Cross-National Heterogeneity in Online Advertising: A Panel Data Analysis of the Effect of Data Privacy Laws

Full Paper

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Abstract

There is large cross-country variation in the development of the online advertising industry and market. This paper’s primary objective is to provide theoretical and empirical evidence demonstrating the role of the strictness of data privacy regulations on online ad spending. An empirical analysis of data for forty economies for a nine year period (2003-2011) indicated that the strictness of data privacy laws is negatively related to online ad spending. Further analyses indicate insignificant effects of the strictness of data privacy regulations on per capita ad spending across all media as well as on per capita non-online ad spending. Our findings thus suggest that strict data privacy laws influence online advertising in a way that is unique to this form of advertising.

Keywords: data privacy laws; online advertising; cloud-based advertising; the European Union Data Protection Directive; time-series cross-sectional (TSCS) models

Introduction

According to eMarketer, businesses worldwide spent US$102 billion in online advertising in 2012 (emarketer.com, 2013). Likewise, Gartner predicted that from 2013 to 2016, US$677 billion will be spent on cloud services globally of which $310 will be spent on cloud advertising (StorageNewsletter.com, 2013). There is, however, large cross-country variation in the development of the online advertising market. For instance, per capita online ad spending in the economies analyzed in this paper varied from US$0.10 in India to US$160 for Norway.

Scholars have shown that there is an increasing concern about data privacy (Eastlick et al., 2006; Rapp et al., 2009). We show that strict data privacy laws may constrain the abilities of advertisers and advertising providers to effectively utilize online advertising. For this purpose, we provide a comparison between the European Union (EU) economies and the U.S. Thanks to the U.S. fair use doctrine, digital advertising providers such as Google have a wider latitude in the U.S. to provide enhanced search engine services and effectively utilize user created content. Such activities are severely restricted in the EU economies. In December 2012, Google settled a copyright infringement suit with Belgian newspapers for about US$6.5 million worth of ad inventory (Levine, 2013). Likewise, in February 2013, Google settled another dispute regarding whether it should pay to display news content in its search results. Overall, data privacy laws influence online advertising in a way that is unique to this form of advertising.

This paper’s primary objective is to provide theoretical and empirical evidence demonstrating the role of the strictness of data privacy regulations on online ad spending. We use the EU’s Data Protection Directive as an important benchmark to assess the strictness of data privacy laws.
Data privacy and online advertising

A number of mechanisms can contribute to the relative unattractiveness of online advertising for potential advertisers in economies with strict data privacy regulations. From the perspective of an online advertiser, for instance, the EU’s strict data privacy laws often lead to unavailability of, and low quality information about consumers, which would hamper effectiveness of advertising and discourage online advertisers.

In order to illustrate the above point, we consider the rapidly growing apps market, which has greatly facilitated online advertising through mobile devices. For instance, Apple sold its 50 billionth app in May 2013 and in July 2013, Google announced that downloads of its Android apps crossed 50 billion. Advertisers are increasingly relying on the apps to reach their target consumers. According to an estimate of the research firm Strategy Analytics, advertisers spent about $3 billion on in-app advertising in 2012 and consumers spent more than $26 billion purchasing apps (Prodhan, 2012).

Leontiadis et al.’s (2012) analysis of more than 250,000 apps in the Android Market indicated that 73% of them were free, and the business models of 80% of the free apps relied mainly on targeted advertising as (Leontiadis et al., 2012). It is also worth noting that free apps have drastically higher rates of download than paid apps. For instance, Leontiadis et al. found that only 20% of paid apps were downloaded more than 100 times and only 0.2% of such apps had more than 10,000 downloads. On the contrary 20% of free apps were downloaded 10,000 times or more.

The effectiveness of an online advertiser is tightly linked to the amount and quality of information on the user. In an in-app ad framework, the collection of information on users is typically delegated to the target app. The app then feeds the information to the advertiser (Leontiadis et al., 2012). Information collected by the apps included a user’s location, phone number, contacts, as well as more sensitive data such as e-mail messages, SMS, contacts, calendar, phone number and IMEI (Leontiadis et al., 2012).

Regulators’ tolerance levels towards the collection of personal and sensitive data by online advertisers and app developers are expected to vary widely. While most governments have not yet addressed this issue, EU regulators have been quick to point out that when app developers allow third parties’ access of user data (e.g., an ad network accessing a device’s geo location data to deliver contextual or behavioral advertising), they must employ sufficient mechanisms to comply with the EU legal framework. In its February 2013 report, European Commission’s Article 29 working group on data protection has expressed its opinion that “whenever a party involved in the development, distribution and operation of apps is deemed to be a controller, such a party is responsible, alone or jointly with others, for ensuring compliance with all the requirements set forth under the Data Protection Directive” (Article 29 Data Protection Working Party, 2013).

There are at least three critical reasons that would explain why strict data privacy laws may hamper the growth of online ad spending:

Amount of information on consumers

In economies with strict data privacy regulations, online advertising providers are often unable to attract consumers who would view and/or click on online ads. We demonstrate this by highlighting relationship between public cloud spending and online ad spending. According to Gartner, public cloud revenue for “business process services” was US$60.3 billion in 2010, of which “cloud-based advertising services” was US$36.5 billion. The growth in cloud-based advertising is driven by the free availability of a variety of cloud-based applications such as photo-sharing websites (Flickr, Picasa), web-based e-mail (Gmail, Hotmail), and office software suites (Google Docs), which generate revenues for the cloud providers through advertising (Berry and Reisman, 2012). Cloud providers offer these services for free in exchange of accurate and detailed information on users, which is used by advertisers to make decisions about the selection of target audience. Cloud providers have a low degree of incentives to provide such services in economies that have regulatory restriction on their ability to collect information on users. This means that online advertisers are likely to have limited potential reach of target audience in markets with strict data privacy laws. A high degree of strictness of data privacy regulations may thus result in low degree of attractiveness of free services.
Quality of information on consumers

Advertisers will need access to high-quality information on consumers for informed decision making. In this regard, the second observation is that strict data privacy laws would result in low quality of information on consumers, which would reduce the effectiveness of online advertising. For instance, as some categories of people are more active and aware of their privacy rights than others, the removal of data on certain types of people may make the dataset skewed and incomplete (Graham, 2012).

Costs associated with acquiring consumer information

In general, strict data privacy laws may result in higher costs for online advertising providers, which would translate to higher costs for online advertisers. For instance, the EU laws may allow individuals to ask advertisers and advertising services providers to remove or refrain from processing personal data (Graham, 2012). For instance, the "right to be forgotten" clause in the EU’s privacy proposal would force social networking websites such as Facebook and Twitter to remove private data on individuals if they ask to do so. Likewise, it is argued that search engines such as Google are required to removing search results on individuals (Whittaker, 2013). The requirement to comply with individual requests could result in an increased cost for an advertiser.

Methods

Our unit of analysis is a national economy.

Dependent Variable

The dependent variables are online ad spending, ad spending across all media and non-online ad spending, all per capita.

Explanatory Variables

The explanatory variable is a dummy variable that measures whether an economy has strict data privacy laws (SDP). More specifically, as noted earlier, the EU’s Data Protection Directive served as the criterion for the dummy explanatory variable. The Directive, which came into force in 1995 (95/46/EC) has been the major legislative instrument for the protection of consumer data in the 27 Member States. The Directive, which was not revised during the period of this study, provides a strict protection of data privacy. One of the key features of the Directive is that it makes it illegal to transfer EU citizens’ personal data to jurisdictions outside the EU that do not provide an “adequate level of protection”. The European Commission has recognized nine economies--Andorra, Argentina, Canada, the Faeroe Islands, Guernsey, Isle of Man, Israel, Jersey, Switzerland, and Uruguay-- that meet the standards set by the Directive. We assigned the value of 1 for the variable related to the strictness of data privacy law if an economy was an EU member for the year under consideration or if it was recognized by the EU that it met the standards set by the Directive, and 0 otherwise. For a newly joined EU member, the value of 1 was assigned for the year it joined the EU and the following years and 0 before becoming an EU member.

Control variables

We used income, political freedom and FDI as control variables. Past empirical studies provide guidance for the choice of control variables. Below we provide the rationales for the three control variables.

Per capita income (GDPPC)

Bagwell and Ramey (1994) argue that a firm that spends on advertising expects greater market share and profit, something that appears to be more likely in a country that has a higher income level and thus a higher purchasing power. Notwithstanding the contrarian arguments of (Leff and Farley, 1980), the level of economic development is likely to be associated with the adoption of modern marketing practices.
including advertising (Chan and Cui, 2004). Ad spending as a proportion of national income can be thus expected to be higher in in economies with higher income.

**Political freedom measured by the civil liberty index (LACKCL)**

It is argued that advertising is the “essence of democracy” (Carter, 1997). Economies with stable democratic institutions are characterized by a higher media penetration and freedom of the press and of speech and consumers’ media literacy, where the efforts to control advertisings are viewed as an infringement on the freedom (Lewis and Jhally, 1998; Martinson, 2005). In authoritarian regimes, on the other hand, there is no unfettered access to media for advertisers. For instance, despite its economic prosperity, Singapore ranks near the bottom on the Paris-based Reporters without Borders’ index of press freedom. In 2006, Singapore banned distribution of Far Eastern Economic Review magazine, arguing that it had not complied with media regulations (Agence France Presse, 2007). In 2008, the country’s Media Development Authority fined a TV operator for a commercial that showed lesbians kissing. Likewise, the Chinese athletes participating in the 2008 Olympic Games faced difficulties to gain TV advertising deals. Chinese government officials proposed to ban athletes’ engagement in advertising and public relations. China’s regulations introduced in 2002 also threatened to fine or shut down Internet publishers and portals disobeying the state’s guidelines. Portals and search engines, which did not follow the guidelines, were banned. Contrast these situations with the U.S., where interest groups such as the American Association of Advertising Agencies have promoted “constitutional protection for commercial speech” and there have been arguments regarding commercial entities’ free speech (Baker, 2004). For instance, firms in the U.S. tobacco industry capitalize on the “free speech” arguments to influence public policy.

**Per capita foreign direct investment (FDIPC)**

Prior researchers have recognized that FDI plays an important role in driving the growth of the advertising industry. From the standpoint of marketing, there is a contrast between local firms and MNCs. While local firms tend to focus on price competition, MNCs spend on expensive ad campaigns and devote more resources to promote their products and establish global brands (Caves, 1982; Ray and Rahman, 2006). This is because globalizing companies with heavy ad spending can create intangible assets such as brand equity that give them a relative advantage over local rivals (Kogut and Singh, 1988; Morck and Yeung, 1991). For MNCs, advertising has been one of the cornerstones to build a uniform global brand image (Duncan and Ramaprasad, 1995).

As another mechanism, Cowling and Tomlinson (2005) suggested that MNCs divert competition away from price towards product/advertising where “retaliatory lags” are longer. For instance, in the automobile industry, Japanese automobile firms (Cowling and Sugden, 1989) and Volkswagen (Kiley, 2007) employed this strategy, which arguably worked (Cowling and Tomlinson, 2005). In this way, a high level of ad spending can elevate entry barriers (Ray and Rahman, 2006).

Evidence from international business (Tahir and Larimo, 2004) and technology management (Cheung and Lin, 2004) literatures suggests that they can also operate in the stimulation of the local advertising industry. MNCs’ operations in an economy, for instance, also lead to a cross-border transfer of marketing skills and technologies enabling advertising (Tahir and Larimo, 2004). Using provincial data, Cheung and Lin (2004) found demonstration effects of FDI on local companies’ innovations in China. Note that demonstration effects arise if the observation of foreign advertisers affects local companies’ advertising.

Compared to local firms, MNCs possess skills and resources needed for effective advertising (Caves, 1982; Ray and Rahman, 2006; Riordan, 2007). For instance, advertising/sales ratio, which is often used as a proxy to measure firm-specific advantages (Delios and Beamish, 2001) is higher for MNCs compared to local firms. Moreover, when industrialized world-based firms invest abroad, transnational advertising agencies tend to expand to host countries to service their home clients. For instance, global agencies such as Leo Burnett’s, Ogilvy & Mather, Bates Asia and Euro serve big Chinese firms.
**Data Sources**

Forty economies were analyzed for which data on dependent and independent variables were available. Tables 1 and 2 present descriptive statistics and the correlation matrix for the beginning and the ending years of the 9-year period (2003 and 2011).

Data related to ad spending, GNPPC and FDIPC were obtained from Euromonitor. Euromonitor data have been used in several studies (Coulter et al., 2003; Kshetri et al., 2007; Blecher, 2010; Kopf and Enomoto, 2011; Kshetri and Bebenroth, 2012). Data on civil liberty index were obtained from the Freedom House’s Annual Surveys of Political Rights and Civil Liberties. As is the case with Euromonitor data, researchers have used Freedom House’s political freedom related data (e.g., Diamond, 1992; Goldsmith, 1999; Kshetri et al., 2007; Kshetri and Bebenroth, 2012). We have denoted this variable by LACKCL to indicate that a higher value indicates more violation of civil liberty.

**Statistical Analysis**

**Time-series cross-sectional (TSCS) models**

We analyzed annual data for nine years (2003–2011). TSCS models allow for differences in behavior over cross sectional units and also for differences in behavior over time for a given cross section. In this way, such models are likely to be consistent with the way the data were generated (Fomby et al., 1984).

We first employed TSCS models in the following form:

\[
PCOAD_{it} = \beta_{1i} + \sum_{k=2}^{K} \beta_{ki}X_{it} + \epsilon_i \tag{1},
\]

Where,

PCOAD = per capita online ad spending.

\(\beta_{1i}\) is the dummy variable for the \(i^{th}\) country for the \(t^{th}\) time period and \(\beta_{ki}\) (\(k \geq 2\)) are the slopes. \(X_{kit}\) (\(k \geq 2\)) is the value of the predictor \(X_k\) for the \(i^{th}\) country in time \(t\). In order to examine whether the effect of the strictness of data privacy regulations on other forms of ad spending is different, we also estimated (1) for per capita non-online ad spending (PCNOAD) as well as per capita ad spending across all media (PCADALL) as dependent variables.

Several factors need to be taken into consideration in selecting the best TSCS model. The first is the choice between fixed and random effect models. For the fixed effect (or dummy variable) model, the intercept term \(\beta_{1i}\) in (1) can be written as

\[
\beta_{1i} = \alpha_i + \tau_t \tag{2},
\]

where \(\alpha_i\) are the country “dummies” and \(\tau_t\) are the time “dummies”. The dummy variable model, however, eliminates a major portion of the variation among explained as well as explanatory variables if the between-country and between-time period variation is large.

These problems can be overcome by treating \(\alpha_i\) and \(\tau_t\) as random in which case only two parameters corresponding to each, the mean and the variance of the \(\alpha\)'s (and similarly for \(\tau\)'s), are estimated instead of \(N+T\) parameters in dummy variable models, where \(N\) is the number of cross-sections and \(T\) is the number of time periods. The procedure of treating \(\alpha_i\) and \(\tau_t\) as random can be rationalized by arguing that the
dummy variables do in effect represent some ignorance – just like $\varepsilon$. Maddala (1971) argues that this type of ignorance, or “specific ignorance,” can be treated in the same manner as $\varepsilon$. Therefore, the residual can be written as:

$$uit = \alpha_i + \tau_t + \varepsilon_{it} \quad (3).$$

We performed Hausman test comparing the fixed effects and random effects estimators. The Hausman tests indicated that the country-level effects are random and the coefficients estimated by the random effects model are efficient. Hence, we present our results for the period 2003-2011 based on the random effects model in Table 2.

**OLS estimates**

In order to increase validity of the results, we have also reported OLS estimates for cross-sectional regressions for the 2003 and 2011 data, which are the beginning and the ending years for our panel data.

**Results and Discussion**

As the descriptive statistics and correlations matrices of Tables 1 and 2 indicate, there are fundamental differences among the economies analyzed in this article in terms of the explanatory and dependent variables. For our sample, the measurements of variability as indicated by the coefficient of variation ($\frac{S.D}{\text{Mean}}$) for 2003 and 2011 are higher for per capita online ad spending (1.431 and 1.119 respectively) than for per capita non-online ad spending (0.877 and 0.851 respectively).

The TSCS results and OLS estimates for cross-sectional regressions for 2003 and 2011 are presented in Table 3. The variance inflation factors in all regression models reported in Table 3 are all below 3, indicating no multicollinearity.

The TSCS results (Table 3) indicate that our hypothesis is supported ($p < .01$) for online ad spending (Model 8). Similar results have been obtained for OLS estimates for cross-sectional regressions for 2003 (Model 2) ($p < .05$) and 2011 (Model 5) ($p < .1$) data. We also estimated these models for per capita ad spending across all media (Models 1, 4 and 7) and per capita non-online ad spending (Models 3, 6 and 9) as dependent variables. Results in Table 3 indicate insignificant effects of data privacy regulations on ad spending across all media as well as on non-online ad spending. All this has to be contrasted with the control variable per capita GDP, which has significant effect on online ad spending, ad spending across all media as well as non-online ad spending. The results thus suggest that strict data privacy laws influence online advertising in a way that is unique to this form of advertising.

**Limitations and future research**

There are limitations to our analysis. First, online advertising is virtually non-existent in low-income countries. Our sample thus excludes most such economies. A second limitation concerns a dummy variable nature of the explanatory variable. A dummy variable is not able to capture the difference in strictness of data privacy regulations across the countries that take the value of zero or one.

Future researchers can help us better understand the relationship between data privacy regulations and online advertising by addressing some of the above limitations. As online advertising data become available for developing and least developed economies, the generalizability of the model presented in this paper can be tested in the contexts of these economies.

In future research scholars also need to consider cross-national heterogeneity in different categories of online advertising such as Banner, Pop-up and Interstitial as well as online advertising across multiple platforms such as social media and mobile devices. Economic, social and political factors may have differential effects on the various types of online ads.
<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>S.D.</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>PCAD ALL</td>
<td>145.61</td>
<td>128.64</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>PCOAD</td>
<td>4.36</td>
<td>6.24</td>
<td>0.77</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>PCNOAD</td>
<td>141.26</td>
<td>123.88</td>
<td>1.00</td>
<td>0.75</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>GDPPC/1000</td>
<td>17.01</td>
<td>14.84</td>
<td>0.88</td>
<td>0.77</td>
<td>0.88</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>LACKCL</td>
<td>1.85</td>
<td>1.21</td>
<td>-0.61</td>
<td>-0.42</td>
<td>-0.61</td>
<td>-0.62</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>FDI PC/1000</td>
<td>0.74</td>
<td>1.41</td>
<td>0.49</td>
<td>0.32</td>
<td>0.49</td>
<td>0.62</td>
<td>-0.33</td>
</tr>
<tr>
<td>7</td>
<td>SDP</td>
<td>0.45</td>
<td>0.50</td>
<td>0.43</td>
<td>0.22</td>
<td>0.43</td>
<td>0.56</td>
<td>-0.48</td>
</tr>
</tbody>
</table>

Table 1: Descriptive Statistics and Correlation Matrix (2003)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>S.D.</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>PCAD ALL</td>
<td>229.87</td>
<td>195.38</td>
<td></td>
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<td></td>
</tr>
<tr>
<td>2</td>
<td>PCOAD</td>
<td>37.32</td>
<td>41.75</td>
<td>0.80</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>PCNOAD</td>
<td>192.55</td>
<td>163.86</td>
<td>0.99</td>
<td>0.70</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>GDPPC/1000</td>
<td>28.44</td>
<td>23.29</td>
<td>0.84</td>
<td>0.63</td>
<td>0.85</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>LACKCL</td>
<td>1.68</td>
<td>1.16</td>
<td>-0.50</td>
<td>-0.41</td>
<td>-0.49</td>
<td>-0.51</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>FDI PC/1000</td>
<td>1.70</td>
<td>5.43</td>
<td>0.28</td>
<td>-0.06</td>
<td>0.35</td>
<td>0.65</td>
<td>-0.16</td>
</tr>
<tr>
<td>7</td>
<td>SDP</td>
<td>0.58</td>
<td>0.50</td>
<td>0.20</td>
<td>0.06</td>
<td>0.23</td>
<td>0.31</td>
<td>-0.51</td>
</tr>
</tbody>
</table>

Table 2: Descriptive Statistics and Correlation Matrix, Year 2011
Table 3: Longitudinal and cross-sectional regression for per capita online ad spending, per capita ad spending across all media and per capital non-online ad spending as the dependent variables

<table>
<thead>
<tr>
<th></th>
<th>Year 2003</th>
<th>Year 2011</th>
<th>Year 2003-2011</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>GDPFC/1000</strong></td>
<td>8.02</td>
<td>0.46</td>
<td>7.57</td>
</tr>
<tr>
<td></td>
<td>(1.04)***</td>
<td>(0.06)***</td>
<td>(1.02)***</td>
</tr>
<tr>
<td>LACKCL</td>
<td>-12.05</td>
<td>-3.62</td>
<td>-3.62</td>
</tr>
<tr>
<td></td>
<td>(10.47)</td>
<td>(15.32)</td>
<td>(3.61)</td>
</tr>
<tr>
<td>FDIPC/1000</td>
<td>-6.00</td>
<td>-5.66</td>
<td>-6.31</td>
</tr>
<tr>
<td></td>
<td>(8.92)</td>
<td>(8.80)</td>
<td>(3.36)***</td>
</tr>
<tr>
<td></td>
<td>(24.13)</td>
<td>(23.79)</td>
<td>(31.03)</td>
</tr>
<tr>
<td>Constant</td>
<td>49.90</td>
<td>51.67</td>
<td>5.16</td>
</tr>
<tr>
<td></td>
<td>(33.00)</td>
<td>(32.53)</td>
<td>(51.13)</td>
</tr>
<tr>
<td>R²</td>
<td>0.80</td>
<td>0.79</td>
<td>0.84</td>
</tr>
<tr>
<td>N</td>
<td>40</td>
<td>40</td>
<td>40</td>
</tr>
</tbody>
</table>

*p < 0.1; ** p < 0.05; *** p < 0.01
References and Citations


