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Economic Impacts of Mobile Broadband Innovation: Evidence from the Transition to 4G

Jeffrey A. Eisenach[†] and Robert Kulick[‡]

May 2020

Abstract

This study reports estimates from a model of the economic effects of 4G mobile wireless technology adoption in the United States on employment and economic growth and, based on those results, projects the economic benefits of 5G adoption under different counterfactual scenarios. Using panel vector autoregression techniques and state-level data on 4G adoption from Q3 2010 to Q4 2014, we find strong evidence of a direct relationship between the pace of 4G adoption and growth in employment and output. We project that if 5G adoption follows the path of 4G adoption in the United States, then, at its peak, 5G will contribute approximately 3 million jobs and $635 billion in GDP to the U.S. economy in the fifth year following its introduction. However, if 5G follows the slower, shallower path at which 3G technology was adopted, then it will contribute approximately 1.2 million jobs and $264 billion to the U.S. economy at its peak in the sixth year following its introduction.

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Mobile broadband technology has become a ubiquitous part of everyday life impacting both commercial and leisure activities. It has also been the subject of a vast amount of attention in recent years as fifth generation (5G) mobile broadband technology, the initial deployment of which is underway in several countries, has the potential to offer greatly enhanced mobile broadband service to consumers and enable a host of applications across many industries not possible with previous generations of technology. The Council of Economic Advisors (CEA) has repeatedly emphasized the potential for 5G to accelerate economic activity and increase employment in the United States (e.g., CEA 2018, 2019, 2020).

Despite its economic significance, there are surprisingly few econometric studies quantifying the economic consequences of mobile broadband technology in either the United States (e.g., Shapiro and Hassett, 2012) or the rest of the world (e.g., Edquist et al., 2018); and, to our knowledge, no econometric studies have examined the economic impact of the most recent generation of mobile broadband technology, 4G. Yet, consideration of the specific economic consequences of 4G technology represents a question of significant importance both because of the dramatic increase in commercial and consumer applications enabled by 4G relative to previous generations of mobile wireless technology and because evaluation of the economic effects of 4G technology likely presents the best available benchmark for projecting the potential economic impact of 5G.

Using survey data on 4G adoption from Q3 2010 to Q4 2014 across the 50 U.S. states, we estimate a panel vector autoregression (VAR) model that quantifies the effect of 4G adoption on employment and economic growth. The panel VAR methodology is attractive in this setting both because of its usefulness as a tool for projecting future outcomes and because it allows for direct analysis of the direction of the link between the variables of interest. We then use our estimates to model the potential economic benefits of 5G under two

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counterfactual adoption scenarios, one in which 5G adoption follows the relatively rapid pace of 4G adoption and the second in which 5G is adopted at the slower pace of 3G. The significant differences in economic effects between the two scenarios illustrate the benefits of achieving a more rapid 5G adoption path.

While the econometric literature specifically considering the economic consequences of mobile broadband adoption is small, there is a larger literature assessing the economic impact of fixed broadband technology (e.g., Crandall, Lehr and Litan, 2007; Czernich et al., 2011), wireless telephony (e.g., Lam and Shiu, 2010; Gruber and Koutroumpis, 2011) and, more generally, information and communications technology (ICT) (e.g., Hardy, 1980; Röller and Waverman, 2001). It is widely recognized that a positive relationship between economic growth and ICT adoption could in principle reflect causality in either of two directions: faster growth may lead to more rapid ICT adoption; or, faster ICT adoption may promote more rapid growth. Since the latter relationship is of primary interest from a policy perspective, the focus of this literature has been to evaluate whether there is evidence of a causal relationship from ICT to economic growth.

Most of the literature has relied on either instrumental variable techniques or simultaneous equations models to address the "reverse causality" problem. However, these approaches have important limitations, including the difficulty of finding credible instruments that create exogenous variation in mobile broadband adoption and the structure and complexity introduced by simultaneous equations models. Our study follows a small but growing subset of the literature that uses VAR techniques to assess the direction of causality (Lam and Shiu, 2010; Shapiro and Hassett, 2012; Pradhan et al., 2014). However, unlike previous studies, our study specifically quantifies the effect of 4G technology on economic outcomes. It is also distinct methodologically in that rather than focusing on the question of the direction of causality alone, it emphasizes the interpretation, predictive power, and

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robustness of the VAR coefficient estimates as well. This approach provides a more fulsome basis for projecting the potential economic benefits of future adoption of mobile wireless technology and for assessing whether mobile broadband adoption has a causal effect on economic outcomes.

Based on our primary model, which includes eight lags of the dependent variable (either employment or GDP) and eight lags of the 4G adoption variable, we estimate that a one-percentage point increase in adoption in each of the eight previous quarters would increase job creation in a given quarter by 0.097% of the level of employment in the previous quarter and increase GDP by 0.560% of the level of GDP in the previous quarter. For both employment and GDP, the coefficients on the lagged 4G coefficients are uniformly positive. For the employment model, seven of the eight lagged 4G coefficients are individually significant, and for the GDP model, all eight of the 4G coefficients are individually significant. In both cases, there is a significant Granger Causal relationship from 4G adoption to the dependent variable.

As we explain, adoption of 5G technology is likely to have economic impacts analogous to the effects of 4G. Assuming this is the case, we apply our coefficient estimates to project the economic impact of 5G adoption under two different scenarios. We estimate that if 5G follows the same adoption path as 4G, then, at its peak, 5G will contribute approximately 3 million jobs to the U.S. economy and $635 billion in GDP, with these effects being realized in the fifth year following the introduction of 5G. In contrast, if 5G follows the same adoption path as 3G, then, at its peak, it will contribute approximately 1.2 million jobs to the U.S. economy and over $264 billion in GDP with these effects being realized in the sixth year following the introduction of 5G technology. Thus, our results provide support for public policy efforts to accelerate the pace of 5G deployment and adoption (Pai 2019).

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The remainder of this study is organized as follows. Section I presents the econometric model, discusses the methodology used to determine the appropriate lag structure, and the data used in estimating the model. Section II presents the results of the econometric analysis of the effects of 4G adoption on employment and economic growth and evaluates the robustness of the estimates. Section III provides a brief overview of the evolution of mobile wireless technology from 1G to 5G, discusses previous estimates of the potential economic effects of 5G technology, and presents our projection of the potential economic benefits of 5G based on the two counterfactual adoption scenarios. Section IV discusses some of implications of our results. Section V provides a brief conclusion.

II. Methodology and Data

This section describes our econometric methodology and the data we use to estimate the model.

A. Econometric Methodology

The starting point for our econometric model is derived from the VAR model presented in Shapiro and Hassett (2012). Specifically,

$$\Delta \ln(Y_{it}) = \sum_{\theta=1}^{m} a_\theta \, \Delta \ln(Y_{it-\theta}) + \sum_{\theta=1}^{m} \beta_\theta \, \Delta \, New\ Tech\ Adoption_{it-\theta} + \eta_i + \tau_t + \epsilon_{it}$$

where $\ln(Y_{it})$ represents the log value of a measure of economic performance (Shapiro and Hassett consider only employment, whereas we consider both employment and (real) GDP). The first set of right-hand side variables represent m lags of the dependent variable, and the second set of right-hand side variables represent m lags of the change in the adoption rate of the new technology (3G in Shapiro and Hassett, 4G in our model). The variable η_i represents a state fixed effect, τ_t represents a quarter fixed effect, and ϵ_{it} is the error term.

Shapiro and Hassett estimate this model using ordinary least squares (OLS) with dummy variables to account for the individual state effects. A problem with this methodology

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is that the presence of the state fixed effect combined with the dynamic structure of the model causes OLS and the fixed-effects within estimator to yield biased estimates (Nickell, 1981; Anderson and Hsiao, 1982; Holtz-Eakin et al., 1988). However, the model can be estimated consistently using techniques developed by Holtz-Eakin et al. (1988), Arellano and Bond (1991), and Blundell and Bond (1998). We apply the "systems" Generalized Methods of Moments (GMM) estimator developed by Blundell and Bond (1998).[1]

While the econometric literature we rely upon is focused largely on assessing the direction of causality in a particular model, our interest in estimating accurately the impact of mobile broadband adoption on economic outcomes makes model selection an important consideration. The lag length for the primary specification of the model was chosen after considering two criteria for determining lag length: the Akaike Information Criterion (AIC) and the "Hayashi Rule." As is common in VAR studies, we limit consideration to cases where the lag lengths of each time series are symmetric. Table 1 shows the number of lags indicated by each methodology.

Table 1: Number of Lags Determined by AIC and Hayashi Rule

Dependent Variable	AIC	Hayashi
Δ ln(Employment)	9	9
Δ ln(GDP)	10	8

One advantage of considering both of these criteria is that they approach the question of model selection using completely distinct methodologies. AIC is a measure of the information content across candidate models. Specifically, it measures the goodness-of-fit using the model's likelihood function. The Hayashi Rule takes an alternative approach, where the model is initially estimated with a prespecified maximum lag length (in this case, ten). If the last lag of the variable of interest is significant for a given p-value (in this case, 10%), then this lag length is chosen. However, if the last lag is not significant, the model is re-

[1] In Appendix A, which describes the results of several robustness checks, we present the results of estimating the model using OLS. The results are similar to the primary estimates.

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estimated with one fewer lag. The procedure is iterated until the coefficient on the last lag in the model is significant (Hayashi, 2000). Reassuringly, both procedures recommend similar lag lengths; in our primary specification we apply the most conservative lag length estimate of eight lags (m=8) in estimating both models.[2] All specifications of the model are population weighted, so that the results are nationally representative, and standard errors are clustered by state.[3]

B. Variables and Data Sources

The model is estimated on 4G adoption data for the 50 U.S. states from Q3 2010 (the quarter in which 4G adoption reached measurable levels) to Q4 2014 (18 quarters) sourced from HarrisX's Mobile Insights Survey. The survey samples approximately 30,000 U.S. residents (13 and over) each month via the Internet and telephone. Respondents identify their specific mobile phone make and model, which is mapped by HarrisX to a mobile wireless technology generation (2G, 3G, 4G). 4G adoption in a given state and quarter is defined as the number of 4G mobile phone users as a share of total mobile phone users. HarrisX classifies the LTE, WiMax, and HSPA+ standards as 4G. Quarterly employment data are sourced from the Bureau of Labor Statistics and quarterly GDP data are sourced from the Bureau of Economic Analysis. The variables used in estimating the model are defined in Table 2.

[2] As shown in Appendix A, our results are robust to alternative specifications that use seven, nine, and ten lags.

[3] Weighting serves two purposes in the analysis. First, the HarrisX wireless adoption estimates upon which we rely for the *New Tech Adoption* variable exhibit greater variability for less populated states than for more populated states, as the underlying sample sizes are smaller. Second, population weighted estimates provide a representative basis for making national projections about the economic effects of wireless adoption (Shapiro and Hassett, 2012).

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Table 2: Variable Definitions

Variables	Definition	Source
Dependent		
Δ ln(Employment)	Change in log of seasonally-adjusted non-farm employment	BLS
Δ ln(GDP)	Change in log of real Gross Domestic Product in 2009 chained USD	BEA
Independent		
Δ New Tech Adoption	Percentage point change in new mobile technology adoption	HarrisX; TeleGeography

Table 3 presents summary statistics for each variable. The underlying data reflect sufficient variation in 4G adoption to obtain economically and statistically significant results.

Table 3: Summary Statistics

Variables	Number of Observations	Mean	Standard Deviation	10th Percentile	90th Percentile
New Tech Adoption	900	0.240	0.203	0.007	0.544
Δ New Tech Adoption	900	0.034	0.041	-0.002	0.085
Employment (Millions)	900	2.7	2.8	0.4	5.7
GDP ($Billions)	900	$75.5	$91.7	$12.2	$161.2

III. Results

This section describes our empirical results, beginning with the results from estimating the VAR model and then turning to testing the robustness of the estimates to alternative assumptions about the degree of autocorrelation and applying Granger causality tests to the lagged *New Tech Adoption* variables.

A. VAR Results

Table 4 presents the results from estimating the model with the two dependent variables of interest: employment and GDP.

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Table 4: VAR Estimates

Variables	Δ ln(Employment$_t$)	Δ ln(GDP$_t$)
Δ ln(Y) Lags		
Δ ln(Y$_{t-1}$)	0.1779***	-0.0995*
	(0.0396)	(0.0561)
Δ ln(Y$_{t-2}$)	0.1985***	0.0284
	(0.0341)	(0.0546)
Δ ln(Y$_{t-3}$)	0.2479***	0.0652**
	(0.0290)	(0.0321)
Δ ln(Y$_{t-4}$)	0.0752**	0.0453
	(0.0333)	(0.0453)
Δ ln(Y$_{t-5}$)	0.1044***	0.0937***
	(0.0362)	(0.0306)
Δ ln(Y$_{t-6}$)	0.0643**	-0.0083
	(0.0287)	(0.0218)
Δ ln(Y$_{t-7}$)	0.0530*	0.0410
	(0.0301)	(0.0392)
Δ ln(Y$_{t-8}$)	-0.1391***	-0.0362
	(0.0482)	(0.0614)
Δ New Tech Adoption Lags		
Δ New Tech Adoption$_{t-1}$	0.0064**	0.0306**
	(0.0032)	(0.0125)
Δ New Tech Adoption$_{t-2}$	0.0114**	0.0409**
	(0.0050)	(0.0203)
Δ New Tech Adoption$_{t-3}$	0.0133**	0.0623*
	(0.0068)	(0.0357)
Δ New Tech Adoption$_{t-4}$	0.0196***	0.0840**
	(0.0073)	(0.0413)
Δ New Tech Adoption$_{t-5}$	0.0171***	0.0964**
	(0.0061)	(0.0393)
Δ New Tech Adoption$_{t-6}$	0.0125***	0.1101***
	(0.0043)	(0.0319)
Δ New Tech Adoption$_{t-7}$	0.0126***	0.0884***
	(0.0043)	(0.0240)
Δ New Tech Adoption$_{t-8}$	0.0043	0.0478*
	(0.0055)	(0.0275)
Observations	900	900

*** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level. Regressions are population weighted and include quarter fixed effects. Standard errors are clustered by state.

The estimated coefficients on the $\Delta\ New\ Tech\ Adoption$ lags are uniformly positive and, in all but one case, individually statistically significant. The coefficients on the $\Delta\ New\ Tech\ Adoption$ lags indicate the effect of a one-percentage point increase in mobile

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broadband adoption in a prior quarter (quarter t-1, quarter t-2, etc.) on the dependent variable in the current quarter (quarter t). For example, the coefficients on the $\Delta\ New\ Tech\ Adoption$ lags in the second column of the table indicate that a one-percentage point increase in mobile broadband adoption in quarter t-1 is associated with an increase in job creation in quarter t of 0.006% of the employment level in quarter t-1; a one-percentage point increase in mobile broadband adoption in quarter t-2 is associated with an increase in job creation in quarter t of 0.011% of the employment level in quarter t-1; and so forth. The sum of the coefficients on the $\Delta\ New\ Tech\ Adoption$ lags in each column is the cumulative effect of a sustained one-percentage point increase in mobile broadband adoption in each of the prior eight quarters. Thus, a one-percentage point increase in mobile broadband adoption in each of the previous eight quarters would increase job creation in the current quarter by 0.097% of the level of employment in the previous quarter and increase GDP by 0.560% of the level of GDP in the previous quarter. To provide some context for the economic significance of these results, using Q4 2019 employment and GDP as benchmarks, the results imply that a sustained one-percentage point increase in mobile broadband adoption across the previous eight quarters would increase employment in a quarter by approximately 147,000 jobs and increase GDP by $121.0 billion on an annualized basis.

B. Autocorrelation and Causality Tests

This section assesses the robustness of the model to higher order autocorrelation and then presents the results from applying Granger Causality tests to the lagged *New Tech Adoption* variables. The primary model specification we employ treats only the first lags of each time series as endogenous. However, when the model is characterized by higher order autocorrelation, additional lags may become endogenous, leading to inconsistent estimates. The solution to this problem is to use a restricted set of instruments that does not include any of the endogenous variables.

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Arellano and Bond (1991) developed a test for autocorrelation to help determine whether to consider estimating the model using a restricted instrument set. Table 5 shows the results of applying the Arellano-Bond test for (second order) autocorrelation to the primary regression results.

Table 5: Arellano-Bond Tests

Dependent Variable	Z-Stat	P-Value
Δ ln(Employment)	0.82	0.413
Δ ln(GDP)	2.01	0.045

The null hypothesis under the test is that there is no autocorrelation. Thus, the failure to reject the null for employment indicates that there is a low likelihood of potentially problematic autocorrelation. For GDP, the null hypothesis is rejected, indicating that additional analysis is warranted. The standard approach is then to consider a specification where the set of instruments begins with the third lag of each time series. The results of re-estimating the model in this way are presented in Table 6.[4]

[4] Although we fail to reject the null hypothesis for employment, we still re-estimate the employment model using this as a robustness test.

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Table 6: Instrument Set Beginning with Third Lag Regression Results

Variables	Δ ln(Employment$_t$)	Δ ln(GDP$_t$)
Δ ln(Y) Lags		
Δ ln(Y$_{t-1}$)	0.2157***	-0.1629***
	(0.0568)	(0.0629)
Δ ln(Y$_{t-2}$)	0.1853***	0.0217
	(0.0354)	(0.0602)
Δ ln(Y$_{t-3}$)	0.2353***	0.0591*
	(0.0300)	(0.0304)
Δ ln(Y$_{t-4}$)	0.0635*	0.0409
	(0.0338)	(0.0417)
Δ ln(Y$_{t-5}$)	0.1010***	0.1022***
	(0.0373)	(0.0293)
Δ ln(Y$_{t-6}$)	0.0745***	0.0251
	(0.0286)	(0.0302)
Δ ln(Y$_{t-7}$)	0.0602*	0.0653
	(0.0358)	(0.0401)
Δ ln(Y$_{t-8}$)	-0.1438***	-0.0335
	(0.0460)	(0.0605)
Δ New Tech Adoption Lags		
Δ New Tech Adoption$_{t-1}$	0.0066	0.0554***
	(0.0044)	(0.0186)
Δ New Tech Adoption$_{-2}$	0.0110**	0.0608**
	(0.0056)	(0.0245)
Δ New Tech Adoption$_{t-3}$	0.0125*	0.0736*
	(0.0065)	(0.0378)
Δ New Tech Adoption$_{t-4}$	0.0188***	0.0878**
	(0.0071)	(0.0418)
Δ New Tech Adoption$_{t-5}$	0.0160***	0.0985***
	(0.0060)	(0.0381)
Δ New Tech Adoption$_{t-6}$	0.0114**	0.1131***
	(0.0046)	(0.0303)
Δ New Tech Adoption$_{t-7}$	0.0117***	0.0923***
	(0.0043)	(0.0249)
Δ New Tech Adoption$_{t-8}$	0.0035	0.0474*
	(0.0055)	(0.0285)
Observations	900	900

*** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level. Regressions are population weighted and include quarter fixed effects. Standard errors are clustered by state.

As a comparison with Table 5 reveals, the results of estimating the model with the restricted instrument set beginning with the third-lag are very similar, both qualitatively and quantitatively, to the results of the primary specification. As shown in Table 7, when the

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Arellano-Bond autocorrelation test is applied to the re-estimated model, it fails to reject the null hypothesis for both dependent variables.

Table 7: Instrument Set Beginning with Third Lag Arellano-Bond Tests

Dependent Variable	Z-Stat	P-Value
Δ ln(Employment)	1.49	0.137
Δ ln(GDP)	0.65	0.514

Another potential concern when using dynamic panel estimators like the systems GMM estimator used here is the possibility of finite sample bias resulting from having too many instruments relative to the cross-sectional sample size. We address this issue in Appendix A, showing our results are robust to an estimation strategy that uses only the second through eighth lags as instruments.

As for causality, in time series models, tests for Granger Casualty are used to assess the direction of causality between variables (Granger, 1969). While it is widely recognized that in the time series setting, Granger Causality does not account for the potential confounding effect of unobserved variables, applying the test in the context of a panel VAR model using appropriate estimation techniques allows for conclusions about causality to be drawn accounting for the effect of geographic and temporal fixed effects.

Because the focus of this study is the direct effect of increased adoption on economic outcomes, the hypothesis of primary interest is whether there is a causal relationship from the adoption of new wireless technology to the dependent variable. Testing this hypothesis involves specifying the null hypothesis that the coefficients on the $\Delta\, New\ Tech\ Adoption$ lags are jointly equal to zero.

Table 8 presents the results of the Granger Causality tests. For both dependent variables the null hypothesis is rejected at the 5% level.

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Table 8: Granger Causality Tests

Dependent Variable	χ^2-Stat	P-Value
Δ ln(Employment)	19.99	0.010
Δ ln(GDP)	21.27	0.007

The Granger Causality tests indicate that economic performance responds directly to changes in mobile wireless technology adoption, rather than changes in mobile wireless technology adoption merely being a by-product of economic growth. Combined with the uniformly positive coefficient estimates on $\Delta\, New\ Tech\ Adoption$ lags, these results provide strong evidence that increases in the adoption of new mobile broadband technology lead to increases in economic performance.[5]

III. Quantifying the Potential Economic Contribution of 5G Adoption

In this section, we use our estimates of the economic effects of the transition from 3G to 4G mobile wireless technology as a foundation for projecting the impact of the 4G-to-5G transition that is now beginning. We discuss the progress of mobile wireless technologies and then apply our coefficient estimates to two different counterfactual 5G adoption scenarios.

A. The Evolution of Mobile Wireless Technology and Current Literature on 5G

Since its initial deployment in the 1980s, mobile wireless technology has progressed through four "generations." First generation (1G) technology enabled analog telephone calls but could not transmit data and was extremely limited in terms of capacity. Second generation (2G) technology increased capacity through the use of digital technology and allowed for limited data transmission and short message services (SMS) (Zahariadis and Doshi, 2004). Third generation (3G) systems dramatically enhanced data transmission

[5] For both dependent variables, applying the Granger Causality test in the opposite direction also indicates a statistically significant relationship from the dependent variables to new mobile broadband technology adoption. In this sense, the estimates presented here of the economic impact of mobile wireless technology adoption are conservative because they abstract from multiplier effects created by the feedback relationships between the variables.

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speeds, allowing for mobile access to the Internet and facilitating widespread adoption of smartphones (Kumar et al., 2013). Fourth generation (4G) technology offered significant further improvements in data speeds and capacity, and spurred the development of mobile broadband services, such as music and video streaming, Voice over Internet Protocol (VoIP) telephony, and a multitude of location-based applications, like Lyft and Uber (Kumar et al., 2013).

5G represents a further development in the evolution of mobile wireless technology. The economic benefits of 5G are expected to be driven by four primary features: (1) faster transmission speeds (measured in Gigabits per second rather than Megabits); (2) greater network capacity; (3) lower latencies (the time between making a request for data and receiving the data on a given device); and (4) higher reliability (fewer dropped packets). As a result of these characteristics, 5G will likely enhance the consumer oriented mobile broadband use cases made possible by 4G and will extend commercial application of mobile wireless technology to business and industrial use cases not possible with previous technology, including enabling the Internet of Things (IoT) (Tech4i2 et al., 2016; Safer et al., 2018; Campbell et al., 2019).

Prior studies of the economic benefits of 5G adoption have applied a variety of approaches, including Input-Output analysis, general equilibrium modeling, and growth accounting (Tech4i2 et al., 2016; Mandel, 2016; American Consumer Institute Center for Citizen Research, 2017; Australian Bureau of Communications and Arts Research 2018; Campbell et al., 2019). In addition, three studies of which we are aware have applied the Shapiro and Hassett coefficient estimates to project the macroeconomic benefits of 5G (Al Amine et al., 2017; Safer et al., 2018; Eisenach, 2018). All of these studies estimate significant economic benefits from accelerating 5G adoption.

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B. 5G Adoption Counterfactuals

In this section we apply the coefficient estimates from our primary specification and mobile broadband adoption data from TeleGeography to generate estimates of the benefits of 5G adoption under two scenarios. In the first scenario, 5G adoption follows the path of 4G adoption; in the second scenario, 5G adoption follows the (slower and flatter) path of 3G adoption. We present the results on a quarterly basis for six years following the initial adoption of 5G – a time span sufficient to capture the peak economic contribution for all economic outcome variables of interest under both scenarios.[6] Figure 1 shows the quarterly adoption path under both scenarios indexed by the variable *q*. Because the econometric model is in lagged differences, 5G does not begin to have economic effects until the quarter after introduction. Thus, we set *q=0* for the first quarter with positive adoption so that *q=1* is the first quarter where adoption creates economic benefits.

[6] We use TeleGeography data for the counterfactual analysis in this section because the HarrisX data used to estimate the model does not cover a long enough time period to capture the full 3G and 4G adoption paths from initial adoption to the enablement of peak economic benefits. However, the Telegeography data is national rather than state-level and, thus, cannot be used to estimate a panel VAR model of new mobile technology adoption.

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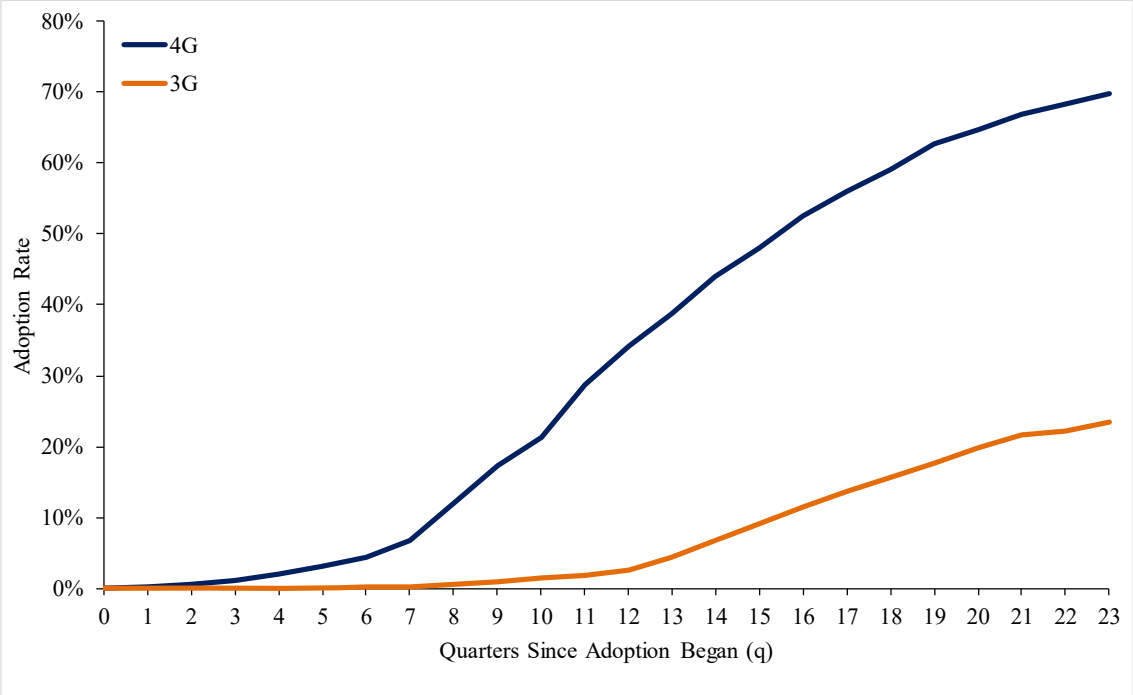
Figure 1: 3G and 4G Adoption Paths



As shown in Figure 1, the 4G adoption curve is both faster and deeper than the 3G adoption curve. Thus, consideration of these scenarios provides a counterfactual analytical framework for assessing the incremental benefits of policies that encourage more rapid and more widespread 5G adoption.

In projecting the economic benefits of 5G based on a model estimated using 4G adoption data, we note first that the effects of 5G deployment are expected to be at least qualitatively similar to those that resulted from 4G, including more advanced consumer applications, more efficient business processes, and new business models (e.g., Tech4i2 et al., 2016; Campbell et al., 2019). Moreover, both 4G and 5G represent "general purpose technologies," which have broad effects on economic processes across multiple economic sectors (e.g., Campbell et al., 2019). Indeed, many observers predict the beneficial effects of 5G will exceed those of 4G (e.g., Campbell et al., 2019). To the extent they are correct, the projections presented here understate the potential contribution of 5G technology. In addition, as noted above, we do not attempt to estimate multiplier effects due to the potential

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bidirectional relationship between economic growth and 5G adoption, nor do we incorporate indirect supply-chain or induced spending effects as is common in Input-Output analyses.

Our projection of the effect of 5G adoption on economic performance involves four steps:

(1) We use quarterly 3G, 4G, and total mobile subscriber data from TeleGeography to calculate quarterly 3G and 4G adoption in the United States. Because the differences in the quarter-to-quarter changes in 5G adoption are the appropriate input for counterfactual analysis using the econometric model, it is then necessary to convert the quarterly adoption rates to quarterly changes. As noted above, since the model projects economic benefits beginning in the quarter after initial adoption, a 5G adoption curve modeled from *q=0* to *q=23* translates into economic benefits modeled from *q=1* to *q=24.*

(2) Since the output of the econometric model is in percentage terms, estimating the level increase in each measure of economic performance requires a forecast of the level but-for the increase in 5G adoption. This study uses the average quarterly levels of employment and GDP in 2019 (150.9 million in employment and $5.4 trillion in GDP).[7]

(3) For each quarter, the lagged mobile wireless adoption coefficients from the econometric model are multiplied by the percentage point changes in quarter-to-quarter 5G adoption. For example, for *q=10*, the coefficient estimate on the eighth lag of the mobile wireless adoption variable is multiplied by the percentage point change in 5G adoption in *q=2*. The resulting percentage is multiplied by the level of the dependent variable from step (2) to estimate the change in the magnitude of the dependent variable for the current quarter.

(4) Finally, the quarterly increases in the dependent variables are adjusted to account for cumulative effects. For employment, because the output of the model is the change in

[7] By using economic data from 2019, we abstract from any economic disruption caused by COVID-19. To the extent that the pandemic represents a temporary economic shock, projections based on 2019 are likely to be more accurate. However, if the pandemic results in a long-term structural change to the U.S. economy, then a benchmark taking into account these effects may be more appropriate.

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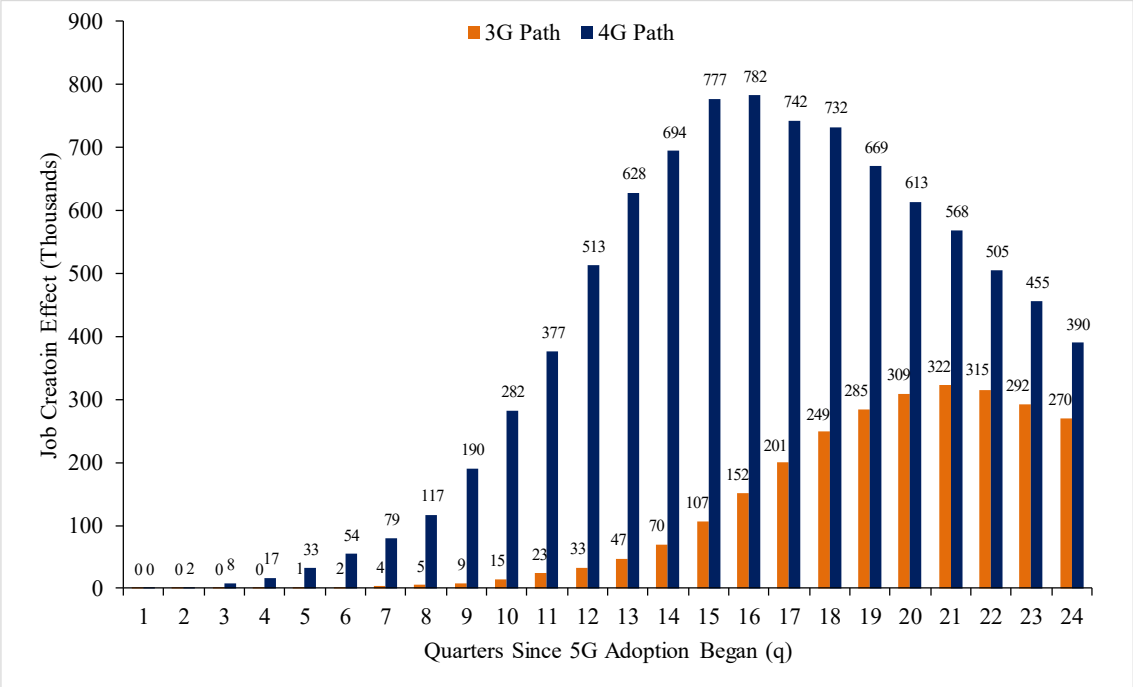
employment from *q-1* to *q* this quantity corresponds to the net job creation attributable to 5G in quarter *q*. Converting job creation into the increase in the level of employment due to 5G adoption requires making an assumption about the duration of a job. If we conservatively assume that a job lasts for one year, then the effect of 5G adoption on employment in a given quarter *q* is given by:

$$\Delta EMP_q^{5G} = \sum_{i=0}^{3} \Delta JC_{q-i}^{Model}$$

where ΔJC_q^{Model} is the change in job creation in *q* projected by the model. That is, the increase in the level of employment due to 5G adoption in any given quarter is the sum of job creation in that quarter and the three preceding quarters. For GDP, we simply annualize the projected effect in each quarter.

Figure 2 shows the estimated quarterly job creation effects of 5G adoption under the two adoption paths starting in *q*=1, the first quarter following initial adoption.

Figure 2: Estimated Effect of 5G Adoption on New Job Creation (Thousands)



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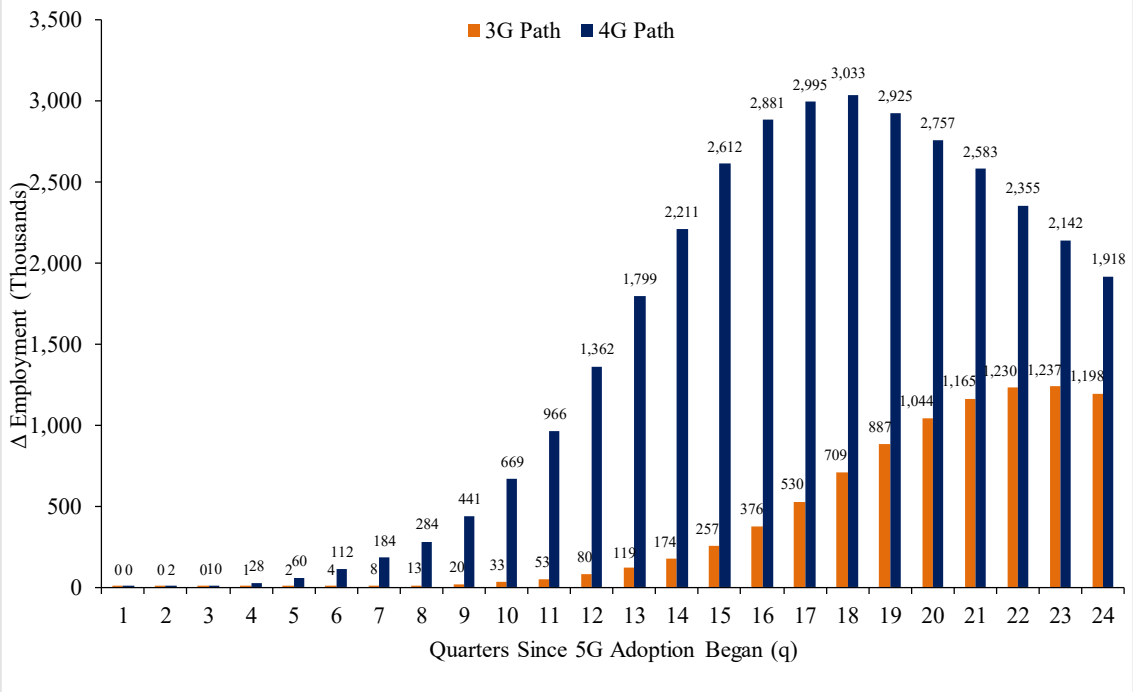
Under the 4G adoption path scenario, job creation due to 5G reaches its peak value of approximately 782,000 jobs in *q=16*. Under the 3G adoption path scenario, job creation due to 5G reaches its peak value of approximately 322,000 jobs in *q=21.* Thus, the peak job creation effect is over twice as large under the faster/deeper adoption scenario and occurs over one-year earlier.

Because it is often more intuitive for policy makers to think in terms of employment versus job creation, Figure 3 illustrates the increase in the level of employment due to 5G adoption under the assumption that a job lasts one year.

Figure 3: Estimated Effect of 5G Adoption on Employment (Thousands)



Under the 4G adoption path scenario, employment due to 5G reaches its peak value of approximately 3,000,000 jobs in *q=18*. Under the 3G adoption path scenario, job creation due to 5G reaches its peak value of approximately 1,237,000 jobs in *q=23*.[8]

[8] Many studies considering the employment effects of ICT technology, including Crandall, Lehr, and Litan (2007) and Shapiro and Hassett (2012), treat jobs as permanent following creation rather than existing for a set period of time. We have chosen to explicitly assume that a job disappears after one year both to be conservative and to emphasize the differing dynamics of the two counterfactual scenarios in terms of the timing of the peak effects.

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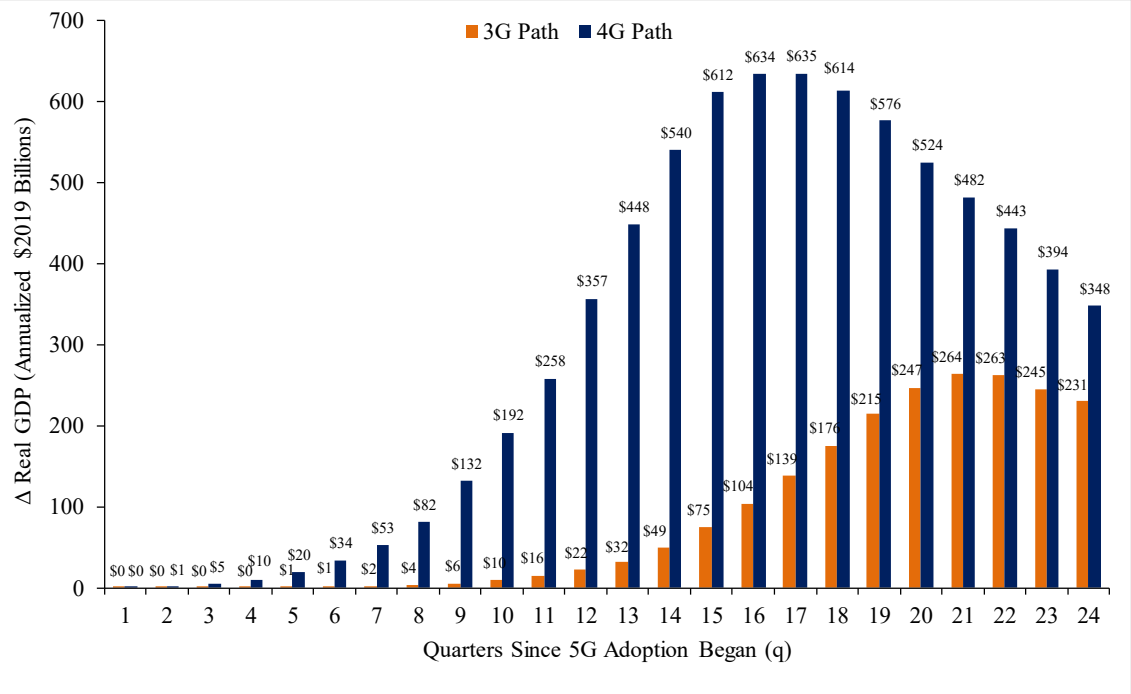
Figure 4 presents the estimated annualized quarterly increases in real GDP due to 5G adoption under both scenarios.

Figure 4: Estimated Effect of 5G Adoption on GDP (Annualized $2019 Billions)



Under the 4G adoption path scenario, the contribution of 5G to GDP reaches its peak value of approximately $635 billion in *q=17*. Under the 3G adoption path scenario, the contribution of 5G to GDP reaches its peak value of approximately $264 billion in *q=21*.Thus, a 5G adoption path following the 4G adoption path rather than the 3G adoption path would confer large incremental benefits on the U.S. economy both in terms of magnitude and timing.

IV. Discussion

Our econometric analysis presents strong evidence of an economically significant positive relationship from mobile broadband adoption to employment and economic growth. Because it is the most similar paper to this one methodologically and because it serves as the

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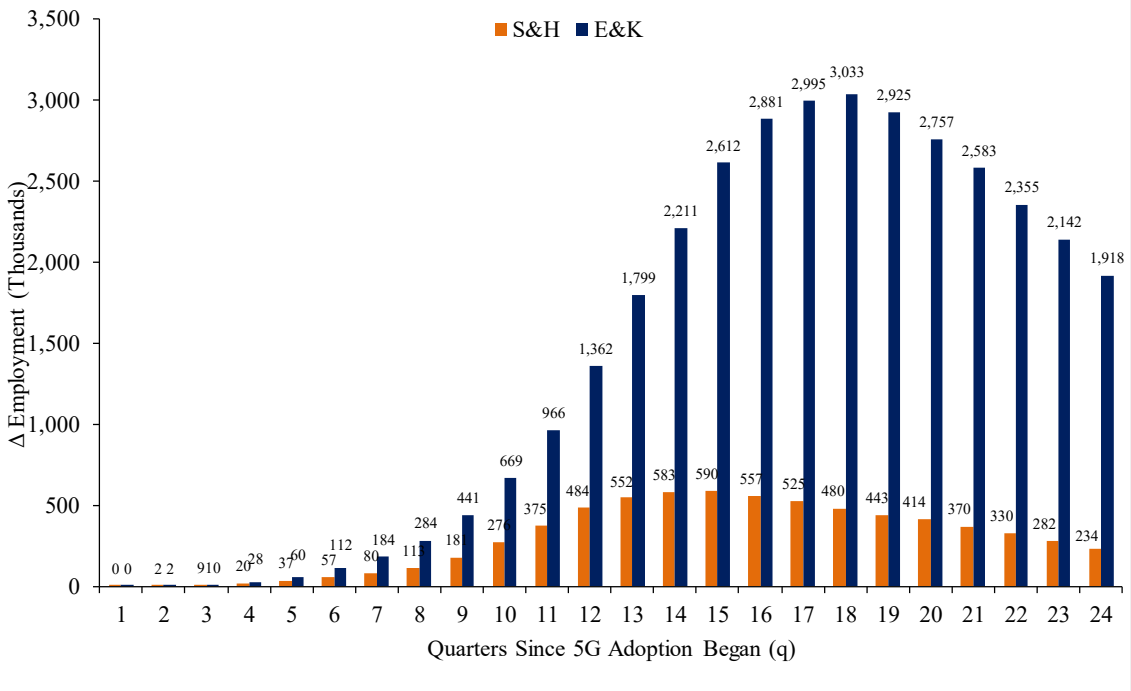
sole econometric basis in the current 5G literature for projections of the potential economic benefits of 5G, it is useful to compare our findings to those from Shapiro and Hassett (2012).[9]

The magnitude of the estimated impact on job creation can be directly compared to the sum of Shapiro and Hassett's coefficient estimates. Their estimates imply that job creation would increase by 0.018% of the level of employment in the previous quarter, or 26,800 jobs (based on the same Q4 2019 baseline used for the calculations above), as a result of a one-percentage point increase in adoption in each of the previous eight quarters, approximately one sixth of the magnitude of this study's results. Figure 5 compares the estimated effects of 5G adoption on employment based on the 4G path using our coefficients to the equivalent effects using the coefficients from Shapiro and Hassett (2012).

Figure 5: Comparison with Estimated Effect of 5G Adoption on Employment Based on Shapiro and Hassett (2012) (Thousands)



[9] While the Shapiro and Hassett model is not estimated using a dynamic panel data estimator, our analysis of the OLS results in Appendix A indicates that the OLS results are sufficiently similar to the systems GMM estimates to allow direct comparison of the two. Although we cannot be certain this is true of the Shapiro and Hassett model estimates as well, the similarity of the underlying data and the model suggest to us that comparison is appropriate.

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These results indicate that the transition from 3G to 4G had a much stronger effect on economic performance than the transition from 2G to 3G. Given the dramatic advances in functionality and the wide variety of use cases associated with the transition from 3G to 4G, it is not surprising the economic effects are substantially stronger than for the transition from 2G to 3G. Our peak estimate of the contribution of 5G – over 3 million jobs and over $630 billion in GDP – is also larger and achieved earlier than the estimate by Al Amine et al. (2017) that 5G adoption would create 2.2 million and increase annual GDP by $420 billion in the United States in the seven years following initial adoption.

However, our results are modest relative to previous studies of the contribution of ICT to employment in the United States that do not explicitly attempt to unravel the potentially confounding problem of reverse causality. For instance, in a highly cited study, Crandall, Lehr, and Litan (2007) found that a one-percentage point increase in broadband penetration lifts employment by 0.2% to 0.3% per year. The findings presented here imply a much smaller effect, i.e., that that a one-percentage point increase in mobile wireless adoption in a quarter increases employment by approximately 0.05% over the next year.[10] This suggests that the overall ICT literature's emphasis on finding strategies to account for potential endogeneity is particularly important for making accurate projections. Our analysis also suggests more modest benefits attributable to 5G than some of the most optimistic projections of its effect on the U.S. economy such as the prediction that by 2030 5G will contribute $2.7 trillion to U.S. GDP by Mandel (2016). Yet, our results do not preclude this possibility, but simply emphasize these more optimistic estimates depend on the assumption that 5G ultimately will enable significantly greater increases in productivity and commercial activity than 4G.

[10] This figure is the sum of the coefficients on the first four lags of 4G adoption multiplied by one percentage point: (0.006 + 0.011 + 0.013 + 0.020) × 0.01 = 0.0005 = 0.05%, which is substantially lower than the annual effect estimated by Crandall, Lehr, and Litan (2007).

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Our results suggest that policies that accelerate 5G adoption have the potential to create substantial economic benefits. For instance, Strategy Analytics, a technology research firm, has projected that the merger of T-Mobile and Sprint will increase 5G adoption in the United States by 17% through 2023 (Strategy Analytics 2018), and in approving the transaction, the Federal Communications Commission (FCC) cited accelerated 5G adoption as an important public interest benefit (FCC 2019). Our analysis suggests that if Strategy Analytics' estimate is correct, the merger will add approximately 220,000 jobs to the U.S. economy and approximately $41 billion in annual output by the end of 2023.[11] In general, the results presented here provide support for the proposition put forward by the CEA, the FCC, and many policy analysts that faster, more widespread 5G adoption has the potential to create large benefits for the U.S. economy.

V. Conclusion

Given the increasing relevance of 5G from a policy perspective and the large potential benefits of 5G technology for the U.S. and world economy, it is clear that more econometric research is warranted on this topic. While this study presents one approach we believe is informative and useful for evaluating the question, more evidence using a variety of approaches is necessary to gain a better understanding of the potential economic benefits of 5G and future generations of mobile broadband technology.

[11] For the purposes of this calculation, we assume that the increase in 5G adoption projected by Strategy Analytics is spread evenly across quarters from 2021 to 2023.

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Appendix A

A.1 OLS Estimates

Table A1: OLS Regression Results

Variables	**Δ ln(Employment$_t$)**	**Δ ln(GDP$_t$)**
Δ ln(Y) Lags		
Δ ln(Y$_{t-1}$)	0.1866***	-0.0790
	(0.0367)	(0.0553)
Δ ln(Y$_{t-2}$)	0.2084***	0.0382
	(0.0358)	(0.0479)
Δ ln(Y$_{t-3}$)	0.2633***	0.0640**
	(0.0243)	(0.0299)
Δ ln(Y$_{t-4}$)	0.0750***	0.0614
	(0.0241)	(0.0460)
Δ ln(Y$_{t-5}$)	0.0390	0.0236
	(0.0357)	(0.0368)
Δ ln(Y$_{t-6}$)	0.0292	-0.0307
	(0.0272)	(0.0234)
Δ ln(Y$_{t-7}$)	0.0247	0.0581**
	(0.0222)	(0.0274)
Δ ln(Y$_{t-8}$)	-0.0832**	-0.0451
	(0.0311)	(0.0445)
Δ New Tech Adoption Lags		
Δ New Tech Adoption$_{t-1}$	0.0068**	0.0285**
	(0.0033)	(0.0141)
Δ New Tech Adoption$_{-2}$	0.0125**	0.0410*
	(0.0051)	(0.0222)
Δ New Tech Adoption$_{t-3}$	0.0145**	0.0639*
	(0.0070)	(0.0373)
Δ New Tech Adoption$_{t-4}$	0.0206***	0.0860*
	(0.0072)	(0.0449)
Δ New Tech Adoption$_{t-5}$	0.0187***	0.0936**
	(0.0059)	(0.0431)
Δ New Tech Adoption$_{t-6}$	0.0150***	0.1080***
	(0.0043)	(0.0352)
Δ New Tech Adoption$_{t-7}$	0.0157***	0.0875***
	(0.0046)	(0.0247)
Δ New Tech Adoption$_{t-8}$	0.0061	0.0483*
	(0.0060)	(0.0268)
Observations	900	900
R-squared	0.5954	0.2734

*** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level. Regressions are population weighted and include quarter fixed effects. Standard errors are clustered by state.

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A.2 Alternative Lag Specifications

Table A2: Seven-Lag Model Regression Results

Variables	Δ ln(Employment$_t$)	Δ ln(GDP$_t$)
Δ ln(Y) Lags		
Δ ln(Y$_{t-1}$)	0.1787***	-0.0979*
	(0.0405)	(0.0571)
Δ ln(Y$_{t-2}$)	0.1959***	0.0365
	(0.0353)	(0.0493)
Δ ln(Y$_{t-3}$)	0.2393***	0.0698**
	(0.0300)	(0.0302)
Δ ln(Y$_{t-4}$)	0.0642**	0.0469
	(0.0316)	(0.0424)
Δ ln(Y$_{t-5}$)	0.0866**	0.0925***
	(0.0378)	(0.0331)
Δ ln(Y$_{t-6}$)	0.0381	-0.0105
	(0.0249)	(0.0233)
Δ ln(Y$_{t-7}$)	0.0269	0.0446
	(0.0300)	(0.0398)
Δ New Tech Adoption Lags		
Δ New Tech Adoption$_{t-1}$	0.0072**	0.0328***
	(0.0032)	(0.0123)
Δ New Tech Adoption$_{-2}$	0.0129***	0.0414**
	(0.0047)	(0.0203)
Δ New Tech Adoption$_{t-3}$	0.0144**	0.0640*
	(0.0068)	(0.0359)
Δ New Tech Adoption$_{t-4}$	0.0197***	0.0824**
	(0.0073)	(0.0417)
Δ New Tech Adoption$_{t-5}$	0.0171***	0.0952**
	(0.0060)	(0.0391)
Δ New Tech Adoption$_{t-6}$	0.0116**	0.0971***
	(0.0048)	(0.0318)
Δ New Tech Adoption$_{t-7}$	0.0110**	0.0604***
	(0.0048)	(0.0203)
Observations	900	900

*** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level. Regressions are population weighted and include quarter fixed effects. Standard errors are clustered by state.

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Table A3: Nine-Lag Model Regression Results

Variables	Δ ln(Employment$_t$)	Δ ln(GDP$_t$)
Δ ln(Y) Lags		
Δ ln(Y$_{t-1}$)	0.1839***	-0.1006*
	(0.0412)	(0.0597)
Δ ln(Y$_{t-2}$)	0.1902***	0.0272
	(0.0330)	(0.0556)
Δ ln(Y$_{t-3}$)	0.2407***	0.0636*
	(0.0298)	(0.0356)
Δ ln(Y$_{t-4}$)	0.0653*	0.0437
	(0.0335)	(0.0452)
Δ ln(Y$_{t-5}$)	0.0925***	0.0928***
	(0.0358)	(0.0317)
Δ ln(Y$_{t-6}$)	0.0550*	-0.0089
	(0.0291)	(0.0242)
Δ ln(Y$_{t-7}$)	0.0374	0.0409
	(0.0325)	(0.0395)
Δ ln(Y$_{t-8}$)	-0.1540***	-0.0368
	(0.0466)	(0.0626)
Δ ln(Y$_{t-9}$)	0.0526*	-0.0007
	(0.0305)	(0.0523)
Δ New Tech Adoption Lags		
Δ New Tech Adoption$_{t-1}$	0.0067**	0.0304**
	(0.0033)	(0.0129)
Δ New Tech Adoption$_{-2}$	0.0116**	0.0403*
	(0.0051)	(0.0207)
Δ New Tech Adoption$_{t-3}$	0.0142**	0.0619*
	(0.0067)	(0.0358)
Δ New Tech Adoption$_{t-4}$	0.0204***	0.0836**
	(0.0072)	(0.0414)
Δ New Tech Adoption$_{t-5}$	0.0181***	0.0966**
	(0.0059)	(0.0391)
Δ New Tech Adoption$_{t-6}$	0.0129***	0.1095***
	(0.0043)	(0.0316)
Δ New Tech Adoption$_{t-7}$	0.0168***	0.0914***
	(0.0044)	(0.0283)
Δ New Tech Adoption$_{t-8}$	0.0137**	0.0560
	(0.0061)	(0.0410)
Δ New Tech Adoption$_{t-9}$	0.0161***	0.0155
	(0.0060)	(0.0365)
Observations	900	900

*** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level. Regressions are population weighted and include quarter fixed effects. Standard errors are clustered by state.

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Table A4: Ten-Lag Model Regression Results

Variables	Δ ln(Employment$_t$)	Δ ln(GDP$_t$)
Δ ln(Y) Lags		
Δ ln(Y$_{t-1}$)	0.1828***	-0.1043*
	(0.0411)	(0.0588)
Δ ln(Y$_{t-2}$)	0.1899***	0.0353
	(0.0327)	(0.0490)
Δ ln(Y$_{t-3}$)	0.2398***	0.0546
	(0.0297)	(0.0420)
Δ ln(Y$_{t-4}$)	0.0645*	0.0482
	(0.0339)	(0.0479)
Δ ln(Y$_{t-5}$)	0.0917**	0.0907***
	(0.0366)	(0.0292)
Δ ln(Y$_{t-6}$)	0.0544*	-0.0127
	(0.0289)	(0.0264)
Δ ln(Y$_{t-7}$)	0.0373	0.0332
	(0.0329)	(0.0390)
Δ ln(Y$_{t-8}$)	-0.1548***	-0.0478
	(0.0472)	(0.0655)
Δ ln(Y$_{t-9}$)	0.0522*	-0.0019
	(0.0305)	(0.0507)
Δ ln(Y$_{t-10}$)	-0.0004	0.1031*
	(0.0244)	(0.0581)
Δ New Tech Adoption Lags		
Δ New Tech Adoption$_{t-1}$	0.0066**	0.0286**
	(0.0033)	(0.0123)
Δ New Tech Adoption$_{-2}$	0.0116**	0.0422**
	(0.0052)	(0.0192)
Δ New Tech Adoption$_{t-3}$	0.0141**	0.0643*
	(0.0070)	(0.0336)
Δ New Tech Adoption$_{t-4}$	0.0204***	0.0821**
	(0.0074)	(0.0397)
Δ New Tech Adoption$_{t-5}$	0.0182***	0.0935**
	(0.0060)	(0.0387)
Δ New Tech Adoption$_{t-6}$	0.0130***	0.1058***
	(0.0043)	(0.0300)
Δ New Tech Adoption$_{t-7}$	0.0169***	0.0883***
	(0.0044)	(0.0266)
Δ New Tech Adoption$_{t-8}$	0.0144**	0.0600
	(0.0066)	(0.0442)
Δ New Tech Adoption$_{t-9}$	0.0175**	0.0283
	(0.0071)	(0.0426)
Δ New Tech Adoption$_{t-10}$	0.0028	0.0319
	(0.0068)	(0.0289)
Observations	900	900

*** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level. Regressions are population weighted and include quarter fixed effects. Standard errors are clustered by state.

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A.3 Restricted Instrument Estimation Results

Table A5: Instrument Set Restricted to Second Though Eighth Lags Regression Results

Variables	Δ ln(Employment$_t$)	Δ ln(GDP$_t$)
Δ ln(Y) Lags		
Δ ln(Y$_{t-1}$)	0.1837***	-0.1257**
	(0.0395)	(0.0632)
Δ ln(Y$_{t-2}$)	0.2038***	-0.0007
	(0.0369)	(0.0657)
Δ ln(Y$_{t-3}$)	0.2504***	0.0374
	(0.0280)	(0.0402)
Δ ln(Y$_{t-4}$)	0.0794**	0.0207
	(0.0342)	(0.0508)
Δ ln(Y$_{t-5}$)	0.1126***	0.0732**
	(0.0371)	(0.0312)
Δ ln(Y$_{t-6}$)	0.0721**	-0.0229
	(0.0298)	(0.0221)
Δ ln(Y$_{t-7}$)	0.0577*	0.0266
	(0.0298)	(0.0416)
Δ ln(Y$_{t-8}$)	-0.1385***	-0.0475
	(0.0473)	(0.0645)
Δ New Tech Adoption Lags		
Δ New Tech Adoption$_{t-1}$	0.0062**	0.0316**
	(0.0032)	(0.0135)
Δ New Tech Adoption$_{-2}$	0.0106**	0.0440**
	(0.0049)	(0.0219)
Δ New Tech Adoption$_{t-3}$	0.0123*	0.0661*
	(0.0069)	(0.0373)
Δ New Tech Adoption$_{t-4}$	0.0183**	0.0879**
	(0.0072)	(0.0440)
Δ New Tech Adoption$_{t-5}$	0.0156**	0.1013**
	(0.0063)	(0.0429)
Δ New Tech Adoption$_{t-6}$	0.0108**	0.1171***
	(0.0047)	(0.0359)
Δ New Tech Adoption$_{t-7}$	0.0109**	0.0975***
	(0.0048)	(0.0272)
Δ New Tech Adoption$_{t-8}$	0.0031	0.0542*
	(0.0057)	(0.0287)
Observations	900	900

*** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level. Regressions are population weighted and include quarter fixed effects. Standard errors are clustered by state.

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