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The Demographic and Economic Drivers of Broadband Adoption in the United States

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Abstract: In this POLICY PAPER, we analyze the variation in broadband adoption rates among the respective United States. Significantly, we find that 91% of the variation is explained by demographic and economic conditions, such as household income, education and, most significantly, income inequality. Our research therefore indicates that policies that focus on these demand-side factors perhaps offer more "bang for the buck" in terms of increasing broadband penetration than supply-side policies, including subsidies for networks or regulation of providers. For example, programs that focus upon educational institutions in low-income communities with school age children—like ConnectKentucky's "No Child Left Offline" initiative—may boost broadband adoption rates considerably, as they leverage demand-side drivers that encourage broadband subscription (having a child in school) in a way that may overcome or mitigate the problem of income inequality. Programs that target broadband education for older and retired persons may also be helpful.

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TABLE OF CONTENTS:

I. Introduction

While it is generally understood that broadband adoption rates vary across countries, it is also true that the rate of broadband adoption in the United States varies substantially among the states. According to data collected by the Federal Communications Commission, state-by-state broadband penetration rates vary widely—from 0.87 broadband subscribers per household in New Jersey to only 0.25 subscribers per household in Mississippi.[1] The pace of broadband availability and adoption is drawing increased attention from policymakers at the state, local and federal level, as a growing body of evidence shows a strong link between broadband and economic development. A recent report prepared for the U.S. Department of Commerce states that "broadband access does enhance economic growth and performance," noting that communities in which mass-market broadband was available "experienced more rapid growth in employment, the number of businesses overall, and businesses in IT-intensive sectors, relative to comparable communities without broadband." But the report specifically found that for most of those impacts to appear, "*broadband had to be used*, not just available."[2]

[1] *See* Table 1 *infra*.

[2] S.E. Gillett, W.H. Lehr & M. Sirbu, *Measuring Broadband's Economic Impact,* Final Report (Feb. 28, 2006)(emphasis added)(available at: http://www.eda.gov/ImageCache/EDAPublic/documents/pdfdocs2006/mitcmubbimpactreport_2epdf/v1/mitcmubbimpactreport.pdf) at 3; *see also* G. Ford & T. Koutsky, *Broadband and Economic*

(Footnote Continued. . . .)

Numerous states have implemented programs to encourage broadband deployment and adoption, including the successful ConnectKentucky program, which is becoming a national benchmark.[3] However, the differences in broadband adoption rates among the states can be a thorny issue politically, as the debate can often degenerate into a discussion of "rankings" that treat broadband adoption like the college football season. This emphasis upon subscription rankings ignores the substantial role that demographic and economic conditions play in the adoption of broadband technology by households and businesses. As noted by John B. Horrigan of the Pew Internet & American Life Project, "the tenor of the current debate obscures" an important question: "What is the nature of unmet demand for broadband in the United States?"[4]

Earlier this year, PHOENIX CENTER POLICY PAPER NO. 29 demonstrated that demographic and economic conditions, such as income, income inequality, education level, geographic density and population age, explain approximately 86% of the variation of broadband adoption rates in OECD member countries, leaving very little variation that could be explained by differences in policy regimes. After accounting for the respective economic endowments of the OECD countries, we created an index of performance for the OECD countries based on the difference between expected and actual broadband subscription rates. This Broadband Performance Index, or BPI, provided a very different picture of the relative performance of the countries than did raw subscription numbers.

Development: A Municipal Case Study from Florida, 17 REVIEW OF URBAN & REGIONAL DEVELOPMENT STUDIES 216 (2005)

3 The National Conference of State Legislatures maintains a list of state "broadband statutes" that currently lists forty-eight state legislative initiatives designed to spur broadband or advanced service deployment, either through favorable taxation or financing terms, "coordination and leadership" initiatives, or deregulation. Nat'l Conf. of State Legislatures, *Broadband Statutes* (available at: http://www.ncsl.org/programs/lis/legislation/broadbandstatutes.htm) (last visited Nov. 8, 2007). The NCSL list may not be comprehensive but it does indicate that there is broad range of state activity focused on one goal—increasing broadband penetration. *See Wiring Rural America: A Public-Private Partnership Success,* THE ECONOMIST (Sep. 13, 2007) (available at: http://economist.com/world/na/displaystory.cfm?story_id=9803963&CFID=21015017&CFTOKEN=15191272) ("ConnectKentucky is just one effort among many programmes in different states and within the federal government to wire up the American countryside. . . . But not all have been as successful as Kentucky's.").

4 J.B. Horrigan, *Why it will Be Hard to Close the Broadband Divide,* Pew Internet & American Life Project (Aug. 1, 2007) (available at: http://www.pewinternet.org/pdfs/Broadband_Commentary.pdf) at 1.

Clearly, a relatively poor country like Turkey will not have as high a subscription rate as a wealthy country like Luxembourg, but our analysis showed that broadband penetration in Turkey exceeded its demographic and economic expectations, while broadband in Luxembourg lagged behind. Broadband "miracles" such as Japan and Korea were found to have subscriptions rates essentially consistent with their endowments. These findings suggest that simply comparing raw subscription numbers across countries with different economic endowments is misguided and does not paint an accurate picture as to whether policy in those countries is succeeding or failing.[5]

In this PAPER, we apply a similar statistical approach to data on broadband adoption domestically and look at the demographic and economic factors that influence subscription rates among the respective states. Utilizing data released by the FCC and U.S. Bureau of the Census, we show that demographic and economic conditions explain about 91% of variation of broadband penetration among the states. The findings are consistent with those of our international research—broadband adoption is positively related to income, population density, and education, and negatively related to income inequality and age. We also find that once other demographic and economic factors like household income are taken into account, the nation's immigrant community is substantially more likely to subscribe to broadband services than the native-born population. Broadband service also appears to be integral to a modern education—households with at least one family member in school and the percent of college educated persons in a state are very important determinants of broadband subscription.

Our analysis therefore indicates that demographic and economic endowments, and not necessarily specific regulatory policies directed at broadband providers or subsidizing broadband networks, are the most important drivers of broadband adoption. For all intents and purposes, the factors that we identify by and large describe almost all of the differences in broadband adoption among the states that we analyze. In other words, despite large actual differences in subscription rates among the states, demographic and economic factors explain almost all of the differences.

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5 G.S. Ford, T.M. Koutsky & L.J. Spiwak, *The Broadband Performance Index: A Policy-Relevant Method of Comparing Broadband Adoption Among Countries*, PHOENIX CENTER POLICY PAPER NO. 29 (July 2007)(available at: http://wwwe.phoenix-center.org/pcpp/PCPP29Final.pdf).

That said, public policy is not irrelevant. Indeed, our results should encourage policymakers to focus their attention on policies that will cultivate or enhance the endowments that increase broadband penetration or that will counterbalance the adverse effects of endowments that suppress penetration. For example, programs focused on overcoming the effect of income and income inequality might significantly spur broadband adoption. Income inequality is found to have a considerably suppressive effect on broadband penetration, similar to our international findings in PHOENIX CENTER POLICY PAPER NO. 29. This effect domestically is substantial—a 10% increase in the Gini Coefficient (a measure of income inequality) decreases broadband subscriptions in a state by about 15.1%. In fact, the effect of income inequality is of far larger magnitude than income itself or the presence of rural and farm households in a state.[6] Taken together, these findings indicate that programs that focus upon low-income communities with school age children may provide the largest "bang for the buck" in terms of increasing broadband penetration. ConnectKentucky's "No Child Left Offline" is one example of such a program.[7] Programs that target broadband education for older and retired persons may also be helpful, as might improvements in and deployment of telehealth technology.

Broadband adoption is an input that is expected to improve economic growth and development, facilitate education and healthcare, and positively impact well being in a variety of other ways. As a result, broadband policy should be considered as part of a range of public policy choices that serve the same end, and all policy recommendations should be accompanied by a cost-benefit analysis. Our analysis suggests that broadband adoption is intimately tied to demand-side factors like income inequality and education, and policies directed at those factors may be more cost effective than supply-side subsidies and regulation.

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[6] Obviously, the subscription to broadband service is dependent on computer ownership, and many poorer households cannot afford a computer. *See, e.g.*, http://www.connectkentucky.org/technology_solutions/no_child_left_offline.php.

[7] B. Marshall, "No Child Left Offline," *Richmond Register* (Sep. 25, 2007) (available at: http://connectkentucky.org/NR/rdonlyres/378120B6-E7D2-48E4-AC58-9FCA2C588E6A/0/Article_NCLO_ModelLab_92507.pdf).

II. An Empirical Approach to Analyzing the Conditions that Affect Broadband Penetration

The number of residential and business broadband connections per household varies considerably across the U.S. states. Table 1 presents data derived from the FCC's June 2006 High Speed Internet Access Report and the Census Bureau. As of June 2006, per household broadband subscription rates ranged from 0.87 in New Jersey to 0.25 in Mississippi—a difference of over 300%.[8] However, this outcome is less shocking when one considers that the average household income in New Jersey is more than twice that in Mississippi ($73,260 to $32,315), that nearly twice as people in New Jersey have a college degree or better than do so in Mississippi (28% to 16%), and that only 5% of households in New Jersey are classified as being rural while 51% of Mississippi households are in rural areas. At first glance, it appears economic endowments matter, so looking solely at raw subscription figures might paint an inaccurate picture on broadband adoption in the United States.

[8] The FCC does not consistently release broadband subscription information for Hawaii, so the analysis in this PAPER considers the remaining 49 states and the District of Columbia. The FCC Report does not present data on a per-household basis but instead reports raw subscription numbers. As we noted in PHOENIX CENTER POLICY PAPER NO. 29, we believe that normalizing broadband subscriptions on a "per household" and not population is appropriate because broadband services are typically purchased by consumers on a household basis.

Table 1. Broadband Subscription per Household, U.S. States June 2006

State	Subs/HH	State	Subs/HH
New Jersey	0.87	Nebraska	0.53
Nevada	0.82	Delaware	0.53
California	0.82	Tennessee	0.52
District of Columbia	0.81	North Carolina	0.51
Connecticut	0.79	Indiana	0.51
Maryland	0.75	Wisconsin	0.50
Massachusetts	0.74	Maine	0.48
Arizona	0.73	Michigan	0.47
Colorado	0.70	Missouri	0.46
Florida	0.70	Vermont	0.45
Washington	0.69	Louisiana	0.44
New York	0.69	Idaho	0.43
Georgia	0.68	Wyoming	0.43
Rhode Island	0.68	Oklahoma	0.42
Utah	0.67	South Carolina	0.42
Virginia	0.66	Kentucky	0.40
Oregon	0.64	Montana	0.39
New Hampshire	0.64	Iowa	0.39
Texas	0.59	New Mexico	0.37
Kansas	0.57	Alabama	0.35
Illinois	0.57	Arkansas	0.35
Alaska	0.56	West Virginia	0.33
Minnesota	0.56	South Dakota	0.29
Pennsylvania	0.55	North Dakota	0.27
Ohio	0.54	Mississippi	0.25

Source: FCC, HIGH-SPEED SERVICES FOR INTERNET ACCESS: STATUS AS OF JUNE 30, 2006 (Jan. 2007) at Table 10.

But it is one thing to say that differences in income, education, and population density impact broadband adoption—it is quite another matter to study the extent and magnitude of those effects.[9] Understanding the relative importance of those differences can have a substantial impact upon public policy,

9 In particular, the Pew Internet & American Life Project has conducted two nationwide surveys on Americans' use of the Internet. That data reveals some trends about broadband adoption broken down by income, ethnicity, and age. *See* J.B. Horrigan & A. Smith, *Home Broadband Adoption 2007,* Pew Internet & American Life Project (Jul. 3, 2007) (available at: http://www.pewinternet.org/pdfs/PIP_Broadband%202007.pdf); J.B. Horrigan, *Home Broadband Adoption 2006,* Pew Internet & American Life Project (May 28, 2006) (available at: http://www.pewinternet.org/pdfs/PIP_Broadband_trends2006.pdf).

because policymakers should seek to adopt programs that will have the greatest possible impact on broadband adoption.

The purpose of this PAPER is to quantify the relationship between economic and demographic factors and broadband subscription among the U.S. states. We do so using an econometric analysis similar to the method we used to study broadband adoption among the OECD countries. Our method crystallizes and quantifies the demographic and economic factors that impact broadband adoption, because cultivating or overcoming those important factors—and not necessarily subsidization of network construction or regulation of carrier conduct—will be crucial to increasing broadband adoption. We hope by providing policymakers with realistic guideposts that better, more focused policy initiatives will result, as will more realistic expectations of the results of government interventions.

A. *The Empirical Model*

A household's decision to subscribe to broadband is influenced by a number of factors, including income, education and availability. Similarly, businesses decide whether or not to subscribe to broadband service based on demand and supply conditions. When it comes to subscription rates and rankings, however, this seemingly obvious fact is typically ignored in policy debates, where the broadband subscription rate becomes solely a matter of pride. Here, we set pride aside and focus on the genuine determinants of broadband subscription, which include economic and demographic endowments such as income, education and population density. As we just discussed with regard to New Jersey and Mississippi, all states are not working with the same set of endowments, thus all states cannot be expected to have the same adoption rates.

To determine the relationship between state *i*'s endowments, which we call X_i, and broadband subscription, which we call B_i, we estimate the following econometric model

$$\sqrt{B_i} = \sum_{j=1}^{k} \alpha_k X_{k,i} + \varepsilon_i \tag{1}$$

where ε_i is the zero-mean econometric disturbance term, and the α are coefficients for each of the *k* endowments (including a constant term). Equation (1) has a square-root transformation of the dependent variable. This transformation performed best in terms of specification testing. We include in *X* the following variables, utilizing data from the U.S. Census Bureau:

- Average household income (*INCOME*);

- Income inequality, measured by the state's Gini coefficient (*GINI*);
- The percentage of population living in cities with more than 100,000 people (*CITY100*);
- The percentage of rural households (*RURAL*);
- The percentage of farm households (*FARM*);
- The percentage of families where English in the primary language (*ENGLISH*);
- The percentage of foreign-born population (*IMMIG*);
- The percentage of the population with a college degree or better (*EDUC*);
- The percentage of households where at least one member is in some level of school (*INSCHOOL*); and
- The percentage of households receiving retirement income (*RETIRE*) which we use as an additional proxy for age.

Population density is very difficult to measure, and the effects are likely to be highly non-linear. Thus, in addition to these variables, we include interaction terms of *CITY100*, *RURAL*, and *FARM*, to allow for non-linearity in density.

In preliminary and investigative work, we considered a wide range of other variables, including alternative measures of density, household characteristics, cost of living indexes, and so forth. In the end, most of these other variables were not consistent contributors to the explanatory power of the model, and some had weak theoretical justification. In some cases, the correlation with other variables was too high to warrant inclusion.[10] Also, we have chosen to use the

[10] We considered various measures of age, population density (*e.g.,* road miles, rural road miles, population per square mile), and income (per capita, median household income), telephone subscription, and many other variables. The variables we use in the model produce the best model we could derive that best explains the variation in broadband subscription among the states. This does not mean to imply that the variables we rejected (such as income per capita) are not relevant but simply that the *INCOME* variable we selected (average household income) *better* explains the differences in broadband adoption we observe.

variable *RETIRE* rather than simply including a variable for the percent of population age 65 or older (*AGE65*). Surprisingly, we did not find any statistically significant result on *AGE65* across a wide range of models. However, the *RETIRE* variable was consistently found to be an important determinant of subscription. This indicates that age alone may not be as related to broadband adoption in the U.S. as is whether or not the potential user is in the active workforce.[11]

Finally, unlike our international analysis, we do not include a measure of broadband price in the regression. We suspect that there is very little variation in average broadband prices across the United States (when measured on a statewide basis), so our model assumes that to be the case. Moreover, we have not found any reliable data source for broadband prices (either advertised prices or actual prices) at the state level. The information used in our international analysis consists of nationwide average advertised prices compiled by the OECD; no similar data for each state in the U.S. are available. Without variation across states, the effect of price is included in the constant term of the regression. Our specification does allow price to change over time, but price is assumed not to vary across states.

Variable selection is, of course, a very important component of our model. As described below, the variables we have selected explain approximately 91% of the variation in broadband adoption rates among the states, and statistical tests indicate the model is well specified. It is possible that other factors that we did not consider may play a role in explaining the pace of broadband adoption.[12] Different models that consider other variable of course may produce different results, but we expect that alternative, well-specified models will lead to similar conclusions.

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[11] Further research on these results is warranted. To explore this point further, we considered including homes receiving social security income in this variable, but rejected that approach, due to the potential for double counting and the fact that social security income may be paid to people who are not in the older age groups.

[12] The specification test RESET has power against omitted variables and we cannot reject the null hypothesis of that test for our chosen model. However, this result does not imply that other factors are irrelevant to the explanation of broadband subscription rates, but rather suggests that the estimated coefficients are not much impacted the exclusion of these other determinants.

B. *Data and Expectations*

The data on broadband subscriptions is provided by the FCC's *High-Speed Services for Internet Access* report.[13] We include in the sample subscription rates for June 2005 and December 2005. For these periods, data is available for forty-nine states and the District of Columbia. Because the FCC has not consistently reported data for Hawaii, we exclude that state. The data comes as raw counts of broadband connections. For our regression analysis, we divide these connections by total households in the state.

While the FCC has published data on broadband subscriptions for each state in June and December 2006, the use of this state-specific data is complicated by the marked growth in reported mobile broadband lines. We believe that excluding these observations is necessary because the FCC itself has stated that it does not appear to be counting wireless broadband lines in the same way that it counts wireline broadband lines. Earlier this year, the FCC noted that the instructions for FCC Form 477 direct mobile providers to report the number of handsets and devices that are "capable" of sending or receiving data at 200 kbps or above, without regard as to whether subscribers actual subscribe to a mobile broadband data service plan, stating that "the current [data reporting] instructions make it likely that more and more mobile voice service subscribers will be reported as mobile broadband subscribers merely by virtue of purchasing a broadband-capable handset, rather than a specific Internet plan."[14] This approach of reporting broadband "capability," rather than actual broadband

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13 Industry Analysis and Technology Division, Wireline Competition Bureau, Federal Communications Commission, HIGH-SPEED SERVICES FOR INTERNET ACCESS: STATUS AS OF JUNE 30, 2006 (Jan. 2007) (available at: http://hraunfoss.fcc.gov/edocs_public/attachmatch/DOC-270128A1.pdf) at Table 10. The same data is available in Industry and Analysis and Technology Division, Wireline Competition Bureau, Federal Communications Commission, TRENDS IN TELEPHONE SERVICE, (Feb. 2007) (available at: http://hraunfoss.fcc.gov/edocs_public/attachmatch/DOC-270407A1.pdf) at Table 2-7. We discuss the quality of FCC broadband data in Section III *infra*.

14 *In the Matter of Development of Nationwide Broadband Data to Evaluate Reasonable and Timely Deployment of Advanced Services to All Americans, Improvement of Wireless Broadband Subscribership Data, and Development of Data on Interconnected Voice over Internet Protocol (VoIP) Subscribership,* WC Docket No. 07-38, Notice of Proposed Rulemaking (rel. Apr. 16, 2007) (*Broadband Data Collection NPRM)* at ¶ 12 (quoting current FCC Form 477). In short, the current instructions indicate that all owners of a 3G-capable phone (like the Motorola RAZR) will be reported as a "broadband" line once a mobile network is upgraded to 3G, even if the subscriber does not subscribe to any 3G data package. A similar instruction of broadband "capability" is not present for wireline broadband service.

connections, is different than the data collected for wireline broadband service. As a result, over the last two reporting periods (June and December 2006), this reporting quirk has had a substantial and growing impact on the FCC broadband data reports.[15] Moreover, an inspection of the data suggests that mobile broadband capability is not being incorporated into the state-specific estimates consistently—some states experienced sizeable increases in reported mobile lines in June 2006 whereas others reported sizeable increases in December 2006.

The FCC has noted that "we are currently unable to determine from the reported data the number of subscribers who make regular use of a broadband Internet access service as part of their mobile service package."[16] For purposes of our analysis, we are of course interested in the household's decision to subscribe to broadband service and not the purchase of equipment that may not be used for broadband service. Moreover, it is impossible to adjust much of the state-specific subscription counts for this irregularity, because of missing and redacted data. As a result, until these data reporting issues are addressed, we believe it important to exclude the effect of these mobile devices from our analysis and limit our analysis to year 2005 data. For those interested, we also report in Appendix A the estimated model including June 2006 and both June and December 2006 data.

Census data is used for the variables measuring economic and demographic endowments.[17] Based upon our regression results in POLICY PAPER NO. 29 and other research on broadband subscription, we have the following expectations regarding the regressors.[18] We expect broadband subscription to be positively related to income (*INCOME*) but negatively related to income inequality (*GINI*). Research also shows those with more education have a higher demand for

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[15] For example, from December 2005 to June 2006, the number of reported mobile broadband connections in the state-specific data rose from 3 million to 11 million, or from about 6% of the total to 17% of the total over a of six month period. From June 2006 to December 2006, FCC data states that the number of mobile broadband lines doubled, from 11 million to 22 million, and the total now represents 27% of broadband subscriptions. *See* Industry Analysis and Technology Division, Wireline Competition Bureau, Federal Communications Commission, HIGH-SPEED SERVICES FOR INTERNET ACCESS: STATUS AS OF DECEMBER 31, 2006 (Oct. 2007) (available at: http://hraunfoss.fcc.gov/edocs_public/attachmatch/DOC-277784A1.pdf) at Table 10.

[16] *Broadband Data Collection NPRM*, *supra* n. 14 at ¶ 12.

[17] We use DataFerret to extract the data from the 2000 Census.

[18] *See* PHOENIX CENTER POLICY PAPER NO. 29, *supra* n. 5 at 10, n. 9.

broadband service, so *EDUC* should have a positive coefficient.[19] We also expect homes with students will have a larger demand for broadband, so we expect a positive coefficient on the variable *INSCHOOL*. Research, including ours, suggests older persons are less likely to buy broadband.[20] If so, then we expect a negative sign on *RETIRE*. Survey research suggests subscription in rural areas is lower, so we expect negative signs on *RURAL* and *FARM*, with a larger effect expected on *FARM*, and a positive sign on *CITY100*. Subscription rates increase over time, so the *JUNE05* and *DEC05* dummy variables will have negative signs. Finally, we make no a priori predictions as to the signs on *ENGLISH* or *IMMIG*. Descriptive statistics are provided in Table 2.

C. *Estimation Details*

We considered a variety of functional forms for the least squares model, but the square-root transformation of the broadband per household subscription rate (the dependent variable) was preferred by specification tests (RESET and White) across a range of specifications and data sets.[21] These tests did not indicate that a transformation of the regressors was desirable, so we use the linear form of the regressors. We could not reject the null hypothesis of homoscedasticity, so we proceeded with ordinary least squares estimation. We do, however, use White's robust standard errors to compute the t-statistics.[22] Our total sample contains 100 observations (49 states, Hawaii excluded, and the District of Columbia over 2 semi-annual periods).

Our model has period-specific dummy variables for each time period in the sample. Given that the regressors are held constant over the time period, we cannot include state-specific dummy variables (i.e., fixed effects estimation).

19 Horrigan & Smith, *supra* n. 9.

20 *Id*; PHOENIX CENTER POLICY PAPER NO. 29, *supra* n. 5.

21 D. Gujarati, BASIC ECONOMETRICS (1995) at 78-80, 464-6. Given the large number of regressors, White's test for heteroscedasticity is based on regressing the squared residuals on the fitted and square of the fitted value from the regression. As detailed by Wooldridge, this test is useful in that the test statistic (χ^2) has only two degrees of freedom yet remains asymptotically valid. It is a special case of White's test for heteroscedasticity. J. Wooldrige, ECONOMETRIC ANALYSIS OF CROSS SECTION AND PANEL DATA (2002) at 126-27, 177-78. For the 2005 data, the linear specification of the dependent variable was also a valid specification. The marginal effects were very similar to those reported for the square-root transformation.

22 Gujarati, *supra* n. 21 at 383.

Given fixed value regressors, state-specific dummy variables will be collinear with the regressors.

D. *Least Squares Results*

The regression results are summarized in Table 2, including approximate elasticities based on a 10% change in the regressor, the Partial R^2 which is a measure of relative explanatory power, and the descriptive statistics of the regressors.[23] The model fits the sample data very well, with an R^2 of 0.91. Thus, about 91% of the variation in broadband subscription rates is explained by the regressors in the model, which is similar to model in POLICY PAPER NO. 29 that analyzed OECD data (with an R^2 of 0.86). Most of the variables in the model are statistically different from zero at the 5% level or better, with only the interaction terms being of weak significance. Two of the marginal effects of the density variables are statistically different from zero at better than the 5% level, whereas one is statistically significant only at the 12% level.[24] We can easily reject the null hypothesis that the coefficients of the interaction terms are jointly zero indicating that the non-linear specification of density is preferred to a simpler model.[25] The null hypothesis of the RESET ("no specification error") and White's Test ("homoscedastic disturbances") are not rejected even at the 10% level. Overall, the model appears to be good one.

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[23] It is "approximate" in the sense that a 10% change is "large," and the elasticities of the semi-log model are not constant. The percentage change in the dependent variable with respect to the percentage change in an X_k (the elasticity) is $2 \cdot Y^{0.5} \cdot \alpha_k \cdot 0.1 \cdot X_k / Y$. The slope and the elasticities are not constant in the square root formulation. For our computations, we use the mean of $\underline{Y}$ and the X's, and we also use the means to compute the marginal effect of the interaction terms. For the time dummy variables, the marginal effect is $2 \cdot Y^{0.5} \cdot \alpha_k / Y$. The Partial R^2 $[t^2/(t^2 + n - k)]$ is based on the model without the interaction terms. See A. Darnell, A DICTIONARY OF ECONOMETRICS (1994) at 301-02.

[24] If $y = a_1 x + a_2 x \cdot z$, then the marginal effect $dy/dx = a_1 + a_2 \cdot z$. We set z equal to the mean of the data.

[25] The test results are $\chi^2 = 10.2$, probability < 0.05.

Table 2. Regression Results and Statistics

	Coef. (t-stat)	Approximate Effect (10% Increase)	Partial R^2	Mean (St. Dev.)
Constant	0.073	…	…	…
	(0.68)			
INCOME	0.002	3.8%	0.07	53.889
	(2.53)*			(8.120)
GINI	-1.068	-15.1%	0.33	0.448
	(-7.61)*			(0.026)
IMMIG	0.644	1.4%	0.29	0.070
	(5.22)*			(0.055)
ENGLISH	0.146	3.9%	0.04	0.855
	(2.12)*			(0.085)
INSCHOOL	1.238	28.1%	0.30	0.221
	(6.00)*			(0.042)
EDUC	0.336	2.4%	0.10	0.718
	(2.51)*			(0.017)
RETIRE	-0.773	-4.0%	0.08	0.165
	(-3.30)*			(0.021)
CITY100	0.050	0.6%[a]	0.18	0.189
	(3.05)*			(0.166)
RURAL	-0.140	-0.7%	0.07	0.292
	(-2.79)*			(0.155)
FARM	-4.666	-0.8%[a]	0.05	0.014
	(-2.25)*			(0.015)
CITY100·RURAL	-0.094	…		0.042
	(-0.94)			(0.034)
CITY100·FARM	5.629	…	…	0.002
	(2.22)*			(0.003)
RURAL·FARM	6.055	…	…	0.005
	(1.29)			(0.007)
JUNE05	-0.061	-19.3%	0.58	0.333
	(-11.28)*			(0.473)
R^2	0.91			
RESET F	1.03			
White χ^2	2.59			

* Statistically significant at the 5% level or better.
** Statistically significant at the 10% level or better.
[a] Joint-test Statistically significant at the 5% level or better (computed at means).

All expectations regarding signs are confirmed. Similar to our findings in the international arena, higher incomes (*INCOME*) increase subscription, but income inequality (*GINI*) reduces the subscription rate. A 10% rise in average household income increases subscriptions per household by 3.8%, where a 10% increase in income inequality reduces subscriptions by 15.1% (a very large effect). A more educated population (*EDUC*) increases broadband subscription, with a 10% rise in persons with at least a college degree increasing the subscription rate by about 2.4%. Having a household member in school (*INSCHOOL*) has a positive and large effect, with a 10% rise in such homes increasing the subscription rate by nearly 28.1%, the largest effect by far. Obviously, education is a key driver of broadband subscription, and broadband appears to be an important if not essential ingredient in the modern education.[26] As expected, states with a larger share of older persons (*RETIRE*) have a lower broadband subscription rate. Based on the marginal effects computed at the means, the larger the percentage of homes in sparsely populated rural (*RURAL*) and farm areas (*FARM*), the lower is broadband subscription, whereas the higher the population in large cities (*CITY100*), the greater is subscription. However, these population density effects, while present and statistically significant, are not as large as other demand-side effects like education, income and age. The negative coefficients on the time dummies indicate broadband subscription rates grew about 20% in the second half of 2005.

There were two variables whose effects were not predicted—*ENGLISH* and *IMMIG*. Both variables have positive and statistically significant coefficients. The estimated regressions indicate that states with a larger share of families speaking primarily English have a higher level of broadband subscription. However, states with a larger portion of foreign born citizens also have higher broadband subscription levels. These results are interesting, and several hypotheses can be postulated to explain the result. The Pew Internet & American Life Project has studied the broadband subscription patterns of the Hispanic community and found that the relatively low rate of online usage in the Hispanic community largely "explained by socio-economic differences" between ethnic groups, although it did reveal a substantial divide between Spanish-speaking and English-speaking households with regard to online activity.[27] As a result, our analysis gives reason for optimism, because if socio-economic factors like education and income inequality can be overcome, broadband growth in immigrant communities could be substantial.

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[26] For example, Tutorvista.com offers on-line scholastic tutoring services for $99.99 per month on all subjects. Tutorvista.com utilizes VoIP, instant messaging and electronic blackboards to provide U.S. students access to an English-speaking tutor—that happens to be in India.

[27] S. Fox & G. Livingston, *Latinos Online*, Pew Internet & American Life Project (Mar. 14, 2007) (available at: http://www.pewinternet.org/pdfs/Latinos_Online_March_14_2007.pdf) at 3.

Table 3. Broadband Subscription and Endowments

Variable Ranked by Size Effect	Magnitude of Effect (for 10% increase)	Variable Ranked by Partial R^2	Partial R^2
INSCHOOL	28.1%	GINI	0.33
GINI	-15.1%	INSCHOOL	0.30
RETIRE	-4.0%	IMMIG	0.29
ENGLISH	3.9%	CITY100	0.18
INCOME	3.8%	EDUC	0.10
EDUC	2.4%	RETIRE	0.08
IMMIG	1.4%	INCOME	0.07
FARM	-0.8%	RURAL	0.07
RURAL	-0.7%	FARM	0.05
CITY100	0.6%	ENGLISH	0.04

Table 3 presents the results of the first regression shown in Table 2 in a different format. In Table 3, we rank the endowments by their relative impacts on broadband subscription, and do so based on two measures of "impact." To show which demographic and economic condition have the most impact on broadband subscriptions, the left side of Table 3 simply sorts the factors we study based on their marginal effects as summarized in Table 2. Other than the time dummies, the largest marginal effect (measured as an elasticity) is the *INSCHOOL* variable, with *GINI* being second. Other large effects are observed for *ENGLISH, EDUC* and *RETIRE*. The right-hand side of Table 3 sorts the regressors by their partial-R^2, which is a measure of their independent contribution to the explanatory power of the regression. The five factors contributing most to explaining the variance in broadband subscriptions are the percentage of foreign born citizens (*IMMIG*), income inequality (*GINI*), the percentage of farm population (*FARM*), rural population (*RURAL*), the having a family member in school (*INSCHOOL*).

From this analysis, it appears that an effective broadband policy must deal with issues that arise from income inequality. As Horrigan (2007) suggests, "[o]ne answer is to renew focus on demand-side stimulation targeted at hard-to-reach populations."[28] Ideas might include programs that counterbalance the effects of poverty by making computers available to poorer households—as with the "No Child Left Offline" program in Kentucky or Nicholas Negropante's "One Laptop Per Child" program, which could have both domestic and international implications.[29] Education policy is likewise implicated, since broadband appears to now be an important, even essential, ingredient in modern education. For example, both the *INSCHOOL* and *EDUC* variables suggest that Georgia's use of lottery funds to provide large numbers of college scholarships is likely to increase broadband subscription in that state.

III. The Impact of Data Collection and Quality

There is considerable debate about the quality of the FCC's data on broadband availability and adoption, and the FCC is currently considering changes to its data collection methodology.[30] As discussed above, however, the inclusion of "capable" mobile devices in subscription counts is plainly invalid and requires us to exclude data from 2006 for our analysis. Appendix A contains the results of our model if we do include FCC data from 2006, which includes broadband "capable" mobile devices.

We also note that there may be reporting problems, however, even with the earlier data. For instance, the most-recent FCC data report changes the 2005 figures for both North and South Dakota without explanation. As a result, we believe it important to examine the sensitivity of our model to the possibility of errors in the data that we utilize.

Under plausible conditions, the actual and potential data defects may not substantially bias our coefficients estimates reported in Table 2 and Table A-1. However, these expected data problems are sufficiently severe to prevent us

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28 Horrigan (2007), *supra* n. 4 at 4.

29 *See* http://www.connectkentucky.org/projects/nclo (Kentucky program), and http://laptop.org/en/contact.shtml (One Laptop per Child); http://www.ted.com/index.php/talks/view/id/41?gclid=CJH89tGE0I8CFQ66PAoddGb2_g (One Laptop Per Child).

30 *See Broadband Data Collection NPRM, supra* n. 14; C. Boles, *FCC's Martin Proposes Changes to Broadband Data Collection*, DOW JONES NEWSWIRES (Oct. 31, 2007).

from computing the Broadband Performance Index (or BPI) for each state as we did in POLICY PAPER NO. 29 for the OECD countries. To demonstrate why, say the reported broadband subscriptions contain a error component u, so that broadband subscriptions are $B + u$. A regression model of subscriptions on endowments now looks like

$$B_i = \sum_{j=1}^{k} \alpha_k X_{k,i} + \varepsilon_i + u_i \ . \tag{2}$$

Under certain conditions, the error in the measurement of B_i does not impact the coefficient values, since the disturbance of the regression simply incorporates both the idiosyncratic component ε_i and the mismeasurement component u_i.[31] The standard errors of the coefficients, however, are inflated, thereby reducing the t-statistics on the coefficients. In other words, the estimated coefficients and their marginal effects summarized in Table 2 remain legitimate, although the t-statistics will be understated. (Compare Table 2 and Table A-1 for a demonstration of the stability of the estimated effects across datasets despite known data defects.) Since most variables are statistically significant at the 5% level or better, the inflation of the standard errors does not appear to be of much significance. In contrast, because the BPI is derived directly from the residual, the BPI calculation will suffer markedly if there are mismeasurements in the data. With error in the subscription count, a state's BPI includes two components, ε_i and u_i. Therefore, the BPI reflects not only idiosyncratic deviations from average performance but also includes the measurement error directly. As a consequence, we do not include in this POLICY PAPER the calculation of the BPI for the states.

IV. Conclusion

The rate of broadband adoption is strongly related to a number of demographic and economic conditions, including household income, income inequality, and education. In this PAPER, we provide a method that quantifies each of these important variables in a way that provides a useful "snapshot" of the reasons that broadband subscription currently varies widely throughout the United States.

[31] These assumptions include $E(u_i) = E(\varepsilon_i) = 0$; $cov(X_i,u_i) = 0$; $cov(X_i, \varepsilon_i) = 0$; and $cov(u_i, \varepsilon_i) = 0$. *See* Gujarati, *supra* n. 21 at 468.

We find that income inequality is a significant driver in suppressing broadband penetration in the United States. This result is consistent with our international analysis in PHOENIX CENTER POLICY PAPER NO. 29. Education is also an important factor that increases broadband growth. In fact, income and education effects impact broadband adoption at a far larger magnitude than the extent of rural and farm households in a state. These findings are important for policy they identify the areas where targeted programs might increase broadband subscription substantially and cost-effectively. In particular, our analysis shows that demand-side factors like income inequality and education matter more for broadband adoption than supply-side factors, such as population density.

As a result, policies that focus on these demand-side factors perhaps offer more "bang for the buck" in terms of increasing broadband penetration than supply-side policies such as subsidies for networks or regulation of providers. For example, our research indicates that programs that focus upon demand-side factors, such as those programs that focus on educational institutions in low-income communities with school age children, may boost broadband adoption rates considerably, as they leverage a demand-side drivers that encourage broadband subscription (having a child in school) in a way that may overcome or mitigate the problem of income inequality. Such policies, like ConnectKentucky's "No Child Left Offline" initiative, may be substantially more cost-effective in driving broadband adoption than subsidies for construction of networks. Programs that target broadband education for older and retired persons may also be helpful.

APPENDIX A:

Table A-1 summarizes the regression output when using the2006 data on broadband subscriptions. In the first two columns, the results are based on December 2005 and June 2006 data. In the second two columns, the results are based on the June 2006 and December 2006 data. In both cases, there are 100 observations. The marginal effects are very similar to those reported in Table 2.

Table 2. Regression Results and Statistics (Using 2006 Data)

	Coef. (t-stat)	Approximate Effect (10% Increase)	Coef. (t-stat)	Approximate Effect (10% Increase)
	December-05, June-06 Data		June-06, December-06 Data	
Constant	0.169		0.621	
	(0.81)		(2.96)*	
INCOME	0.002	3.5%	0.001	1.2%
	(2.56)*		(0.67)	
GINI	-1.232	-15.7%	-1.516	-17.1%
	(-6.87)*		(-7.43)*	
IMMIG	0.670	1.3%	0.599	1.1%
	(5.51)*		(3.34)*	
ENGLISH	0.189	4.6%	0.171	3.7%
	(2.33)*		(1.51)	
INSCHOOL	1.317	26.9%	1.066	19.2%
	(4.15)*		(3.14)*	
EDUC	0.405	2.6%	0.672	3.7%
	(2.81)*		(3.28)*	
RETIRE	-0.866	-4.1%	-0.697	-2.9%
	(-3.30)*		(-1.77)**	
CITY100	0.066	0.6%[a]	0.104	0.3%
	(2.06)*		(3.59)*	
RURAL	-0.281	-1.0%[a]	-0.339	-1.9%[a]
	(-5.39)*		(-5.50)*	
FARM	-7.699	-1.0%[a]	-6.733	-0.9%[a]
	(-4.99)*		(-3.22)*	
CITY100·RURAL	-0.164		-0.439	
	(-1.01)		(-2.04)*	
CITY100·FARM	7.019		5.420	
	(3.38)*		(1.96)**	
RURAL·FARM	13.693		11.041	
	(4.82)*		(2.69)*	
DEC05	-0.077	-22.0%	…	.
	(-12.84)*			
JUNE06	…	…	-0.111	-27.8%
			(-12.54)*	
R^2	0.92		0.88	
RESET F	0.15		0.88	
White χ^2	0.01		1.75	

* Statistically significant at the 5% level or better.
** Statistically significant at the 10% level or better.
[a] Joint-test Statistically significant at the 5% level or better (computed at means).