A Decomposition of the Relationship Between Internet Access and Earnings

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Gains in internet access and quality have increased output and revenue for companies, but these gains are not uniformly distributed across regions, industries, or worker types. I examine county-level wage and income measures on time-dynamic broadband uptake rates, mobile internet access, and local education levels. Datasets from the Census and FCC are combined to construct a rich dataset of all counties in the continental US from 2010-2019. Interaction terms between internet access, duration of access, and educational levels are included to capture the heterogeneous relationship between internet access and wages across across different levels of education. Decompositions of these regressions indicate that only 25% of the differences in wages and income are driven by heterogeneous returns to internet access and education across metro densities, with the majority of the difference determined by the levels of these variables themselves.

Keywords: decomposition, internet, education, earnings

INTRODUCTION

Companies utilize the Internet to expand their consumer base, gather market data, and enhance worker connectivity and communication productivity (Akerman et al., 2015; Bertschek et al., 2013; Bertschek & Niebel, 2016). However, these gains in firm productivity have not always translated to labor market gains for workers. Research has found both gains and losses for workers post-internet expansion in rural and urban areas (Akerman et al., 2015; Atasoy, 2013; Whitacre et al., 2015).

These variations stem from differences in measurements, methodologies, and the Internet's use across space and time (Atasoy, 2013; Dettling, 2017; Whitacre et al., 2014b). All general-purpose technological advancements, like the Internet, can complement or substitute for labor, resulting in firms either expanding employment or outsourcing, automating, and eliminating positions (Kolko, 2012; Mack & Faggian, 2013). Whether an individual worker is helped or hurt by expanded internet uptake is determined mainly by their skills and specific job tasks (Ackermen et al., 2015; Atasoy, 2013; Foreman et al., 2012; Mack and Faggian, 2013).

This study analyzes the impact of household internet uptake on wage and income measures at the county level. I expand upon the existing literature by incorporating measures of mobile internet access and length of time with hardwired or mobile access. I further decompose differences in income and wages to determine what percent of the differences between metropolitan and nonmetro areas can be attributed to variations in internet access and worker education versus the different returns to those characteristics.

RETURNS TO INTERNET ACCESS AND ADOPTION

Internet access and adoption growth was slower in nonmetro areas compared to metro (Kruger, 2009; 2019; Kruger & Gilroy, 2016, Preiger, 2013). This discrepancy is partly driven by demand dynamics, as urban areas with higher consumer incomes, more educated workforces, and a higher concentration of computer-oriented companies were more willing to pay for services (Hoffler, 2007; Lee et al., 2011). Private telecommunications companies prioritized these lucrative markets, providing them with more substantial capital investments than their rural counterparts (Hoffler, 2007; Lee et al., 2011). Additionally, the virtuous cycle of the Internet, by which the value of building business sites or offering gig work increases the more people engage with the Internet, means counties that had earlier rollout may reap higher benefits than counties with later rollout (Sarkar & Khare, 2019; Wu et al., 2020). Bridging the "digital divide" is a significant focus, with state and federal programs implemented to improve internet access in rural areas (Kruger, 2009; Harjai, 2023); however, surveys indicate that rural adoption rates continue to lag. Non-purchasers in rural regions cited less desire or need for the internet than their urban counterparts (Whitacre et al., 2015).

These lower uptake rates may also reflect fewer benefits derived from internet adoption by businesses and citizens. The Internet may not facilitate as many gains from access to information, employment options, or increased earnings. Studies have yielded mixed results, with some indicating that counties with higher broadband availability had lower income growth in nonmetropolitan areas between 2000 and 2010 (Whitacre et al., 2014b). However, the same researcher used propensity score methodology to find that higher adoption rates were associated with increased median household income and decreased unemployment growth in similar rural counties (Whitacre et al., 2014a). Further, Ivus and Boland (2015) found that internet expansion in Canada helped to grow wages in rural service sectors from 1997-2011. These varying outcomes highlight the influence of worker and industry composition and regional demographics on internet expansion's effects on wage and income.

Mack and Faggian (2013) aptly characterized broadband adoption as "skill-biased technological change" (p. 410). They and other researchers find firms that use the Internet as a complement for skilled workers completing non-routine or abstract tasks but tend to use it as a substitute for unskilled workers completing routine tasks (Poliquin, 2020). Although gains are found for the highly educated, broadband adoption decreased wages in counties with a higher proportion of non-college-educated workers (Akerman et al., 2015; Mack & Faggian, 2013). Forman et al. (2012) found that, for counties that invested in Internet infrastructure from 1995- 2000, the bulk of wage growth post-investment was concentrated in counties with high incomes and skills. Atasoy (2013) furthered this analysis, showing that most positive gains associated with internet adoption from 2000 – 2007 were concentrated in counties that had industries utilizing highly educated workers. Industries with online consumption substitutes, like entertainment and retail, or those with route tasks or increased supply, like administrative services and transportation, tended to see declines in labor market outcomes (Atasoy, 2013).

When high-speed Internet first began to expand, some researchers were able to quantify potentially causal impacts utilizing sources for instrumental variables capable of predicting hardwired broadband adoption. Some examples include housing patterns (Dettling, 2017), steepness of terrain (Ivus & Boland, 2015; Kolko, 2012), previous period's concentration of technology firms (Forman et al., 2012), historical telephone patterns (Czernich et al., 2011), and distance to infrastructure (Fabritz, 2013; Forman et al., 2012; Larose et al., 2011). However, these techniques are only valid for hardwired internet access and tended to work best in early periods of internet adoption, when many faced binding constraints to adoption.

The most recent of the IV technique papers cited above utilize data from up to 2010 at the latest. While these strategies had explanatory power in early periods of hardwired internet adoption, they became less powerful with greater broadband penetration and expansion of mobile access. By 2015, desktop computer ownership had plateaued, and mobile internet plans and devices became a prominent substitute for hardwired internet (Anderson, 2015). To date, there are no known instruments for predicting mobile internet access. Despite this lack of exogeneity, including measures of mobile internet is important for capturing true access and use of the internet, as mobile Internet is both a substitute for and a complement to hardwired internet (Horrigan & Duggan, 2015).[1]

Although the initial impact of internet access on the labor market was estimated in the papers discussed above, there is no reason to assume the magnitude or direction of these coefficients stayed fixed. Throughout the decade following 2010, the number of users and types of internet use expanded greatly. Despite a lack of exogeneity, I seek to build on the existing research by examining the changing dynamic of the internet and skilled labor markets throughout the aughts.

The Internet and workforce composition combine to change the underlying labor market in numerous ways. I do not attempt to disentangle the different pathways, such as increased small businesses or shifting industry composition. I assume that local technology uptake and the education of the labor force are fundamental drivers of these changes, and I quantify gross differences across the inputs and their correlation with differences in wages and income across metropolitan and non-metropolitan counties.

DATA

To estimate and decompose the heterogeneous effects of internet access across worker education and urban density, I construct a balanced panel of county-level measures across the continental United States from 2010 to 2019. This period captures a crucial phase of internet uptake, starting with lower saturation rates, including the 2011 release of the iPhone for non-exclusive sale, and increased adoption rates with better speed and quality of hardwired and mobile internet through the decade.[2]

The key independent variables of interest are derived from the Federal Communications Commission (FCC), which collects information from providers on high-speed internet connections (minimum of 200 kbps in each direction) and publishes data on connections per 1,000 households in quintile-based categories. [3] The FCC also tracks the number of cell phone providers in each county offering mobile data plans above 200kbps, which I use as a proxy for cell phone usage and market saturation.

Mobile data plans were on the rise during this period in terms of expanded infrastructure, competition among firms, and the variety of features, prices, and quality available (Villas-Boas, 2018).[4] Research indicates that the number of mobile providers increases consumer uptake statistically significantly (Gruber, 2001; Lee et al., 2011). Greater competition in the telecommunications industry increases the quality and speed of service and lowers costs, which are all significant in mobile uptake, particularly for consumers who exclusively use mobile internet connections (Höffler, 2007; Manlove & Whitacre, 2019). Therefore, measuring the number of carriers in the county can act as a reasonable proxy for consumer demand.

Lastly, because the Internet is subject to network externalities (Lin & Lu, 2011; McGee & Sammut-Bonnici, 2015) with the uses of the technology expanding as more people use it, I also measure the length of time a county has had high broadband or mobile access. I construct additive variables that measure the number of years since the county attained 60% or higher broadband uptake or 4+ mobile carriers within the sample period of 2010-2019.

TABLE 1
DESCRIPTIVE STATISTICS BY METROPOLITAN STATUS

	USA	Metropolitan Counties	Non-Metro Counties
Observations	3,110	1,161	1,949
Sample as % of total Counties	100	37.33	62.66
Sample as % of total Population	100	85.31	16.69
VARIABLES	mean	mean	mean
Average Annual Payroll (QCEW)	$40,618	$44,689	$38,193
	(9,357)	(10,653)	(7,509)
Individual Income (ACS)	$25,853	$28,694	$24,160
	(5,515)	(5,997)	(4,410)
High Broadband = 1	0.2777	0.552	0.114
60% or more of HH have BB	(0.45)	(0.50)	(0.32)
Years Since High Broadband	1.092	2.36	0.336
	(1.91)	(2.30)	(1.06)
High Mobile Data= 1	0.678	0.9069	0.542
4 or more Cell Phone Data Carriers	(0.47)	(0.29)	(0.50)
Years Since High Mobile	3.006	4.337	2.212
	(2.19)	(1.48)	(2.16)
Percent College Grad & Above	20.076	24.612	17.374
	(8.91)	(10.34)	(6.58)
Total Population	99,548	227,479	23,342
	(317,473)	(4,931,493)	(21,794)
Population Density per Sq Mile	262.01	630.15	42.72
	(1,745)	(2,816)	(95)

All data measured in 2014, with geography defined by the USDA rural-metro index. All dollars measured in 2019 inflation adjusted dollars.
Internet and cell phone measures taken from the Federal Communications Commission. Average Pay come from Quartrly Census of Employment and Wages. Population, Median Income, & Education data taken from the American Community Survey

The Quarterly Census of Employment and Wages (QCEW) provides firm-reported payroll expenses and includes all wages and other compensation paid to employees as a measure of labor market outcomes. [5] The QCEW covers about 97% of wage and salary civilian employment but excludes independent contractors or other potential income sources. [6] I use data from the American Community Survey (ACS) five-year averages to capture other ways the Internet may impact earnings and income. Internet expansion and mobile platforms have increased the ease by which people can earn income outside of traditional wage based labor markets. Individual income, as measured in ACS, includes earnings from independent contractor work, rental property income, the sharing economy, self-employment, investments, and family or government transfers in addition to wage earnings. [7]

Additionally, the ACS measures workforce skills through educational attainment and provides other county-level controls. Consistent with previous researchers, I distinguish between metropolitan and non-metropolitan counties (Liao et al., 2016; Manlove & Whitacre, 2019; Prieger, 2013; Whitacre et al., 2015). Classifications come from the USDA's rural-urban continuum, distinguishing metro and nonmetro counties based on population size, urbanization, adjacency to a metro area, and rural status.

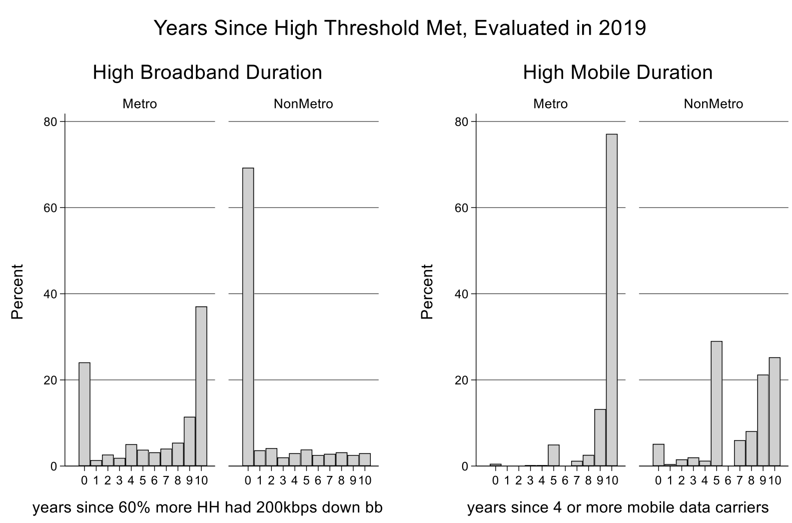
As shown in Table 1, wages, income, and all measures of internet uptake, access, and duration are higher in metropolitan counties in 2014, the middle of the sample period. All variables reported in the table are statistically significantly different between metro and nonmetro counties at a 5% level. Education is highest in metropolitan counties with approximately 25% of those over 25 years of age holding a bachelor's degree or higher, versus 17% in nonmetro counties. Average wages and overall income (in 2019 dollars) are also higher in metropolitan areas. The income reported by those in the ACS is lower on average than wages reported by QCEW. On average, more individuals report income than wages in a county, as income includes wages along with earnings from independent contracting, sole proprietor work, and alternate sources of income, such as child support, investments, or social security.

METHODOLOGY

The Blinder-Oaxaca decomposition technique (Blinder, 1973; Oaxaca, 1973) breaks down outcome differences into "explained differences" resulting from variations in independent variables and "unexplained differences" arising from differences in coefficients or returns on the independent variables (Jann, 2008). This technique has long been employed to quantify disparities in labor market outcomes based on race, gender, and citizenship (Darity et al., 1996; Jagsi et al., 2012; Oaxaca & Ransom, 1994; Ransom & Oaxaca, 2005). Researchers have expanded its use to examine geographical differences in student return to technology, expansion of internet infrastructure, and mobile internet uptake rates (Liao et al, 2016 ; Manlove & Whitacre, 2019; Whitacre et al., 2015).[8]

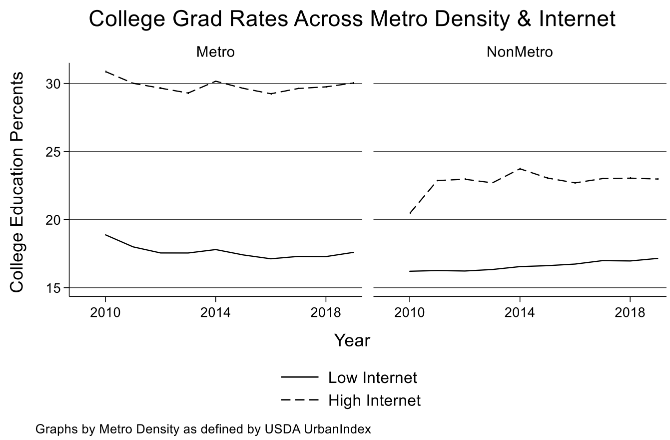
I employ a Blinder-Oaxaca decomposition to examine the difference in average wages and personal income across metro and nonmetro counties and quantify the percent of this difference due to different levels, or endowments, of internet access and worker education. The endowments of internet and educated workers are unevenly distributed across urban densities (Figures 1 & 2).

FIGURE 1
DIFFERENCES IN ENDOWMENTS: BROADBAND & MOBILE DURATION OF ACCESS



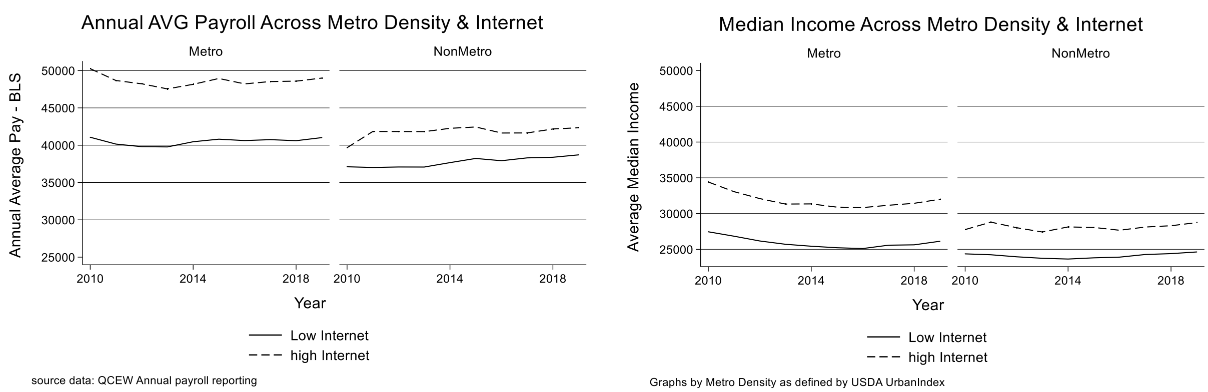
Metro areas were far more likely in 2019 to have had high broadband adoption and multiple mobile internet providers for longer periods of time (Figure 1). Additionally, high-access counties consistently correlate with a higher concentration of college-educated workers over the decade (Figure 2).

FIGURE 2
DIFFERENCES IN ENDOWMENTS: PERCENT OF COLLEGE GRADUATES



Additionally, average employee pay and individual median income (Figure 3) are higher in counties with 60% or higher household internet adoption. Wages show an overall metro premium and are almost as high for low-internet metro areas as for high-internet nonmetro counties.

FIGURE 3
DIFFERENCES IN OUTCOMES:
WAGES & INCOME ACROSS METRO & INTERNET CLASSIFICATION



The decomposition process begins by estimating the difference in mean outcomes across the two geographical classifications. This difference can be rewritten and simplified using the value function and assumptions of OLS error terms, as shown in Equation 1.[9]

$$Difference = E(Y_{metro}) - E(Y_{nonmetro}) = E(X_m)'\beta_m - E(X_{nm})'\beta_{nm} \quad (1)$$

The decomposition process quantifies how much of the differences in mean wages and income can be attributed to the differences in endowment levels and how much is from different rates of return, or coefficients, on internet access and education levels.

The regression equations I will decompose are estimated separately for metropolitan and nonmetro counties.

$$Earnings\ Measure_{c,y} = \alpha + \beta_1\ BB_{High_{c,y}} + \beta_2 Mobile_{high} + \beta_3\ Years\_BB_{High_{c,y}} + \beta_4 Years\_Mobile_{high_{c,y}} + \beta_5 CollegeGrad\%_{\ c,y} + County + Year + \varepsilon \quad (2)$$

Average annual wages and median income are regressed on broadband adoption rates, the number of mobile data providers, and the duration of use. Broadband and mobile are measured by the previously discussed dummy variables for high hardwired or mobile access and count variables of the years post most these thresholds. [10]

To measure local human capital, the percent of the population over age 25 whose highest level of education is a BA or higher are included. Additional controls from the ACS and QCEW are included to measure the local economy and labor force demographics. Controls for labor force participation, employment rate, and workforce age are included.[11] All specifications also include county-level fixed effects to demean annual growth in earning and income outcomes over time at the county level and year dummies to demean national-level annual averages in outcomes.

The OLS, fixed-effects strategy assumes that counties that experienced gains in internet availability and those that did not would have the same trending labor market outcomes, net controls, without broadband. However, counties with higher broadband adoption had different trends before the sample period that increased employment and income and partially drove broadband uptake. Consequently, the results cannot be interpreted as causal. However, the results are still informative for estimating the observed relationship between broadband and labor market outcomes and decomposing the trend during this pivotal decade of adoption.

RESULTS

OLS Results

Results in Table 2 show average yearly pay as reported by employers as a function of internet and education across metro and nonmetro counties. In columns 2 and 4, interactions between the percent of the population who graduated college and measures of internet access are included.

In metropolitan areas, high broadband uptake had a positive but insignificant association with general wages, which declined slightly over time. A high number of mobile carriers is associated with an almost $245 increase in annual wages initially for an average worker, but decreased on average by $70 annually after reaching four or more carriers.

When internet uptake and access are interacted with the percent college educated, highly differential patterns are observed across education distributions. Metro counties with low levels of college graduates observed an initial increase in wages post broadband adoption but this gain declined each year post 60% adoption by households. Mobile expansion is correlated with a further decline in earnings for metro counties with a low concentration of college-educated workers. Earnings in metro counties with high college concentrations observed a decrease in earnings after high broadband adoption, which grew less negative each year until reaching a null effect and positive growth approximately 3 to 4 years post 60% or more uptake. In contrast to that, mobile access in a hypothetical metro area with 100% college-educated population broadband expansion would be associated with the most significant wage increase, at approx. 3,990 a year, but would decrease by approximately $250 each year after high mobile access was attained. Every standard deviation increase in college-educated workers (10.53%) predicts an annual gain of $373 in average wages in metro counties with 4+ mobile providers and less college-educated workers.

Similar to metro, returns of hardwired internet uptake in nonmetro areas are positive and slightly larger in magnitude and more statistically significant. Mobile access in non-interacted models is also negative and at an increasing rate over time. However, in column 4, interaction effects show that the adverse effects are driven by rural counties with lower concentrations of college-educated workers. In nonmetro counties with more educated workers, earnings initially decrease post 60% or more broadband adoption and gradually increase towards a positive effect approximately 3 years later. Like metro areas, high mobile access only correlates with increases in average annual wages in nonmetro counties with higher concentrations of college workers.

TABLE 2
RETURN TO INTERNET & EDUCATION ON EARNINGS

	Y = Average Annual Payroll			
	metro		non-metro	
Variables	(1)	(2)	(3)	(4)
High BB Adoption (above 60% HH)	93.31	629.11+	284.97**	918.99**
	(89.87)	(356.66)	(90.64)	(284.31)
Years Since High BB Adopt	243.98+	-506.59	-83.02	-424.42*
	(135.96)	(500.46)	(65.06)	(188.26)
High Mobile Access (Above 3 Carriers)	-3.17	-176.60	20.00	-177.83*
	(34.86)	(119.53)	(24.53)	(77.74)
Years Since High Mobile	-69.95	-23.30	-53.04*	-52.03
	(69.32)	(132.87)	(23.22)	(49.21)
College BA /plus (%)	66.44*	25.89	26.64	7.18
	(29.02)	(37.94)	(19.28)	(21.75)
High BB Adopt* College Grad Plus (%)		-1,910.67		-2,814.36*
		(1,491.61)		(1,104.70)
Years Since BB * College Grad Plus (%)		669.44		827.70**
		(487.16)		(296.97)
High Mobile * College Grad Plus (%)		3,991.60+		2,057.39*
		(2,266.77)		(1,008.32)
Years Since Mobile*College Grad Plus (%)		-254.52		-14.14
		(465.24)		(206.90)
Observations	11,167	11,167	16,443	16,443

Sample Years: 2010-2019 Each regression contains county fixed effects and year dummy variables . Control Variables include: Percent men, Gini coefficient, Percent of People New To County In Last Year (from other county, state, or abroad), Percent of People per Age by Bracket (0-19, 20-34, 35-44, 45-54, 55 -64, 64+), and the percent of people who are black, white, or Asian
Robust Standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.10

Mobile internet access in a hypothetical nonmetro county with 100% college-educated workers would be associated with an average increase of over $2,000 a year. For every standard deviation increase in college-educated workers in nonmetro counties (6.7%), the associated annual gain in average wages is approximately $123 in a county with high mobile internet access.[12] The typical net impact of mobile internet is larger in magnitude than the hardwired connection coefficients, supporting the significance of including mobile internet measurements in empirical specifications of internet use.

TABLE 3
RETURN TO INTERNET & EDUCATION ON INCOME

	Y= Individual Income			
	metro		non-metro	
Variables	(1)	(2)	(3)	(4)
High BB Adoption (above 60% HH)	18.60	172.78	-99.79	173.97
	(52.03)	(185.57)	(66.65)	(197.24)
Years Since High BB Adopt	187.99*	-377.80	159.87***	113.94
	(79.66)	(234.48)	(46.16)	(152.72)
High Mobile Access (Above 3 Carriers)	-43.36**	-154.66***	21.58	-20.49
	(14.01)	(44.05)	(17.53)	(55.13)
Years Since High Mobile	-82.63*	22.98	-94.27***	-94.03**
	(38.35)	(56.84)	(19.28)	(33.91)
College BA /plus (%)	214.43***	205.20***	184.54***	183.48***
	(21.08)	(27.73)	(14.79)	(17.25)
High BB Adopt* College Grad Plus (%)		-532.66		-1,276.61
		(798.90)		(882.78)
Years Since BB * College Grad Plus (%)		521.10**		185.81
		(190.87)		(242.29)
High Mobile * College Grad Plus (%)		2,845.36*		273.39
		(1,207.13)		(929.27)
Years Since Mobile*College Grad Plus (%)		-485.90**		-2.47
		(185.45)		(152.22)
Observations	10,865	10,865	15,750	15,750

Sample Years: 2010-2019 Each regression contains county fixed effects and year dummy variables . Control Variables include: Percent men, Gini coefficient, Percent of People New To County In Last Year (from other county, state, or abroad), Percent of People per Age by Bracket (0-19, 20-34, 35-44, 45-54, 55 -64, 64+), and the percent of people who are black, white, or Asian
Robust Standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.10

In Table 3, the outcome of interest is individual income, which is a broader measure of total earnings than firm-reported wages. Generally, the coefficients remain quite similar to those observed for wages but are of lower magnitude and higher statistical significance. A significant difference is observed for nonmetro counties between wage and income effects. In uninteracted models of nonmetro counties, broadband is initially positive with increasing returns, but income is initially negative and insignificant.

Similarly, the expansion of mobile providers initially had negative effects on wages that got more negative over time at statistically significant rates. In contrast, they are initially positive for income and become negative over time. Mobile internet is not associated with large gains in reported income for nonmetro counties with higher concentrations of college-educated workers. Although higher education slows the predicted decline, lower-educated and high college educated counties both suffer income losses after approximately 4 years of high mobile access.

Decomposition Results

Table 4 shows the Blinder-Oaxaca decompositions of the above regressions. In any decomposition, selecting the "true" coefficient vector is crucial for obtaining unbiased estimates. How to calculate this "true" vector, β*, that is, the average treatment effect of increased internet uptake on earnings and income for the population, is subject to debate. The difference in means previously shown in equation 2 can be rewritten as equation 3 using β*, as shown below. Several methods have been proposed to determine the most valid or potentially unbiased baseline coefficient estimates, β* (Oaxaca & Ransom, 1994; Cotton, 1998; Neumark, 1998).[13] If the estimation strategy assumes metro coefficients are the true population effect, it implies that rural areas are subject to a penalty (Jann, 2008).[14]

$$Diff = \{E(X_m) - E(X_{nm})\}'\beta^* + E(X_{nm})'(\beta_m - \beta^*) + E(X_{nm})'(\beta^* - \beta_{nm}) \tag{3}$$

$$Endowment\ Portion = \{E(X_m) - E(X_{nm})\}'\beta^* \tag{4}$$

$$Coefficient\ Portion = E(X_{nm})'(\beta_m - \beta^*) + E(X_{nm})'(\beta^* - \beta_{nm}) \tag{5}$$

Consistent with existing applied literature on the internet and economic growth, I provide estimates with metro as the baseline and with baseline coefficients estimated from a pooled regression including a dummy for Metro classification (Liao et al., 2016, Jann, 2008; Manlove & Whitacre, 2019). The first left-hand term is the portion of the decomposition determined by the endowments, and the second two provide the "unexplained" portion or the percent explained by differences in return to the endowments.

TABLE 4
DECOMPOSITION OF EFFECTS OF BROADBAND AND MOBILE INTERNET ON EARNINGS

Decomposition	Average Payroll		Individual Income	
Raw Difference in Predicted Y *Urban minus Rural*	6957.82		4757.97	
Baseline Coefficients from Metro group				
Characteristics	5137.13	73.83%	3992.51	83.91%
Coefficients	1820.69	26.17%	765.46	16.09%
Baseline Coefficients from Pooled Regression				
Characteristics	5051.64	72.59%	3820.12	80.29%
Coefficients	1906.18	27.41%	937.84	19.71%

Observations: 27,124
Pooled regressions include an indicator variable for metro.

Table 4 presents the decomposition results with the metro coefficients used as the baseline in the top panel and the pooled regression in the bottom. Internet and mobile internet had different effects on earnings and income across time and urban density. Although there were a number of different coefficients between metropolitan and nonmetropolitan regressions for both wages and income, the decomposition finds that the vast majority, approximately 74%, of the differences at the mean are still determined by education and interent access, with differential returns to these attributes accounting for only 26%. Endowments are responsible for an even greater percent of the income gap, at 84%.

The results are robust to the baseline selection with metro and pooled coefficients resulting in similar estimates. Additionally, results are robust to alternate specifications testing changes in functional form, variable thresholds, and time periods. Appendix Table A1 shows that, regardless of the specification, the Blinder-Oaxaca decomposition finds that endowments explain more than 70% of the metro-nonmetro gap. As shown in the supporting Appendix tables A2-A6, regression specifications with logged dependent variables to estimate growth rates, a lower threshold of 40% for "high" internet access, and estimates of subsample periods 2010-2014 and 2015-2019 show consistent patterns in coefficients signs and magnitudes.

CONCLUSION

The decomposition results are consistent with the coefficient estimates found across earnings and income. Much of the variation observed in the impact of the internet across metropolitan densities is driven by educational differences, differences in internet saturation and duration rates, and their interaction across urban densities. Decomposition results indicate the majority of the income and earnings gap is due to endowments, with approximately 15-30% coming from the heterogenous return. These findings can be viewed optimistically, as they support that policy interventions aimed at increased educational attainment and internet saturation in nonmetro areas may help close urban-rural income gaps. As internet quality in nonmetro areas and work-from-home options expand, especially after this sample period and post the Coronavirus pandemic of 2020, we will likely see changes in average earnings and income differences across urban densities. These migrations may help further close these gaps as workers begin to distribute more evenly and endowment levels creep closer together.

ENDNOTES

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1. In later years where fewer constraints exist, the local average treatment effect (LATE) found from instrumental variables is identified off fewer and fewer observations that are induced to adopt the internet based on variation in these secondary variables. Further, these estimates may not be estimating the impact of access to the internet, which may be accomplished through mobile plans in later years, but the impact of a hardwired connection only.
2. Apple had an exclusive contract with AT&T when the iPhone was released in June 2007, which remained in place until iPhone4 became available with Verizon (02/2011), Sprint (10/2011), Cricket (05/2012), and Tmobile (04/2013) (Lewis, 2007; CBS News, 2011; Reardon, 2013). The first Android-enabled device was released exclusively at Tmobile in January of 2009, followed by the Samsung Galaxy S more broadly in late 2009 (Cha, 2009; Herrman; 2009).
3. The FCC collects information from internet providers on high-speed internet through Form 477. Starting in 2016, the FCC published retroactive data on alternate measures of highspeed with a threshold of 10 mbps and 25 mbps. However, it is not reliably available and tends to have a high variance, with counties gaining and losing access at somewhat unpredictable rates.
4. Mobile Network Operators (MNOs), like Verizon, AT&T, T-Mobile, Sprint, and US Cellular, maintain the infrastructure and deliver services directly to consumers. For more information, see https://en.wikipedia.org/wiki/List_of_mobile_network_operators_of_the_Americas#United_States. Mobile Virtual Network Operators (MNVOs) lease access to the network services from MNOs and repackage it for sale to consumers. There were 139 MVNOs operating within the US in 2016, such as Boost Mobile, Cricket, Metro Wireless, and Walmart Family Mobile. For more information, see: https://en.wikipedia.org/wiki/mobile_virtula_network_operator.com . Increases in carriers provide consumers with more choices in bundling options, such as minutes, data limits and speeds, hotspot streaming, international options, and family and pre-paid plans, allowing more consumers to find a carrier that fits their needs (Villas-Boas, 2018).
5. In addition to wages, this measure also includes bonuses, stock options, severance pay, profit distributions, cash value of meals and lodging, tips and other gratuities, and, in some States, employer contributions to 401(k) plans. See https://www.bls.gov/cew/cewover.htm for more info

6. The QCEW is collected quarterly from firms when they file required documents with the Unemployment Insurance (UI) programs. The payroll figures collected thoroughly account of labor benefits for those employed under a W-4. UI coverage excludes self-employed workers, most agricultural workers, all members of the Armed Forces, elected officials in most states, most employees of railroads, some domestic workers, most school student workers, and some small nonprofit employees.
7. For a comprehensive measure of nonmetro areas, the 5-year estimates must be used. ACS data is suppressed for counties with populations under 65,000 (Bureau, 2009).
8. Researchers have also used these decompositions outside of the labor market to study obesity trends (Le Cook et al., 2009), school enrollment rates (Boorooah & Iyer, 2006), smoking behavior (Bauer et al., 2007), license application rates (Munn & Hussain, 2010), and health insurance coverage (Bustamante et al., 2009).
9. Jann (2008) provides a thorough discussion of the statistical underpinnings of the Blinder-Oaxaca decomposition technique as well as its application in the STATA program. Sinning et al. (2008) expands the Blinder-Oaxaca STATA tools to include Nonlinear regressions.
10. Robustness Checks to these variable specifications, such as using a lower threshold or varying the sample years, are shown in Appendix Table A1 and discussed in the robustness section.
11. Percent of People per Age by Bracket (0-19, 20-34, 35-44, 45-54, 55-64, 64+)
12. Estimate calculated from Colum 4 coefficients: (2057 *(1)*(0.06)) - ((14*(1)*(0.06))
13. Methods of determining β* vary: Reimers (1983) proposed giving equal weight to coefficients from the separate regressions. Cotton (1988) suggested observation weighting the coefficients from the separate regressions. Other researchers have proposed no weights, but using coefficients estimated from a regression pooling observations from both groups as the baseline. The form of the pooled regression varies by including a dummy variable for the group indicator (Jann, 2008) or not (Neumark, 1988).
14. The differential could also be weighted in terms of rural areas if we wish to model nonmetro areas earning the "true" return and metro areas receiving a premium. See Jann (2008) for additional discussion on baseline selection and weighting.

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APPENDIX

TABLE A1
ROBUSTNESS CHECK OF DECOMPOSITION RESULTS

	Logged Outcomes		Medium Broadband	
Decomposition	Avg Payroll	Income	Avg Payroll	Income
Raw Difference in Predicted Y	0.1572	0.1719	$6,957.82	$4,757.97
Urban minus Rural				
Baseline Coefficients from Metro group				
Characteristics	85.65%	74.39%	87.92%	77.26%
Coefficients	14.35%	25.61%	12.07%	22.74%
Baseline Coefficients from Pooled Regression				
Characteristics	82.60%	79.78%	85.19%	84.96%
Coefficients	17.40%	20.22%	14.81%	15.03%
Observations	31,096	29,920	31,096	29,920

Pooled regressions include an indicator variable for metro.
The Medium broadband specification utilizes a dummy variable for 40% or more broadband uptake and time since 40% threshold was met, instead of a 60% threshold. All supporting OLS regression results are available in a digital appendix upon request.

TABLE A2
ROBUSTNESS CHECK OF DECOMPOSITION RESULTS – SAMPLE YEARS

	Years 2010-2014		Years 2014-2019	
Decomposition	Avg Payroll	Income	Avg Payroll	Income
Raw Difference in Predicted Y	$6,800.60	$5,028.06	$7,115.88	$4,456.40
Urban minus Rural				
Baseline Coefficients from Metro group				
Characteristics	87.37%	77.58%	87.17%	87.45%
Coefficients	12.63%	22.42%	12.83%	12.55%
Baseline Coefficients from Pooled Regression				
Characteristics	82.40%	81.95%	78.82%	92.88%
Coefficients	17.60%	18.05%	21.18%	7.12%
Observations	15,549	15,549	15,547	14,371

Pooled regressions include an indicator variable for metro.
The Medium broadband specification utilizes a dummy variable for 40% or more broadband uptake and time since 40% threshold was met, instead of a 60% threshold. All supporting OLS regression results are available in a digital appendix upon request

TABLE A3
RETURN TO INTERNET & EDUCATION ON LOGGED EARNINGS & INCOME

	Y = ln(Average Annual Payroll)				Y = ln (Individual Income)			
	metro		non-metro		metro		non-metro	
Variables	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
High BB Adoption (above 60% HH)	0.0026	0.0106+	0.0069***	0.0212**	0.0008	0.0065	-0.0019	0.0039
	(0.0019)	(0.0064)	(0.0020)	(0.0076)	(0.0020)	(0.0072)	(0.0024)	(0.0073)
Years Since High BB Adopt	-0.0001	-0.0012	-0.0002	-0.0031+	-0.0014**	-0.0043*	0.0000	0.0007
	(0.0006)	(0.0019)	(0.0006)	(0.0018)	(0.0005)	(0.0017)	(0.0006)	(0.0018)
High Mobile Access (Above 3 Carriers)	0.0074*	-0.0056	-0.0001	-0.0117*	0.0048	-0.0101	0.0068***	0.0046
	(0.0033)	(0.0121)	(0.0017)	(0.0046)	(0.0032)	(0.0098)	(0.0020)	(0.0059)
Years Since High Mobile	-0.0026+	-0.0023	-0.0020***	-0.0012	-0.0044**	-0.0027	-0.0051***	-0.0060***
	(0.0014)	(0.0024)	(0.0006)	(0.0012)	(0.0015)	(0.0024)	(0.0008)	(0.0014)
College BA /plus (%)	0.0012+	0.0007	0.0005	0.0003	0.0077***	0.0071***	0.0074***	0.0072***
	(0.0006)	(0.0009)	(0.0005)	(0.0005)	(0.0007)	(0.0009)	(0.0006)	(0.0007)
High BB Adopt* College Grad Plus (%)		-0.0342		-0.0663*		-0.0195		-0.0300
		(0.0268)		(0.0314)		(0.0327)		(0.0314)
Years Since BB * College Grad Plus (%)		0.0044		0.0129+		0.0121		-0.0033
		(0.0078)		(0.0071)		(0.0074)		(0.0078)
High Mobile * College Grad Plus (%)		0.0704		0.0688**		0.0790+		0.0144
		(0.0536)		(0.0241)		(0.0461)		(0.0331)
Years Since Mobile*College Grad Plus (%)		-0.0023		-0.0049		-0.0084		0.0045
		(0.0077)		(0.0053)		(0.0074)		(0.0063)
Observations	11,614	11,614	19,482	19,482	11,295	11,295	18,625	18,625

Sample Years: 2010-2019 Each regression contains county fixed effects and year dummy variables . Control Variables include: Percent men, Gini coefficient, Percent of People New To County In Last Year (from other county, state, or abroad), Percent of People per Age by Bracket (0-19, 20-34, 35-44, 45-54, 55 -64, 64+), and the percent of people who are black, white, or Asian
Robust Standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.10

TABLE A4
RETURN TO MEDIUM INTERNET & EDUCATION ON EARNINGS & INCOME

	Y = Average Annual Payroll				Y = Individual Income			
	metro		non-metro		metro		non-metro	
Variables	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Medium BB Adoption (above 40% HH)	248.05	848.42	161.57*	302.96	99.72	634.66*	-42.72	6.33
	(220.20)	(686.31)	(75.69)	(227.85)	(99.93)	(290.29)	(61.87)	(177.23)
Years Since High BB Adopt	22.13	-138.29	36.87	-125.84*	-41.33	-85.60	34.49*	-42.72
	(54.34)	(162.61)	(23.38)	(53.76)	(31.61)	(74.92)	(15.39)	(39.64)
High Mobile Access (Above 3 Carriers)	251.57+	-285.88	-55.83	-375.44*	224.48**	-168.90	163.92**	91.48
	(151.25)	(584.46)	(69.42)	(185.00)	(86.75)	(259.77)	(50.32)	(154.18)
Years Since High Mobile	-102.75	10.89	-61.19*	84.54	-147.72***	-81.52	-154.86***	-86.99+
	(65.87)	(204.19)	(25.00)	(62.93)	(41.23)	(95.20)	(21.28)	(46.71)
College BA /plus (%)	75.97**	45.94	7.01	-13.13	214.55***	227.57***	191.47***	183.94***
	(28.35)	(48.95)	(21.46)	(23.22)	(20.36)	(28.24)	(17.60)	(19.77)
High BB Adopt* College Grad Plus (%)		-3,148.04		-476.21		-3,430.93*		-123.37
		(3,556.17)		(1,354.42)		(1,673.76)		(1,150.28)
Years Since BB * College Grad Plus (%)		860.34		917.18***		308.59		439.98+
		(763.79)		(277.10)		(380.49)		(227.16)
High Mobile * College Grad Plus (%)		3,060.19		1,793.07+		2,075.70		375.34
		(2,603.21)		(1,001.93)		(1,304.73)		(935.69)
Years Since Mobile*College Grad Plus (%)		-565.47		-780.44**		-327.50		-360.25
		(740.19)		(298.73)		(377.54)		(236.95)
Observations	11,614	11,614	19,482	19,482	11,295	11,295	18,625	18,625

Sample Years: 2010-2019 Each regression contains county fixed effects and year dummy variables . Control Variables include: Percent men, Gini coefficient, Percent of People New To County In Last Year (from other county, state, or abroad), Percent of People per Age by Bracket (0-19, 20-34, 35-44, 45-54, 55 -64, 64+), and the percent of people who are black, white, or Asian
Robust Standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.10

TABLE A5
RETURN TO INTERNET & EDUCATION ON EARNINGS & INCOME (2010-2014)

	Y = Average Annual Payroll				Y = Individual Income			
	metro		non-metro		metro		non-metro	
Variables	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
High BB Adoption (above 60% HH)	169.08*	521.98+	-31.00	-305.12	100.34+	57.32	18.77	-83.90
	(83.39)	(287.61)	(169.79)	(403.25)	(56.03)	(202.67)	(98.44)	(289.99)
Years Since High BB Adopt	-74.14*	-236.27+	144.81	534.22*	-140.23***	-227.56**	-17.74	145.54
	(36.76)	(133.66)	(90.55)	(221.12)	(22.74)	(77.06)	(49.96)	(145.58)
High Mobile Access (Above 3 Carriers)	90.53	-681.40+	138.77	-145.51	202.33**	77.45	217.00***	254.47
	(142.03)	(405.86)	(85.01)	(217.31)	(74.57)	(201.60)	(55.81)	(169.28)
Years Since High Mobile	-100.29+	-37.13	-127.59***	29.63	-126.84***	-1.92	-158.17***	-79.75
	(59.17)	(119.44)	(37.77)	(88.19)	(37.99)	(71.98)	(23.07)	(48.72)
College BA /plus (%)	-16.36	-39.81	-38.42	-32.93	199.50***	206.22***	164.82***	171.83***
	(40.21)	(44.48)	(29.53)	(30.58)	(27.16)	(28.72)	(19.02)	(19.97)
High BB Adopt* College Grad Plus (%)		-1,415.40		884.46		179.51		295.93
		(1,141.52)		(1,498.14)		(870.23)		(1,236.36)
Years Since BB * College Grad Plus (%)		665.71		-1,416.96+		475.00		-561.53
		(527.01)		(730.82)		(331.47)		(536.99)
High Mobile * College Grad Plus (%)		4,325.73*		1,623.66		535.65		-316.29
		(1,877.18)		(1,190.71)		(1,058.70)		(1,073.11)
Years Since Mobile*College Grad Plus (%)		-402.15		-889.38*		-578.35*		-433.99+
		(463.53)		(408.61)		(294.64)		(252.11)
Observations	5,809	5,809	9,740	9,740	5,809	5,809	9,740	9,740

Sample Years: 2010-2014 Each regression contains county fixed effects and year dummy variables . Control Variables include: Percent men, Gini coefficient, Percent of People New To County In Last Year (from other county, state, or abroad), Percent of People per Age by Bracket (0-19, 20-34, 35-44, 45-54, 55 -64, 64+), and the percent of people who are black, white, or Asian
Robust Standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.10

TABLE A6
RETURN TO INTERNET & EDUCATION ON EARNINGS & INCOME (2015-2019)

	Y = Average Annual Payroll				Y = Individual Income			
	metro		non-metro		metro		non-metro	
Variables	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
High BB Adoption (above 60% HH)	169.08*	521.98+	-31.00	-305.12	100.34+	57.32	18.77	-83.90
	(83.39)	(287.61)	(169.79)	(403.25)	(56.03)	(202.67)	(98.44)	(289.99)
Years Since High BB Adopt	-74.14*	-236.27+	144.81	534.22*	-140.23***	-227.56**	-17.74	145.54
	(36.76)	(133.66)	(90.55)	(221.12)	(22.74)	(77.06)	(49.96)	(145.58)
High Mobile Access (Above 3 Carriers)	90.53	-681.40+	138.77	-145.51	202.33**	77.45	217.00***	254.47
	(142.03)	(405.86)	(85.01)	(217.31)	(74.57)	(201.60)	(55.81)	(169.28)
Years Since High Mobile	-100.29+	-37.13	-127.59***	29.63	-126.84***	-1.92	-158.17***	-79.75
	(59.17)	(119.44)	(37.77)	(88.19)	(37.99)	(71.98)	(23.07)	(48.72)
College BA /plus (%)	-16.36	-39.81	-38.42	-32.93	199.50***	206.22***	164.82***	171.83***
	(40.21)	(44.48)	(29.53)	(30.58)	(27.16)	(28.72)	(19.02)	(19.97)
High BB Adopt* College Grad Plus (%)		-1,415.40		884.46		179.51		295.93
		(1,141.52)		(1,498.14)		(870.23)		(1,236.36)
Years Since BB * College Grad Plus (%)		665.71		-1,416.96+		475.00		-561.53
		(527.01)		(730.82)		(331.47)		(536.99)
High Mobile * College Grad Plus (%)		4,325.73*		1,623.66		535.65		-316.29
		(1,877.18)		(1,190.71)		(1,058.70)		(1,073.11)
Years Since Mobile*College Grad Plus (%)		-402.15		-889.38*		-578.35*		-433.99+
		(463.53)		(408.61)		(294.64)		(252.11)
Observations	5,809	5,809	9,740	9,740	5,809	5,809	9,740	9,740

Sample Years: 2015-2019 Each regression contains county fixed effects and year dummy variables . Control Variables include: Percent men, Gini coefficient, Percent of People New To County In Last Year (from other county, state, or abroad), Percent of People per Age by Bracket (0-19, 20-34, 35-44, 45-54, 55 -64, 64+), and the percent of people who are black, white, or Asian
Robust Standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.10