Macro influencers of electronic health records adoption

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Abstract: While adoption rates for electronic health records (EHRs) have improved, the reasons for significant geographical differences in EHR adoption within the USA have remained unclear. To understand the reasons for these variations across states, we have compiled from secondary sources a profile of different states within the USA, based on macroeconomic and macro health-environment factors. Regression analyses were performed using these indicator factors on EHR adoption. The results showed that internet usage and literacy are significantly associated with certain measures of EHR adoption. Income level was not significantly associated with EHR adoption. Per capita patient days (a proxy for healthcare need intensity within a state) is negatively correlated with EHR adoption rate. Health insurance coverage is positively correlated with EHR adoption rate. Older physicians (>60 years) tend to adopt EHR systems less than their younger counterparts. These findings have policy implications on formulating regionally focused incentive programs.

Keywords: EHRs; electronic health records; adoption; macroeconomic factors; and macro health environment.

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Ravi Chinta, PhD, is a Department Head, Business Administration, College of Business, University at Montgomery, AL. He has 36 years of work experience (14 in academia and 22 in industry). He worked in venture-capital industry, business start-ups and large multi-billion global firms such as IBM; Reed-Elsevier; LexisNexis; and Hillenbrand Industries. He has over 50 peer-reviewed publications in journals such as Academy of Management Executive, Journal of Small Business Management, Long Range Planning, Management Research News, Journal of Technology Management in China, and International Journal of Strategic Business Alliances, etc.

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1 Background and significance

The reasons for state-level differences in EHR Adoption remain largely underexplored. A recent survey of the Center for Disease Control (CDC) confirmed a significant presence of state-level disparities in the adoption of EHRs (Hing and Hsiao, 2012). According to this survey, the percentage of adoption ranged from a high of 83% in North Dakota, to a considerably low rate of adoption in Connecticut and New Jersey with 30% and 21%, respectively. Stateline/Inquirer, reporting on this survey stated that it is unclear why there are disparities in EHR adoptions among states (Vestal, 2014). Our study is an attempt to provide an explanation for these differences in EHR adoption.

Although the adoption of EHR has been studied at many levels, much of the focus in prior studies has been predominantly on the individual and professional factors that cause EHR adoption. Studying factors only at the organisational or individual level may help understanding individual provider level adoption but does not explain the drastic differences in EHR adoption at the state level. While the supply of physicians has exhibited regional differences (Cooper, 2009), there appears to be no reason to believe that the individual physician characteristics vary across regions to explain the extreme differences in state-level adoption.

Studies focusing on macro-economic influencers of EHR do exist (e.g., Abdolrasulnia et al., 2008), but they have been relatively rare. In this study, we attempt to explore possible macroeconomic factors and macro health environment factors responsible for EHR adoption. The fact that despite personal and professional barriers, some states
within the USA have been better adopters of electronic technologies suggests that factors other than personal, professional or organisational nature are also responsible for EHR adoption. For example, a recent study reported that there are differences in adoption rate among different states within the USA (Xierali et al., 2013). Another study done in 2008 concluded that hospitals or medical centres in the western region of the USA were more likely to use electronic health records (EHRs) (DesRoches et al., 2014). Our current investigation attempts to elicit the macro influencers that cause variances in EHR adoption within the USA.

The barriers or facilitators for EHR adoption have been identified and studied for a long time now (Vishwanath and Scamura, 2007; Menachemi, 2006). Although these barriers continue to exist, changes in clinicians’ economics, more computer literacy in the general population, and most importantly, changes in government policies and increased support for clinical computing have created a more favourable environment for EHR adoption (Berner et al., 2005). Influencers other than personal and organisational nature have been studied previously. For example, a prior study (Abdolrasulnia et al., 2008) found that the adoption of these systems has been slow among community-based physicians. Health maintenance organisation penetration rate and poverty level were not found to be significantly related to EHR adoption. However, practice size, years in practice, Medicare payer mix, and measures of technology readiness were found to independently influence physician adoption of EHR. Our current study is based on the premise that additional focus on the macroeconomic or macro health environment of a region can shed further light on EHR adoption. Additionally, the unit of analysis in the Abdolrasulnia study is individual physician practice whereas we focus on understanding regional or interstate variations in adoption.

Another study exploring non-personal factors of adoption has investigated payer-mix differences in EHR adoption (Menachemi et al., 2007). This study examined how different proportions of Medicare, Medicaid, and privately insured patients in physicians’ practices influence EHR adoption.

Wide gaps in knowledge, including information about EHR use pose critical challenges for the development of policies aimed at speeding adoption (Jha et al., 2006). The nation’s health information technology system passed a major milestone in 2013 when the government announced that more than half of all USA physicians now use EHR (Conn, 2013). Despite the increased adoption of EHRs, the disparities among individual states continue to exist. Some researchers have suggested that there could be differences in hospital adoption of EHRs based on whether they are teaching hospitals (Jha et al., 2009). Stronger homogeneity among small, rural, and non-teaching hospitals may be driven by greater reliance on vendors and less variation in the types of care they deliver (Adler-Milstein et al., 2014).

Other studies have addressed state-level or regional differences (Abramson et al., 2014; Samuel, 2014). However the Abramson study limited itself to the adoption of EHR in nursing homes. The Samuel (2014) study is somewhat closer to our approach as it investigated county-level differences in EHR adoption and found areas with greater Medicaid and Medicare enrollees or greater presence of regional extension centres had higher level of EHR adoption. It concluded that geographic variations in EHR diffusion indicate that greater attention needs to be paid to ensuring equitable use of EHRs throughout the USA. Our present research is an effort in this direction.
Another recent study (Nambisan et al., 2013) provided an integrative understanding of EHR adoption by considering factors at the economic, social and organisational levels. Nambisan study considers economic incentives for adoption. But, the economic incentives provided to the adopters through current governmental initiatives did not differentiate among the states and hence the question why certain states had better or poor EHR adoption rates remains largely unanswered. We consider the economic profile of the states such as the general income level rather than the economic incentives provided to likely adopters, which have been uniformly available to providers across all states. Nambisan study also considers communication as a macro level influencer. By communication, it refers to both the content and target of communication efforts explaining the benefits of EHR adoption. Our study focuses on a different dimension of this communication – internet usage. From our perspective of studying the inter-state differences, a general macro factor such internet usage is more appropriate than marketing and communication efforts directed at the individual adopters.

In considering previous studies and their role in motivating this study, it is important to remember that our goal here is to explain the inter-state differences in EHR adoption. Our unit of analysis is the state-level adoption. The factors, even the ones that appear to be at an individual level such as income-level, literacy, internet-usage, are aggregated at the state level to see whether these differences among the states sufficiently alter the profile of a state leading to differences in the EHR adoption. In this study we have identified factors that have been studied in prior research either in the context of EHR adoption or in other related areas. The following section provides the rationale for selection and inclusion of relevant macroeconomic and macro health factors and proposes research hypotheses for empirical verification.

2 Macroeconomic influencers

A standard approach to studying adoption of technologies such as the EHR is the technology acceptance model (TAM) (Venkatesh and Davis, 2000). The TAM has received wide-acceptance and usage for a long time and has continued to do so even currently (Wallace and Sheetz, 2014). However the level of analysis of the current study is the state-level differences in the adoption of EHRs. The sociological factors that are generally studied in the context of TAM studies centre around physician attitudes and physician patient relationships (Morton and Wiedenbeck, 2009). Measures such as neighbourhood education, neighbourhood income, and participation in Medi-Cal (Medicaid) or other state-subsidised healthcare coverage programs are some of macroeconomic factors that have been used to study participation in healthcare systems (Koebnick et al., 2012). A key study has also found that environmental uncertainty, type of system affiliation, size and urbaneness were significantly associated with EMR adoption while other generally studied organisational characteristics such as public payer mix and effects of competition were not (Kazley and Ozcan, 2007). Prior research exploring variation in hospital discharge rates has also considered socioeconomic factors as possible influencers (McLaughlin et al., 1989).
2.1 Income level

Metrics of socioeconomic status have been studied in the context of healthcare consumption in general even in some early studies summarised below. For certain conditions identified as ambulatory care, hospitalisation rates were higher in low-income areas than they were in higher-income areas where appropriate outpatient care was more readily available (Billings et al., 1993). Socioeconomic composition of neighbourhoods has long been the focus of healthcare research and geocoding and measurement of neighbourhood socioeconomic position has been the focus of public health research in general (Kawachi and Berkman, 2003). Income level has also been studied as a factor determining acceptance of technology in general such as in the use of online banking (Pikkarainen et al., 2004). This trend in studying the income level of the population in healthcare related activities by physicians has continued till date. A recently study (Mazurenko and Herald, 2015) has found that income level and poverty were associated with a physician’s engagement in communication activities. In addition, the average income of the population in different states is an important factor in defining the profile of a state. Ultimately, at least a portion of the costs associated with EHR implementation has to be borne by the healthcare consumers. The income level is thus a reasonable predictor that can explain the differences in EHR adoption. We posit that the higher the income levels in a state the greater is the likelihood of EHR adoption.

\[ H1: \text{There is a positive relationship between the income levels of states and their EHR adoption.} \]

2.2 Internet usage

Prior research has examined demographic variables (gender, age, educational level) and motivation variables (perceived ease of use, perceived enjoyment, perceived usefulness) associated with internet usage activities (defined in terms of messaging, browsing, downloading and purchasing) (Teo, 2001). It has also been found in an earlier study that interaction through social networks increased physician adoption of EHR systems (Zheng et al., 2010). It is reasonable to assume that there is an association of general internet usage in a population with favourable attitudes towards computers and computer applications in the present context of EHR adoption. Internet usage also serves as a proxy for computer literacy. In addition internet usage directly improves the patients’ ability to access the EHR systems. Providers who serve consumers with higher literacy levels and internet usage are likely to have market pressures on adoption EHR systems.

\[ H2: \text{There is a positive relationship between the internet usage of states and their EHR adoption.} \]

2.3 Literacy

General literacy has been found to correlate with general exposure to print media (Stanovich and Cunningham, 1992). We believe that such general literacy levels of a region will be associated with the adoption of technological innovation for both the providers and consumers of healthcare. The link between the general literacy that
we measure and the health literacy that determines attitudes toward technologies such as EHR is also supported by prior studies. It has been found health literacy scores were lower for participants who were older, less educated, and male at an individual level (Morrow et al., 2006). It has also been found that education and health literacy potentially influence a person’s ability to be involved in decisions about their health in general (Smith et al., 2009). The organisation for standardisation (ISO) has defined EHR to mean a repository of patient data in digital form, stored and exchanged securely, and accessible by multiple authorised users (Koong et al., 2012). EHRs can provide access to patients to monitor their health metrics and hence we suggest that higher the literacy levels of the consumers the greater is the likelihood of EHR adoption.

\[ H3: \text{There is a positive relationship between literacy levels of states and their EHR adoption.} \]

3 Macro health environment influencers

3.1 Patient days

Patient days for a given level of population is a variant across states that is an indicator of severity of illnesses and may indirectly influence market decisions of hospitals and its neighbourhood physicians. We contend that this metric (per capita patient days within a state) indicates the healthcare need intensity. A higher score on this metric for a given state means that the healthcare need intensity in that state is high. It has also been found that a prolonged Emergency Department (ED) length of stay (LOS) is also linked to adverse outcomes, decreased patient satisfaction, and ED crowding (Wiler et al., 2012). Physicians’ decision to adopt an EHR may be impacted by an environment with increased severity of illnesses and decreased patient satisfaction. Hospitals invest in EHR to lower costs and improve quality of care (Mitchell and Yaylacicegi, 2012). The higher the patient days the greater will be the attention paid to lowering costs and improving the quality of care and the greater the likelihood of EHR adoption.

\[ H4: \text{There is a positive relationship between patient days for a given population and EHR adoption.} \]

3.2 Physician density

There are regional differences in the availability of physicians. It has been found that quality of care is better in states with more physicians, both specialists and family physicians. Access depends on total physician supply, irrespective of specialty. Population density, per capita income, and regional factors all influence this relationship (Cooper, 2009). This may influence a physician’s predisposition to adopt EHR as there are network influences in states with greater physicians per fixed number of population. The supply of primary care physicians exhibits differences from state to state (Hing and Hsiao, 2012). Studies support the relationship of environmental market characteristics and EHR adoption. It has been found, for example, that health maintenance organisations’ penetration, a measure of market dynamism was found to be positively
associated with EHR adoption (Menachemi et al., 2007). Infrastructure and workforce related barriers continue to exist for EHR adoption (Skillman et al., 2014) and market forces of physicians’ supply in turn may impact this as well. A recent study has found that health professional shortage area was negatively associated with EHR adoption (Samuel, 2014). Previous studies have also found that physicians located in counties with higher physician concentration were more likely to adopt EHRs (Abdolrasulnia et al., 2008). We believe that a measure of physician supply is an important macro health environment influencer that must be further investigated.

\[ H6: \text{There is a positive relationship between the number of physicians for a given population and EHR adoption.} \]

### 3.3 Physicians’ age profile

There are regional differences not just in the availability of physicians but also in the age profiles of the available physicians. This may influence a physician’s predisposition to adopt EHR as there are network influences in states with greater physicians per fixed number of population. We studied the percent of physicians of age groups below 40 and age group above 60 to see their influence on EHR adoption. At an individual level, age has often been studied as a contributing factor (Wylie et al., 2014) showing that younger physicians are more likely to adopt EHR. It is reasonable to assume that if states substantially differed in their composition of these age groups of physicians it may result in differential rates of adoption.

\[ H5: \text{There is a negative relationship between the proportion of older physician population and EHR adoption.} \]

### 3.4 Insurance coverage

Insurance coverage has been studied previously as an organisational and environmental determinant of EHR adoption of hospitals (Kazley and Ozcan, 2007). Insurance coverage might impact the pricing conditions in a given region or impose certain organisational requirements of adoption and thus indirectly influence the EHR adoption. The payer mix affects the profitability of healthcare organisations and especially in the case of smaller organisations such as small practices, this influence may be more pronounced (Menachemi et al., 2007). Any state-level difference in the insurance coverage of its population may explain the interregional differences. We measured the percentage of population that remained uninsured as there were different types of insurance and different levels of coverage for those who had health insurance coverage. A higher score on this metric for a given state means that the state has a lower degree of health insurance coverage.

\[ H7: \text{There is a positive relationship between the health insurance coverage in a given population and EHR adoption.} \]

The research model incorporating both the macroeconomic and macro health environment factors is provided in Figure 1.
3.5 EHR adoption

EHR adoption data has been studied by multiple organisations from different perspectives. There is evidence supporting that EHR adoption is related to quality of care and patient safety (Mitchell and Yaylacicegi, 2012). We have analysed the data from both the American Board of Family Medicine as well as four different measures from the National Ambulatory Care Medical Survey. While EHR adoption rates may appear to be conceptually the same from different sources, closer scrutiny of these five EHR adoption measures reveals significant measurement differences among them (e.g., nature of the sample respondents, systems measured for EHR, etc.). These granular differences provide greater empirical insights into the phenomenon of EHR adoption. For example, there are significant differences between clinical and non-clinical electronic information systems. For example, a non-clinical information system used by providers may be just a patient scheduling system. Each source of EHR adoption rate clearly defines their measure, which must be reckoned with in the interpretation of the empirical findings. We have excluded all the personal influencers such as an individual physician’s age and gender from our study. While they may affect an individual physician’s attitude toward EMR adoption, they do not sufficiently explain the differences across states. We have tested three different statistical models based on the above research model for each of the five measures of EHR adoption. The three models include

- the macro economic factors
- macro health environment factors
- all factors together in one aggregate model.
4 Methods

We conducted a secondary analysis of the data compiled from multiple reliable sources to study the relationship of macro factors and EHR adoption. We used a standard multiple regression, as the dataset was modest representing the 50 states of the USA measured at a given time. In a limited dataset such as the one that we have compiled employing specialised techniques such as non-linear regression might overfit the model to the current dataset. We opted to keep the statistical analysis simple and wanted to avoid the problems of over fitting.

The EHR adoptions at the state level have been reported by multiple organisations. There are five different measures of EHR adoption and this data is available for different years using different samples. The years for the EHR adoption data related to mostly years 2011–2012. The next section provides an explanation of the different measures of EHR adoption. These research hypotheses were separately tested for these five groups: the applicants for American Board of Family Medicine data, NAMCS family physicians data, NAMCS non-family physicians, NAMCS basic EHR system data and the NAMCS any system data. The regression models were analysed using these five different measures of EHR adoption.

4.1 Measurement of predictors and outcome variables

Our dataset was assembled from multiple reputable secondary sources that were mostly governmental agencies or professional associations entrusted with the data collection task for health-related topics. Thus each agency followed its own sampling strategies the details of which are described in their technical briefs. A pointer to these sources is presented in Table A1 of Appendix. The data for the adoption rate came from a study that originally used the data from the candidates applying for the American Board of Family Medicine (ABFM) as well as the National Ambulatory Care Medical Survey (NAMCS) (Xierali et al., 2013). The data from this source was aggregated at the state level. The unit of analysis of the present study is the state level adoption of EHRs. The NAMCS is conducted by the National Center for Health Statistics (NCHS) and it is an annual survey of visits to office-based physicians that collects information on the adoption and use of EHRs. We ran separate analyses for NAMCS reports of EHR adoption among family physicians, other office-based physicians as well as the adoption rate from ABFM. In addition, we separately analysed the data reported from the 2012 mail survey of physicians in the national ambulatory medical care survey (NAMCS) and earlier years of NAMCS (Hing and Hsiao, 2012). There is support for hypothesising differences in EHR adoption based on physician specialty (Teo, 2001). Table A1 in Appendix provides a description and source of the measures of EHR adoption and the predictor variables (macroeconomic and macro health factors) used in this study.

Figures 2 and 3 show the statewide disparities in the EHR adoption on the last two measures. internet usage data were obtained from Internet World Stats, which summarises data from trustworthy sources such as Nielsen; literacy estimates were obtained from the data published by National Center for Education Statistics; educational attainment data were obtained from the data (US Census Bureau – Statistical Abstract of the US: 2012 – Table 233) and Personal Income data was gathered from published data of US Census Bureau (State and country literacy estimates, US Department of Education; Internet Usage in Different States. Internet World Stats; Income Level of States US
Census Bureau). All hospital profile data were gathered from American Hospital Directory website. The insurance coverage data for the uninsured were gathered from the Kaiser Family Foundation website.

All statistical analyses were performed in R version 3.1.1.

**Figure 2** EHR adoption percentage of office based physicians (any system) (see online version for colours)

**Figure 3** EHR adoption percentage of office based physicians (basic system) (see online version for colours)
5 Results

Descriptive statistics of the five measures of EHR adoption, three macroeconomic influencers, and four macro health environment influencers are given in Table 1. The range of dependent variables is the widest for adoption of office-based physicians’ basic system. Literacy estimates do not vary sufficiently across states but income level does. Among other macro health predictor variables, number of physicians for a given level of population, health insurance coverage and patient days for a given level of population all vary widely across states.

Table 1 Descriptive statistics of all measures

<table>
<thead>
<tr>
<th>EHR adoption measures</th>
<th>MIN</th>
<th>MAX</th>
<th>RANGE</th>
<th>SKEW</th>
<th>KURTOSIS</th>
<th>SE</th>
</tr>
</thead>
<tbody>
<tr>
<td>ABFM_EHR</td>
<td>47.1</td>
<td>94.9</td>
<td>47.8</td>
<td>0.7</td>
<td>−0.13</td>
<td>1.63</td>
</tr>
<tr>
<td>NAMCS_FP_EHR</td>
<td>44</td>
<td>87.6</td>
<td>43.6</td>
<td>0.39</td>
<td>−0.62</td>
<td>1.64</td>
</tr>
<tr>
<td>NAMCS_NonFP_ABFM</td>
<td>38</td>
<td>86.3</td>
<td>48.3</td>
<td>0.87</td>
<td>0.44</td>
<td>1.45</td>
</tr>
<tr>
<td>OfficeBasedPhysicians</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AnySystem</td>
<td>53.8</td>
<td>89.2</td>
<td>35.4</td>
<td>−0.07</td>
<td>−0.37</td>
<td>1.17</td>
</tr>
<tr>
<td>OfficeBasedPhysicians</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BasicSystem</td>
<td>22.4</td>
<td>70.6</td>
<td>48.2</td>
<td>0.9</td>
<td>0.33</td>
<td>1.53</td>
</tr>
<tr>
<td>Macroeconomic influencers</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Literacy</td>
<td>76.95</td>
<td>94.18</td>
<td>17.23</td>
<td>−0.67</td>
<td>−0.39</td>
<td>0.61</td>
</tr>
<tr>
<td>Internet</td>
<td>59.3</td>
<td>90.1</td>
<td>30.8</td>
<td>−0.46</td>
<td>−0.38</td>
<td>0.95</td>
</tr>
<tr>
<td>Income</td>
<td>28,065.91</td>
<td>63,936.21</td>
<td>35,870.3</td>
<td>1.9</td>
<td>5.38</td>
<td>888.67</td>
</tr>
<tr>
<td>Macro health environment influencers</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No_of_physicians_Pop</td>
<td>159.4</td>
<td>612.7</td>
<td>453.3</td>
<td>4.03</td>
<td>21.09</td>
<td>9.2</td>
</tr>
<tr>
<td>Physicians_age_60_and_older_percent</td>
<td>20.7</td>
<td>30.8</td>
<td>10.1</td>
<td>0.35</td>
<td>−0.56</td>
<td>0.33</td>
</tr>
<tr>
<td>HealthInsuranceCoverage</td>
<td>3.59</td>
<td>20.28</td>
<td>16.69</td>
<td>0.19</td>
<td>−0.29</td>
<td>0.52</td>
</tr>
<tr>
<td>PatientDays_Pop</td>
<td>23,820.65</td>
<td>61,453.75</td>
<td>37,633.09</td>
<td>−0.29</td>
<td>−0.87</td>
<td>1422.13</td>
</tr>
</tbody>
</table>

The EHR adoption data was tested in three models with five different measures of EHR adoption rate. The first set of models explained EHR adoption in terms of only the macroeconomic factors. The second set of models explained EHR adoption in terms of only the macro health factors. The third set of models included both macroeconomic and macro health factors to explain EHR adoption. All regression models excepting the full models including all predictors for EHR adoption using ABFM data showed a sufficiently low p value to be considered valid.

We tested for the problems of multicollinearity in each of the regression models. The variance inflation factor (VIF) is a measure of the severity of multicollinearity in ordinary least squares regression analysis. Different standards are used for the acceptable threshold values for this statistic with the higher end of the range of about 3.33–10. The lower this statistic the less severe is the problem of multicollinearity (Cenfetelli and Bassellier, 2009). All VIF values in this study were lower than 2 indicating that there are no problems of multicollinearity.
The results are presented in Tables 2 and 3. Overall, we find that internet usage, patient days for a given population do generally exhibit significance in predicting EHR adoption in models where these were studied in separate clusters: macroeconomic and macro health factors. In model incorporating all factors at the same time the findings suggest that health insurance coverage is an important predictor variable and the model using National Ambulatory Medical Care survey’s (Adoption NAMCS_FP) measure of EHR adoption shows significance in most predictor variables.

**Table 2** Regression coefficients for the macroeconomic and macro health predictors

<table>
<thead>
<tr>
<th></th>
<th>Adoption ABFM</th>
<th>Adoption NAMCS_FP</th>
<th>Adoption NAMCS_NonFP</th>
<th>Office based physicians any system</th>
<th>Office based physicians basic system</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Model with only macroeconomic predictors</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Income</td>
<td>-0.0003</td>
<td>-0.0005</td>
<td>-0.0001</td>
<td>-0.0003</td>
<td>-0.0005</td>
</tr>
<tr>
<td>Internet</td>
<td>0.6649*</td>
<td>1.244***</td>
<td>0.4816*</td>
<td>0.4317*</td>
<td>0.4139</td>
</tr>
<tr>
<td>Literacy</td>
<td>0.3221</td>
<td>-0.1200</td>
<td>0.8305*</td>
<td>0.3374</td>
<td>0.7488*</td>
</tr>
<tr>
<td>Model $R^2$</td>
<td>0.1730</td>
<td>0.4101</td>
<td>0.2767</td>
<td>0.1887</td>
<td>0.2305</td>
</tr>
<tr>
<td>$p$-value</td>
<td>0.0485</td>
<td>0.00005</td>
<td>0.0015</td>
<td>0.0191</td>
<td>0.0060</td>
</tr>
<tr>
<td><strong>Model with only macro health predictors</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Patient days/Pop</td>
<td>-0.0002</td>
<td>-0.0005***</td>
<td>-0.0004**</td>
<td>-0.0002*</td>
<td>-0.0001</td>
</tr>
<tr>
<td>% of Older (&gt;60) Physicians</td>
<td>-1.0052</td>
<td>-0.2119</td>
<td>-1.4660*</td>
<td>-0.9259</td>
<td>-1.3640*</td>
</tr>
<tr>
<td>Physician/population</td>
<td>0.0767</td>
<td>0.0565</td>
<td>0.0548</td>
<td>-0.0005</td>
<td>-0.0175</td>
</tr>
<tr>
<td>Health insurance coverage</td>
<td>-0.5372</td>
<td>-0.7805</td>
<td>-0.5738</td>
<td>-0.7314*</td>
<td>-1.0670*</td>
</tr>
<tr>
<td>Model $R^2$</td>
<td>0.2263</td>
<td>0.4226</td>
<td>0.3522</td>
<td>0.2831</td>
<td>0.2510</td>
</tr>
<tr>
<td>$p$-value</td>
<td>0.0326</td>
<td>0.0001</td>
<td>0.0005</td>
<td>0.0041</td>
<td>0.0099</td>
</tr>
</tbody>
</table>

Significance codes: *0.05; **0.01; ***0.001; ~0.1.

**Table 3** Regression coefficients for the full model including both macroeconomic and macro health predictors (full model)

<table>
<thead>
<tr>
<th></th>
<th>Adoption ABFM</th>
<th>Adoption NAMCS_FP</th>
<th>Adoption NAMCS_NonFP</th>
<th>Office based physicians any system</th>
<th>Office based physicians basic system</th>
</tr>
</thead>
<tbody>
<tr>
<td>Income</td>
<td>-0.0008</td>
<td>-0.0006*</td>
<td>-0.0004</td>
<td>-0.0006</td>
<td>-0.0005</td>
</tr>
<tr>
<td>Internet</td>
<td>0.2547</td>
<td>0.7277*</td>
<td>0.1606</td>
<td>0.1456</td>
<td>0.3344</td>
</tr>
<tr>
<td>Literacy</td>
<td>-0.6590</td>
<td>-0.9847*</td>
<td>0.1957</td>
<td>-0.4537</td>
<td>0.0590</td>
</tr>
<tr>
<td>Patient days/Population</td>
<td>-0.0003</td>
<td>-0.0004*</td>
<td>-0.0003*</td>
<td>-0.0003*</td>
<td>-0.00007</td>
</tr>
<tr>
<td>Percent of older (&gt;60) Physicians</td>
<td>-1.2550</td>
<td>-0.3232</td>
<td>-1.2289</td>
<td>-1.1460*</td>
<td>-1.1110</td>
</tr>
</tbody>
</table>
Table 3  Regression coefficients for the full model including both macroeconomic and macro health predictors (full model) (continued)

<table>
<thead>
<tr>
<th></th>
<th>Adoption ABFM</th>
<th>Adoption NAMCS_FP</th>
<th>Adoption NAMCS_NonFP</th>
<th>Office based physicians any system</th>
<th>Office based physicians basic system</th>
</tr>
</thead>
<tbody>
<tr>
<td>Physician/population</td>
<td>0.1346</td>
<td>0.0247</td>
<td>0.0728</td>
<td>−0.0409</td>
<td>−0.0122</td>
</tr>
<tr>
<td>Health insurance coverage</td>
<td>−1.0270</td>
<td>−1.3320**</td>
<td>−0.4516</td>
<td>−0.9499*</td>
<td>−1.0280~</td>
</tr>
<tr>
<td>Model  R²</td>
<td>0.2892</td>
<td>0.5557</td>
<td>0.3731</td>
<td>0.3582</td>
<td>0.2815</td>
</tr>
<tr>
<td>p-value</td>
<td>0.0619</td>
<td>0.00003</td>
<td>0.0042</td>
<td>0.0063</td>
<td>0.0404</td>
</tr>
</tbody>
</table>

Significance codes: *0.05; **0.01; ***0.001; ~0.1.

6 Discussion

Our study corroborates the recent findings by the CDC study (Hing and Hsiao, 2012), which also found statewide disparities, and further adds to the extant knowledge on EHR adoption. While the CDC study found statewide disparities in EHR adoption, it was unclear on the reasons or causes for such disparities. Our study fills that gap in existing literature at the level of states using macroeconomic and macro health factors.

Our findings provide support to the contention that macroeconomic factors do impact EHR adoption rates. More importantly the study revealed that income disparities across states do not result in disparities in EHR adoption rates. That is, affluent states and poorer states are equally prone to or apathetic to EHR adoption. One possible explanation is that healthcare sector is unique in that the consumers and providers of healthcare are distinct groups and the consumers are only indirectly paying their healthcare costs. Another possible explanation for this unexpected finding may be that the income levels of providers and facilitators of healthcare (doctors, hospital administrators, regulators and EHR professionals that provide the information systems infrastructure) do not exhibit much variance across states. The income measure in our study is at the state level and therefore we suggest a more definitive study to examine the income level at the provider level and its impact on EHR adoption rate. The expectation is that income levels at the provider level will have more significant impact on EHR adoption rates than income level at state level.

Our findings also corroborate the expected positive linkage between literacy rates and EHR adoption rates in one measure of EHR adoption. It is too simplistic to say that literacy leads to more effective and efficient delivery of healthcare. Both providers and patients seek the most effective and efficient ways if there is high literacy, especially healthcare literacy. Increasingly evidence-based medicine is becoming the norm in this quest for effective and efficient healthcare delivery (Rousseau and Barends, 2011). We considered that the state level literacy estimates should be incorporated in the model as we are referring to EHR (and not EMR), which implies some level of patient access to the health records. As it turned out, literacy was NOT a significant predictor variable in at least some of the models. We believe that this was because the range of variation in literacy across states was narrow.
The findings also show the expected positive relationship between general internet usage within a state and all measures of EHR adoption except the clinical EHR systems. This is not a surprising result given that clinical EHR systems’ adoption warrants specialist knowledge and not general internet use experience.

With regard to the effects of macro health environmental factors on EHR adoption, the findings in Table 2 reveal three statistically significant results:

- per capita patient days (a proxy for healthcare need intensity within a state) is negatively correlated with EHR adoption rate
- health insurance coverage is positively correlated with EHR adoption rate
- older physicians (>60 years) tend to adopt clinical EHR systems less than their younger counterparts.

The ranges of income and patient days per population are too wide. Thus the regression coefficients for them are small and may need to be viewed with caution. The regression coefficients for the insurance coverage are mostly negative but they do indicate a positive relationship since the data comprised of percentage of population that remained uninsured. Physician age, however, did not impact the adoption of general (non-clinical) electronic information systems. Each of these results warrants further reflection to derive insights and implications. These findings are consistent even in the full model results shown in Table 3.

It is possible that in a situation requiring intense clinical focus and effort, non-clinical and efficiency-oriented processes such as EHR adoption may have lesser significance. States laden with the burden of higher per capita patient days may be slower in EHR adoption rate as our results show. Greater health insurance coverage drives greater EHR adoption since EHR is ubiquitously seen as a process improvement that reduces cost of healthcare. In many respects, EHR adoption is aligned with the expectation of lean process thinking theory. Any EHR adoption process evidences the overarching concepts of lean process thinking such as standardisation, value stream mapping, eliminating excess, and process improvement (Bush, 2007; Young and McClean, 2008; Joosten et al., 2009). Finally, it is not surprising to find that older physicians, while adopting general electronic information systems, are hesitant to progress to ‘Basic’ systems that require specialist knowledge and mandate low error rates.

EHR adoption phenomenon can be explained by many factors that are not studied in our research. For example, incentives may play a role in EHR adoption. Health insurers are keenly interested in making the non-clinical processes that support clinical processes more efficient. EHR adoption is one key emphasis in this pursuit of efficiency by health insurers. For example, Medicare and Medicaid have now mandated the use of EHR for all providers who do business with them. To accelerate the adoption of EHR, additional bonus payments are made for those providers who use EHRs. Finally, older physicians (>60 years old) may need other stakeholder groups to institutionalise EHR adoption within their clinical practices.

The differences in the predictors and their influence on the EHR adoption may be explained both by the presence of incentives in some cases and the lag in measurement years. ABFM data was not influenced by the presence of incentives whereas other measures of EHR adoption were influenced by the presence of incentives.
6.1 Limitations of the study

The compilation of the dataset from multiple secondary sources poses certain limitations. First, all the data were not collected at the same time and the time lags in data collection for both predictor and dependent variables could be construed as a limitation. We still chose to combine data this way for two reasons: first, the time lag was only less than five years and we believe that predictor variables such as macroeconomic and macro health state characteristics do not change widely within the short time frame; second, the dataset was compiled by reputable governmental or professional agencies specifically entrusted with the task of data collection and the quality of the data can mitigate the limitation of time lags in data collection. A limitation of the study is in its choice of the geographic region at the state level within a single country – the USA. But it is relatively easy to replicate the study for different regions when sufficient data are available.

6.2 Implications for theory and practice

From a practical standpoint the findings can direct certain policy changes. For example, EHR incentives can be directed to states with certain macroeconomic and health profiles. States with higher patient days per population, for example, can receive greater incentives. Hospital providers can be incentivised to perform better on metrics that are associated with inferior EHR adoption. While altering incentive patterns at the national level is tall order, states aiming to improve EHR adoption can direct policies to alter the profile of the state in these metrics – especially in areas such as health insurance coverage. Such regionally focused incentive programs will be a major shift to generalised incentive programs that are implemented now. From a theoretical perspective, this study can lead to developing models with greater sophistication to study regional differences not just in EHR adoption but also help us in understanding whether these predictors can explain differences in general health IT utilisation.

7 Conclusion

While adoption of EHR is progressively getting better, we still need to further our understanding in areas such as explaining differences in adoption owing to regional or provider type differences.

An important contribution of the study is its recognition of the relevance of macroeconomic factors in the adoption of EHRs to explain state level differences. While personal and organisational factors have been studied extensively, they can only explain why a physician or a hospital adopted or not. We feel that macroeconomic factors have not received their due attention especially in light of the variances in adoption rates across states within the USA. And only a macroeconomic or macro health environment factor can explain regional differences. When state level EHR adoption shows a great variance, it often unclear as to why such differences exist. While a strong theoretical justification may not exist already, this study attempts to develop key macro factors relevant for EHR adoption by first compiling relevant data and then empirically examining to elicit how internet usage and literacy levels of a region are associated with higher levels of EHR adoption.
References


Macro influencers of electronic health records adoption


**Websites**


## Appendix

### Table A1 Measures and sources of EHR adoption rates and predictor variables

<table>
<thead>
<tr>
<th>Source</th>
<th>Brief definition of EHR adoption measure</th>
</tr>
</thead>
<tbody>
<tr>
<td>National Ambulatory Care Medical Survey – Non-Family Practitioners (NACMS_NonFP)</td>
<td>National Ambulatory Medical Care Survey (NAMCS) (2001–2011) (<a href="http://annfammed.org/content/suppl/2013/01/11/11.1.14.DC1/Xierali_Supp_Table.pdf">http://annfammed.org/content/suppl/2013/01/11/11.1.14.DC1/Xierali_Supp_Table.pdf</a>)</td>
</tr>
<tr>
<td>Office Based Physicians (Any System – includes non-clinical systems)</td>
<td>Data are reported from the 2012 mail survey of physicians in the National Ambulatory Medical Care Survey (NAMCS) and earlier years of NAMCS. Obtained from ‘yes’ responses to the question, “Does this practice use electronic medical records or electronic health records (not including billing records)?” (Hsiao and Hing, 2012)</td>
</tr>
<tr>
<td>Office Based Physicians (EHR Basic – Clinical systems stages 1–4)</td>
<td>Data are reported from the 2012 mail survey of physicians in the National Ambulatory Medical Care Survey (NAMCS) and earlier years of NAMCS. A system that has all of the following functionalities: patient history and demographics, patient problem lists, physician clinical notes, comprehensive list of patients’ medications and allergies, computerised orders for prescriptions, and ability to view laboratory and imaging results electronically (Hsiao and Hing, 2012)</td>
</tr>
<tr>
<td>Internet usage</td>
<td>Internet Usage in Different States. Internet World Stats. (<a href="http://www.internetworldstats.com/stats26.htm">http://www.internetworldstats.com/stats26.htm</a>)</td>
</tr>
<tr>
<td>Income</td>
<td>Income Level of States. US Census Bureau (<a href="https://www.census.gov/compendia/statab/cats/income_expenditures_poverty_wealth/personal_income.html">https://www.census.gov/compendia/statab/cats/income_expenditures_poverty_wealth/personal_income.html</a>)</td>
</tr>
<tr>
<td>Health insurance coverage</td>
<td>Health insurance coverage of the Total Population (2014) (<a href="http://kff.org/other/state-indicator/total-population/">http://kff.org/other/state-indicator/total-population/</a>)</td>
</tr>
</tbody>
</table>