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The Effects of ARRA Funding on Broadband Availability and Adoption

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The Effects of ARRA Funding on Broadband Availability and Adoption

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The Effects of ARRA Funding on Broadband Availability and Adoption

Submitted in partial fulfillment
of the requirements
for the Murray State University Honors Diploma

Katie Waide

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Abstract

The American Recovery and Reinvestment Act (ARRA), passed in 2009, provided funds to help the American economy recover from the 2008 economic crisis. More than $7 billion was designated to the advancement of broadband services, and critically, improvement in broadband infrastructure and adoption in underserved areas. This thesis sought to discover if there is a significant causal relationship between the amount of ARRA funding given to a U.S. state and its increase of broadband availability/adoption rates between 2010 (when all ARRA projects were announced), 2013, and 2016 (after all projects were completed). After running various regressions, I found that there is no such relationship between a state's logarithmic level of ARRA funding and percent increases in either availability or adoption rates. In fact, only one regression displayed any significant causal relationship at all: a *negative* relationship between funding received and a state's 2016 adoption rate. The results, explained below, contain lessons for policymakers going forward as society's dependence on high-speed internet continues to increase.

Keywords: broadband, ARRA, infrastructure, economic development

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The Effects of ARRA Funding on Broadband Availability and Adoption

The aftermath of 2008's "Great Recession" revealed an array of critical weaknesses in the American economy. After the collapse of the financial markets with Lehman Brothers' bankruptcy and the rupture of the housing bubble, legislators rushed to create a stimulus that would both kickstart the failing economy and address the vulnerabilities uncovered by the crisis. Recognizing the socioeconomic divides and deteriorating infrastructure that contributed to the historic recession, lawmakers passed the American Recovery and Reinvestment Act in early 2009 with the objective of "making supplemental appropriations for job preservation and creation, infrastructure investment, energy efficiency and science, assistance to the unemployed, and state and local fiscal stabilization" (American Recovery and Reinvestment Act [ARRA], 2009, p. 1).

One vulnerability that received attention from ARRA was broadband accessibility/adoption, particularly in unserved and underserved areas. ARRA directed $7.465 billion of funding toward three major agencies to accomplish its broadband infrastructure goals (Kruger, 2015). First, to tackle ARRA's emphasis on transparency, the act funneled $293 million to State Broadband Initiative (SBI) grants, allocated toward collecting, maintaining, and providing broadband data, alongside creating a publicly-accessible broadband map. Second, the National Telecommunications and Information Administration (NTIA) – overseen by the U.S. Department of Commerce (DOC) – received $3.936 billion for their Broadband Technology Opportunity Program (BTOP) to lay broadband infrastructure and encourage sustainable adoption of broadband services. Most of the BTOP funding – $3.46 billion – was allocated toward infrastructure (88%), with small percentages going toward public computer centers (5%) and sustainable broadband adoption programs (5%). Third, with an aim to address the particularly underserved rural areas of the U.S., the U.S. Department of Agriculture's (USDA) Rural Utilities Service (RUS) received $3.529 billion for broadband projects that impacted areas of at least 75% rural classification. Grants and loans allocated to RUS were managed through the Broadband Initiatives Program (BIP). Whereas the majority of BTOP's projects were "middle mile" projects – projects that process/enhance Internet services rather than cater to end users like firms and households – most BIP projects were "last mile", or accessible to the end user (Kruger, 2015).

One may question the true definition of *broadband adoption*, a valid concern given the vast number of changes that definition has undergone in recent years. One component of the definition is the infrastructure itself. The Federal Communication Commission (FCC) outlines six formats for broadband infrastructure – (1) digital subscriber line (DSL), (2) cable modem, (3) fiber optic cable, (4) wireless (i.e. Wi-Fi), (5) satellite, and (6) broadband over powerline (BPL) – with fiber optic cable having the fastest download/upload speeds (Federal Communication Commission [FCC], 2014). The type of infrastructure receiving investment is an important contributor to broadband adoption rates (see Prieger, 2015), and therefore, it is prudent to mention that the aforementioned infrastructure formats are included in our definition of broadband, but *mobile telephone* services (i.e. 3G, LTE) are not, as they did not receive outright funding from ARRA. As such, I do not measure mobile telephone adoption in this paper's analysis.

Perhaps more integral to broadband's definition, however, is the speed at which the end-user (i.e. the "last mile") can download/upload data, measured in bits-per-second (bps). In the FCC's First Broadband Deployment Report published in 1999, the benchmark definition of broadband – the benchmark which the ARRA first aimed to meet – was 200 kbps for both downloads and uploads. While an adequate benchmark at the time of its inception, the 200 kbps download/200 kbps upload benchmark soon became unreliable as the Internet transformed from almost entirely text-based websites to a network of complex, image-/video-embedded sites. In 2010, shortly after the passing of ARRA, the FCC published its Sixth Broadband Deployment Report, where the benchmark was raised to 4 Mbps download/1 Mbps upload. And now, the complexity of the Internet and its intended uses have again eclipsed the viability of the 2010 benchmark; with the popularization of video-based social media platforms such as Facebook, Instagram, and Twitter, the benchmark for the FCC's broadband adoption metrics have increased to its current state of 25 Mbps/3 Mbps. This benchmark was established in the FCC's 2015 Broadband Progress Report, announced before all ARRA projects were to be completed. In this paper, I will use the current 25 Mbps/3 Mbps benchmark as the standard for comparing broadband adoption between years, as it demonstrates if ARRA funding had a *sustainable* impact on broadband adoption.

As the world becomes increasingly interconnected, reliable broadband access is now critical to economic growth. And now, over a year into the COVID-19 pandemic and trudging through another world-changing recession, our communication infrastructure is experiencing unprecedented pressure to perform. Thus, it is timely to examine the success of ARRA to determine if large-scale national broadband funding has realistically led to significant increases in broadband availability and adoption, and if those outcomes still meet the relevant benchmark set by the FCC today.

Historically, analyses of ARRA and broadband adoption have either focused on specific subsections of the act – for example, BTOP's impact on adoption – or analyzed the more general topic of state aid on broadband adoption (Hauge & Prieger, 2015; Whitacre & Gallardo, 2020). Few researchers have specifically revisited ARRA using data *after* all ARRA projects were to be completed, which was in 2015. Therefore, this research will add valuable insight to the literature, as it reinvestigates the holistic success of ARRA using data following the 2015 project deadline imposed on award grantees. In Section II, I will review relevant literature regarding this topic. This will be followed by a brief overview of the data in Section III, including the methods used to build the regressions. Section IV will explain the results of the regressions, and the study will conclude in Section V.

II. Literature Review

To demonstrate the validity of ARRA funding as a method to encourage availability/adoption, I first analyze the factors that might affect a population's willingness or ability to adopt. Ford (2020) suggests two primary reasons why potential customers may not adopt broadband services: lack of availability, and price versus perceived relevance to the user. To reach the FCC's 25 Mbps/3 Mbps benchmark, internet service providers (ISPs) face the immense cost of installing infrastructure such as fiber optic cable, which USTelecom reported to average around $27,000 per mile in 2017 (Aman, 2017). For urban areas, it is often easy for an ISP to justify covering the entire census block (i.e. the narrowest level at which coverage is reported); urban blocks may indeed cover only a mile or two, and dense populations can make the investment quickly profitable. However, in sparsely populated rural areas, ISPs have little incentive to install hundreds of miles of cable to cover the widely-dispersed houses across a census block. And perhaps more importantly, census blocks can be considered "covered" if ISPs provide services to only *one* house in the block – and coverage means less competition. After all, in order to attract customers, ISPs in a competitive environment must incentivize their customers to choose their services over the competition's, either through lowering prices and/or providing higher quality services. To bypass the lower cost/higher quality requirement, then, ISPs often only provide coverage to a few houses in a block to "cover" the census block and ward off potential competition. However, this mischaracterization ultimately leaves massive rural populations in the "last mile" without broadband access. Therefore, because of a lack of availability, rural broadband adoption rates are relatively low compared to urban areas. And because broadband is now a necessity rather than a luxury, yet is not sufficiently allocated by the private sector, this issue reveals a market failure that necessitates some form of public funding to alleviate.

This lack of availability in rural and minority populations has led to the creation of broadband monopolies, where the lack of competition means that consumers have fewer choices regarding Internet services: cost, quality, customization, etc. The Institute for Local Self-Reliance (ISLR) details this in a 2018 study, finding that "when it comes to ISPs, subscribers often have a faux choice between unequal services, such as one telephone company offering slow DSL and one cable company that offers faster cable Internet access. People in rural America often have even fewer options because cable

ISPs do not provide broadband in less populated rural areas" (Trostle & Mitchell, 2018, para. 3). Monopolies, by definition, have no competition to regulate prices; and as the demand for broadband services increases, monopolies can charge high prices that may leave a lot of underserved, price-sensitive populations behind. If these populations do not perceive broadband as particularly relevant in their daily lives – which may often be the case in rural and underserved areas, where broadband/computer education is low – and services are provided at unattainable prices, broadband adoption rates will remain at uninspiring levels for affected communities (Ford, 2020).

Other researchers echo this analysis, with several additions to the discussion. The 2012 FCC report covered various reasons for the then-lackluster 40% adoption of Americans able to adopt benchmark services, including "lack of affordability, lack of digital literacy, and a perception that the Internet is not relevant or useful to them" (FCC, 2012, p. 5). Also, the 2015 Current Population Survey (CPS) Computer and Internet Use Supplement cited "Don't Need It/Not Interested" as the primary reason for non-adoption (55.2%), followed by "Too Expensive" (23.5%) and "No Computer" (7.3%), which supports the cruciality of price and relevance for adoption rates (U.S. Census Bureau, 2015). Additional context may be found in the research of Horrigan and Satterwhite (2010), who conclude that, alongside infrastructure and innovation, social support for users is vital to increased broadband adoption. The authors define social support as "the 'demonstration effect' that comes when people see others in their social networks using something new, which in turns helps people understand the value of trying something new" (Horrigan & Satterwhite, 2010, p. 2). This suggests that areas with few broadband education programs and low perceived importance of broadband will likely have low levels of adoption as well. This suggestion is supported by Prieger (2015) and Gant et al. (2010), who explain that the historic gaps in economic opportunity for US minorities have contributed to a lack of digital inclusion – and therefore a lack of social support – for fixed broadband access, which may explain the large gaps in fixed broadband adoption between whites and minorities. (It is important to note that this does not necessarily apply to mobile broadband services, however.)

It seems, then, that broadband funding directed toward concerns of price, relevance, social support, and broadband literacy/education would have a significant effect on broadband adoption rates. Ford does explain in a 2020 study that past broadband subsidies may have played a role in encouraging price-sensitive customers to adopt, alluding to the idea that state aid may effectively address the price factor of adoption. Belloc et al. (2012) also confirm this idea, finding both a positive and significant impact of demand- and supply-side investment on broadband penetration when policies target underserved areas. (Though it is important to note that only demand-side policies led to significant penetration in areas where broadband diffusion was in an advanced stage.) Another study conducted in the German state of Bavaria concludes that aid targeting underserved rural areas contributed to an 16.8-23.2% increase in broadband coverage depending on the resulting infrastructures' speed (Briglauer et al., 2016). However, while closing the "digital divide" between Bavarian rural and urban areas was an oft-used target by state funding efforts, the researchers found that the increases in broadband coverage did not significantly affect rural economic growth.

ARRA itself has received mixed reviews on its effectiveness. On one hand, its goals with the SBI, BTOP, and BIP grants all seem to point toward addressing the most important obstacles of broadband adoption. For example, by providing $293 million dollars to the SBI for improved transparency through broadband mapping, ARRA should have hypothetically curbed ISPs' monopoly power. Coverage information is now publicly available with more accurate data for potential public or private investors. This transparency should have paved the way for more competition, and because more competition leads to lower prices and more choices for consumers, one might suspect that ARRA funding would increase broadband adoption. As another example, BTOP was designed to catalyze adoption through its various projects: 123 grants for infrastructure, 66 grants for creation/expansion of public computer centers, and 44 grants for general sustainable broadband adoption (Kruger, 2015). Through the multifaceted funding of various availability/adoption factors (i.e. price reduction, relevance boosting, infrastructure provision, etc.), one might expect BTOP funding to play a significant role in broadband adoption. Jayakar and Park (2012) echo this idea by discussing the components of successful public computer center grants, praising BTOP's requirement of technical feasibility and community accessibility estimations for all grant applicants, which forces applicants to specify how the funding will directly address adoption components like availability, price, etc.

However, in their aforementioned study, Jayakar and Park (2012) also found that demand, more than supply, influences one's willingness to adopt broadband services; and BTOP is primarily a supply-side investment with few demand-side specifications. This led the researchers to conclude that BTOP may not have been a wholly efficient distribution of funds. Other studies have also found that the altruistic theory behind ARRA may not have necessarily led to its hoped-for outcomes in practice. In 2013, the same researchers found that BTOP, contrary to its intended purpose, was realistically allocated to areas that were not underserved and already had high broadband penetration. Additionally, Hauge and Prieger (2015), after an intensive econometric study, found that the effect of BTOP spending was relatively weak. "With such a high degree of uncertainty in the results, no sweeping claims can be made for the success of BTOP as regards the goal of sustainable adoption… Merely spending large amounts of money does not guarantee measurable gain in broadband adoption" (p. 27). Regarding broadband mapping, while transparency is a key for the prevention of monopolies, the world of telecom has long realized that the SBI-funded broadband mapping is misleading at best (Ford, 2019; Mack, 2019). As mentioned before, because broadband is only reported on the census block level using ISPs' self-reports (i.e. "Form 477"), many underserved households are being mischaracterized as "covered" – a mischaracterization that could be as high as 38% of households in some rural areas (Taglang, 2020). Therefore, the $293 million dollars granted to transparency through broadband mapping could, in the opinions of some, support the *sustainment* of monopolies rather than their dissolution (Mitchell, 2010). If these monopoly-like industries persist, they may encourage higher prices, less competition, and a larger divide between underserved and adequately served populations.

Between both positive and negative critiques of ARRA and general public broadband aid, there is a need to continue deciphering the overall effect of broadband financing if legislators and investors are to continue investing in broadband infrastructure. While a large body of literature exists covering various aspects of ARRA broadband – focuses on BTOP, rural funding, racial/ethnic gaps, etc. – there remains little research on the holistic impact of ARRA funding between states. Therefore, between the economic transformation awaiting life after COVID-19 and the aforementioned gaps in research, this project stands to add valuable insight to the existing literature.

III. Data and Methodology

The research question explored in this paper is as follows: *Is there a causal relationship between a state's ARRA award and its change in 25 Mbps/3 Mbps broadband availability/adoption in the years 2013 and 2016?* This question, though seemingly a simple one, explores ARRA funding from a variety of angles. For example, while one question, it actually examines four different subparts: (a) the effect of ARRA funding on benchmark broadband *availability* in *2013*, (b) the effect of ARRA funding on *availability* in *2016*, (c) the effect of ARRA funding on *adoption* in *2013*, and (d) the effect of ARRA funding on *adoption* in *2016*. The multidimensional examination of these subparts allows for more robust conclusions; if trends move in the same direction when comparing the subparts, then our analysis should possess additional evidence in support of its accuracy – and vice versa if this is not the case. Also, this question explores ARRA-funded projects in their most important stages of development: inception (i.e. 2010), construction (i.e., 2013), and completion (i.e. 2016). Though this study is a cross-sectional study, the research question itself explores data in a chronological way. By examining years throughout the ARRA projects' progress, we can explore the speed at which availability and adoption increased from the outset of the program and determine if time is also a factor in any possible significance of ARRA funding.

To start the process, data corresponding to the treatment variable – the natural logarithm of grants and loans awarded during ARRA funding – was found. The data used to measure these grants and loans originates from the NTIA's 2010 report, and was sourced from Kruger's *Background and Issues for Congressional Oversight of ARRA Broadband Awards* (2015). It is worth noting that these grants and loans – expressed in millions of dollars in Kruger's (2015) dataset – were allocated differently according to the program from which they were granted. BTOP, the subsidiary of NTIA, solely awarded grants as a part of its program, meaning awardees were not required to pay back monies to NTIA after its award had been allocated. On the other hand, BIP could be allocated in the form of grants, loans, or grant/loan combinations, which required the loan awardees to pay back either a portion or the full amount of the loan (plus interest) once the project had been completed. Though perhaps not explicit, one potential effect of BIP loans on broadband availability/adoption could be the difficulty of paying back loans during the aftermath of the Great Recession. One such example is the Lake County Fiber Network in Lake County, MN, whose project was suspended due to financial instability and likelihood of default (Kruger, 2015). If a state received more loan money relative to grant money, then there could be a higher chance that the project was not completed due to financial instability, which could play a small role in the state's availability/adoption in later years. Still, because it is fairly implicit, this effect will simply be included in the error term.

For the dependent variables, I examined the change in broadband adoption/availability rates per state from 2010 to 2013, then 2010 to 2016. To start, data from SBI's September 2011 National Broadband Map Dataset were used for the 2010 benchmark broadband availability/adoption (State Broadband Initiative [SBI], 2011). According to the FCC (2015), "The SBI data provide information for each census block about each broadband provider's advertised ability to deliver broadband services. The SBI data identify the maximum speed a provider asserts that it can deliver, if requested, within a typical service interval" (p. 38). Interestingly, the maximum-advertised download speed by any state in 2010, according to the SBI's national datasets, was 11 Mbps, which does not come close to meeting today's 25 Mbps benchmark. Therefore, for both availability and adoption of 25 Mbps/3 Mbps in 2010, all states' 2010 rates were set to 0%, as *no* provider in *no* census block in *no* state had reached the required 25 Mbps download speed. Next, the availability/adoption rates for 2013 and 2016 were extracted from the FCC's 2015 Broadband Progress Report and 2018 Broadband Progress Report, respectively. (Note the lag in data collection, as the 2015 report's most current data is from 2013. The same applies for the 2018 Broadband Progress Report's current data from 2016.) Broadband *availability* data originates from SBI national datasets in December 2013; and while earlier data is used from SBI in the progress report, the 2018 report uses Form 477 data to measure 2016 broadband availability (SBI, 2014; FCC, 2016). Form 477 data is collected by the FCC, and is the standardized, mandatory form for ISPs to self-report the range and quality of their broadband services per census block. As previously discussed, Form 477 data is not celebrated as being particularly accurate and is widely known to overstate broadband coverage across the US, especially in rural areas. However, as this is the most standardized form of broadband coverage data available, Form 477 is still the most reliable data for research. Broadband *adoption* data for both 2013 and 2016 also originate from Form 477 data, and are sourced from the FCC's 2015 and 2018 broadband reports, respectively (FCC, 2013; FCC, 2016).

One may note that the National Broadband Map provides more granular data than the regression in this study covers. Still, while more narrow data – even down to the census block – is available for the dependent variables, the most granular, publicly-available data for ARRA funding (i.e. the treatment variable) is at the state level, which is why I make state-by-state comparisons instead of county-by-county or block-by-block. In the future, this project may be improved upon by requesting permission from the NTIA and USDA, if possible, for more miniscule funding data regarding ARRA funding divisions.

To prevent omitted variable bias, controls were added to the regressions as well. As for availability, the primary influence on broadband coverage outside of ARRA funding is, in fact, other funding from the private and public sector. While ARRA represents a major portion of funding from 2010-2016, it was by no means the only source, and those other sources may have played a role in changing broadband coverage from 2010 to 2013 and 2016. For example, in the later years of the ARRA construction period, projects like 2014's $3.75 billion Connect America Fund (CAF) were also awarded to promote broadband deployment (U.S. Department of Commerce [DOC], 2015). However, partly due to time constraints and partly due to very limited access to the necessary data, the influences of these outside funding initiatives were not included in this study’s regression controls; they are instead included in the error term. Part of this exclusion is justified by limiting availability/adoption data to 2010-2016, when ARRA funding made up the vast majority of funding initiatives and CAF projects were mostly still under construction, and thus unlikely to significantly influence availability/adoption rates. Still, excluding outside funding may contribute to some omitted variable bias, and thus is another item for future improvement discussed further in Section V.

To make up for this omission, I included other controls that may influence private investment, the key to broadband availability. The first is *median household income*. As discussed in Section II, states with a higher median household income have historically attracted more broadband investment from the private sector because people with higher incomes are able to pay higher prices. Additionally, as higher paying jobs are now generally internet-dependent, states with higher median household incomes will likely have a higher demand for high-speed internet access, which makes private broadband investment even more lucrative. Due to this potential impact on broadband availability, its effect is controlled using state-by-state median household income data from the 2010 American Community Survey via the U.S. Census Bureau (2010a). Next, I use the *concentration of minorities* and *percentage of rural population*. Traditionally, rural and minority groups have been underserved in broadband coverage, as ISPs invest where they know their investment will be profitable. As previously explained, the fiber optic cable necessary for 25 Mbps/3 Mbps speeds costs more than $27,000 per mile. For populations that are less likely to pay for the ISPs services and/or are widely dispersed – where there are only a few potential subscribers per mile – ISPs are less likely to find their investment profitable, and may refrain from providing broadband services to these areas. Therefore, to control for the potential negative effect of minority and rural populations on private broadband investment (and therefore availability), I include two variables: the state-by-state percentage of blacks from the 2010 American Community Survey and the state-by-state percentage of rural populations from the 2010 U.S. Census (U.S. Census Bureau, 2010a; 2010b). Our final control is *education*. Similar to the discussion for median household income, a higher level of education attracts more advanced industries; as these industries often have a dependence on broadband, education makes an area more lucrative for private broadband investment. To control for education's impact on broadband availability, I use two state-by-state samples – the percentage of people with *only* a high school degree, and the percentage of people with a graduate degree – from the 2010 American Community Survey (U.S. Census Bureau, 2010a). I run two separate regressions for each question subpart, divided between GED percentage and graduate degree percentage, for two reasons. First, any attempt to include them in the same variable (i.e. the percentage of people with a GED or higher) was met with multicollinearity issues, and thus required more narrow data. Multicollinearity is shown in Figures 1 and 2. Second, the two variables explore somewhat separate effects; a relatively high percentage of GED-only residents may lead to relatively lower broadband investment, while a relatively high percentage of graduate degree recipients may lead to the opposite. Therefore, I found it prudent to explore both effects separately.

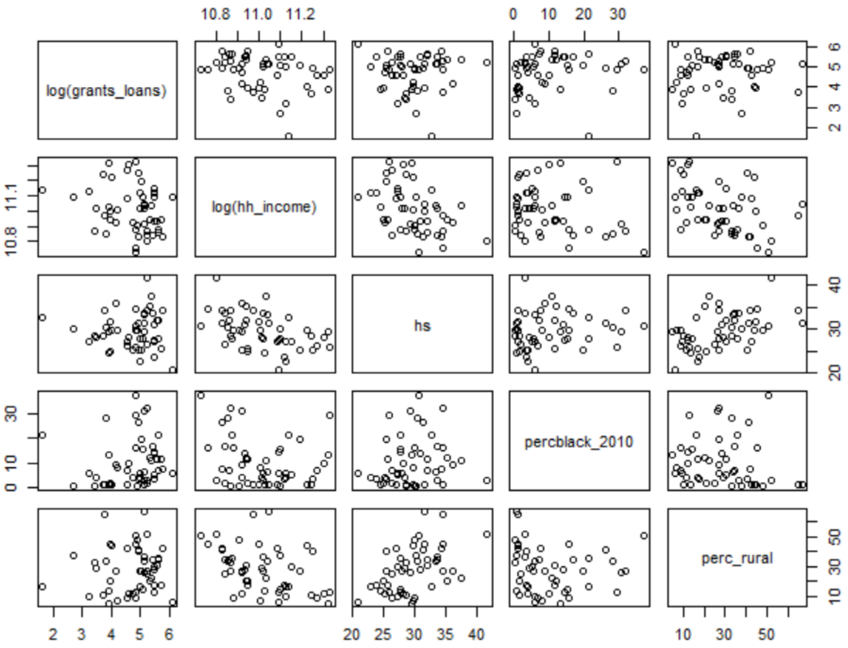


Figure 1. Multicollinearity of GED control.

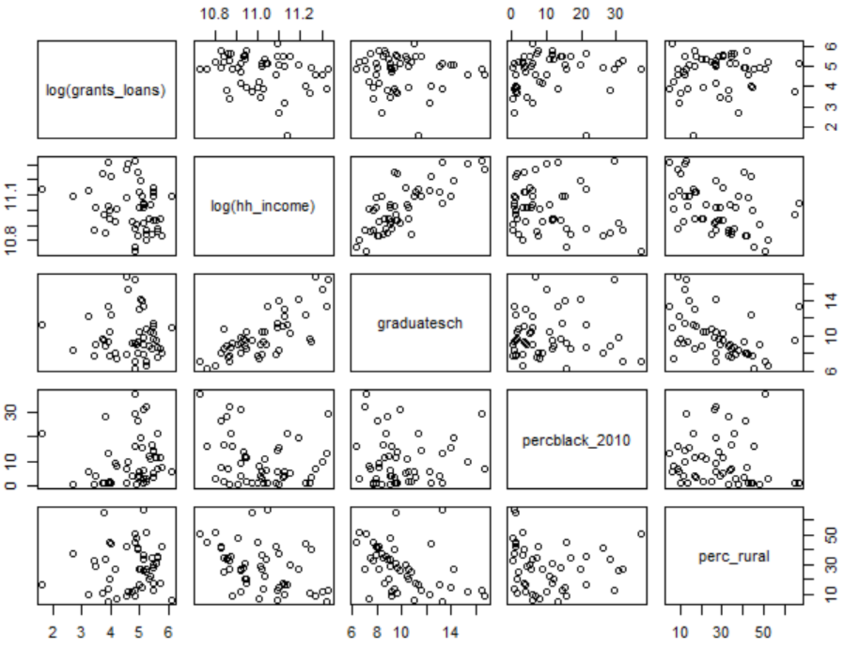


Figure 2. Multicollinearity of graduate degree control.

Controls for the adoption regressions will use the same controls to the availability regressions: the state's median household income, percentage of black residents, percentage of rural residents, and education (GED and graduate degree). However, whereas the controls for availability correspond with the potential behavior of investors, the controls for adoption correspond with the potential behavior of consumers. The main influences that may have impacted adoption in 2010, covered in Section II, were relevance, price, social support, literacy/education, and concentration of underserved populations (rural and minority). Median household income covers the majority of these factors. A highly-paid worker likely sees broadband as both relevant and affordable, and will have the resources and social support to ease the adoption process, making him or her more likely to adopt. States, then, with higher median household incomes may experience higher adoption rates independent of ARRA funding, necessitating a control. Next, minorities and rural populations often must pay unfeasible prices for broadband, and because broadband is often not widely available due to insufficient private investment, they often do not have the resources or social support that boost subscribership. Therefore, relatively higher percentages of these groups compared to other states could stymie broadband adoption, which also necessitates a control. Finally, states with high percentages of GED-only residents likely have lower literacy/education on broadband services and may have many residents who see broadband adoption as unnecessary; the opposite is true for states with a large graduate-degree population. As these populations may have influenced adoption in years following ARRA, I included separate education controls for GED and graduate degree percentages as I did for availability.

Table 1 shows a summary of descriptive characteristics for outcome measures, the treatment variable, and control variables.

	Overall (N=50)
ARRA Funding	
Mean (SD)	146 (94.0)
Median [Min, Max]	141 [5.00, 444]
ARRA Funding (Log)	
Mean (SD)	4.70 (0.880)
Median [Min, Max]	4.95 [1.61, 6.10]
25/3 Broadband Availability 2013 (Percent)	
Mean (SD)	77.6 (19.5)
Median [Min, Max]	83.0 [13.0, 99.0]
25/3 Broadband Availability 2016 (Percent)	
Mean (SD)	89.8 (6.77)
Median [Min, Max]	90.8 [72.3, 99.1]
25/3 Broadband Adoption 2013 (Percent)	
Mean (SD)	28.9 (13.0)
Median [Min, Max]	29.0 [3.00, 52.0]
Missing	8 (16.0%)
25/3 Broadband Adoption 2016 (Percent)	
Mean (SD)	51.5 (13.9)
Median [Min, Max]	50.9 [28.8, 81.7]
Missing	2 (4.0%)
Household Income	
Mean (SD)	61300 (9630)
Median [Min, Max]	60500 [45500, 83100]
Household Income (Log)	
Mean (SD)	11.0 (0.153)
Median [Min, Max]	11.0 [10.7, 11.3]
Black Population (Percent)	
Mean (SD)	10.3 (9.60)
Median [Min, Max]	7.00 [0.500, 37.3]
Rural Population (Percent)	

	Overall (N=50)
Mean (SD)	28.0 (15.2)
Median [Min, Max]	27.0 [5.08, 67.0]
Population with GED ONLY (Percent)	
Mean (SD)	29.7 (4.05)
Median [Min, Max]	29.6 [20.8, 41.6]
Population with Graduate Degree (Percent)	
Mean (SD)	9.99 (2.47)
Median [Min, Max]	9.40 [6.30, 16.7]

Table 1. Descriptive statistics.

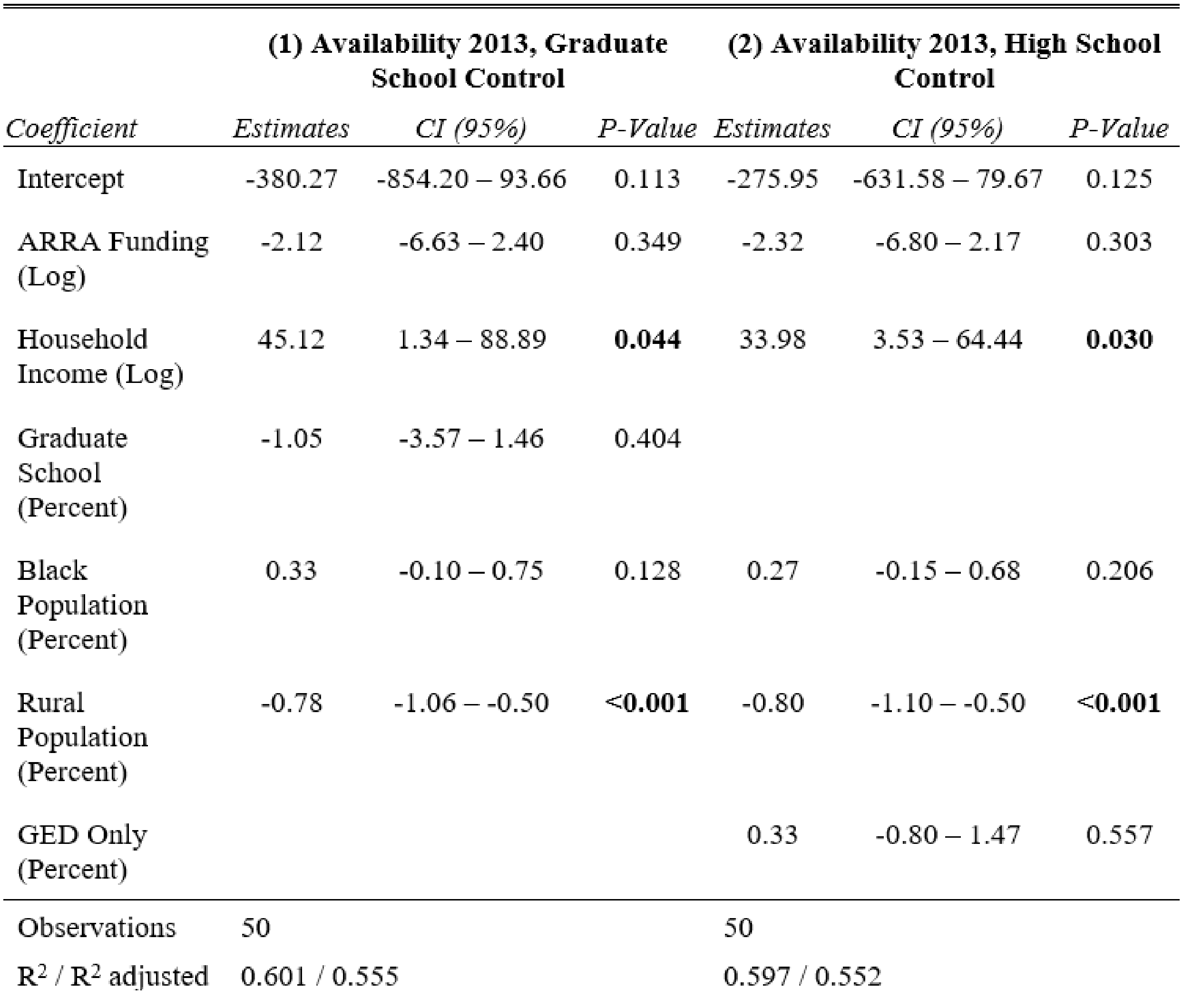
Let β_1 denote the coefficient for log ARRA award amount awarded in state *i*, where awards are in millions of dollars, and let β_0 denote the intercept. Then, let y_i denote broadband availability rates, and let z_i denote broadband adoption rates. Control coefficients, all values in 2010, will be denoted as follows: β_2 for the natural logarithm of median household income, β_3 for the percentage of black residents in a state's population, β_4 for the percentage of rural residents in a state's population, β_5 for the percentage of residents with only a GED, and β_6 for percentage of residents with a graduate degree. The error term is denoted by ε_{it}. The following eight regressions will be used for this thesis:

1. 2013, $y_i = \beta_0 + \beta_1 log(ARRA_i) + \beta_2 log(Income_i) + \beta_3 Black_i + \beta_4 Rural_i + \beta_5 GED_i + \varepsilon_i$
2. 2013, $y_i = \beta_0 + \beta_1 log(ARRA_i) + \beta_2 log(Income_i) + \beta_3 Black_i + \beta_4 Rural_i + \beta_6 Grad_i + \varepsilon_i$
3. 2016, $y_i = \beta_0 + \beta_1 log(ARRA_i) + \beta_2 log(Income_i) + \beta_3 Black_i + \beta_4 Rural_i + \beta_5 GED_i + \varepsilon_i$
4. 2016, $y_i = \beta_0 + \beta_1 log(ARRA_i) + \beta_2 log(Income_i) + \beta_3 Black_i + \beta_4 Rural_i + \beta_6 Grad_i + \varepsilon_i$
5. 2013, $z_i = \beta_0 + \beta_1 log(ARRA_i) + \beta_2 log(Income_i) + \beta_3 Black_i + \beta_4 Rural_i + \beta_5 GED_i + \varepsilon_i$

6. 2013, $z_i = \beta_0 + \beta_1 log(ARRA_i) + \beta_2 log(Income_i) + \beta_3 Black_i + \beta_4 Rural_i + \beta_6 Grad_i + \varepsilon_i$
7. 2016, $z_i = \beta_0 + \beta_1 log(ARRA_i) + \beta_2 log(Income_i) + \beta_3 Black_i + \beta_4 Rural_i + \beta_5 GED_i + \varepsilon_i$
8. 2016, $z_i = \beta_0 + \beta_1 log(ARRA_i) + \beta_2 log(Income_i) + \beta_3 Black_i + \beta_4 Rural_i + \beta_6 Grad_i + \varepsilon_i$

IV. Results and Discussion

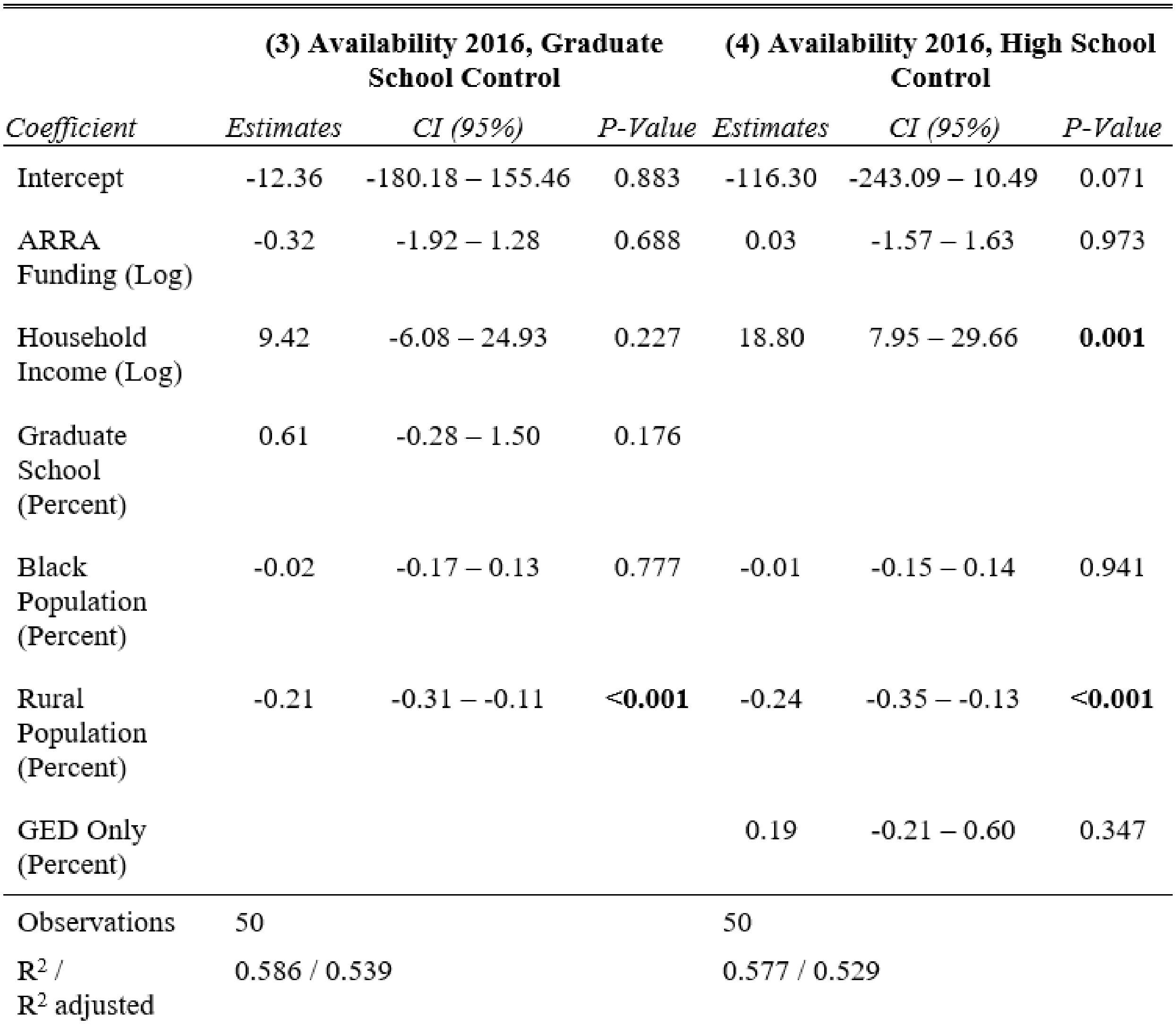
The results for the regressions above are displayed in Tables 2-6.



	(1) Availability 2013, Graduate School Control			**(2) Availability 2013, High School Control**		
Coefficient	*Estimates*	*CI (95%)*	*P-Value*	*Estimates*	*CI (95%)*	*P-Value*
Intercept	-380.27	-854.20 – 93.66	0.113	-275.95	-631.58 – 79.67	0.125
ARRA Funding (Log)	-2.12	-6.63 – 2.40	0.349	-2.32	-6.80 – 2.17	0.303
Household Income (Log)	45.12	1.34 – 88.89	**0.044**	33.98	3.53 – 64.44	**0.030**
Graduate School (Percent)	-1.05	-3.57 – 1.46	0.404			
Black Population (Percent)	0.33	-0.10 – 0.75	0.128	0.27	-0.15 – 0.68	0.206
Rural Population (Percent)	-0.78	-1.06 – -0.50	**<0.001**	-0.80	-1.10 – -0.50	**<0.001**
GED Only (Percent)				0.33	-0.80 – 1.47	0.557
Observations	50			50		
R^2 / R^2 adjusted	0.601 / 0.555			0.597 / 0.552		

Table 2. Results from regressions 1 and 2.

First, Table 2 shows the results of regressions measuring the effect of ARRA funding and various controls on broadband availability rates in 2013, separated by controls for graduate and high school levels of education. For regressions 1 and 2, the coefficients achieving a p-value of less than 0.05 – the definition of “significant” used in this study – were the natural logarithm of household income and the state’s percentage of rural population. In other words, the significant coefficients in, say, regression 2 first show that a 10% increase in a state’s median household income correlates with around a 3.4% increase in 25 Mbps/3 Mbps broadband availability in the state. Then, for every 1% more concentrated a state’s rural population is compared to other states, there is a small but very significant decrease in availability of 0.8%. The same progression applies



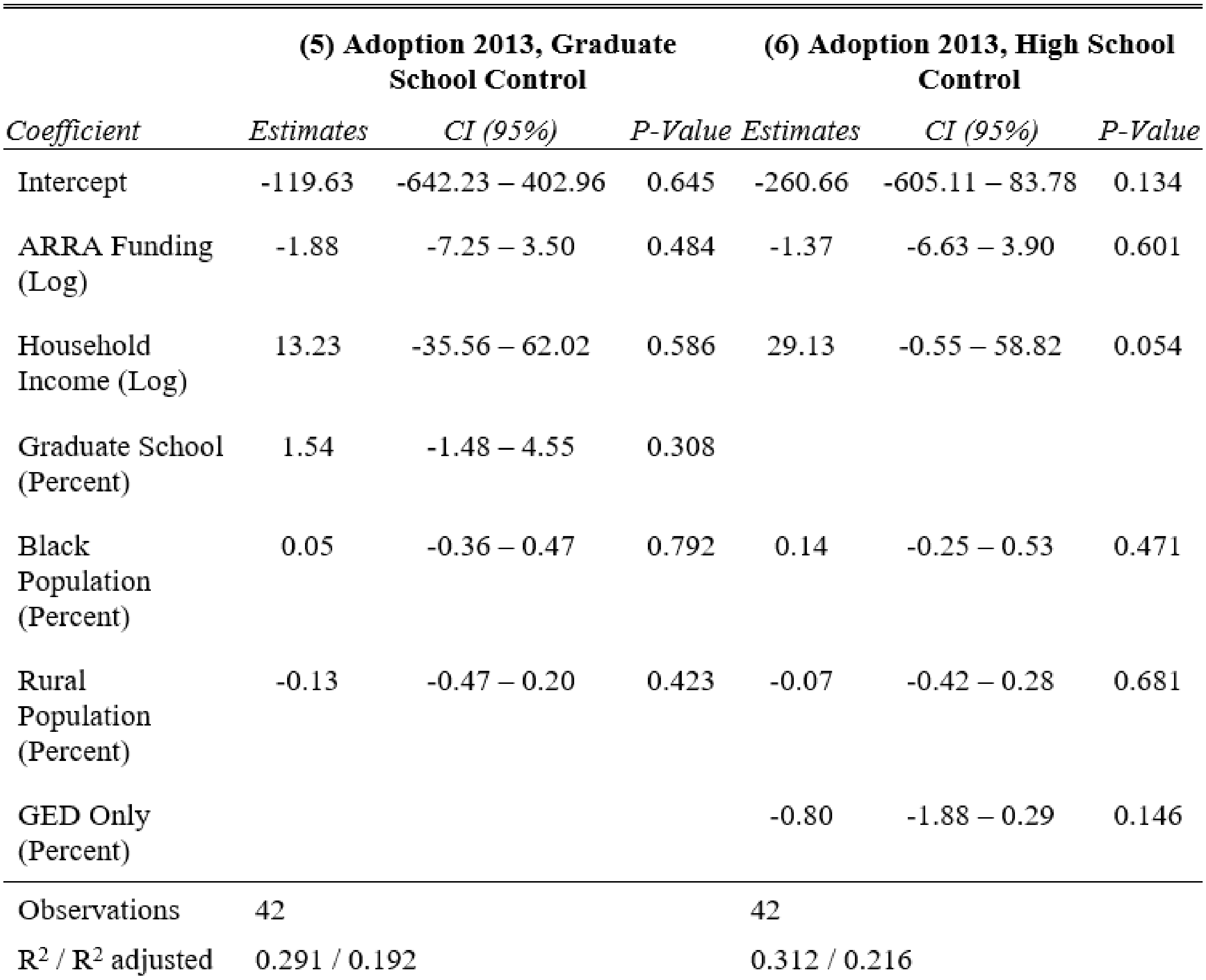
	(3) Availability 2016, Graduate School Control			**(4) Availability 2016, High School Control**		
Coefficient	*Estimates*	*CI (95%)*	*P-Value*	*Estimates*	*CI (95%)*	*P-Value*
Intercept	-12.36	-180.18 – 155.46	0.883	-116.30	-243.09 – 10.49	0.071
ARRA Funding (Log)	-0.32	-1.92 – 1.28	0.688	0.03	-1.57 – 1.63	0.973
Household Income (Log)	9.42	-6.08 – 24.93	0.227	18.80	7.95 – 29.66	**0.001**
Graduate School (Percent)	0.61	-0.28 – 1.50	0.176			
Black Population (Percent)	-0.02	-0.17 – 0.13	0.777	-0.01	-0.15 – 0.14	0.941
Rural Population (Percent)	-0.21	-0.31 – -0.11	**<0.001**	-0.24	-0.35 – -0.13	**<0.001**
GED Only (Percent)				0.19	-0.21 – 0.60	0.347
Observations	50			50		
R^2 / R^2 adjusted	0.586 / 0.539			0.577 / 0.529		

Table 3. Results from regressions 3 and 4.

to regression 1 as well; however, because regression 2 suffers from less multicollinearity issues than regressions 1 (due to the graduate school variable having relatively higher correlation with other variables), more focus will be put on the results of high-school-controlled regressions.

As for Table 3, the results of regressions measuring the effect of ARRA funding and various controls on broadband availability rates in 2016 – when all ARRA projects were completed – are displayed. For regression 4, the most significant effects on broadband availability were again the natural logarithm of household income and the state's percentage of rural population. However, for regression 3 – controlling for graduate degrees instead of high school degrees – only the percentage of a state's rural population had any significant impact on broadband availability (which, again, was a negative effect). In regression 4, the significant coefficients first show that a 10% increase in a state's median household income leads to a 1.88% increase in broadband availability in the state. Then, for every 1% relative increase in a state's rural population, there is again a slight but very significant decrease in availability of 0.24%.

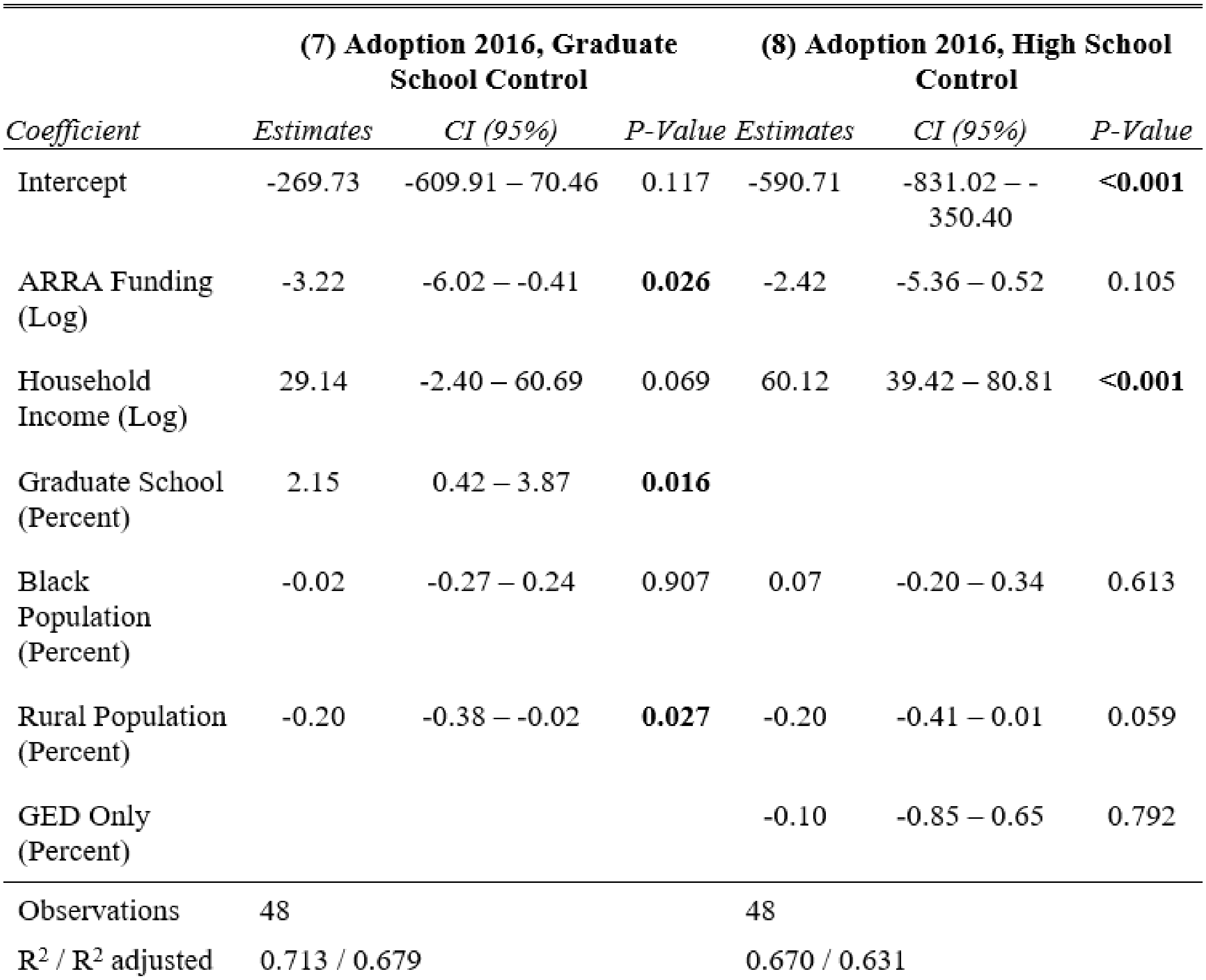
Next, we turn from availability to adoption rates. Interestingly, when examining Table 4, there is no significant coefficient on adoption in 2013 included in the regression. This outcome may be partly due to time; at least where construction of ARRA projects is concerned, it is possible that not enough time has passed for any effect of ARRA on availability to be significant. However, time cannot necessarily explain the insignificance of all these variables, and in fact, the coefficients from these regressions only explain about 30% of the variation in broadband availability rates from 2010 to 2013. Compared to regression 7, where coefficients explain over 70% of the variation in 2016 broadband adoption, an R^2 of 30% is not as suitable for reliable analysis. As explained before, omitted variable bias could also be an explanation for this discrepancy, especially regarding private broadband funding. However, given our restraints in using private funding data, regressions 5 and 6 will simply be considered non-explanatory for this study.



	(5) Adoption 2013, Graduate School Control			**(6) Adoption 2013, High School Control**		
Coefficient	*Estimates*	*CI (95%)*	*P-Value*	*Estimates*	*CI (95%)*	*P-Value*
Intercept	-119.63	-642.23 – 402.96	0.645	-260.66	-605.11 – 83.78	0.134
ARRA Funding (Log)	-1.88	-7.25 – 3.50	0.484	-1.37	-6.63 – 3.90	0.601
Household Income (Log)	13.23	-35.56 – 62.02	0.586	29.13	-0.55 – 58.82	0.054
Graduate School (Percent)	1.54	-1.48 – 4.55	0.308			
Black Population (Percent)	0.05	-0.36 – 0.47	0.792	0.14	-0.25 – 0.53	0.471
Rural Population (Percent)	-0.13	-0.47 – 0.20	0.423	-0.07	-0.42 – 0.28	0.681
GED Only (Percent)				-0.80	-1.88 – 0.29	0.146
Observations	42			42		
R^2 / R^2 adjusted	0.291 / 0.192			0.312 / 0.216		

Table 4. Results from regressions 5 and 6.

Finally, in Table 5, we examine the results of regressions measuring the effect of ARRA funding and various controls on broadband adoption rates in 2016. The only significant effect captured in regression 8 – the high-school-controlled regression – was the natural logarithm of the median household income; for every 10% relative increase in a state's median household income, the state's adoption rate increased by about 6%. In regression 7, however, there are three significant coefficients, including the treatment variable: ARRA funding. First, regarding the graduate school coefficient, a 1% relative increase in a state's percentage of graduate degree holders leads to a 2.15% increase in the state's adoption rate. Then, for every 1% relative increase in a state's rural population, there is an unsurprising significant decrease in adoption of 0.20%. Most surprising, however, is the coefficient of the ARRA funding variable. Discussed further



	(7) Adoption 2016, Graduate School Control			**(8) Adoption 2016, High School Control**		
Coefficient	*Estimates*	*CI (95%)*	*P-Value*	*Estimates*	*CI (95%)*	*P-Value*
Intercept	-269.73	-609.91 – 70.46	0.117	-590.71	-831.02 – -350.40	**<0.001**
ARRA Funding (Log)	-3.22	-6.02 – -0.41	**0.026**	-2.42	-5.36 – 0.52	0.105
Household Income (Log)	29.14	-2.40 – 60.69	0.069	60.12	39.42 – 80.81	**<0.001**
Graduate School (Percent)	2.15	0.42 – 3.87	**0.016**			
Black Population (Percent)	-0.02	-0.27 – 0.24	0.907	0.07	-0.20 – 0.34	0.613
Rural Population (Percent)	-0.20	-0.38 – -0.02	**0.027**	-0.20	-0.41 – 0.01	0.059
GED Only (Percent)				-0.10	-0.85 – 0.65	0.792
Observations	48			48		
R^2 / R^2 adjusted	0.713 / 0.679			0.670 / 0.631		

Table 5. Results from regressions 7 and 8.

below, a 10% in a state’s ARRA funding actually led to a significant *decrease* in adoption of 0.322%, which is certainly counterintuitive to the goals of ARRA.

Before we examine the possible reasoning behind this occurrence, it is prudent to acknowledge some other interesting phenomena from the resulting statistics. First, one interesting result reinforced by multiple regressions is a highly significant decrease in availability and adoption related to the presence of a higher rural population. Perhaps this result should not be fully surprising. Before ARRA projects were completely finished (i.e. 2013), it would make sense that urban states would have higher levels of availability due to the lucrativeness of private broadband investment in highly-populated areas; the higher the rural percentage, the lower the broadband availability. This idea is shown in Figure 3. Yet as one might hope, ARRA funding seemed to have some effect in levelling the playing field, at least for broadband availability. From 2010 to 2013, a 1% increase in a state’s rural population percentage caused a 0.80% reduction in its relative broadband availability. However, from 2010 to 2016, that number dropped to only a 0.24% decrease. While the optimal result would be 0% (i.e. a state’s rurality has no effect on its broadband availability), the closing discrepancy between rural and urban states’ availability is encouraging. However, due to the uncertain results of 2013, no such comparison can be made for adoption, and should be expanded upon in further studies.

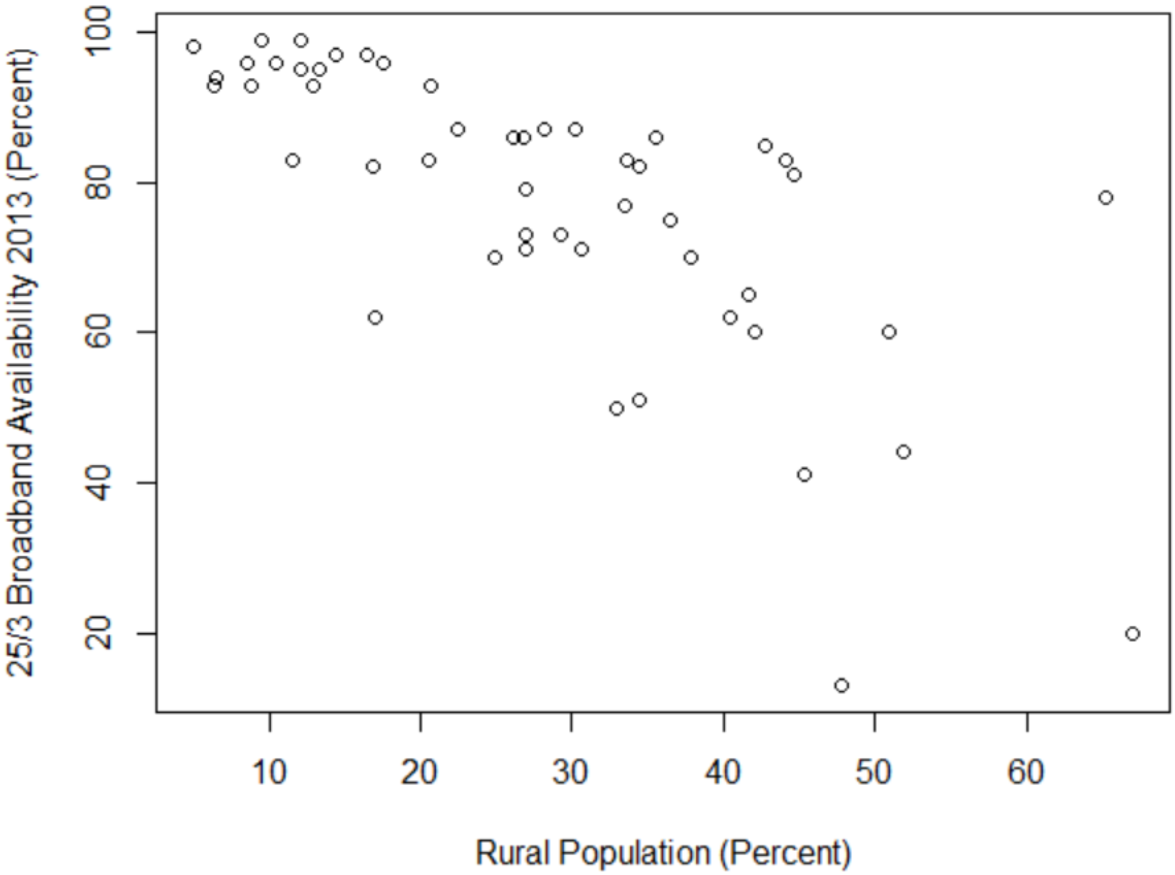


Figure 3. The effect of rural population on availability rates in 2013.

Most important to the discussion, however, is the effect of ARRA funding on the dependent variables. There are two primary concerns that come from the outcomes in Tables 2-6. The first is that, for all regressions except regression 7, the natural logarithm of ARRA funding had no significant effect on availability nor adoption. For example, according to Table 3, there is a 95% chance that a 10% increase in ARRA funding caused anything from a 0.157% decrease to a 0.163% increase in 2016 broadband availability. Said differently, there is a 97.3% chance that the resulting coefficient of 0.03% was caused by something other than ARRA funding. Therefore, we cannot say that funding played any important role in improving broadband availability or adoption.

Why did this outcome occur? One reason may again be time constraints. Regarding the 2013 regressions, many ARRA projects were not yet completed, and some had not even broken ground. The resulting lag could explain why the vast majority of changes in broadband availability/adoption between 2010 and 2013 were not due to ARRA funding, but because of other forces already at work during the time period.

However, even in 2016 – when all projects were to be completed – ARRA funding only had a significant effect in one regression…and it was *negative*. This is the other concern from the outcomes of Tables 2-6. In regression 7, the coefficient for a 10% increase in a state's ARRA award is -0.322%; therefore, if a state's relative award increases by 10%, their percentage of broadband adoption decreases by 0.322%. This result may seem counterintuitive. After all, if a state receives funding for express purpose of increasing broadband adoption, how could adoption decrease? The story lies in the spread. Figure 4 shows the relationship between ARRA funding and adoption rates in 2016. Notably, the top three highest and lowest adoption rates belonged to states in the bottom 50% – below $140.24m – of award recipients:

1) New Jersey (81.7%, $49.7m)
2) Delaware (81.2%, $5m)
3) Massachusetts (79.1%, $94.5m)

-

48) Maine (30.2%, $42.6m)
49) Arkansas (29.3%, $128.5m)
50) Mississippi (28.8%, $127.3m)

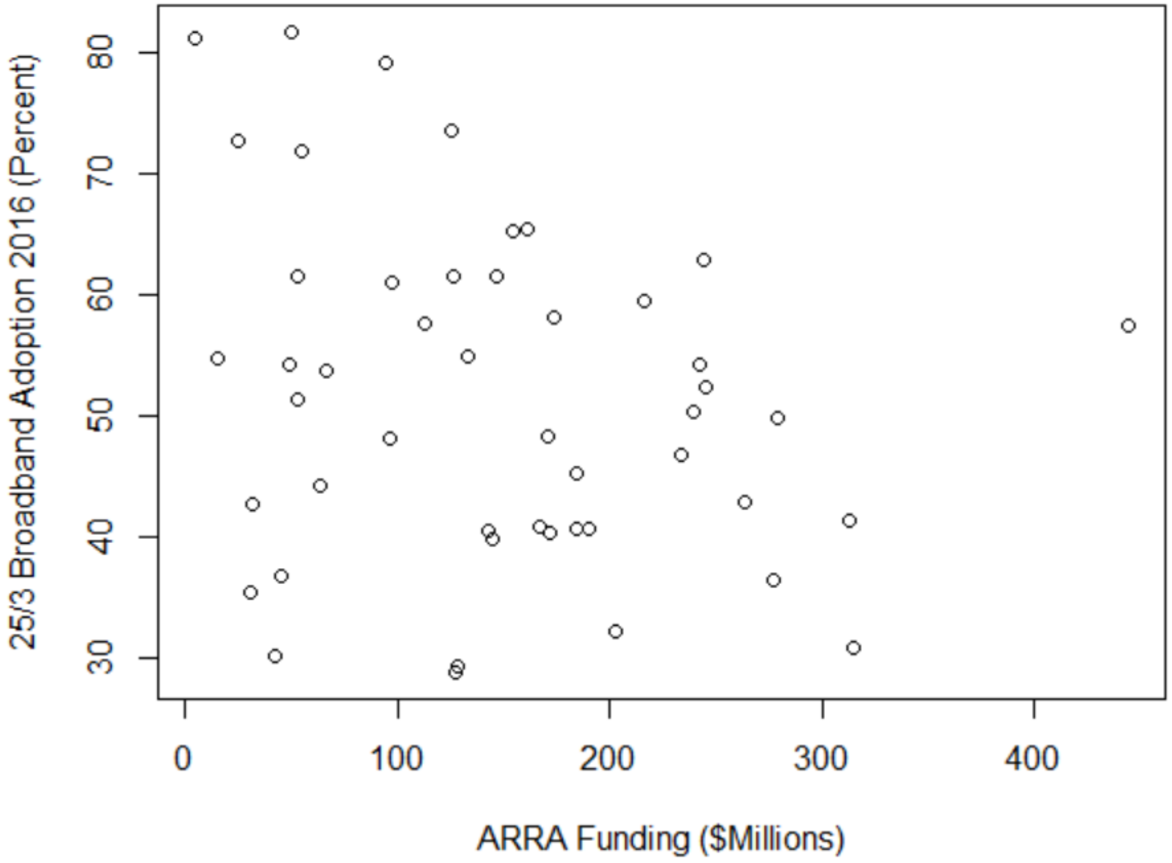


Figure 4. The relationship between ARRA funding and adoption rates in 2016.

Because the spread of adoption is so wide for lower amounts of funding, yet there is less of a spread (and lower rates) at higher amounts, the coefficient is negative. Still, one might question why the spread of adoption rates is so large among lower amounts of funding, or perhaps even more importantly, why adoption rates were consistently lower for states that received larger amounts of funding. For low amounts of funding, the spread of adoption could be high for a variety of reasons. One is that, at least on the high end of broadband adoption, the states that received the least amount of funding should have been the ones who needed the least public assistance. This matches the picture painted in the FCC's 2015 Broadband Progress Report; the top three states for adoption rates already possessed the highest adoption rates for lower broadband speeds (10 Mbps/1 Mbps, specifically), so they were less likely to be classified as “underserved” and less likely to receive high amounts of ARRA funding. Consequently, these states also happen to rank in the top ten for median household income (U.S. Census Bureau, 2010). Therefore, consistent with the findings of Horrigan and Satterwhite (2010), these states likely offer an environment where broadband adoption is not only supported by social networks, but also *required* by higher-paying, internet-dependent industries. Their high spikes in adoption, then, are likely due to an already-fertile environment for broadband adoption to occur rather than high amounts of ARRA funding. In other words, these places did not need much incentive to adopt broadband because they already have the income and support to do so, so even the little investment they received caused a large increase in adoption. However, the opposite is true for states on the lower end of the adoption spectrum. Arkansas and Mississippi, the states with the lowest adoption rates, also ranked 49th and 50th for household income in 2016. They were also among the 5 lowest adopters of 10 Mbps/1 Mbps broadband. Still, they received below-median amounts of ARRA funding, which explains the large spread of adoption rates below the median funding amount. It does not, however, explain why the struggling states did not get higher amounts of funding, especially considering that ARRA was specifically designed to provide broadband services in underserved and underequipped states. The fact that Arkansas and Mississippi – the states with the lowest household incomes in 2016 – also received the lowest amounts of ARRA funding should be a red flag for the effectiveness of ARRA allocation, as ARRA was supposed to target underserved areas.

Finally, the question of adoption for the upper half of awardees: Why did broadband adoption become relatively lower as the amount of ARRA funding increased? According to Figure 4, states receiving over $300m – Texas and Kentucky – possessed some of the lowest adoption rates in 2016, perhaps providing evidence that ARRA funding was wasted. (Note: California received the highest amount at $444.3m, but is an outlier regarding adoption, and therefore not included in this discussion). Still, one probable explanation matches the description above. The states that received the highest amounts of funding, for good reason, were on the low end of household income and 10/1 broadband adoption. However, because they were on the lower end of those spectrums, they likely did not have the social support or literacy required to promote the *adoption* of broadband initiatives, even if the funding played any role in promoting infrastructure. The findings of Jayakar and Park (2013) offer additional insight in explaining that ARRA was, in general, a supply-side initiative. It focused on building: installing infrastructure, constructing computer centers, laying fiber. Yet according to these authors and Belloc et al. (2012), the policies that significantly improve broadband adoption rates are the ones that encourage residents to *demand* broadband, and ARRA had few parameters that targeted demand. This idea is also supported by the data; Texas was among the top 20 states in 2016 availability rates – meaning broadband infrastructure made services *available* – yet had one of the lowest rates of adoption. This means, then, that there are other factors besides availability (i.e. supply) that lead to adoption. Because ARRA focused much less on those who would actually adopt the provided services and more-so on the infrastructure itself, the states with infertile broadband environments did not see dramatic increases in adoption. Therefore, the states that rightfully received higher amounts of ARRA funding – Texas and Kentucky – were not as prepared to put it to good use because the environment was not fertile for adoption; funding did not generally help residents understand or support broadband, so high amounts of funding per state do appear to cause lower levels of adoption.

All in all, this study matches the literature in finding that, holistically, ARRA funding did not have much significant effect on broadband adoption or availability. On the positive note, it does seem that, generally, ARRA funding was allocated somewhat consistently based on states' needs. Those who had relatively high median household incomes and high previous adoption of 10/1 broadband received relatively lower amounts of funding, while states with low incomes and low adoption of 10/1 received some of the highest amounts of funding in 2016. However, this optimistic allocation does not apply to all states, as struggling states like Mississippi were in the bottom half of awardees, while tech-leader California received a whopping $444.3m. While it would be harsh to deem the program a waste of funding, policymakers undoubtedly must re-examine the priorities of future broadband investments by balancing both supply-side and demand-side issues.

V. Conclusion

Broadband is no longer a luxury. As schools move online, jobs migrate from offices to homes, and innovation depends on download speed, the economy is becoming increasingly dependent on reliable broadband connection. Still, as dependency increases and the world rapidly advances toward an online economy, millions of U.S citizens still find themselves falling behind. The sheer importance of programs like ARRA comes from a need not being met. Private ISPs have failed to provide broadband to those who are underserved, and this reality calls for public investment to realize the vision with which ARRA was passed. This sentiment is encapsulated in the FCC's 2015 Broadband Progress Report by Chairman Tom Wheeler, who was responsible for setting the current 25/3 benchmark:

> "Are [broadband] services being 'deployed to all Americans in a reasonable and timely fashion?' Simply put, no… In rural areas, more than half lack access to broadband at the new benchmark; in Tribal lands, it's almost two thirds that lack access. The disparity persists at all speeds… Sadly, we wouldn't be where we need to be on broadband deployment to all Americans, even if we hadn't increased the benchmark speed… The FCC doesn't just have a statutory obligation to report on the status of broadband deployment; we have a duty to take immediate action if we assess that the goal of deployment to all Americans is not being met. And act we have… But we acknowledge that more efforts may be needed" (p. 106-107).

To encourage additional broadband investment projects in the future, more research must be completed to discover the best possible implementation methods. This study can be continued and improved upon in multiple ways. First, a narrower look at various states' success with ARRA may reveal helpful patterns. For example, an in-depth study of New Jersey's ARRA projects may show why some states succeeded in boosting availability and adoption, while others – even with large amounts of funding – saw much lower increases in those rates. Another interesting study may be qualitative case study on a small sample of ARRA projects. Homing in on a limited number of projects – some very successful, some less-so – and determining the factors that contributed to their various levels of success may yield helpful results for policymakers, and those results may show interesting patterns when extrapolated to a state- or nation-wide context. Second, it may be the case – at least for broadband adoption – that there is simply a longer lag for funding to take any effect. It would be prudent, then, to look at years past 2016 to see if adoption does indeed increase with time. The reason this was not done in this thesis was a lack of control data; in order to perform such a study, researchers would need a state-by-state distribution of all other private and public investment awarded during and after 2016 to isolate the effect of ARRA funding, which was not readily available during the time of the study. Finally, this project may be expanded upon by examining the effect of ARRA funding on lower speeds broadband services. Admittedly, this project does not focus on the parameters that were considered when ARRA was passed and funds were allocated; at that time, the goal was to provide the *2010* benchmark levels of broadband, which were 200 Kbps/200 Kbps and eventually 4 Mbps/1 Mbps. Perhaps part of the reason for ARRA's insignificant effect is that, from the time of its passing to 2015, the benchmark for broadband was 4 Mbps/1 Mbps, so much of the infrastructure being installed and adopted did not meet the benchmark used for this study. Therefore, it would be prudent to explore if ARRA funding played a significant role in improving the availability/adoption rates of its original goal speeds.

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Appendix A: R Script File

```
# SETTING UP
setwd("C:/Users/Katie Waide/Desktop/KATIE/Education/4 - Senior - Spring/ECO 4
99/Thesis")

library(readxl)
library(dplyr)
library(stringr)
library(panelr)
library(tidyr)
library(table1)
library(sjPlot)
library(sjmisc)
library(sjlabelled)

# LOADING DATA
ARRA_Funding <- read_excel("ARRA_Funding.xlsx", na = "")
Availability_2013 <- read_excel("Broadband_Progress_Report_2013.xlsx", na = "
")
Availability_2016 <- read_excel("Broadband_Progress_Report_2016.xlsx", na = "
")
Adoption_2013 <- read_excel("Adoption_2013_Report.xlsx", na = "")
Adoption_2016 <- read_excel("Adoption_2016_Report.xlsx", na = "")
ACS_2010 <- read.csv("Census_ACS_2010_data.csv", na = "")
Ed_2010 <- read.csv("Census_Ed_2010_data.csv", na = "")
Income_2010 <- read.csv("Census_HHIncome_2010_data.csv", na = "")
RU_2010 <- read.csv("Census_RU_2010_data.csv", na = "")

# MANIPULATING DATA
# ARRA Funding
ARRA_Funding <- dplyr::select(ARRA_Funding, state, grants_loans)

# Availability 2013
Availability_2013 <- dplyr::select(Availability_2013, state,
                            allarea_noaccperc2013)
Availability_2013 <- mutate(Availability_2013, percavail_2013 = 100 - (allare
a_noaccperc2013 * 100))
Availability_2013 <- dplyr::select(Availability_2013, - allarea_noaccperc2013
)

# Availability 2016
Availability_2016 <- dplyr::select(Availability_2016, - pop_eval2016 &
                              - pop_accfixed2016 &
                              - pop_accLTE2016 &
                              - pop_accLTEperc2016 &
                              - pop_evalLTE10_2016 &
                              - pop_accLTE10_2016 &
                              - pop_accLTE10perc_2016)
Availability_2016 <- mutate(Availability_2016, percavail_2016 = (pop_accfixed
```

```
perc2016 * 100))
Availability_2016 <- dplyr::select(Availability_2016, - pop_accfixedperc2016)
Availability_2016 <- filter(Availability_2016, state != "RuralAreas")
Availability_2016 <- filter(Availability_2016, state != "UrbanAreas")

# Adoption 2013
Adoption_2013 <- mutate(Adoption_2013, percadop_2013 = down25_up3)
Adoption_2013 <- dplyr::select(Adoption_2013, state, percadop_2013)

# Adoption 2016
Adoption_2016 <- mutate(Adoption_2016, percadop_2016 = down25_up3)
Adoption_2016 <- dplyr::select(Adoption_2016, state, percadop_2016)

# CONTROLS
# ACS
ACS_2010 <- dplyr::select(ACS_2010, state, percblack_2010, perchisp_2010)
ACS_2010 <- filter(ACS_2010, state != "DistrictofColumbia")
ACS_2010 <- filter(ACS_2010, state != "PuertoRico")
ACS_2010 <- filter(ACS_2010, state != "UnitedStates")

# Education
Ed_2010 <- dplyr::select(Ed_2010, state, pop_over25yr, midsch, hs, associate,
bachelor, graduatesch, perc_hsup, perc_bachup)
Ed_2010 <- filter(Ed_2010, state != "DistrictofColumbia")
Ed_2010 <- filter(Ed_2010, state != "PuertoRico")
Ed_2010 <- filter(Ed_2010, state != "UnitedStates")

# Household Income
Income_2010 <- dplyr::select(Income_2010, state, households, hh_income)
Income_2010 <- filter(Income_2010, state != "DistrictofColumbia")
Income_2010 <- filter(Income_2010, state != "PuertoRico")
Income_2010 <- filter(Income_2010, state != "UnitedStates")

# Rural and Urban
RU_2010 <- dplyr::select(RU_2010, state, urban, rural, pop)
RU_2010 <- filter(RU_2010, state != "DistrictofColumbia")
RU_2010 <- filter(RU_2010, state != "PuertoRico")
RU_2010 <- filter(RU_2010, state != "UnitedStates")
RU_2010 <- mutate(RU_2010, perc_rural = rural / pop)
RU_2010 <- mutate(RU_2010, perc_rural = perc_rural * 100)
RU_2010 <- dplyr::select(RU_2010, state, perc_rural)

# MERGING DATA
Availability <- merge(ARRA_Funding, Availability_2013, by = "state")
Availability <- merge(Availability, Availability_2016, by = "state")
Availability <- mutate(Availability, percavail_2010 = 0)
Availability <- mutate(Availability, percadop_2010 = 0)
Availability <- merge(Availability, Adoption_2013, by = "state")
Availability <- merge(Availability, Adoption_2016, by = "state")
Availability <- merge(Availability, ACS_2010, by = "state")
```

```
Availability <- merge(Availability, Ed_2010, by = "state")
Availability <- merge(Availability, Income_2010, by = "state")
Availability <- mutate(Availability, lhh_income = log(hh_income))
Availability <- mutate(Availability, lgrants_loans = log(grants_loans))
Availability <- merge(Availability, RU_2010, by = "state")

rm(ARRA_Funding)
rm(Availability_2013)
rm(Availability_2016)
rm(ACS_2010)
rm(Ed_2010)
rm(Income_2010)
rm(RU_2010)
rm(Adoption_2013)
rm(Adoption_2016)

# SETTING UP REGRESSIONS
Availability$diff_percavail_2013 <- Availability$percavail_2013 - Availabilit
y$percavail_2010
Availability$diff_percavail_2016 <- Availability$percavail_2016 - Availabilit
y$percavail_2010
Availability$diff_percadop_2013 <- Availability$percadop_2013 - Availability$
percadop_2010
Availability$diff_percadop_2016 <- Availability$percadop_2016 - Availability$
percadop_2010

# Regressions: Availability (2013)
avmodelgrad_2013 <- lm(diff_percavail_2013 ~ log(grants_loans) + log(hh_incom
e) + graduatesch + percblack_2010 + perc_rural, data = Availability)

avmodelhs_2013 <- lm(diff_percavail_2013 ~ log(grants_loans) + log(hh_income)
+ hs + percblack_2010 + perc_rural, data = Availability)

# Regressions: Availability (2016)
avmodelgrad_2016 <- lm(diff_percavail_2016 ~ log(grants_loans) + log(hh_incom
e) + graduatesch + percblack_2010 + perc_rural, data = Availability)

avmodelhs_2016 <- lm(diff_percavail_2016 ~ log(grants_loans) + log(hh_income)
+ hs + percblack_2010 + perc_rural, data = Availability)

# Regressions: Adoption (2013)
admodelgrad_2013 <- lm(diff_percadop_2013 ~ log(grants_loans) + log(hh_income
) + graduatesch + percblack_2010 + perc_rural, data = Availability)

admodelhs_2013 <- lm(diff_percadop_2013 ~ log(grants_loans) + log(hh_income)
+ hs + percblack_2010 + perc_rural, data = Availability)

# Regressions: Adoption (2016)
admodelgrad_2016 <- lm(diff_percadop_2016 ~ log(grants_loans) + log(hh_income
) + graduatesch + percblack_2010 + perc_rural, data = Availability)
```

```
admodelhs_2016 <- lm(diff_percadop_2016 ~ log(grants_loans) + log(hh_income)
+ hs + percblack_2010 + perc_rural, data = Availability)
```