respectively. $Comcast_p$ is an indicator for Comcast availability in PUMA p. $Post_t$ is an indicator for post-Internet Essentials launch in 2012. Column 3 replaces the income thresholds for treated (185% FPL for five- and six-person family) and control (185% FPL for seven- and eight-person family) groups. Group means of dependent variables (percent, loan counts, and $ thousands) are reported as of 2011, the last pre-treatment year. I control for loan characteristics at origination (column 1), average income and loan amount (columns 2, 3, 4, and 5), and household characteristics (column 6). Group-year, group-census tract/PUMA, and census tract/PUMA-year fixed effects are used depending on the level of geography. Robust standard errors reported in parentheses are clustered by PUMA. ***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

		Originations				
Dependent variable	Prepayment	Baseline	Placebo cutoff	Placebo ISP		Log(rent payment)
	(1)	(2)	(3)	(4)	(5)	(6)
$Eligible_{i,c,t} \times Comcast_c \times Post_t$	0.028**	0.061**	0.004			
	(0.013)	(0.024)	(0.011)			
$Eligible_{i,c,t} \times AT\&T_c \times Post_t$				-0.005		
				(0.022)		
$Eligible_{i,c,t} \times Charter_c \times Post_t$					-0.010	
					(0.045)	
$Eligible_{i,p,t} \times Comcast_p \times Post_t$						0.002
						(0.013)
Mean of dependent variable						
Eligible	41.99	6.48	6.46	6.48	6.48	0.67
Ineligible	57.93	6.09	6.79	6.09	6.09	0.70
Controls						
Loan characteristics	✓					
Eligibility group		✓	✓	✓	✓	
Household						✓
Fixed effects	✓	✓	✓	✓	✓	✓
Observations	214,264	81,782	76,972	81,782	81,782	290,044
Adjusted R^2	0.21	0.64	0.64	0.64	0.64	0.52

Table 10

Falsification Tests for Likelihood of Program Access

This table provides falsification tests for the effect of Internet Essentials. The dependent variable in all specifications is the number of refinance originations by eligibility group. The sample is restricted to urban metropolitan census tracts between 2008 and 2015. $Eligible_{i,c,t}$ is an indicator for whether group i qualifies for Internet Essentials, $Comcast_c$ is an indicator for Comcast availability in census tract c, and $Post_t$ is an indicator for post-Internet Essentials launch in 2012. Column 1 is the baseline specification that includes all census tracts. Columns 2 to 4 subset the census tracts into the bottom quartile (low), top quartile (high), and the 25th to 75th percentile (mid) by the fraction of households in owner-occupied dwellings with at least one child under the age of 18 as of 2011. Columns 5 to 7 subset census tracts by the fraction of cost-burdened homeowners (paying 30 percent or more of income on housing costs) as of 2011. Columns 8 to 10 subset census tracts by the fraction of low-income homeowners with a school-aged child that reported having a high-speed broadband connection. This variable is obtained from the 2013 ACS 1-year microdata and assignment is at the PUMA level. Means of sorting variables are reported in percent. Group means are reported as of 2011, the last pre-treatment year. All specifications include controls for household characteristics. Eligibility-year, eligibility-census tract, and census tract-year fixed effects are used depending on the level of geography. Robust standard errors reported in parentheses are clustered by PUMA. ***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

		School-aged children			Cost-burdened homeowners			Broadband subscription rate		
Dependent variable: Originations	Baseline	Low	Mid	High	Low	Mid	High	Low	Mid	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$Eligible_{i,c,t} \times Comcast_c \times Post_t$	0.061***	0.010	0.077***	0.076**	0.023	0.054	0.165***	0.055	0.038	0.086***
	(0.024)	(0.038)	(0.028)	(0.032)	(0.031)	(0.037)	(0.044)	(0.041)	(0.036)	(0.032)
Mean of sorting variable		19.64	30.82	44.55	30.10	45.10	61.07	74.36	85.40	94.05
Mean of dependent variable										
Eligible	6.48	5.42	6.65	7.08	6.71	6.79	5.57	5.56	7.02	5.98
Ineligible	6.09	4.68	6.38	6.84	6.84	6.26	4.62	5.36	6.47	5.89
Eligibility group controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	81,782	21,244	33,340	27,198	31,440	31,614	19,018	23,414	36,444	21,924
Adjusted R^2	0.64	0.59	0.64	0.67	0.65	0.65	0.59	0.61	0.66	0.63

Internet Appendix

"The Digital Divide and Refinancing Inequality"

October 2024

A Voluntary Prepayment and Refinance Probabilities

A.1 Data Construction

As a robustness test, I study the voluntary prepayment of first-time mortgages originated between 2004 and 2008. A key benefit of this exercise is that I can directly model the causal effect of Internet Essentials on households' probability of refinancing. Moreover, the GSE performance data provided by Fannie Mae and Freddie Mac include information on original interest rates, debt-to-income ratios (DTI), combined loan-to-value ratios (CLTV), and credit scores, which can be used as controls for known refinancing incentives and frictions. The only unobserved variable in the GSE data is household income, which is crucial to assign treatment status. I use a programmatic matching technique to match each GSE loan to its corresponding HMDA entry, which I detail below.

I first construct indicator variables for whether a 30-year fixed rate mortgage purchased by Fannie Mae or Freddie Mac has been voluntarily prepaid at any point between 2009 and 2011 (pre-Internet Essentials), between 2012 and 2015 (post-Internet Essentials), and as of each year from 2009 to 2015. The last set of dummy variables are used to study dynamic effects. Then, I programmatically merge the GSE filings to HMDA data using six exact match categories (year of origination, agency, owner occupancy, loan type, number of applicants, and loan amount) and a fuzzy match category (location). Matching the location is difficult because the GSE data only report each home's 3-digit zip code for privacy reasons. 3-digit zip codes encompass a much larger footprint than a census tract and do not exactly coincide with the Census geographies, resulting in a large number of duplicate matches. I break many-to-many matches and ties randomly. The resulting data set covers between 20 and 30 percent of all mortgages originated and sold to the two GSEs.[27] The matched data also provides the union of loan-level covariates (GSE) and demographic characteristics (HMDA). Lastly, I calculate a measure of each loan's remaining maturity at each period, which helps control for projected savings from a refinance.

[27] These match rates are low but reasonable given the inconsistencies in geographies and possible differences in rounding practices for income and loan amount. Moreover, GSE loan performance files do not include adjustable-rate mortgage loans, balloon loans, interest-only mortgages, mortgages with prepayment penalties, government-insured mortgage loans such as Federal Housing Authority loans, Home Affordable Refinance Program mortgage loans, Refi PlusTM mortgage loans, or nonstandard mortgage loans. The data also excludes loans that do not reflect current underwriting guidelines, such as loans with originating LTVs over 97% and mortgage loans subject to long-term standby commitments, those sold with lender recourse or subject to other third-party risk-sharing arrangements, or those acquired by Fannie Mae on a negotiated bulk basis.

A.2 Dynamic Treatment Effects

In the main robustness analysis, I show that mortgage prepayment probabilities increased by around 2.8 percent as a result of Internet Essentials (Table 9, column 1). One concern of using a higher income control group (roughly \$50,000 to \$100,000) is the increased likelihood of non-parallel trends, which may be driven by unobserved changes in group-specific outcomes that correlate with Comcast availability.

To address this issue, I study treatment effects over time in an event study setting. I estimate the following equation

$$\begin{aligned} prepay_{i,c,t} =& \alpha + \sum_t \beta_t (Eligible_{i,c,t} \times Comcast_c \times Year_t) + Y'_{i,c,t}\Phi + \rho_1(\lambda_t \times \gamma_c) \\ & + \rho_2(Eligible_{i,c,t} \times \lambda_t) + \rho_3(Eligible_{i,c,t} \times \gamma_c) + \epsilon_{i,c,t}, \end{aligned} \tag{A.1}$$

where $t \in \{2009, 2010, 2011, 2012, 2013, 2014, 2015\}$. Figure A.5 plots the regression results. I find no evidence of pre-trends in the years leading up to program rollout, indicating that differences in eligibility groups' refinancing behavior are not systematically related to Comcast availability. Notably, the treatment effect becomes positive and statistically significant in the later years (2014 and 2015) as take-up of Internet Essentials increases. These findings support my baseline results that use refinance originations and mortgage costs as dependent variables.

B Rural Broadband Access and Refinancing Inequality

B.1 Overview

Unlike most broadband initiatives that focus on building infrastructure, Internet Essentials provided instant and measurable gains in accessibility to a large subset of the U.S. population. Throughout the paper, I use program eligibility as an exogenous negative shock to refinancing transaction costs for low-income households without internet. The key constraint in this setting is affordability, because the vast majority of households in my sample have access to an ISP in the area.

Another important dimension of the digital divide is households' physical access to an ISP. As broadband infrastructure is costly to build and maintain, there exists a large gap in broadband availability between urban and rural areas irrespective of demand. In this section, I study an alternative quasi-experimental setting to corroborate my baseline finding that reducing transaction costs via the internet improves refinancing outcomes. Specifically, I analyze the refinance wave in the early months of the COVID-19 pandemic. The sudden interest rate cuts sparked a large refinance wave that was importantly muted among low-income and minority borrowers (Agarwal, Chomsisengphet, Kiefer, Kiefer and Medina, 2023). I argue that national stay-at-home orders due to COVID-19 led to a sharp increase in refinancing transaction costs; in-person mortgage services such as consultations, applications, appraisals, and closing were all severely limited during this period.

As physical channels shut down, households had to rely on online services to exercise the refinance option at historically low interest rates.[28] In this setting, treatment refers to whether a census tract can minimize the increase in transaction costs via a resilient broadband environment. I hypothesize that refinancing would have grown much faster in census tracts with better ex-ante broadband access prior to the pandemic, and test this directly using high-frequency data on prepayment speeds.

B.2 Empirical Strategy

B.2.1 Data and Sample Selection

Broadband Index. Following the prior literature, I measure broadband access as the number of ISPs that report offering any broadband service (min. 25 mbps) in a census tract. This data is obtained from the FCC's Form 477 as of October 2019 and also captures the quality (via infrastructure sharing and local market competition) of service provided. I then rank the rural census tracts in my sample and designate the top tercile "high access" and the bottom tercile "low access."

Prepayment Speeds. The main outcome variable of interest is prepayment speed, which is defined as 1 minus the ratio of realized mortgage balance in a given month to scheduled balance at the end of the previous month. Intuitively, high prepayment speeds can be interpreted as increased refinancing activity. I obtain monthly data on census tract-level prepayment speeds for 30-year, fixed-rate, single-family mortgages in good standing from Recursion, a data vendor that uses machine learning techniques to match more than 90 percent of GSE performance files to

[28] Online mortgage lenders such as Rocket Mortgage experienced significant growth during this period (Wall Street Journal, 2022), but many traditional brick-and-mortar lenders also offered end-to-end services online. In this exercise, I am agnostic about the differences between the two channels and consider the effect of internet on transaction costs more generally (e.g. ability to participate in virtual closings).

origination information in HMDA. Monthly prepayment speed is winsorized at the 1 percent level.

Mortgage and Demographic Covariates. The availability of loan-level information at origination allows me to directly control for known determinants of refinancing. These variables include the refinance incentive (interest rate at origination minus benchmark prevailing rate given homeowner characteristics), loan-to-value ratio, and the debt-to-income ratio. Recursion provides a weighted-average census tract index for each variable using the outstanding loan amount of current mortgages as weights. I also control for monthly house price changes using data from the FHFA and, importantly, monthly estimated unemployment rates throughout 2020 (DEEP-MAPS, 2020). These covariates capture census tract-level exogenous changes in refinance propensities throughout the pandemic.

Final Sample. Motivated by the significant struggles of remote areas to get online during the pandemic, I restrict my focus to rural census tracts. While these areas exhibit lower broadband access on average, there is still significant variation due to various factors such as state-level broadband initiatives and geography (e.g., terrain, proximity to key infrastructure). Importantly, rural broadband access need not be driven by affordability; in fact, a large number of high-income rural communities were also affected as they transitioned to stay-at-home orders with poor internet. The sample period spans January 2019 to December 2020, resulting in 24 monthly observations for each rural census tract.

Table A.2 provides summary statistics. In columns 1 and 2, I calculate the average of all variables for low (bottom tercile by provider count) and high (top tercile by provider count) census tracts leading up to March 2020. Prior to the pandemic, high broadband tracts tend to have more favorable economic characteristics (e.g. outstanding loan amount, home price appreciation, income, credit score, educational attainment) relative to their counterparts. This implies that ISP location choice is likely to be endogenous. Interestingly, disparities in broadband access does not seem to be driven by race (63.5 percent white in high broadband census tracts vs. 73.3 percent in low broadband census tracts). In columns 3 and 4, I use propensity score matching to make the two groups more comparable.

B.2.2 Regression Design

I estimate the following difference-in-difference regression:

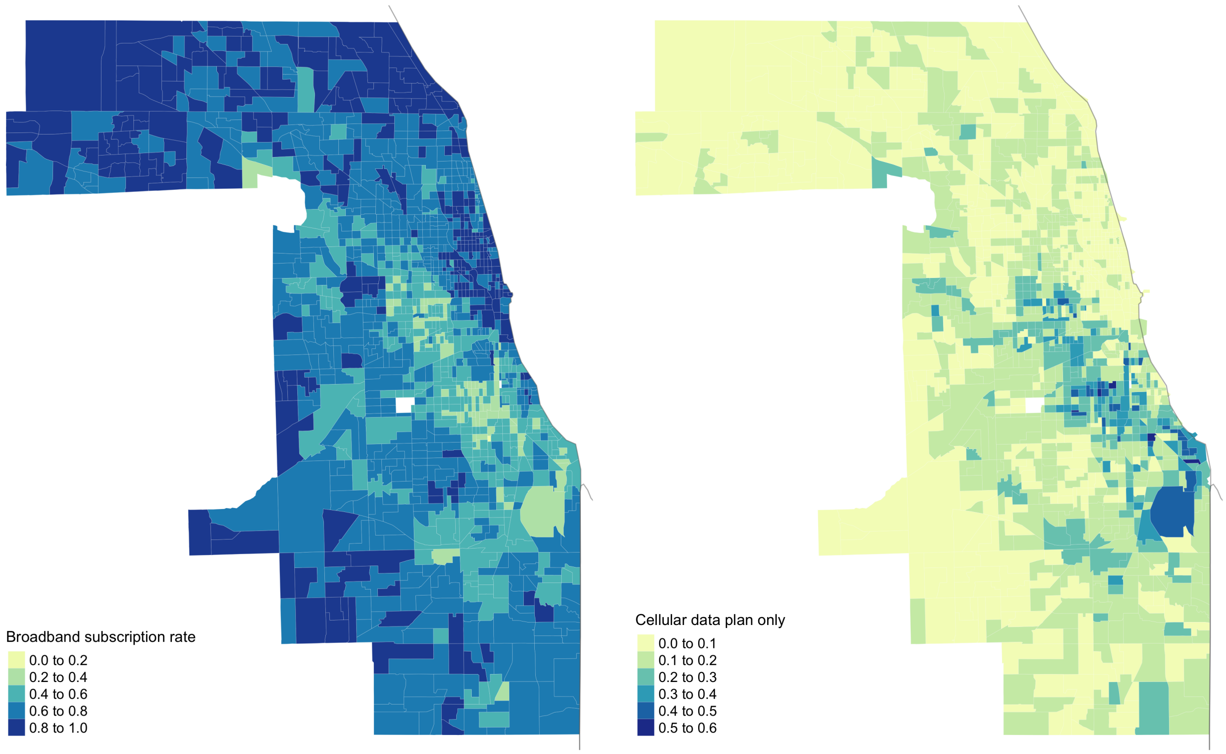
$$pspeed_{i,c,t} = \beta_0 + \beta_1 Post_t + \beta_2 Treat_i + \beta_3 (Post \times Treat)_{i,t} + X'_{i,t-1}\delta + \epsilon_{i,c,t}, \qquad \text{(B.1)}$$

where $pspeed_{i,c,t}$ is the 1-month voluntary prepayment speed, $Post_t$ is an indicator for after April 2020, and $Treat_i$ is an indicator for whether census tract i's internet access index is in the top tercile of national distribution as of October 2019. $X'_{i,t-1}$ is a vector of 1-month lagged mortgage-related and economic variables for census tract i. β_2 captures the treatment effect of being a high broadband census tract after March 2020. Standard errors are clustered at the county level to reflect the common implementation of stay-at-home orders.

B.3 Results

Table A.3 presents the regression results from equation B.1. Columns 1 and 2 show that prepayment speeds increased by 1.55 to 1.71 percentage points depending on whether control variables are added, which translates to between 10 and 11 percent (base of 15.59 percent). In column 3, I find that the results still hold after using propensity score matching to subset the census tracts. A 1.23 percentage point increase off a base of 12.81 percent implies a 10 percent increase in prepayment speeds. These effects are economically large but should be interpreted with some caution; while I directly control for various refinance drivers and unemployment outcomes during this period, there still remains a possibility of an unobserved factor that is correlated with both broadband access and refinancing outcomes. To sum, I use natural experiments from two recent crises to show suggestive evidence that lowering transaction costs via improved internet access can help households refinance optimally.

C Supplementary Figures and Tables



(a) Affordability (b) Cellular Substitution

Figure A.1: Local Geography of Broadband Adoption (Cook County, IL)

Note: This figure plots the geographic distribution of broadband and cellular access in Cook County, IL. Each unit of observation is a census tract. Panel (a) shows the fraction of households with a broadband subscription at home, and panel (b) reports the fraction of households without broadband that use a cellular data plan only. Source: 2019 ACS 5-year estimates.

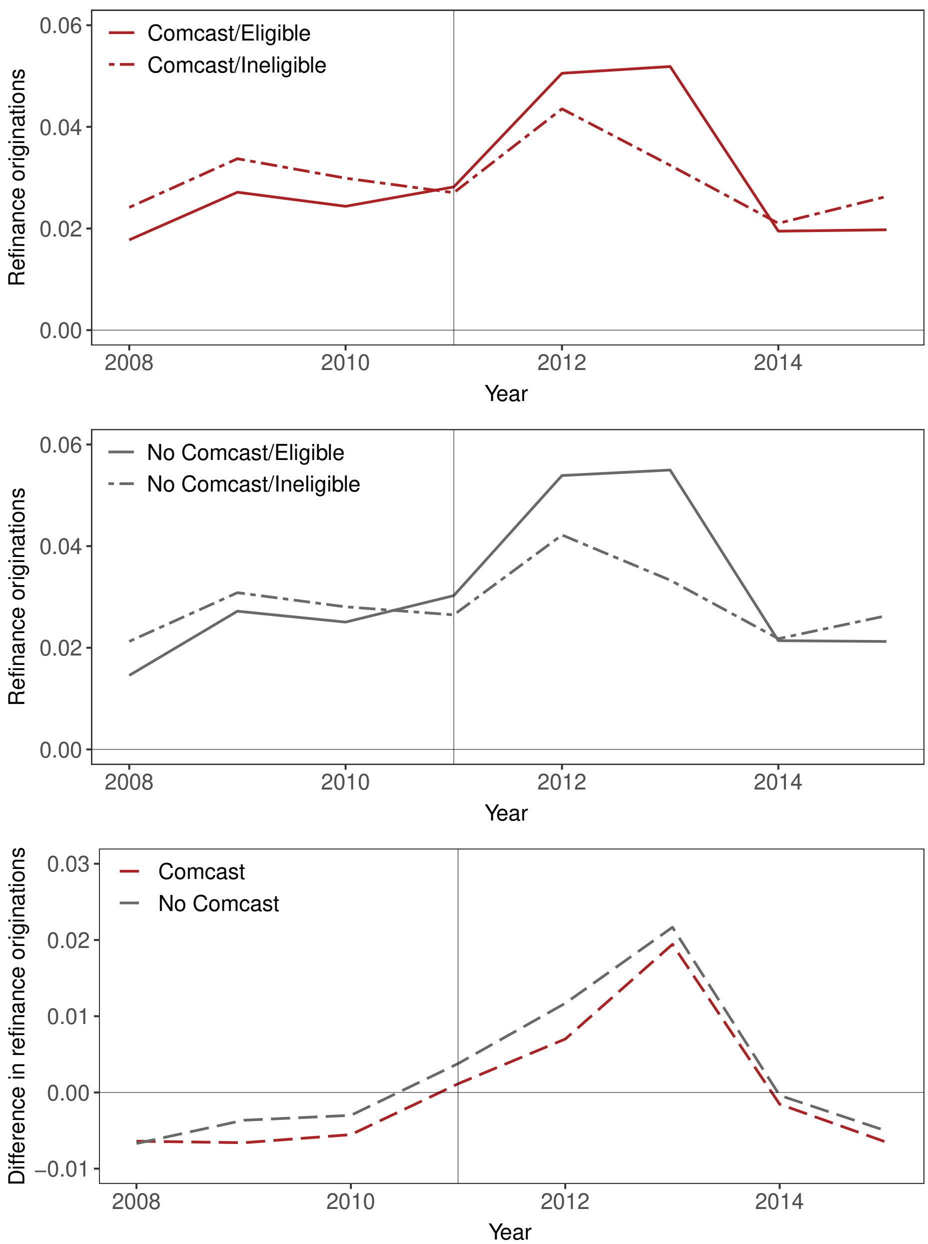


Figure A.2: Unconditional Trends in Refinancing Activity

Note: This figure illustrates the triple differences empirical design by plotting the unconditional refinancing trends between eligibles and ineligibles across Comcast and no Comcast census tracts. Refinance originations are measured as the number of loans originated by eligibility group divided by the imputed stock of owner-occupied households with a mortgage, and is residualized with respect to proxies for house prices (value of newly originated mortgages) and economic conditions (income). The bottom panel plots the difference in the two series by Comcast and no Comcast status. The sample covers large central metro census tracts.
Source: HMDA, 2011 ACS 5-year estimates, 2010 Decennial Census.

Figure A.3: Internet Essentials Online Learning Center

Source: Comcast Corporation (2015). Archived website accessed using the Wayback Machine.

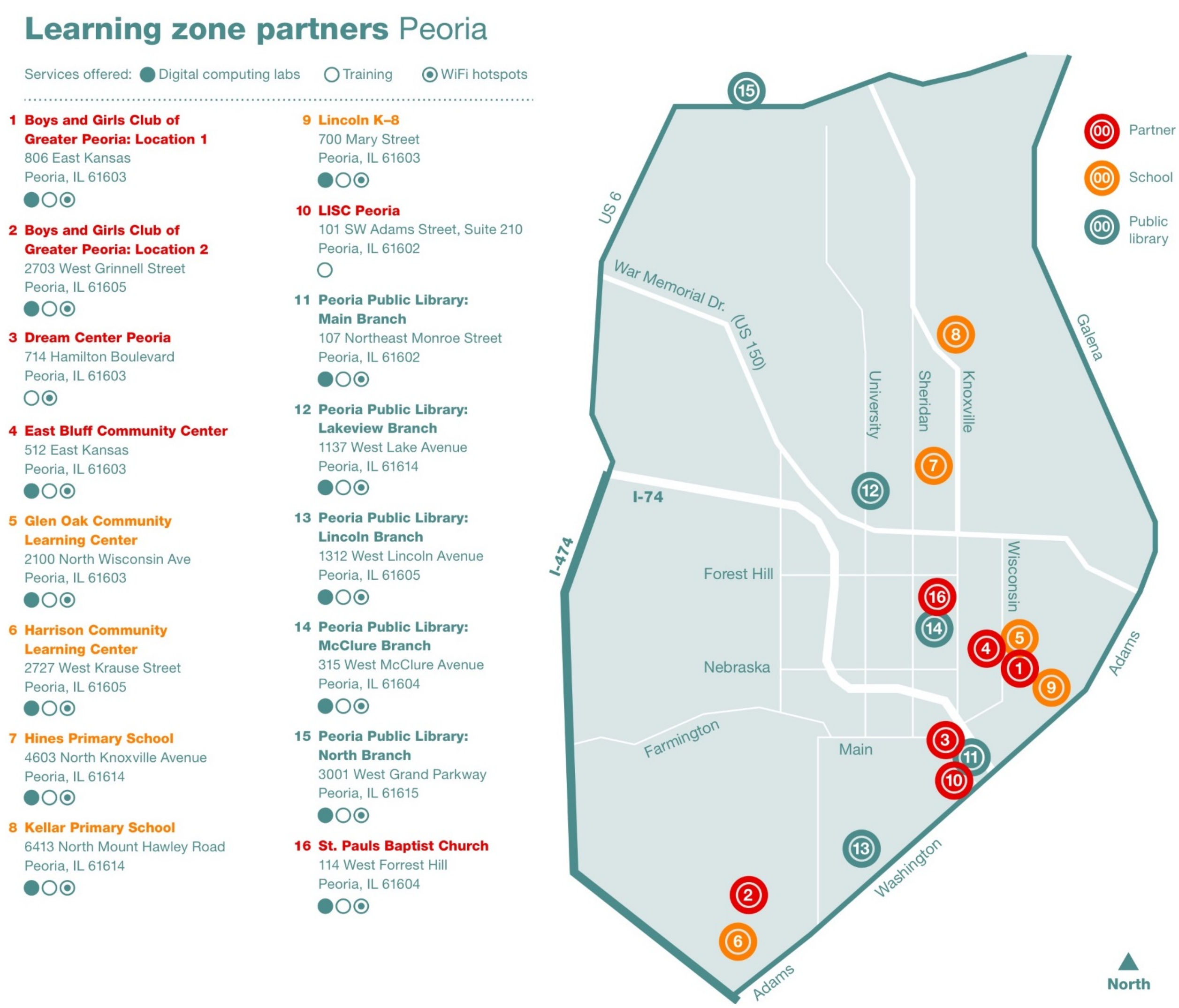


Figure A.4: Internet Essentials Learning Zones (Peoria, IL)

Source: Comcast Corporation (2014)

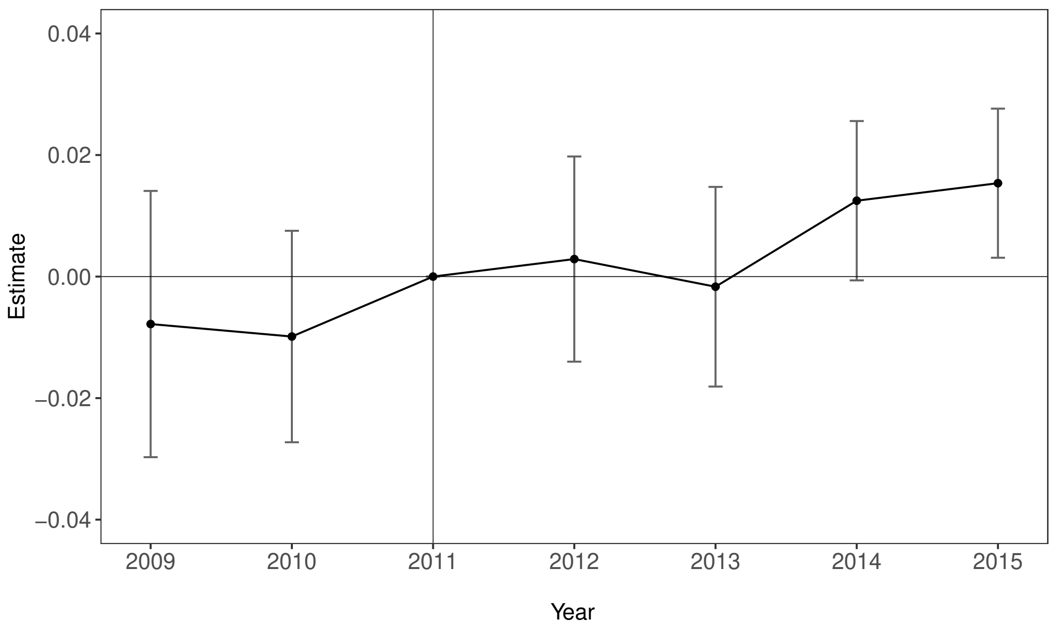


Figure A.5: Event Study Estimates for Mortgage Prepayment

Note: This figure plots dynamic triple difference estimates (β_t) and 95 percent confidence intervals for mortgage prepayment. The estimating equation is:

$$\begin{aligned} prepay_{i,c,t} =& \alpha + \sum_t \beta_t (Eligible_{i,c,t} \times Comcast_c \times Year_t) + Y'_{i,c,t}\Phi + \rho_1(\lambda_t \times \gamma_c) + \rho_2(Eligible_{i,c,t} \times \lambda_t) \\ &+ \rho_3(Eligible_{i,c,t} \times \gamma_c) + \epsilon_{i,c,t}, \quad t \in \{2009, 2010, 2011, 2012, 2013, 2014, 2015\}. \end{aligned}$$

The interaction term in the final pre-treatment period (2011) is omitted. Robust standard errors are clustered at the PUMA level.
Source: HMDA, Fannie Mae, Freddie Mac.

Table A.1

Income Thresholds for Internet Essentials Eligibility

This table reports changes in annual income thresholds for Internet Essentials eligibility, which is in turn determined by household size and poverty status. I define households with annual income less than 185 percent of the FPL for a three-person household as eligible. For the ineligible group, I assign the minimum and maximum income as 185 percent of the FPL for a five-person and six-person household, respectively. All thresholds are shown in dollars (thousands).

	Eligible		Ineligible	
Year	Min	Max	Min	Max
2008	0	32.56	45.88	52.54
2009	0	33.87	47.71	54.63
2010	0	33.87	47.71	54.63
2011	0	34.28	48.42	55.48
2012	0	35.32	49.97	57.30
2013	0	36.13	51.01	58.44
2014	0	36.61	51.63	59.15
2015	0	37.17	52.56	60.26
Average	0	34.98	49.36	56.55

Table A.2

Alternative Setting: Descriptive Statistics

This table reports summary statistics for key variables on refinancing during the COVID-19 pandemic. Low (high) broadband census tracts are in the bottom (top) tercile of weighted ISP count as of October 2019. Columns 1 and 2 compare the full sample of low and high broadband tracts. Columns 3 and 4 use a propensity score matching method to standardize the sample census tracts based on observable characteristics. All data are monthly and span the pre-pandemic period from January 2019 to March 2020.

	Raw		Matched	
	Low Broadband (1)	High Broadband (2)	Low Broadband (3)	High Broadband (4)
1-month prepayment speed (pct.)	10.77	15.59	9.89	12.81
Total census tract loan amount ($ thousands)	2,471.48	3,835.85	1,682.02	2,448.71
Loan-to-value ratio (pct.)	87.59	86.27	88.35	88.40
Debt-to-income ratio (pct.)	33.52	34.08	32.77	32.61
Applicant credit score	736.12	741.24	734.41	735.63
Home price appreciation (pct.)	18.53	20.75	18.47	18.61
Refinance incentive (pct.)	0.83	0.78	0.82	0.81
Number of borrowers	1.46	1.47	1.48	1.47
Median tract income ($ thousands)	59.88	65.90	56.36	56.30
Population white (pct.)	73.26	63.51	83.45	83.54
Population working age (pct.)	59.94	61.84	58.56	58.54
Educational attainment (pct.)	85.93	87.81	87.94	87.88

Table A.3

Rural Broadband Access and Prepayment Speeds

This table reports the effect of broadband access on refinancing outcomes during the COVID-19 pandemic. I estimate the following difference-in-differences regression:

$$pspeed_{i,c,t} = \beta_0 + \beta_1 Post_t + \beta_2 Treat_i + \beta_3 (Post \times Treat)_{i,t} + X'_{i,t-1}\delta + \epsilon_{i,c,t}.$$

The dependent variable in all specifications is the 1-month prepayment speed for fixed-rate, 30-year, single-family home mortgages. Columns 1 and 2 study the full sample of rural census tracts. Column 3 uses propensity score matching to restrict the sample to comparable high and low broadband census tracts. Columns 2 and 3 include lagged covariates relating to refinancing demand (e.g. rate differential, house price appreciation, and unemployment rates). Robust t-statistics reported in parentheses are clustered by county. ***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

	All		Matched
	(1)	(2)	(3)
$(Treat \times Post)_{i,t}$	1.55***	1.71***	1.23***
	(4.34)	(4.74)	(2.59)
Obs.	116,400	116,400	63,894
Matched	N	N	Y
Controls	N	Y	Y
FE	Tract, Year-month	Tract, Year-month	Tract, Year-month