Patient Portals in Primary Care:
Impacts on Patient Health and Physician Productivity*

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Interest in innovative health care delivery models has increased due to measures such as the Affordable Care Act, which is designed to expand insurance coverage and contain health care costs. The goal of these innovations is to increase physician productivity without sacrificing quality of care. One innovation that has been forwarded as a low-cost alternative to physician office visits is “e-visits,” or secure messaging between patients and physicians via patient portals. We evaluate the effect of e-visit adoption on patient health and physician productivity using a six-year panel dataset from a large primary care provider in the United States. The main challenge in evaluating e-visits is that there could be unobservable selection: in particular, a naïve analysis regressing the number of office visits (our measure of physician productivity) on patient e-visit adoption is biased downward if patients adopt e-visits because they are already on a trajectory toward improved health. We address this selection problem by implementing an instrumental variable analysis that leverages the differential propensities of physicians to adopt e-visits over time, since this variation affects patient e-visit adoption arguably independent of their health conditions. We find large selection effects: our instrumental variable estimates show that e-visit adoption doubles the number of annual office visits from 3 to 6, whereas a naïve analysis predicts an effect of the opposite sign. Meanwhile, we find no evidence that e-visits affect patient health as measured by emergency room visit frequency, blood cholesterol (LDL), or blood glucose (HbA1c) levels. We supplement our analysis with an event study design, and also conduct robustness checks using data on telephone visits.

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1. Introduction

Electronic communication between patients and physicians ("e-visits") is a recent technological innovation in primary care that affords patients a low-cost alternative to physician office visits. Medical providers have promoted the usage of e-visits over the past decade, hoping that they can substitute for office and telephone visits to allow for larger panel sizes and improved patient health. The efforts have been successful; the percentage of physicians who indicate that they use secure messaging, instant messaging, or video conferencing with their patients increased from about 25% to 40% between 2005 and 2011 (Wall Street Journal 2012). E-visits can also play an important role in mitigating rising health care costs (Centers for Medicare and Medicaid Services 2011) and the projected shortage of primary care physicians (Petterson et al. 2012)—30 million newly insured patients are expected following the Affordable Care Act alone (Hofer et al. 2011)—but their effectiveness in meeting these goals has been challenging to evaluate.

In this paper, we use data from a large primary care provider in the United States to investigate the impacts of using e-visits on physician productivity and patient health. We measure physician productivity by the number of office and telephone visits that a physician allocates to each patient because these measures have direct implications for physician panel size—the number of patients cared for by a physician. The intuition is that the time a physician spends on each patient is inversely related with the number of patients that she can handle. We measure patient health using data on blood cholesterol (LDL levels), blood glucose (HbA1c levels), and the number of emergency room visits. These measures are especially helpful in evaluating the effectiveness of e-visits in improving the health of chronically ill patients.

The empirical evaluation of e-visits is challenging because various sources of endogeneity may bias the results. The patients who choose to adopt e-visits may be different from those who do not in ways that are correlated with health outcomes, and these characteristics can be observable or unobservable. Previous papers on this topic have addressed the problem of observable selection by using matching methods (Zhou et al. (2007), Zhou et al. (2010)), but the limitation of this approach is that there may still be bias from unobservable selection. Further, selection based on unobservable characteristics can be based on time-invariant or time-varying patient characteristics—for example, time-invariant and typically unobserved patient characteristics such as income and education can influence both e-visit adoption and patient health (Ettner (1996), Cutler and Lleras-Muney (2012)). Selection based on unobservable and time-varying patient characteristics can also present a problem. For example, it may be the case that patients who are on a positive health trajectory (e.g., recovering from an illness) are systematically more likely to adopt e-visits: the empirical signature of this in the data would be a correlation between e-visits and observed health status, independent of whether e-visits causally affect health outcomes.
Our study is the first to explicitly deal with selection on both time-invariant and time-varying unobserved patient characteristics in e-visit adoption. First, our estimation models include patient fixed effects—this approach allows us to control for all unobserved patient characteristics that are time-invariant over the span of our panel. Second, we use the intensity of e-visit usage by a patient’s provider for her other patients to construct a conventional leave-one-out instrumental variable for patient e-visit adoption. The instrumental variable analysis relies on the assumption that the intensity with which the provider uses e-visits with her other patients only affects an individual patient’s outcomes via his own e-visit adoption. Third, we conduct an event study adapted from Campbell and Frei (2010), which evaluates the effect of online banking adoption on customer behavior. In our setting, we exploit the group of patients who adopt e-visits, but do not subsequently use them, as a refined control group for the patients who use e-visits at higher intensities. The underlying assumption in this design is that changes in patient outcomes between the different groups are due to differences in the intensive margin of e-visit usage, not the extensive margin of adoption.

There are several unique features in our data that allow us to obtain unbiased estimates of the effect of e-visit adoption on patient health and physician productivity. We observe the behavior of a large patient panel (over 140,000 patients) over the 2008 to 2013 period during which e-visits were introduced. Figure 1 shows the adoption of e-visits over time in the health system that we study; e-visits were introduced around 2008, and their usage has grown rapidly since then. For perspective, the number of e-visits increased from 96 in the first two months of our data (January and February 2008) to 6,449 in the most recent two months of our data (January and February 2013). Meanwhile, the number of office and telephone visits appear relatively unchanged over the same time horizon.

We establish two main results with our instrumental variable analysis. First, the number of patient primary care encounters increases dramatically with e-visit adoption: the number of office visits doubles, suggesting an average of one additional visit every four months, and the number of telephone visits increases by over 80%, suggesting an average of one extra telephone visit every three months. Second, we show that e-visit adoption, combined with the additional primary care encounters, does not significantly affect patient health as measured by blood cholesterol (LDL level), blood glucose (HbA1c level), or emergency room visits. Together, these results suggest that e-visits serve as complements, not substitutes, to the traditional models of primary care delivery. Our instrumental variable estimates also reveal large selection effects, since our ordinary least squares estimates (which do not deal with unobservable patient characteristics) suggest a negative effect of e-visit adoption on the number of primary encounters, and statistically significant positive effects on patient health.
The rest of this paper is organized as follows. In Section 2, we review the existing literature; we present our hypotheses in Section 3. In Section 4, we explain the main features of our dataset and the institutional features of the health system that we study in our analysis. We show our econometric specifications in Section 5, and our results for the effect of e-visits on office visits, telephone visits, and patient health are presented and discussed in Section 6. We conclude and highlight areas for future research in Section 7.

2. Literature Review

The existing literature regarding the substitutability of e-visits for more traditional forms of physician contact is mixed. Several studies have found that e-visits reduce a patient’s demand for telephone and office visits (Bergmo et al. (2005), Kilo (2005), Kummervold (2006), Zhou et al. (2007)) and improve patient health outcomes (Zhou et al. (2010), Baer (2011)), but other studies suggest that e-visits have no discernible effect on reducing physician workload (Katz et al. (2003), Katz et al. (2004)). These studies rely on cross-sectional analysis that are unable to identify the causal effect of e-visits on outcomes if there is unobservable selection of patients into e-visit adoption. This problem of endogenous adoption of electronic service delivery channels exists in other settings—for example, in the banking sector, research shows that online customers tend to be younger, are more profitable, and have shorter relationships with the bank (Frei and Harker (2000), Degeratu et al. (2000), Hitt and Frei (2002), Xue et al. (2007), Campbell and Frei (2010)). The contribution of this paper is to leverage a large panel of patient visits from a major United States health provider and implement both event study and instrumental variable techniques to isolate the causal effect of e-visits on primary care outcomes.

There is an extensive literature documenting the predictors of the frequency of primary care encounters in medicine. The bulk of these papers are concerned with the relationship between observed covariates, e.g., patient age and health status, on visit frequency. The general finding in these studies is that observed patient characteristics have an impact on patient revisit frequency, but physician practice style is also found as a key determinant of patient revisit frequency (Tobacman et al. (1992), Schwartz et al. (1999), DeSalvo et al. (2000), DeSalvo et al. (2003)). Drawing on these findings, we include physician fixed effects throughout our analysis. Moreover, the potential value in decreasing patient revisit frequency is highlighted in a study by Schectman et al. (2005) in which the authors successfully decrease the number of patient office visits without affecting patient health outcomes.

There is a growing number of papers related to primary care in the operations literature. Green et al. (2007) provide guidelines for physician panel sizing, and a number of other researchers have focused on considering practice features such as no-show rates for appointment scheduling
(examples include Green and Savin (2008), Robinson and Chen (2010), Zacharias and Pinedo (2013), Liu and Ziya (2013)). Zacharias and Armony (2013) study the joint problem of appointment scheduling and determining panel size, and Ozen and Balasubramanian (2012) quantify the effect of case-mix on physician panel size. Balasubramanian et al. (2011) highlight the importance of provider flexibility in primary care and show the trade-off between continuity of care and access.

This paper also contributes to the literature on electronic health records and health information technology (examples include Poissant et al. (2005), Adler-Milstein and Huckman (2013), Miller and Tucker (2011)). E-visits provide physicians and patients with a direct line of communication that is related to the broader role of health information technology—without electronic health records or patient portals, e-visits are difficult for physicians to provide. The specific role of e-visits, however, is distinct from other aspects of electronic health records because e-visit are used to deliver care and communicate with patients rather than facilitating the work-flow of the physician’s office.

3. Hypotheses Development

We begin our empirical analysis by assessing the impact of e-visit adoption on physician productivity. We measure physician productivity by the number of primary care encounters that a patient has with his physician. Specifically, the variables we use to measure productivity are (1) the monthly frequency with which the patient sees his physician in her office and (2) the monthly frequency with which the patient has a telephone visit with his physician. These variables are important for measuring physician productivity because they have direct effects on physician workload, patient health, and health care costs (Welch et al. (1999), Chapko et al. (1999)). The frequency with which a patient sees his physician has direct relevance for the panel size—the number of patients that a physician can handle. For example, a physician who sees her patients once every two months can handle twice as many patients as a physician who sees her patients once every month (Bavafa et al. 2013). The case is analogous for telephone visits.

Figure 2 illustrates the trade-off between quality and productivity in primary care. As we move on the curve from the upper-left quadrant to the bottom-right quadrant, patients have fewer visits with the physician, so quality drops while the physician becomes more productive. The upper-left corner in this figure represents an “excellent” health plan where the patient and provider are frequently in touch through office and telephone visits, so patient health is good. The physician, however, is not productive and will not be able to handle a large number of patients because she utilizes a large number of office and telephone visits to treat each of her patients. The goal of the traditional primary care system is to strike a balance between patient health and physician

1 Panel size might not exactly double because lower frequency of visits can affect patient health. See Bavafa et al. (2013) for an analytical characterization of this possibility.
productivity and is typically located in the lower-right corner of Figure 2. The hope is that e-visits push the efficient frontier to the top right, meaning higher productivity for the physicians and better health for patients. Thus, the key question of interest in our study is whether e-visits push the efficient frontier toward $E$ in Figure 2.

3.1. The Effect of e-Visit Adoption on the Number of Office and Telephone Visits

After the adoption of e-visits, patients have an additional channel to communicate with their providers. Patients can use this additional channel to receive a portion of the care that they used to receive from office visits and telephone visits. If this is the case, the adoption of e-visits would result in fewer office and telephone visits by patients; we call this the substitution effect. A number of researchers have argued for this effect, including Bergmo et al. (2005), Kilo (2005), Kummervold (2006), and Zhou et al. (2007).

On the other hand, for the patients who adopt e-visits, electronic communication is a low-cost channel for reaching their physicians and bypassing the usual practice gatekeepers, such as nurses and scheduling clerks. If this is the case, more communication with the provider obliges the provider to see the patients in the office or have a telephone conversation with the patient, so the numbers of office and telephone visits will not decrease, and they might even increase; we call this the gateway effect. There are studies in support of this hypothesis in the literature on e-visits, e.g., Katz et al. (2003) and Katz et al. (2004). Moreover, this hypothesis is consistent with studies based on randomized controlled trials, which show that more frequent telephone contact increases the chance of patient readmission to the hospital (Roudebush et al. (1999), Weinberger et al. (1996)).

It is important to note that the content, usage, and duration of office and telephone visits are different. In contrast to office visits, telephone visits do not require the patient to be physically present at the primary care practice, are often short in duration, and might be in the form of exchanged messages between patients and the physician via an intermediary. Therefore, one might expect e-visits to be particularly good substitutes for telephone visits.

To investigate the effects of e-visit adoption on the number of patient office and telephone visits, we test the following hypotheses:

**Hypothesis 1a.** The number of patient office visits does not change following the adoption of e-visits.

**Hypothesis 1b.** The number of patient office visits changes following the adoption of e-visits (“substitution” or “gateway” effect).

**Hypothesis 2a.** The number of patient telephone visits does not change following the adoption of e-visits.
Hypothesis 2b. The number of patient telephone visits changes following the adoption of e-visits (“substitution” or “gateway” effect).

The key variables in this analysis are the number of office and telephone visits per month for each patient. Figure 3 shows a histogram of the number of office visits per month. Patients use office visits at different rates, and what we want to investigate is the effect of e-visit adoption on the number of monthly office and telephone visits.

3.2. The Effect of e-Visit Adoption on Patient Health

The impact of e-visit adoption on patient health is another important consideration for patient portals. First, using e-visits might impact patient health through changes in service consumption as discussed earlier. Second, an e-visit is a new channel for care delivery, and patient health can improve by receiving more care and increased monitoring (Zhou et al. (2010) and Baer (2011)).

To investigate whether e-visits improve patient health, we consider three patient health outcomes that are used extensively in the literature related to primary care: blood glucose (hemoglobin A1c or HbA1c), blood cholesterol (low density lipoprotein or LDL), and emergency room visits. These health outcome metrics are used frequently in the health literature because they are easy to measure and sensitive to the quality of primary care services. For the case of patient portals, LDL and HbA1c levels have been used before (Zhou et al. 2010).

Testing of HbA1C levels is used to monitor diabetes control. The value of LDL, also known as “bad cholesterol,” is a measure of health for patients with cholesterol problems. Overall, the levels of HbA1c and LDL are such that lower levels are better for patients. Also, these two measurements have cutoff values that indicate whether the patient’s condition is “under control” or not. The cutoff values for blood sugar and bad cholesterol are 7% and 100 mg/dL respectively. We investigate whether e-visits have an effect on these two patient measurements by testing the following hypotheses:

Hypothesis 3a. There is no change in patient “blood sugar” control following the adoption of e-visits.

Hypothesis 3b. Patient “blood sugar” control improves following the adoption of e-visits.

Hypothesis 4a. There is no change in patient “bad cholesterol” control following the adoption of e-visits.

Hypothesis 4b. Patient “bad cholesterol” control improves following the adoption of e-visits.

When patients are not able to reach their providers, they have to resort to other channels of care such as the emergency room. If e-visits significantly improve patient access to primary care, they may prevent emergency room visits.
HYPOTHESIS 5A. There is no change in the number of patient emergency room visits following the adoption of e-visits.

HYPOTHESIS 5B. Patients use fewer emergency room visits following the adoption of e-visits.

Together, these hypotheses provide several testable implications that form the basis of our empirical work.

4. Data and Sample Definition

We use a panel dataset from a major health system in the United States. In our data, we observe all primary care encounters (office visits, telephone visits, and e-visits) for our patient population. We observe 143,025 patients and 2,566,145 primary care encounters between January 2008 and March 2013. During this time period, the health system rapidly adopted e-visits (see Figure 1). The adoption curve in our health system enables us to observe patients before and after adoption of e-visits and compare their behavior and health outcomes. In our sample, we observe 14,772 patients who use e-visits at least once. We observe all visits for 91 primary care physicians in our data. These physicians belong to nine different departments located in a similar geographical vicinity. Table 1 shows the summary statistics for adopters and non-adopters of e-visits. Based on Table 1, e-visit users have a significantly higher likelihood to be older, white, and have fewer office visits.

To perform analysis on this dataset, we process our data in the following way. First, we restrict our sample to patients who have at least one primary care encounter per year. This leaves us with 65,282 unique patients. Second, we define the number of office and telephone visits at a monthly level. That is, for each patient-month we observe the number of office and telephone visits, and this value can be zero if the patient had no office or telephone visits in that month. This leaves 2,385,224 patient-month observations. Similarly, for the outcome measures of LDL and HbA1c, our variable of interest is whether the patient had an “out of control” observation in a month. The “out of control” cutoff values for blood sugar and bad cholesterol are 7% and 100 mg/dL respectively.

In our sample, we use the term “e-visit adopters” for patients who have used e-visits at least once, i.e., patients who have communicated with their providers via the secure messaging service of our patient portal. Therefore, adoption in our analysis refers to using the service once, not just signing up for e-visits. We need to know the patient’s provider for each patient-month, but there are months that the patient does not have any visits. For those months, we assign the last provider who had an office visit with the patient as the provider. Although we observe all patient encounters for 91 physicians, our patients have encounters with other providers in the system. We control for the fact that the patient is seeing other providers in the system, categorizing the rest of our providers into six groups: “other physician,” “other nurse practitioner,” “other physician assistant,” “other fellow,” “other resident,” and “other nurse.”
5. Research Methodology

5.1. The Effect of e-Visit Adoption on the Number of Patient Office and Telephone Visits

As mentioned earlier, the main empirical challenge in this analysis is accounting for both \textit{time-invariant} and \textit{time-varying} unobservable patient characteristics. Time-invariant unobservable characteristics include socioeconomic status and comfort with and access to technology, both of which we expect to stay constant in a five-year window. These factors are correlated with e-visit adoption, office and telephone usages, and patient health. It has been shown that income and education are related to health (Ettner (1996) and Cutler and Lleras-Muney (2012)) and access to technology plays an important role in adoption of new technological innovations. Our analysis uses patient fixed effects to account for this set of time-invariant unobservable patient characteristics.

Time-varying unobservables do not have a standard econometric treatment, and specifically, in our setting, one needs to worry about patient health trajectory. Patients who are on a positive health trajectory are more likely to engage in e-visits; these patients will also have fewer office and telephone visits because their health is improving. Patients and physicians observe the patient health trajectory, but we do not observe this variable in the data. Therefore, a naïve analysis would conclude that e-visit adoption reduces the number of office and telephone visits even if e-visits have no causal effect on the number of office and telephone visits.

We use two separate approaches to deal with unobservable patient health trajectory and identify the effect of e-visits on office and telephone visits. In our first approach, we perform an event study on the e-visit adopters. We take adopters who use e-visits once and never afterward as our control group and run a difference-in-differences model. This analysis allows us to compare the effects of moderate versus heavy e-visit usage on the number of office and telephone visits. In our second approach, we use an instrumental variable approach to account for the remaining selection on unobservable patient characteristics.

5.1.1. Event Study  To identify the effect of e-visit adoption on office and telephone visits, we need a carefully constructed control group. We adopt the methodology used in Campbell and Frei (2010) to study the effect of online banking adoption on customer behavior. The basic lesson from that analysis is that it is inappropriate to use non-adopters as a control group in this setting because they may systemically differ from the patients who adopt e-visits. Specifically, using this group will not address our main concern regarding patient health trajectory. Instead, in our analysis, we use patients who use e-visits once and never use it post-adoption as our control group. A substantial number of patients fall into this category in our data. The existence of this group of patients is consistent with findings in existing literature in online services. For example, Parthasarathy and
Bhattacherjee (1998) show that a large group of customers adopt online services but do not use them post-adoption.

As described earlier, we use patient fixed effects in our models to account for time-invariant patient unobservables. In this analysis, we also limit our observations to the people who adopted e-visits, and this provides us with two advantages. First, patients who adopt e-visits and never use the service after adoption provide us with a control group that is immune to many potential selection issues that may arise if users were simply compared to non-users. Specifically, the health trajectory of this group of patients is closer to the other e-visit adopters because based on their observable and unobservable characteristics, they have used e-visits at least once. Second, this analysis compares e-visits usage intensity among patients who adopt e-visits. Thus, by limiting ourselves to e-visit adopters, we can see whether high versus low e-visit usage has any effect on the number of office and telephone visits used by patients.

For this analysis, we construct a subsample of our data where we only include patients who adopt e-visits, i.e., sent at least one email to their provider, and we observe them for six months before and after adoption. In this sample, as per Campbell and Frei (2010), we divide the patients to three groups: “inactive,” “passive,” and “active.” The inactive e-visit users do not use e-visits after adoption, and the passive and active e-visit users adopt e-visits and use them with low and high intensity, respectively. We measure usage intensity with the number of e-visits per month, so passive (active) patients are the ones whose e-visit usage intensity is below (above) median usage intensity of the sample.

Each patient in this sample has a “pre-adoption” and a “post-adoption” period. We limit our sample to those patients that have at least a six month period in either state, and construct a variable $POST$, which is a binary variable that is activated when the patient is in the post-adoption period. Also, we call a patient inactive if he does not use the e-visits after adoption, i.e., the total number of e-visits used by the patient is one. In the group of patients who are not inactive, we compute the intensity with which the patients use e-visits as the number of e-visits per month:

$$e\text{-Visit Usage Rate} = \frac{\text{Number of e-Visits Used}}{\text{Number of Post-Adoption Months}}.$$  

The median number of e-visits per year is four in our sample, so patients with e-visit usage rates above four messages per year are considered active, whereas patients with e-visit usage rates equal to, or below, four messages per year are considered passive.

To check whether the level of e-visit activity impacts the usage of office and telephone visits, we estimate the following difference-in-differences regression:

$$y_{it} = \gamma_0 + \gamma_1 POST_{it} + \gamma_2 POST_{it} \times PASSIVE_i + \gamma_3 POST_{it} \times ACTIVE_i$$
where \( y_{it} \) represents the number of office or telephone visits by patient \( i \) in month \( t \), \( \Lambda_t \) includes the month and year fixed effects to control for common trends and seasonality, \( \delta_i \) is the patient fixed-effect. We also include a provider fixed effect; \( \kappa_{it} \) refer to patient \( i \)'s provider in month \( t \). We defined \textit{POST}, \textit{PASSIVE}, and \textit{ACTIVE} earlier in the paper.

The value of \( \gamma_1 \) captures the changes in the value of \( y_{it} \) (number of office and telephone visits) after the adoption of e-visits. If using e-visits results in patients substituting e-visits for office and telephone visits, we expect \( \gamma_2 \) and \( \gamma_3 \) to be negative with \( \gamma_2 > \gamma_3 \). We expect \( \gamma_2 \) and \( \gamma_3 \) to be both positive and \( \gamma_3 > \gamma_2 \) if the gateway hypothesis is true.

In our specification, we control for \textit{AdoptionMonth}_{it} because patients are more prone to adopt e-visits after having an interaction with their providers via a telephone or office visit. Our results are robust to changing this variable to include one month before and one month after adoption.

The identifying assumption in this study is that changes in the outcome variables for patients who belong to the three different groups (inactive, passive, and active) is only due to the intensity with which they use e-visits. To address the concerns over the validity of this assumption, we use an instrumental variable analysis that is introduced in the following subsection.

### 5.1.2. Instrumental Variable Study

In our second approach to evaluating the effect of e-visit adoption on patient office and telephone visits, we construct a panel where the unit of observation is patient-month, i.e., each data point is the number of visits (office or telephone) for patient \( i \), at month \( t \). Also, at each month \( t \), if the patient has adopted e-visits, we have \( e\text{Visit}_{it} = 1 \) and \( e\text{Visit}_{it} = 0 \) otherwise. Note that adoption of e-visits is “sticky” in our model; that is, for each patient \( i \) the value of \( e\text{Visit}_{it} \) is zero in all month before adoption, and after the patient uses e-visits once, the value \( e\text{Visit}_{it} \) stays 1 for all months after adoption.

Our linear fixed-effect specification for this analysis is the following:

\[
y_{it} = \alpha \cdot e\text{Visit}_{it} + \Lambda_t + \delta_i + \kappa_{it} + \theta \cdot \text{AdoptionMonth}_{it} + \epsilon_{it},
\]

where \( \Lambda_t \) includes the month and year fixed effects to control for common trends and seasonality, \( \delta_i \) is the patient fixed-effect, and \( \kappa_{it} \) is the provider fixed effect.

The specification problem with (3) is that the number of visits per month is discrete and often zero. To deal with these two problems, we use the conditional fixed-effect Poisson model (Hausman et al. 1984). In this model, the probability of observing \( y_{it} \) visits for patient \( i \) at time \( t \) is

\[
P(y_{it}) = \frac{e^{-\lambda_{it}} \lambda_{it}^{y_{it}}}{y_{it}!},
\]
where $\lambda_i$ is the Poisson parameter that is equal to the expected value of $y_{it}$. Therefore, our fixed
effect regression specification is the following:

$$
E(y_{it}) = \exp(\alpha \cdot eVisit_{it} + \Lambda_t + \delta_i + \kappa_{it} + \theta \cdot AdoptionMonth_{it}).
$$

(5)

As we show later, the estimates from this specification have the same direction and magnitude as
the linear fixed-effect model.

To account for the endogeneity of e-visit adoption, we run an instrumental variable analysis.
Our instrumental variable is defined as follows for provider $j$ in month $t$:

$$
ProviderAdoption_{jt} = \frac{\text{Number of eVisits}_{jt}}{\text{Number of Office Visits}_{jt}}.
$$

(6)

To avoid mechanical correlation between our instrumental variable and endogenous regressor, we
define “Provider Adoption” in the form of a leave-one-out instrument for each patient. In other
words, when we compute the provider’s adoption for patient $i$, we leave the observation of patient $i$
out from the calculation of the instrument value for patient $i$. The validity of this instrument rests on
its ability to predict e-visit adoption, i.e., a relevant first stage, and otherwise be uncorrelated with
the number of traditional visits undertaken by the patient, i.e., satisfying the exclusion restriction.
That is, the identifying assumptions are that the intensity with which the provider uses e-visits
with her other patients is a good proxy for whether a particular patient adopts e-visits, and second,
that this intensity affects patient outcomes only via the channel of e-visits.

Figure 6 is a plot of provider adoption for four physicians in our dataset. The physicians show
different adoption behaviors both in terms of timing and slope, and this is the variation that we
use in our analysis. That is, after controlling for patient and provider fixed effects, we take the
variation in the adoption rates of the patient’s provider on the provider’s other patients to be
exogenous with respect to the patient’s office visits. Thus, our instrumental variable is separate
from time trend because the rates of e-visit usage by different providers are different and they
change differently over time.

The two-stage least squares (2SLS) specification based on (3) is the following:

$$
eVisit_{it} = \gamma \cdot ProviderAdoption_{it} + \Lambda_t + \delta_i + \kappa_{it} + \epsilon_{it},
$$

(7)

$$
y_{it} = \alpha \cdot eVisit_{it} + \Lambda_t + \delta_i + \kappa_{it} + \xi_{it},
$$

(8)

where $ProviderAdoption_{it}$ is the leave-one-out instrument for patient $i$’s provider in month $t$.

The first stage regression is presented in (7). In the first stage, we predict whether the patient
has adopted e-visits using provider adoption and other controls: provider fixed effect, patient fixed

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2 This problem is commonly studied in the economics literature on “program evaluation” since similar selection issues
arise in evaluating many social policies (Heckman et al. (1996), Heckman (1997)).
effect, and month and year fixed effects. In the second stage, i.e., (8), we use the predicted probability of using e-visits, i.e., $\hat{e}_{Visit_{it}}$ to estimate the selection corrected $\alpha$.

In our analysis, we include patient and provider fixed effects in all our models. Including patient fixed effects is motivated by the need to control for all time-invariant patient characteristics, and the inclusion of provider fixed effects is motivated by different practice style among providers in our data. We are able to separately identify physician and patient fixed effects because some of the patients in our data move between providers. Following a similar logic as the one in Abowd et al. (1999)$^3$, a relatively small amount of patient mobility would suffice to identify patient and provider fixed effects separately. In our dataset, the median number of physicians that a patient interacts with is 2 (the mean is 2.1).

5.2. The Effect of e-Visit Adoption on Patient Health

We use similar specifications to estimate the effect of e-visit adoption on patient health. LDL (bad cholestrol) and HbA1c (blood sugar) are the two health outcomes measures that we use to evaluate the effect of e-visit adoption on patient health. The general rule is that the higher the levels of LDL and HbA1c, the worse is patient health, but there are important cutoff values that are used in medicine to define whether patient health is “under control” or not. We define $HbA1c_{it}$ and $LDL_{it}$ to take the value of 1 if the measurement value is above the cutoff point and 0 if the observation is below the cutoff point. In addition, we look at emergency room visits, defining $ER_{it}$ to equal 1 if patient $i$ visited the emergency room at month $t$ and zero otherwise.

6. Results

In this section, we first present the results of the event study on office and telephone visits. We show that e-visits are not substitutes for office or telephone visits, and, instead, that higher usage of e-visits results in more office and telephone visits. Then, we use our instrumental variable approach to show the estimates that are immune to biases from patient unobservable characteristics, e.g., patient health trajectory. Finally, we show the instrumental variable results for patient health outcomes.

6.1. The Effect of e-Visit Adoption on the Number of Office and Telephone Visits

6.1.1. Event Study Results (Hypotheses 1 and 2) Before discussing the regression results, we motivate our analysis with two plots. Figure 4 shows the mean number of office visits for

$^3$Abowd et al. (1999) examine the effect of worker and firm heterogeneity as well as observable worker characteristics on worker wages. They show that a relatively small amount of worker movement between firms suffices to identify firm and worker fixed effects. The patients in our study are like the workers in the Abowd et al. (1999) paper, and the providers are like the firms.
the e-visit adopters before and after adoption. This figure suggests that adoption results in fewer office visits because the mean number of office visits in the post-adoption region falls below the ones in the pre-adoption region. Another observation from this figure is the increase in the number of office visits around the month of adoption. This effect occurs because the probability of adopting e-visits increases with provider interaction. Campbell and Frei (2010) had a similar observation in the adoption of online banking; customers who sign up for online banking call the bank or visit the branch to set up their account. This effect in our data is consistent with the identification assumption of our instrumental variable: patients may adopt e-visits at the encouragement of their provider.

Figure 5 plots the number of monthly office visits before and after adoption for all three groups of adopters: inactive, passive and active. In other words, Figure 5 is the stratified version of Figure 4 where we draw a curve for each group of adopters. This figure suggests that e-visits are not a substitute for office visits because patients who are heavy-users (i.e., active adopters) of e-visits have more post-adoption office visits than all other adopters, whereas active and inactive adopters have similar numbers of office visits pre-adoption.

Column (1) in Table 2 shows the estimates for the number of office visits for inactive, passive, and active adopters before and after adoption of e-visits. The estimates for the number of office visits are consistent with our observations in Figure 5. These estimates are also consistent with the existence of the positive health trajectory in patients who adopt e-visits. The coefficient for POST is negative and significant. Patients who adopt e-visits and never use it post-adoption have fewer office visits (-0.19, \( p < .05 \)). Moreover, patients who use e-visits, i.e., passive and active adopters, use significantly more office visits (0.06 and 0.13 with \( p < .05 \) for both). Further, the active adopters use more office visits compared with the passive adopters (\( p < .05 \)).

The coefficients in Table 2 come from the Poisson regression specification described in (4) and (5). Therefore, the interpretation of the coefficients is different from a linear regression: although the direction of the estimates are given correctly by the Poisson coefficients, interpreting the magnitude requires more care because of the inherent nonlinearity in the Poisson model. For example, the percentage increase in the number of office visits post-adoption for active adopters compared to the Inactive adopters (our control group) can be computed by: \( 100^\ast(\exp(\gamma_1 + \gamma_3) - \exp(\gamma_1)) = 11.5\% \).

The results for the number of telephone visits are similar. Column (2) in Table 2 presents the estimation results for the number of telephone visits. Similar to the results on office visits, there is a significant drop in the number of telephone visits post-adoption for the inactive adopters (-0.06, \( p < .05 \)). Also, passive and active patients use more telephone visits compared with the inactive adopters (0.04 and 0.13 with \( p < .05 \) for both). Again, consistent with the gateway hypothesis, the coefficient for active adopters is significantly higher than the one for passive adopters (\( p < .05 \)).
Overall, these estimates suggest that e-visits “complement” office visits rather than substituting for them, evidence in support of 1B and 2B in the direction of “gateway” hypothesis.

6.1.2. Instrumental Variable Results (Hypotheses 1 and 2) Column (2) of Table 3 shows the results of a naïve analysis where we run the regression in (5) only on patients who adopted e-visits. The identification in this model comes from patients who adopt e-visits at different months in our data. This estimate suggests a 8.9% decrease in the number of office visits after the adoption of e-visits. Column (1) of Table 3 runs a similar analysis based on the linear specification in (3). This estimate shows that in a linear model, the number of office visits decreases by 7.6% in the post-adoption period. The estimates in columns (1) and (2) of Table 3 have the same sign and are close in magnitude, and this similarity between the linear and Poisson specifications gives us confidence to proceed with the instrumental variable analysis that is based on a linear specification.

Our instrumental variable approach shows that the number of office visits increased by 96% after adoption of e-visits: the mean number of office visits per month is 0.28 and the coefficient in column (3) of Table 4 shows an increase of 0.27 ($p < .05$). In other words, e-visit adoption leads to an average of 6.6 office visits per year for adopters versus 3.3 office visits per year for non-adopters.

We find similar results for telephone visits. The coefficient in column (6) of Table 4 shows that the number of telephone visits increases by 83%; the mean number of telephone visits are 0.41 and the increase in this value is 0.35 post-adoption. Overall, similar to what we showed in the event study, we find support for 1B and 2B in the direction of “gateway” hypothesis.

We test for autocorrelation in our dataset using the test provided in Wooldridge (2002). This is a test for serial correlation in the idiosyncratic errors of a linear panel data model with good size and power properties (Drukker 2003). We obtain a $p$-value of 0.64, which means that we cannot reject the hypothesis that the data are free of serial correlation. We also show in column (7) of Table 4 that our instrumental variable performs well and is relevant in predicting e-visit adoption of patients. Moreover, our results are robust to flexible controls for time and other covariates.\textsuperscript{4} We use robust standard errors and cluster them by patient.

6.2. The Effect of e-Visit Adoption on Patient Health (Hypotheses 3, 4 and 5)

Column (1) and (3) of Table 5 show the results for patients who adopt e-visits with the specification in (3). Consistent with our belief on positive health trajectory at the time of adoption, we observe a health improvement post-adoption for the LDL and HbA1c outcomes. However, the

\textsuperscript{4}To supplement this analysis, we run an instrumental variable analysis where we use the adoption of all providers but the patient’s provider in the same department as an instrument for patient’s adoption. This is a weaker instrumental variable, so the estimates for the “e-Visit” variables become large and hard to interpret. However, the direction of the estimate is the same as the one that we obtain from our instrumental variable analysis in Table 4.
instrumental variable results are not significantly different from zero. Indeed, the standard errors for the instrumental variable estimate are wide and include the estimates of column (1) and (3), but the point estimates, which are unbiased, are close to zero. In other words, although our results suggest that e-visit adoption has no effect on patient health, with our current estimates, we cannot reject existence of some improvements in patient health.

Our analysis of patient health outcomes is valid if there is no relationship between e-visit adoption and the frequency with which patients perform LDL and HbA1c tests. Otherwise, it could be the case that the health statuses of patients who adopt e-visits have improved to the extent that they do not need further testing and are censored from our dataset. We performed the following test to rule out this possibility. We use the analysis that we proposed for the effect of e-visits on the number of office and telephone visits, apply it to the number of tests per month, and find no significant effect.

Table 6 presents the results regarding the impact of e-visit adoption on the number of emergency room visits. Both OLS and instrumental variable regressions suggest no effect on the number of emergency room visits. However, emergency room visits are rare events in our data: we observe a total of 1,731 emergency room visits for our patient population; only 248 of them are for e-visit adopters. This small sample size reduces our power, but the point estimates are close to zero and this suggests no effect.

7. Conclusion

E-visits have the potential to enhance primary care delivery by both improving the quality of care and reducing costs, and health care providers are increasingly adopting e-visits (Wall Street Journal 2012). This technology provides a new way for patients to manage their health and increases their access to primary care services. Additionally, patients are typically able to contact their providers directly, bypassing the usual gatekeepers in the practice such as scheduling clerks. Also, e-visits are easier to schedule because they do not require simultaneous availability of the provider and the patient for an interaction.

This paper is the first to explicitly address the possibility of selection based on unobservable patient characteristics in e-visit adoption. The first section of the paper investigates whether e-visits provide a substitute for traditional forms of primary care delivery. We establish that e-visits increase the number of traditional primary care encounters that a patient has with his primary care provider, via both telephone and office visits. We then apply this finding to investigate the effect of e-visits on patient health outcomes. Our panel data include information on blood cholesterol, measured by LDL levels, blood glucose, measured by HbA1c levels, and emergency room visits. Using our instrumental variable approach, we find that e-visits have no discernible effect on patient
health. Our findings are in stark contrast to the existing literature (Zhou et al. (2007), Zhou et al. (2010)), which argues that e-visits improve patient health on similar measures. Interestingly, we replicate these findings if we do not account for unobservable selection in e-visit adoption and in particular, the difference in estimates stems from the selection of patients into e-visit adoption on unobservable time-varying factors.

Our results highlight the importance of considering patient and physician responses as well as other existing “frictions” when introducing new models of service delivery in health care. Existing literature in health care operations has examined some of these factors. Dobson et al. (2009) show that the use of non-physician providers may not enhance physician capacity because of the “coordination costs” that can outweigh the benefits. Also, using an analytic framework that endogenizes patient demand for care, Bavafa et al. (2013) show that physician compensation combined with patient responses have significant impacts on the equilibrium system outcomes (physician panel size, patient health, and physician compensation) following the introduction of non-physician providers and e-visits. Identifying other factors that affect the effectiveness of new models of service delivery in primary care is a promising direction for future research.

Beyond examining the effect of patient portals, our study contributes to the literature on patient revisit intervals in primary care. There is an ongoing debate in this literature regarding the optimal frequency of patient visits in primary care (Tobacman et al. (1992), Schwartz et al. (1999), DeSalvo et al. (2000), DeSalvo et al. (2003)). We show that increasing the frequency of patient encounters, combined with e-visits, does not have a measurable effect on patient health. Our results are consistent with Schectman et al. (2005), which shows that decreasing the frequency of patient visits does not have a significant effect on patient health. Further examination of the relationship between the frequency of patient encounters and patient health is one direction for future research.

Our study is based on data from a health system in which providers are compensated on a fee-for-service basis, and there is evidence that physician incentives affect physician behavior and treatment choices (Shumsky and Pinker (2003), Gosden et al. (2004), Lee et al. (2010)). Although fee-for-service is still the most prevalent compensation schedule in the United States (Centers for Disease Control and Prevention 2010), it may be the case that physicians behave differently under capitation or salaried payments. Future work can extend the current analysis to settings where physicians are compensated with incentive schemes other than fee-for-service. Another related topic for future research is to study the impact of tying financial incentives to e-visits. Currently, most health plans (including Medicare and Medicaid) do not reimburse providers for e-visits (Bishop et al. 2013); this is also true in our setting. However, a handful of health institutions have experimented with charging patients annual fees (Reijonsaari et al. 2005) or co-payments (Fairview Health Services 2013) for e-access to their physicians.
References


Notes: Adoption of e-visits in the health system of this study from 2008 until the first quarter of 2013 (data for the rest of 2013 are extrapolated). The adoption rate of e-visits is substantial and allows us to observe patients before and after adoption.
**Figure 2** The efficient frontier for patient health and physician productivity

*Notes:* This figure depicts the trade-off between patient health and physician productivity. If the physician interacts with the patient too often, the patient will have good health, but the physician will not be able to handle a large panel of patients, and vice versa. Patient portals have the potential to push the traditional efficient frontier “T” to “E,” where the physicians are more efficient and patients are healthier. The “E’” frontier is for the case where e-visits do not help with either patient health or physician productivity.
Figure 3  Histogram of the mean patient monthly office visits

Notes: This figure shows the histogram of the number of office visits per month for patients. The mean number of office visits per month is 0.28.
Figure 4  Mean monthly office visits before and after adoption

Notes: This figure shows the mean number of office visits per month for patients who adopted e-visits. There is a drop in the number of office visits in the post-adoption period. The peak in at the adoption month originates from patients signing up for e-visits in the month that they see their providers.
Figure 5  Mean monthly office visits before and after adoption for different groups of adopters

Notes: This figure shows the mean number of office visits per month for patients who adopted e-visits stratified by usage intensity. “inactive” adopters do not use e-visits after adoption, “passive” adopters use e-visits with below-median intensity, and “active” adopters use e-visits with above-median intensity. The difference between the number of office visits between the inactive adopters (blue dashed line) and the active adopters (the solid red line) is much more significant in the post-adoption period.
Figure 6  Adoption of e-visits by physicians

Notes: Adoption of e-visits by four different physicians from 2008 until the first quarter of 2013. Adoption for Physician $j$ in month $t$ is defined as $\frac{\text{Number of e-Visits}_{jt}}{\text{Number of Office Visits}_{jt}}$. 

2008 2009 2010 2011 2012
<table>
<thead>
<tr>
<th></th>
<th>All patients</th>
<th>Non-adopters</th>
<th>Adopters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age (in 2013)</td>
<td>52.14</td>
<td>51.77</td>
<td>55.93</td>
</tr>
<tr>
<td>Male</td>
<td>0.41</td>
<td>0.41</td>
<td>0.43</td>
</tr>
<tr>
<td>Black</td>
<td>0.29</td>
<td>0.31</td>
<td>0.17</td>
</tr>
<tr>
<td>White</td>
<td>0.57</td>
<td>0.55</td>
<td>0.73</td>
</tr>
<tr>
<td>Office visits per month</td>
<td>0.25</td>
<td>0.26</td>
<td>0.21</td>
</tr>
<tr>
<td>Phone visits per month</td>
<td>0.34</td>
<td>0.34</td>
<td>0.36</td>
</tr>
<tr>
<td>High HbA1c (glucose)</td>
<td>0.30</td>
<td>0.31</td>
<td>0.24</td>
</tr>
<tr>
<td>High LDL (cholesterol)</td>
<td>0.57</td>
<td>0.57</td>
<td>0.58</td>
</tr>
</tbody>
</table>

Notes: The patients who adopt e-visits are on average healthier from a blood glucose (HbA1c) standpoint and have fewer office visits per month. The difference in adoption rate between races is substantial.
Table 2  Event study regressions for office and telephone visits

<table>
<thead>
<tr>
<th></th>
<th>Office Visits</th>
<th>Telephone Visits</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>POST</td>
<td>-0.19***</td>
<td>-0.06***</td>
</tr>
<tr>
<td></td>
<td>(0.017)</td>
<td>(0.013)</td>
</tr>
<tr>
<td>POST × PASSIVE</td>
<td>0.06***</td>
<td>0.04***</td>
</tr>
<tr>
<td></td>
<td>(0.019)</td>
<td>(0.014)</td>
</tr>
<tr>
<td>POST × ACTIVE</td>
<td>0.13***</td>
<td>0.13***</td>
</tr>
<tr>
<td></td>
<td>(0.017)</td>
<td>(0.0120)</td>
</tr>
<tr>
<td>Adoption Month</td>
<td>0.74***</td>
<td>0.66***</td>
</tr>
<tr>
<td></td>
<td>(0.012)</td>
<td>(0.009)</td>
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</table>

<table>
<thead>
<tr>
<th></th>
<th>✓</th>
<th>✓</th>
</tr>
</thead>
<tbody>
<tr>
<td>Patient FE(s)</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Provider FE(s)</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Month FE(s)</td>
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<td>✓</td>
</tr>
<tr>
<td>Year FE(s)</td>
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<td>✓</td>
</tr>
<tr>
<td>Observations</td>
<td>347,993</td>
<td>347,993</td>
</tr>
<tr>
<td># of patients</td>
<td>7,409</td>
<td>7,409</td>
</tr>
</tbody>
</table>

Notes: This table presents the results of the event study in which we use the patients who adopt e-visits and do not use them post-adoption as our control group. The estimates are based on a Poisson model. Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the patient level.
Table 3  Poisson and linear specifications

<table>
<thead>
<tr>
<th></th>
<th>OLS</th>
<th>Poisson</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>e-Visit Adoption</td>
<td>-0.02***</td>
<td>-0.11***</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.011)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>✓</th>
<th>✓</th>
</tr>
</thead>
<tbody>
<tr>
<td>Patient FEs</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Provider FEs</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Month FEs</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Year FEs</td>
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<tr>
<td>Observations</td>
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<td>347,993</td>
</tr>
<tr>
<td># of patients</td>
<td>7,409</td>
<td>7,409</td>
</tr>
</tbody>
</table>

Notes: The estimates from the linear specification and the Poisson specification have the same sign and similar magnitudes. The -0.02 OLS translates to about 8% decrease in the number of office visits because the mean number of office visits is 0.28. Similarly, the Poisson specification suggests about 9% decrease in the number of office visits. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the patient level.
Table 4  The Impact of e-Visit Adoption on Office and Telephone Visits

<table>
<thead>
<tr>
<th></th>
<th>Office Visits</th>
<th></th>
<th>Telephone Visits</th>
<th></th>
<th>First Stage</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>OLS (1)</td>
<td>OLS (2)</td>
<td>IV (3)</td>
<td>OLS (4)</td>
<td>OLS (5)</td>
</tr>
<tr>
<td>e-Visit Adoption</td>
<td>-0.02***</td>
<td>0.007**</td>
<td>0.27***</td>
<td>0.018**</td>
<td>-0.005</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.013)</td>
<td>(0.013)</td>
<td>(0.008)</td>
<td>(0.004)</td>
</tr>
<tr>
<td>Adoption Month</td>
<td>0.19***</td>
<td>0.20***</td>
<td>0.28***</td>
<td>0.29***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.007)</td>
<td>(0.007)</td>
<td></td>
</tr>
<tr>
<td>Provider Adoption</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.180***</td>
</tr>
<tr>
<td>Patient FEs</td>
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<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Provider FEs</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Month FEs</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Year FEs</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Observations</td>
<td>347,993</td>
<td>2,385,224</td>
<td>2,385,224</td>
<td>347,993</td>
<td>2,385,224</td>
</tr>
<tr>
<td># of patients</td>
<td>7,409</td>
<td>65,282</td>
<td>65,282</td>
<td>7,409</td>
<td>65,282</td>
</tr>
<tr>
<td>Sample</td>
<td>Adopters All</td>
<td>All</td>
<td>All</td>
<td>Adopters All</td>
<td>All</td>
</tr>
</tbody>
</table>

Notes: Regression results for the effect of e-visits on the number of office and telephone visits are presented here. The results for the number of office visits are presented in columns (1)-(3) and the results for the number of telephone visits are presented in columns (4)-(6). The estimates in columns (1) and (4) are for the e-visit adopter only without an instrumental variable. The estimates in (2) and (5) are for all patients without an instrumental variable. Finally, the results in (3) and (6) come from the 2SLS instrumental variable regression. Column (7) presents the coefficient of provider adoption in the first stage of the instrumental variable analysis. Standard errors in parentheses, * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors are clustered at the patient level.
### Table 5  The Impact of e-visit adoption on patient health

<table>
<thead>
<tr>
<th></th>
<th>LDL</th>
<th>HbA1c</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>OLS</td>
<td>IV</td>
</tr>
<tr>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>e-Visit Adoption</td>
<td>-0.022***</td>
<td>-0.001</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>Patient FEs</td>
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</tr>
<tr>
<td>Provider FEs</td>
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<td>✓</td>
</tr>
<tr>
<td>Month FEs</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Year FEs</td>
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<tr>
<td>Observations</td>
<td>47,180</td>
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</tr>
<tr>
<td># of patients</td>
<td>9,953</td>
<td>54,615</td>
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<tr>
<td>Sample</td>
<td>Adopters</td>
<td>All</td>
</tr>
</tbody>
</table>

**Notes:** This table presents the results for the analysis for the impact of e-visit adoption on patient health outcomes. Columns (1) and (2) are for the “bad cholesterol” outcomes and columns (3) and (4) are for “blood glucose” outcomes. The OLS results show improvements in patient health but the IV results are not significantly different from zero. However, IV estimates have wide standard errors and their confidence intervals include the OLS estimates. Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the patient level.

### Table 6  The Impact of e-visit adoption on emergency room visits

<table>
<thead>
<tr>
<th></th>
<th>OLS</th>
<th>OLS</th>
<th>IV</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>e-Visit Adoption</td>
<td>-1e-04</td>
<td>-8e-05</td>
<td>2e-04</td>
</tr>
<tr>
<td></td>
<td>(6e-05)</td>
<td>(6e-05)</td>
<td>(3e-04)</td>
</tr>
<tr>
<td>Patient FEs</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Provider FEs</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Month FEs</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Year FEs</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Observations</td>
<td>537,182</td>
<td>2,385,224</td>
<td>2,385,224</td>
</tr>
<tr>
<td># of patients</td>
<td>10,507</td>
<td>65,282</td>
<td>65,282</td>
</tr>
<tr>
<td>Sample</td>
<td>Adopters</td>
<td>All</td>
<td>All</td>
</tr>
</tbody>
</table>

**Notes:** All our estimates for the effect of e-visit adoption on the number of emergency room visits are insignificant. Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the patient level.