

The Digital Divide and Refinancing Inequality

Edward T. Kim*

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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 the gap in access to modern information and communications technology. Using granular spatial variation of a large-scale broadband subsidy program, I show that high-speed internet facilitates refinancing activity 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 for low-income households. The growth of refinancing is pronounced in underserved areas with low access to bank branches and among populations that are likely to have low financial and digital literacy.

*UCLA Anderson School of Management. Email: edward.kim.phd@anderson.ucla.edu. I am grateful to my advisors Andrea Eisfeldt (chair), Mark Garmaise, Barney Hartman-Glaser, and Antoinette Schoar for their invaluable guidance and support. For helpful comments and suggestions, I thank Neil Bhutta, Mikhail Chernov, John Driscoll, Stuart Gabriel, Arpit Gupta, Valentin Haddad, Lu Han, Bernard Herskovic, Matthias Kahl, Amir Kermani, Shohini Kundu, Lars Lochstoer, Konstantin Milbradt, Tyler Muir, Stavros Panageas, Gregor Schubert, James Vickery, Ivo Welch, Jinyuan Zhang, George Zuo, Eric Zwick, and seminar participants at UCLA Anderson. I also thank Katherine Allison for providing informative details regarding the Internet Essentials program. I acknowledge the generous financial support of the UCLA Ziman Center for Real Estate's Rosalinde and Arthur Gilbert Program in Real Estate, Finance and Urban Economics and the UCLA Fink Center for Finance. All errors are my own.

1 Introduction

Mortgage refinancing is an important mechanism for household wealth accumulation in the United States; however, many Americans do not refinance their mortgages optimally due to frictions such as high origination costs or limited financial sophistication (Campbell, 2006). This phenomenon is concentrated among low-income and minority households, implying a potential imbalance in the transmission of monetary policy during economic downturns that can exacerbate wealth inequality. In this paper, I study whether at-home access to modern information and communications technology can help mitigate refinancing frictions. Specifically, I demonstrate that access to broadband internet increases refinancing activity and reduces housing costs for low-income households.

High-speed internet can significantly lower the shadow costs associated with applying to refinance a mortgage. 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 et al., 2019). To the extent that online resources allow households to obtain information about the value of refinancing, the internet can also reduce the incidence of suboptimal refinancing driven by behavioral mistakes.

Despite the internet’s large role in streamlining the refinance process, it is inaccessible to millions of American households living without a wired broadband connection at home. The persistent gap in access to information technology, known as the “digital divide,” has become an important policy issue in recent decades due to its influence on household well-being (White House, 2022). In 2019, less than 70 percent of the population reported having a broadband subscription at home, with low-income households reporting significantly lower subscription rates (Figure 1). This trend is not entirely driven by imbalances in physical access to a broadband provider; of the low-income households living in urban areas with near-complete broadband coverage, only 65 percent subscribed to broadband during this period.

Studying the effects of broadband access on refinancing inequality is difficult for several reasons. First, the spatial distribution of broadband providers is correlated with subscriber characteristics such as employment and educational attainment. As these characteristics are also correlated with refinancing demand, estimates of refinancing outcomes that relate to heterogeneity in broadband availability will most likely be biased. Second, it is difficult to 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 in quantifying the effect of broadband access on refinancing, I analyze the Internet Essentials program by Comcast, one of the largest broadband providers in the United States. Introduced in 2012 to receive regulatory approval 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 fees related to activation and equipment (averaging more than \$100 upfront and up to \$10 per month, respectively) 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 associated with other broadband initiatives not only take time but also can increase local house prices, confounding the estimated impact of broadband access on refinancing (Knutson, 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 exhibits low refinancing behavior most prominently. Third, internet usage at broadband speeds would have been a binding constraint for households to access banking services during the study period. Lastly, the program coincides with the prolonged recovery period after the Great Recession when refinancing incentives and potential monetary savings were high throughout the income distribution.

This paper exploits geographic, temporal, and household-level variation in Internet Essentials eligibility to estimate the impact of broadband access on refinancing demand and mortgage costs. Specifically, I compare the outcomes of eligible and ineligible low-income households 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 the Internet Essentials program. 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 coverage rates at the census tract level to the universe of refinance applications and originations by income eligibility between 2008 and 2015. I also enhance my analysis using a matched panel data set of prepayment propensities for home purchase mortgages originated between 2004 and 2008, as well as American Community Survey (ACS) microdata on mortgage payment 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 effects along the intensive margin (lower interest rates). Using household-level survey data, I corroborate the findings of increased refinancing propensity with evidence of decreased mortgage payment burdens. 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 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. I estimate that the program generated up to \$100 million in additional refinance savings across Comcast area households and reduced refinancing inequality by up to 14 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 instead (the next two largest broadband providers by subscriber count) and find no effects of broadband access on refinancing outcomes. Third, the results disappear when I use households with incomes marginally above the eligibility threshold as the treated group, supporting the identifying assumption that the program only affected eligible low-income households. Fourth, treatment effects are concentrated in census tracts with a high likelihood of being affected by Internet Essentials.

Related Literature. This paper is related to the growing literature on the determinants of mortgage refinancing behavior. [Campbell \(2006\)](#) documents low levels of refinancing among low-income borrowers in the early 2000s. In more recent work, [Andersen et al. \(2020\)](#); [Agarwal et al. \(2013, 2016, 2020\)](#); [Defusco and Mondragon \(2020\)](#); [Gerardi et al. \(2020, 2021\)](#); [Goodstein \(2013\)](#); [Johnson et al. \(2018\)](#); [Keys et al. \(2016\)](#) all find evidence of suboptimal refinancing behavior driven by income and race, particularly during the aftermath of the Great Recession and the recent COVID-19

pandemic. Other works identify specific behavioral channels such as financial illiteracy (Agarwal et al., 2017; Bajo and Barbi, 2018), inattention (Byrne et al., 2022), distrust of financial institutions (Johnson et al., 2018; Yang, 2021), and peer effects (Maturana and Nickerson, 2018). To my best knowledge, this paper is the first to analyze the role of a relatively understudied but influential aspect of everyday life — broadband internet — that can impact both the demand for and supply of refinance credit especially for disadvantaged populations. My results are also relevant for the implementation of broadband infrastructure initiatives, which has become an integral part of public policy discourse in recent years.

The literature on the role of financial technology in household finance, most notably Philippon (2016), Buchak et al. (2018), Di Maggio et al. (2021), and Bartlett et al. (2022), has documented technology’s large impact on mortgage market composition and lending practices. This paper serves as a complement to Fuster et al. (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 broadband internet can indeed reduce refinancing frictions. In addition, recent works on financial inclusion highlight the persistent importance of bank branches in the modern era (Brown et al., 2019; Célerier and Matray, 2019; Fonseca and Matray, 2022; Jung and Zentefis, 2022) and the implications of digital disruption (Jiang et al., 2022). Yogo et al. (2021) also find that financial participation depends on household income rather than race or access to financial services. My paper contributes to this literature by showing that the inability of low-income households to afford broadband internet can be a significant impediment to financial inclusion.

Lastly, this paper is related to the literature on the economic importance and benefits of broadband access. Akerman et al. (2015), Dettling (2016), Hjort and Poulsen (2019), and Kolko (2012) study the effect of broadband introduction 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 estimate positive labor market outcomes. My paper makes substantial contributions relative to that study in terms of the empirical framework and the subject matter, by focusing on a household financial activity (refinancing) that is conditional on stable employment. I thus analyze whether broadband induces a reduction in behavioral mistakes and informational barriers as opposed to an increase in active job search and training. In general, the two works are highly complementary and describe two distinct benefits of broadband access.

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

2 Background

2.1 Mortgage Refinancing

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 et al., 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. The importance of housing is particularly large 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 purchased 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 through additional savings.

Prior research has documented that many households fail to refinance their mortgages when it is

optimal to do so (Agarwal et al., 2016; Keys et al., 2016; Johnson et al., 2018; Andersen et al., 2020). These financial mistakes are particularly pronounced among low-income households; of the mortgages originated between 2004 and 2008 by households making less than \$35,000 in annual income, 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 refinancing propensity of loans originated by households making more than \$75,000 (80 percent). This trend is monotonic throughout the income distribution and also prevalent in large central metro 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 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 provides evidence that borrower frictions relating to information technology plays an important role in explaining this disparity.

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 such as work, education, and entertainment. In this paper, I define broadband as a residential, high-speed, wireline internet service available in a 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 Dial-up internet service, which typically has a maximum download speed of 56 kilobytes per second (Kbps), is considered inadequate for more complex daily activities and thus outside the scope of this paper. Lastly, I only consider wireline service provided through physical broadband infrastructure. 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

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

a broadband subscription.² Survey results from the Pew Research Center reveal that the price of subscription (59 percent) and cost of computer equipment (45 percent) are the top two reasons for not subscribing to broadband (Horrigan and Duggan, 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. This distinction 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 Refinancing Inequality

At-home internet access is relevant for refinancing inequality due to the unique properties of a refinance mortgage. First, refinancing is relatively standardized and highly compatible with technological innovation. In most cases of a interest rate refinance, the housing asset in question is already determined and the prospective borrower is in good standing on the existing mortgage.³ Borrower uncertainty is thus low, allowing a large part of the refinance process to be streamlined and automated. Recent innovations in online approval and underwriting technology have led to a significant decrease (up to 30 percent from an average of 51 days) in processing time for refinance applications (Fuster et al., 2019). The internet has also enabled both bank and non-bank lenders to reach populations outside their immediate geographic markets, improving the access to refinancing credit for underbanked households.

Second, refinancing involves high shadow costs for borrowers (i.e., time and cognitive effort) that can be drastically reduced through internet usage. A refinance typically takes several months to complete, largely 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). For the majority of American households that use online banking, these materials can be conveniently accessed and transmitted online with a computer and broadband connection.⁴ Furthermore, applicants with broadband can use e-mail to communicate with a loan officer and make fewer branch visits. To the extent that the internet can also increase households' awareness and provide resources to shop around for lenders and rates, broadband access at home has become an important way to reduce the shadow costs associated with

²Statistics are compiled from the 2015 FCC Broadband Progress Report and author's calculations using ACS 2017 5-year estimates.

³Since 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.

⁴55.1 percent of the population reported using online banking and one-third reported using it as the main method to access bank accounts (Federal Deposit Insurance Corporation, 2013).

refinancing. Indeed, Figure 4 shows that local area broadband access is correlated with online search activity for information about refinancing and current mortgage rates.

In this paper, I argue that refinancing inequality arises in part due to heterogeneity in broadband access. As low-income households typically face volatile employment prospects and work longer hours, they may find it particularly difficult to fulfill the verification and qualification requirements for a refinance without the help of 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 via brick-and-mortar branch networks is limited.⁵ Lastly, information frictions regarding upfront costs (which can be rolled into payments or entirely waived under certain circumstances) can further reduce refinancing activity for low-income households that typically lack savings in financial assets.⁶ Figure 5 shows that broadband access is correlated with disparities in realized refinancing outcomes: voluntary prepayment propensities for households with high refinance likelihood are generally lower in census tracts with limited broadband access, with a larger gap for 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

⁵27 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).

⁶Bhutta 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.

cost of a comparable unsubsidized broadband plan (Hussain et al., 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 a sizeable amount 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

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

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

I discuss two important challenges for quantifying the causal effect of Internet Essentials on refinancing. First, it is difficult to compare refinance outcomes of income-eligible (treated) and income-ineligible (control) households within Comcast areas due to non-parallel trends. As income is a primary predictor of mortgage principal, and by extension, monetary savings from refinancing, ineligible households with marginally higher incomes are more likely to refinance early when interest rates fall.⁸ Moreover, refinancing is a typically one-time decision for most homeowners due to large origination costs. This leads to a natural attrition of the ineligible group’s potential refinance pool in the early years following the Great Recession. Thus, any positive effects of Internet Essentials’ introduction in 2012 will be biased upwards by the higher trend of refinancing activity by eligible low-income households throughout the recovery period.

Second, it is not feasible to directly compare refinance outcomes of eligible households in Comcast and non-Comcast areas. Importantly, Comcast has near-complete coverage in certain major 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 regions within a small geographic footprint with varying levels of coverage. As a result, a standard study of differences in refinancing behavior between Los Angeles and Sacramento (or between Chicago and New York) is likely to be driven by unobservable confounders. Even after controlling for economic and financial indicators that motivate a household’s refinance decision (for instance, house prices and interest rates), I cannot rule out the impact of factors such as industry-by-tract employment outcomes, migration patterns, or nuanced changes in lending standards that may bias my estimates.

To overcome these limitations, I study Internet Essentials’ impact on refinancing by addressing 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

⁸This fact is further supported by the monotonous increase in refinancing propensities visualized in Figure 2.

differences”) design introduced by Gruber (1994) to compare changes in the *gap* of refinancing outcomes between eligible and ineligible groups across Comcast and no Comcast census tracts. Under my empirical setting, any confounders at the census tract level that impact both eligible and ineligible groups concurrently will be 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 coverage before and after 2012, except through the impact of Internet Essentials.

Figure 6 illustrates the intuition behind the triple differences design. All three panels plot the residualized number of annual refinance originations by each eligibility group at the census tract level — one of the main outcome variables of interest. The top panel shows that eligible and ineligible groups within Comcast areas follow divergent trends in refinancing behavior prior to the program’s launch in 2012. In the middle panel, I show that the two groups in no Comcast census tracts also exhibit similar trends in refinancing behavior throughout the study period. Lastly, the gap in refinancing originations between eligible and ineligible groups in non Comcast areas is consistent with the corresponding gap in Comcast areas leading up to the program’s introduction in 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.⁹ As required by law, each ISP self-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 service and aggregate the information up to the census tract level to compute coverage rates.

Mortgage Applications and Originations. The Home Mortgage Disclosure Act (HMDA) provides loan-level data 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.¹⁰ Importantly, HMDA data reports an applicant’s income and location of the property at the census tract level, along with demographic characteristics such as race and sex. The main dependent variable in my analysis captures 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

⁹Recent provider data after 2014 are compiled centrally by the FCC through Form 477. The FCC also reports census tract- and county-level information on the number of broadband connections per 1,000 households.

¹⁰Conventional mortgages are not insured or guaranteed by the Federal Housing Administration (FHA), Veterans Administration (VA), Farm Service Agency (FSA) and Rural Housing Service (RHS).

households in a given urban 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.

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 as an additional proxy for refinancing activity.¹¹ First, I measure prepayment of mortgages originated between 2004 and 2008 using loan performance data supplied by two major government sponsored enterprises (GSEs). In particular, I assign an indicator for whether a 30-year fixed rate mortgage purchased by Fannie Mae or Freddie Mac is prepaid between 2008 and 2011 (pre-Internet Essentials), and another indicator for whether the mortgage is prepaid between 2012 and 2015 (post-Internet Essentials). While the performance data also contain the location of the home at the 3-digit zip code level as well as useful loan characteristics, they importantly do not report borrower income that is required for assigning treatment status. Thus, 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).¹² The resulting data set covers between 20 and 30 percent of all mortgages originated and sold to the two GSEs. In addition to the demographic characteristics available in HMDA, the matched data provides important loan-level covariates at origination such as interest rates, debt-to-income ratios (DTI), combined loan-to-value ratios (CLTV), and credit scores. I also calculate a time-varying measure of each loan’s remaining maturity at the time prepayment is observed.

Interest Rates. I test whether broadband access reduces the incidence of suboptimal refinancing by analyzing interest rate outcomes. Loan-level interest rates are available in the GSE performance data, while borrower income is only reported in HMDA. I employ the matching process detailed above to merge the two data sources 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 sold to Fannie Mae and 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

¹¹The vast majority of voluntary prepayments are as a result of refinancing, and prior research has studied prepayment speeds as a proxy for refinancing activity (Schwartz and Torous, 1989; Stanton, 1995; Longstaff, 2005; Deng and Quigley, 2012).

¹²Further details on the matching process can be found in the Internet Appendix.

as relevant covariates on home value 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. Geographic location is identified at the PUMA level (average population above 100,000), which is significantly larger than a census tract (average population of 4,000).

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 treatment and control groups are likely to experience shocks in these factors concurrently, I additionally incorporate controls for group-level changes in economic outcomes using HMDA data. In particular, I construct a time-varying proxy for house prices as the logarithm of 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 2 mile radius of the population centroid as of 2010. Location information for the center of population is obtained from the Census.¹³

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 suggested by [Buchak et al. \(2018\)](#) and [Fuster et al. \(2019\)](#). 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 crucially driven by disparities in economic outcomes across urban and rural areas. To address this, I classify census tracts into urban

¹³While most studies on “banking deserts” measure branch access within a 10-mile radius of the population centroid. I follow the 2-mile radius convention used by [Covas \(2019\)](#). As the census tracts in my sample are geographically small (about 7 square miles on average) and concentrated in urban clusters, using the measure using the 10-mile radius is likely to overstate true bank access.

and rural areas using the scheme provided by the National Center for Health Statistics (NCHS).¹⁴ In particular, I use the 2006 delineation of county-level urbanicity and match it to each census tract. Demographic characteristics such as tract-level 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 important sources of variation: Comcast coverage rates 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 block-level data as of December 2011 (the year prior to Internet Essentials) by calculating:

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

where $Population_{b,2010}$ refers to the population of block b and $\mathbf{1}(Comcast_{b,2011})$ is an indicator for whether Comcast provides broadband service in block b in 2011. $Comcast_{c,2011}$ captures the fraction of tract c ’s population that has access to Comcast broadband.¹⁵ I address possible time-varying changes in coverage by using the same method to calculate $Comcast_{c,2014}$ and taking the average of the two rates to compute $Comcast_c$. Panel (a) in 7 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 given the size of the household, neither of which I can directly observe from the HMDA or GSE data. In my analysis, I first assume that all homeowners have a school-aged child between ages 6 and 18. Next, I assign low-income status based on a four-person household, which corresponds to the average household size of Internet Essentials subscribers. The

¹⁴https://www.cdc.gov/nchs/data_access/urban_rural.htm.

¹⁵Under 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 bias of actual broadband access.

income threshold for a four-person household increases slightly each year to account for inflation and averages \$42,000 between 2008 and 2015. 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 analysis to account for possible measurement error. This classification method allows me to compute an intent-to-treat effect that is plausible as long as I can rule out differential biases in assignment across geographic areas that correlate with Comcast coverage. 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 allows me to focus on two groups with relatively similar income. The resulting annual thresholds for Internet Essentials eligibility are tabulated in Table 2.

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 a cleaner assignment to Internet Essentials eligibility. In particular, 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 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 relevant because Internet Essentials' initial success was primarily led by Comcast's partnerships with local governments and school districts in urban areas. Limiting the analysis to urban areas 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 that did not receive any refinance applications (regardless of income) in any given year between 2008 and 2015.

The final sample consists of 5,256 census tracts covering 57 MSAs. 2,430 tracts have higher than 50 percent Comcast coverage and 2,826 have less than 50 percent coverage.¹⁶ Table 3 reports 15 high

¹⁶I use a continuous measure of Comcast coverage as the treatment indicator in all regression analyses. This is largely inconsequential because the distribution of coverage rates, as shown in Figure 7, is highly concentrated at

Comcast and 15 no Comcast metropolitan statistical areas (MSA) ranked by population served. The lack of overlap between the two groups implies that Comcast does not operate alongside other major ISPs in cities and rules out potential spillover effects across adjacent tracts with opposite coverage status. Additionally, the large number of census tracts within each MSA provides support for an empirical strategy that controls for tract-specific trends.

In Figure 7, panel (b), I map all census tracts in my sample and show that Comcast coverage also does not exhibit any patterns of regional clustering. Importantly, most of the census tracts without Comcast have permanent presence of either AT&T or Charter. This means that broadband environments in Comcast and no Comcast areas will mostly be similar; both areas will have comparable levels of broadband provider access, network quality and customer service, with the only major difference being that eligible households in Comcast census tracts could save up to 75% on their subscription costs starting in 2012.

Table 4 presents descriptive statistics for select variables in Comcast and no Comcast tracts. While Comcast census tracts are slightly less populated on average, the two groups share very similar characteristics in terms of income distribution, urbanicity, median age, average household size, owner-occupancy rates, mortgage cost burdens, employment rates, and education levels. Interestingly, Comcast census tracts tend to have a higher concentration of bank branches near the population center, and also exhibit higher broadband subscription rates.

Table 5 further reports descriptive statistics for mortgages and homeowner demographics in Comcast and no Comcast tracts by eligibility status. Columns 2 and 3 (5 and 6) show that ineligible households have higher income and credit scores, purchase higher-valued homes, and receive more favorable interest rates than their eligible counterparts. Note that even control households still have substantially lower income relative to the rest of the population (Columns 1 and 4). For the average low-income mortgage originated between 2004 and 2008, the interest rate differential for refinancing between 2008 and 2011 was between 1.2 and 1.3 percentage points, which exceeds the typical threshold for optimal refinancing cited in the literature (Agarwal et al., 2013). Average interest rates fell further by a percentage point between 2012 and 2015, which contributed to a large refinancing wave throughout the income distribution. Comcast tracts also tend to have a larger fraction of black homeowners and smaller fraction of hispanic homeowners than low Comcast tracts. In general, the difference in observable mortgage-related outcomes between eligible and ineligible groups are consistent across regions, both for homes purchased before the Great Recession and for

0 and 100 percent. All results are robust to using an indicator variable for whether $Comcast_c$ is above 70 percent (treated) and below 30 percent (control).

homes refinanced in the early recovery period of 2008 to 2011.

3.5 Effects of Internet Essentials on Refinancing

Refinance Originations 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:

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

where $y_{i,c,t}$ is the number of refinance originations made 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 tease out refinancing demand and credit standards, respectively. $Eligible_{i,c,t}$ is a binary indicator for group i 's Internet Essentials program eligibility, $Comcast_c$ is a continuous measure of Comcast coverage rates in census tract c , and $Post_t$ indicates years after the introduction of 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 high and low Comcast coverage would have trended the same in the absence of Internet Essentials.

In an additional test, I analyze whether households with Internet Essentials 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 the HMDA source 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 et al., 1984; Silva and Tenreyro, 2006; Correia et al., 2019). Standard errors are conservatively clustered at the PUMA level

to address the possibility that Internet Essentials may have been 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 federal funds rate started to rise 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 refinancing is that housing-related costs should decrease following a refinance. However, it is difficult to directly measure changes in payment burdens at the household level as an old mortgage cannot be linked to the refinanced mortgage using HMDA data. In this section, I use annual survey responses 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:

$$m_{i,p,t} = \alpha + \beta(\text{Eligible}_{i,p,t} \times \text{Comcast}_p \times \text{Post}_t) + Z'_{i,p,t} \Phi + \rho_1(\lambda_t \times \gamma_p) + \rho_2(\text{Eligible}_{i,p,t} \times \lambda_t) + \rho_3(\text{Eligible}_{i,p,t} \times \gamma_p) + \epsilon_{i,p,t}, \quad (3)$$

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 . $\text{Eligible}_{i,p,t}$ 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 further 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 covered by Comcast (control group with less than 10 percent in coverage). The redefinition of Comcast_p is necessary because PUMAs are on average 10 times larger than census tracts in terms of population; PUMAs with medium levels of coverage may confound the results as they might be areas with more than one major ISP in operation (including Comcast).¹⁷ $Z_{i,p,t}$ 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 in order to reduce the increased demand on the data arising from PUMA level variation. Concerns of confounding trends as a result of this adjustment are low due to the cleaner identification of household-level eligibility status. Multi-way fixed effects absorb any variation that might threaten

¹⁷In unreported results, I verify that the regression results do not change materially when using the continuous measure of Comcast coverage as in equation (2).

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) at the eligibility group level. Column 1 in Table 6 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 an average of 6 mortgages. These results are statistically significant at the 5 percent level. Figure 8 graphically illustrates these results by plotting time-varying triple difference estimates of treatment effects. I find no evidence of non-parallel trends in the pre-treatment period, confirming the validity of a granular identification strategy that exploits variation between groups and across census tracts. Importantly, the coefficient estimates on refinance originations steadily grow over the early years of the program and become statistically significant in 2013 and 2014. The gradually increasing trend also mirrors the subscriber growth pattern between 2012 and 2015 (Comcast Corporation, 2016). The treatment effect falls marginally 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 creditworthiness that is marginally sufficient to qualify for a mortgage, it is possible that the growth in refinance originations masks an increase in costly denials. I indirectly test the hypothesis that access to the internet can have the unintended consequence of disseminating misinformation or inflating the perceived likelihood of approval using applications and denial rates data from HMDA. In column 2 of Table 6, 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 corroborates these results that there is no effect on refinance 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 suboptimal refinancing behavior. Moreover, banks and mortgage lenders do not seem to adjust lending standards in response to the increase in applications, which is plausible given the comparison of outcomes for two similar groups within a census tract.

Internet Essentials also did not induce borrowers to obtain more favorable interest rates conditional on approval. Column 4 shows a non-significant effect of treatment on interest rates controlling for a

rich set of loan-level covariates. This can be explained by the relative uniformity of conventional mortgages compared to other types of programs. In addition, fintech lenders did not have a large market share in retail mortgages during this period, which may have led to higher frictions for online rate-shopping activities (Figure 9). Even if online rate search tools are utilized by homeowners, online lenders tend to charge similar or higher interest rates than their brick-and-mortar counterparts to compensate for improved convenience (Buchak et al., 2018).

The monetary savings from refinancing are economically substantial, especially for low-income households that have most of their wealth tied to home equity. The average homeowner in my sample that purchased a home between 2004 and 2008 had a mortgage principal of around \$120,000 and an interest rate of 6.2 percent at the time of origination. Applying the prevailing interest rate of 4 percent for comparable loans between 2012 and 2015, each household that refinanced its mortgage would have saved \$110 dollars a month before any adjustments. These households still come out ahead by around \$100 after accounting for the cost of Internet Essentials, which corresponds to about 5 percent of disposable income for the average household in this group. 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.¹⁸ These lifetime savings account for around one-third of the median net worth of all households and about 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 refinances 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, and the the upper bound of national savings attributable to Internet Essentials is around \$100 million.¹⁹ 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 line, the mortgage cost savings

¹⁸To 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 et al. (2013) and Keys et al. (2016) would further reduce the estimated savings to \$15,000, which is still very high for this group of homeowners.

¹⁹Urban 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).

combined with other documented economic benefits such as increased employment outcomes (Zuo, 2021) imply that providing subsidized broadband can indeed be a desirable government policy.

Mortgage Payments. I further test whether Internet Essentials indeed led to lower mortgage payments. This is an important empirical exercise given the incidence of suboptimal refinancing behavior particularly among low-income households (Agarwal et al., 2016). Even if mortgage payments decrease, 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 7 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). Additionally, Panel B improves on the identification 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 of 3.8 percent. In Figure 10, 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 and data limitations.

The magnitude of treatment effects in Table 7 provide important baseline estimates for the monetary savings from refinancing. The average pre-treatment mortgage payment for treated households is around \$700, which is consistent with the statistics obtained from HMDA. A 4 percent decrease in payment corresponds to \$30 in monthly savings or \$5,500 in adjusted present value terms. This serves as the lower bound for the treatment effect of Internet Essentials on mortgage payments, as the ACS does not directly collect information about mortgage refinancing activity. Even if we take the estimates at face value, I argue that \$30 a month could make a large difference in financial health when accumulated over several decades. This is because disposable income and discretionary savings for low-income households are extremely low. In fact, 32.8 percent of households that are income-eligible for Internet Essentials reported to be “food insecure,” which means they did not have access to enough food for an active, healthy life for all household members (Coleman-Jensen et al.,

2016).

4.2 Mechanisms

In this section, 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 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 informational frictions.

Lending Channels and Financial Inclusion. Access to traditional financial services such as a mortgage is particularly challenging for the 20 percent of American households that are classified as underbanked (Federal Deposit Insurance Corporation, 2013).²⁰ Between 2008 and 2016, more than 6 percent of bank branches closed throughout the nation, making it difficult for households living in underserved areas to refinance their mortgages conveniently (National Community Reinvestment Coalition). Branch closure rates are in fact more pronounced in urban areas with relatively high internet access levels (Jiang et al., 2022); for instance, 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.

I outline two supply-related predictions for the refinancing activity of households with limited access to bank branches. First, broadband access may encourage homeowners to refinance through online (fintech) lenders that are more efficient in processing applications. Alternatively, broadband access can facilitate the refinance process via traditional banking relationships by reducing shadow costs or search frictions.

Table 8 empirically tests these two hypotheses. In column 1, I replace $y_{i,c,t}$ in equation (2) with the fraction of fintech originations to all refinance originations. I do not find any effect of Internet Essentials on fintech relationships, which can partially be explained by the relatively low levels of fintech penetration across eligible and ineligible income groups during this period (4.3 percent and 7.2 percent). This fact is also supported by Figure 9, which shows that Google search activity for the top fintech lenders remained muted until 2015.

²⁰A 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.

In columns 2 to 4, 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 2 miles of the population center. I find that the treatment effect is largest (9.1 percent) when comparing the refinancing gap across Comcast and no Comcast census tracts in the bottom quintile of bank branch density (average of 4.12 branches around population center). The treatment effect is smaller and not significant for the middle quintile, and importantly, I find no effect when comparing census tracts with the highest levels of branch access. These results imply that Internet Essentials had the largest impact in areas where households face high shadow costs of refinancing. This is consistent with the findings of [Argyle et al. \(2020\)](#) that low bank branch access is associated with higher search costs and worse consumer financial outcomes. Furthermore, low-income households are likely to be constrained in their ability to make long-distance branch visits as they are generally in service, natural resources, maintenance, and construction occupations that exhibit limited flexibility in work schedules.²¹ Thus, I demonstrate that broadband improves low-income households' refinancing outcomes by reducing the shadow costs of accessing traditional brick-and-mortar lenders, which are still considered the main source of credit for disadvantaged populations.

Determinants of Refinancing Demand. In this section, I disentangle the possible determinants of increased refinancing demand following Internet Essentials. [Zuo \(2021\)](#) shows that the program led to increased employment and income for eligible households residing in Comcast areas. Given this, improved financial health may have enabled refinancing for households that previously did not have enough savings or work flexibility to cover monetary origination costs as well as shadow costs. For this hypothesis to hold true, it must be the case that income for eligible homeowners, which account for less than half of all households in this income group, indeed increased as a result of the program. I test whether the results on income from [Zuo \(2021\)](#) hold when restricting the sample to homeowners only. Specifically, I replace the dependent variable in equation (3) with the log of income conditional on having a mortgage and being employed. This is because refinancing is only relevant for employed households in most circumstances. 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 9 shows that Internet Essentials in fact did not have any effect on income for employed households with a mortgage. This result rules out the possibility that refinancing demand increased due to the reduction of opportunity costs.

An alternative explanation for increased refinancing demand is that Internet Essentials bridged the large gap in digital and financial literacy between connected and unconnected households. In

²¹Bureau of Labor Statistics (2014).

particular, survey results indicate that online access of banking and financial services is much higher among households with high digital skills (60 percent) than households with low digital skills (39 percent) (Horrigan, 2019). Recognizing the importance of training programs that help households transition daily activities online, Comcast invested \$300 million into digital literacy initiatives that were accessed by 30 percent of subscribers.(Comcast Corporation, 2016). The programs, which were offered free of charge through multiple outlets, covered a wide range of topics on digital readiness (e.g., internet security and e-mail) as well as general well-being (e.g., employment, social services, and personal finance).

I test whether the refinancing growth among treated households can be explained by an increase in digital and financial literacy (measured by educational attainment). Columns 2 to 4 of Table 9 estimate regression (2) with refinance origination counts as the dependent variable. I again divide the census tracts into three groups based on the fraction of the population with a high school degree or higher. Column 2, which compares the refinancing gap between eligible and ineligible households in urban census tracts with low levels of educational attainment as of 2011, reveals a positive and statistically significant coefficient of 12.5 percent. I find no treatment effect in the middle group of census tracts, and a positive and significant coefficient of 6 percent for high literacy census tracts.

In order to tease out these channels more directly, I also estimate regression (3) using log mortgage payment as the dependent variable and then 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 geography-specific education levels, I focus on household-level variation in educational attainment in this specification. Columns 5 to 8 provide further support of this channel: Internet Essentials reduced mortgage payments by 5.4 to 8.3 percent among low literacy groups, but had no effect on high literacy households.

Taken together, these results confirm that Internet Essentials increased refinancing demand by improving the digital and financial literacy of low-income households. Households with higher ex-ante levels of digital and financial literacy were not differentially impacted by Internet Essentials, implying that if desired, they would have refinanced one way or another even without an at-home broadband connection.

5 Robustness and Falsification Tests

Alternative Measure of Refinancing. While loan counts provide the most direct and comprehensive measure of refinancing activity, it importantly 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:

$$\begin{aligned} \text{prepay}_{i,c,t} = & \alpha + \beta(\text{Eligible}_{i,c,t} \times \text{Comcast}_c \times \text{Post}_t) + Y'_{i,c,t} \Phi \\ & + \rho_1(\lambda_t \times \gamma_c) + \rho_2(\text{Eligible}_{i,c,t} \times \lambda_t) + \rho_3(\text{Eligible}_{i,c,t} \times \gamma_c) + \epsilon_{i,c,t}, \end{aligned} \quad (4)$$

where $\text{prepay}_{i,c,t}$ is a binary indicator for whether loan i in census tract c has prepaid by year $t \in \{2011, 2015\}$. $\text{Eligible}_{i,c,t}$ now indicates whether loan i qualifies for Internet Essentials at the time of origination, and I assume that eligibility status stays constant between origination and 2015. To address the concern that households with marginally higher income between 2004 and 2008 may have subsequently qualified for the program by 2012, I construct an additional control group with annual income between 185 percent and 370 percent of a seven-person household (\$55,000 to \$110,000). $Y'_{i,c,t}$ is now 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. Census tract by year fixed effects ($\lambda_t \times \gamma_c$) absorb all census tract-specific trends that are invariant to Internet Essentials eligibility and the interaction $\text{Eligible}_{i,c,t} \times \lambda_t$ controls for aggregate time-varying differences between eligible and ineligible groups. Similarly, $\text{Eligible}_{i,c,t} \times \gamma_c$ controls for permanent differences between eligible and ineligible groups in each census tract.

Column 1 of Table 10 shows that the prepayment probability of a conventional mortgage originated by a low-income household before the Great Recession increased by 3.3 percent as a result of Internet Essentials. The effect is economically large given the average pre-treatment prepayment propensity of 42 percent, and is statistically significant at the 1 percent level.

Direct measurement of prepayment outcomes also allows me to compute how much of the reduction in refinancing inequality between the top and bottom income deciles between 2011 and 2015 can be attributed to Internet Essentials. First, the effect of prepayment activity estimated in Table 10 implies that Internet Essentials can explain up to 10 percent of the growth in prepayment for the lowest income decile.²² 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 14 percent. These estimates reflect an upper bound as the reduction in refinancing gap is largely a result of

²²A 3.3 percent increase off a base of 65 percent implies a 2 percentage point increase in prepayment. I then divide this number by the total prepayment growth by this group during this period (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.

mechanical convergence over time.²³

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. While the fact that income conditional on homeownership does not increase helps rule out the possibility of an ineligible household becoming ineligible again, 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 groups of lower-middle income households that are both unlikely to be impacted by Internet Essentials. In column 2 of Table 10, I show that assigning a placebo treated group at the 5-6 person income threshold and control group at the 7-8 person income threshold does not yield statistically significant effects on mortgage refinancing. The disappearance of an 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 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 test 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 10 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 the prominent alternative housing tenure choice for households. Unlike mortgages, 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 converting into lower rent payments are less likely to be consequential for low-income households. As such, outcomes on rental payments should not change as a result of Internet Essentials. I test this prediction using ACS data on renters and confirm that households do not take advantage

²³At 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).

of Internet Essentials to reduce their rent payments (Table 10, 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.²⁴ 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 11, 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 (16.3 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.

6 Conclusion

Failing to refinance a mortgage when it becomes profitable to do so leads to large welfare losses. This phenomenon is particularly prominent among low-income households and has contributed to the growing wealth inequality in recent decades. In this paper, I study whether disparities in access to the internet explains suboptimal refinancing behavior by exploiting a natural experiment that brought broadband to more than low-income 750,000 households between 2012 and 2015. Using an identification strategy that accounts for geographic, temporal, and household-level variation in program availability, I find a strong and positive effect on refinancing outcomes that lead 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 net worth of low-income households. The effects are

²⁴Zuo (2021) estimates a program take-up rate of 10.6 percent across all Comcast areas between 2012 and 2015.

driven by areas that are underbanked as well as areas with low levels of digital and financial literacy. I conduct various robustness and falsification tests to confirm that my findings are indeed driven by increased access to broadband internet.

This paper provides important implications for monetary policy, mortgage contract design, and infrastructure policy. First, the pass-through of accommodative monetary policy via refinancing may be hindered by shadow costs that differentially affect households with or without internet access. Since the digital divide persists along the income dimension and 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 exacerbates wealth inequality by placing the burden of refinancing solely on households. Over the past several decades, low-income and minority families have been stymied by the mismatch between following 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 and financial institutions should consider developing alternative mortgage products that target these populations and dynamically induce refinancing behavior. Lastly, large-scale efforts to get Americans connected to broadband should continue via improvements in affordability and expanded physical access.

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 also be given to other aspects of household finance such as savings and investment behavior.

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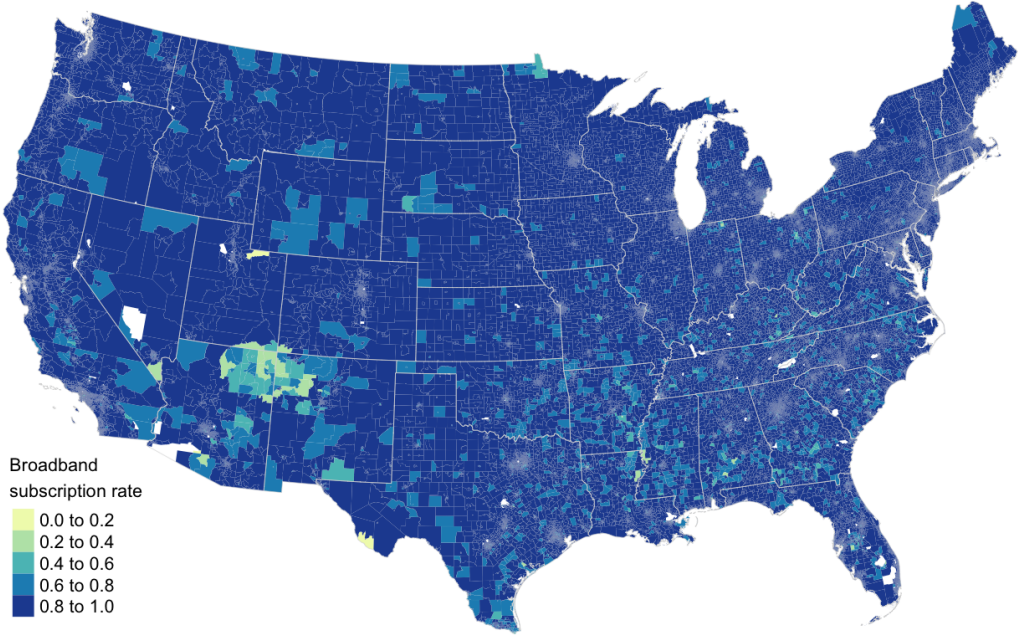
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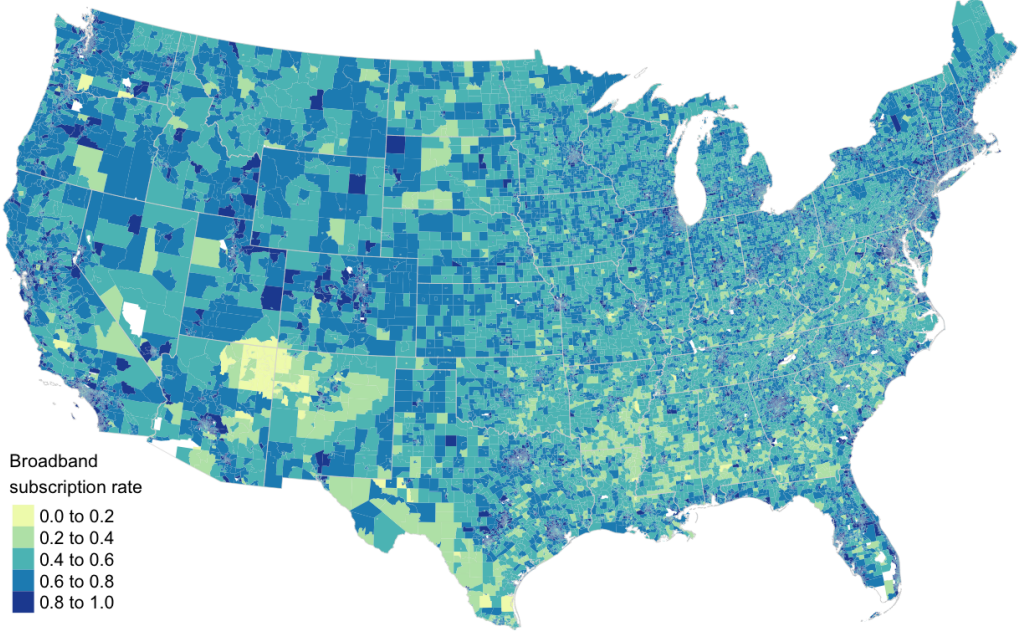
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Figures and Tables



(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 2019 inflation-adjusted dollars. Source: 2019 ACS 5-year estimates.

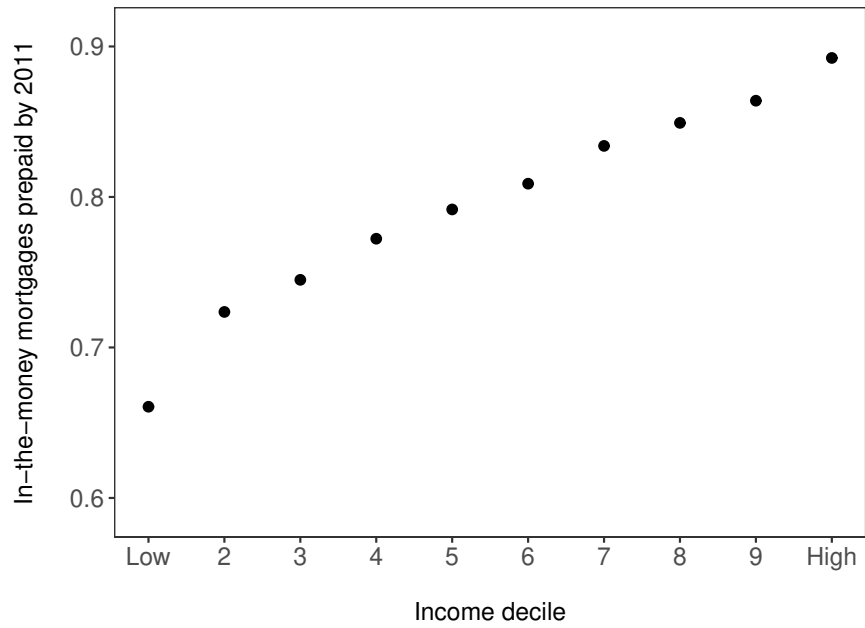


Figure 2: Household Income and Refinancing Inequality

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 mortgages 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.

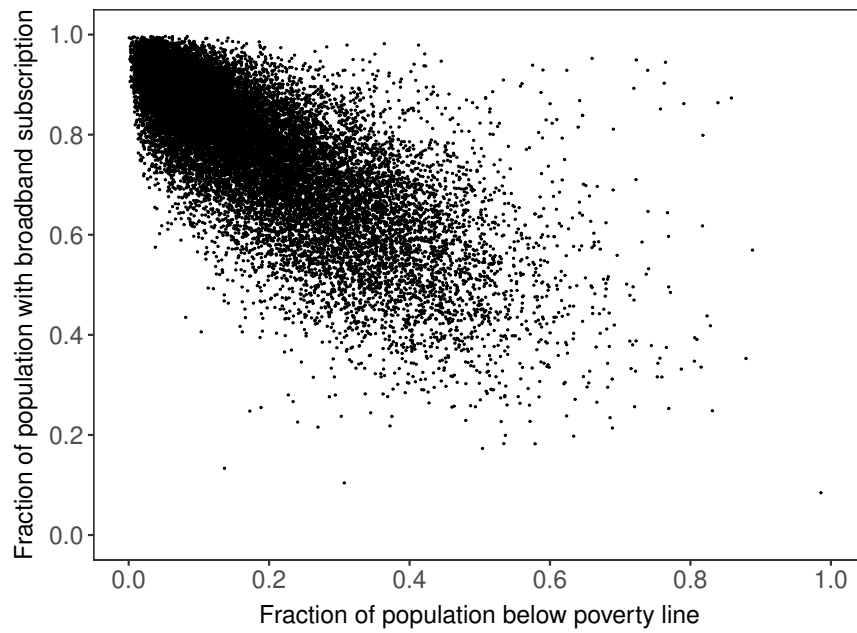


Figure 3: The Digital Divide in Large Central Metro Counties

Note: This figure shows broadband inequality in large central metro counties 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.

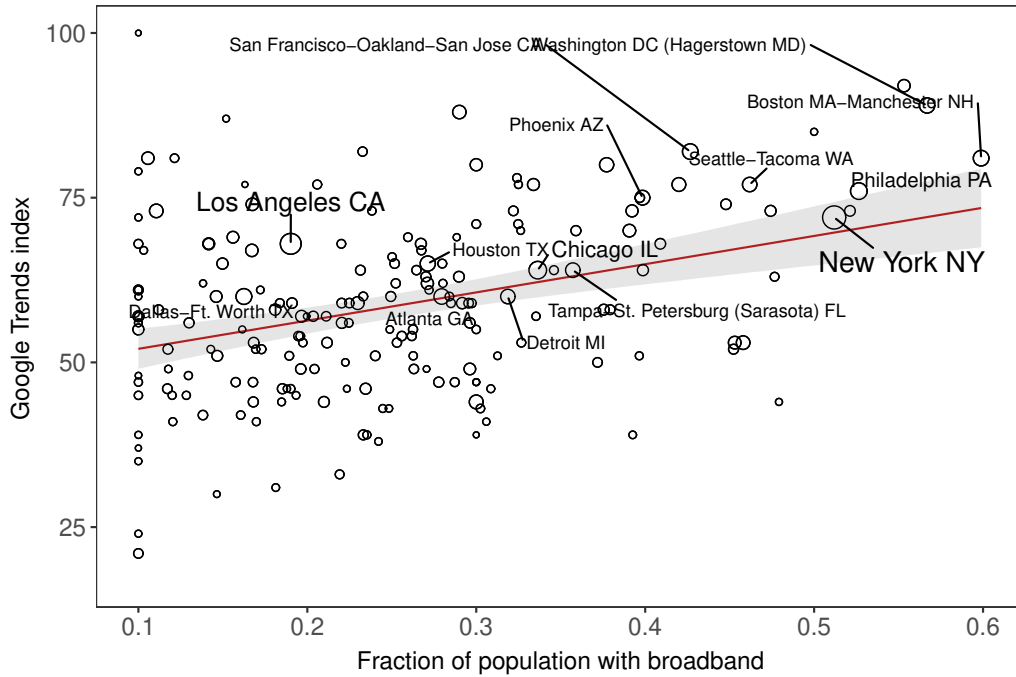


Figure 4: Broadband Access and Refinancing Demand

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.

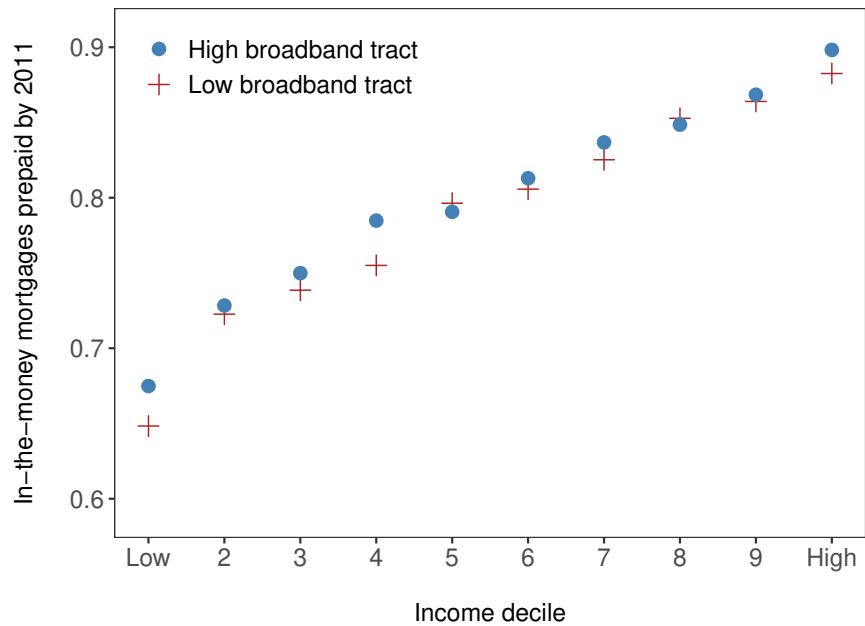


Figure 5: Refinancing Inequality and Broadband Access

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 mortgages 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 urban central metro areas. Source: HMDA, Fannie Mae and Freddie Mac loan performance files, FCC Form 477, and author’s calculations.

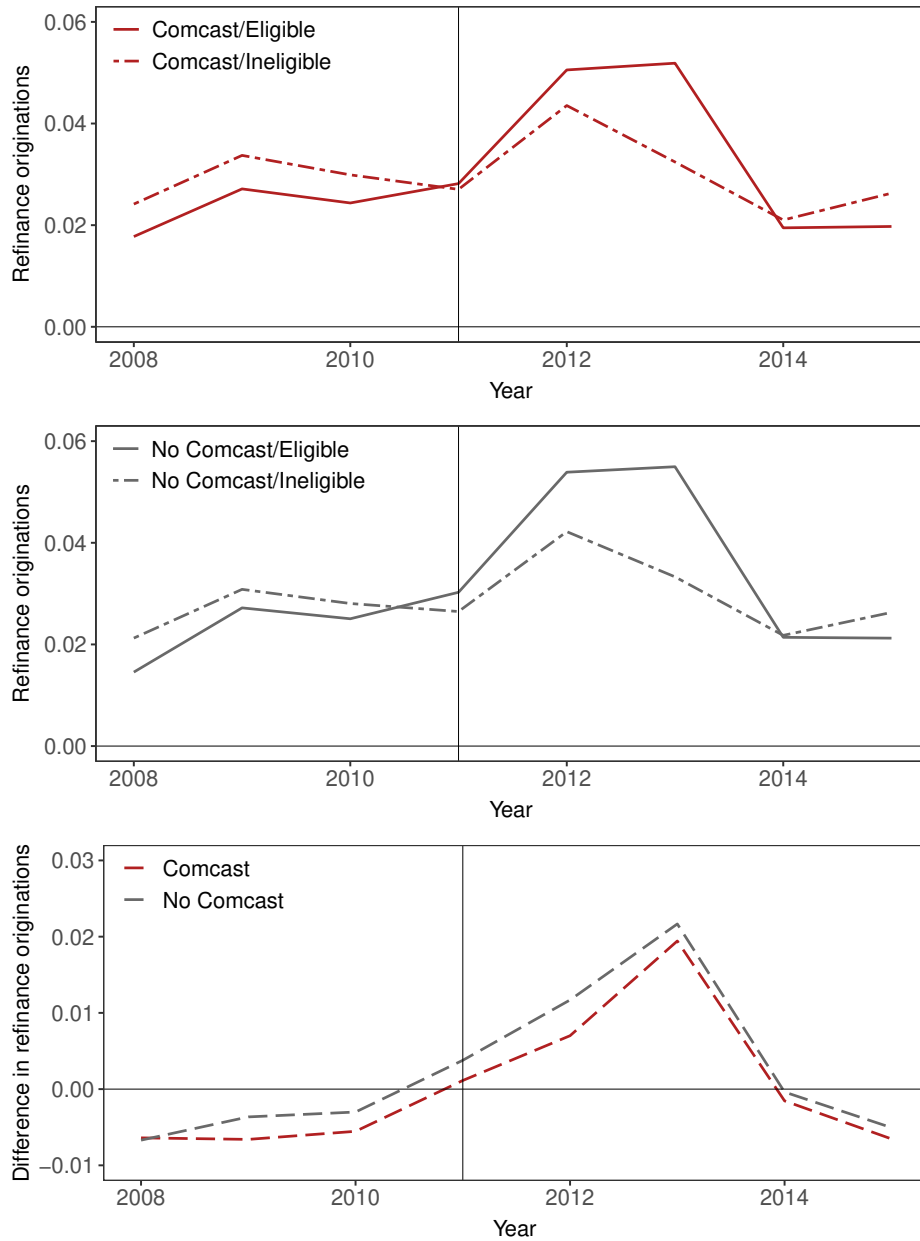
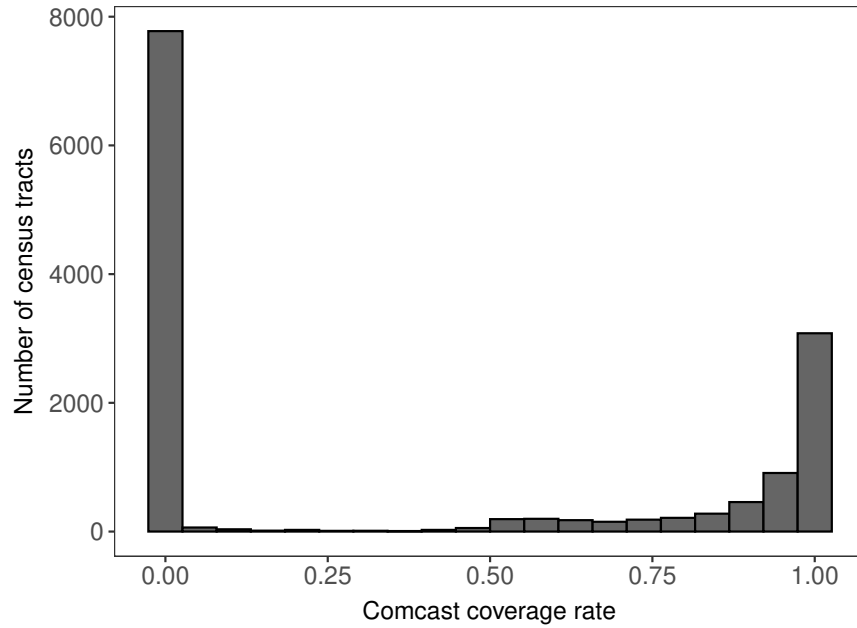


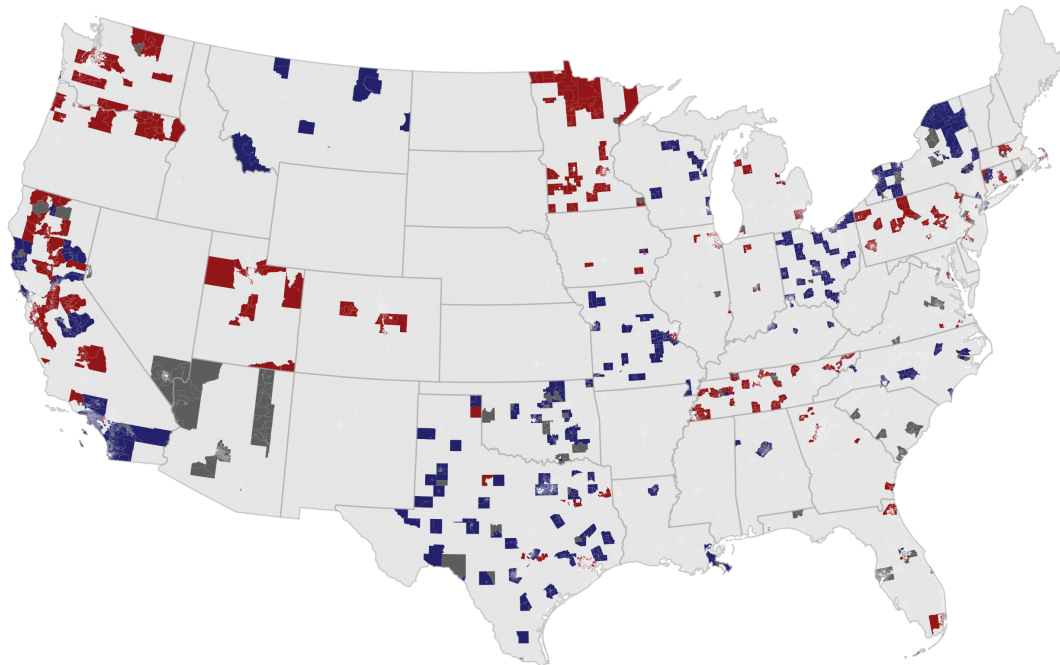
Figure 6: Unconditional Trends in Refinancing Activity

Note: This figure illustrates the triple differences empirical design by plotting the unconditional refinancing trends between eligibles and ineligible across Comcast and no Comcast census tracts. Refinance originations is 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.



(a) Histogram of Comcast Coverage Rates



(b) Map of Comcast and No Comcast Census Tracts

Figure 7: Comcast Coverage Rates

Note: This figure plots the statistical and geographical distributions of Comcast coverage in large central metro census tracts. For each census tract, I first calculate the fraction of 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 SBI, NCHS.

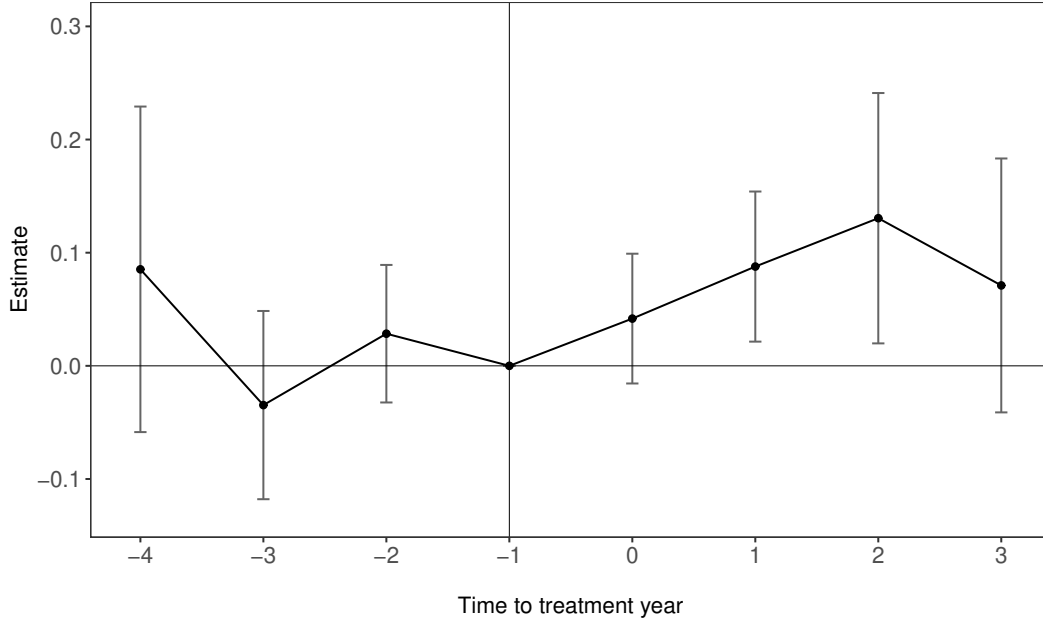


Figure 8: Event Study Estimates for Refinance Originations

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:

$$y_{i,c,t} = \alpha + \sum_t \beta_t (Eligible_{i,c,t} \times Comcast_c \times Year_t) + X'_{i,c,t} \Phi + \rho_1(\lambda_t \times \gamma_c) + \rho_2(Eligible_{i,c,t} \times \lambda_t) + \rho_3(Eligible_{i,c,t} \times \gamma_c) + \epsilon_{i,c,t}, \quad t \in \{-4, -3, -2, 0, 1, 2, 3\}.$$

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, ACS IPUMS microdata.

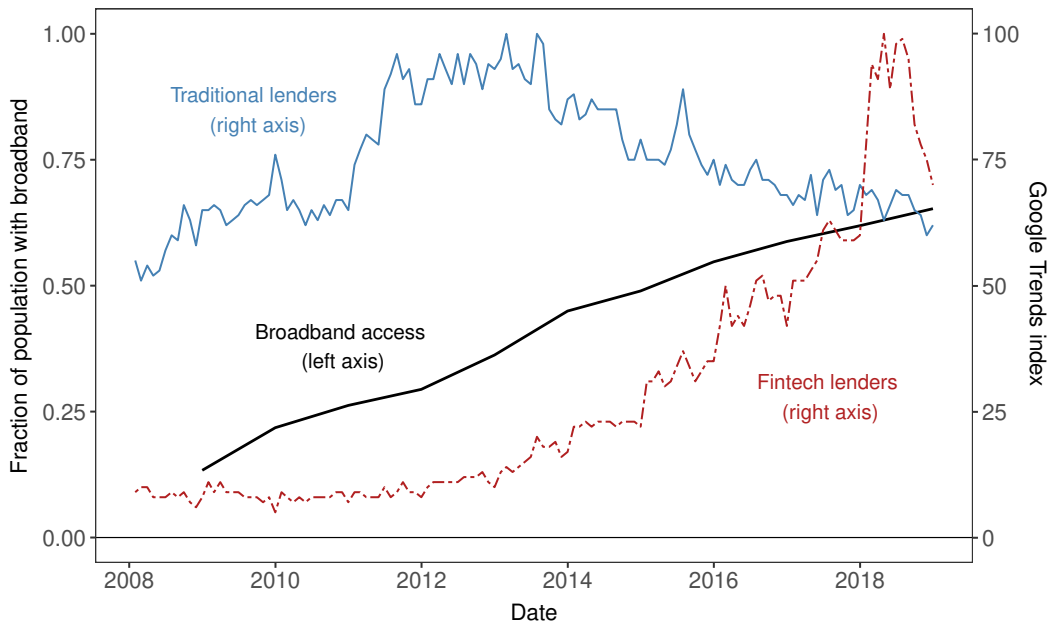


Figure 9: Trends in Online Search for Refinancing

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 et al. (2018) and Fuster et al. (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.

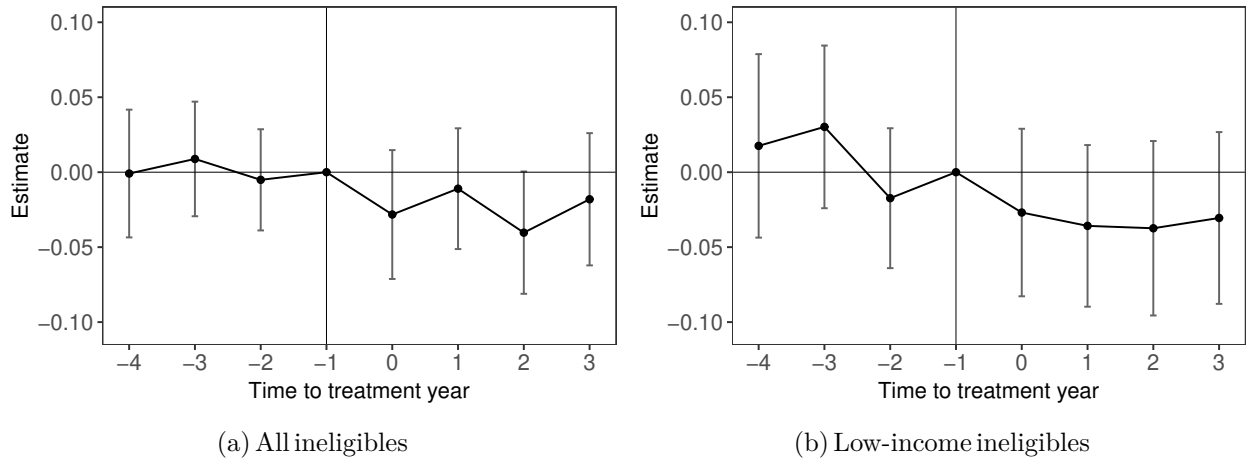


Figure 10: Event Study Estimates for Mortgage Costs

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

$$m_{i,p,t} = \alpha + \sum_t \beta_t (Eligible_{i,p,t} \times Comcast_p \times Year_t) + Z'_{i,p,t} \Phi + \rho_1(\lambda_t \times \gamma_p) + \rho_2(Eligible_{i,p,t} \times \lambda_t) + \rho_3(Eligible_{i,p,t} \times \gamma_p) + \epsilon_{i,p,t}, \quad t \in \{-4, -3, -2, 0, 1, 2, 3\}.$$

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, 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**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).

Year	Eligible		Ineligible	
	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 3**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 obtained from the 2010 Census. The resulting MSAs are then ranked by population size.

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

Table 4
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 3 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 (<i>N</i> = 2, 430)		No Comcast (<i>N</i> = 2, 826)		Diff. (5)
	Mean (1)	SD (2)	Mean (3)	SD (4)	
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 5
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 (<i>N</i> = 2, 430)			No Comcast (<i>N</i> = 2, 826)		
	All (1)	Eligible (2)	Ineligible (3)	All (4)	Eligible (5)	Ineligible (6)
HH income (\$ thousands)						
<i>'04-'08 purchase</i>	98.75	24.00	45.71	113.41***	23.90	45.65
<i>'08-'11 refinance</i>	99.94	24.77	50.21	104.21***	24.81	50.21
Loan count						
<i>'04-'08 purchase</i>	646.16	30.15	49.34	661.30	38.49***	51.84***
<i>'08-'11 refinance</i>	389.01	20.09	21.51	324.44***	21.55***	21.17
Loan amount (\$ thousands)						
<i>'04-'08 purchase</i>	233.50	114.08	135.74	291.05***	117.84**	139.00***
<i>'08-'11 refinance</i>	203.13	122.83	148.46	245.20***	136.01***	166.76***
Interest rate (percent)						
<i>'04-'08 purchase</i>	6.06	6.18	6.09	6.06	6.18	6.09
<i>'08-'11 refinance</i>	4.98	4.88	4.89	4.98	4.86	4.88
Debt-to-income						
<i>'04-'08 purchase</i>	36.49	36.46	37.54	37.37***	36.44	37.50
<i>'08-'11 refinance</i>	31.81	31.92	32.47	33.46***	33.03***	33.00**
Combined loan-to-value						
<i>'04-'08 purchase</i>	80.32	77.37	80.68	78.19***	76.65	77.71***
<i>'08-'11 refinance</i>	67.05	58.97	63.60	63.76***	57.67**	61.93***
Credit score						
<i>'04-'08 purchase</i>	734.61	726.86	732.75	735.59**	726.63	733.93
<i>'08-'11 refinance</i>	753.31	756.39	756.67	752.94	756.80	757.57
Male (percent)						
<i>'04-'08 purchase</i>	59.29	45.46	53.26	60.09***	46.52**	54.39***
<i>'08-'11 refinance</i>	57.17	40.42	50.54	58.50***	43.21***	53.52***
Black (percent)						
<i>'04-'08 purchase</i>	19.05	20.10	20.89	14.87***	15.41***	15.53***
<i>'08-'11 refinance</i>	18.63	18.93	18.67	14.82***	14.56***	14.40***
Hispanic (percent)						
<i>'04-'08 purchase</i>	12.88	14.45	13.23	20.27***	20.39***	18.60***
<i>'08-'11 refinance</i>	9.61	11.53	11.00	17.12***	19.94***	18.87***

Table 6
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):

$$y_{i,c,t} = \alpha + \beta(\text{Eligible}_{i,c,t} \times \text{Comcast}_c \times \text{Post}_t) + X'_{i,c,t}\Phi + \rho_1(\lambda_t \times \gamma_c) + \rho_2(\text{Eligible}_{i,c,t} \times \lambda_t) + \rho_3(\text{Eligible}_{i,c,t} \times \gamma_c) + \epsilon_{i,c,t}.$$

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. $\text{Eligible}_{i,c,t}$ 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 a continuous measure for the fraction of a census tract's population with Comcast access 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)
$(\text{Eligible}_{i,c,t} \times \text{Comcast}_c \times \text{Post}_t)$	0.060*** (0.025)	0.060** (0.020)	0.002 (0.007)	0.003 (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 7

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:

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

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 in metropolitan PUMAs. 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 low-income and higher income ineligible. Panel B only uses low-income ineligible 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 since household moved to area, indicator for taxes included in mortgage payments, poverty status, and the Hauser and Warren Socioeconomic Index. All specifications incorporate eligibility-year, eligibility-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) (1)	Mortgage to income (2)
Panel A: All ineligible control group		
$(Eligible_{i,p,t} \times Comcast_p \times Post_t)$	-0.025** (0.011)	-0.015*** (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
Panel B: Low-income ineligible control group		
$(Eligible_{i,p,t} \times Comcast_p \times Post_t)$	-0.038** (0.015)	-0.014*** (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 8
Heterogeneous Effects by Bank Branch Access

This table reports the heterogeneous effects of Internet Essentials based on bank branch access. I estimate the following triple differences regression at the eligibility group level:

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

Dependent variables $y_{i,c,t}$ are the fraction of refinances mortgages originated by fintech lenders (column 1) and the number of originations (column 2). 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 a continuous measure for the fraction of a census tract's population with Comcast access 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 2 mile radius of a census tract's population center. I classify census tracts as low (bottom quintile), mid (third quintile), and high (top quintile) based on bank branch access. Group means (percent and loan count) are reported as of 2011, the last pre-treatment year. Column 1 reports OLS results and columns 2 through 4 report PPML results. All specifications include controls for average income and loan amount as well as 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	% Fintech (1)	Originations		
		Low (2)	Mid (3)	High (4)
$(Eligible_{i,c,t} \times Comcast_c \times Post_t)$	-0.006 (0.009)	0.091*** (0.035)	0.050 (0.036)	-0.021 (0.068)
Number of bank branches < 2 mi		4.12	14.97	57.92
Mean of dependent variable				
Eligible	4.30	7.08	6.34	3.93
Ineligible	7.16	6.70	5.82	3.82
Eligibility group controls	✓	✓	✓	✓
Fixed effects	✓	✓	✓	✓
Observations	72,578	22,626	18,608	4,872
Adjusted R^2	0.11	0.67	0.62	0.43

Table 9

Heterogeneous Effects by Educational Attainment

This table reports the heterogeneous effects of Internet Essentials relating to 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). The sample is from 2008 to 2015. $Eligible_{i,c,t}$ ($Eligible_{i,p,t}$) is an indicator for whether an eligibility group (household) qualifies for Internet Essentials. $Comcast_c$ is a continuous measure of Comcast coverage in census tract c and $Comcast_p$ is a binary indicator for Comcast availability in 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 (ACS 2007-2011 5-year estimates). Low and high census tracts refer to the bottom and top quartiles, respectively. In columns 5, 6, 7, and 8, I study owner-occupied households (with a mortgage) whose heads' educational attainment is high school diploma or less (low) and at least some college education (high). Columns 5 and 6 incorporate all ineligible as the control group and columns 7 and 8 only use low-income ineligible 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). Eligibility-year, eligibility-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)				
	Log(income) (1)	Low (2)	Mid (3)	High (4)	All ineligible Low (5)	High (6)	Low (7)	High (8)
$(Eligible_{i,p,t} \times Comcast_p \times Post_t)$	0.004 (0.012)				-0.054*** (0.015)	0.006 (0.013)	-0.083*** (0.020)	0.012 (0.020)
$(Eligible_{i,c,t} \times Comcast_c \times Post_t)$		0.125** (0.053)	0.044 (0.032)	0.059** (0.028)				
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 10

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 areas between 2008 and 2015. $Eligible_{i,c,t}$ ($Eligible_{i,p,t}$) is an indicator for whether a loan or eligibility group (household) qualifies for Internet Essentials. $Comcast_c$, $AT\&T_c$, and $Charter_c$ are continuous measures of Comcast, AT&T, and Charter coverage in census tract c , respectively. $Comcast_p$ is a binary 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. All specifications include controls for loan characteristics at origination (column 1), average income and loan amount (columns 2, 3, 4, and 5), and household characteristics (column 6). Eligibility-year, eligibility-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					
	Prepayment (1)	Baseline (2)	Placebo cutoff (3)	Placebo ISP (4)	Log(rent payment) (6)	
$(Eligible_{i,c,t} \times Comcast_c \times Post_t)$	0.033** (0.014)	0.060** (0.025)	0.003 (0.011)			
$(Eligible_{i,c,t} \times AT\&T_c \times Post_t)$			-0.009 (0.023)			
$(Eligible_{i,c,t} \times Charter_c \times Post_t)$						
$(Eligible_{i,p,t} \times Comcast_p \times Post_t)$				-0.009 (0.045)	0.006 (0.013)	
Mean of dependent variable						
Eligible	41.99	6.48	6.46	6.48	6.48	
Ineligible	59.76	6.09	6.79	6.09	6.09	
Controls						
Loan characteristics	✓	✓	✓	✓	✓	
Eligibility group						
Household						
Fixed effects	✓	✓	✓	✓	✓	
Observations	220,898	81,782	76,972	81,782	238,188	
Adjusted R^2	0.21	0.64	0.64	0.64	0.42	

Table 11
Falsification Tests for Likelihood of Program Access

This table studies the effect of Internet Essentials in census tracts that are more or less likely to be impacted by the program. The dependent variable in all specifications is the number of refinance originations by eligibility group. The sample is restricted to urban metropolitan areas between 2008 and 2015. $Eligible_{i,c,t}$ is an indicator for whether group i qualifies for Internet Essentials. $Comcast_c$ is a continuous measure of Comcast coverage in census tract c . $Post_t$ 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.

Dependent variable: Originations	School-aged children			Cost-burdened homeowners			Broadband subscription rate			
	Baseline (1)	Low (2)	Mid (3)	High (4)	Low (5)	Mid (6)	High (7)	Low (8)	Mid (9)	High (10)
$(Eligible_{i,c,t} \times Comcast_c \times Post_t)$	0.060*** (0.020)	0.007 (0.040)	0.078*** (0.030)	0.076*** (0.021)	0.024 (0.033)	0.054 (0.039)	0.163*** (0.047)	0.049 (0.044)	0.038 (0.037)	0.092*** (0.035)
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