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The Rewards of Municipal Broadband: An Econometric Analysis of the Labor Market

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The Rewards of Municipal Broadband: An Econometric Analysis of the Labor Market

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Abstract: Worried about being left behind in the Digital Age, a few hundred municipalities have chosen to construct and operate high-speed Internet networks. Above all else, it is the impacts on the labor market—*i.e.,* the promise of "more jobs"—that form the policy justification for these municipal investments, though evidence of such effects is informal and anecdotal. In this POLICY PAPER, we offer (to our knowledge) the first statistical evidence on the effects on labor market outcomes of municipal broadband systems. Using data obtained from the U.S. Census Bureau's American Community Survey, we apply the Difference-in-Differences estimator, augmented with Coarsened Exact Matching and the wild bootstrap, to quantify the economic impact, if any, of the county-wide government-owned network ("GON") in Chattanooga Tennessee on labor market outcomes. Across a variety of empirical models, we find no payoffs in the labor market from the city's broadband investments. An automotive plant built in the area is, however, found to substantially increase automobile manufacturing employment. Since Chattanooga's system is an overbuild of multiple private providers, we stress that our findings may not be generalized to areas where broadband services are not available absent the municipal system. Also, our results cannot speak to the benefits of high-speed Internet services generally, since broadband Internet service was and remains available in Chattanooga absent the municipal system.

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I. Introduction

In the last three decades, economic growth in the United States has been concentrated along the nation's coasts, in areas populated by high-skilled workers.[1] These areas have also led in technological innovation, which itself has led to wage inequality.[2] Cities left behind by the technological hubs have grappled

[1] E. Moretti, THE NEW GEOGRAPHY OF JOBS (2012).

[2] D.H. Autor and D. Dorn, *The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market*, 103 AMERICAN ECONOMIC REVIEW 1553-1597 (2014) (available at: https://www.aeaweb.org/articles?id=10.1257/aer.103.5.1553).

(Footnote Continued. . . .)

to find policies that would promote growth and development, especially rural areas whose economies have lagged their urban counterparts for many decades.[3]

One piece of infrastructure most associated with the prosperous labor markets of today is high-speed Internet access services. Worried about being left behind in the Internet Age and unsatisfied with the quality and geographic scope of private-sector network deployment, a number of municipalities have turned to constructing and operating broadband systems of their own.[4] Many of these government-owned networks ("GONs") are found in smaller cities and towns where the economics of private-sector deployment are challenging, but a few are found in medium-sized cities where private broadband provision existed prior to the government's deployment.[5]

Above all else, the purported economic development benefits of broadband access, especially impacts on the labor market, form the policy basis for municipal investment in high-speed internet to underserved areas.[6] Yet, evidence on the

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[3] G.S. Ford, *Is Faster Better? Quantifying the Relationship Between Broadband Speed and Economic Growth*, 42 TELECOMMUNICATIONS POLICY 766-777 (2018) (available at: https://ssrn.com/abstract=3138739).

[4] A map of these networks is available at: https://muninetworks.org/communitymap. For a broad economic analysis of municipal broadband projects, *see* G.S. Ford, *The Impact of Government-Owned Broadband Networks on Private Investment and Consumer Welfare*, State Government Leadership Foundation (2016) (available at: http://sglf.org/wp-content/uploads/sites/2/2016/04/SGLF-Muni-Broadband-Paper.pdf). Details for specific municipal broadband projects are provided in, for example, C. Davidson and M. Santorelli, *Understanding the Debate over Government-Owned Broadband Networks: Context, Lessons Learned, and a Way Forward for Policy Makers*, New York Law School (June 2014) (available at: http://www.nyls.edu/advanced-communications-law-and-policy-institute/wp-content/uploads/sites/169/2013/08/ACLP-Government-Owned-Broadband-Networks-FINAL-June-2014.pdf); C. Yoo and T. Pfenninger, *Municipal Fiber in the United States: An Empirical Assessment of Financial Performance*, Center for Technology, Innovation and Competition, University of Pennsylvania Law School (2017) (available at: https://www.law.upenn.edu/live/files/6611-report-municipal-fiber-in-the-united-states-an).

[5] Ford, *Impact of Government-Owned Broadband Networks*, *id*., at Figure 2.

[6] For instance, a 2015 press release by Electric Power Board—the municipally-owned electricity utility that operates the fiber optic network in Chattanooga, TN—pointed to a study by Professor Bento Lobo (University of Tennessee-Chattanooga) claiming the city-owned fiber optic network generated significant economic and social benefits and created thousands of jobs for Chattanooga and Hamilton County, Tennessee. *See Economic Study Affirms Value of EPB Fiber Optics Network,* EPB PRESS RELEASE (September 15, 2015) (available at: https://epb.com/about-epb/news/articles/54) (citing B.J. Lobo, *The Realized Value of Fiber Infrastructure in Hamilton County, Tennessee*, Working Paper (June 18, 2015) (available at:

(Footnote Continued. . . .)

economic rewards of city-wide fiber-optic GONs is scarce, and what does exist is informal and anecdotal. The lack of a measurable economic reward is troubling since broadband systems are very costly to construct and challenging to operate. Nearly all GONs exhibit poor financial performance, typically following a pattern of years of financial losses ending in privatization.[7] Perhaps the sizable financial losses could be justified if there were broad economic gains to the local economy, but evidence of such rewards is lacking, in part because most municipal systems are deployed in small, rural towns where the quality and quantity of data necessary for empirical research is limited.

In this POLICY PAPER, we offer (to our knowledge) the first statistical evidence on the effects on labor market outcomes of municipal broadband systems. For such evidence, we look to a city widely-held as the "poster child" of government networks: the broadband network of Chattanooga, Tennessee's municipal electric

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http://ftpcontent2.worldnow.com/wrcb/pdf/091515EPBFiberStudy.pdf)); *see also* J. Engebretson, *Fact Sheet Documents Community Broadband Job* Creation, TELECOMPETITOR (November 13, 2012) (available at: https://www.telecompetitor.com/fact-sheet-documents-community-broadband-job-creation); *Muni Networks 101: What You Need to Know About Municipal Broadband Networks*, TELEQUALITY (November 07, 2017) (available at: https://www.telequality.com/blog/2017/11/3/muni-networks-101-what-you-need-to-know-about-municipal-broadband-networks); J. Baller, *The Killer App: Economic Development and Job Creation*, Paper Presented at 2012 FTTH Conference & Expo: The Future is Now (2012) (available at: http://www.baller.com/wp-content/uploads/Baller_KillerApp_FTTH2012.pdf).

7 *See*, *e.g*., Ford, *Impact of Government-Owned Broadband Networks*, *supra* n. 4; G.S. Ford, *Financial Implications of Opelika's Municipal Broadband Network*, PHOENIX CENTER POLICY PERSPECTIVE No. 17-11 (available at: https://ssrn.com/abstract=3138859); L. Jackon, *Opelika to Sell OPS ONE in $14 Million Deal*, OANEWS.COM (October 16, 2018) (available at: https://www.oanow.com/news/local/opelika-to-sell-ops-one-in-million-deal/article_bc83bb0c-d1b4-11e8-b751-e729151e7f20.html); J. Malcomb, *Rural Minnesota County Built a Fiber Network, but Now Taxpayers Face Huge Bills*, LAKE COUNTY NEWS-CHRONICLE (August 3, 2018) (available at: http://www.govtech.com/network/Rural-Minnesota-County-Built-a-Fiber-Network-but-Now-Taxpayers-Face-Huge-Bills.html); J. Coates, *Fibrant-Hotwire Lease Approved in Salisbury*, SALISBURY POST (May 9, 2018) (available at: https://www.salisburypost.com/2018/05/09/fibrant-hotwire-lease-approved-in-salisbury-referendum); D. McGee, Sunset, *BVU Optinet Deal Finalized*, BRISTOL HERALD COURIER (August 2, 2018) (available at: https://www.heraldcourier.com/news/sunset-bvu-optinet-deal-finalized/article_8b746332-2ee1-5565-b52f-8678020c9277.html); F. Stanfield, *Leesburg to Sell Fiber Optic System for $7.25 Million*, DAILY COMMERCIAL (December 5, 2017) (available at: http://www.dailycommercial.com/news/20171205/leesburg-to-sell-fiber-optic-system-for-725-million); P. Cuno-Booth, *FastRoads Sold to Nashua Fiber-Optics Company*, SENTINEL SOURCE (July 21, 2017) (available at: https://www.sentinelsource.com/news/local/fastroads-sold-to-nashua-fiber-optics-company/article_0003be6f-efb7-5bc7-a606-7db5dd9eb555.html); C.S. Yoo and T. Pfenninger, *supra* n. 4.

(Footnote Continued. . . .)

utility.[8] Using data obtained from the U.S. Census Bureau's American Community Survey, we apply the Difference-in-Differences estimator to quantify the economic impact, if any, of Chattanooga's GON on labor market outcomes. We find no payoffs in the labor market from the city's broadband investments (about one-third of which was federal subsidy money): private-sector labor force participation, employment status, wages, information technology employment, self-employment, and business income appear unaffected by the GON. We do, however, find strong evidence of an increase in automotive manufacturing employment in Chattanooga linked to a new Volkswagen plant opened at nearly the same time as the GON began operations. Marginal employment effects in auto manufacturing closely match the plant's employment levels, indicating our empirical strategy is a capable approach.

Our analysis is subject to three important caveats. First, our analysis looks for effects only in the labor market; there may be other effects of GONs not realized in the labor market. Second, since Chattanooga's system overbuilt private providers, our findings may not be generalized to areas where broadband services are not available absent the municipal system. Third, our results cannot speak to the benefits of high-speed Internet services generally, since broadband Internet service was—and remains available—in these cities absent the municipal system. Thus, our results indicate only that building a GON in markets where privately-provisioned broadband is generally available has no favorable effect on labor market outcomes. Any improvements or declines in Chattanooga's labor market, or changes in the mix of employment toward information technology, are no different than those observed in comparable cities without a municipal broadband network.

This POLICY PAPER is outlined as follows. In Section II, we describe our empirical strategy and our data. In this section we discuss the selection of a control

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[8] *See, e.g.*, T. Wheeler, *Removing Barriers to Competitive Community Broadband*, FEDERAL COMMUNICATIONS COMMISSION BLOG (June 10, 2014) (Chattanooga's GON is the "poster child" for "the benefits of community broadband networks.") (available at: https://www.fcc.gov/news-events/blog/2014/06/10/removing-barriers-competitive-community-broadband); *but c.f.*, G.S. Ford, *Why Chattanooga is not the "Poster Child" for Municipal Broadband*, PHOENIX CENTER POLICY PERSPECTIVE NO. 15-01 (January 20, 2015) (available at: http://www.phoenix-center.org/perspectives/Perspective15-01Final.pdf). While much hyperbole surrounds the Chattanooga system, a thoughtful outline of the recent history of the city is provided in D.A. Martin, *The Real Story Behind Chattanooga's 'Gig City' Resurgence*, WEEKLY STANDARD (August 2, 2017) (available at: https://www.weeklystandard.com/david-allen-martin/the-real-story-behind-chattanoogas-gig-city-resurgence).

(Footnote Continued. . . .)

group using matching. In Section III, we summarize the results of multiple econometric models estimating using either Least Squares or Logit. We present only the results of primary interest (details are offered in the Appendix). In the final section, we offer conclusions.

II. Empirical Strategy

Despite the significant policy relevance of municipal broadband (and the aggressive promotion thereof) there has been almost no systematic empirical investigation of the economic impacts of city-wide, government-owned broadband systems offering service to both residential and business customers.[9] What evidence exists is casual, anecdotal and often inaccurate. Consider, for instance, Chattanooga's Mayor Andy Berke's claim that the city's nearly $400-million network was responsible for a decline in unemployment in the city from 7.8% to 4.1% over the 2012-2015 period.[10] While an impressive decline, over the same post-recession period the nationwide unemployment rate fell from 7.5 percent to 4.7 percent.[11] In fact, with respect to the decline in unemployment over the period, Chattanooga ranked twenty fourth of twenty-six Tennessee cities for which the Bureau of Labor Statistics keeps detailed records.[12]

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9 *See, e.g., Remarks by the President on Promoting Community Broadband*, White House Office of the Press Secretary (January 14, 2015) (available at: https://obamawhitehouse.archives.gov/the-press-office/2015/01/14/remarks-president-promoting-community-broadband); *In the Matter of City of Wilson, North Carolina, Petition for Preemption of North Carolina General, Statute Sections 160A-340 et seq.; The Electric Power Board of Chattanooga, Tennessee, Petition for Preemption of a Portion of Tennessee Code Annotated Section 7-52-601*, FCC 15-25, MEMORANDUM OPINION AND ORDER, 30 FCC Rcd 2408 (rel. March 12, 2015), *rev'd sub nom., Tennessee v. FCC,* 832 F.3d 597 (6th Cir. 2016). Ford and Koutsky (2005) evaluate the effect of a limited deployment to businesses and government in Lake County-Florida. G.S. Ford and T.M. Koutsky, *Broadband and Economic Development: A Municipal Case Study from Florida*, 17 REVIEW OF URBAN & REGIONAL DEVELOPMENT STUDIES 216-229 (2005).

10 J. McGee, *Chattanooga Mayor: Gigabit Speed Internet Helped Revive City*, THE TENNESSEAN (June 14, 2016) (available at: https://www.tennessean.com/story/money/2016/06/14/chattanooga-mayor-gigabit-speed-internet-helped-revive-city/85843196).

11 G.S. Ford, *Questionable Economic Benefits of Chattanooga's Gig*, THE TENNESSEAN (August 17, 2016) (available at: https://www.tennessean.com/story/opinion/contributors/2016/08/17/questionable-economic-benefits-chattanoogas-gig/88908270). Over the period, Tennessee cities operating broadband systems saw unemployment decline by 4.0 percentage points, whereas those cities without such systems saw unemployment fall by 4.7 points, a statistically-significant difference.

12 *Id*.

(Footnote Continued. . . .)

After the decision was made to construct the network but before it was deployed, Lobo, Ghosh and Novobilski (2008) used Input-Output analysis to claim the broadband investments to be made by Chattanooga's electric utility would create 2,600 new jobs in Hamilton County, Tennessee.[13] In later work, Lobo (2015) raised the estimate to between 2,800 and 5,200 jobs over the period 2011-2015.[14] Predictions from Input-Output Models (and other types of educated guessing) have their place, but are superfluous when actual labor market outcomes are observed and measured.[15] If the benefits of municipal broadband systems on labor market outcomes are meaningful, then such effects should be quantifiable in actual economic data. It is to that task we now turn.

A. *The Difference-in-Differences Estimator*

Our empirical strategy is as follows. Say there are two sequential time periods (1 and 2) in areas where a GON is deployed. In the first period, only privately-provisioned broadband is available in a city or county, whereas in the second period the residents of the same city or county may also obtain broadband service from a GON. Let Y_1 and Y_2 be an outcome of interest in these cities or counties in the first period (say, jobs or unemployment), and let $\Delta Y = Y_2 - Y_1$, which is simply the change in the outcomes between the two periods. If ΔY was in some sense favorable, then it might be tempting to conclude that the causal effect of the GON was favorable. Yet, ΔY is not expected to be a valid measure of the effect of the GON, for the very reasons discussed above in relation to Mayor Berke's unemployment claims. While we might observe a decline in unemployment after the GON is built, if unemployment also fell in areas without a GON, then we cannot attribute the decline exclusively to the GON. A causal effect requires separating the effects of other economic conditions (e.g., a recovery from a recession) from those of the GON.

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13 Lobo, B. J., S. Ghosh, and A. Novobilski, *The Economic Impact of Broadband: Estimates from a Regional Input-Output Model*, 24 JOURNAL OF APPLIED BUSINESS RESEARCH 103-114 (2008).

14 B.J. Lobo, *The Realized Value of Fiber Optic and Smart Grid Infrastructure in Hamilton County, Tennessee*, *supra* n. 6.

15 Multipliers are based on historical relationships among industries and thus questionably apply to one-time massive injections of investment dollars well outside the range of normal activity. Also, the Input-Output Models typically show large gains in employment from almost any investment, since it is capturing the historic relationship between economic product and jobs. Thus, if a $100 million dollars were invested in a factory to produce slide rules, a multiplier model would *predict* a large increase in manufacturing employment and totally sidestep the issue that slide rules are rarely purchased in modern times so there would be reason to employ anyone to make them.

We seek to obtain an estimate of the causal effect of the GON using the Difference-in-Differences estimator. In addition to the two periods, let there be two groups in the sample, one that receives the treatment (the treated group) in period 2 and one that does not (the control group). Neither group receives the treatment in the first period. Let $Y_{T,1}$ be the outcome for the treated group in the first period, and $Y_{T,2}$ the outcome in the second period after the treatment is rendered. Similarly, we have $Y_{C,1}$ and $Y_{C,2}$ for the control group. The treatment effect of the GON may then be calculated as,

$$\delta = (Y_{T,2} - Y_{T,1}) - (Y_{C,2} - Y_{C,1}), \tag{1}$$

where δ contrasts the difference in the treated group to the difference in the control group between two the periods. Equation (1) is the standard approach of experimental research and is referred to as the Difference-in-Differences estimator ("DiD"), a name derived from the fact the formula is literally a difference in differences.[16] The DiD estimator is perhaps the most popular empirical strategy for estimating the effect of a policy change. Absent the treatment, it is assumed that δ is zero, an assumption known as the "parallel paths" or "common trends" assumption.[17] While our data is observational and not experimental, if the treatment is as good as randomly assigned (that is, there is no selection bias) and the two groups evaluated satisfy the common trends assumption, then δ measures the effect of the treatment.[18]

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16 J.M. Wooldridge, ECONOMETRIC ANALYSIS OF CROSS SECTION AND PANEL DATA (2010) at pp. 147-151.

17 B.D. Meyer, *Natural and Quasi-Experiments in Economics*, 13 JOURNAL OF BUSINESS & ECONOMIC STATISTICS 151-161 (1995); J.D. Angrist and J.S. Pischke, MOSTLY HARMLESS ECONOMETRICS: AN EMPIRICIST'S COMPANION (2008); *see also* D. Card, *The Impact of the Mariel Boatlift on the Miami Labor Market*, 43 INDUSTRIAL AND LABOR RELATIONS REVIEW 245-257 (1990); S. Galiani, P. Gertler, and E. Schargrodsky, *Water for Life: The Impact of the Privatization of Water Services on Child Mortality*, 113 JOURNAL OF POLITICAL ECONOMY 83-123 (2005) (available at: http://sekhon.berkeley.edu/causalinf/papers/GalianiWater.pdf).

18 J.S. Angrist and J. Pischke, MASTERING 'METRICS: THE PATH FROM CAUSE TO EFFECT (2015), at Ch. 5; J.D. Angrist and A.B. Krueger, *Empirical Strategies in Labor Economics*, in HANDBOOK OF LABOR ECONOMICS (Volume 3A) (1999) (O. Ashenfelter and D. Card, eds.) at Ch. 23.

(Footnote Continued. . . .)

B. *Estimation Approach*

The most common approach to estimate and test the DiD estimator is regression analysis. With observations on labor market outcomes for the two groups and periods, the DiD estimator can be estimated using a regression equation of the form (ignoring subscripts),

$$Y = \beta_0 + \beta_1 T + \beta_2 P + \delta P \cdot T + u \,, \tag{2}$$

where T is a dummy variable that equals 1.0 for the treated group, P is a dummy variable that equals 1.0 for period 2, $P{\cdot}T$ is the interaction of the two dummy variables, and u is an econometric disturbance term.[19] Simple algebra reveals that the estimate of δ from Equation (2) is equal to the DiD estimator of Equation (1), with its components being: $Y_{T,1} = \beta_0 + \beta_1$; $Y_{T,2} = \beta_0 + \beta_1 + \beta_2 + \delta$; $Y_{C,1} = \beta_0$; and $Y_{C,2} = \beta_0 + \beta_2$. The regression equation provides for a direct test of the null hypothesis that $\delta = 0$.

We may also specify a richer regression equation,

$$Y = \delta P \cdot T + \alpha X + \lambda + \tau + u \,, \tag{3}$$

where X is a vector of covariates (and α a vector of coefficients) accounting for the possibility that the random samples within each group are systematically different over time, λ are the time fixed effects and τ are the cross section fixed effects.[20] In our analysis, the covariate vector X includes dummy variables indicating whether the individual is female, Black, Hispanic, married, has a bachelor's degree, and a continuous variable of the person's age and its square. All of our estimates are based on Equation (3) and we include or exclude the regressors in different specifications. The interpretation of δ is identical between Equations (2) and (3).

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19 *Id.*; Wooldridge, *supra* n. 16.

20 Wooldridge, *id*. These fixed effects are collinear the independent variables T and P, but the not their interaction, so the two variables are excluded from the estimation model. The interpretation of δ as the DiD estimator is unchanged.

(Footnote Continued. . . .)

C. *Data*

To estimate the effects of Chattanooga's GON using the DiD estimator, we obtain data from the U.S. Census Bureau's American Community Survey ("ACS"), a micro-level dataset on individuals.[21] This data includes demographic information, some location data, as well as labor market outcomes on survey respondents. The GON treatment is applied to geographic areas, not individuals, so we draw samples of individuals from assorted geographic areas, including Chattanooga, to determine whether labor market outcomes for these individuals differ according to treatment.

We obtain data for the years 2005 through 2017. Chattanooga's network began signing up customers in late 2009, so we define year 2010 as the treatment date.[22] As our data spans the 2010 Census, we define the geographic footprint of Chattanooga, as well as other areas, using Consistent Public Use Microdata Areas (CPUMA).[23] Chattanooga has a population of approximately 200,000 persons, Hamilton County has a population of about 350,000 persons, and the entire Chattanooga, TN-GA Metropolitan Statistical Area ("MSA") has a population of 550,000 persons.[24] The population of the CPUMA covering Chattanooga (or Hamilton County) contains an average population of 243,066 persons over the sample period.[25]

Chattanooga's broadband network required a $390 million investment, with $111.6 million coming from federal taxpayers in the form of economic stimulus

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21 S. Ruggles, S. Flood, R. Goeken, J. Grover, E. Meyer, J. Pacas, and M. Sobek, *IPUMS USA: Version 9.0*, Minneapolis, MN: IPUMS (2019). Data available at: https://www.census.gov/programs-surveys/acs/data/pums.html.

22 The first customers were signed up in September 2009. *EPB Fiber Optics Reaches Milestone of Serving 100,000+ Customers*, EPB PRESS RELEASE (October 19, 2018) (available at: https://epb.com/about-epb/news/articles/epb-fiber-optics-reaches-milestone-of-serving-100000-customers).

23 Available at: https://usa.ipums.org/usa/volii/cpuma0010.shtml. Chattanooga's broadband system serves the entirety of Hamilton County, Tennessee.

24 Data obtained from https://www.worldatlas.com. *See also* https://www.muninetworks.org; Yoo and Pfenninger, *supra* n. 4; *EPB Annual Report 2017*, City of Chattanooga (2017) (available at: https://static.epb.com/annual-reports/2017//media/EPB_2017_Annual_Report.pdf).

25 The population count is the sum of the *perwt* variable.

(Footnote Continued. . . .)

from the American Recovery and Reinvestment Act of 2009 (approximately $1 for every U.S. household).[26] As is common with municipal broadband networks, the City of Chattanooga operates a municipal electric system. While electric and broadband distribution networks may share some complementary assets (e.g., billing systems, labor, trucks, rights-of-way), another reason for the coincidence of networks is that captive electric ratepayers are a source of profits to cover losses realized from network deployment and operation of a broadband network.[27] In Chattanooga, the electric division took on $229 million in debt for construction and operation and an additional $50 million was loaned from the electric to the broadband division.[28]

From the Census Data we are able to specify a fairly comprehensive set of labor market outcomes. Traditional labor market indicators include: (a) labor force participation; (b) employment; and (c) the wage rate.[29] Proponents of municipal broadband often point to the need for these sizable government investments to modernize the labor force for the Digital Age. We look for evidence of such effects using three outcomes: (d) employment in an Information Technology ("IT") job; (e) employment in industries that have a high share of IT jobs; and (f) employment in the Information Sector. IT employment includes occupational codes such as

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26 This investment is enormous. For instance, Chattanooga could have attracted 1,000 high quality school teachers to the area by giving each of them a $390,000 home to anyone promising to commit to a career in teaching.

27 For a detailed financial analysis of such cross-subsidies, *see* G.S. Ford, *Financial Implications of Opelika's Municipal Broadband Network*, PHOENIX CENTER POLICY PERSPECTIVE No. 17-11, *supra* n. 7.

28 Locating the debt on the books of the electric utility is often justified as "smart grid" investment, though audits and admissions by municipal officials belie this explanation. *See*, *e.g.*, *An In-Depth Look at Click! Financials*, Tacoma Public Utilities (May 20, 2015) (available at: http://www.clickcabletv.com/file_viewer.php?id=1911) ("Tacoma Power doesn't need a wired telecommunications network for metering (at p. 24)"; "Did not foresee the industry evolution to wireless power metering systems (at p. 23)".); P. Fuhr, W. Manges, T. Kuruganti, *Smart Grid Communications Bandwidth Requirements: An Overview*, SG COMMUNICATIONS TECHNOLOGY REVIEW (February 2011) (available at: http://trustworthywireless.ornl.gov/pdfs/Smart-Grid-Communications-Overview-Bandwidth2011.pdf); C. Butler, *Chattanooga Residents Get Internet, Courtesy of Taxpayers*, TENNESSEEWATCHDOG.NET (December 21, 2011) (available at: http://watchdog.org/1019/tn-chattanooga-residents-get-internetcourtesy-of-taxpayers) ("the manager of Chattanooga's system] admitted last month they could get the same information, and with the same accuracy, without the Smart Grid").

29 The employment rate, as measured here, is the number of employed persons per capita. We do not restrict the employment outcome to the labor force.

(Footnote Continued. . . .)

Computer Programmers, Database Administrators, and Computer and Information Systems Management. Industries with high shares of IT employment (by three-digit NAICS) include sectors like Data Processing, Hosting, and Related Services; Professional, Scientific, and Technical Services; Computer and Electronic Product Manufacturing; Telecommunications; Other Information Services; Publishing Industries (except Internet); Management of Companies and Enterprises; and Electronics and Appliance Stores.[30] The Information Services sector, which overlaps with the IT industries, includes: Publishing Industries (except Internet); Motion Picture and Sound Recording Industries; Broadcasting; Telecommunications; Data Processing, Hosting, and Related Services; and Other Information Services.[31] High-speed broadband networks have also been claimed to expand opportunities for entrepreneurship. We attempt to capture such an effect by looking at (f) self-employment and (g) business income.

Employment in automotive manufacturing is also considered.[32] After years of planning and site location, Volkswagen announced it would construct an automobile manufacturing plant in Chattanooga in 2008 and initialized operations in 2011, employing about 800 persons in 2010.[33] By 2015, the plant employed about 2,400 persons. Certainly, we expect to find an increase in automotive manufacturing employment, so looking at automotive employment serves to verify both the data and the regression models to detect changes in labor market

[30] The NAICs codes included are those with IT worker shares one standard deviation above the mean (or, about 7% of total labor, based on author calculations): 334, 443, 511, 517, 518, 519, 522, 52M, 541, and 55.

[31] The Information Sector is NAICS 51 and includes Publishing, Motion Pictures, Broadcasting, Telecommunications, Data Processing, and Other Information Services (https://www.bls.gov/iag/tgs/iag51.htm).

[32] Auto manufacturing includes NAICS 3361, 3362, and 3363 (available at: https://www.bls.gov/iag/tgs/iag336.htm).

[33] W. Schultz, *Chattanooga Chosen For $1 Billion Volkswagen Plant*, THE CHATTANOOGAN (July 15, 2008) (available at: https://www.chattanoogan.com/2008/7/15/131480/Chattanooga-Chosen-For-1-Billion.aspx); M. Pare, *VW More Than a Job, New Hires Say*, TIMES FREE PRESS (June 27, 2010) (available at: https://www.timesfreepress.com/news/volkswagen/story/2010/jun/27/0627-vw-more-than-a-job-new-hires-say/21396) ("VW has hired about 818 workers to date"); M. Pare, *VW Now Hiring 200 Workers in Chattanooga*, TIMES FREE PRESS (June 19, 2015) (available at: https://www.timesfreepress.com/news/business/aroundregion/story/2015/jun/19/vw-plant-adding-200-productiworkers/310410) ("VW now employs about 2,400 people in the city").

(Footnote Continued. . . .)

outcomes.[34] The location decision for the plant long preceded the county-wide deployment of fiber optics to the residential segment, though Volkswagen did require from Chattanooga's electric utility enhanced reliability for its facility.[35] The county-wide deployment to all businesses and residences is the decision we study here, and that deployment post-dated and had no effect on Volkswagen's site choice.

In all, we consider nine labor market outcomes (including auto manufacturing), seven of which are dichotomous outcomes. Both wages and business income, the two continuous outcomes, are expressed in constant dollars.[36] We apply the natural log transformation to wages (so the δ measures a percentage change), but do not do so for business income due to the presence of negative values.

D. *Model Selection*

Equations (2) and (3) are estimated by Ordinary Least Squares ("OLS"), which for the dichotomous variables is a Linear Probability Model ("LPM"). While dichotomous outcomes are often estimated using Probit or Logit Models, which are designed for dichotomous dependent variables, the δ coefficients from LPM are easier to interpret and, under some conditions, provides consistent and efficient estimates.[37] Many of our dichotomous outcomes, however, have means

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[34] A statistically insignificant result may indicate there is "no effect," but insignificant results may also be the consequence of bad data or a poorly-specified statistical model. A failure to detect a change in auto manufacturing employment would lead to questions about the data or the models.

[35] J. Taplin, *Chattanooga Has Its Own Broadband—Why Doesn't Every City?*, DAILY BEAST (July 24, 2017) (available at: https://www.thedailybeast.com/chattanooga-has-its-own-broadbandwhy-doesnt-every-city) ("the city sits in the middle of Tornado Alley, and the electricity goes out several times a year during big storms. Since the plant was going to be highly roboticized, electrical outages would be particularly problematic. So the EPB promised to build a smart grid so that when a tree fell on the wires on Flynn Street, only Flynn Street would go dark, because the smart grid would route power around the trouble.").

[36] Nominal dollars are converted using the Implicit Price Deflator for Personal Consumption Expenditures (available at: https://fred.stlouisfed.org/series/DPCERD3A086NBEA).

[37] *See*, *e.g.*, Wooldridge, *supra* n. 16 at Ch. 15; G. King and L. Zeng, *Logistic Regression in Rare Events Data*, 9 POLITICAL ANALYSIS 137–163 (2001); J.S. Long, REGRESSION MODELS FOR CATEGORICAL AND LIMITED DEPENDENT VARIABLES (1997). A summary discussion is provided by P. Von Hippel, *Linear vs. Logistic Probability Models: Which is Better, and When?*, STATISTICAL HORIZONS (July 5, 2015) (available at: https://statisticalhorizons.com/linear-vs-logistic).

(Footnote Continued. . . .)

close to zero or one, and at these extremes support for the LPM is weaker. Consequently, results from the Logit Model are also provided.

E. *Sampling Weights*

As a stratified sample, the ACS data includes sample weights for the individual respondents.[38] When computing descriptive statistics, the application of the weight is clearly appropriate, and the weights aim to make the descriptive statistics represent population parameters. In regression analysis, however, the use of weights is not so clear cut.[39] If the objective is to obtain a population average coefficient, then weights might be used. In estimating causal effects, however, the use of weights is generally discouraged. For completeness, we present both the weighted and unweighted estimates.

F. *The Control Group*

The DiD estimator compares outcomes between a treated and a control group, the latter of which represents the non-treated outcomes for the treated group (i.e., the counterfactual). Thus, the control group is not just a sample of persons living in places without a GON (i.e., untreated areas), but is a group expected to have identical outcomes to the treated group if the treated group did not receive the treatment. A control group is a "stand in" for the treatment group absent the treatment and thus provides the counterfactual outcome.

Research indicates the control group should satisfy two key conditions. First, the *common trends* assumption requires that the pattern of outcomes of the treated and control groups would be equal before and after the treatment if the treatment was not rendered. That is, the δ of Equation (1) is expected to be zero if a treatment was not given. While this assumption cannot be formally tested, researchers often ensure that the trends in outcome during the pre-treatment window are very similar between the treatment and control groups. Second, *common support* (or covariate balance) requires that the characteristics (or distributions thereof) of control and treatment groups be very similar. We take care to address common

[38] The weight for individual is *perwt*. Information on the weight is available at: https://usa.ipums.org/usa-action/variables/PERWT#description_section.

[39] G. Solon, S.J. Haider and J.M. Wooldridge, *What Are We Weighting For?*, 50 JOURNAL OF HUMAN RESOURCES 301-316 (2015) (earlier version available at: https://www.nber.org/papers/w18859).

support for factors known to influence labor market outcomes such as education, race, gender, and age.

As a first cut to address common trends and common support, from the ACS we obtain a sample of individuals from Tennessee and its nearest neighboring southern states including Alabama, Arkansas, Georgia, Kentucky, Mississippi, Missouri, North Carolina, South Carolina, and Virginia. Our ACS sample begins in 2005 and the Chattanooga system began taking customers in September 2009. With few years in the pre-treatment period, it is not feasible to sufficiently evaluate the common trends assumption with this data. Instead, we obtained data on private employment and wages for MSAs in these same states from the Bureau of Labor Statistics ("BLS") and the Bureau of Economic Analysis ("BEA").[40] The employment data spans 1990-2008 and the wage data 2001-2008. Using this data, we may narrow our analysis to CPUMAs within MSAs that have pre-treatment trends in employment and wages very similar to the Chattanooga MSA.[41] Our final selection includes CPUMAs from fourteen MSAs: Atlanta-Sandy Springs-Roswell, GA; Birmingham-Hoover, AL; Blacksburg-Christiansburg-Radford, VA; Columbia, SC; Decatur, AL; Goldsboro, NC; Greenville-Anderson-Mauldin, SC; Jackson, MS; Little Rock-North Little Rock-Conway, AR; Louisville/Jefferson County, KY-IN; Nashville-Davidson-Murfreesboro-Franklin, TN; Richmond, VA; and Virginia Beach-Norfolk-Newport News, VA.[42] A total of 45 CPUMA fall within these broader areas.

[40] Bureau of Labor Statistics data webpage is: https://www.bls.gov/data. The MSA is a larger geographic area than the CPUMA, an unavoidable consequence of data availability. We believe this trend analysis almost certainly improves the case for common trends.

[41] Visual inspection and statistical analyses are used to evaluate the trends. In order to mechanize the process as much as possible, the final method for choosing controls is to place bounds around the centered series values for Chattanooga and select only MSAs that fall within those bounds. We compute the means every third year for employment and every second year for wages with the final year always being 2008.

[42] A search for municipal broadband systems in matched PUMAs was conducted using https://muninetworks.org/communitymap and https://broadbandnow.com, as well as general Internet searches. Any area with a municipal broadband system was excluded, which here includes only Memphis, TN (a now defunct system).

Figure 1. Pre-Treatment Trends

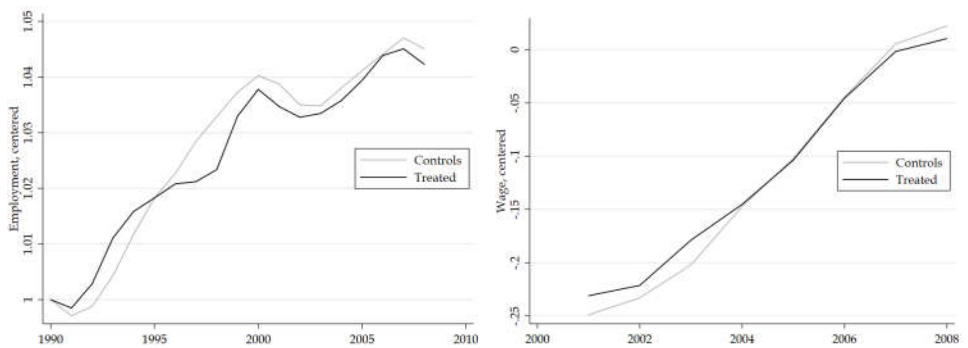

Figure 1 illustrates the trends across the treated and control units. Visually, the trends between the two groups are satisfactorily similar. Testing for differential growth rates between the groups, we are unable to reject the null hypothesis of equal growth rates during the pre-treatment period (through 2008). For employment, the slope coefficient is 0.005 (t-stat = 34.57) and the difference in the growth rates is -0.0003 (t-stat = -1.13). With wages, the slope coefficient is 0.003 (t-stat = 32.14) and the difference in the growth rates is -0.0003 (t-stat = -1.38). So, it appears we have addressed common trends, at least to the extent feasible.

Since the control group's outcomes are projected on the treatment group (as a counterfactual for the treatment group if it were untreated), we must ensure the sorts of persons in the control and treated groups have similar distributions of factors that influence labor market outcomes. Also, common support improves the efficiency of the estimates. Following Blackwell, *et al*. (2009) and Austin (2010), we construct a control group from the MSAs satisfying common trends using a 2:1 Coarsened Exact Matching ("CEM") matching algorithm on five of our six exogenous variables (female, married, age, Black, Hispanic), with matches chosen in each year.[43] The control group exactly matches the treated observations across

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[43] M. Blackwell, S. Iacus, G. King, and G. Porro, *cem: Coarsened Exact Matching in Stata*, 9 THE STATA JOURNAL 524, 541-2 (2009) ("a good use of `cem` would be to reduce the data to common support before applying another matching solution"). On the 2:1 matching approach, *see* P.C. Austin, *Statistical Criteria for Selecting the Optimal Number of Untreated Subjects Matched to Each Treated Subject When Using Many-to-One Matching on the Propensity Score*, 172 AMERICAN JOURNAL OF EPIDEMIOLOGY 1092-1097 (2010) (available at: https://academic.oup.com/aje/article/172/9/1092/147493) ("in the majority of settings, using 1:1 or 2:1 matching will result in optimal estimation of treatment effects when employing fixed *M*:1 matching."). M. Iacus, G. King. G. Porro, C*ausal Inference without Balance Checking: Coarsened Exact Matching*, Working Paper (June 26, 2008) (available at:

(Footnote Continued. . . .)

all dichotomous variables and the bins for age only span a few years. The treated observations are one-third of the total matched sample, by design.[44]

Table 1: Standardized Differences

Variable	Total Sample	Chattanooga	Controls	Stan. Diff.
Female	0.522	0.522	0.522	0.000
Married	0.554	0.554	0.554	0.000
Age	43.35	43.35	43.36	0.000
Black	0.161	0.161	0.161	0.000
Hispanic	0.030	0.030	0.030	0.000
Bachelors	0.214	0.207	0.218	0.029

Means and standardized differences for demographic traits including are provided in Table 1. Due to the matching procedure, the means across the two groups are nearly identical and the standardized (or normalized) differences are all near zero (i.e., a useful rule of thumb for an impactful difference is 0.25).[45] The

https://ssrn.com/abstract=1152391), later published *Causal Inference without Balance Checking: Coarsened Exact Matching*, 20 POLITICAL ANALYSIS 1-24 (2012) (available at: https://gking.harvard.edu/files/political_analysis-2011-iacus-pan_mpr013.pdf). We do not match on bachelor's degree since a college education often viewed as a human capital, which may be viewed as a labor market outcome. *See*, *e.g.*, T. Schiller, *Human Capital and Higher Education: How Does Our Region Fare?*, FEDERAL RESERVE BANK OF PHILADELPHIA: BUSINESS REVIEW (2008) (available at: https://www.philadelphiafed.org/-/media/research-and-data/publications/business-review/2008/q1/schiller_human-capital-and-higher-education.pdf). Statistics available at: https://www.census.gov/quickfacts/fact/table/US/PST045217. *See also,* C.L. Ryan and K. Bauman, *Educational Attainment in the United States: 2015*, U.S. Census Bureau (March 2016) (available at: https://www.census.gov/content/dam/Census/library/publications/2016/demo/p20-578.pdf).

44 Chattanooga represents only about 2.6% of observations in the full sample.

45 The standardized difference is equal to the absolute value of the means difference divided by the square root of the average variances of the treated and control groups. This difference is similar to the calculation of a t-statistic but excludes the adjustment for sample size. *See*, *e.g.*, G. Imbens and J. Wooldridge, *Recent Developments in the Econometrics of Program Evaluation*, 47 JOURNAL OF ECONOMIC LITERATURE 5-86 (2009), at p. 24 ("with a normalized difference exceeding one quarter, linear regression methods tend to be sensitive to the specification"); P.C. Austin, *Balance Diagnostics for Comparing the Distribution of Baseline Covariates Between Treatment Groups in Propensity-Score Matched Samples*, 28 STATISTICS IN MEDICINE 3083-3107 (2009) ("Effect Size Indices of 0.2, 0.5, and 0.8 can be used to represent small, medium, and large effect sizes"). In the psychological literature, the standardized difference is referred to as Cohen's Effect Size Index. J. Cohen, STATISTICAL POWER ANALYSIS FOR THE BEHAVIORAL SCIENCES (1988).

(Footnote Continued. . . .)

largest difference is for the unmatched variable (bachelor's degree), but the standardized difference is also very small for this variable. We thus conclude that the control group satisfies both common support and common trends, at least as best as can be determined.

In some respects, the sample is not typical of the nation, demonstrating the importance of addressing common support. Approximately 21% of the sample has a college degree, which is below the national average of about one-third.[46] The percent Black population of 20% is above the national average of 13% while the percent Hispanic population is only 3%, which is well below the national average of about 18%.[47] The average age of the working population, the marriage rate, and percent female are comparable to national averages.[48]

G. *Descriptive Statistics*

Table 2 presents means and standard deviations for the outcome variables for the estimation sample and for the treated and untreated groups before and after the treatment period. Sampling weights from the ACS are used to be representative of the population. The means for labor force participation, employment, and wages all decline between the pre- and post-treatment periods in both groups, a result likely reflecting the recession. Labor force participation fell by 0.025 in Chattanooga and 0.018 in the control group, and the number of jobs per-capita (employment) fell 0.024 in the treated and 0.022 in the control group. Business income dropped $824 in the treated area but fell $790 in the control areas. IT employment rises between the periods, which is no surprise, but employment in IT-heavy industries and in the Information Sector declined.[49]

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46 Statistics available at: https://www.census.gov/quickfacts/fact/table/US/PST045217.

47 *Id*.

48 Age data available at: https://www.bls.gov/emp/tables/median-age-labor-force.htm. Marriage statistics available at: https://statisticalatlas.com/United-States/Marital-Status. Gender data available at: https://mchb.hrsa.gov/whusa13/population-characteristics/p/us-population.html and *id*.

49 *Number of IT Workers Has Increased Tenfold Since 1970, Census Bureau Reports*, U.S. CENSUS BUREAU RELEASE NUMBER BC16-136 (August 16, 2016) (available at: https://www.census.gov/newsroom/press-releases/2016/cb16-139.html).

Table 2: Summary Statistics, Outcomes

Mean (Standard Deviation)

Outcome	Full Sample	Treated Before	Treated After	ΔY_T	Controls Before	Controls After	ΔY_C
Lab Force Part.	0.7437	0.7587	0.7337	-0.0250	0.7556	0.738	-0.0176
	(0.437)	(0.428)	(0.442)		(0.430)	(0.440)	
Employment	0.6872	0.7020	0.6777	-0.0243	0.7020	0.6797	-0.0223
	(0.464)	(0.457)	(0.467)		(0.457)	(0.467)	
Wage	23.391	22.125	21.52	-0.6050	24.392	24.131	-0.2610
	(43.47)	(40.35)	(38.73)		(34.52)	(50.55)	
IT Employment	0.0253	0.0171	0.0194	0.0023	0.0261	0.0301	0.0040
	(0.157)	(0.130)	(0.138)		(0.159)	(0.171)	
IT-Heavy Sectors	0.0983	0.0769	0.0735	-0.0034	0.1162	0.1071	-0.0091
	(0.298)	(0.266)	(0.261)		(0.320)	(0.309)	
Information Sector	0.0190	0.0163	0.0126	-0.0038	0.0256	0.0193	-0.0064
	(0.136)	(0.127)	(0.111)		(0.158)	(0.137)	
Self Employed	0.0927	0.0967	0.0818	-0.0149	0.1058	0.0896	-0.0162
	(0.290)	(0.295)	(0.274)		(0.308)	(0.286)	
Business Income	2211.1	2747.6	1923.9	-823.70	2716.1	1926.6	-789.50
	(17352)	(19769)	(16373)		(19339)	(15874)	
Auto Manuf.	0.0110	0.0043	0.0142	0.0099	0.0117	0.0109	-0.0008
	(0.744)	(0.759)	(0.734)		(0.756)	(0.738)	
Observations	82,299	9,989	17,445		19,977	34,888	

Data weighted by perwt.

Many of the changes between periods (ΔY) appear quite small, but the total effect may still be large with a treated population of 243,066 persons and a treated labor force of 180,503 persons (on average across the sample period).[50] In Chattanooga, the decline in labor force participation equals about 6,000 persons leaving the labor force [= -0.025·243066]. Using the ΔY_C as a comparison, the reduction in the labor force is 4,300, so the loss relative to the control group is only 1,700 jobs. Similarly, the average wage rate in Chattanooga fell by $0.61 but for the control group fell by $0.26, for a net difference of -$0.35, a much smaller effect. These examples show the importance of using the DiD estimator rather than the change in Chattanooga alone. We note, however, that these changes between the periods and groups are merely suggestive because the means between the groups are slightly different. The regression model of Equation (3) will compute the DiD estimator after centering the groups on their means using both cross-section and time fixed effects.

50 The total size of the population and labor force is computed by summing the *perwt* variable.

III. Estimation Results

Our empirical approach aims to estimate the causal effect of municipal broadband on labor market outcomes. To do so, we employ the DiD estimator δ, which is a standard approach in a quasi-experimental setting. The DiD estimator of Equation (1) is estimated and tested using Equation (3) both with and without the covariate vector X. Our data is a pooled cross section of persons living either in a treated or untreated area, some before and others after the treatment. The treated sample is one-third of the sample. These samples are very large and so we expect our statistical tests to have high power; that is, even small differences may be statistically different from zero.

A. *Basic DiD Regression*

To begin, we first estimate Equation (3) without the covariates; both year and CPUMA fixed effects are included in all models. We cluster the standard errors on the forty-four CPUMA in the sample. The null hypothesis $\delta = 0$ is normally tested directly using the t-statistic of the δ coefficient, but research suggests that using few clusters, or even few treated clusters, tends to understate the standard errors (leading to too many statistically-significant results).[51] While 44 clusters is sufficiently large for clustering, only one of the CPUMAs is treated (Chattanooga). Following MacKinnon and Webb (2017) and Cameron, Gelbach, and Miller (2008), we apply the wild bootstrap for hypothesis testing of the DiD estimators.[52] The probability levels of the traditional clustered t-statistics are also provided for comparison purposes.

In Table 4, we summarize the OLS/LPM estimates of Equation (3) using weighted data. We offer only the δ coefficients, though more detail is offered in the Appendix. For the dichotomous outcomes, the δ coefficient measures the change in the probability of the dependent variable from the GON treatment. For log wage, the percent change in the wage of the treatment is computed using the expression $[\exp(\delta) - 1]$, and for business income the coefficient measures the dollar change of the treatment.

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[51] T.G. Conley and C.R. Taber, *Inference with "Difference in Differences" with a Small Number of Policy Changes*, 93 REVIEW OF ECONOMICS AND STATISTICS 113–125 (2011).

[52] A.C. Cameron, J.B. Gelbach and D.L. Miller, *Bootstrap-Based Improvements for Inference with Clustered Errors*, 90 REVIEW OF ECONOMICS AND STATISTICS 414-427 (2008); J.G. MacKinnon and M.D. Webb, *The Wild Bootstrap for Few (Treated) Clusters*, 21 ECONOMETRICS JOURNAL 114-135 (2018).

Table 4: LPM/OLS, Weighted, No Covariates

		Probability Level		
Outcome	$\hat{\delta}$	Bootstrap	Asymptotic	Obs.
Lab Force Part.	-0.0113	0.224	0.043	72,030
Employment	-0.0035	0.616	0.570	72,030
ln(Wage)	0.0025	0.827	0.833	49,948
IT Employment	-0.0017	0.471	0.395	72,030
IT-Heavy Sectors	0.0038	0.394	0.300	72,030
Information Sector	0.0018	0.482	0.365	72,030
Self Employed	0.0029	0.558	0.500	59,743
Business Income	-19.5832	0.943	0.939	72,030

Data weighted by perwt.

Table 4 summarizes the estimates of Equation (3) for all the outcomes weighted by the sampling weights and estimated by OLS (or LPM).[53] All the regressions have a statistically-significant F-statistic at the 1% level or better, indicating the regressions have explanatory power. Despite the large sample sizes, none of the DiD estimators is statistically different from zero at anywhere near traditional levels (i.e., 10% or better) when using the bootstrap procedure that accounts for the single treatment cluster. Ignoring this feature of the data, the asymptotic results indicates the reduction in labor force participation of about 1% (-0.0113, or 2,700 persons) is statistically different from zero at the 5% level. Research indicates the bootstrapped probability level is preferred, so across the board we cannot reject the null hypothesis that the Chattanooga GON has had "no effect" on labor market outcomes.

53 Detailed estimates are provided in the Appendix.

Table 5: LPM/OLS, Unweighted, No Covariates

		Probability Level		
Outcome	$\hat{\delta}$	Bootstrap	Asymptotic	Obs.
Lab Force Part.	-0.0106	0.198	0.020	72,030
Employment	-0.0065	0.325	0.165	72,030
ln(Wage)	-0.0006	0.951	0.956	49,948
IT Employment	0.0003	0.857	0.836	72,030
IT-Heavy Sectors	0.0012	0.747	0.735	72,030
Information Sector	0.0018	0.436	0.326	72,030
Self Employed	0.0077	0.243	0.052	59,743
Business Income	251.0904	0.441	0.326	72,030

Table 5 summarizes the same model using unweighted data. The results are comparable in that none of the DiD coefficients is statistically different from zero based on the bootstrap procedure. Asymptotically, both labor force participation and self-employment are statistically significant at better than the 10% level, but the bootstrap tests suggests these t-statistics are inflated. There are a few sign changes, which is not unexpected given the wide confidence intervals on small coefficient estimates and, of course, the lack of sample weights. A rather large difference in the coefficient for business income is observed, but the result is not statistically significant at anywhere near standard levels. In all, labor market outcomes in Chattanooga are equal to those in comparable southern cities.

B. *Including Covariates*

In Table 6, we summarize the results from the estimation of Equation (3) including the covariate vector X. For these results, the DiD estimator δ is conditioned on the X and the data is weighted. For expositional reasons, we do not provide the coefficients on the Xs since they are not of primary interest (see Table 9 for a review of the estimated coefficients).[54] We note that almost all of the coefficients on the covariates are statistically different from zero, usually at the 5% level or better (asymptotically).

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[54] Again, detailed tables of these models are offered in the Appendix for interested readers.

Table 6: LPM/OLS, Weighted, with Covariates

		Probability Level		
Outcome	$\hat{\delta}$	Bootstrap	Asymptotic	Obs.
Lab Force Part.	-0.0106	0.214	0.047	71,302
Employment	-0.0039	0.517	0.495	71,302
ln(Wage)	-0.0054	0.571	0.564	49,650
IT Employment	-0.0018	0.450	0.378	71,302
IT-Heavy Sectors	0.0036	0.422	0.333	71,302
Information Sector	0.0018	0.479	0.353	71,302
Self Employed	0.0018	0.674	0.655	59,325
Business Income	-66.2828	0.807	0.802	71,302

Data weighted by perwt.

Including the additional covariates did not alter the results by much. All of the DiD estimators reported in Table 6 are statistically indistinguishable from zero using the bootstrap procedure and similar in size to those in Table 4. Labor force participation is again statistically significant at the 5% level for the asymptotic test. In no case can we reject the null hypothesis of "no effect" of the GON treatment for the more reliable bootstrap tests.

Table 7: LPM/OLS, Unweighted, with Covariates

		Probability Level		
Outcome	$\hat{\delta}$	Bootstrap	Asymptotic	Obs.
Lab Force Part.	-0.0093	0.203	0.025	71,302
Employment	-0.0055	0.325	0.165	71,302
ln(Wage)	-0.0047	0.606	0.592	49,650
IT Employment	0.0009	0.963	0.962	71,302
IT-Heavy Sectors	0.0009	0.814	0.805	71,302
Information Sector	0.0017	0.438	0.339	71,302
Self Employed	0.0076	0.241	0.050	59,325
Business Income	233.2886	0.468	0.382	71,302

Table 7 summarizes the estimates of Equation (3) with unweighted data. The results are comparable to those in Table 5. We cannot reject the null hypothesis of "no effect" of the GON treatment for any of the outcomes using the bootstrap procedure. As in Table 5, the negative sign for labor force participation and positive coefficient for self-employment are statistically significant at the 10% level or better for the asymptotic tests, but these test statistics appear too large as a result of the single treated cluster. For labor market outcomes, Chattanooga is unremarkable despite a near $400 million investment in its GON.

C. *The Logit Model*

Many of our outcomes are dichotomous with values near zero or one. The Logit Model may be better for these outcomes. We summarize the results from the Logit estimation of the dichotomous outcomes by Equation (3) in Table 8. Results are provided for both the weighted and unweighted data and the models include the covariates *X*, so the results are most comparable to those in Tables 6 and 7. Probability levels are based on the wild bootstrap.

Table 8: Logit Results of Equation (3)

	Weighted		Unweighted	
Outcome	$\hat{\delta}$	Prob.	$\hat{\delta}$	Prob.
Lab Force Part.	-0.0112	0.218	-0.0097	0.206
Employment	-0.0040	0.504	-0.0058	0.319
IT Employment	0.0003	0.779	0.0010	0.364
IT-Heavy Sectors	0.0016	0.507	-0.0006	0.816
Information Sector	-0.0003	0.746	0.0000	0.972
Self Employed	0.0003	0.917	0.0059	0.246

Probabilities based on bootstrap tests.

The coefficients of the Logit model do not measure the marginal effects, so the marginal effects are reported in Table 8 so that they may be compared to the LPM estimates. The Logit estimates are not much different than those from the LPM. As before, none of the δ coefficients are statistically different from zero using the bootstrap procedure. There are no discernable labor market effects from the GON.

D. *A Brief Discussion of the Xs*

Since we are interested mostly in the DiD estimator, we did not summarize the coefficients on the covariates included in Equation (3).[55] We note that many of the covariates' coefficients are (asymptotically) statistically different from zero, usually at the 5% level or better. We summarize in Table 9 the covariates' coefficients and briefly discuss them. The results in Table 9 are from the LPM of Equation (3) using the weighted data (as summarized in Table 6 above).

55 As before, detailed estimates of the model are offered in the Appendix.

Table 9: Covariate Coefficients, LPM/OLS, Weighted

Outcome	Female	Black	Hispanic	Married	Bach.	Age	Age^2
Lab Force Part.	-0.12***	-0.020***	-0.021*	0.020***	0.066***	0.044***	-5.8e-04***
Employed	-0.11***	-0.063***	-0.016	0.051***	0.084***	0.046***	-6.0e-04***
ln(Wage)	-0.20***	-0.21***	-0.31***	0.23***	0.31***	0.076***	-7.3e-04***
IT Emp.	-0.022***	-0.0083**	-0.023***	0.0065***	0.033***	0.0031***	-4.0e-05***
IT Sector	-0.0096**	-0.046***	-0.072***	0.028***	0.090***	0.0076***	-9.4e-05***
Inf. Sector	-0.0073***	0.0003	-0.0090**	-0.001	0.015***	0.0015***	-1.8e-05***
Self Employed	-0.047***	-0.044***	-0.017*	0.025***	0.0038	0.0058***	-3.2e-05***
Bus. Income	-2,475.2***	-1,172.2***	-4.77	1,322.1***	231.0	302.0***	-2.9e+00***

Stat. Sign. *** (1%), ** (5%), * (10%).
Data weighted by perwt.

In Table 9, we see that females and Blacks earn wages about 18% lower than males [=exp(-0.20) – 1] and Hispanics earn about 27% lower wages. A Bachelor's Degree increases wages by about 36%. Married persons also earn higher wages. A person with a bachelor's degree is more likely to be in the labor force (0.066) and have a job (0.084). Older persons generally have more favorable outcomes across the board, though the effects are sometimes non-linear. For instance, business income is maximized at 52 years of age [= 302/2·2.9]. Based on the existing literature and common knowledge regarding the labor market, these results are largely expected. We stress, however, that our model is not a test of gender, race or age discrimination in labor markets.[56]

E. *Automobile Manufacturing*

A battery of statistically insignificant treatment effects may be the result of there actually being "no effect," a consequence of bad data, or the product of a poor empirical model. As shown in Table 9, however, almost all of the covariates are statistically different from zero, so the data and the model are capable of producing significant and reasonable results. Still, our interest is in the effect on labor market outcomes of a treatment. We may exploit the introduction of an automobile manufacturing plant to Chattanooga in 2010, a treatment certain to increase employment in automobile manufacturing, to evaluate whether our model is capable of measuring labor market effects. Results from the estimation of Equation (3) including the covariates are summarized in Table 10 for both

56 *See*, *e.g*., D. Neumark, *Experimental Research on Labor Market Discrimination*, 56 JOURNAL OF ECONOMIC LITERATURE 799-866 (2018) and M. Bertrand and E. Duflo, *Field Experiments on Discrimination*, in HANDBOOK OF ECONOMIC FIELD EXPERIMENTS (Vol. 1) (2017) at pp. 309-393.

weighted and unweighted data. Probability levels are based on the wild bootstrap.

Table 10: Automobile Manufacturing, Equation (3)

	Weighted		Unweighted	
Outcome	$\hat{\delta}$	Prob.	$\hat{\delta}$	Prob.
LPM				
Auto Manuf.	0.0126	<0.01	0.0102	<0.01
LOGIT				
Auto Manuf.	0.0088	<0.01	0.0074	<0.01

Bootstrapped probabilities shown.

Across all the estimates we find statistically-significant effects (at the 1% level or better) of the auto-plant treatment. The average marginal effect for auto manufacturing is 0.0096, which implies an increase in employment in this sector by about 2,300 jobs. In 2015, the Volkswagen plant employed about 2,400 persons.[57] The estimated employment effect, which is an average effect over the sample, is very close to the actual employment levels, affirming our empirical strategy is capable of detecting labor market impacts (and doing so accurately). It is interesting to note that while the auto plant employment rose by a few thousand jobs, we find no effect on total employment in the area, so the increased manufacturing employment at the expense of other forms of employment (or else attracted employees from out of the area).

F. *Robust Standard Errors*

In the above analysis we employed clustered standard errors for the hypothesis tests but used the wild bootstrap to correct for the (likely) understatement of the standard errors resulting from having only a single treated cluster. Another approach is to ignore clustering altogether and use heteroscedasticity-consistent (or robust) standard errors.[58] In Table 11, we provide the results for Equation (3) using weighted data and including the covariates.

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57 M. Pare, *Chattanooga's Volkswagen Plant Expansion Gets Supersized*, TIMES FREE PRESS (April 5, 2015) (available at: https://www.timesfreepress.com/news/local/story/2015/apr/05/vw-plant-expansigets-supersized/297001).

58 H. White, *A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity*, 48 ECONOMETRICA 817–838 (1980); J.G. MacKinnon and H. White, *Some Heteroskedastic-Consistent Covariance Matrix Estimators with Improved Finite Sample Properties*, 29 JOURNAL OF ECONOMETRICS 305–325 (1985).

Table 11: LPM/OLS, Weighted, with Covariates, Robust SE

		Probability Level		
Outcome	$\hat{\delta}$	Bootstrap	Clustered	Robust
Lab Force Part.	-0.0106	0.214	0.047	0.204
Employment	-0.0039	0.517	0.495	0.666
ln(Wage)	-0.0054	0.571	0.564	0.737
IT Employment	-0.0018	0.450	0.378	0.512
IT-Heavy Sectors	0.0036	0.422	0.333	0.528
Information Sector	0.0018	0.479	0.353	0.526
Self Employed	0.0018	0.674	0.655	0.778
Business Income	-66.2828	0.807	0.802	0.853
Auto Manuf.	0.0126	<0.01	<0.01	<0.01

Data weighted by perwt.

Table 11 replicates most of Table 6, adding an additional column for the probability levels based on the robust standard errors and including the results for auto manufacturing from Table 10. The estimated coefficients are the same as those reported in Table 6. As with the bootstrapped method, the robust standard errors produce no statistically significant DiD coefficients except for auto manufacturing. The probability levels are broadly consistent with their bootstrapped counterparts.

G. *Carving Out the Middle*

Using the CEM-matched sample, in Table 12 results are provided when excluding years 2008 through 2012 from the sample. These years were a turbulent economic period including and following the Great Recession. Also, the effects of the GON may take some time to develop. By excluding these years, we may avoid the labor market peculiarities of the recession and look for the longer-term effects of the GON.

Table 12: Equation (3), OLS/LPM & Weighted
(Excluding Years 2008-2012)

		Probability Level		
Outcome	$\hat{\delta}$	Bootstrap	Asymptotic	Obs.
Lab Force Part.	-0.0047	0.567	0.529	44,235
Employment	0.0021	0.838	0.823	44,235
ln(Wage)	-0.0014	0.902	0.896	30,939
IT Employment	-0.0017	0.571	0.527	44,235
IT-Heavy Sectors	0.0006	0.906	0.905	44,235
Information Sector	0.0039	0.385	0.180	44,235
Self Employed	0.0028	0.612	0.556	36,712
Business Income	-78.1618	0.836	0.810	44,235
Auto. Manuf.	0.0160	<0.010	<0.010	44,235

Data weighted by perwt.

There are no meaningful differences in these results from those presented earlier. None of the labor force outcomes is statistically different from zero. Auto manufacturing employment rises by about 3,900 jobs, exceeding the plant's employment alone, and the coefficient is statistically different from zero at the 1% level or better. Car plants increase auto manufacturing labor, by the GON has had no effect. Despite the large rise in auto employment, the coefficient on total employment is not statistically different from zero. In Chattanooga, labor has shifted toward car building and away from other forms of employment.

H. *Caveats*

The data suggest local governments must look outside the labor market to justify the sizable investments in municipal broadband systems. That said, we note three caveats. First, our analysis is limited to labor market outcomes only. Second, Chattanooga had private providers offering broadband services prior to and subsequent to the deployment of the GONs. Consequently, our findings may not be generalized to areas where broadband services may not be available absent the municipal system. That said, if a city already has broadband service, then our analysis suggests adding a municipal system is unlikely to produce meaningful improvements, if any improvement at all, in labor market outcomes. Third, our results cannot speak to the benefits of high-speed Internet services generally, since broadband Internet was and is largely available in these cities absent the municipal system. Put simply, our results suggest that building GONs in markets where privately-provisioned broadband is already available has no favorable effect on labor markets.

IV. Conclusion

In this POLICY PAPER, we offer (to our knowledge) the first statistical evidence on the labor market effects of municipal broadband systems. Using the Difference-in-Differences estimator and Census data, we find almost no statistically significant effects for a wide range of important labor market variables, with the possible exception of a reduction in labor force participation. Employment status, wages, information technology employment, self-employment, and business income appear unaffected by the introduction of a government-owned broadband network. As such, local governments must look outside the labor market to justify the sizable investments in these broadband systems.

Our results are, perhaps, not surprising in light of the vast literature on development economics. In many cases, including the municipal broadband system studied here, the government-owned network competes with existing broadband providers by offering relatively small increases in coverage and modest (and often unusable) upgrades in download speeds. These relatively small additions to broadband infrastructure are not expected to have broad effects in the labor market.

Our analysis is subject to three important caveats. First, our analysis is limited to labor market outcomes. There may be other effects of the GON. Second, since Chattanooga's system overbuilt private providers, our findings may not be generalized to areas where broadband services are not available absent the municipal system. Third, our results cannot speak to the benefits of high-speed Internet services generally, since broadband Internet was and is largely available in these cities absent the municipal system. What our results do indicate is that building a government-owned network in markets where privately-provisioned broadband is generally available has no favorable effect on labor market outcomes.

APPENDIX

This Appendix provides more detailed estimates from the regression models summarized in Table 4 through 8, 10 and 11, which are labeled here Tables A-4 through A-11. Table 9 is based on results reported in Table A-6.

Table A-4. Detailed Results

	LFP	EMP	lnWage	IT Emp.	IT Sec.	Inf. Sec.	Self-Emp	Bus. Inc.
δ	-0.011**	-0.0035	0.0025	-0.0017	0.0038	0.0018	0.0029	-19.6
	(-2.08)	(-0.57)	(0.21)	(-0.86)	(1.05)	(0.92)	(0.68)	(-0.08)
Female	...	...	...	...	...	...	...	...
Black	...	...	...	...	...	...	...	...
Hispanic	...	...	...	...	...	...	...	...
Married	...	...	...	...	...	...	...	...
Bachelors	...	...	...	...	...	...	...	...
Age	...	...	...	...	...	...	...	...
Age^2	...	...	...	...	...	...	...	...
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CPUMA FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.0096	0.0100	0.0276	0.0078	0.0167	0.0058	0.0046	0.0026
Obs.	72030	72030	49948	72030	72030	72030	59743	72030

Clustered t-statistics in parenthesis.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A-5. Detailed Results

	LFP	EMP	lnWage	IT Emp.	IT Sec.	Inf. Sec.	Self-Emp	Bus. Inc.
δ	-0.011**	-0.0065	-0.00059	0.00034	0.0012	0.0018	0.0077*	251.1
	(-2.42)	(-1.41)	(-0.06)	(0.21)	(0.34)	(0.99)	(2.00)	(0.99)
Female	...	...	...	...	...	...	...	...
Black	...	...	...	...	...	...	...	...
Hispanic	...	...	...	...	...	...	...	...
Married	...	...	...	...	...	...	...	...
Bachelors	...	...	...	...	...	...	...	...
Age	...	...	...	...	...	...	...	...
Age^2	...	...	...	...	...	...	...	...
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CPUMA FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.0105	0.0111	0.0286	0.0079	0.0179	0.0057	0.0036	0.0024
Obs.	72030	72030	49948	72030	72030	72030	59743	72030

Clustered t-statistics in parenthesis.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A-6. Detailed Results

	LFP	EMP	lnWage	IT Emp.	IT Sec.	Inf. Sec.	Self-Emp	Bus. Inc.
δ	-0.011**	-0.0039	-0.0054	-0.0018	0.0036	0.0018	0.0018	-66.3
	(-2.05)	(-0.69)	(-0.58)	(-0.89)	(0.98)	(0.94)	(0.45)	(-0.25)
Female	-0.12***	-0.11***	-0.20***	-0.022***	-0.0096**	-0.0073***	-0.047***	-2475.2***
	(-17.16)	(-16.89)	(-19.66)	(-8.90)	(-2.29)	(-5.27)	(-9.07)	(-13.24)
Black	-0.020***	-0.063***	-0.21***	-0.0083**	-0.046***	0.00029	-0.044***	-1172.2***
	(-2.86)	(-8.70)	(-8.28)	(-2.36)	(-5.62)	(0.18)	(-8.83)	(-7.81)
Hispanic	-0.021*	-0.016	-0.31***	-0.023***	-0.072***	-0.0090**	-0.017*	-4.77
	(-1.88)	(-1.25)	(-13.29)	(-5.43)	(-11.46)	(-2.58)	(-1.94)	(-0.01)
Married	0.020***	0.051***	0.23***	0.0065***	0.028***	-0.00099	0.025***	1322.1***
	(3.75)	(8.27)	(30.98)	(4.23)	(5.35)	(-0.69)	(6.75)	(5.06)
Bachelors	0.066***	0.084***	0.31***	0.033***	0.090***	0.015***	0.0038	231.0
	(13.31)	(14.99)	(30.40)	(10.28)	(15.35)	(5.52)	(1.06)	(0.87)
Age	0.044***	0.046***	0.076***	0.0031***	0.0076***	0.0015***	0.0058***	302.0***
	(26.03)	(24.83)	(20.08)	(4.61)	(4.84)	(4.06)	(8.22)	(9.70)
Age^2	-5.8e-04***	-6.0e-04***	-7.3e-04***	-4.0e-05***	-9.4e-05***	-1.8e-05***	-3.2e-05***	-2.9e+00***
	(-34.23)	(-31.56)	(-15.72)	(-4.77)	(-5.01)	(-4.19)	(-4.22)	(-7.80)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CPUMA FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.1198	0.1084	0.2585	0.0252	0.0452	0.0090	0.0418	0.0138
Obs.	71302	71302	49650	71302	71302	71302	59325	71302

Clustered t-statistics in parenthesis.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A-7. Detailed Results

	LFP	EMP	lnWage	IT Emp.	IT Sec.	Inf. Sec.	Self-Emp	Bus. Inc.
δ	-0.0093**	-0.0055	-0.0047	0.000081	0.00093	0.0017	0.0076*	233.3
	(-2.33)	(-1.31)	(-0.54)	(0.05)	(0.25)	(0.97)	(2.02)	(0.88)
Female	-0.12***	-0.11***	-0.21***	-0.024***	-0.014***	-0.0077***	-0.052***	-2886.5***
	(-23.53)	(-21.48)	(-18.15)	(-9.14)	(-2.74)	(-6.44)	(-15.43)	(-12.75)
Black	-0.049***	-0.089***	-0.23***	-0.0093***	-0.049***	0.00086	-0.047***	-1412.2***
	(-6.72)	(-12.22)	(-8.65)	(-2.83)	(-5.92)	(0.48)	(-8.65)	(-8.15)
Hispanic	-0.019**	-0.015*	-0.31***	-0.022***	-0.069***	-0.0096***	-0.0063	-401.8
	(-2.16)	(-2.00)	(-14.83)	(-5.58)	(-8.58)	(-3.27)	(-0.84)	(-1.22)
Married	0.022***	0.051***	0.23***	0.0052***	0.028***	-0.00081	0.028***	1506.9***
	(4.33)	(9.41)	(29.80)	(3.68)	(6.19)	(-0.58)	(6.89)	(5.79)
Bachelors	0.070***	0.085***	0.29***	0.030***	0.087***	0.014***	0.0058**	376.7
	(18.52)	(18.44)	(24.58)	(10.35)	(15.56)	(5.76)	(2.48)	(1.61)
Age	0.045***	0.047***	0.081***	0.0034***	0.0083***	0.0016***	0.0048***	285.2***
	(32.73)	(30.64)	(23.65)	(6.32)	(5.89)	(4.08)	(8.24)	(10.68)
Age^2	-5.9e-04***	-6.1e-04***	-7.9e-04***	-4.3e-05***	-1.0e-04***	-2.0e-05***	-1.9e-05***	-2.7e+00***
	(-42.42)	(-38.69)	(-17.96)	(-6.44)	(-5.93)	(-4.28)	(-2.93)	(-8.55)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CPUMA FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.1216	0.1155	0.2547	0.0246	0.0454	0.0092	0.0414	0.0147
Obs.	71302	71302	49650	71302	71302	71302	59325	71302

Clustered t-statistics in parenthesis.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A-8. Detailed Results, Weighted

	LFP	EMP	IT Emp.	IT Sec.	Inf. Sec.	Self-Emp
δ	-0.060**	-0.019	0.023	0.024	-0.025	0.0035
	(-2.02)	(-0.65)	(0.30)	(0.65)	(-0.33)	(0.08)
Female	-0.67***	-0.55***	-0.98***	-0.11***	-0.37***	-0.52***
	(-15.22)	(-15.38)	(-16.16)	(-2.63)	(-5.76)	(-7.40)
Black	-0.11***	-0.30***	-0.41***	-0.58***	0.020	-0.61***
	(-2.89)	(-9.08)	(-2.80)	(-8.91)	(0.26)	(-5.24)
Hispanic	-0.12*	-0.080	-1.34***	-0.99***	-0.51**	-0.14
	(-1.74)	(-1.25)	(-3.82)	(-7.51)	(-2.34)	(-1.22)
Married	0.13***	0.27***	0.27***	0.29***	-0.047	0.26***
	(4.19)	(9.13)	(5.59)	(8.04)	(-0.66)	(6.02)
Bachelors	0.43***	0.47***	0.92***	0.72***	0.56***	0.036
	(14.17)	(14.84)	(13.56)	(14.82)	(7.99)	(0.99)
Age	0.22***	0.22***	0.17***	0.093***	0.084***	0.13***
	(22.79)	(23.68)	(7.36)	(7.11)	(5.88)	(13.01)
Age^2	-3.0e-03***	-2.8e-03***	-2.1e-03***	-1.1e-03***	-1.0e-03***	-1.1e-03***
	(-29.44)	(-29.70)	(-7.91)	(-7.54)	(-6.23)	(-10.61)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
CPUMA FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo-R^2	0.10	0.087	0.10	0.062	0.042	0.068
Obs.	71302	71302	71302	71302	71302	59325

Clustered t-statistics in parenthesis.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A-8. Detailed Results, Unweighted

	LFP	EMP	IT Emp.	IT Sec.	Inf. Sec.	Self-Emp
δ	-0.050**	-0.027	0.071	-0.0080	0.0025	0.075**
	(-2.28)	(-1.28)	(1.13)	(-0.23)	(0.04)	(2.04)
Female	-0.65***	-0.54***	-0.99***	-0.14***	-0.39***	-0.53***
	(-20.40)	(-19.85)	(-20.12)	(-3.14)	(-6.77)	(-13.25)
Black	-0.25***	-0.42***	-0.47***	-0.60***	0.046	-0.63***
	(-7.22)	(-13.17)	(-3.11)	(-6.93)	(0.57)	(-5.53)
Hispanic	-0.11**	-0.083**	-1.17***	-0.85***	-0.54***	-0.0064
	(-2.14)	(-2.12)	(-5.59)	(-8.43)	(-3.31)	(-0.07)
Married	0.14***	0.27***	0.21***	0.28***	-0.042	0.28***
	(4.85)	(10.42)	(4.73)	(10.06)	(-0.60)	(6.51)
Bachelors	0.44***	0.47***	0.84***	0.68***	0.57***	0.055**
	(19.84)	(19.00)	(14.73)	(17.96)	(10.72)	(2.51)
Age	0.22***	0.22***	0.17***	0.096***	0.094***	0.12***
	(28.69)	(28.97)	(14.04)	(9.54)	(6.29)	(14.93)
Age^2	-2.9e-03***	-2.8e-03***	-2.1e-03***	-1.2e-03***	-1.2e-03***	-9.4e-04***
	(-36.42)	(-36.06)	(-15.13)	(-9.66)	(-6.91)	(-11.90)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
CPUMA FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.10	0.093	0.096	0.060	0.042	0.064
Obs.	71302	71302	71302	71302	71302	59325

Clustered t-statistics in parenthesis.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A-10. Detailed Results

	LPM, Wgt	LPM, Unw.	Logit, Wgt	Logit, Unw
δ	0.013***	0.010***	1.29***	1.12***
	(9.47)	(8.15)	(12.16)	(11.02)
Female	-0.013***	-0.013***	-1.17***	-1.17***
	(-6.75)	(-7.41)	(-9.77)	(-10.13)
Black	0.0072**	0.0064***	0.60***	0.56***
	(2.68)	(2.73)	(3.03)	(3.23)
Hispanic	-0.0049	-0.0050*	-0.58	-0.62
	(-1.51)	(-2.00)	(-1.14)	(-1.54)
Married	0.0017	0.0013	0.15*	0.12*
	(1.67)	(1.67)	(1.92)	(1.92)
Bachelors	-0.0037***	-0.0031***	-0.33***	-0.28**
	(-3.38)	(-2.90)	(-2.71)	(-2.55)
Age	0.0021***	0.0020***	0.20***	0.19***
	(6.24)	(6.74)	(7.93)	(10.20)
Age^2	-2.5e-05***	-2.3e-05***	-2.4e-03***	-2.3e-03***
	(-6.43)	(-6.95)	(-8.61)	(-10.96)
Time FE	Yes	Yes	Yes	Yes
CPUMA FE	Yes	Yes	Yes	Yes
R^2	0.0157	0.0153	0.11	0.11
Obs.	71302	71302	70766	70766

Clustered t-statistics in parenthesis.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A-11. Detailed Results

	LFP	EMP	lnWage	IT Emp.	IT Sec.	Inf. Sec.	Self-Emp	Bus. Inc.	Auto. Manuf.
δ	-0.011	-0.0039	-0.0054	-0.0018	0.0036	0.0018	0.0018	-66.3	0.013***
	(-1.27)	(-0.43)	(-0.34)	(-0.66)	(0.63)	(0.63)	(0.28)	(-0.18)	(6.04)
Female	-0.12***	-0.11***	-0.20***	-0.022***	-0.0096***	-0.0073***	-0.047***	-2475.2***	-0.013***
	(-30.16)	(-25.97)	(-26.54)	(-15.80)	(-3.50)	(-5.63)	(-15.61)	(-15.38)	(-12.23)
Black	-0.020***	-0.063***	-0.21***	-0.0083***	-0.046***	0.00029	-0.044***	-1172.2***	0.0072***
	(-3.44)	(-10.01)	(-19.11)	(-4.10)	(-12.57)	(0.15)	(-11.59)	(-7.20)	(4.29)
Hispanic	-0.021*	-0.016	-0.31***	-0.023***	-0.072***	-0.0090***	-0.017**	-4.77	-0.0049**
	(-1.93)	(-1.29)	(-14.63)	(-8.15)	(-12.08)	(-2.71)	(-2.12)	(-0.01)	(-2.02)
Married	0.020***	0.051***	0.23***	0.0065***	0.028***	-0.00099	0.025***	1322.1***	0.0017
	(4.69)	(10.87)	(27.78)	(3.92)	(8.77)	(-0.66)	(7.17)	(7.70)	(1.46)
Bachelors	0.066***	0.084***	0.31***	0.033***	0.090***	0.015***	0.0038	231.0	-0.0037***
	(14.83)	(17.35)	(33.07)	(12.90)	(20.46)	(7.34)	(0.97)	(1.06)	(-3.14)
Age	0.044***	0.046***	0.076***	0.0031***	0.0076***	0.0015***	0.0058***	302.0***	0.0021***
	(43.95)	(44.28)	(38.32)	(11.48)	(13.03)	(5.27)	(8.06)	(9.51)	(9.08)
Age^2	-5.8e-04***	-6.0e-04***	-7.3e-04***	-4.0e-05***	-9.4e-05***	-1.8e-05***	-3.2e-05***	-2.9e+00***	-2.5e-05***
	(-51.00)	(-49.89)	(-30.85)	(-12.34)	(-13.80)	(-5.79)	(-3.62)	(-7.56)	(-9.21)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CPUMA FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.1198	0.1084	0.2585	0.0252	0.0452	0.0090	0.0418	0.0138	0.0157
Obs.	71302	71302	49650	71302	71302	71302	59325	71302	71302

Robust t-statistics in parenthesis.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A-12. Detailed Results

	LFP	EMP	lnWage	IT Emp.	IT Sec.	Inf. Sec.	Self-Emp	Bus. Inc.	Auto. Man.
δ	-0.0047	0.0021	-0.0014	-0.0017	0.0006	0.0039	0.0028	-78.2	0.016***
	(-0.63)	(0.23)	(-0.13)	(-0.64)	(0.12)	(1.36)	(0.59)	(-0.24)	(8.40)
Female	-0.12***	-0.12***	-0.20***	-0.024***	-0.011*	-0.0097***	-0.044***	-2504.0***	-0.015***
	(-17.49)	(-16.59)	(-18.18)	(-9.83)	(-1.87)	(-4.73)	(-8.34)	(-11.29)	(-6.00)
Black	-0.015**	-0.057***	-0.21***	-0.0059	-0.050***	-0.0001	-0.042***	-1157.0***	0.010***
	(-2.25)	(-7.68)	(-8.31)	(-1.57)	(-5.75)	(-0.05)	(-6.33)	(-5.22)	(3.70)
Hispanic	-0.023*	-0.010	-0.32***	-0.021***	-0.064***	-0.0083*	-0.018	-123.5	-0.0051
	(-1.73)	(-0.77)	(-12.02)	(-3.86)	(-8.34)	(-1.76)	(-1.42)	(-0.12)	(-0.90)
Married	0.028***	0.051***	0.25***	0.0095***	0.033***	-0.0017	0.023***	1176.9***	0.0036**
	(3.93)	(5.88)	(26.50)	(4.64)	(5.93)	(-0.97)	(4.04)	(3.31)	(2.66)
Bachelors	0.068***	0.087***	0.31***	0.033***	0.088***	0.015***	0.0039	411.8	-0.0042***
	(15.86)	(16.53)	(34.12)	(8.54)	(13.39)	(3.80)	(0.74)	(1.17)	(-3.39)
Age	0.043***	0.046***	0.074***	0.0031***	0.0070***	0.0017***	0.0070***	338.8***	0.0020***
	(21.08)	(21.28)	(18.60)	(4.18)	(3.87)	(4.59)	(7.63)	(9.04)	(4.53)
Age^2	-5.7e-04***	-5.9e-04***	-7.1e-04***	-4.0e-05***	-8.8e-05***	-2.0e-05***	-4.7e-05***	-3.3e+00***	-2.4e-05***
	(-27.61)	(-26.93)	(-14.05)	(-4.32)	(-4.05)	(-4.54)	(-4.27)	(-7.35)	(-4.86)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CPUMA FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.1213	0.1144	0.2581	0.0267	0.0466	0.0102	0.0410	0.0145	0.0190
Obs.	44235	44235	30939	44235	44235	44235	36712	44235	44235

Clustered t-statistics in parenthesis.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.