Policy & Internet
www.policyandinternet.org

Volume 3, Issue 4 • 2011 • Article 2

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Fernández-i-Marín, Xavier (2011) "The Impact of e-Government Promotion in Europe: Internet Dependence and Critical Mass," *Policy & Internet*: Vol. 3: Iss. 4, Article 2.
Available at: http://www.psocommons.org/policyandinternet/vol3/iss4/art2
DOI: 10.2202/1944-2866.1093

The Impact of e-Government Promotion in Europe: Internet Dependence and Critical Mass

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Abstract

Governments and public bodies have been fostering the development of e-Government services during the last decade, promoting more and better administrative services through digital channels. The impact of this process, however, has not been fully assessed. This article investigates the relative impact of two key factors on the diffusion of e-Government services; the level of Internet penetration and investment by governments in more and better government services. The aim is to analyze across European countries the impact of e-Government policies on their adoption, under different levels of Internet penetration, enabling an assessment of how promotion of e-Government (through investment in more and better services, for example) can have the maximum impact on citizenship adoption. It reports analysis of a cross-sectional dataset of European countries using a Bayesian linear model. Results show that when Internet users are scarce, policies to foster e-Government adoption will have little - although not negligible - impact. But at a certain level of Internet penetration, focused e-Government policies have a substantial impact on citizens' adoption of the technology. The results also highlight the importance of investing in e-Government in the appropriate moment, that is, when its impact can be greatest. The paper, then, addresses the factors that make eGovernment policy more effective. The Bayesian inference used allows the research to avoid artificial assumptions common in comparative politics research, to design more flexible models and to present the results in a more natural way.

KEYWORDS: e-Government, e-Government promotion, public policy, Internet, Europe, Bayesian linear model

Introduction

Does public investment in electronic services and e-Government promotion increase its adoption by citizens, or does e-Government adoption depend only on the Internet adoption level? e-Government, considered as a major opportunity to improve the efficiency of public administration, has captured much attention in recent years from governments and scholars. However, while governments have devoted many resources to fostering e-Government adoption by its citizens, the impact of these policies remains unclear. Moreover, many international organizations (the United Nations, World Bank) recommend the introduction of e-Government programs (UN 2010; World Bank 2009), without evidence of their impact on citizen adoption.

This article addresses the way in which governments promote the use of e-Government by investing in more and better services, focusing on the effect of this investment on e-Government adoption levels by citizens. Using data from European countries, measured in 2007 and 2009, a Bayesian linear model is fitted in order to assess the adoption of e-Government against Internet adoption and e-Government supply. The results show strong evidence of a clear link between e-Government supply and adoption. By estimating the potential impact of e-Government and the conditions that favor its adoption, this article aims to help policy makers decide the level of investment and the best moment to achieve their goals. The analysis takes account of the fact that institutional factors, such as having a culture of transparency in the administration or higher trust in the government, may play a role in the way in which e-Government is adopted.

This article also argues that it is important to take into account the moment and conditions under which policies are introduced, in order to increase their effectiveness. Based on the empirical findings, it shows that the best strategy for a government is to focus its efforts on raising the Internet adoption level of the general population, and only once a critical mass of Internet adopters has been reached, to then focus efforts on providing more and better e-Government services. This argument relies not only on efficiency (lower impact attained if there are too few Internet adopters), but also on social justice (investing in a service that only a few citizens would be able to use).

The next section discusses the determinants of e-Government adoption and presents the research hypotheses. Data and methods used for empirical validation are then presented, followed by a discussion of the results. The last two sections discuss the policy implications and conclusions.

e-Government Adoption

In June 2005, the European Commission developed a new frame for the Information Society (i2010) termed "A European Information Society for Growth and Employment" (European Commission 2005). The document, among other things, presented an overview of the development of the Information Society in Europe after the launch of "eEurope 2005" in 2003 (eEurope 2005). Addressed to member state governments, it recommended enhancing the development of e-Government policies in order to achieve the society of "growth and employment" of the report's title.

The definition of e-Government used in this article is somewhat restrictive, in that it does not include political participation, and is focused on a single channel and a single target (avoiding business to government relations or inter-governmental relationships). e-Government is considered here as the delivery of public services (services) using the Internet (channel) between public administrations and citizens (impact) for personal purposes (use). This definition most accurately reflects the indicator used by the European Union to compare performance in e-Government supply between member states. Note that by limiting e-Government to the Internet channel, its adoption level cannot be greater than the level of Internet adoption.

Patterns of diffusion of an innovation are associated firstly with the characteristics of individuals—such as their familiarity with the innovation, their status, position in the network, and personal and socioeconomic characteristics (Wejnert 2002). These socio-demographic factors are considered to be the determinants of the "digital divide": one of the major concerns for international bodies such as the United Nations (UN), the Organisation for Economic Cooperation and Development (OECD), and the European Union (EU) with respect to technology adoption (United Nations 2005; OECD 2001; European Commission 2005).

Although there is a large volume of literature on the effects of public intervention on reducing the digital divide associated mainly with the Internet (Milner 2006; Guillén and Suárez 2005; Gil-Garcia, Helbig, and Ferro 2006), much less attention has been paid to the inequalities that result from public promotion of e-Government services. Despite the efforts made by governments, little attention has been paid to capturing the effects of e-Government adoption policies in Europe; neither have the relationships between Internet adoption, e-Government supply, and e-Government adoption been deeply analyzed empirically. Does Internet adoption foster e-Government adoption directly? Is this effect mediated by the pre-existing level of e-Government services? Or does e-Government supply, by increasing the utility of Internet use, increase both Internet and e-Government adoption? Also, what role do institutional features

DOI: 10.2202/1944-2866.1093

such as a culture of transparency in public services provision play in the likelihood of governments creating better electronic services, and the way in which citizens adopt those services?

Policy intervention has been reported to have an impact on Internet adoption—at least when the intervention is focused and the policies are somewhat complex (Jordana et al. 2005). However, the link between policy intervention (such as e-Government supply, or more and better services) and e-Government adoption (demand) has not yet been established, and requires clarification. This is particularly important since a technology (i.e., the Internet) mediates between e-Government services and the demand. Among the gaps in the literature on technology diffusion, Stoneman (2002) mentions the "[lack of] work that looks at diffusion as the result of supply and demand interaction" and the "limited literature on multi-technology issues" (Stoneman 2002, 101–102). This article addresses both supply and demand interactions and multi-technology issues.

Relationships Between Internet Adoption, e-Government Adoption, and e-Government Supply

There are various plausible relationships that could be posited between Internet adoption (I), e-Government adoption (eG_a), and e-Government supply (S). Rationales for each are outlined in this section. Given that for each scenario a specific (empirical) value for each of the parameters must hold, some scenarios are found to be implausible and are hence discarded. The hypotheses that follow below are therefore not a direct check for each of these scenarios, but a comparison of the values of the parameters.

One scenario would be to regard the relationship between the above three factors as leading from Internet adoption (I) to e-Government supply (S) and then to e-Government adoption (eG_a). That is, as more people are connected, governments recognize the technology's potential to deliver services. As a result of an increase in e-Government supply, e-Government adoption increases as well (according to the expected benefit, which depends on the number of Internet adopters). That is, the amount of e-Government supply that the government decides to provide is not independent of the level of Internet adoption: the supply is completely mediated by the Internet. This view assumes that governments regard the supply of e-Government as something that is *dependent* on the level of Internet adoption.

$$I \rightarrow S \rightarrow eG_a$$

A second scenario would be to assume that e-Government supply has no effect on e-Government adoption, and that adoption is only explained by the limits of the parent technology. This view regards e-Government adoption simply as a function of Internet adoption. Hence, e-Government adoption levels (eG_a) differ between countries only because they differ in their Internet adoption levels (I), while having a similar proportion of e-Government adopters *among* Internet adopters.

$$I \rightarrow eG_a$$

A third way to understand the relationship is by considering that e-Government supply has a great impact on society; so great that citizens who were not Internet adopters now adopt the Internet because of the appeal of e-Government services. This would link e-Government supply (S) indirectly with adoption (eG_a) through the increase in Internet adoption (I). However, while the impact of e-Government services can be of general interest in society, it is highly unlikely that individuals would base their decisions to adopt the technology only on the basis of the electronically provided government services.

$$S \rightarrow I \rightarrow eG_a$$

Another view, with weaker assumptions, assumes e-Government adoption (eG_a) to be a function of both Internet adoption (I) and e-Government supply (S), independently. It assumes that e-Government supply is fixed and determined by the government, maybe through the level of political will and institutional features of the country, but not determined by the level of Internet adoption. This differential supply affects e-Government adoption in addition to the Internet adoption level. In this scenario, Internet adoption and e-Government supply are independent.

$$S + I \rightarrow eG_a$$

If this last scenario is true, then it must hold that both Internet adoption and e-Government supply explain e-Government adoption. So the following hypotheses must hold:

Hypothesis 1. Supply of more and better e-Government services increases e-Government adoption.

Hypothesis 2. Internet adoption increases e-Government adoption.

DOI: 10.2202/1944-2866.1093

If there is evidence for Hypothesis 1 but not for Hypothesis 2, then only the first scenario is possible ($I \rightarrow S \rightarrow eG_a$). If there is evidence for Hypothesis 2 but not for Hypothesis 1, then the second and third scenarios are supported ($I \rightarrow eG_a$ and $S \rightarrow I \rightarrow eG_a$). If evidence is found for both Hypothesis 1 and Hypothesis 2, then the last scenario must hold ($S+I \rightarrow eG_a$).

Finally, in addition to the mechanism by which Internet and e-Government supply transfer their importance to e-Government adoption, it is plausible to think that e-Government supply has the same effect at different levels of Internet adoption. That is:

Hypothesis 3. The effect of e-Government supply on the adoption of e-Government is constant at any given Internet adoption level.

Institutional Factors Affecting e-Government Adoption

Blakemore and Lloyd (2007) find that although e-Government supply is important for the adoption of e-Government, institutional characteristics—such as transparency and trust—are also important. In their words, "[w]hile investment in infrastructure and e-Government service development is fundamental to service delivery, the governance characteristics of transparency and trust are critical in legitimating the investment and in creating the conditions for widespread usage of services" (Blakemore and Lloyd 2007, 4). Gefen et al. (2002) and Warkentin et al. (2002) analyze the individual components of e-Government adoption and find that citizen trust is the most important predictor of individual adoption. Carter and Bélanger (2005) find that trustworthiness has an effect on intention to adopt e-Government services, but not on current use. In a recent article, Grimmelikhuijsen (2010) finds evidence that individuals with greater exposure to information are less likely to trust local councils in their decision-making processes.

The literature, therefore, is not very clear about the direction between transparency and trust, and adoption of electronic services. It is even less clear what the underlying mechanism might be through which transparency may foster e-Government adoption. This may simply be that more transparent societies and governments are less hesitant about privacy concerns, so they therefore invest more resources on more and better e-Government services. In this case, transparency would not be linked directly to e-Government adoption, but only through the provision of services. In any case, in order to account for the effect of e-Government supply on its adoption, a control for transparency and trust must be added. Moreover, although at the individual level it seems clear that trust and transparency is a major explanatory variable for e-Government adoption, it remains unclear whether this relationship also holds when data at the aggregate level are used.

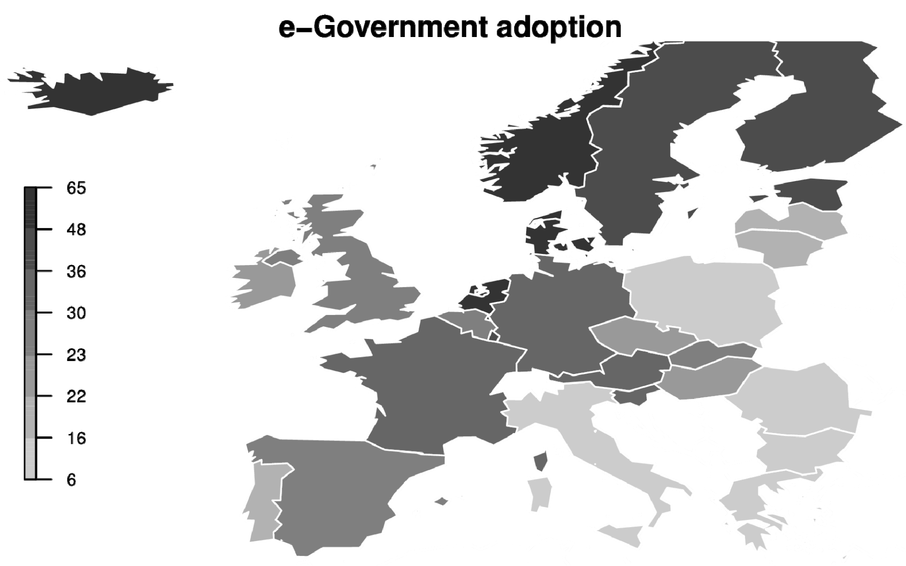
Data and Methods

This section presents the data sources employed to create the variables, the model specification, discusses the priors, and briefly explains the estimation technique.

Outcome Variable: e-Government Adoption

e-Government adoption is measured as the percentage of individuals "who have used the Internet, in the last 3 months, for obtaining information from public authorities websites," with respect to the general population (see the Appendix for detailed information about data sources). Figure 1 presents the spatial distribution of e-Government adoption in Europe in 2009. It ranges from 6 to 65 percent of the population. Lower values tend to correspond to Eastern European countries, while the Nordic countries show the highest values.

Figure 1. Distribution of e-Government adoption in Europe (2009). *Source*: Eurostat (2010)



e-Government adoption has been measured in Europe since 2003 by Eurostat (see the Appendix). Unfortunately the data present some problems when used in a research design. First, the time series is complete for only a few countries.

Second, there are years in which this measure is not reported for any of the countries. Rather than impute missing value information, this article therefore presents a fixed picture of the distribution of e-Government in 2009. While the temporal dynamics have been removed, the variation of e-Government adoption between countries in this dataset is higher—there are limited data for the first years, and they are only available for countries with high e-Government adoption. Limiting the temporal scope therefore widens the variation of the outcome. Data for e-Government supply in Croatia and e-Government adoption in Switzerland are missing, and both have been excluded from the analysis. The final dataset contains 29 observations of e-Government adoption in 2009.

The advantage of restricting the sample to European countries is that a single data source is used, hence making indicators directly comparable and avoiding the problems of using many different sources (for example, definitions of Internet users differ between international agencies: restricting the analysis to Europe avoids this problem).

Covariates

The covariates used in the analysis are Internet adoption, e-Government supply, and transparency level. For robustness checks, a model controlling for wealth (GDP per capita) and education has also been specified. Internet adoption is measured as the percentage of individuals using the Internet at least once a week. The indicator measures the online availability of 20 basic public services of public authorities such as central, regional and local governments, police, and social security organizations (Eurostat 2010). It is the standard measure of governmental effort in meeting the objectives of the i2010 initiative, with availability understood in four levels of sophistication (information, one-way interaction, two-way interaction, and full electronic service). The indicator ranges from 0 to 100, but the observed values are only between 15 and 100. It has been centered to the mean and divided by 100, so values between −0.45 and 0.40 are obtained.

Transparency measures the degree of perceived transparency in the society, using the Corruption Perception Index 2009 from Transparency International (see the Appendix). It has been rescaled to be between −0.27 and 0.28, with higher values representing countries with less perceived corruption, or more transparency. This variable shows high correlation with GDP per capita, the log of Internet adoption, and the log of e-Government adoption (0.7, 0.87, and 0.86, respectively)—specifying a plausible prior specification may therefore help to disentangle its effect. GDP per capita is measured as deviations from the EU mean, with this reference category being equal to 100, and education is measured as the percentage of the population that has completed at least upper secondary education. Trust in the government is measured on a scale from 0 to 10, and is an aggregate measure deriving from individual surveys in European countries (ESS Round 4 2008). With the exception of the transparency and trust indicators, all indicators come from Eurostat (2010). With the exception of transparency, all the covariates are measured with a temporal lag, corresponding to 2007. Transparency, GDP per capita, and education have been recentered to 0 and rescaled so that the range is equivalent (transparency divided by 10; GDP per capita and education divided by 100). The aim is to explain current levels of e-Government adoption by covariates lagged one point in time (see the Appendix for information about the data). Table 1 presents the summary statistics of the variables. They appear in the scale used in the analysis.

Table 1. Descriptive statistics of the distributions of the variables

	Min.	25%	Mean	Median	75%	Max.	SD
e-Government adoption (2009)	0.06	0.21	0.31	0.27	0.43	0.65	0.16
Internet adoption (2007)	0.22	0.42	0.54	0.51	0.65	0.86	0.18
e-Government supply (2007)	–0.45	–0.15	–0.00	0.03	0.14	0.40	0.22
Transparency	–0.27	–0.16	0.00	0.01	0.15	0.28	0.18
GDP per capita	–0.64	–0.33	–0.00	0.01	0.19	1.70	0.47
Education	–0.46	–0.04	–0.00	0.03	0.12	0.18	0.16

Model Specification

This article aims to explain differences in the levels of e-Government adoption (eG_a) in Europe. This level is constrained to be a number between 0 and 1, representing a percentage of adoption in the population. Diffusion of any innovation follows a well-known S-shape curve; that is, the diffusion is not linear—the effort required to increase the adoption level by a single percent point is higher at lower levels of adoption, and lower at higher levels of adoption. A natural log transformation allows one not only to limit the values that the outcome can take, but also to incorporate the S-shape curve into the model. With a natural log transformation it is therefore assumed that the systematic component has a linear relationship with the log of the level of e-Government adoption. In addition to this, Internet adoption is measured on a scale that can approach but never reach 1, so another natural log transformation must be performed.

DOI: 10.2202/1944-2866.1093

Transforming both measures into log scales leads to a log–log model where the relationship between the outcome and the covariate is described in terms of elasticities: a percentage point change in the covariate is associated with a percentage point change in the outcome. Apart from restricting the levels to be bounded into reasonable values, the use of the log transformation has another desirable property: the level for high values of e-Government adoption is limited to be lower than Internet adoption, which is a realistic assumption. Although this restriction would have been possible by using a logit–logit transformation, this last option forces e-Government adoption to tend to Internet adoption in the asymptotic. This is a strong limitation of the logit–logit model that is avoided using the log–log model, although the logit–logit transformation also allows one to specify the S-shaped curve.

Let y be the natural logarithm of e-Government adoption (y=log(eG_a)) in 2009, I be the natural logarithm of Internet adoption (I=log($Internet_a$)) in 2007, and S be the e-Government supply centered at 0 and T in 2007. The model estimates that y is distributed normally, with a systematic component μ and a stochastic component σ:

$$y \sim N(\mu,\sigma)$$

The systematic component is defined as the lineal addition of the effects of Internet adoption and e-Government supply:

$$\mu=\beta_1+\beta_2 I+\theta S$$

The main parameter of interest is θ, which represents the effect of e-Government supply on the adoption of e-Government, having controlled by the level of Internet adoption and other covariates.

Unequal Variance

Previous model specifications (not shown) have found evidence of unequal variance of the residuals at different levels of education. Since this may lead to inefficient estimates, the model controls for heteroskedasticity. That is, the model tries to capture the fact that e-Government adoption is more variable for those countries that lie at the extremes of educational level (*Ed*=*abs*(education)). This is achieved by letting the stochastic component vary by education:

$$\sigma=exp(\lambda_1+\lambda_2 Ed)$$

It is unrealistic to conceive spatial diffusion for the adoption of e-Government adoption, since individuals are restricted to using their own country's services. Hence, no parameters have been introduced to account for any sort of spatial lag or spatial error structures.

Prior Specifications

Bayesian estimation requires the researcher to supply prior distributions for the parameters in the model, in addition to the data. In a context with few observations (as in this case), it is very useful to specify priors—this being a natural way of introducing additional information into the model that can be used to improve the reliability and stability of the estimated parameters. The estimation process is improved, more efficient estimators are obtained, and possible problems of collinearity are rendered unimportant. The advantages of using prior information to distinguish the effect of two collinear variables in the context of comparative research with sparse datasets have been discussed in Western and Jackman (1994).

The intercept (β_1) is the expected e-Government adoption level in the log scale when e-Government supply is at its mean and the log of Internet adoption is 0 (i.e., when Internet adoption is 1). In this scenario, e-Government adoption can only be positive. Let the parameter be centered at 0.5, implying that when the Internet is fully adopted, e-Government is adopted by 50 percent of the population. This implies a prior centered at $log(0.5)=-0.7$, and let us vary it with a standard deviation of 0.25, which corresponds to 95 percent of the prior density between [0.3, 0.81] in the original percent scale (or [−1.2, −0.2] in the log scale). Although by definition e-Government adoption is not restricted to be less than Internet adoption, in practical terms it is, because any e-Government adopter must also be an Internet user.

If Internet adoption and e-Government adoption were increasing at the same rate, this would imply that the country would have the same percentage of e-Government adopters *among* Internet adopters every time. Hence, the expected effect would be equal to 1 (1 percent increase in Internet adoption increases e-Government adoption by 1 percent—not one percentage point). However, the use of e-Government services requires some Internet skills and a level of formal education (Thomas and Streib 2005; Akman et al. 2005). Hence, it is expected that when Internet adoption rises in the general population, the increase in e-Government services would not increase as much, simply because the latest Internet adopters are less skilled and may find it more difficult to deal with e-Government services. Hence, it is expected that as the Internet becomes more popular, e-Government becomes so as well, but at a lower rate. The effect of Internet adoption on e-Government adoption is expected to be less than one (i.e., a

DOI: 10.2202/1944-2866.1093

1 percent increase in Internet adoption is expected to increase e-Government adoption by slightly less than 1 percent). Let the prior density be centered at 0.9 with a standard deviation of 0.5.

According to the literature, the effect of transparency is commonly expected to be positive. The standard deviation of the variable is 0.18. Let us center the prior at an expected effect equal to increasing e-Government adoption by 50 percent when transparency increases from the minimum to the maximum. That is, four standard deviations lead to an increase of 50 percent (4sd=*log*(1.5)). Its prior uncertainty is about 0.08 standard deviations, implying that 90 percent of the prior density is above 0 (positive effect of transparency).

The rest of the priors are normally distributed, centered at 0 with a huge standard deviation that makes them non-informative about the final location of the parameter. The results have been checked for robustness on prior sensitivity and they do not alter substantively the conclusions.

Formal Model

To sum up, Equation 1 presents the complete model specification:

$$\begin{array}{rcl} y & \sim & \mathcal{N}(\mu, \sigma) \\ \mu & = & \beta_1 + \beta_2 I + \theta S \\ \beta_1 & \sim & \mathcal{N}(-0.7, 0.25) \\ \beta_2 & \sim & \mathcal{N}(0.9, 0.5) \\ \theta & \sim & \mathcal{N}(0, 30) \\ \sigma & = & exp(\lambda_1 + \lambda_2 Ed) \\ \lambda_1 & \sim & \mathcal{N}(0, 30) \\ \lambda_2 & \sim & \mathcal{N}(0, 30) \end{array} \tag{1}$$

Estimation

Bayesian methods for inference and data analysis show clear advantages over more traditional frequentist views, particularly in the context of comparative data. Among the most important characteristics are the ability to model a wide class of data types and complex models, a systematic way to make overt assumptions, the clear and intuitive way (probability statements) in which results are presented, the possibility of updating these statements as new information is obtained, the systematic way in which previous knowledge about the subject is incorporated in the analysis, and a clear way to assess model quality and sensitivity to assumptions (Gill 2002, chapter 1).

The idea of using a Bayesian framework that allows for a more intuitive way of presenting results is particularly relevant for public administration research, with deep implications for social science methodology. Since it has a strong prescriptive orientation, the role of public administration research is not only to *explain* what happens, but also to “inform practitioners and interested scholars about how managerial decisions *should* be made” (Wagner and Gill 2005, 7).

The model has been estimated using Markov chain Monte Carlo methods, more specifically, the Gibbs sampler. JAGS (Plummer 2010) has been used for the estimation, while the chains have been analyzed in R (R Development Core Team 2010) with the coda (Plummer et al. 2010) and boa (Smith 2007) libraries. A total of 200,000 samples of the simulated posteriors have been obtained—and then thinned by 50—under different initial values, with a burn-in period of 50,000 iterations. There is no evidence of non-convergence of the series according to the Geweke test (Geweke 1992). The model specification in JAGS can be found in the Appendix.

Results

The model used here to report the results is the most comprehensive model, having discarded parameters that are statistically and practically different from zero. Keeping those variables in the model would only add noise to the estimation, an important consideration in a context like this one, with little data. Table 2 reports the estimated means, standard deviations, and 90 percent credible intervals (with the lower 5 percent and 95 percent limits, containing 90 percent of the density) of the posteriors of the model parameters, with non-relevant variables excluded. Table 3 shows the results for the model with all the variables.

Table 2. Estimated means, standard deviations, and 90 percent credible intervals of the parameters from model 1

	Mean effects	Standard deviation	Low 5% CI	High 95% CI
Intercept (β_1)	–0.37	0.07	–0.49	–0.25
Internet demand (β_2)	1.40	0.09	1.30	1.50
e-Government supply (θ)	0.38	0.12	0.19	0.59
Intercept (λ_1)	–1.50	0.19	–1.80	–1.20
Education (λ_2)	–2.80	1.30	–4.60	–0.41

DOI: 10.2202/1944-2866.1093

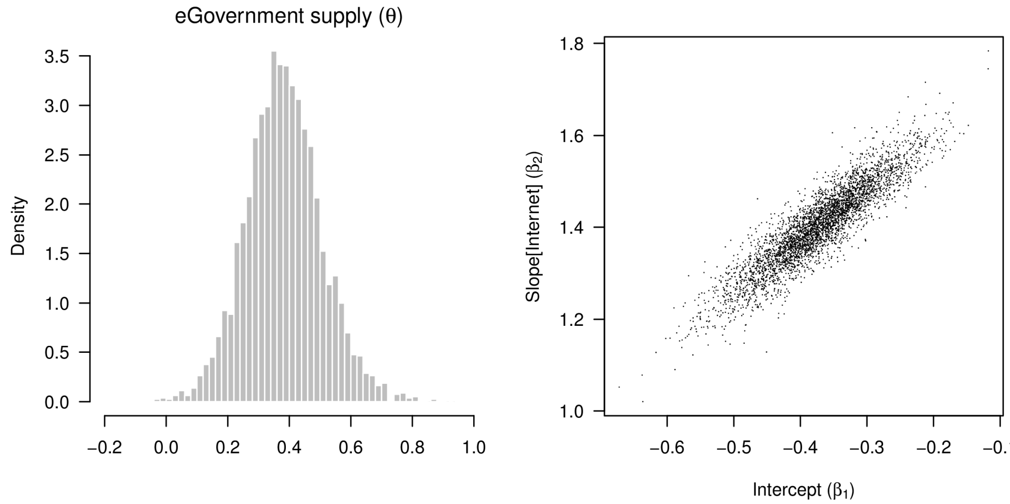
The effects reported in Table 2 are on the log scale of the outcome. The intercept has a mean effect of −0.37, which indicates that for a country with 0.5 Internet adoption and the rest of the variables at their mean, the expected e-Government adoption is $exp(-0.37+1.40*log(0.5))=0.26$. So slightly more than half of the Internet adopters are also e-Government adopters (0.26). When the Internet level reference is 0.05 percent, however, the expected e-Government adoption is much lower ($exp(-0.37+1.4*log(0.05))=0.01$). So in this case, only one in five Internet adopters are also e-Government adopters. The effect of Internet adoption is on the log–log scale, which allows the term to be easily interpreted in terms of "elasticity" or proportional changes in the outcome explained by proportional changes in the covariates. So a 1 percent increase in Internet adoption increases e-Government adoption by 1.4 percent. Results suggest that higher e-Government adoption is associated with the highest levels of Internet adoption, at least for European countries with Internet adoption levels between 0.2 and 0.8.

The effect of Internet adoption on e-Government adoption was expected to be less than one, and a prior was defined accordingly, as explained in the section on prior specifications (Data and Methods). The posterior density of the Internet adoption parameter, however, has most of its density above one. This implies that e-Government is relatively more adopted in countries with yet more Internet adopters; not only in absolute terms but also in relative terms. That is, countries with higher levels of Internet adoption are more likely to have a higher percentage of e-Government adopters than countries with fewer Internet adopters.

The effect of e-Government supply is captured by θ, which represents the main parameter of interest. Its effect is centered on 0.38 with a 90 percent credible interval between 0.18 and 0.59. This means that increasing the supply of e-Government by 0.20 percentage points (which corresponds to an increase of approximately one standard deviation) multiplies the adoption of e-Government by $exp(0.38*0.20)=1.08$. In other words, an increase in the e-Government supply indicator of 20 points is associated with an 8 percent increase in e-Government adoption. Figure 2a shows the density of the θ parameter. It can be seen that almost all the density is on the positive side, centering around 0.38.

Hypothesis 1 stated that there is a positive link between the government provision of more and better e-Government services, and e-Government adoption by citizens. The support for Hypothesis 1 according to the model in Equation 1 is 99.8 percent. The supply of e-Government services therefore has an effect on the adoption of e-Government.

Figure 2. (a) Posterior of the effect of e-Government supply on the adoption of e-Government. (b) Densities of the posteriors for the Intercept and the slope for the effect of Internet adoption. Notice that both parameters exhibit a high correlation. *Source*: Estimated from the model in Equation 1



The λ parameters (Table 2) account for the fact that there is heteroskedasticity in the model. The parameter, associated with the absolute value of education levels, is positive. This finding indicates that for countries with education far from the EU mean, the expected residual of the e-Government adoption is lower than for countries at the mean. In other words, the model predicts well those cases that are countries with either high or low levels of formal education, but predicts poorly the cases with mean levels.

Finally, Hypothesis 3 (that the effect of e-Government supply on the adoption of e-Government is constant at any given Internet adoption level) is not directly interpretable from the model parameters. Figure 3 presents the differential effect of e-Government supply over the range of Internet adoption levels. It shows the expected difference that a 40 percentage point increase in e-Government supply makes on e-Government adoption. A 40 percentage point increase corresponds to half the range that the variable can take (two standard deviations). It can be observed that the effect is not linear over the Internet adoption range, rising from 1–2 percentage points at the lowest levels of Internet adoption to 10 percentage points at the highest levels of Internet adoption. This finding therefore does not support Hypothesis 3—that is, the effect of e-Government supply on increasing e-Government adoption is not constant for every level of Internet adoption.

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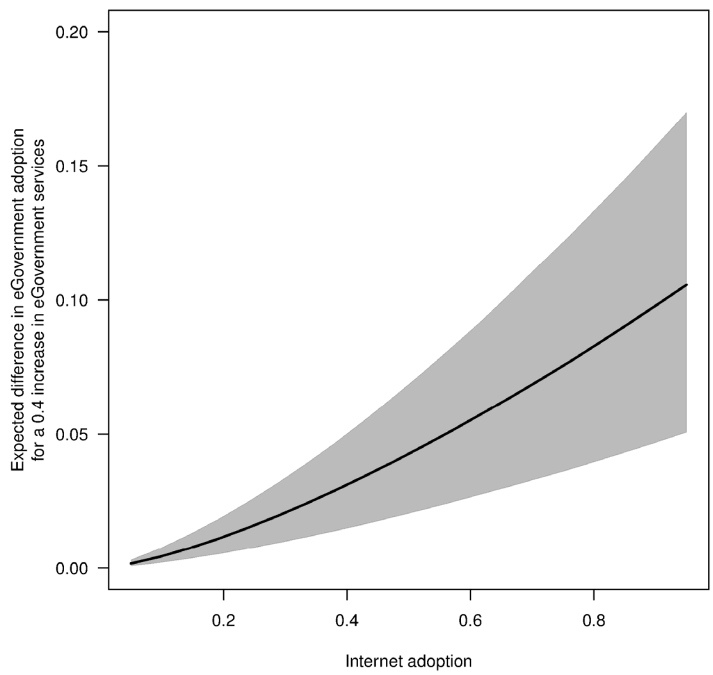
Figure 3. Expected e-Government adoption difference for the whole range of Internet adoption, when the e-Government supply increases by 40 percentage points. Note that at higher Internet adoption levels, an increase in the supply of e-Government services has a larger impact on the percentage of citizens that adopt e-Government. Gray area shows 90 percent credible intervals. *Source*: Computed from the model in Equation 1



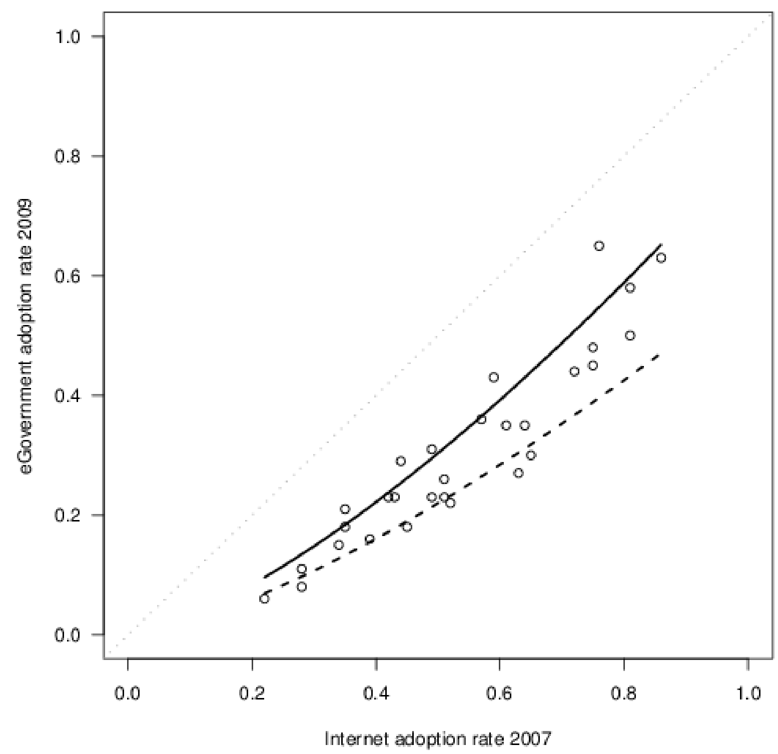
Robustness Checks

Robustness checks include assessing the fit of the model to the data, model comparison, and sensitivity to the prior specifications.

The model fit to the data can be seen in Figure 4, which shows the Internet adoption levels in the EU country dataset in 2007 (*x*-axis) and the e-Government adoption levels in 2009 (*y*-axis). Note that the upper left space delimited by the dotted gray line is the area where it is theoretically not possible to observe any country (i.e., where e-Government adoption is greater than Internet adoption). The dashed black line is the expected fit for countries with the minimum observed value of e-Government supply, and the solid line represents the expected fit for countries with the highest observed value of e-Government supply. Notice again how the difference in e-Government adoption between countries with low and high e-Government supply is greater at the highest levels of Internet adoption.

The model represents the data quite accurately. Aside from the fit of the model to the data, Figure 4 provides a clear way of understanding how e-Government adoption behaves with changes in Internet adoption.

Figure 4. Observed e-Government adoption level (2009) against Internet adoption (2007) level. Lines represent the fitted model with e-Government supply at the minimum (dashed) and maximum (solid) observed values. The dotted gray line represents the situation where all Internet adopters are also e-Government adopters. The lines have been estimated from the results of the model in Equation 1



The results have proved to be quite robust to different settings and model specifications. Table 3 shows the results from a model that includes all the potential covariates. The effect of the parameter of interest (θ, e-Government supply) is 0.37, compared with 0.38 in the working model. The uncertainty, however, is much greater, with a 90 percent credible interval ranging from 0.03 to 0.8 (compared to 0.18–0.59 in the working model). So excluding some variables from the final model does not affect substantively the mean effect of the parameter of interest, which suggests that the model is quite robust.

DOI: 10.2202/1944-2866.1093

Table 3. Estimated means, standard deviations, and 90 percent credible intervals of the parameters from model 1

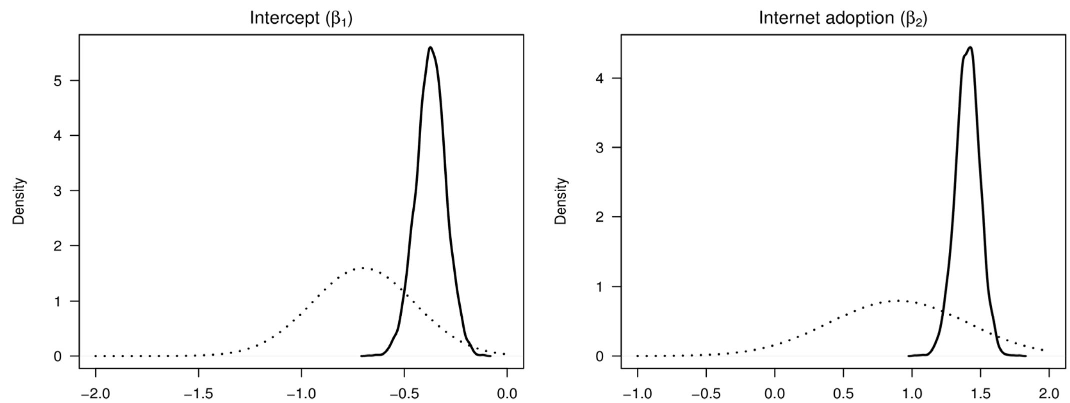
	Parameter mean	Standard deviation	Low 5% CI	High 95% CI
Intercept (β_1)	–0.32	0.13	–0.54	–0.12
Internet demand (β_2)	1.50	0.18	1.20	1.70
Transparency (β_3)	–0.01	0.40	–0.63	0.67
GDP per capita (β_4)	0.03	0.09	–0.10	0.17
Education (β_5)	0.07	0.25	–0.30	0.51
Political constraints (β_6)	–0.66	0.57	–1.50	0.33
e-Government supply (θ)	0.37	0.24	0.03	0.80
Intercept (λ_1)	–1.20	0.44	–1.80	–0.39
abs(Education) (λ_2)	–4.10	2.50	–8.70	–0.38
abs(e-Government supply) (λ_3)	–1.00	1.70	–3.70	1.90
GDP per capita (λ_4)	–0.91	0.91	–2.40	0.49
Transparency (λ_5)	1.40	2.00	–1.80	4.80

All the control variables appear to be either statistically or practically significant, with standard deviations around or even greater than their means. A model with trust in the legal system instead of transparency has been tested (not reported) and does not show any significant difference with the model reported in Table 3. This, again, reinforces the robustness of the model.

The logit–logit specification has also been tested (logit transformations of the e-Government adoption level and the Internet adoption level), with similar results. Support for Hypothesis 1 of a positive link between the government provision of more and better e-Government services and citizen adoption of e-Government is 98.8 percent in this scenario, compared with 99.8 percent under a log–log specification. The parameter for the e-Government supply is not in the same scale as the main model and, hence, the effects are not directly comparable. In this case, a 20 percentage point increase in e-Government supply would multiply the expected e-Government adoption by 9 percent. In any case, the effect holds in a different model specification, supporting the robustness of the results.

The final robustness check addresses the sensitivity of the posterior to the prior specifications. Figure 5 shows the posterior (solid line) and prior (dashed line) densities for the intercept and slope parameters of the model. Note that the specified prior for the slope of Internet adoption was less than one, but the evidence contained in the data has shifted this effect to be greater than one. Moreover, note that the uncertainty of the posterior is lower, because the data have provided evidence of its final distribution. The effect of transparency has proved to be quite close to the posterior, but without much increase in its precision, suggesting that the data incorporate little evidence of this effect to be able to shift the posterior or to narrow its uncertainty.

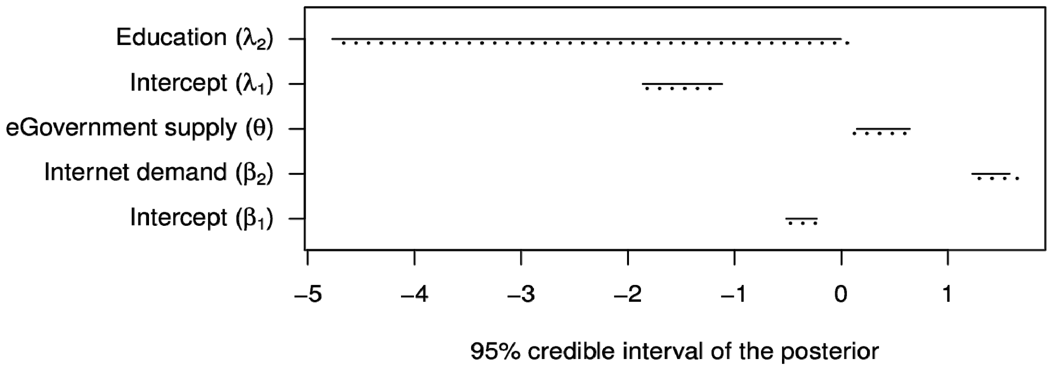
Figure 5. Posterior density (solid line) and prior (dashed line) for the Intercept and slope parameters of the model in Equation 1



Apart from comparing the prior and posterior distributions after fitting the model, it is important to compare the resulting model with another specified with uniform priors. Figure 6 provides a comparison of the 95 percent credible intervals of the posteriors of the model (solid line) with the same intervals for a model specified with uniform priors (dashed line). The density of the main parameter of interest (θ) is virtually identical in both models, increasing again the robustness of the conclusions. The first thing to notice is that specifying non-uniform priors for the β parameters has helped to narrow their uncertainty. The effect of Internet adoption on e-Government adoption appears to be slightly lower in a model with uniform priors (the dashed line is shifted towards 0). However, no results change substantively, providing additional evidence for the robustness of the model.

DOI: 10.2202/1944-2866.1093

Figure 6. 95 Percent credible interval for the posteriors of the model with informative priors (solid lines) and the model with uninformative uniform priors (dashed lines)



Discussion

This article has presented empirical evidence for e-Government supply having an effect on e-Government adoption. This effect is robust when controlling for GDP per capita, education, transparency, and Internet adoption. Moreover, e-Government adoption rises more steeply than Internet adoption. So although Internet adoption must come first, and a certain level of Internet adoption must be attained, e-Government adoption increases relatively quicker than Internet adoption.

Figure 4 complements the results from Table 2, showing the expected e-Government adoption level against the Internet adoption level, for a country with the highest observed level of e-Government services (solid line) compared with a country with the lowest observed level of e-Government services (dashed line). The figure shows an important feature of the data: the difference that e-Government supply generates in the expected adoption of e-Government is higher at high levels of Internet adoption. This is a relevant finding, since it suggests that public investment in e-Government services has a different impact at different stages of Internet adoption. So for a country with, say, 20 percent Internet adoption (in the minimum of the range of Internet adoption observed in Europe), having the minimum or the maximum index of e-Government supply results in only a small difference in e-Government adoption, whereas for a country with 80 percent Internet adoption, this difference results in a much greater impact.

The results from Figure 3 suggest that governments must choose the right moment to invest carefully in e-Government services in order to achieve certain outcomes. The best strategy for a government is to focus its efforts on encouraging citizens to get online, and once a critical mass of Internet users has been reached, to focus its efforts on more and better e-Government services. Unless there is a high enough initial level of Internet adoption, investing in e-Government is a non-optimal allocation of resources.

The practical policy recommendations can be more easily understood by inspecting Table 4. The first column shows the predicted increase in e-Government adoption when the government increases its e-Government supply from its current value to the maximum of the e-Government readiness index. Note that countries with expected negative change (Austria) are those for which e-Government supply is already at, or very close to, the maximum. Note also that the 50 percent credible intervals overlap 0 in some cases. By contrast, the third column shows the predicted change in e-Government adoption if Internet adoption were raised by 10 percentage points. The table provides a clear way of comparing the counterfactuals of what would happen to e-Government adoption if the government focused its efforts on increasing the e-Government supply, in contrast to what would happen if efforts centered on achieving higher Internet adoption. For example, Iceland would increase its e-Government adoption by 7.8 percentage points by increasing its supply of e-Government services to the maximum, whereas e-Government adoption would increase by 6.1 percentage points if there were a 10 percentage point increase in Internet adopters. Whether it is easier for Iceland to increase e-Government adoption by its citizens by focusing on e-Government supply or on Internet adoption—and also the associated costs—will depend on the policy choices of public decision makers.

DOI: 10.2202/1944-2866.1093

Table 4. Predicted change in the adoption level of e-Government (2009) if countries had raised the supply of e-Government services to the maximum in 2007 (columns one and two), or if the countries had raised Internet adoption by 10 percentage points (columns three and four).

	Δ e-Gov. supply	50% CI	Δ Int. adoption	50% CI	e-Gov supply
Iceland	11.00	(3.6, 20)	9.50	(2.3, 17)	50
Luxembourg	11.00	(4, 18)	7.80	(1.8, 14)	40
Latvia	7.60	(3.9, 11)	6.90	(3.7, 10)	30
Netherlands	7.50	(−0.6, 17)	9.70	(1.4, 20)	63
Denmark	7.30	(0.022, 16)	9.00	(1.9, 17)	63
Slovakia	6.70	(3.6, 10)	7.00	(4, 9.9)	35
Finland	6.50	(0.088, 14)	9.20	(2.8, 16)	67
Lithuania	5.90	(3.1, 8.7)	6.60	(4.1, 9.3)	35
Belgium	5.80	(0.6, 12)	8.10	(2.4, 14)	60
Ireland	5.50	(1.4, 10)	7.30	(3.1, 12)	50
Poland	5.30	(3, 7.8)	6.00	(3.8, 8.5)	25
Hungary	5.20	(1.6, 9.3)	7.20	(3.5, 11)	50
Norway	4.90	(−2.2, 13)	9.90	(1.8, 19)	78
Sweden	4.50	(−0.92, 11)	9.20	(3.3, 16)	75
Estonia	4.00	(0.57, 8.1)	8.50	(4.4, 13)	70
Germany	4.00	(−0.42, 9)	8.70	(3.9, 14)	74
France	3.90	(−0.86, 9.2)	8.40	(3.4, 14)	70
Czech Republic	3.80	(1.6, 6.2)	7.00	(4.7, 9.8)	55
Bulgaria	3.70	(1.8, 5.8)	5.20	(3.4, 7.4)	15
Cyprus	3.60	(0.9, 6.6)	6.30	(3.3, 9.9)	45
Spain	2.80	(0.75, 5.1)	7.60	(5.2, 10)	70
Greece	2.60	(1.1, 4.2)	5.80	(4.1, 7.7)	45
Romania	2.10	(0.78, 3.7)	5.10	(3.5, 7)	35
Italy	1.90	(0.39, 3.6)	6.80	(5, 9)	70
United Kingdom	1.60	(−4.1, 8.7)	9.50	(2.2, 18)	89
Slovenia	0.98	(−2.1, 4.6)	8.50	(4.5, 13)	90
Portugal	0.65	(−0.13, 1.5)	7.50	(6.4, 8.6)	90
Malta	0.41	(−0.52, 1.4)	8.20	(6.8, 9.8)	95
Austria	−0.15	(−4.6, 5)	9.30	(3.4, 16)	100

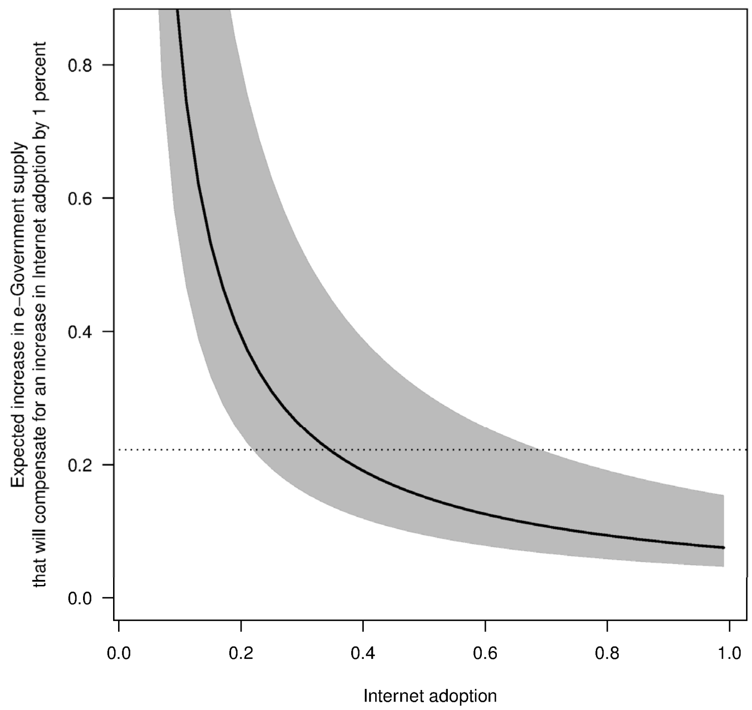
Notes: Median of the prediction and 50 percent credible interval. Countries are sorted by higher increase in e-Government. Notice that prediction intervals are wider than expected intervals, since the uncertainty associated with the model (and not only with the parameters) is also introduced in the estimation. Estimated from the model in Equation 1. The last column is the observed level of e-Government supply.

The counterfactual information presented in Table 4 provides a useful tool for policymakers in decision making, and again stresses the necessity of choosing carefully the moment at which policies are carried out. Given that there is a low impact on e-Government adoption at the early stages of Internet adoption, it may be desirable to invest in achieving higher Internet adoption before serious investment in e-Government is considered. Obviously, this only applies if the aim of the policy is to have an impact in terms of technology adoption: there are many desirable impacts resulting from investment in e-Government (for example regarding regime accountability) that may be more important for policies. But in terms of outcomes, the message here is to focus first on Internet adoption.

Another view of the comparison between increasing Internet adoption and e-Government supply in order to obtain an increase in e-Government adoption is to account for the "compensation" effect. That is, to calculate, at every stage of Internet adoption, the expected increase in e-Government supply that would compensate for an increase of 1 percentage point in Internet adoption. The compensation point is therefore the threshold which equates the effort needed to raise Internet adoption by 1 percentage point or the unknown quantity of e-Government supply. Figure 7 presents the compensation effect. It shows that e-Government supply must increase by slightly more than 0.2 when Internet adoption is around 0.3 in order to achieve the same effect resulting from a one point increase in the Internet adoption level. The same effect, however, can be achieved by raising e-Government supply only by 0.1 when Internet adoption is around 0.8 of the population. At the lowest levels of Internet adoption, however, the increase in e-Government supply hardly compensates for the changes in Internet adoption.

DOI: 10.2202/1944-2866.1093

Figure 7. Expected increase in e-Government supply that will compensate for an increase in Internet adoption by 1 percent, with 90 percent credible interval (gray shading). The horizontal line is set at one standard deviation of the e-Government supply variable. The y-range accounts for the total observed variation of e-Government supply



Summary of the Results

This article has shown that high Internet adoption levels are associated with higher e-Government adoption levels. So it seems that the demographic explanation, which states that the Internet adoption laggards are individuals with less formal education and fewer technical skills, is hard to maintain. A possible interpretation may be that countries with higher Internet adoption levels are usually those in which individuals have been exposed to the Internet the longest. Veteran, more experienced Internet adopters are also less likely to mistrust the Internet, and are therefore more likely to use it for communication with the administration.

The role of transparency on e-Government adoption must also be considered. Countries with higher perceived transparency were expected to show higher levels of e-Government adoption. But our results have proved that once controlling for Internet adoption, what really matters in explaining e-Government adoption is not transparency, but the supply of e-Government services. That is, the findings suggest that if transparency has an effect on e-Government it does so by altering the supply of e-Government, and not by affecting its adoption. So the link between the variables is as follows: there is a certain degree of transparency in a country that causes the government to invest in more (high transparency) or fewer (low transparency) e-Government services. It is this supply which explains why countries have higher or lower levels of e-Government adoption, not the transparency itself. However, more research is needed to fully support this view, and to help clarify the institutional features in a country that favor the introduction of e-Government.

Blakemore and Lloyd (2007) have suggested that both e-Government supply and institutional characteristics are important. The empirical findings, however, tell a different story: there is direct evidence that e-Government supply has an effect on e-Government adoption, and indirect evidence that transparency is not linked directly to e-Government adoption, but to e-Government supply.

The data used only cover democratic EU countries, which show relatively small variation in some of the variables, compared with other regions and countries in the world. This makes the results somewhat limited in scope for all regions and countries. But many lessons can be extracted, at least for developing countries that aim to foster the development of electronic services.

Future research may make use of more data regarding the temporal dimension of the adoption process, and testing relationships between variables over time. Capturing the temporal dynamics may offer a more detailed estimate of the effects of e-Government supply on adoption. More research is also needed to clarify the determinants of e-Government supply. As has been mentioned, e-Government supply may be determined by transparency, as suggested by the results of this article or by other institutional features.

Conclusions

This article has presented empirical evidence of the impact of e-Government policies in EU countries on adoption of e-Government services by citizens. An increase of 20 percentage points in the standard scale of e-Government availability has an expected increase of 8 percent in citizen adoption of e-Government services. Moreover, the expected increase of e-Government adoption due to increased supply of e-Government is higher in countries with high Internet adoption levels.

DOI: 10.2202/1944-2866.1093

Institutional features such as government transparency are usually linked to higher e-Government adoption (Blakemore and Lloyd 2007). But the findings presented here suggest that there is no direct link between greater institutional transparency and a higher e-Government adoption level. The determinants of the e-Government adoption are both the level of Internet adoption and the strength of governmental supply.

The results emphasize the importance of selecting the right moment to launch a policy that aims at increasing the diffusion of a new technology. In the case of e-Government adoption, it has been found that policies favoring electronic services have the highest impact when there is already a critical mass of Internet adopters who may be willing to adopt it. Otherwise, the impact in absolute numbers is low. The evidence that increasing e-Government demand (and adoption) is not simply a matter of the public supply of services is a signal for policymakers to approach the challenges of e-Government and the Internet in a more comprehensive way, involving integration of their policies and planning of public interventions.

Appendix

Data Sources

e-Government adoption: Individuals using the Internet for interaction with public authorities (isoc_pibi_igov). http://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=isoc_pibi_igov&lang=en.

Internet adoption: Individuals using the Internet, accessed, on average, once a week. http://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=isoc_pi_a2&lang=en.

e-Government supply: E-government availability (supply side) (isoc_si_sseg). http://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=isoc_si_sseg&lang=en and http://epp.eurostat.ec.europa.eu/cache/ITY_SSDS/en/tsiir120_esms.htm.

Education: Total population having completed at least upper secondary education—[tps00065]. http://epp.eurostat.ec.europa.eu/tgm/table.do?tab=table&init=1&language=en&pcode=tps00065&plugin=0.

Transparency: Corruption Perception Index, Transparency International. http://www.transparency.org/policy_research/surveys_indices/cpi/2009/cpi_2009_table.

Model specification in JAGS/BUGS

Model in Equation 1.

```
data {
  for (c in 1:C) {
    li[c] <- log(D[1,c,3]/100)                      # log of Internet adoption
    le[c] <- log(D[2,c,2]/100)                      # log of eGovernment adoption
    es.c[c] <- (D[1,c,1] - mean(D[1,,1])) / 100    # eGovernment supply centered at mean
    educ.c[c] <- (D[1,c,7] - mean(D[1,,7])) / 100  # education centered
  }
}

model {
  for (c in 1:C) {
    le[c] ~ dnorm(mu[c], tau[c])
    mu[c] <- beta[1]
           + beta[2] * (li[c])
           + theta[1] * (es.c[c])
    tau[c] <- pow(sigma[c], -2)
    sigma[c] <- exp(lambda[1] + (lambda[2] * abs(educ.c[c])) )
  }

  # priors for heteroskedastic component
  for (l in 1:2) {
    lambda[l] ~ dnorm(0, 0.001)
  }

  # informative priors
  beta[1] ~ dnorm(-0.7, 16)
  beta[2] ~ dnorm(0.9, 4)
  theta[1] ~ dnorm(0, 0.001)
}
```


DOI: 10.2202/1944-2866.1093

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