

# A FRAMEWORK FOR EVALUATING REGIONAL IMPACTS OF BROADBAND INTERNET ACCESS: APPLICATION TO TELECOMMUTING BEHAVIOR

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## ***Abstract***

*This paper proposes a quantitative framework to evaluate the impacts of broadband internet access on behavioral choices people make, and the consequences of these choices on the society as a whole. The framework includes regional household level choice models to predict behavioral shifts enabled by broadband access, and economic models to measure the public benefits generated by the shift. As an illustration, the paper highlights the relationship between broadband access and the level of telecommuting in a region. The parameters of the model are calibrated using available data from public and proprietary sources. The paper further estimates the impacts of enabling telecommuting behavior nationally on the improvement in productivity and energy efficiency, as well as on reducing environmental impacts. A key issue addressed in the paper is the lack of data that would enable analysts to extend this telecommuting model to other household level activities. The paper concludes with recommendations on large-scale data collection efforts to strengthen our ability to clearly understand and conduct benefit-cost analysis of the investment in broadband as we build a green economy.*

## ***Introduction***

The primary objective of this paper is to develop a framework to study the impacts of broadband on productivity and energy consumption in a comprehensive manner.

There are many macro-economic studies that suggest that a connected society will have higher levels of productivity, implying that connectivity enables more efficient use of energy and natural resources[2][3][4][5]. However, there is little research that measures the impact of connectivity at a household or commercial building level that can help policy makers develop strategic plans related to connectivity. A framework for authoritative measurement of the *green* impact of a broadband lifestyle is needed in order to move discussion from the broad brush strokes of macroeconomics to the level of decisions and policies. Strong policies could be developed that would encourage self-conscious application of broadband and information technology to realize a more sustainable, energy efficient economy. However, this can be achieved only by developing robust quantitative modeling frameworks that can help analyze the direct and induced impacts of policy initiatives.

Quantitative modeling exercises depend heavily on the availability of data. When it comes to broadband and its effects on different aspects human activity and the environment, the available data is very

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sketchy. In this paper, we use one specific impact of broadband – namely, telecommuting - which directly affects energy consumption and reduces pollution. The data related to telecommuting activity is relatively easy to acquire. But to be able to develop analytical methodologies that support an assertion that broadband adoption drives telecommuting and thus contributes to a sustainable economy, additional data collection efforts through large-scale surveys are needed. This paper proposes potential data collection strategies and an econometric modeling framework to model and analyze broadband impacts.

The initial sections of the paper discuss broadband adoption trends in the US, and its potential impacts on lifestyle. The paper lays out a generalized framework for quantitative modeling of broadband impacts, and presents an application of the framework to telecommuting. It proposes an analytical model to quantify the likelihood of telecommuting as a function of broadband penetration in an area and to develop a quantitative insight on the level of emissions displaced.

The paper discusses the level of estimated impact with expansion to broadband coverage, and closes with a listing of other direct and indirect impacts and possible measurement frameworks to quantify these.

## ***Background***

Recent studies have shown that a growing proportion of American workers telecommute on a regular basis. The American Psychological Association study in 2007 indicated that telecommuters reported higher job satisfaction, less stress and improved work-life balance. Many organizations view telecommuting as the most effective employee retention strategy.

Connected Nation's household survey<sup>2</sup> showed that broadband connectivity is an absolute necessity for telecommuting in most cases [21]. This would mean that strategies related to telecommuting should go hand-in-hand with programs to spur broadband adoption and use.

In this study, we propose a household level modeling framework for evaluating broadband impacts. Broadband access will likely change the profile of almost all activities in which a household is involved. More people will start telecommuting, more shopping trips will move online, health systems will improve, educational facilities will improve, and energy consumption will become more efficient, and new job opportunities will be created. Modeling each and every one of these impacts is not a trivial exercise. A large-scale household-level model taking into account all these impacts will be of great value. But before we can take this up, significant data collection efforts have to be undertaken,

This paper is an effort to develop a framework to enable this type of modeling. We used some available data and focused on one aspect, namely telecommuting. We developed a model of the effect of

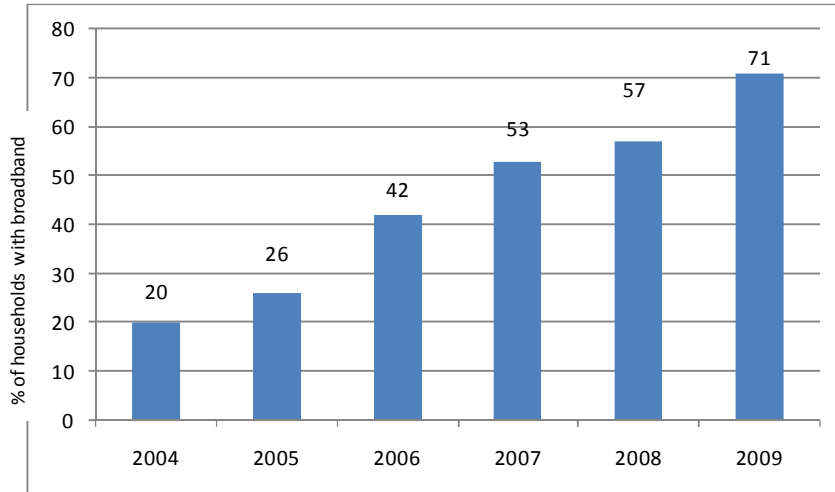
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<sup>2</sup> The survey results are presented in "Consumer Insights to Broadband" a report soon to be published by Connected Nation.

household level broadband access on the likelihood of telecommuting and calibrated this model with the data from surveys and connectivity data where available.

### ***The American Household and Broadband***

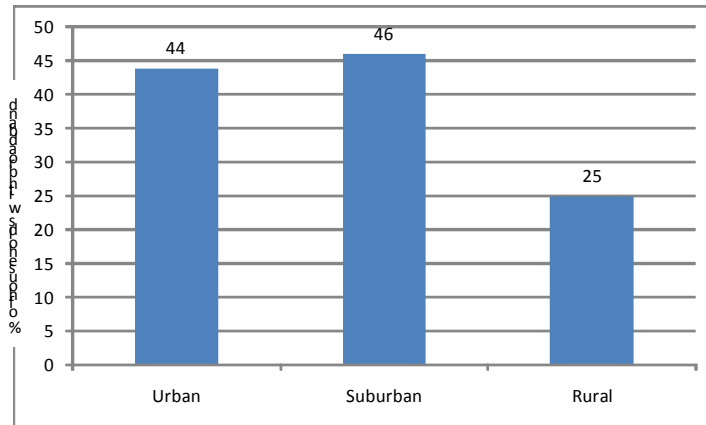
Although the United States ranks 17<sup>th</sup> in broadband adoption at a consumer level in the world, recent years have seen significant growth in deployment and adoption. In 2004, only 20% of American households had broadband access. By 2009, this has increased to 71%. This growth, shown in Figure 1, translates to a CAGR of more than 28%.



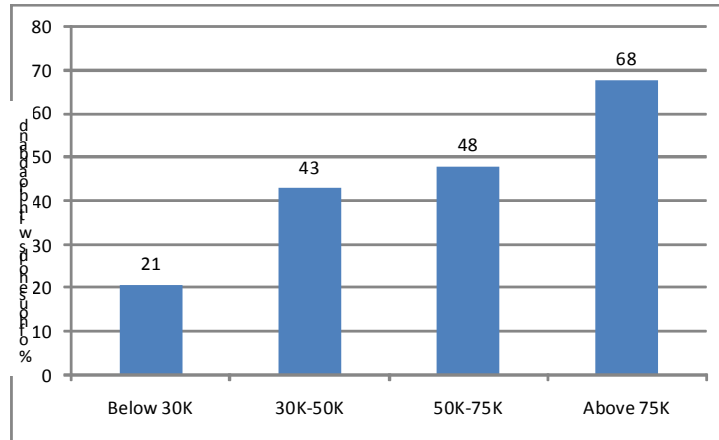
Source: Broadband Internet Access and Service at Home, Leichtman Research, 2009

Figure 1: Growth in Broadband Adoption in the US

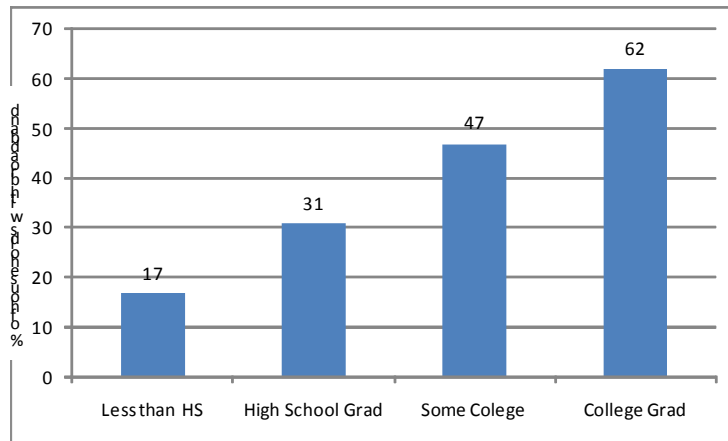
This growth in adoption has not been uniformly distributed across all types of households. It varies by the area type, demographics, and education level. As expected, early adopters of technology have adopted broadband much more readily. As shown in Figures 2 through 4, college graduates in the higher income group living in the urban and suburban areas have shown a higher adoption of broadband access and availability.



**Figure 2 Variance in Broad Adoption by Area Type**



**Figure 3 Variance in Broad Adoption by Income Level**



**Figure 4 Variance in Broad Adoption by Education Level**

This rapid growth in household level broadband access has affected almost every facet of life and is changing the behavioral pattern of consumers significantly. Current efforts aimed at increasing broadband adoption and use at a national level can be expected to have major impacts on the American way of life.

### ***Behavioral Shifts with Broadband Access***

Access to broadband increases opportunities for a household dramatically and alters the way people conduct day to day activities. Table 1 lists the improvements that broadband access offer to a household, and the resulting behavioral shifts by consumers. The societal impacts of these behavioral shifts are also listed in the table. As shown, broadband access can impact almost every aspect of household life ranging from work to social and cultural activities.

<b>Category</b>	<b>Broadband Enabled Improvement</b>	<b>Behavioral Shift by Consumers</b>	<b>Societal Impact</b>
Work	Increased connectivity to people and content	Increase in Telecommuting  Increase in productive work hours	Increased productivity, efficient energy utilization, and reduced environmental impacts
Personal Finance	More access to information through rich content  Very efficient online financial service	Increase in subscription and access to online sites  Increase in online banking enrollment	Increases transparency and efficiency of financial systems
Shopping	More selection and price efficiency  Aggregated shipping	Access to price comparison and collective buying websites  More online shopping	Improves the efficiency and velocity of transactions in the economy
Education	Increased opportunities  Distance learning to improve skills and productivity	Increased subscriptions to and enrollment in distance learning opportunities	Helps create a skilled, productive and globally competitive labor force
Health and Fitness	More efficient diagnosis and prescription  General healthcare system integration	Increase in online physician visit scheduling  Increase in online prescription and medication delivery	Improves the velocity of healthcare, improving quality of life and increasing productivity
Living conditions	Access to information on optimal usage	More efficient use of utilities such as gas and	More efficient use of energy

	Better quality of life	electricity	
Communication	Increased ability to communicate and share thoughts and ideas  Real time alerts	Larger network of friends and relatives in touch with  Increased use of online maps and directions	A connected nation with free flowing ideas and thoughts
Entertainment	Increased access to rich content online  Ability to shape and share creativity easily and at low cost	Increased online video and music downloads  Increased creation and upload of music, video and other content	Good quality of life
Social and cultural activities	Increased ability to network and stay connected  Higher ability to create and join in special interest groups  Improved ability to organize social dialogues and activities	Increased organizing through online event organizing applications  Increased participation in public and political issues  Increased social awareness	A very effective democracy with grass roots level participation

**Table 1 Potential Shifts in Household Behavior Enabled by Broadband Access**

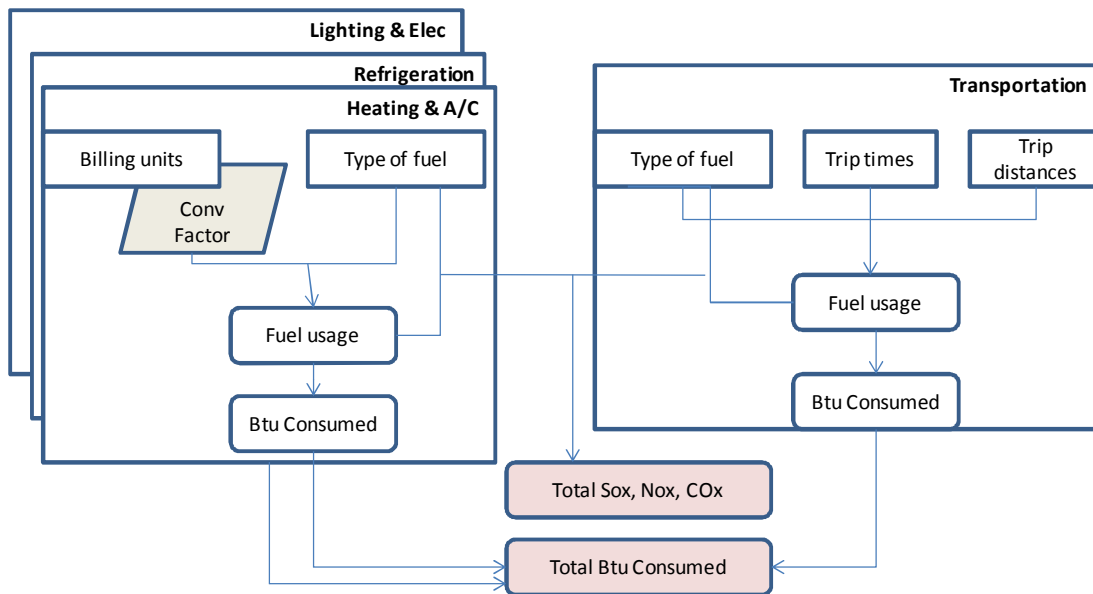
### ***A Framework for Modeling Broadband Impact on Energy Consumption at Household Level***

When a household has broadband connectivity, it generally improves their quality of life without increasing energy use, and possibly even reducing energy use. A quantitative framework to measure this impact requires a viable metric to represent energy consumption and a methodology to accurately measure it. This section describes a household level energy consumption model and an approach to investigate the level of impact that broadband has on reducing consumption and associated environmental effects.

The energy consumption profile of a household can be measured in terms of daily Btu's per capita. The resulting environmental footprint of the level of usage can be measured in terms of the SO<sub>x</sub>, NO<sub>x</sub> and CO<sub>x</sub> emissions resulting from this consumption. The primary sources of household energy use are:

- Space heating
- Water heating
- Air-conditioning
- Refrigeration
- Lighting
- Transportation

By measuring the level of usage, and the type of fuel used, the Btu's consumed and the COx emitted can be estimated at a household level for each of these modes of energy use. Figure 5 shows a structural schematic for measuring a household's energy profile. Clearly, the level of consumption varies with the region, season, and household attributes such as household size, income level, education level, type of building etc.



**Figure 5 Schematic for Measuring Household Level Energy Consumption**

By grouping households of similar attributes, we can construct a profile of energy consumption for each household type and region. Table 2 shows the 2005 domestic energy consumption and expenses estimated by the Energy Information Administration (EIA). As shown in the table, an average household in the US consumes approximately 100 million Btu's per year, or about 260,000 Btu's per day.

Housing Unit Characteristics and Energy Usage Indicators	U.S. Households (millions)	Number of Members per Household	Floor space per Household (Square Feet)	Energy Consumption				Energy Expenditures			
				Total U.S. (Quadrillion Btu)	Per Household (million Btu)	Per Household Member (million Btu)	Per Square Foot (thousand Btu)	Total U.S. (billion Dollars)	Per Household (Dollars)	Per Household Member (Dollars)	Per Square Foot (Dollars)
Northeast	20.6	2.56	2,334	2.52	122.2	47.7	52.4	47.72	2,319	905	0.99
New England	5.5	2.34	2,472	0.71	129.3	55.3	52.3	13.27	2,428	1,038	0.98
Middle Atlantic	15.1	2.64	2,284	1.81	119.7	45.3	52.4	34.45	2,279	862	1.00
Midwest	25.6	2.47	2,421	2.91	113.5	46.0	46.9	45.73	1,786	724	0.74
East North Central	17.7	2.49	2,483	2.09	117.7	47.3	47.4	32.10	1,808	728	0.73
West North Central	7.9	2.43	2,281	0.82	104.1	42.9	45.7	13.30	1,735	715	0.76
South	40.7	2.52	2,161	3.25	79.8	31.6	37.0	71.56	1,758	696	0.81
South Atlantic	21.7	2.50	2,243	1.65	76.1	30.4	33.9	36.94	1,703	680	0.76
East South Central	6.9	2.42	2,137	0.60	87.3	36.1	40.9	11.54	1,674	692	0.78
West South Central	12.1	2.62	2,028	1.00	82.4	31.4	40.6	23.07	1,903	726	0.94
West	24.2	2.76	1,784	1.87	77.4	28.1	43.4	36.06	1,491	541	0.84
Mountain	7.6	2.67	1,951	0.68	89.8	33.7	46.0	12.42	1,644	617	0.84
Pacific	16.6	2.80	1,708	1.19	71.3	25.7	42.0	23.64	1,421	508	0.83
<b>Total</b>	<b>111.1</b>	<b>2.57</b>	<b>2,171</b>	<b>10.55</b>	<b>94.9</b>	<b>37.0</b>	<b>43.7</b>	<b>201.07</b>	<b>1,810</b>	<b>705</b>	<b>0.83</b>

Source: Energy Information Administration 2005

**Table 2 US Household Energy Consumption Estimates**

The estimate above represents only the domestic energy consumption and does not include any energy used outside of home, including transportation. An average household consumes about 13 Gallons of fuel per week, or 1.85 Gallons per day. Each Gallon of fuel corresponds to 129,054 Btu's. This translates to another 240,000 Btu's per day. Thus, an average household in the US consumes about 500,000 Btu's of energy on a daily basis or 200,000 per capita (based on an average household size of 2.57).

As discussed in the previous section, a household with broadband connection is likely to exhibit behavioral differences that would indicate a reduction in per capita consumption of energy. This can be estimated through a comprehensive survey of household energy consumption across a statistically significant sample of households with and without broadband connectivity. Such a survey would combine the data collected by the Residential Energy Consumption Survey (RECS) conducted by Energy Information Administration (EIA) and the National Household Travel Survey (NHTS) conducted by the Department of Transportation overlaid on broadband connectivity data maintained by the Federal Communication Commission (FCC). Overviews of these surveys are given in Appendix 3.

It is difficult to study the energy-efficiency impacts of broadband without data that combines activities and broadband connectivity at the household level, which can only be gathered through extensive surveys or through the tracking of behavior in large pilot projects. However, data summaries at regional levels can be used to model aggregate difference as a function of regional broadband penetration. This framework is described in the next section followed by a detailed application to transportation. In the concluding section, we propose a survey effort that would enable reliable household level modeling.

### ***A Framework for Modeling Broadband Impact at Regional Level***

In order to develop measures of the green impact of broadband and information technology, we will need to track and quantify the behavioral changes and related social impacts that come when a

household or a building decides to connect to the broadband Internet. What we need is a set of analytical models that measure the change in behavior (decrease the number of commute trips, or increase in online banking subscriptions etc) as a function of the likelihood of broadband access.

We propose a household activity level model, wherein we model the behavioral shifts with changes in broadband access profile. Obviously, the adoption rate and the change in behavior will vary by demographic profile and area type of a household. A social utility function could be developed as a weighted aggregation of positive impacts above. We could model the change in this utility value as a function of the change in likelihood of broadband in an area.

The model will have multiple components. Each component will represent a category listed in Table 1. The households in a region will be cross-classified by area type, income group, and education level. Thus, we will have 48 different values for each parameter for each category of household activity.

In addition to the household level direct impact, broadband generates a network effect, meaning that the level of marginal impact is often directly proportional to the extent of broadband penetration. Thus, a generalized cross-classified model will have the following structure.

$$X_l = A_l e^{K_l B}$$

Where  $X_l$  is the behavioral metric (such as number of telecommute days, number of items bought online etc) for the group of households of type  $l$ .  $l$  may be expressed as a vector of cross classification levels.  $B$  is the broadband penetration for the region.  $A_l$  and  $K_l$  are parameters for households of type  $l$ .

The physical significance of parameter  $A_l$  is that it represents the level of activity without dependence on broadband access.  $K_l$  represents the level of potential growth. We expect that the primary drivers of behavior will change among the different categories. While area type may be a big influencer in all cases, job type may be a big driver for telecommuting, and education level may be the big driver for social networking. Thus, it is important to test the model for statistical stability and significance on different cross-classification strategies.

### ***Application to Telecommuting***

In this paper, we illustrate the application of the above modeling framework to telecommuting behavior and its impacts. Many researchers have pointed out that telecommuting depends on the area type and the job type of the households. Thus we would model the likelihood of telecommute on the basis of a cross class strategy of area type by job type.

### **Model Structure**

The general functional form of the model being considered is:

$$T(r,j) = A(r,j)e^{K(r,j)B}$$

In the above equation,  $T$  is the likelihood that a worker of job type  $j$  in a household in area type  $r$  would telecommute at an average level.  $B$  is the proportion of houses with broadband access (which in other words can be interpreted as the likelihood of a household having broadband).

The model represents that a certain level of telecommuting occurs with no dependence on broadband access. This varies with area type and job type. Similarly, the rate of change of likelihood to telecommute varies with increasing broadband access. These are represented by the parameters  $A$  and  $K$ .

It is to be noted that the above model addresses the likelihood of telecommuting as a function of access to broadband. The variance in adoption rates among areas and job types is not explained by the model.

## Model Estimation

For the sake of model calibration, we used three area types based on development density: urban, suburban and rural<sup>3</sup>. A much simpler classification scheme was used for job type: Production (including construction, manufacturing, assembly etc), and Services (including consulting, accounting, and other support services). Several studies have focused on the difference in telecommuting behavior among workers providing different types of services. Most of these focused on survey samples. For the purpose of this effort, the differences were not statistically different enough, and hence we chose a simpler cross-classification structure.

## Data Sets Used

We used the following data sets to calibrate the model.

### Household data

- Census 2000 data
- PUMS 2001, 2005, and 2007

We developed growth factors from the PUMS data and applied it to the Census 2000 data to construct a synthetic 2008 Census data.

### Area Type

We used the population and employment density to determine area types by census tracts

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<sup>3</sup> The area types were categorized based on development density estimated as the number of dwelling units per square mile.

### **Job Type Distribution**

The synthetic census data developed above was used to develop job type distribution

### **Travel Data**

Travel data on the distribution of household trips by purpose, average number of work trips, and average commute time and distance data were derived from the National Household Travel Survey obtained from RITA.

### **Telecommute Data**

Telecommute data was obtained from the census data using the “Under\_16\_work\_from\_home” data category. We used the same distribution and applied a growth factor using the PUMS data to align it with more recent development characteristics. This however would fail to capture the recent trends in telecommuting due to a variety of reasons. In order to account for this trend, we calibrated the telecommute data at a county level with data from Connected Nation household survey.<sup>4</sup>

### **Broadband Penetration Data**

We used the data provided by Connected Nation for the states of Kentucky, Ohio and Tennessee for the broadband penetration data.

## **Estimation Methodology**

An OLS (Ordinary Least Squares) regression was done on a log-linear transformation of the model to estimate the parameters **A** and **K** for each area type and job type.

We ran the regression analysis against two models. In the first model, we estimated the parameters for each combination of area type and job type. The results are shown in Appendix 1. As shown, the coefficient for job type was not very significant. On further analysis we discovered significant multi-collinearity between area type and job type, suggesting that the area type of a household was a fairly strong predictor of the job type. This makes intuitive sense based on the data which indicated that a large section of urban and suburban dwellers were employed in the services sector while a majority of rural dwellers were involved with production sector<sup>5</sup>.

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<sup>4</sup> Connected Nation study showed the percentage of workers that currently did active telecommuting, and those that would if possible. This survey was conducted over the households in Kentucky, Tennessee and Ohio. Therefore, the model estimation is based on the data from these states.

<sup>5</sup> This conclusion is based on the current demographic patterns. Increase in telecommuting opportunities may certainly impact these location choices and encourage urban and suburban dwellers to move to rural areas. However, there is no data available currently to model this impact on demographic migration patterns.

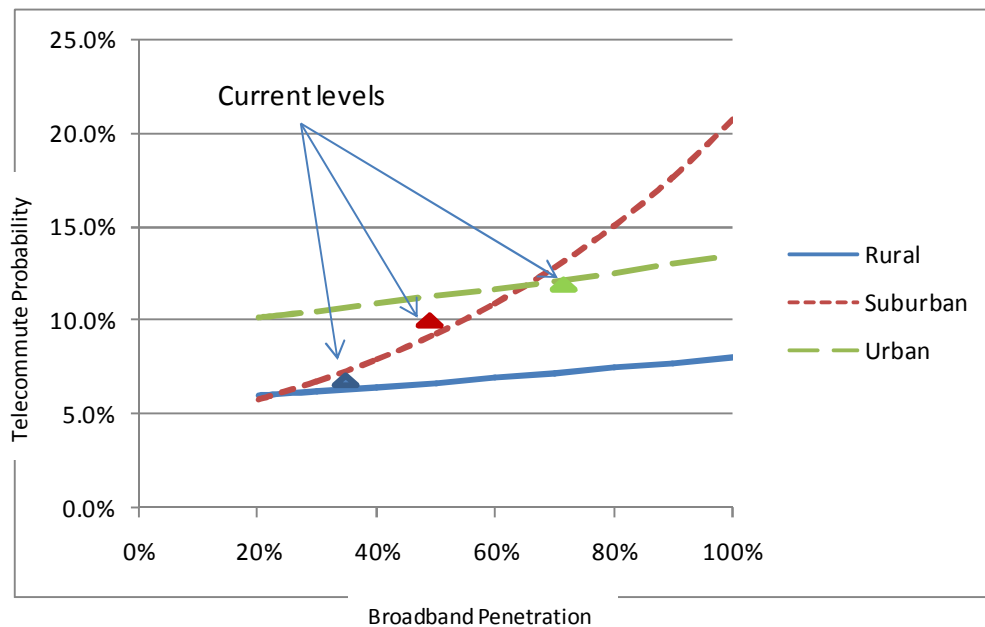
In the second run, we ran the model estimation using just the area type as the exogenous variable. The parameters had a much higher level of significance. We expected that the elasticities would be significantly different among the area types, and hence ran three different estimations rather than use an area type dummy. The results are shown in Appendix 2.

### Model Parameters

The model parameters **A** and **K** for each area type are shown in Table 3 below. As shown, there is a considerable difference in the telecommute likelihood among the areas. The change in estimated likelihood of telecommuting based on broadband access is shown in Figure 6 below. As shown in the figure, suburban dwellers were more sensitive to broadband access as far as pursuing telecommuting opportunities. Urban dwellers are either close enough to work, or are already taking advantage of the opportunities, while the rural dwellers are less likely to move to telecommuting than suburban. This may be attributable to the primarily production type of jobs in the rural areas which are not compatible with telecommuting. Again, this assertion does not take into account the potential shifts in demographic patterns or that broadband connectivity can be used to bring service jobs to rural communities [23].

Area Type	Current Aggregate Levels		Parameters	
	Broadband %	Telecomm %	A	K
Rural	34%	6.5%	0.06	0.37
Suburban	54%	10.5%	0.04	1.61
Urban	76%	12.5%	0.09	0.35

**Table 3 Parameters for the Broadband-Telecommute Model**



**Figure 6 Broadband-Telecommute Model**

## **Estimated Telecommuting Impacts from Large Scale Broadband Adoption**

The model calibrated above can be used to estimate the potential telecommuting effects of large-scale efforts to increase broadband adoption and use, and its derived benefits. Telecommuting increases productivity by reducing travel time spent getting to work and back. It leads to energy saving by directly impacting fuel usage and office space operating costs. Reduced travel can also lead to environmental benefits by reducing emissions and reducing congestion.

The traveler survey responses by Connected Nation, as well as that done by the Washington Metropolitan Transit Authority (WMATA) indicated that broadband was a must for telecommuting. Therefore it is fair to assume that the level of telecommuting would be negligible without broadband, even though the model would theoretically indicate some level of telecommuting without broadband. This is useful to estimate the current level of benefit that broadband access offers. Travel surveys also indicated that the majority of telecommuters do so under informal arrangements. With formal policy support and access to broadband a full 30% of respondents indicated that they would telecommute some days every week.

We used the model calibrated based on data from 3 states to estimate impacts at a nationwide level. While evaluating the impacts, we considered 4 different telecommuting scenarios:

1. No measurable telecommute (could be perceived as a surrogate for no broadband connectivity)
2. Current level of telecommuting(nationally 10%) supported by the existing level of broadband access
3. Telecommute aided by full broadband adoption (estimated from the model based on 100% connected)
4. Telecommuting aided by full broadband and policy support

The proposed model allows for the estimation of likelihood for telecommuting, and the associated impacts on productivity, energy, and environment.

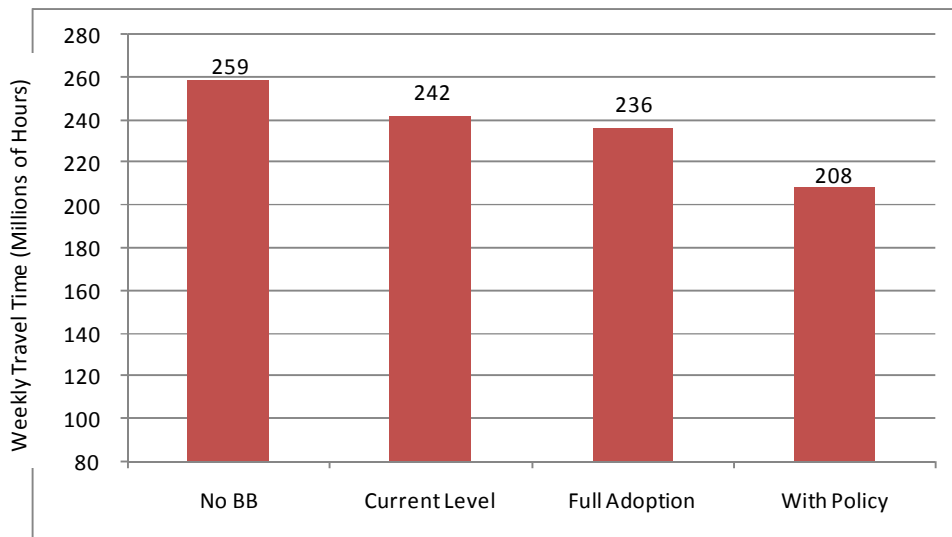
### **Productivity Gains**

Shown in Table 4 are the estimated number of work trips under each of the four scenarios, and the travel time estimates based on census data. According to the model estimates it shows that efforts to encourage broadband adoption supported by formal policy level initiatives to promote telecommuting can result in a total increase of productive work hours by about 34 million hours at a weekly level.

Scenario	Miles	Weekly Travel Time (Millions of hours)	Weekly Fuel Consumption (Millions of Gallons)
No BB	5,174,830,769	259	344.99
Current Level	4,838,466,769	242	322.56
Full Adoption	4,727,466,649	236	315.16
With Policy	4,165,738,769	208	277.72
Weekly time savings (mill hours/mill Gallons)		34	45
Value per hour		\$ 42.58	
Weekly savings (monetized)		\$ 1,432	
Annual Savings		\$ 74,476.37	2,332

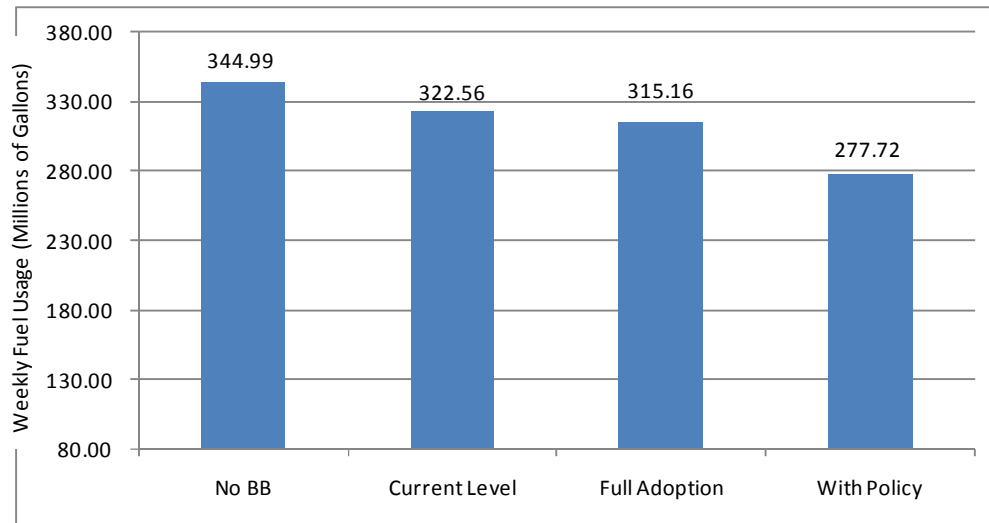
**Table 4 Impacts on Travel Time and Fuel Usage**

This in turn translates to almost \$ 75 Billion of gain in productivity annually<sup>6</sup>. Figure 7 shows the relative levels.



**Figure 7 Estimated Commuter Travel Time Savings**

<sup>6</sup> The figure of \$42.58 per hour of productivity was derived from the Bureau of Labor Statistics estimate of hourly earnings and contribution to GDP by worker type. It is debatable whether the time saved from not traveling to work will be used directly for work. But it will clearly be utilized for some activity that the worker engages in voluntarily



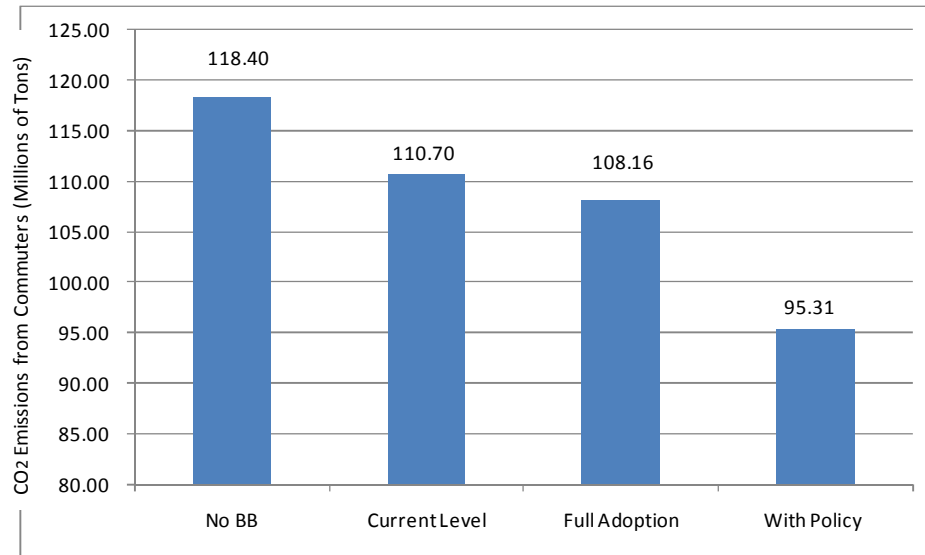
**Figure 8 Estimated savings in Fuel Usage**

### Environmental Benefits

Savings in miles of travel can result in reducing pollution. American workers contribute more than 100 Million tons of CO<sub>2</sub> into the atmosphere annually. Table 5 shows the application of the model to estimate the potential savings in CO<sub>2</sub> emissions. As shown in the tables and Figure 9, proper implementation of telecommuting can reduce about 15 million tons of CO<sub>2</sub> emissions.

	Workers		Miles for commute		TeleW%	Tonnes of CO <sub>2</sub> Emission
	Regular	Telework	Regular	Telework		
No BB	120,130,000	-	5,174,830,769	-	0%	2,276,926
Current	108,117,000	12,013,000	4,657,347,692	181,119,077	10%	2,128,925
Full Adoptic	104,152,710	15,977,290	4,486,578,277	240,888,372	13%	2,080,085
W Policy	84,091,000	36,039,000	3,622,381,538	543,357,231	30%	1,832,925
Weekly Reduction in tonnes of CO <sub>2</sub>						296,000
Annual Reduction in tonnes of CO <sub>2</sub>						15,392,017

**Table 5 Estimation of CO<sub>2</sub> Emission Savings under Alternative Scenarios**



**Figure 9 Estimated Savings in CO<sub>2</sub> Emissions**

## Summary

In summary, the model indicates that efforts aimed at deploying broadband infrastructure across the nation and driving strategies to increase adoption will certainly increase telecommuting, resulting in several benefits including increased productivity, improved energy consumption, and reducing environmental impacts. However, the lack of formal policies to support telecommuting will constrain the growth in telecommuting.

## Conclusion

The paper proposes an analytical framework for quantifying the effects of broadband adoption and use. But we need a lot of data to calibrate the parameters properly and make this framework usable.

The paper illustrates the use of this framework to model one direct effect of broadband – namely, telecommuting. A variety of data sources from census to household level surveys were used to calibrate the model parameters. The paper shows how we can use this framework to quantify the social benefits of broadband investment from a telecommuting standpoint. Table 1 presents a whole host of possible impacts of broadband access on a household and its life. It broadly identifies the metrics to be used for each of these impacts.

Creating a nationwide survey of households to gather comprehensive information on the different choices people make, and developing an understanding of whether these choice vary with access to broadband will improve our ability to conduct powerful analysis of the impact of broadband adoption. This type of analysis will help us develop a cogent national broadband strategy. An urgent need is to focus on how broadband policies can help energy efficiency and greening initiatives. In order to develop

supporting analytical frameworks, we propose a survey that would gather the following data elements at a statistically significant sample of households (estimated at 5,000 – 6,000 households).

#### Household attributes:

- Household size
- Income level
- Education level
- Region

#### Energy Consumption

Type of fuel and average daily consumption:

- Space heating
- Water heating
- Air-conditioning
- Refrigeration
- Lighting and other

Number of daily trips:

- By purpose
- By mode
- Occupancy level

#### Broadband

- Type and presence
- Usage profile (work, entertainment, information, other)
- Behavioral patterns from Table 1.

An analysis of this survey results would indicate the difference in energy consumption profiles of households, and would help us quantify the impact of broadband on reducing the number of Btu's per household. This would represent the contribution of broadband to energy efficiency and sustainability of the nation.

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## ***Acknowledgements***

This study would not have been possible without the help from several individuals and organizations. The following individuals provided data, advice, and feedback at different stages of the study.

- Chuck Wilsker of The Telework Coalition
- Dr. Darryl Banks
- Drew Clark of Broadbandcensus.com
- Hon. Graham Richard, Former Mayor of Ft. Wayne, Indiana
- Janaki Parameswaran and Anne Suissa of US Department of Transportation
- Laura Taylor and Chris McGovern of Connected Nation
- Larry Plumb and C.T. Lloyd of Verizon
- Ron Milone of the Metropolitan Washington Council of Governments (MWCOG)

This research was made possible with funding obtained from Verizon.

## ***Appendix 1 Output from Statistical Analysis of Model with Dual Cross-Classification (Area Type and Job Type)***

### SUMMARY OUTPUT

<i>Regression Statistics</i>	
Multiple R	0.116286
R Square	0.013522
Adjusted R Square	0.009446
Standard Error	0.365408
Observations	244

ANOVA					
	<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>	<i>Significance F</i>
Regression	1	0.442932	0.442932	3.317258	0.069791
Residual	242	32.31266	0.133523		
Total	243	32.75559			

	<i>Coefficient</i>	<i>Standard Error</i>	<i>t Stat</i>	<i>P-value</i>	<i>Lower 95%</i>	<i>Upper 95%</i>	<i>Lower 95.0%</i>	<i>Upper 95.0%</i>
Intercept	-2.89232	0.071802	-40.2822	2.7E-109	-3.03376	-2.75089	-3.03376035	-2.750888908
BB	0.372037	0.204266	1.821334	0.069791	-0.03033	0.774404	-0.03032962	0.774403894

The model was run for each area type with a service level variable indicating the percentage of household involved in service sector

## Appendix 2 Output from Statistical Analysis of Model with Single Cross-Classification Scheme (Area Type Only)

### Area Type 1 (Rural)

SUMMARY OUTPUT

<i>Regression Statistics</i>	
Multiple R	0.116286
R Square	0.013522
Adjusted R Square	0.009446
Standard Error	0.365408
Observations	244

ANOVA					
	<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>	<i>Significance F</i>
Regression	1	0.442932	0.442932	3.317258	0.069791
Residual	242	32.31266	0.133523		
Total	243	32.75559			

	<i>Coefficients</i>	<i>Standard Error</i>	<i>t Stat</i>	<i>P-value</i>	<i>Lower 95%</i>	<i>Upper 95%</i>	<i>Lower 95.0%</i>	<i>Upper 95.0%</i>
Intercept	-2.89232	0.071802	-40.2822	2.7E-109	-3.03376	-2.75089	-3.03376035	-2.750888908
BB	0.372037	0.204266	1.821334	0.069791	-0.03033	0.774404	-0.03032962	0.774403894

### Area Type 2 (Suburban)

SUMMARY OUTPUT

<i>Regression Statistics</i>	
Multiple R	0.573269
R Square	0.328638
Adjusted R Square	0.31097
Standard Error	0.280456
Observations	40

ANOVA					
	<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>	<i>Significance F</i>
Regression	1	1.463097	1.463097	18.60133	0.00011
Residual	38	2.988909	0.078655		
Total	39	4.452006			

	<i>Coefficients</i>	<i>Standard Error</i>	<i>t Stat</i>	<i>P-value</i>	<i>Lower 95%</i>	<i>Upper 95%</i>	<i>Lower 95.0%</i>	<i>Upper 95.0%</i>
Intercept	-3.18004	0.200835	-15.8341	2.54E-18	-3.58661	-2.77347	-3.586605592	-2.773467986
BB	1.606358	0.372452	4.312926	0.00011	0.852368	2.360348	0.852368239	2.36034761

### **Area Type 3 (Urban)**

#### SUMMARY OUTPUT

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<i>Regression Statistics</i>	
Multiple R	0.202541
R Square	0.041023
Adjusted R Square	-0.01539
Standard Error	0.125801
Observations	19

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#### ANOVA

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	<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>	<i>Significance F</i>
Regression	1	0.011509	0.011509	0.727218	0.405641
Residual	17	0.269042	0.015826		
Total	18	0.280551			

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	<i>Coefficient</i>	<i>Standard Error</i>	<i>t Stat</i>	<i>P-value</i>	<i>Lower 95%</i>	<i>Upper 95%</i>	<i>Lower 95.0%</i>	<i>Upper 95.0%</i>
Intercept	-2.35997	0.235506	-10.0208	1.5E-08	-2.85684	-1.86309	-2.85684143	-1.863091053
BB	0.354618	0.415841	0.852771	0.405641	-0.52273	1.231966	-0.52273122	1.231966327

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## ***Appendix 3 Overview of National Survey Frameworks***

This section briefly describes the two national surveys that measure energy consumption at a household level.

### **Residential Energy Consumption Survey**

The Residential Energy Consumption Survey (RECS) conducted by Energy Information Administration (EIA) provides information on the use of energy in residential housing units in the United States. This information includes:

- the physical characteristics of the housing units,
- the appliances utilized including space heating and cooling equipment,
- demographic characteristics of the household,
- the types of fuels used, and
- other information that relates to energy use

The RECS also provides energy consumption and expenditures data for:

- natural gas,
- electricity,
- fuel oil,
- liquefied petroleum gas (LPG), and
- kerosene

The RECS is a national area-probability sample survey that collects energy-related data for occupied primary housing units. The survey was initiated in 1978, and the twelfth RECS was conducted in 2005. The 2005 survey collected data from 4,382 households in housing units statistically selected to represent the 111.1 million housing units in the United States.

RECS data come from three sources:

- 45-minute in-person interviews with householders of sampled housing units.
- Mail questionnaires from or in-person or telephone interviews with rental agents for sampled rental units where some or all energy costs were included in the rent.
- Mail questionnaires from energy suppliers who provide actual energy consumption and expenditure data for the sampled housing unit.

## **The National Household Travel Survey**

The National Household Travel Survey (NHTS) is a US Department of Transportation (DOT) effort sponsored by the Bureau of Transportation Statistics (BTS) and the Federal Highway Administration (FHWA) to collect data on both long-distance and local travel by the American public. The joint survey gathers household level trip-related data on:

- Purpose of trips
- Duration of trips
- Distance of trips
- Mode of travel

In addition, it collects data on household level characteristics:

- Geographic characteristics
- Demographic characteristics
- Household size
- Vehicle ownership

NHTS data was based on interviews conducted over 66,000 households across the nation.