Because the Internet: The Effects of Fiber Optic Internet Availability on Skilled Employment

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**Abstract**

Does the availability of fiber optic internet increase the likelihood of employment amongst skilled workers? Utilizing the framework of the capital skill complementarity hypothesis, this study examines the effects of increased internet speeds as a possible explanation for high skilled job creation, and ultimately wealth disparity, in the United States. Analyzing a natural experiment that arises from the arrival of mass-market fiber optic internet providers like Google Fiber, the study utilizes data from the American Community Survey (ACS) to deduce a possible effect between high speed internet availability and high skilled employment. A differences in differences framework was utilized to examine this relationship. Overall, analysis of the data yields little; there was a statistically insignificant effect between fiber optic availability and high skilled employment on the metropolitan level. Although these results are not consistent with the capital skill complementarity hypothesis, the data yields important considerations for any cost benefit analysis about fiber optic internet investment.

**Introduction**

Boasting download speeds several magnitudes faster than standard DSL connections, the highspeed internet connections enabled via fiber optics have significantly increased across the country. Additionally, internet service providers have increased speeds as the technology becomes cheaper and more diffuse. Fiber optic internet has caught the attention of consumers, internet service providers, and regulators not only for its speed but also for its potential benefits. Over time, increased access to this technology has enabled economic development and growth throughout the United States. Although the definitive benefits of fiber optic internet are still widely debated, its effects on transaction speed are largely unambiguous (Grimes, Ren, & Stevens, 2011). In a growing digital economy that continues to support an exponentially increasing volume of transactions, liquidity costs will continue to decrease as internet speeds increase.

As efforts to revitalize America’s telecommunication networks become less costly over time, increased adoption of fiber optics technology is inevitable. However, solely relying on internet service providers to upgrade networks is not a reasonable approach for profit maximizing firms; investing in fiber optic technology requires significant capital expenditures that would decrease profits in the short run. As such, the optimal investment solution requires government subsidization. The role of the government, however, is variable. To policy makers, the decision to increase American industry via improved telecommunications infrastructure boils down to a cost-benefit analysis on local and national levels. With this is mind, fiber optic internet is an investment with significant costs; as an upper bounds, a national broadband network would cost an estimated $51 billion dollars to construct (Park & Jayakar, 2013). Even if fiber optic networks were to be subsidized on a local level, the installation costs per mile are $42,900 on average (Bai, 2017). Ultimately, the costs of investment must be carefully balanced with returns enabled by job creation and productivity increases.

Literature about fiber optic internet can be dichotomized between studies examining the effects of adoption or the effects of availability; the latter field is the most applicable for this study. Studies about fiber optic availability primarily examine the effects of speed on productivity and employment. In a study about productivity in New Zealand-based firms, faster internet speeds increased productivity by a factor of 7-10% (Grimes, Ren, & Stevens, 2011). This study notes the importance of several factors that enable this productivity, including: firm size, location, and sector knowledgeability. Unfortunately, there is not a single consensus on high speed internet’s effects on employment. Because studies range in scope, various studies at national and county levels indicate different magnitudes of change. While there is not a single statistic that can quantify employment growth, change is positive. Generally, countries with greater fiber optic availability experience faster growth (Lapointe, 2015). In addition, there exists a positive relationship between economic growth and telecommunications technology (Park & Jayakar, 2013). Because the body of literature agrees upon this variable, positive effect, policy makers have gradually begun to recognize the utility of fiber optic internet speeds.

As fiber optic internet technology becomes cheaper to implement via subsidization or technological advancement, it is important to consider the effects of increased speeds on specific occupations. In an era of increasing economic inequality, employment access, wealth disparity, and social mobility have become seemingly intertwined. Debate about employment has become an increasingly tense exercise as investments in physical capital increase while wages decrease. This study approaches fiber optic internet’s effects on high skilled employment through the framework of the capital skill complementarity hypothesis. Shifting to capital intensive means of production is a hallmark of the modern economy. Practically, investment in fiber optic internet equates to investment in capital. As the price of capital falls, increased investment in capital leads to increases in labor demand for “skilled workers”. Simultaneously, this decrease in the price of capital leads to a decrease in labor demand for “unskilled worker”. As firms shift away from labor intensive methods of production, workers with higher human capital investment are employed to manage this capital. As such, some labor economists believe that the decreasing cost of technology perpetuates a wealth gap in America. Therefore, as workers with higher skill levels continuously benefit from investment in technology, the capital skill complementarity hypothesis becomes a practical way to evaluate wealth disparity.

Testing the capital skill complementarity hypothesis was achieved through a differences in differences framework. Utilizing data from the US Census Bureau’s American Community Survey (ACS), variables representing employment, occupation, and fiber optic internet access served as a base regression that derived the effects of fiber internet access on skilled employment between the years 2014 and 2015. The research design checks for balance; the sample is comprised of individuals from the metropolitan areas of Austin, Texas and Fort Worth, Texas. These metropolitan areas are located within the same state, thus the sample tries to establish a reasonable basis for a ceteris paribus relationship. Because literature recognizes that internet access carries ethnographic bias, subsequent regression specifications implement controls for socioeconomic factors that may affect the probability of high skilled employment (Park & Jayakar, 2013). Intuitively, these factors are implemented to control for unseen effects amongst varying socioeconomic groups.

Evaluating the means of the Austin and Fort Worth regions for the years 2014 and 2015 revealed a 0.04 difference in fiber optic internet usage and a 0.01 difference in general employment probability. After checking the means, the differences in differences model was used to measure the effects of fiber optic internet usage on high-skilled employment. Overall, these effects were not statistically significant. Even after controlling for added socioeconomic variables, the treatment effect lacked significance. While insignificant, the coefficient experienced signs of negative omitted variable bias. In addition, standard errors did not fluctuate significantly. Intuitively, this lack of effect indicates no discernable change in employment amongst high skilled workers. As such, the unchanged probability of employment is not consistent with the capital-skill complementarity hypothesis.

Structurally, the paper contains four additional sections that discuss the complementarity hypothesis, the model, the model’s results, and major takeaways. The second section elucidates theory underlining the paper’s motivation and details the complementarity hypothesis. Section three provides an analysis on the paper’s descriptive statistics. This section includes a discussion about the data set utilized, its sampling methodology, and some basic results. The fourth section examines the model’s regression results. Specifically, this section addresses the treatment effect over several specifications, any threats to model validity, and the intuition underlying the results of the differences in differences model. The final section, the conclusion, provides a comprehensive review of the study. In addition to summarizing the results of the paper, the conclusion addresses additional avenues for research and parting thoughts on fiber optic availability.

**Theory**

The capital skill complementarity hypothesis merits some discussion before a formal analysis of the data. In a basic production function, labor and physical capital are paired to produce some quantity of output (Griliches, 1969). Within this basic model, labor can be subdivided into two categories: “skilled” or “unskilled” labor. In the body of literature, skilled labor is comprised of individuals with significant human capital investment, primarily in education. Raw or unskilled labor is comprised of workers who choose to not invest in human capital. Having established variable levels of human capital investment, skilled and unskilled labor become heterogenous inputs in production. Within this study, fiber optic acts as a proxy for physical capital while white-collar occupations act as a proxy for skilled labor.

Empirically, the elasticity of substitution between physical capital and unskilled labor is greater than that of physical capital and skilled labor (Goldin & Katz, 1998). There are several important implications for this disparity. First, it recognizes that skilled labor is, on average, a complement to physical capital. As such, those with higher human capital investment are more likely to benefit from decreases in the cost of technology (Krusell, Ohanian, Ríos-Rull, & Violante, 2000). Whether this be through remaining employed or garnering a greater probability of employment, high skilled workers have more job security. Second, investment in physical capital increases the value of the marginal product of labor for skilled labor (Goldin & Katz, 1998). Thus, as skilled workers become more productive and garner a comparative advantage, disemployment amongst unskilled labor is more likely and the elasticity of labor demand amongst skilled workers increases. Finally, the wages of unskilled labor that is not disemployed begin to decrease over time. This reality has manifested in America. Over the last 30 years, gradual wage reductions amongst unskilled workers have reduced the purchasing parity of America’s middle class (Krusell, Ohanian, Ríos-Rull, & Violante, 2000).

Skill distributions within the labor market have become more divergent over time. Although investment in human capital via education has become more ubiquitous, the share of labor income is biased towards workers with higher educational attainment. Although various government policies attempt to ameliorate this gap through on-the-job training programs and required levels of educational attainment, the cost of capital continues to decrease and the wealth gap grows wider. According to Krusell et. al, “the stock of equipment has been growing at about twice the rate of either capital structures or consumption,” leading to increasing levels of wealth disparity in the US. Fundamentally, technology’s role in wealth disparity may be undervalued by policy makers. While improved technology is a boon to the economy as an aggregate, evaluating the returns of technology amongst specific groups is an important consideration. Ultimately, decreasing purchasing parity, stagnant wages, and lower returns on education can be encapsulated under the capital-skill complementarity hypothesis’ broad theoretical framework.

**Descriptive Statistics**

The study’s data comes from the American Community Survey Public Use Microdata Sample (ACS PUMS), a yearly study conducted by the United States Bureau of Labor Statistics. Individuals are asked to fill out a survey that contains question about general population characteristics, including, but not limited to: housing amenities, family background, and labor force characteristics. Split into distinct geographic regions, the sample comprises approximately 1% of the US population. Regions are comprised of various statistical areas with approximately 100,000 people; a random sample of 1,000 people is taken from each region.

The ACS suffers from several forms of bias that are relevant to the study at hand. The first, and most important, is nonresponse bias. Across variables, particularly amongst fiber optic availability and employment, some respondents did not leave answers. In order to garner the most comprehensive picture of the data, values that were missing were replaced. In particular, individuals with missing fiber optic values were assumed to have no fiber optic internet. Although this may underestimate the effects of the model, inclusion of missing data points achieves a conservative estimate by establishing a lower bounds for availability. As a result, this acts as a lower bounds for the impact of fiber optic availability on skilled employment. Because fiber optic usage is not ubiquitous throughout the United States, this lower estimate is in line with contemporary availability standards. In addition, individuals who did not leave an employment status were considered not in the labor force. The ACS has hundreds of different occupation designations, thus classifying a worker under a specific occupation would be imprecise. Because we cannot infer occupational characteristics from other variables that were answered, it is safe to classify the worker as out of the labor force. Maintaining the logic advocating for conservative estimates, replacing data for employment provides a lower bounds.

While measurement error arises from missing values, it is also important to consider the effects of treatment spillover that may come from Dallas, Texas. As one of the largest metropolitan areas within the United States, Dallas boasts the infrastructure to enable widespread adoption and availability of fiber internet access. Because the Fort Worth and Dallas metropolitan area are often conflated into one region, there may be some other fiber optic internet providers from the Dallas metropolitan region that affect the reliability of the sample. Because there is not a simple method to model this spillover, it is important to acknowledge its existence and potential hand in affecting the data of this study.

The ACS data has numerous advantages when analyzing fiber optic availability. First, it provides a large sample of observations that can be easily located by geography. In the case of this natural experiment resulting from Google Fiber’s intervention, the ability to easily quantify fiber optic availability serves as a basis step for the study at hand. Secondly, the ACS data has numerous socioeconomic variables that limit endogeneity resulting from omitted variable bias. Specifically, variables detailing race, income, and education ameliorate endogeneity issues that arise from ethnographic bias. Finally, the data in question elucidates the conditions of local infrastructure. Important variables that monitor the conditions of regional utilities provide a broad view of regional investment and the quality of infrastructure attainment. These socioeconomic conditions arising from the availability and adoption of fiber optic internet are useful for answering whether further infrastructure investment is warranted. Although variables concerning infrastructure are not included within this particular model, they serve as an important basis for future research.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Variables** | **Means in 2014** | | | **Means in 2015** | | |
|  | Austin | Ft. Worth | t-statistic | Austin | Ft. Worth | t-statistic |
| Employment | 0.61 | 0.59 | -2.90 | 0.62 | 0.59 | -4.31 |
|  | (0.005) | (0.006) |  | (0.005) | (0.006) |  |
| Fiber Optics | 0.088 | 0.199 | 20.69 | 0.104 | 0.172 | 13.15 |
|  | (0.003) | (0.005) |  | (0.003) | (0.004) |  |
| White-Collar Occupations | 0.176 | 0.134 | -8.761 | 0.175 | 0.139 | -7.71 |
|  | (0.003) | (0.003) |  | (0.003) | (0.003) |  |
| Female | 0.50 | 0.52 | 3.57 | 0.50 | 0.52 | 3.31 |
|  | (0.004) | (0.005) |  | (0.004) | (0.005) |  |
| U.S. Citizen | 0.89 | 0.90 | 3.71 | 0.90 | 0.92 | 5.04 |
|  | (0.003) | (0.003) |  | (0.003) | (0.003) |  |
| ln(income) | 11.22 | 10.96 | -19.93 | 11.30 | 11.01 | -22.59 |
|  | (0.009) | (0.010) |  | (0.008) | (0.009) |  |
| ln(income)^2 | 126.82 | 121.04 | -20.90 | 128.55 | 122.09 | -23.76 |
|  | (0.188) | (0.202) |  | (0.185) | (0.199) |  |
| White | 0.78 | 0.73 | -10.24 | 0.76 | 0.73 | -5.93 |
|  | (0.004) | (0.004) |  | (0.004) | (0.004) |  |
| Black | 0.05 | 0.13 | 20.53 | 0.05 | 0.13 | 20.68 |
|  | (0.002) | (0.003) |  | (0.002) | (0.003) |  |
| Asian | 0.07 | 0.03 | -12.88 | 0.06 | 0.03 | -12.87 |
|  | (0.002) | (0.002) |  | (0.002) | (0.002) |  |
| Other | 0.05 | 0.06 | 5.19 | 0.07 | 0.06 | -2.57 |
|  | (0.002) | (0.002) |  | (0.002) | (0.002) |  |
| High School Dropout | 0.28 | 0.33 | 7.24 | 0.27 | 0.32 | 7.57 |
|  | (0.004) | (0.005) |  | (0.004) | (0.005) |  |
| High School Degree | 0.14 | 0.19 | 9.49 | 0.13 | 0.20 | 13.10 |
|  | (0.003) | (0.004) |  | (0.003) | (0.004) |  |
| College Degree | 0.24 | 0.18 | -11.75 | 0.25 | 0.18 | -14.21 |
|  | (0.004) | (0.004) |  | (0.004) | (0.004) |  |
| Graduate Degree | 0.12 | 0.07 | -14.92 | 0.12 | 0.07 | -14.74 |
|  | (0.003) | (0.002) |  | (0.003) | (0.002) |  |
| Number of Observations | 13,522 | 9,988 |  | 14,001 | 10,355 |  |

**Table 1- Means of Key Variables**

*Notes:* See Table 2 for variable definitions. Standard errors given in parentheses.

There are systemic differences between Austin and Fort Worth’s employment and fiber optic availability. Although these populations are in close proximity to one another, there are still differences in the means of both metropolitan populations. In 2014, employment probabilities in Austin and Fort Worth are similar. Employment probabilities of 0.61 and 0.59 exist, respectively. Fiber optic internet availability in Austin equals 0.088; given the size of the city, a relatively small proportion maintains a broadband connection. In 2014, there is a -0.111 difference in fiber optic availability between Austin and Fort Worth. This disparity may arise due to greater levels of infrastructure investment in Fort Worth; as a city adjacent to Dallas, Fort Worth may have parallel levels of development. By 2015, Austin’s employment probability grew by 0.01 to 0.62; Fort Worth did not experience any employment growth between the two years. Austin’s fiber optic availability also increased by 0.016 between 2014 and 2015. On the other hand, Fort Worth experienced a decrease in fiber optic availability between 2014 and 2015; availability decreased by 0.027 to 0.172. This decrease has two plausible explanations. First, given that the data is a repeated cross section, Fort Worth’s randomly sampled population may have had lower availability in 2015. Second, the northern regions of Texas experienced severe weather throughout much of the year; flooding, tornados, and other serious weather events may have temporarily damaged Fort Worth’s telecommunications infrastructure and decreased fiber optic availability. By the end of the model’s time period, a 0.043 difference in fiber optic availability and a 0.01 difference in employment probability exist between Austin and Fort Worth.

**Table 2 – Variable Definitions**

|  |  |
| --- | --- |
| **Name** | **Definition** |
| employment | response variable measuring probability of employment |
| fiberop | dummy variable indicating availability of high speed internet |
| whitecollar | dummy variable for occupation; equals one when individual has occupation meeting high-skill threshold |
| empdiff | interaction term between fiberop and whitecollar; measures the treatment effect: fiber optic availability’s effect on high skilled employment |
| Austin | dummy variable for region; equals one for the Austin, Texas metropolitan area |
| time | variable controlling for time fixed effects |
| female | dummy variable for gender; equals one when individual is female |
| citizen | dummy variable for whether worker is a citizen; equals one when individual is a citizen |
| ln(income) | continuous variable for natural log of total household income |
| ln(income)^2 | continuous variable for natural log of total household income squared |
| white | dummy variable controlling for race; equals one when an individual is white |
| black | dummy variable controlling for race; equals one when an individual is black |
| asian | dummy variable controlling for race; equals one when an individual is Asian |
| other race | dummy variable controlling for race; equals one when an individual is a race not specified as white, black, or Asian |
| high school dropout | dummy variable controlling for race; equals one when an has received not received a high school diploma |
| high school diploma | dummy variable controlling for education; equals one when an individual's highest educational attainment is a high school diploma |
| college degree | dummy variable controlling for education; equals one when an individual's highest educational attainment is a college degree |
| graduate degree | dummy variable controlling for education; equals one when an individual's highest educational attainment is a graduate degree |

The means of high skilled occupations differ between the two cities. The proportion of so called “white-collar” occupations changes drastically between the two years. In 2014, Austin’s proportion of white-collar occupations is centered around 0.176, Fort Worth’s proportion is 0.134. This gap in high skilled workers could potentially be explained by the commuting patterns of residents. As such, Fort Worth’s proximity to Dallas may alter the living patterns of professionals. Overall, there is a sizable commute between both cities. High skilled workers originally living in Fort Worth but working in Dallas may choose to live in Dallas over time. Although this settling decision is dictated by numerous variables, workers with higher earnings and better amenities may choose to pay more living expenses to forgo the costly commute between the two metropolitan areas. By 2015, Austin’s proportion of white-collar occupations decreased by 0.001; Fort Worth experienced a gain of 0.005. Considering each population’s characteristics, these changes are quite minor. This increase in white-collar occupations may again be explainable by Fort Worth’s poor weather throughout 2015. Changes in wage due to temporary population relocations and negative shocks to labor supply throughout the Fort Worth region may have influenced more white-collar individuals to find jobs in the area.

Austin and Fort Worth also have differences between the means of their socioeconomic characteristics. In terms of race, Austin’s population contains more white and Asian individuals. Fort Worth’s population is comprised of more black individuals and individuals of another race. In terms of sex, Fort Worth’s population has a slightly larger proportion of women. While both locations are comprised by a majority of US citizens, Fort Worth’s population has a higher proportion of US citizens. Household income is markedly larger in Austin; Austin even experienced a 0.03 increase between the two years. On average, Austin’s citizen have more wealth and a higher purchasing parity. In addition, Austin’s population is more educated. Although a greater proportion of Fort Worth’s population has acquired a high school diploma, Austin’s population has a larger proportion of college and graduate degrees. Overall, Fort Worth’s population intrinsically has a greater portion of underrepresented groups. The differences between racial, sex, income, and educational characteristics indicate that there are a systemic differences that may be a product of a discriminating workforce. Although there is no overt evidence indicating discrimination amongst specific firms, the differences in population characteristics indicate that there is a regional preference for characteristics and that individuals are compensated according to these preferences.

|  |  |
| --- | --- |
| *Variable* | *Employment* |
| Fiber Optics | 0.021\*\* |
|  | (0.009) |
| White-Collar Occupations | 0.264\*\* |
|  | (0.007) |
| empdiff | -0.012 |
|  | (0.018) |
| R-Squared | 0.056 |

**Table 3 - OLS Regression Results**

*Notes:* Standard errors are in parentheses, n = 29,930; *p < 0.1 = \**, *p < 0.05 = \*\**

The treatment effect, represented by the variable empdiff, represents the change in white-collar employment as a result of fiber optic availability between 2014 and 2015. A simple OLS estimate of fiber optic’s effects on white-collar employment yields a negative, statistically insignificant effect. The arrival of fiber optic internet providers notwithstanding, the data does not indicate any plausible difference in employment amongst white-collar workers. Fundamentally, this result is not consistent with the capital-skill complementarity hypothesis. Despite the large amount of observations regressed, the treatment’s standard error is larger than the coefficient itself. Ultimately, this may not be a large enough sample size to determine a significant effect. Because this data only represents two regions, a national evaluation with multiple cities or additional years may be necessary for significance. The validity of the data may be threatened by endogeneity. Although biases introduced by non-responsive individuals and treatment spillover have been considered, the model does not contain controls that limit the threat of omitted variable bias. Barring the treatment’s insignificance, the sign of the coefficient is not consistent with the capital skill complementarity hypothesis; overall, the hypothesis requires a positive effect for the treatment. Additional regressors may introduce negative omitted variable bias to the model and affect the coefficient’s sign. Utilizing additional specifications, the model will explore the effects of differing socioeconomic characteristics on the treatment effect’s significance. These regressions will appear in the following section.

**Main Estimation**

As additional controls were added to mitigate endogeneity issues within the model, there was no change in the treatment’s significance. Tables 4 and 5 contain all regression specifications that led to this conclusion. Although variables besides the treatment had statistically significant effects on the probability of employment throughout the model, there appears to be no discernable effect between fiber optic internet and the the probability of white-collar employment. Specification II adds on to the original OLS specification by controlling for time and region dummies. While the addition of these variables yielded a small degree of negative variable bias, the results remain statistically insignificant. Barring the treatment’s insignificance, this negative omitted variable bias may be explained by the omission of the time dummy. Because there is an intuitive, positive relationship between Austin, employment, and the treatment given the population’s characteristics, it must be the case that the time dummy has a larger negative effect on the treatment’s coefficient. Intuitively, there is a positive correlation between time and fiber optic use and a negative relationship between time and employment. As time extends, fiber optic use grows. As workers get older, the probability of employment goes down, especially amongst jobs that require significant human capital investment.

Subsequent additions to the model factor in variables controlling for sex and citizenship. Although the treatment effect is insignificant, there appears to be signs of positive omitted variable bias in specification III. Intuitively, this relationship exists due to positive omitted variable bias from both variables. One would expect that females, due to factors such as statistical discrimination, have a lower probability of employment amongst workers of equal skill. One would also expect that the treatment would have a negative correlation with females; it is well documented that internet usage tends to be biased towards males, thus biasing attainment of high skilled employment (Dixon, et al., 2014). These two negative signs equate to positive omitted variable bias. Intuitively, there is a positive correlation between US citizenship, the probability of employment, and the treatment. We would expect a positive sign between employment and US citizenship and a positive sign between the treatment and US citizenship. With little change in the standard error of the treatment, it is utile to add regressors to control for additional socioeconomic characteristics.

**Table 4 – First Six Regression Specifications**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| *Variables* | (I) | (II) | (III) | (IV) | (V) | (VI) |
| Fiber Optics | 0.021\*\* | 0.025\*\* | 0.026\*\* | 0.003 | 0.005 | 0.008 |
|  | (0.009) | (0.009) | (0.009) | (0.233) | (0.009) | (0.009) |
| White-Collar Occupations | 0.264\*\* | 0.262\*\* | 0.261\*\* | 0.233\*\* | 0.235\*\* | 0.236\*\* |
|  | (0.007) | (0.007) | (0.007) | (0.007) | (0.007) | (0.007) |
| empdiff | -0.012 | -0.011 | -0.015 | -0.002 | -0.003 | -0.007 |
|  | (0.018) | (0.018) | (0.018) | (0.018) | (0.018) | (0.018) |
| Austin |  | 0.021\*\* | 0.017\*\* | 0.008 | 0.010 | 0.008 |
|  |  | (0.006) | (0.005) | (0.005) | (0.005) | (0.005) |
| Time |  | 0.006 | 0.006 | 0.003 | 0.003 | 0.003 |
|  |  | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) |
| Female |  |  | -0.123\*\* |  |  | 0.116\*\* |
|  |  |  | (0.005) |  |  | (0.005) |
| U.S. Citizen |  |  | -0.024\*\* |  |  | 0.046\*\* |
|  |  |  | (0.009) |  |  | (0.009) |
| ln(income) |  |  |  | 0.075\*\* | 0.224\*\* | 0.211\*\* |
|  |  |  |  | (0.003) | (0.027) | (0.027) |
| ln(income)^2 |  |  |  |  | -0.007\*\* | 0.006\*\* |
|  |  |  |  |  | (0.001) | (0.001) |
| R- Squared | 0.056 | 0.056 | 0.074 | 0.076 | 0.076 | 0.092 |

*Notes:* standard errors are included in parentheses*. n = 29,390*; *p < 0.1 = \**, *p < 0.05 = \*\**

Additional variables serving as controls for personal income were instituted in specifications IV and V. Again, no significant treatment effect could be discerned from the inclusion of these variables and standard errors remained stagnant. Barring insignificance, there was discernable amounts of negative omitted variable bias when natural income and its quadratic were included within the model. Although the treatment is insignificant, variables controlling for income may act as better indicators for the complementarity hypothesis within this model. When all previous regressors were factored into the model in specification VI, the treatment remained insignificant. There is no change to the standard error of the treatment’s coefficient; despite the negative omitted variable bias from the income variables, there is a greater positive omitted variable bias resulting from the inclusion of both female and US citizenship variables. Overall, the first six specifications yielded no significant effects. Intuitively, there is no tangible effect between fiber optic availability and white-collar employment.

**Table 5: Additional Regression Specifications**

|  |  |  |  |
| --- | --- | --- | --- |
|  | (VII) | (VIII) | (IX) |
| Fiber Optics | 0.009 | -0.003 | -0.001 |
|  | (0.009) | (0.009) | (0.009) |
| White-Collar Occupations | 0.239\*\* | 0.203\*\* | 0.204\*\* |
|  | (0.007) | (0.007) | (0.007) |
| empdiff | -0.009 | 0.000 | -0.001 |
|  | (0.018) | (0.017) | (0.017) |
| Austin | 0.009 | -0.004 | -0.003 |
|  | (0.005) | (0.005) | (0.005) |
| Time | 0.003 | 0.004 | 0.003 |
|  | (0.005) | (0.005) | (0.005) |
| Female | -0.116\*\* | -0.120\*\* | -0.120\*\* |
|  | (0.005) | (0.005) | (0.005) |
| U.S. Citizen | -0.041\*\* | -0.107\*\* | -0.101\*\* |
|  | (0.010) | (0.009) | (0.010) |
| ln(income) | 0.205\*\* | 0.235\*\* | 0.228\*\* |
|  | (0.027) | (0.027) | (0.027) |
| ln(income)^2 | -0.006\*\* | -0.008\*\* | -0.007\*\* |
|  | (0.001) | (0.001) | (0.001) |
| White | -0.039\*\* |  | -0.050\*\* |
|  | (0.016) |  | (0.016) |
| Black | -0.020 |  | -0.028 |
|  | (0.019) |  | (0.019) |
| Asian | -0.056\*\* |  | -0.078\*\* |
|  | (0.019) |  | (0.019) |
| Other | 0.034\* |  | 0.062\*\* |
|  | (0.020) |  | (0.020) |
| High School Dropout |  | -0.195\*\* | -0.203\*\* |
|  |  | (0.010) | (0.010) |
| High School Degree |  | -0.035\*\* | -0.037\*\* |
|  |  | (0.008) | (0.008) |
| College Degree |  | 0.027\*\* | 0.031\*\* |
|  |  | (0.007) | (0.007) |
| Graduate Degree |  | 0.017\* | 0.023\*\* |
|  |  | (0.009) | (0.009) |
| R-Squared | 0.094 | 0.111 | 0.114 |

*Notes:* standard errors are included in parentheses*. n = 29,390*; *p < 0.1 = \**, *p < 0.05 = \*\**

Additional regression specifications were run in order to control for invariant socioeconomic characteristics that may influence bias in the study. Implicitly, educational attainment and racial characteristics have a tangible impact in the labor market and internet usage. As they were factored into subsequent specifications, however, no significant relationship appeared between fiber optic availability and employment probability amongst white collar workers.

Table 5 provides a statistical overview of additional regressions run to accommodate for integral socioeconomic controls. Specification VII includes additional controls for race. Literature on internet availability has indicated that wireless internet is more diffuse amongst white individuals (Park & Jayakar, 2013). As such, racial dummies were included to minimize racial within the sample. Controlling for racial groups did not yield statistically significant effects. Although the inclusion of racial variables led to an increase in the treatment’s coefficient, the presence of negative omitted variable bias is not relevant. Specification VIII included the educational attainment dummies but excluded racial dummies. Although the inclusion of education dummies displays signs of positive omitted variable bias, the results indicate that there is not an effect of fiber optic internet on the probability of white-collar employment. Barring the insignificance of the treatment, signs of positive omitted variable bias exist between those with college and graduate degrees, the treatment, and employment. It appears, however, that the negative omitted variable bias resulting from individuals with lower educational attainment, those with a high school diploma or less, surpasses the positive relationship between higher educated individuals.

Specification IX is the most comprehensive regression run; all socioeconomic controls are regressed within the model. As before, there is no statistically significant effect between fiber optic availability and high skill employment probability. The coefficient, while insignificant, experiences a small amount of positive omitted variable bias when all race and education dummies are included in the model. As indicated before, omitted variable bias may be positive overall due to the inclusion of the educational attainment dummies. Because there is not a definitive effect in the model, there may be several concerns about the model’s validity. As such, it is important to address the external and internal validity of the model before any significant conclusions can be made about the results.

The most pressing threat to internal validity arises from time invariant variables and omitted variable bias. Controls for citizenship, sex, education, and race are all immutable characteristics between the two years. Although variables gradually implemented in the model tend to be time invariant, the large sample relaxes this strict criteria.. Variables omitted from the model do not include a variety of pertinent regressors that measure socioeconomic status; factors such as age and number of children are not incorporated and tend to vary with time. Because these variables may maintain some correlation between the treatment and the probability of employment, they could be utilized in additional models. To test for additional signs of omitted variable bias, regressions will need to be run with these added variables and their polynomial terms. Focusing on the model specifications in this study, there is not significant change in the standard errors as additional controls are implemented. Given that the last model has a standard error that is slightly lower than the OLS regression, a factor of 0.001, there is reason to believe that the final specification is the most representative of the study.

Other internal threats created by endogeneity issues may arise from simultaneous causality. While there are reasons for concern about white collar employment’s effects on employment probability, several intuitive explanations can ameliorate any issues. First, wireless internet access, specifically amongst cities that have large telecommunications infrastructure, is a ubiquitous commodity. Wireless internet is easily accessible, often available at libraries and other public forums. Second, because the data is comprised of a large sample of individuals, there is not a reasonable basis for reverse causality between employment and internet access. Given these two factors, it is not reasonable to assume that there is a threat to internal validity due to simultaneous causality.

There may be measurement error that arises from the construction of the variables, specifically amongst the white-collar dummy. The ACS contains hundreds of potential occupational codes that indicate industry and role. To code for a white-collar occupation dummy, individual occupations were assessed based upon a human capital investment decision. Generally, jobs were considered white collar if they required significant investments in education and specific human capital. Because this classification was largely subjective, specifically when quantifying the level of specific human capital, the construction of the white-collar dummy may be fallible. Different studies may set different criteria for white-collar occupations, thus this variable is dependent on the tastes and preferences of any author. Given the three previous threats to endogeneity, the model may be misspecified. Unfortunately, utilizing the differences in differences model to address this hypothesis only takes care of omitted variable bias. Overall, the use of an instrumental variable model may be warranted here. To ameliorate these three endogeneity issues, finding an appropriate instrument correlated with the availability of fiber optic internet may yield significant effects.

A final consideration about the model’s internal validity arises from sample construction. The data represented in this study is a repeated cross section of the metropolitan regions of Austin and Fort Worth. The data does not sample a wide geographic area. Overall, data in this sample may be predisposed to geographical quirks that arise from this unique region. In addition, because different individuals are randomly sampled by year, a consistent estimate is very unlikely. Although these two regions were selected because they come from a similar geographic region and fit the characteristics needed to evaluate the natural experiment, the sample is slightly unbalanced. To consider the true effects of fiber optic internet on high skilled employment, a broader sample will need to be constructed in future studies.

Evaluating external validity, the model’s greatest advantage comes from its ability to measure a direct effect between fiber optic availability and the probability of high skilled employment. The data’s recency, being only five years old, is also an important factor that provides policy makers with relevant information. Unfortunately, returns may gradually decrease over time. The greatest threat to external validity, then, results from disproportionate returns as a result of early adoption. Intuitively, returns to fiber optics may be variable amongst different geographical locations. Because different areas of the country have variable levels of investment in their telecommunications infrastructure, there are significant barriers to entry in the fiber optic internet business. Greater expenses may hurt smaller or less developed areas of the country, as they would not find this investment profitable. Although this study provides a relevant and time appropriate consideration for areas of similar infrastructure, the gains may be spread unevenly over time due to disparities in investment. Fundamentally, those who adopt sooner may acquire more benefit compared to those who choose to adopt later.

Literature agrees that fiber optic internet availability has a variable, yet positive impact on employment. As such, the insignificance of this model may indicate important labor market patterns generated by an increase in fiber optic internet availability. While increased availability may not lead to more high skilled employment as an aggregate, two realities may arise. First, industries most affected by the increase, such as finance or entertainment, may be underrepresented. Fundamentally, their diminished presence may impact the significance of the outcome. Second, new industries may appear due to faster internet speeds. Theoretically, increases in fiber optic availability may decrease jobs in one sector but increase jobs in another by creating new fields that cannot be easily qualified. There is no real way to measure this trend with the data at hand. Given that occupational designations do not change regularly, it may be more apt to use another, more current dataset. When considering the capital-skill complementarity hypothesis in the scope of the occupational codes defined by the census, the effects amongst new industries may not be fully realized, reducing the overall impact on high skilled employment. In total, there may be unseen changes or counterpoising forces that are reducing the impact on the probability of employment. Future research can adopt more precise requirements that evaluate the changes that take place between industries to measure the probability of employment.

**Conclusion**

This study utilized a standard differences in differences framework in order to test whether fiber optic internet availability affected the probability of employment amongst high skilled workers. Motivated by the increasing availability of fiber optic internet and the capital skill complementarity hypothesis, this study sought to evaluate the effect increasing technology availability may have on a heterogeneous labor supply. Overall, continuous decreases in the prices of technology may have a sizable role in the wealth gap that is forming across America. As the declining prices of technology and subsequent investment in physical capital shrink the wages of America’s middle class, idyllically represented by so called blue collar workers, fiber optic internet may exacerbate differences in earnings as its adoption continues throughout the United States. A natural experiment arising from the arrival of broadband service Google Fiber was used to test this hypothesis. Utilizing Austin, Texas, the recipient of the mass-market broadband provider, and Fort Worth, Texas as contrasting regions, the effects between two years were evaluated in tandem with various socioeconomic controls.

Ultimately, the results of the study do not yield any significant effects between fiber optic internet and the probability of high skilled employment. After regressing several combinations of socioeconomic controls , no statistically significant effect could be found. Overall, this may elucidate several points. First, the sectors that experience the most change may not be equally represented within the model. Although a majority of workers in the Austin and Fort Worth region are considered low skill, industries that are most impacted by the increase in fiber optic internet may not be appropriately represented in region. Because the white collar employment dummy aggregates all high skilled industries, this may diminish the treatment’s significance and total effect. In addition, the data may not contain the relevant industries that experienced the most change. Given that fiber optic internet may give rise to industries that do not exist, the occupational classifications defined by the census may not accommodate for changes in skilled employment. As such, the prevailing effects amongst occupations that benefit the most may be hidden due to the aggregation of all high skilled and low skilled employment classifications. In total, unseen labor market forces may reduce the overall explanatory power of the model, thus it is important that future studies fully consider alternative methods in evaluating the data.

General fixes for the model can be implemented in order to reevaluate this study. First, additional time periods could be considered within the model. Additional time periods would not only add additional observations, but also account for the delayed effects that fiber optic internet may have on high skilled employment. This two year time frame may be too limited in scope to assess the real returns. Second, adding additional regions affected by the arrival of mass-market broadband provider Google Fiber may ameliorate sampling bias. Areas such as Atlanta, Georgia and the Research Triangle located in North Carolina have all been recipients of the service. Adding these regions may be of some utility to the explanatory power of the model. Although these regions may not have common trends, the large amount of observations will allow for the relaxation of this assumption. Finding a sample with a balanced panel is quite difficult, thus results may be variable. Adopting a wider framework in terms of geographic location may provide a broader portrait of the fiber optic’s effects that was not available within this study. To test these questions, it may be useful to either use a different dataset that has a strict focus on fiber optic availability or define occupation designations utilizing strict criteria. Finally, adopting an instrumental variable approach may ameliorate concerns about model misspecifications, simultaneous causality, or measurement error. Adopting a different functional approach to the capital skill complementarity hypothesis may be more utile in examining changes amongst white collar employment. While the ACS contains hundreds of variables, finding a valid instrument may not be possible within the dataset. As such, appending several datasets may serve as a firm basis for testing an instrument variable model.

The availability of fiber optic internet is becoming an increasingly relevant issue to consumers and policy makers. Broadly, improving America’s telecommunications infrastructure can expand the country’s total economic output. As the federal government, local governments, and internet service providers continue to invest in the technology, the far reaching effects of fiber optic internet will need to be considered. Although this study attempts to find some relationship utilizing the capital skill complementarity hypothesis, future research will need to explore the effects on heterogeneous labor supply. Among other things, wealth disparity has become a policy implication attached to the availability of fiber optic internet. With this in mind, it is important that policy makers consider the wellbeing of the American laborer in an age of cheap and continuously improving technology. Crafting policies that safeguard the American middle class from market forces is no simple task. However, as America continuously leans towards capital intensive methods of production, it is important to invest in the skills and human capital of laborers such that their position in the labor market is safeguarded by systemic protections.

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