The Impact of e-Visits in Primary Care: Evidence on Visit Frequencies and Patient Health

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Interest in innovative health care delivery models has surged in recent years, partly owing to measures such as the Affordable Care Act which have expanded insurance coverage and spotlighted the need to contain health care costs. The goal of these innovations is to increase physician capacity without sacrificing quality of care. One innovation that has been proposed as a low-cost alternative to traditional office and phone visits is "e-visits," or secure messaging between patients and physicians via patient portals. Using a panel dataset from a large primary care provider in the United States, we impact of patient adoption of e-visits on their subsequent frequency of office and phone visits, and also their subsequent health statuses. We study the 2008 to 2013 time period for our system which covers the first adoption of e-visits and their following promotion. The data enable a variety of difference-in-differences, matching, and instrumental variable analyses due to the variation in timing of both patient and physician adoption of e-visits, which allow us to carefully consider both observable and unobservable factors that drive patient e-visit adoption. Our study is the first to document strong evidence that contrary to current beliefs, e-visits serve to "trigger" additional office and phone visits without consistently measured improvements in patient health as measured by levels of blood cholesterol and blood glucose. The instrumental variable analysis provides suggestive evidence that patients on a healthy trajectory may be adopting e-visits at higher rates.

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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. Many medical providers promoted the use of e-visits through patient portals over the past decade, hoping that they can substitute for office and phone visits to allow for larger panel sizes and improved patient health. The efforts to diffuse the technology have been successful; according to a 2012 survey, 57% of health care providers have a patient portal and many of those that do not have a patient portal intend to deploy one (KLAS Research 2012). In addition to providing patients with e-visits, these portals typically help patients access their laboratory results and medical histories, appointment scheduling, and prescription refills. E-visits can also play an important role in mitigating rising health care costs and dealing with the projected shortage of primary care physicians—22.8 million newly insured patients have resulted recently from the Affordable Care Act alone (Carman et al. 2015)—but their effectiveness in meeting these goals has not yet been evaluated.

We are the first study to find that e-visits may "trigger" additional primary care encounters without obvious benefits to patient health. Formally, we estimate the impact of e-visit usage on visit frequency of office and phone encounters as well as on patient health outcomes to inform managerial decisions about whether and how to promote this technology. Visit frequency is important because it has direct consequences for physician panel sizes and also the cost of accessing care for patients. Studying patient health is important because its improvement is the core goal of any medical innovation, and e-visits may impact this important goal in unknown ways. Our main measures of patient health include blood cholesterol[1] (LDL) and blood glucose (HbA1c) levels. These measures are especially helpful in evaluating the effectiveness of e-visits in improving the health of chronically ill patients, and are commonly measured for a significant fraction of the population. E-visits may directly affect these outcomes—perhaps the physician sends useful advice regarding diet and exercise, for example—or e-visits may lead to increased visit frequency of office and phone visits, which may improve patient health outcomes through a multitude of traditional channels. Together, visit frequency and patient health also provide useful information about the impact of e-visits on physician productivity, though we do not study productivity directly in this paper due to imperfect data on appointment duration and related variables.

The empirical evaluation of e-visits is challenging because of the difficulty in obtaining the necessary micro-data required to properly estimate important model components such as physician fixed effects, along with a concern about unobservable selection in e-visit usage. If patients who adopt

[1] Throughout this paper, we define blood cholesterol as the "bad" cholesterol LDL (low-density lipoproteinor.)

e-visits are systematically different from non-adopters in ways that are correlated with their visit frequencies and/or health outcomes, a credible research strategy requires a source of experimental or quasi-random variation in e-visit usage to be reassured that unobservable characteristics are not biasing the key estimates. Likely due to the lack of such variation in existing settings, previous papers on this topic have limited their approaches to addressing only observable selection, typically via matching methods (Zhou et al. (2007), Zhou et al. (2010)). Further complicating the standards for proper analysis, patient selection in e-visit usage may be 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 e-visit usage, visit frequency, 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 use e-visits as a way to substitute for office visits. The empirical signature of this type of bias in the data would be a positive correlation between e-visits and health outcomes, and/or a negative correlation between e-visits and visit frequency, since then it would not be clear whether e-visits have a causal impact on these outcomes, or if patients select into e-visit usage on these outcomes.

Using data from a large primary care provider in the United States, our study is the first to explicitly deal with selection on both time-invariant and time-varying unobserved patient characteristics in e-visit adoption. We deal with time-invariant unobservables by employing estimation models that include patient fixed effects. This strategy allows us to control for *all* unobserved patient characteristics that are time-invariant over the span of our panel. We address time-varying unobservables using an instrumental variable approach that exploits variation in the patient's physician's propensity to engage in e-visits. Specifically, we use the number of e-visits that a patient's physician conducts with all other patients in a given month to construct an instrumental variable for patient e-visit adoption in that month. The identifying assumption is that the physician's intensity of e-visit usage with other patients does not directly influence a particular patient's visit frequency or health outcomes, which is a tenuous assumption if physician practice styles are changing along with their adoption of e-visits. To ensure that this assumption is plausible, we gather data on physician appointment scheduling and find no differences in the number of appointments provided or the duration of each appointment, which gives us some comfort in our assumption that practice styles do not fundamentally change at the time of e-visit adoption.

Several unique features in our data allow us to obtain unbiased estimates of the effect of e-visit adoption on visit frequency and patient health. First, we observe the behavior of a large patient and physician panel (more than 140,000 patients interacting with 90 physicians and many other non-physician providers) over the 2008 to 2013 period during which e-visits were introduced and promoted. Figure 1 illustrates the growth of e-visit usage over this time period by plotting the system-wide usage of e-visits, office visits, and phone visits. The figure shows that while office and phone visits experience a mild increase over the time period studied (likely due to general expansion of the practices we study), the usage of e-visits sharply increased since their introduction in 2008. Specifically, the number of e-visits increased from 96 in the first two months of 2008 to 6,449 in the first two months of 2013. We are aware that there was a particular push toward promoting e-visits in April and May of 2012, which appears in our data. Second, the data feature all patient interactions for 90 physicians and additional non-physician providers, allowing us to implement an instrumental variable analysis that leverages these providers' differential timings and intensities of e-visit adoption.

We begin our analyses by focusing on visit frequency and replicating the results in Zhou et al. (2007) and Zhou et al. (2010). In this exercise, we conduct what we label a "naive" difference-in-differences as it uses data only on patients who ultimately adopt e-visits and is identified off the variation in timing of adoption. This analysis suggests that e-visits substitute office visits by reducing them by about 10%, which matches the findings in the previous literature. We do not find any significant effect on phone visits, however. Next, we leverage data from our full sample of patients and conduct a difference-in-differences analysis of the impact of e-visit adoption on office and phone visit frequency. and find evidence that e-visits may in fact "trigger" about 6-7% additional encounters for both office and phone visits. These results persist in an analysis restricted to a sample of patient adopters who are matched to non-adopters on key variables such as physician, baseline visit frequencies, and baseline measures of blood cholesterol and blood glucose.

As motivation for our exploratory instrumental variable (IV) analysis that follows, we observe differences among e-visit adopters and non-adopters among multiple observable characteristics such as age and race. The differences in these observable dimensions raise concerns about possible differences in unobservable dimensions, even with the richness of our data. The IV analysis shows that as we suspect, our difference-in-differences estimates may suffer from attenuation bias. The selection-corrected estimates on the impact of e-visit adoption on office visit frequency is six times larger than our previous effect sizes of 6-7% and is statistically significant at the 5% level, though the confidence interval includes our earlier estimates. We do not find any significant results for phone visits. The IV results are hence indicative, though not confirmatory, of patients with a positive health trajectory selecting into e-visit adoption.

Having established that e-visits appear to "trigger" office visits in particular, we turn our attention to patient health outcomes. In our full difference-in-differences analysis, we find that e-visit adoption is correlated with statistically significant improvements in both blood cholesterol and

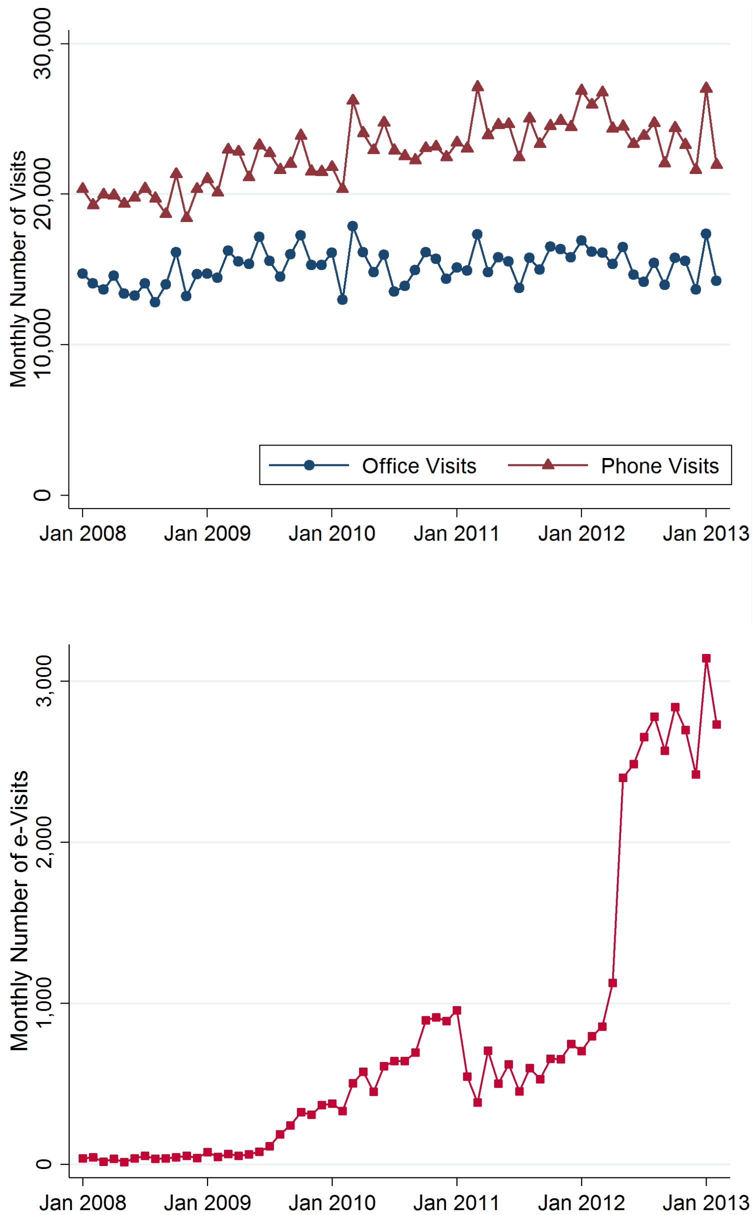


Figure 1 **Monthly Primary Care Encounters in the Studied Health System over Analysis Period**

blood glucose: the likelihood of an unhealthy observation in either measurement reduces by 3.5% and 7%, respectively. The matching analysis shows statistically insignificant results on blood cholesterol, however, and our IV results show statistically insignificant impacts of e-visits on both health outcomes. Interestingly, we do find that statistically significant improvements in blood cholesterol and blood glucose appear in just one month following patient e-visit adoption, which is consistent with adoption being systematically more likely among those on a trajectory toward improved health.

Our results withstand a variety of robustness checks. Most importantly, our results are stable to different definitions of patient e-visit usage. The main definition of e-visit usage in this paper is simply whether the patient has ever used an e-visit, but our results are robust to whether we refine this binary variable to turn on with the patient's second e-visit, or whether we define the variable more subtly by allowing the variable to stay "on" for only three months after each e-visit. We also conduct a placebo analysis and randomize e-visit adoption among our sample to verify that these placebo-induced adoptions do not lead to spurious results. Together, we feel that these results provide evidence that e-visits may be triggering additional encounters without any obvious improvements in patient health.

The remainder of this paper is organized as follows. We present our theoretical motivation for our key outcomes in Section 2. In Section 3, we explain our dataset and the institutional features of the health system that we study in our analysis. We discuss in detail our empirical strategies in Section 4, followed by our results on visit frequency and patient health and their discussion in Sections 5 and 6, respectively. Section 7 provides robustness checks on our estimates and we conclude and highlight areas for future research in Section 8.

2. Theoretical Motivation for Outcomes

In this section, we use insights from the literature to develop hypotheses about the relationship between e-visit adoption and the two sets of outcomes we study: visit frequency and patient health.

2.1. e-Visit Adoption, Visit Frequency, and the Gateway Effect

The first goal of our analysis is to estimate the impact of e-visit adoption on visit frequency, or the number of primary care encounters that a patient has with his or her physician. We measure this by summing up separately the number of office visits and phone visits conducted each month by each patient. These variables are important because they directly affect physician workload, patient health, and health care costs. The frequency with which patients require primary care encounters also has a mechanical impact, all else equal, on the number of patients that a physician can serve: a physician whose patients visit once every months can handle twice a panel size compared to a physician whose patients visit every month. The case is analogous for phone visits.

Our study on visit frequency contributes to three main streams in the literature. First, our work adds to operations management literature within primary care examining the impact of various operational interventions such as provider flexibility on system outcomes (Green and Savin (2008), Zacharias and Pinedo (2013), Liu and Ziya (2013), Balasubramanian et al. (2012), and Deo et al. (2013)). Second, because e-visits are only one component of the comprehensive set of services offered by patient portals, our findings inform the literature evaluating the impact of adoption of health information technology (Adler-Milstein and Huckman (2013), Angst et al. (2011), and

Devaraj et al. (2013)). Third, but not least, our paper joins the small number of studies within the medical literature examining various aspects of e-visits including what types of patients use them and what impacts they have on care quality and visit frequency (Leveille et al. (2016), North et al. (2014), Irizarry et al. (2015), Zhou et al. (2007) and Zhou et al. (2010).)

Conceptually, the addition of e-visits to a health system can change several features of the way in which physicians take care of patients.[2] Because e-visits provide patients with a new, additional (and typically free, as is in our system) channel through which they can communicate with their providers, they can be used to either substitute or complement traditional visits. If patients use e-visits to substitute for office and phone visits, patient e-visit adoption would be expected to lower their frequency of office and phone visits. A number of researchers have argued for this substitution effect, including Bergmo et al. (2005), Kilo (2005), and Zhou et al. (2007).

A number of factors may lead to an increase in the frequency of visits following the adoption of e-visits. First, e-visit adopters may view electronic communication as a low-cost channel for reaching their physicians and bypassing the usual practice gatekeepers, such as office staff and nurses. If this is the case, more communication with the physician obliges the physician to see the patients in the office or have a phone conversation with the patient, so the numbers of office and phone visits will not decrease, and they might even increase. Overall, the value proposition of the e-visit channel could be different from the phone and office visits. For example, in the used car market, Overby and Jap (2009) show that buyers and sellers use physical and electronic channels for different types of transactions.

Second, e-visits can be weak in transferring the right types and amounts of information between patients and providers. Prior literature has shown that provision of ambiguous information may lead to more information-seeking behavior (Cox (1967), Murray (1991), and Leckie et al. (1996)). Kumar and Telang (2012) study the effects of a web-based self-service channel at the call center of a United States health insurance firm. They find that if the information is unambiguous and easily retrievable on the web, the related calls decrease by 29%. The authors, however, find the opposite effect for ambiguous information. Similar effects have been shown in the financial sector (Miller 1972).

Third, it is possible that e-visits are adopted systemically by “worried-well” patients who are over-react to typically minor symptoms (Wagner and Curran 1984). In this case, e-visits may aid patient well-being without measurable improvements in patient health. The problem of endogenous adoption of electronic service delivery channels that we face in this setting has beens studied in other settings. For example, in the banking sector, research shows that online customers tend to be

[2] Bavafa et al. (2016) provide a theoretical model of the way in which patient e-visit adoption may impact system outcomes in primary care by endogenizing patient demand for healthcare consumption.

younger, are more profitable, and have shorter relationships with the bank (Frei and Harker (2000), Hitt and Frei (2002), and Xue et al. (2007)). Degeratu et al. (2000) records similar observations for online ordering in supermarkets.

Fourth, behavioral and financial factors can influence physician behavior in initiating office and phone visits following an e-visit (Chandra et al. 2011). In particular, even a small signal such as a message from a patient may trigger further phone and office visits which would not have happened otherwise. The impact of behavioral and environmental factors on server behavior (in our case, doctor behavior) is well-documented in the operations management literature (Kc and Terwiesch (2009), Batt and Terwiesch (2016), Tan and Netessine (2014), Berry Jaeker and Tucker (2016), and Song et al. (2015)).

We call the possibility that e-visit adoption leads to more frequent visits the *gateway* effect. This effect is consistent with studies based on randomized controlled trials, which show that more frequent phone contact increases the chance of patient readmission to the hospital (Weinberger et al. (1996)). Two relevant studies in the literature find that the number of phone visits is not impacted by e-visits (Katz et al. (2003), Katz et al. (2004)). These two studies, however, are limited in size and scope and do not address office visits and patient health. It is worth noting that e-visits may be particularly good substitutes for phone visits because of their similarities in content, usage, and duration. In contrast to office visits, phone 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.

On the other hand, e-visit adoption might encourage an *increase* in service consumption, including office and phone visits. For example, in a consumer bank setting, Campbell and Frei (2010) examine the impact of customer adoption of online banking services and study three outcomes: changes in service consumption (all types), cost to serve, and customer profitability. They show that the adoption of online banking is associated with higher utilization of traditional service delivery channels (branch and call center) while reducing the usage of self-service delivery channels (automated teller machine and voice response unit). Overall, the authors find that adoption of online banking is associated with a higher cost of service.

2.2. e-Visit Adoption and Patient Health

The impact of e-visit adoption on patient health is of central consideration in evaluating patient portals. First, e-visit adoption may impact patient health through changes in the amount of service received through the traditional channels of care delivery—office and phone visits—as discussed earlier. Second, an e-visit is a new channel for care delivery, and patient health could improve from this innovation by receiving more care and increased monitoring (Zhou et al. (2010) and Baer

(2011)). Third, e-visits may improve the quality or efficiency of subsequent visits, which we will attempt to shed light on by supplementing our health analysis with appointment duration data.

In other relevant settings, Miller and Tucker (2011) find significant effects of health information technology adoption on reductions in child mortality. In terms of non-health outcomes, Buell et al. (2010) investigate the impact of multichannel service delivery in the retail banking industry, and find that while these additional self-service delivery channels don't necessarily improve customer satisfaction, they can help retain customer business.

To investigate whether e-visits improve patient health, we consider two patient health outcomes that are used extensively in the primary care literature (Friedberg et al. 2010): blood glucose (hemoglobin A1c, or HbA1c) and blood cholesterol (low density lipoprotein, or LDL). These health outcome metrics are favored in the health literature because they are easy to measure and responsive to the quality of primary care services. They are also particularly relevant for evaluating patient health in primary care due to the prevalence of chronic heart disease and diabetes in the United States: 71 million American adults (33.5%) have high LDL (Centers for Disease Control and Prevention 2011), and 29.1 million people or (9.3%) have diabetes (Centers for Disease Control and Prevention 2014).[3]

3. Data and Sample Definition

We use a panel dataset from a major health system. The health system is involved with research and clinical care in the United States and operates multiple hospitals (with over 2,000 beds in total) and medical centers, along with several primary and specialty care practices in its region. Our data consists of all primary care encounters (office visits, phone visits, and e-visits), all blood cholesterol tests, and all blood glucose tests conducted by patients of the 90 physicians with the largest panel sizes in the health system. These 90 physicians represent nine practices in a similar geographical vicinity, and we obtained data on all patients ever seen by these physicians in the time period studied. This totals 2,566,145 primary care encounters between January 2008 and February 2013 for 143,025 patients, and since the data are structured at the patient level, these encounters can be either with their physician or with non-physician providers such as nurses and residents.

Our only sampling restriction is to keep patients with more than two office visits over the time period studied as our focus is on regular users of primary care services. We enforce this restriction because the focus of our study is active users of primary care in our health system, and prior literature considers a patient to be on a physician's panel if he or she visited the provider in the

[3] In separate analyses provided in Table A14, we also study the impact of e-visits on emergency room visits. Emergency room visits are helpful in evaluating primary care but unfortunately, in our dataset we only observe a subset of all possible emergency room visits, making it difficult to link e-visit usage to this outcome.

past 18 months (Green et al. 2007). Additionally, Murray and Berwick (2003) argue that using a 12 month window may be too strict, while a 24 month window likely overestimates the physician's panel size. This reduces our sample to 96,566 patients, and since we observe each patient for 62 months, we have 5,987,092 patient-month observations. During the 2008 to 2013 time period we study, the health system began offering patients the option of having an e-visit encounter with their providers, and we observe that 12,975 patients (13.4% of our sample) use e-visits at least once. All but five physicians use e-visits in this time period, although the timing of their adoption varies greatly. These varying times and intensities with which both patients and physicians adopted e-visits over this time period lend naturally to difference-in-differences approaches comparing visit frequency and health outcomes for the patients we study.

In keeping with the literature, we define the number of office and phone visits at a monthly level by summing up the number of office visits (and separately, phone visits) for each patient-month. Table 1 shows the summary statistics for all patients, e-visit non-adopters, and e-visit adopters in columns (1), (2), and (3), respectively; column (4) shows the results of t-test on the difference between the adopter and non-adopter samples. We use the term "e-visit adopters" for patients who have communicated with any primary care provider via the secure messaging service of the patient portal at least once. Contrary to traditional technology adoption patterns, we find that e-visit adopters are about five years older than non-adopters (age 56 versus 51 in 2013.) Consistent with technology adoption patterns, however, e-visit adopters in our sample are more likely to be male (41% versus 39%) and non-minority. About 72% of all e-visit users are white even though they consist of only 56% of the sample. On the other hand, only 17% of e-visit users are black even though they comprise 33% of the patient population studied. We also observe a foreshadowing of our results in the summary statistics for the visit frequency outcomes: on average, e-visit adopters have 0.03 additional office visits and 0.07 additional phone visits per month.

Figure 2 shows plots of the four outcomes for the patients that adopt e-visits. The horizontal axis in each of these four graphs is months from the month of adoption, where zero equals the month of adoption. We observe in Panel A of this figure that office visits spike in the month before and the month of adoption, consistent with our expectation that patients tend to adopt e-visits following an office visit. We observe the same trend for phone visits in Panel B, though there is additionally an increased level of phone visits in the month following e-visit adoption. To be on the safe side and focus on longer-term impacts, however, we exclude the month before adoption, the month of adoption, and the month following adoption from all our analyses. The other two panels show plots of the mean fraction of unhealthy observations on blood cholesterol (Panel C) and blood glucose (Panel D) levels. Our sample sizes are smaller for these plots because not all patients have health measurements; however, we do observe a small spike in unhealthy observations of blood cholesterol.

Table 1 Summary Statistics by Patient e-Visit Adoption

	(1) All Patients		(2) Non-Adopters		(3) Adopters		(4) t-stat
	Mean	SD	Mean	SD	Mean	SD	
Demographics							
Age (in 2013)	51.96	19.03	51.34	19.55	55.99	14.59	-25.99***
Male	0.40	0.49	0.40	0.49	0.42	0.49	-5.78***
Black	0.33	0.47	0.36	0.48	0.17	0.38	41.59***
White	0.56	0.50	0.54	0.50	0.72	0.45	-40.46***
Asian	0.03	0.18	0.03	0.18	0.04	0.19	-3.07**
Other Race	0.07	0.26	0.07	0.26	0.06	0.25	4.09***
Outcomes							
Monthly Office Visits	0.16	0.12	0.15	0.12	0.18	0.12	-19.03***
Monthly Phone Visits	0.24	0.28	0.23	0.27	0.30	0.31	-29.39***
Unhealthy Level of LDL[1]	0.49	0.44	0.48	0.44	0.50	0.42	-2.65**
Unhealthy Level of HbA1c[1]	0.14	0.30	0.15	0.31	0.10	0.25	11.38***
Number of Patients	96,566		83,591		12,975		

Notes: Column (4) shows the t-statistic testing the difference of mean summary statistics between non-adopters and adopters. Table A1 provides a correlation table for these variables.
* $p<0.10$, ** $p<0.05$, *** $p<0.01$.
[1]LDL and HbA1c measurements are only available patients have laboratory tests. We observe LDL measurements for 75,777 patients and HbA1c measurements for 35,826 patients. LDL and HbA1c are binary variables that equal 1 if at least one measurement of the relevant outcome is unhealthy in a given month.

On the other hand, we observe a small dip in the unhealthy observations of blood glucose. These spikes are again indicative of abnormal behavior on and potentially around the month of adoption, further supporting our decision to remove these few months from our analyses.

4. Empirical Strategy

We use a four-fold empirical approach to study our two sets of outcomes. First, we conduct what we call a "naive" difference-in-differences analysis to replicate previous studies on this topic by using a sample on e-visit adopters only. Second, we conduct a standard difference-in-differences analysis using data on all e-visit adopters and non-adopters. Third, we use matching on multiple dimensions to obtain a better set of controls for the e-visit adopters and re-estimate our difference-in-differences model on this subset of patients. Finally, to explore the role that time-varying unobserved patient characteristics may play in our analyses, we conduct an instrumental variable analysis where patient e-visit adoption is instrumented by physician intensity of e-visit adoption.

All our analyses are conducted at the patient-month level and include both patient and physician fixed effects. The patient fixed effects ensure that our estimates are immune to biases due to both observable time-invariant patient characteristics such as birth-year and race, also to unobservable (and likely) time-invariant patient characteristics such as income and education level. Physician fixed effects are extremely important and include any time-invariant characteristics such as his or her birth-year, race, education level, general practice style, and so on. We are able to identify

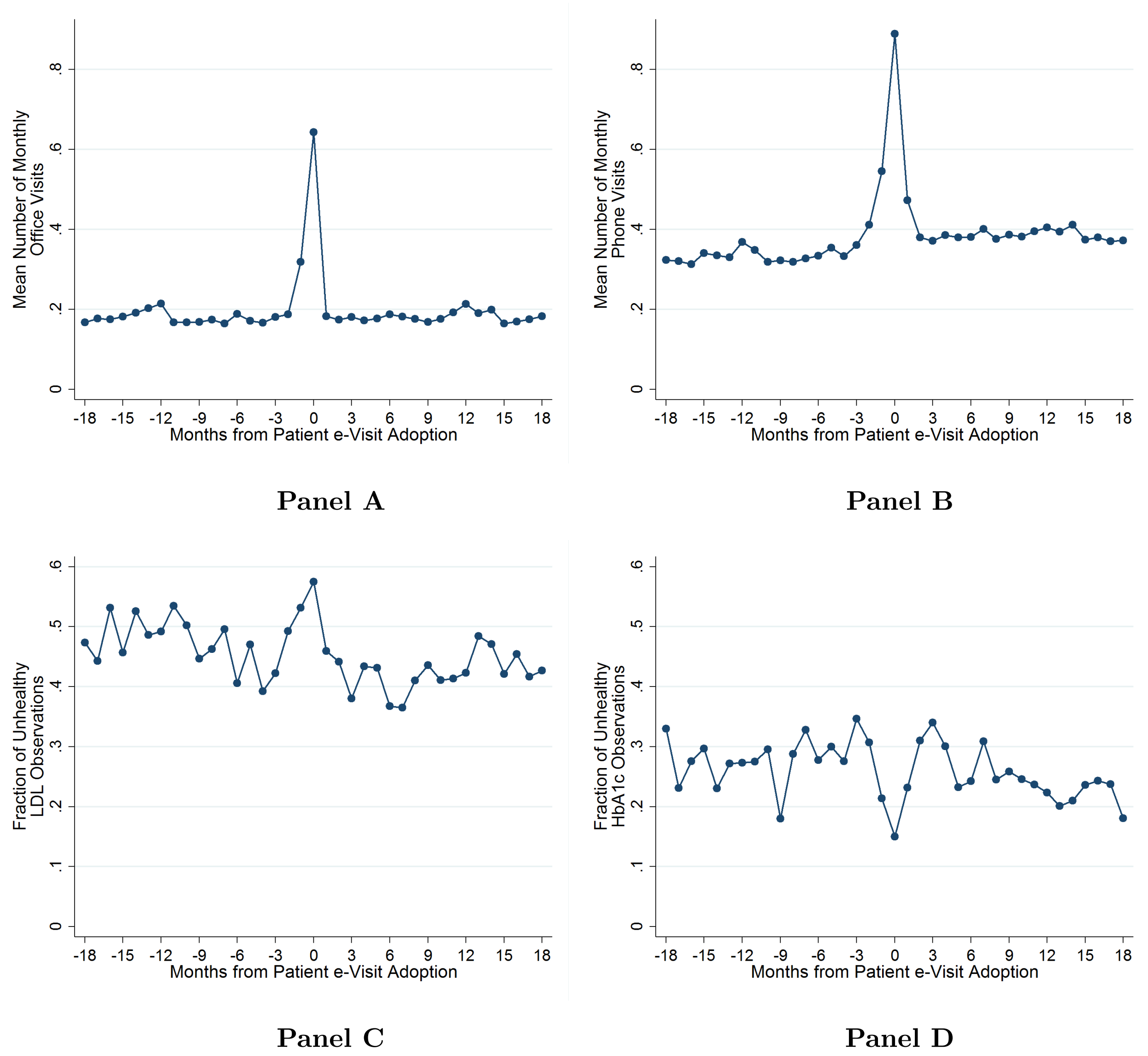


Figure 2 Visit Frequency and Patient Health by Month of e-Visit Adoption

Notes: Panels A and B plot patient-month level data for the 4,837 patients who adopt e-visits and are observed at least for 18 months before and after adoption. Panels C and D plot the health outcomes for this subset of patients. Thus, Panels A and B use data from 178,969 patient-months; Panel C uses 11,773 patient-months; and Panel D uses 5,969 patient-months.

physician and patient fixed effects separately because some of the patients in our data move between providers. Following a similar logic as the one in Abowd et al. (1999), a relatively small amount of patient mobility would suffice to identify patient and physician fixed effects separately. The median number of providers that a patient interacts with in our data is 2 (the mean is 2.1.) The patient-provider assignment process typically involves patients phoning or visiting the primary care offices and having a clerk forward their requests to providers. Throughout our analyses, we cluster our standard errors at both the patient and provider-month levels to account for the common variances in these observations.

One detail in our analyses is that because we structure our analyses at the patient-month level, there are many months in which the patient does not have any primary care encounters. However, we need to assign a physician to that patient in each month to properly estimate the physician fixed effects. The patient's physician in a given month is assigned as follows: in the most recent month where the patient has any primary care encounter, we first look to see whether there was any office visit. If there was, this physician is recorded as the assigned physician. If there was no office visit, we check whether the patient had any phone visit and follow the same rule. If there was no office or phone visit, we check whether the patient had any e-visit and follow the same rule. In cases where the patient has multiple visits of any type in the recent month, we look at the most recent visit of that type in that month. The possible assignments are to one of 90 physicians or seven "other" categories which are recorded in our data as "other physician," "other nurse practitioner," "other physician assistant," "other fellow," "other resident," "other nurse," or "other."' Together, these categories are exhaustive and allows us to assign a provider to each patient in each month. (Because the vast majority of the provider categories represent physicians, we use the terms provider and physician interchangeably.)

A second detail in our analyses is that for e-visit adopters, we omit observations from the month before adoption, the month of adoption, and the month after adoption. The reason we do this is because patients tend to adopt e-visits following an office visit, so including the month prior to and the month of adoption overstates the correlation between e-visits and office visits. We also omit the month after e-visit adoption due to the abnormally high level of phone visits in this month, perhaps due to e-visits occurring just before an already scheduled appointment. To be safe from overstating the relationship between e-visits and other types of primary care encounters, we err on the side of caution and omit this month from our sample.

In what follows, we describe our empirical strategy for our outcome on office visits. We use the same specifications to study phone visits and our outcomes on patient health. Our dependent variable is the number of monthly office or phone visits, so each data point is the number of visits (office or phone) for patient i in month-year t.[4] For each patient-month, we set $\text{eVisit}_{it} = 1$ if patient i has adopted e-visits on or before month t, and we set $\text{eVisit}_{it} = 0$ otherwise. Adoption of e-visits is perfectly "sticky" in our main specifications: for each patient i the value of eVisit_{it} is zero in all months before adoption, and after the patient uses e-visits once, the value eVisit_{it} stays 1 for all months after adoption.

[4] Since our data span 62 months from January 2008 to February 2013, t takes on values 1 to 62.

4.1. "Naive" Difference-in-Differences (on e-Visit Adopters Only)

To estimate the effect of e-visit adoption on visit frequency, we use the following difference-in-differences specification:

$$MonthlyOfficeVisits_{it} = \beta \cdot Patient\ eVisit\ Adoption_{it} + Month_t + Year_t + Provider_{it} + Patient_i + \epsilon_{it}, \tag{1}$$

where β is the coefficient of interest and captures the impact of patient e-visit adoption on monthly office visits. The model also includes fixed effects for patients and providers in addition to fixed effects for month to control for seasonality and for year to control flexibly for time trends. Since this "naive" regression is estimated on adopters only, identification is obtained only from variation in timing of e-visit adoption among patients.

4.2. Difference-in-Differences on e-Visit Adopters and non-Adopters

The strategy in this approach is to estimate the same regression in equation (1) but on the full sample of e-visit adopters and non-adopters. Hence, while identification of β is still obtained from variation in timing of patient e-visit adoption (and some patients simply never adopt), data on non-adopters help better identify common trends and other model components such as physician, month, and year fixed effects. Our clustered standard errors are also estimated more accurately due to the inclusion of non-adopters.

4.3. Difference-in-Differences on Matched Samples

Since we find early on that adopter and non-adopter patients have systematic differences on characteristics such as age and race in Table 1, we undertake several matching strategies to improve the comparison between these groups. We conduct two sets of nearest-neighbor matching analyses to obtain better control groups for our e-visit adopters and then run our difference-in-differences specification in equation (1).[5]

In each matching analysis, we match each patient e-visit adopter to a non-adopter based on age in 2013 (equivalent to matching on birth-year), gender, baseline office visit frequency, baseline phone visit frequency, and baseline health levels (either blood cholesterol or blood glucose.) Because we believe that matching on baseline outcomes is important, we limit our sample to patients who adopted e-visits in January 2010 onward; this provides with 48 months of baseline data from 2008 and 2009. We should add that the few papers studying e-visits that have conducted matching analysis were not able to match on baseline outcomes, so our estimates build on the prior literature by addressing this potentially important set of factors. In the nearest neighbor matching procedure we used, each non-adopter may be matched to multiple adopters, and we verified that our analyses

[5] The matching analyses were implemented using the "teffects nnmatch" in Stata 14 (Abadie et al. 2004).

Table 2 Summary Statistics by Patient e-Visit Adoption for Matched Samples

	LDL Match					HbA1c Match				
	(1) Non-Adopters		(2) Adopters		(3) t-stat	(4) Non-Adopters		(5) Adopters		(6) t-stat
	Mean	SD	Mean	SD		Mean	SD	Mean	SD	
Demographics										
Age (in 2013)	59.10	13.24	59.22	13.03	-0.52	61.86	12.47	61.75	12.27	0.29
Male	0.45	0.50	0.46	0.50	-0.63	0.49	0.50	0.50	0.50	-0.19
Outcomes										
Monthly Office Visits	0.19	0.14	0.19	0.14	0.89	0.23	0.16	0.23	0.16	0.27
Monthly Phone Visits	0.30	0.34	0.30	0.34	-0.44	0.37	0.41	0.37	0.42	-0.21
Unhealthy Level of LDL	0.52	0.46	0.52	0.46	-0.20	-	-	-	-	-
Unhealthy Level of HbA1c	-	-	-	-	-	0.16	0.33	0.16	0.32	0.63
Number of Patients	6,343		7,202			1,980		2,226		

Notes: Columns (3) and (6) show the t-statistic testing the difference of mean summary statistics between non-adopters and adopters in each of the matched samples. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

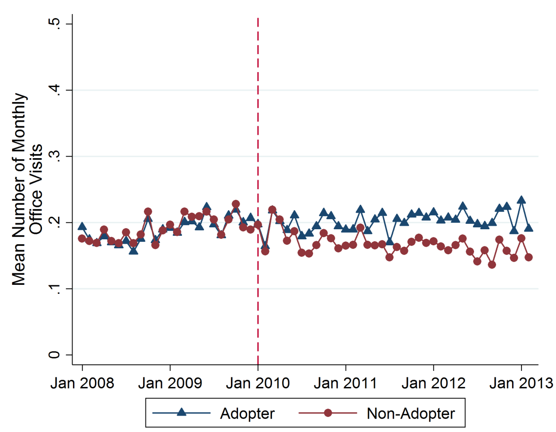
are not sensitive to whether we allow this many-to-one match. The matching procedure uses a weighted function of covariates for each observation to identify a "nearest neighbor" match for each patient adopter.[6]

The first matching analysis further restricts the sample to patients with at least one blood cholesterol (LDL) measurements in 2008 or 2009. We match each patient e-visit adopter (who adopted in January 2010 or afterward) to a non-adopter based on birthyear, gender, baseline office visit frequency, and baseline blood cholesterol levels.[7] The summary statistics for the 7,202 e-visit adopters and their 6,343 non-adopter controls are provided in Table 2. There are no statistically significant differences between the two groups on any of the variables we match on. Figure 3 provides an illustration of our matching on baseline visit frequency and health measures. The differences in visit frequency and health measurements following the baseline time period provide a preview of the results we find regarding these outcomes.

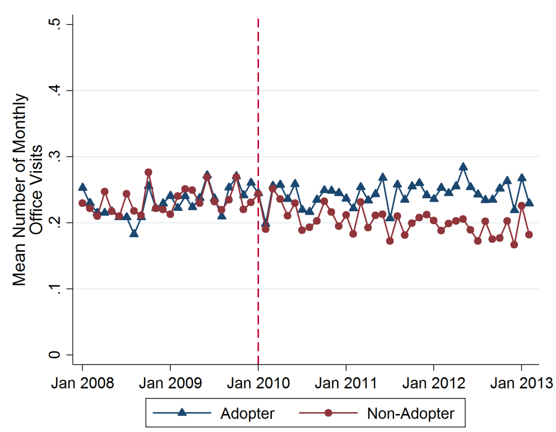
The second matching analysis is different from the first only in that we restrict to patients with at least one blood glucose (HbA1c) measurement in 2008 or 2009, and match on this level in addition to the other variables. Many fewer patients have measurements for blood glucose, but we are able to effectively match our 2,226 e-visit adopters with 1,980 non-adopters and the summary statistics for these groups are provided in Table 2. As in the first matching analysis, the adopter and non-adopter groups have no statistically significant differences on our matching variables.

[6] We provide additional matching estimates, including matches on exact physician, in the appendix (Tables A10 and A11). The reason we do not include these results in the main text is that exact matching on physician results in poorer matches on baseline outcomes, which we feel are more important. We also attempted to match on race, but were unable to achieve this in conjunction with a match on our other covariates.

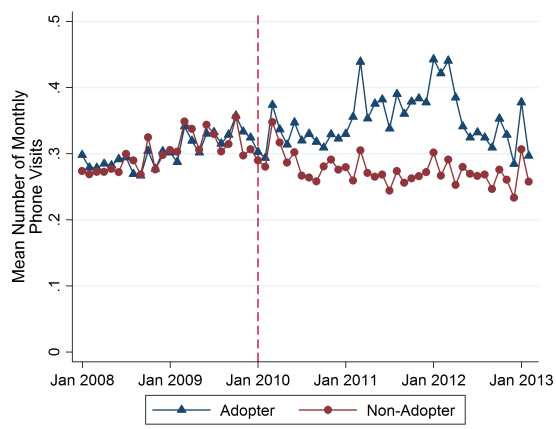
[7] Note that even though we ultimately analyze health outcomes by whether the observed blood cholesterol or blood glucose level registers as "unhealthy", we match patients on the granular levels of these outcomes to improve our comparisons.



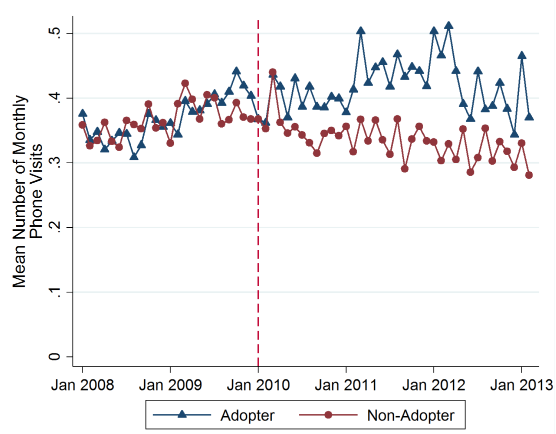
Panel A



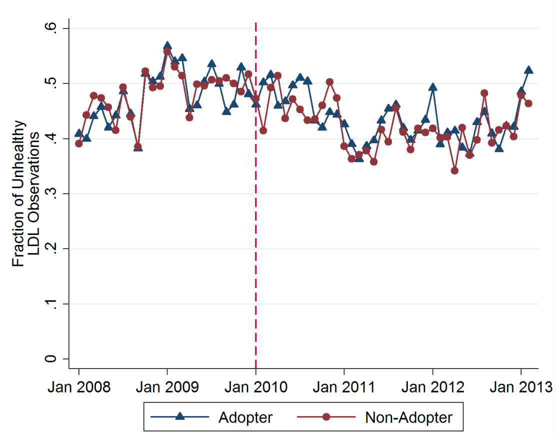
Panel B



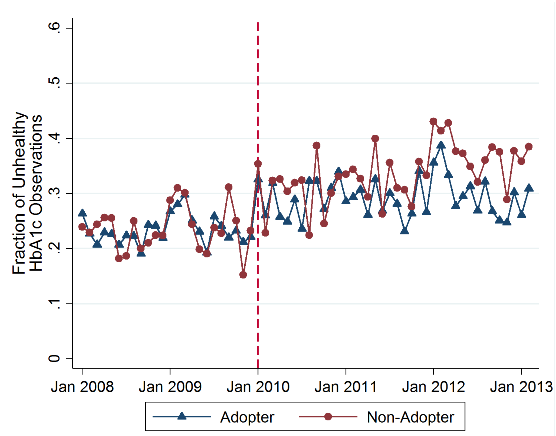
Panel C



Panel D



Panel E



Panel F

Figure 3 Visit Frequency and Patient Health by Month of e-Visit Adoption for Matched Samples

Notes: Panels A through F plot the four outcome variables at the patient-month level for two matched samples. Panels A, C, and E are for the LDL-matched sample and Panels B, D, and F are for the HbA1c-matched sample.

4.4. Instrumental Variable Analysis

One of the empirical challenges in our analyses is accounting for both *time-invariant* and *time-varying* unobservable patient characteristics. All our analysis use patient fixed effects to account for time-invariant unobservable patient characteristics. Time-varying unobservables do not have a standard econometric treatment, however, and there may be concerns about patient health trajectory biasing our estimates of β. Specifically, if patients on a positive health trajectory are more likely to adopt e-visits (as is evidenced by the improvement in LDL even in the month following e-visit adoption, provided in Table A2), methods that do not control for unobservable selection will suffer from attenuation bias in estimating β.

We acknowledge that patient health trajectory is only one possible source of endogeneity: any time-varying patient characteristics that are correlated with e-visit adoption will bias our results. While we believe that the patient health trajectory is the most plausible source of omitted variables bias in our estimation, and have thus made this the motivating example in our paper, our IV estimates hold as long as the endogeneity emerges from any factor correlated with the timing of e-visit adoption (and not correlated with the instrument itself.)

To account for the endogeneity of e-visit adoption, we run an IV analysis where we use the number of e-visits conducted by the patient's physician in a given month-year as an instrument for whether the patient is an e-visit adopter in a given month-year. Keeping with our notation in equation (1) of patient i interacting with physician j in month-year t, our first stage equation is given by:

$$\begin{aligned} \textit{Patient eVisit Adoption}_{it} = {} & \gamma \cdot \textit{Provider's Number of e-Visits with All Other Patients}_{it} \\ & + \textit{Month}_t + \textit{Year}_t + \textit{Provider}_{it} + \textit{Patient}_i + \mu_{it}. \end{aligned} \tag{2}$$

We use a linear probability model despite the binary endogenous variable to accommodate the estimation of fixed effects in our dataset; also, the standard 2SLS estimator must have a linear first stage. This type of instrument is often referred to as as a "leave-one-out" instrument as for each patient-month, the instrument leverages variation in the behavior among all *other* patients in that same month. The second stage equation is then:

$$\begin{aligned} \textit{MonthlyOfficeVisits}_{it} = {} & \beta_{IV} \cdot \boldsymbol{\widehat{\textit{Patient e-Visit Adoption}}}_{it} \\ & + \textit{Month}_t + \textit{Year}_t + \textit{Provider}_{it} + \textit{Patient}_i + \delta_{it}, \end{aligned} \tag{3}$$

where $\boldsymbol{\widehat{\textit{Patient e-Visit Adoption}}}_{it}$ is the predicted value from equation (2), δ_{it} is an error term, and β_{IV} is the selection-corrected 2SLS estimator of the impact of e-visit adoption on monthly office visits.

For the IV analysis to provide an unbiased estimate, two conditions must be satisfied: first, the instrument must be relevant. We can verify this by analyzing the F-statistic associated with γ

in the equation (2). We report the Wald F-statistic and the p-value of the underidentification by Kleibergen and Paap (2006) as well as the 10% critical values of Stock and Yogo (2005) with all IV analyses. Second, the instrument must plausibly satisfy the exclusion restriction, which in this case means that the physician's intensity of e-visit usage with other patients does not directly influence a particular patient's visit frequency or health outcomes.[8] By structure, this assumption cannot be tested, though we offer additional evidence using appointment scheduling data to provide some comfort in its validity.

To satisfy the exclusion restriction, the instrument must not have a direct impact on patient-level visit frequency or health. Our instrument, the number of e-visits that a patients physician conducts in a given month with all other patients, is unlikely to have a direct effect on visit frequency, though this is possible if e-visits with other patients cause appointment durations to change in a way that affects patient health. We show that this particular scenario is not the case using appointment-level data, but there could be other omitted variables confounding our analysis. Physician e-visit usage may also directly affect patient health outcomes if the physician orders fewer laboratory tests, perhaps because these cannot be done via the electronic channel. To address this particular concern, we show that at the patient level, testing rates actually increase with e-visit adoption, likely due to the increases in visit frequency. This analysis is explained further in Section 6. There are yet other ways in which our instrument may fail to satisfy the exclusion restriction, but we have done our best to provide evidence in support of this assumption.[9]

4.4.1. Evidence from Appointment Scheduling Data: One way in which the exclusion restriction assumption is invalidated is if physician practice styles change with the number of e-visits he or she does in each month: the physician may grant *fewer* office and phone appointments, engage in *shorter* office and phone appointments. To ensure that physician practice styles are at least not changing among these possible dimensions, we analyze the appointment scheduling system for the physicians we study.

This data is available for the entirety of the time period studied and contains information at the appointment-level on the patient requesting the appointment, the physician with whom the appointment was scheduled, and the timing of appointment. The timing data is slightly imperfect, however, as it is sometimes recorded as the scheduled appointment time and sometimes recorded

[8] Mathematically, the exclusion restriction requires that the covariance of the instrument, *Provider's Number of e-Visits with All Other Patients*, and the error in the second stage equation, δ, equals zero.

[9] We made an effort to over-identify the model with additional instruments that calculate the number (or fraction) of e-visits conducted by other providers in the same department, and other providers in other departments, but were unable to do so. Specifically, the department-level instrument fails the Sargan test when combined with our current instrument, and the system-level instrument does not pass the relevance criterion. We have included the provider-level instrument in our main analyses as it is very strong and we feel that we can best defend the exclusion-restriction assumption associated with it.

as the appointment check-in time. An additional drawback of this data structure is that we cannot separate out physician slack capacity from a long appointment: if the time between two appointments for a physician is 4 hours, for example, we do not know if this was the result of a very long appointment or due to slack capacity between appointments. Though our results do not depend on the following restriction, we limit our analysis to typical appointments (based on our conversations with the providers in the practice we study) between 10 minutes and 2 hours in our analysis.

Number of Appointments: For each of the 90 physicians in our dataset (we exclude the seven "other" provider categories in this analysis), we calculate the total number of office visits and phone visits provided each month. Since we have 62 months in our study period, the maximum number of physician-month observations is $90 * 62 = 5,580$; because some physicians have no observations in some months (due to late entry or early exit from our sample), we end up with 5,056 physician-month observations. For each physician, we define the variable *Provider e-Visit Adoption* in the same way we define *Patient e-Visit Adoption* in our earlier analyses: the variable equals 1 for the month in which a physician first has an e-visit and for all months afterward. We also include the five physicians who never adopt e-visits in our sample to enable a better difference-in-differences analysis. Specifically, the regression we run is specified by the following equation for physician j in month-year t:

$$Monthly\ Office\ Visits_{jt} = \lambda \cdot Provider\ e\text{-}Visit\ Adoption_{jt} + Month_t + Year_t + Provider_j + \zeta_{jt}. \quad (4)$$

The error term is ζ_{jt} and standard errors are clustered at the physician level to account for common variance among these observations. The same specification in equation (4) is used to study monthly phone visits, and the estimates of λ from these regressions are provided in Table A3. We observe no significant differences in the number of monthly office or phone visits provided by physicians post adoption of e-visits.

Duration of Appointments: Next, we use the appointment scheduling data to determine whether patients of physicians who adopt e-visits experience changes in appointment duration. The basic idea is to see whether appointments provided by a given physician change in duration after the physician begins using e-visits. The regression we run is as follows and all variables are at the appointment level a:

$$AppointmentDuration_a = \alpha \cdot Provider\ e\text{-}Visit\ Adoption_a + Month_a + Year_a + Provider_a + \upsilon_a. \quad (5)$$

We run this regression (where υ_a is an error term) on all patients and also only on patients who adopt e-visits in case only these patients experience changes in appointment duration. The estimates of α from these analyses are in Table A4. Column (1) shows the results for all patients, and column (2) shows the results for appointments made by the subset of patient e-visit adopters. We do not observe any significant changes in appointment duration upon physician adoption of e-visits for either sample.

Since we do not find any evidence that the number of appointments provided or the duration of these appointments change with physician e-visit adoption, we are more comfortable assuming that other factors in physician practice style may also remain unchanged post e-visit adoption.

5. Results on Visit Frequency

Table 3 presents the difference-in-differences for our "naive" (adopter-only) and full patient samples. In column (1) we show that as found in the literature, patient e-visit adoption appears to reduce the frequency of office visits by about 0.015 per month, which off a base of 0.18 per month (from Table 1) is an effect size of about -8%. Our result on phone visits in column (2) is not significant, but the point estimate is similar to that found in Zhou et al. (2007).[10] Column (3) shows the impact of patient e-visit adoption on office visits using the full sample of adopters and non-adopters, and here we find an estimate that remains robust to later analyses. We find that patient e-visit adoption is associated with an *increase* in office visits by about 0.01 each month, which off a base of 0.16 represents an effect size of about 6%. We also find a statistically (and practically) significant effect of patient e-visit adoption on subsequent phone visits: the estimate is 0.017, which off a base of 0.24 is an effect size of about 7%. Taken together, these results illustrate the importance of properly estimating the other components in our regression model (physician fixed effects, seasonality, flexible time trends) which are enabled by the addition of non-adopters to our sample.

Next, we show results for our improved difference-in-differences analysis using matched samples. Table 4 shows estimates from matching on selected covariates and blood cholesterol levels. Our estimate of the impact of patient e-visit adoption on subsequent office visits remains at 0.01, and statistically significant, and our estimate of the impact on phone visits increases from 0.017 in to 0.026. These results are sustained in columns (3) and (4) of Table 4, which show the same estimates on visit frequency for matching on selected covariates and blood glucose levels. The estimate of about 0.01 on office visits is stable and shown in column (3). The estimate on phone visits increases to 0.04 and is statistically significant, although the standard errors include the upper end of the possible estimate in Table 3.

Finally, Table 5 shows the IV results on visit frequency. Column (1) reports the first stage regression, and the instrument is highly statistically significant with a F-statistic of about 135. The

[10] Our phone result is statistically significant if we include the months before and following e-visit adoption in our sample. To err on the side of caution, however, we continue to exclude these two months from all our results.

Table 3 Difference-in-Differences Estimates on Visit Frequency

Estimation Method	"Naive" Diff-in-Diff		Full Diff-in-Diff	
	(1) Office	(2) Phone	(3) Office	(4) Phone
Patient e-Visit Adoption	-0.015***	-0.007	0.010***	0.017***
	(0.003)	(0.005)	(0.002)	(0.004)
Patient FEs	✓	✓	✓	✓
Provider FEs	✓	✓	✓	✓
Month FEs	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓
Mean of Dep. Var.	0.18	0.30	0.16	0.24
R-squared	0.003	0.004	0.002	0.001
Sample	Adopters	Adopters	All	All
Patient-Months	765,597	765,597	5,948,239	5,948,239

Notes: Standard errors in parentheses are robust and two-way clustered at the patient and the provider-month levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4 Difference-in-Differences Estimates from Matched Samples on Visit Frequency

	LDL Match		HbA1c Match	
	(1) Office	(2) Phone	(3) Office	(4) Phone
Patient e-Visit Adoption	0.011***	0.026***	0.013**	0.043***
	(0.003)	(0.006)	(0.005)	(0.012)
Patient FEs	✓	✓	✓	✓
Provider FEs	✓	✓	✓	✓
Month FEs	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓
Mean of Dep. Var.	0.19	0.30	0.23	0.37
R-squared	0.003	0.002	0.004	0.003
Sample	Matched (LDL)	Matched (LDL)	Matched (HbA1c)	Matched (HbA1c)
Patient-Months	818,184	818,184	254,094	254,094

Notes: Standard errors in parentheses are robust and two-way clustered at the patient and the provider-month levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

estimate of 0.001 can be interpreted in the following way: for every 100 e-visits that a patient's provider conducts with all his or her other patients, that patient's likelihood of using e-visits in a given month increases by 10%. The goal with this analysis is to check whether our earlier estimates are upward biased due to negative selection into e-visits. For example, if systematically less healthy patients adopt e-visits, we may be overstating the relationship between patient e-visit adoption and subsequent visit frequency. On the contrary to this plausible story, our IV results indicate that if anything, patients on a *healthier* trajectory may be systematically more likely to adopt e-visits, providing some assurance that our earlier estimates are attenuated and not overstated. In column (2), we find a large estimate of the impact of patient e-visit adoption on office visits: the coefficient is 0.059 and correlates to a 37% effect size. The confidence interval is wide, however, and includes our earlier estimates. Column (3) shows the impact on phone visits, and while our results are noisy, our point estimate is consistent with our earlier estimates. We interpret the large increase in office visits triggered by patient e-visit adoption relative to our earlier estimates to be indicative, but not confirmatory, that patients on a positive health trajectory may have been systematically adopting e-visits and causing attenuation bias in our earlier estimates.

Table 5 Instrumental Variable Estimates on Visit Frequency

	(1) Patient e-Visit Adoption	(2) Office	(3) Phone
	First Stage	Second Stage	Second Stage
Patient e-Visit Adoption		0.059^{**}	0.022
		(0.029)	(0.044)
Provider's Number of e-Visits with all other Patients	0.001^{***}		
	(0.0001)		
Patient FEs	✓	✓	✓
Provider FEs	✓	✓	✓
Month FEs	✓	✓	✓
Year FEs	✓	✓	✓
Mean of Dep. Var.	0.04	0.18	0.30
R-Squared	0.099	-	-
Patient-Months	5,948,239	5,948,239	5,948,239
Weak id. (KP rk Wald F-stat.)	135.36	-	-
Underid. (KP rk LM p-value)	< 0.001	-	-

Notes: The Wald F-statistic and test of underidentification are based on Kleibergen and Paap (2006). The Stock and Yogo (2005) critical value is 16.38 for the IV estimates to have no more than 10% of the bias of the OLS estimates. Standard errors in parentheses are robust and two-way clustered at the patient and the provider-month levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Together, our results on visit frequency show a consistent effect of patient e-visit adoption on subsequent office and phone visits. Our estimate of the impact on office visits using the full sample of adopters and non-adopters ranges 0.010 in Table 3 to 0.059 in Table 5, and the confidence intervals for these estimates overlap. On the low end, an estimate of 0.010 represents an effect size of about 6% and translates to an extra office visit every 100 months. While this is not very large for an individual patient, for an average physician with a 2,300-patient panel size (Altschuler et al. 2012), this amounts to 23 additional visits each month. Given the average appointment duration of about 20 minutes (Shaw et al. 2014), this equals about 7.7 hours of appointments each month (not including the time needed to provide e-visits and the additional phone visits) that may be provided at the expense of panel size.

5.1. Evaluating the Gateway Effect: Who Conducts Additional Visits?

Thus far, we have documented that the patient e-visit adoption is linked with increased office and phone visits post-adoption. One potential mechanism explaining this effect is that e-visits remove the "gatekeeper" between patients and physicians. Consistent with this potential mechanism, we find evidence that patients use e-visits to connect directly to the physician and bypass gatekeepers such as office staff and nurses.

For this analysis, we estimate the regression specified in equation (1) but decompose the dependent variable to four parts: "Monthly Office Visits with a Physician," "Monthly Office Visits with a Resident," "Monthly Office Visits with a Nurse Practitioner," and "Monthly Office Visits with Other," where the last category includes all other provider types. We thus run four new regressions for the office visit analysis and do the same for phone visits. The results of this set of analyses are in Table 6. Recalling that our estimate in our full difference-in-differences analysis was 0.01, we find that this decomposes into 0.012 visits with physicians and -0.002 visits with residents, no additional visits with nurse practitioners, and .001 additional visits with other providers in columns (1) through (4).[11] The observation that the additional office visits are driven by physician encounters indicates that e-visits may allow patients to bypass the usual "gatekeepers" in the primary care system. This is expected given that patients are most likely to be familiar with their own physician, but may post operational challenges in prioritizing physician time.

Table 6 Difference-in-Differences Estimates on the Gateway Effect for Visit Frequency

	Office				Phone			
	(1) Physician	(2) Resident	(3) NP	(4) Other	(5) Physician	(6) Resident	(7) NP	(8) Other
Patient e-Visit Adoption	0.012^{***}	-0.002^{***}	0.000	0.001^{***}	0.028^{***}	-0.008^{***}	0.000	-0.003^{***}
	(0.002)	(0.001)	(0.001)	(0.000)	(0.004)	(0.001)	(0.000)	(0.001)
Patient FEs	✓	✓	✓	✓	✓	✓	✓	✓
Provider FEs	✓	✓	✓	✓	✓	✓	✓	✓
Month FEs	✓	✓	✓	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓	✓	✓	✓	✓
Mean of Dep. Var.	0.12	0.02	0.01	0.01	0.18	0.02	0.01	0.03
R-squared	0.002	0.001	0.000	0.000	0.001	0.001	0.000	0.001
Patient-Months	5,948,239	5,948,239	5,948,239	5,948,239	5,948,239	5,948,239	5,948,239	5,948,239

Notes: This table presents our results for the effect of e-visit adoption on the number of office and phone visits with physicians (columns (1) and (5)), residents (columns (2) and (6)), or nurse practitioners (columns (3) and (7)), and other providers (columns (4) and (8)). Standard errors in parentheses are robust and two-way clustered at the patient and the provider-month levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

We find similar results on phone visits in Table 6. Our earlier 0.017 estimate from the difference-in-differences analysis is decomposed into 0.028 additional phone visits with physicians, -0.008 with residents, no additional ones with nurse practitioners, and -0.003 with other providers in columns (5) through (8). Again, physicians appear to bear the burden of these additional encounters.

[11] The estimates do not add up to 0.01 due to rounding.

6. Results on Patient Health

Our empirical strategy for measuring the impact of e-visit adoption on patient health are the same as the ones that we used for visit frequency, outlined in equations (1) and (3). Our two key measures of health are blood cholesterol (LDL) and blood sugar (HbA1c) levels, which are especially useful in the primary care setting as they are indicators of chronic disease. Higher levels of LDL and HbA1c are generally correlated with worse patient health, and the medical community has also established important cutoff values for each of these measurements that map to whether patient health is "under control" or unhealthy. We define $HbA1c_{it}$ and LDL_{it} to be binary indicators of this cutoff, where 1 indicates an unhealthy observation ($\geq$ 100 mg/dL for LDL and $\geq$ 7 percent for HbA1c.) We also run the analysis using raw levels of LDL and HbA1c; the results are reported in Table A5 and are consistent with our analysis with dichotomized LDL and HbA1c variables.

Table 7 presents the results on patient health for the sample of patients who have at least one observation over the observation period. Columns (1) and (2) show the results of the specification introduced in (1) for patients who adopt e-visits, or what we call the "naive" difference-in-differences. We find no significant changes in health patterns for this sample. In our full difference-in-differences estimates, however, we find in column (3) that the likelihood of an unhealthy observation in LDL decreases by 0.016 off a base of 0.46, reflecting an effect size of about 3%. In column (4), we find that the likelihood of an unhealthy observation of HbA1c decreases by 0.018 off a base of 0.27, reflecting an effect size of about 7%.

Table 7 Difference-in-Differences Estimates from Adopter, Full, and Matched Samples on Patient Health

Estimation Method	"Naive" Diff-in-Diff		Full Diff-in-Diff		LDL Matched Diff-in-Diff	HbA1c Matched Diff-in-Diff
Outcome	(1) LDL	(2) HbA1c	(3) LDL	(4) HbA1c	(5) LDL	(6) HbA1c
Patient e-Visit Adoption	-0.011	-0.014	-0.016**	-0.018**	-0.011	-0.029**
	(0.009)	(0.011)	(0.007)	(0.009)	(0.008)	(0.012)
Patient FEs	✓	✓	✓	✓	✓	✓
Provider FEs	✓	✓	✓	✓	✓	✓
Month FEs	✓	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓	✓	✓
Mean of Dep. Var	0.46	0.22	0.46	0.27	0.52	0.16
R-squared	0.018	0.021	0.013	0.015	0.018	0.024
Sample	Adopters	Adopters	All	All	Matched (LDL)	Matched (HbA1c)
Patient-Months	35,670	17,927	230,351	119,121	58,960	25,083

Notes: LDL and HbA1c are binary variables that equal 1 if at least one measurement of the relevant outcome is unhealthy in a given month. Column (5) shows estimates from a sample of patients matched on baseline LDL along with other covariates, and column (6) shows the equivalent for HbA1c. Standard errors in parentheses are robust and two-way clustered at the patient and the provider-month levels. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Column (5) of Table 7 presents the results on blood cholesterol for the sample of patient e-visit adopters matched with non-adopters based on selected covariates and baseline levels of blood cholesterol; while our point estimate is similar to that in column (3), it is not statistically significant. Our blood glucose measurement remains statistically significant at the 5% level, however, and the point estimate of -0.029 suggests an 18% effect size on the likelihood of an unhealthy observation. Overall, we find small and noisy results of the impact of patient e-visit adoption on blood cholesterol, but stronger results on blood glucose.

Next, we analyze our patient health outcomes using the instrumental variable analysis to check for unobservable, time-varying patient selection into e-visit adoption. Our results are shown in Table 8. We estimate two first stage equations in columns (1) and (3), one for each sample of patients with at least one measurement for the corresponding health outcome. The instrument continues to be highly significant on these subsamples and the F-statistic is about 321 for the LDL sample and about 152 for the HbA1c sample. The coefficients are also similar in magnitude to those found in Table 5. Neither of our IV estimates in columns (2) and (4) on patient health is statistically significant from zero, but the confidence intervals are wide and do not preclude our earlier estimates. The lack of statistical significance in the IV estimates may stem from patients who were anyways on a healthy trajectory adopting e-visits, but given the lack of precision in our IV estimates, we refrain from interpreting them further.

Table 8 Instrumental Variable Estimates on Patient Health

	LDL		HbA1c	
	(1) First Stage	(2) Second Stage	(3) First Stage	(4) Second Stage
Patient e-Visit Adoption		-0.037		-0.041
		(0.028)		(0.039)
Provider's Number of e-Visits	0.002^{***}		0.001^{***}	
with all other Patients	(0.0001)		(0.0001)	
Patient FEs	✓	✓	✓	✓
Provider FEs	✓	✓	✓	✓
Month FEs	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓
Mean of Dep. Var	0.06	0.46	0.07	0.27
R-squared	0.141	-	0.127	-
Patient-Months	235,978	235,978	121,225	121,225
Weak id. (KP rk Wald F-stat.)	320.65	-	151.91	-
Underid. (KP rk LM p-value)	<0.0001	-	<0.0001	-

Notes: LDL and HbA1c are binary variables that equal 1 if at least one measurement of the relevant outcome is unhealthy in a given month. The Wald F-statistic and test of underidentification are based on Kleibergen and Paap (2006). The Stock and Yogo (2005) critical value is 16.38 for the IV estimates to have no more than 10% of the bias of the OLS estimates. Standard errors in parentheses are robust and two-way clustered at the patient and the provider-month levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

When we analyze patient health, there is a concern that e-visit adopters may have systematically fewer measurements of blood cholesterol and blood glucose, which could bias our results. This is especially likely if physicians are less likely to prescribe laboratory tests via e-visits because they cannot be conducted using an electronic channel. If we assume that e-visits do not harm patient health, then under-testing is a problem because we would be systematically missing data from patients who have improved health due to e-visits. To check whether this is a concern in our setting, we examine whether patients who adopt e-visits experience decreases in testing rates post-adoption. Table A6 presents the results on this analysis. Perhaps not surprisingly in the context of our results of patient e-visit adoption on office visits, we find that adopters experience no change in the levels of LDL testing, and increases in the levels of HbA1C testing among patients with at least one test.[12] These findings suggest that e-visit adoption increases care consumption not only through increased office and phone visits with providers, but also through the utilization of other system resources such as the testing facilities.

7. Robustness

Our main results withstand a variety of robustness checks, five of which we describe in this section. First is the measurement of e-visit adoption: in our main analysis, we take e-visit adoption to be a binary variable that equals 1 in the month that a patient first uses e-visits and stays 1 afterward. Since 38% of patients in our sample use e-visits only once, however, there is a concern that our e-visit adoption variable does not accurately reflect users of e-visits. Hence, in our robustness check, we refine our definition of patient adoption to equal 1 in the month of the patient's *second* e-visit, and also 1 for all months afterward. Table A7 contains the results of using this definition for our analyses. Interestingly, we observe an even larger effect of patient e-visit adoption on visit frequency using this measure of e-visit adoption: office visits increase by 0.03 each month, and phone visits by 0.05 each month, and each coefficient is statistically significant at the 1% level. We continue to find no effect on cholesterol but do observe a 2.5% decrease in the likelihood of an unhealthy blood glucose observation post-adoption that is statistically significant.

A related and second robustness check defines the patient e-visit adoption to equal 1 in each month that the patient had an e-visit and for only three months afterward. The goal of this analysis is to test more precisely the "trigger" hypothesis we postulate on e-visits, which would be expected to appear within three months of an e-visit. Table A8 shows the results of this analysis for the full difference-in-differences sample: in column (1) we find that patient e-visit adoption leads to 0.07 additional office visits, and column (2) shows that these patients experience 0.10 additional phone visits. We do not find any effects on blood cholesterol and continue to find statistically significant

[12] In columns (3) and (4) of Table A6, we perform a similar analysis on the full sample by setting the number of monthly tests to zero for all patients who don't have any testing. Estimates are similar in magnitude, but in this case the coefficient of LDL tests is also significant.

improvements in blood glucose. Note that we continue to only drop the original month of adoption, along with the month before and after, in these regressions.

As our third robustness check, we perform a placebo analysis that randomizes the timing of patient e-visit adoption across our sample. The reason for conducting this exercise is to ensure that we are not picking up spurious results in our main analyses as they rely on difference-in-differences estimation. We conduct the placebo check by first randomly assigning 13.4% of all patients to e-visit adoption (based on the percentage of e-visit adoption we observe) and then randomize these patients to a month-year of adoption between January 2008 and February 2013. The results of our placebo analysis is provided in Table A9. We do not find any significant results on visit frequency or patient health, providing some assurance that our main estimates are not spurious.

The fourth robustness check is related to our matched samples. In moving from our "naive" to full difference-in-differences estimates, it is clear that physician fixed effects are important in our analysis. Our matched samples described in Section 4 do not match e-visit adopters with non-adopters that have the exact same physician in the month-year of analysis, however, because imposing this restriction comes at the expense of matching on baseline outcomes. Table A11 provides results obtained from difference-in-differences analysis on matched samples that force an exact match on physician in each month-year of analysis.[13]

Fifth and finally, we run our difference-in-differences estimation controlling for patient health in each month. Since we don't observe patient health in each month, we impute the values of LDL and HbA1c variables based on their last observed value. The results are presented in Tables A12 and A13. If patients on a negative health trajectory are adopting e-visits, we expect the coefficient of e-visit adoption to become smaller, but the coefficients practically stay the same after controlling for e-visits.

8. Conclusion

E-visits have the potential to enhance primary care delivery by enabling cost reductions and larger panel sizes without sacrifices in the quality of care (Green et al. 2013). Almost all large health systems today use patient portals to promote e-visits, telemedicine, and other health technologies. E-visits also improve patients' ability to contact their providers directly, bypassing the usual gatekeepers in the practice such as office staff and nurses. From an operations standpoint, these innovations are easier to use because they do not require simultaneous availability of the physician and the patient for an interaction. The medical education sector is also responding to the market for new skills in online communication: the University of Texas at Austin's new medical school

[13] See Table A10 for summary statistics on matched adopters and non-adopters.

has a focus on the topic, and Kaiser Permanente plans to open a medical school in 2019 that will specialize in training physicians to use online tools (New York Times 2016).

Using difference-in-differences analyses, we show that contrary to common expectations, e-visits may trigger additional phone and office visits without large benefits in patient health. Our analysis improves on those in the literature by better estimation of physician fixed effects, which turn out to be particularly important in this setting. Our main regression models include patient fixed effects, flexible time trends, seasonality, and physician fixed effects. We are also able to explore the role that unobservable and time-varying patient characteristics may play in patient e-visit adoption via an instrumental variable analysis that leverages variation in physician intensity of e-visit usage. Our selection-corrected estimates are suggestive, though not confirmatory, of patients who are on a healthy trajectory systematically being more likely to adopt e-visits. (An additional support for this selection story is that we observe improvements in health immediately following the first e-visit.) Our main results are robust to different specifications of e-visit adoption and we are able to rule out fundamental changes in physician practice style around e-visit adoption including the quantity and duration of office visits provided. Together, our findings highlight the importance of considering patient and physician responses when introducing new models of service delivery in health care (Dobson et al. (2009), Bavafa et al. (2016)).

Our analysis has several limitations that carve the way for future work. First, regarding the visit frequency analyses, 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 type of compensation in the United States, it may be the case that physicians behave differently under capitation or salaried payments. Future work can extend the current analysis to settings in which 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; this is also true in our setting. However, a handful of health institutions have experimented with charging patients annual fees or co-payments for e-access to their physicians.

A second limitation is that we measure patient health via blood cholesterol and blood glucose levels in keeping with the primary care literature (Friedberg et al. 2010), but e-visits may influence other aspects of patient health or satisfaction in ways not captured these outcomes. Improved measures on the quality of post-adoption care would be especially helpful in examining whether office and phone visits following e-visits are more efficient, and measures of patient satisfaction would also be interesting to analyze. Third, while we are able to obtain quasi-random variation in patient e-visit adoption using our instrumental variable analysis, a better study would leverage lottery-like randomization in patient e-visit adoption. Fourth, we study the staggered adoption of e-visits in a relatively short time period of five years, but there may be a novelty effect associated with this technology that dissipates with time, and future work can look at longer-term impacts of such technologies. Until these additional analyses can emerge in the literature, we hope that our study will help inform managerial decisions on whether and how to promote e-visits within primary care systems.

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Appendix Tables

Table A1 Correlation Table of Patient Demographics, Outcomes, and the Instrumental Variable

	Age	Male	White	Black	Asian	Office	Phone	LDL	HbA1c	Instrument
Age	1.000									
Male	0.018	1.000								
White	0.187	0.194	1.000							
Black	-0.175	-0.227	-0.847	1.000						
Asian	-0.048	0.013	-0.176	-0.136	1.000					
Office	-0.038	-0.041	-0.136	0.150	-0.011	1.000				
Phone	-0.048	-0.079	-0.107	0.127	-0.020	0.210	1.000			
LDL[1]	-0.172	-0.118	-0.121	0.123	0.001	0.049	0.031	1.000		
HbA1c[1]	-0.032	-0.005	-0.122	0.149	-0.024	0.020	0.085	-0.026	1.000	
Instrument	-0.026	0.006	0.059	-0.056	-0.002	-0.001	0.029	0.014	-0.048	1.000

Notes: The mean and standard deviation of the instrument, defined as the number of e-visits a patient's provider conducts with all other patients in a given month, are respectively 10.97 and 27.50.
[1]LDL and HbA1c measurements are only available patients have laboratory tests. We observe LDL measurements for 75,777 patients and HbA1c measurements for 35,826 patients. LDL and HbA1c are binary variables that equal 1 if at least one measurement of the relevant outcome is unhealthy in a given month.

Table A2 Difference-in-Differences Estimates on Patient Health One Month Following e-Visit Adoption

	(1) LDL	(2) HbA1c
Patient e-Visit Adoption	-0.035*	-0.039*
	(0.019)	(0.021)
Patient FEs	✓	✓
Provider FEs	✓	✓
Month FEs	✓	✓
Year FEs	✓	✓
R-squared	0.012	0.015
Patient-Months	224,655	114,772

Notes: LDL and HbA1c are binary variables that equal 1 if the measurement is unhealthy. Standard errors in parentheses are robust and two-way clustered at the patient and the provider-month levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3 Throughput Analysis: Provider e-Visit Adoption and Monthly Appointments Scheduled

	(1) Office	(2) Phone
Provider e-Visit Adoption	-0.300	6.996
	(7.139)	(10.766)
Provider FEs	✓	✓
Month FEs	✓	✓
Year FEs	✓	✓
R-squared	0.058	0.036
Provider-Months	5,056	5,056

Notes: Providers only include physicians (e.g., not residents and nurse practitioners.) Standard errors in parentheses are robust and clustered by provider. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4 Provider e-Visit Adoption and Appointment Duration

	(1) Duration (Hours)	(2) Duration (Hours)
Provider e-Visit Adoption	-0.0004	0.0052
	(0.0049)	(0.0066)
Provider FEs	✓	✓
Month FEs	✓	✓
Year FEs	✓	✓
Mean of Dep. Var.	0.47	0.49
R-squared	0.011	0.010
Sample	All Patients	Adopter Patients
Patient Appointments	492,336	78,959

Notes: Providers only include physicians (e.g., not residents and nurse practitioners.) Standard errors in parentheses are robust and clustered by provider. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses are robust and two-way clustered at the patient and the physician levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A5 Difference-in-Differences Estimates on Patient Health (Levels of LDL and HbA1c)

Estimation Method	"Naive" Diff-in-Diff		Full Diff-in-Diff	
	(1) LDL	(2) HbA1c	(3) LDL	(4) HbA1c
Patient e-Visit Adoption	-1.477***	-0.105***	-1.506***	-0.078***
	(0.550)	(0.030)	(0.436)	(0.026)
Patient FEs	✓	✓	✓	✓
Provider FEs	✓	✓	✓	✓
Month FEs	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓
Mean of Dep. Var.	109.79	6.52	109.65	6.74
R-squared	0.033	0.034	0.025	0.015
Sample	Adopters	Adopters	All	All
Patient-Months	35,670	17,927	230,351	119,121

Notes: In this analysis, we use the level (not binary indicator of an unhealthy observation) to define our dependent variables. Standard errors in parentheses are robust and two-way clustered at the patient and the provider-month levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A6 Number of LDL and HbA1c Tests by Patient e-Visit Adoption

	Patients with At least one Test		All Patients	
	(1) LDL Tests	(2) HbA1c Tests	(3) LDL Tests	(4) HbA1c Tests
Patient e-Visit Adoption	0.001	0.009^{***}	0.002^{**}	0.007^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
Patient FEs	✓	✓	✓	✓
Provider FEs	✓	✓	✓	✓
Month FEs	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓
Mean of Dep. Var.	0.058	0.062	0.046	0.023
R-squared	0.001	0.003	0.001	0.001
Patient-Months	4,662,017	2,202,476	5,948,239	5,948,239

Notes: For months in which patients do not have any tests, the number of tests is recorded as zero. Column (1) includes all patients who have at least one LDL test in our time period, and Column (2) includes all patients who have at least one HbA1c test in our time period. Columns (3) and (4) include all patients. Standard errors in parentheses are robust and two-way clustered at the patient and the provider-month levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A7 All Estimates of Patient e-Visit Adoption (Second e-Visit Definition)

	Full Diff-in-Diff				IV			
	(1) Office	(2) Phone	(3) LDL	(4) HbA1c	(5) Office	(6) Phone	(7) LDL	(8) HbA1c
Patient e-Visit Adoption	0.031^{***}	0.046^{***}	-0.008	-0.025^{**}	0.076^{**}	0.029	-0.028	-0.076
(Second e-Visit Definition)	(0.003)	(0.006)	(0.008)	(0.010)	(0.037)	(0.057)	(0.038)	(0.059)
Patient FEs	✓	✓	✓	✓	✓	✓	✓	✓
Provider FEs	✓	✓	✓	✓	✓	✓	✓	✓
Month FEs	✓	✓	✓	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓	✓	✓	✓	✓
R-squared	0.002	0.001	0.013	0.015	-	-	-	-
Sample	All	All	All	All				
Patient-Months	5,948,239	5,948,239	230,351	119,121	5,948,239	5,948,239	230,351	119,121
Weak id. (KP *rk* Wald *F*-stat.)	-	-	-	-	130.61	130.61	271.21	135.22
Underid. (KP *rk* LM *p*-value)	-	-	-	-	$< .001$	$< .001$	$< .001$	$< .001$

Notes: Patient e-visit adoption is defined as 1 for all months in and following the patient's second e-visit, and is zero otherwise. We continue to drop the month before, month of, and month following original e-visit adoption from all our analyses. LDL and HbA1c are binary variables that equal 1 if at least one measurement of the relevant outcome is unhealthy in a given month. The Wald F-statistic and test of underidentification are based on Kleibergen and Paap (2006). The Stock and Yogo (2005) critical value is 16.38 for the IV estimates to have no more than 10% of the bias of the OLS estimates. Standard errors in parentheses are robust and two-way clustered at the patient and the provider-month levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A8 All Estimates of Patient e-Visit Adoption (Less "Sticky" Definition)

	Full Diff-in-Diff				IV			
	(1) Office	(2) Phone	(3) LDL	(4) HbA1c	(5) Office	(6) Phone	(7) LDL	(8) HbA1c
Patient e-Visit Adoption	0.069***	0.102***	-0.006	-0.016*	0.119**	0.045	-0.043	-0.045
(Less "Sticky")	(0.003)	(0.006)	(0.007)	(0.008)	(0.058)	(0.090)	(0.033)	(0.043)
Patient FEs	✓	✓	✓	✓	✓	✓	✓	✓
Provider FEs	✓	✓	✓	✓	✓	✓	✓	✓
Month FEs	✓	✓	✓	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓	✓	✓	✓	✓
R-squared	0.002	0.002	0.013	0.015	0.002	0.002	0.013	0.014
Patient-Months	5,948,239	5,948,239	235,978	121,225	5,948,239	5,948,239	235,978	121,225
Weak id. (KP rk Wald F-stat.)	-	-	-	-	152.00	152.00	315.02	141.07
Underid. (KP rk LM p-value)	-	-	-	-	$< .001$	$< .001$	$< .001$	$< .001$

Notes: Patient e-visit adoption is defined as 1 for the month of a patient's e-visit and for 3 months afterward, and is zero otherwise. We continue to drop the month before, month of, and month following original e-visit adoption from all our analyses. LDL and HbA1c are binary variables that equal 1 if at least one measurement of the relevant outcome is unhealthy in a given month. The Wald F-statistic and test of underidentification are based on Kleibergen and Paap (2006). The Stock and Yogo (2005) critical value is 16.38 for the IV estimates to have no more than 10% of the bias of the OLS estimates. Standard errors in parentheses are robust and two-way clustered at the patient and the provider-month levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A9 Falsification Test on Timing of Patient e-Visit Adoption (Placebo Analysis)

	Full Diff-in-Diff				IV			
	(1) Office	(2) Phone	(3) LDL	(4) HbA1c	(5) Office	(6) Phone	(7) LDL	(8) HbA1c
Patient e-Visit Adoption	0.003	0.003	0.006	0.001	17.260	8.291	3.414	2.627
	(0.002)	(0.003)	(0.007)	(0.009)	(35.967)	(18.476)	(9.122)	(3.333)
Patient FEs	✓	✓	✓	✓	✓	✓	✓	✓
Provider FEs	✓	✓	✓	✓	✓	✓	✓	✓
Month FEs	✓	✓	✓	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓	✓	✓	✓	✓
R-squared	0.002	0.002	0.013	0.014	-	-	-	-
Patient-Months	5,947,707	5,947,707	240,593	123,258	5,947,707	5,947,707	240,593	123,258
Weak id. (KP rk Wald F-stat.)	-	-	-	-	0.230	0.230	0.189	0.785
Underid. (KP rk LM p-value)	-	-	-	-	0.228	0.228	0.664	0.379

Notes: Patient e-visit adoption is randomized across the 62 months of our data for 13.4% of all patients, consistent with the rate of adoption in our actual sample. The IV analysis continues to use as an instrument the number of e-visits that a patient's provider conducts with all other patients in a given month. LDL and HbA1c are binary variables that equal 1 if at least one measurement of the relevant outcome is unhealthy in a given month. Sample includes all patient-months except for the month before adoption, month of adoption, and month after adoption for the patients who adopt e-visits. The Wald F-statistic and test of underidentification are based on Kleibergen and Paap (2006). The Stock and Yogo (2005) critical value is 16.38 for the IV estimates to have no more than 10% of the bias of the OLS estimates. Standard errors in parentheses are robust and two-way clustered at the patient and the provider-month levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A10 Summary Statistics by Patient e-Visit Adoption for Exact-Provider Matched Samples

	LDL Match					HbA1c Match				
	(1) Non-Adopters		(2) Adopters		(3) t-stat	(4) Non-Adopters		(5) Adopters		(6) t-stat
	Mean	SD	Mean	SD		Mean	SD	Mean	SD	
Demographics										
Age (in 2013)	59.14	13.30	59.23	13.02	-0.38	62.30	12.38	61.76	12.27	1.38
Male	0.45	0.50	0.46	0.50	-1.41	0.49	0.50	0.50	0.50	-0.36
Outcomes										
Monthly Office Visits	0.19	0.13	0.19	0.14	-0.12	0.23	0.15	0.23	0.16	-1.01
Monthly Phone Visits	0.29	0.33	0.30	0.34	-1.60	0.34	0.39	0.37	0.42	-2.00*
Unhealthy Level of LDL	0.52	0.46	0.52	0.46	0.04	-	-	-	-	-
Unhealthy Level of HbA1c	-	-	-	-	-	0.15	0.32	0.16	0.32	-0.50
Number of Patients	5,731		7,198			1,783		2,221		

Notes: Patient e-visit adopters and non-adopters are matched on exact provider, age, race, and baseline outcomes on visit frequency and health. Columns (3) and (6) show the t-statistic testing the difference of mean summary statistics between non-adopters and adopters in each of the matched samples. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A11 Difference-in-Differences Estimates from Exact-Provider Matched Samples

	LDL Match			HbA1c Match		
	(1) Office	(2) Phone	(3) LDL	(4) Office	(5) Phone	(6) HbA1c
Patient e-Visit Adoption	0.011***	0.020***	-0.010	0.013**	0.035***	-0.025**
	(0.003)	(0.006)	(0.005)	(0.008)	(0.012)	(0.011)
Patient FEs	✓	✓	✓	✓	✓	✓
Provider FEs	✓	✓	✓	✓	✓	✓
Month FEs	✓	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓	✓	✓
Mean of Dep. Var.	0.19	0.31	0.45	0.23	0.37	0.45
R-squared	0.003	0.002	0.017	0.005	0.003	0.025
Sample	Matched (LDL)	Matched (LDL)	Matched (LDL)	Matched (HbA1c)	Matched (HbA1c)	Matched (HbA1c)
Patient-Months	780,004	780,004	55,731	241,585	241,585	23,805

Notes: Patient e-visit adopters and non-adopters are matched on exact provider, age, race, and baseline outcomes on visit frequency and health. LDL and HbA1c are binary variables that equal 1 if at least one measurement of the relevant outcome is unhealthy in a given month. Standard errors in parentheses are robust and two-way clustered at the patient and the provider-month levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A12 Difference-in-Differences Estimates on Visit Frequency, Controlling for Patient LDL

	Office		Phone	
	(1)	(2)	(3)	(4)
Patient e-Visit Adoption	0.035^{***}	0.035^{***}	0.039^{***}	0.040^{***}
	(0.003)	(0.003)	(0.005)	(0.005)
Unhealthy Observation of LDL		0.003^{***}		0.004^{*}
		(0.001)		(0.003)
Patient FEs	✓	✓	✓	✓
Provider FEs	✓	✓	✓	✓
Month FEs	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓
R-squared	0.010	0.010	0.004	0.005
Patient-Months	3,198,561	3,198,561	3,198,561	3,198,561

Notes: Standard errors in parentheses are robust and two-way clustered at the patient and the provider-month levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A13 Difference-in-Differences Estimates on Visit Frequency, Controlling for Patient HbA1c

	Office		Phone	
	(1)	(2)	(3)	(4)
Patient e-Visit Adoption	0.039^{***}	0.039^{***}	0.042^{***}	0.043^{***}
	(0.004)	(0.004)	(0.009)	(0.009)
Unhealthy Observation of HbA1c		0.056^{***}		0.090^{***}
		(0.003)		(0.007)
Patient FEs	✓	✓	✓	✓
Provider FEs	✓	✓	✓	✓
Month FEs	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓
R-squared	0.011	0.012	0.005	0.005
Patient-Months	1,242,863	1,242,863	1,242,863	1,242,863

Notes: Standard errors in parentheses are robust and two-way clustered at the patient and the provider-month levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A14 Estimates of Patient e-Visit Adoption on Emergency Room Visits

	(1) Full Diff-in-Diff	(2) IV
Patient e-Visit Adoption	-0.00009	0.00061
	(0.00004)	(0.00050)
Patient FEs	✓	✓
Provider FEs	✓	✓
Month FEs	✓	✓
Year FEs	✓	✓
Mean of Dep. Var.	0.0003	0.0003
R-squared	0.0001	-
Patient-Months	5,948,239	5,948,239
Weak id. (KP rk Wald F-stat.)	-	135.36
Underid. (KP rk LM p-value)	-	< 0.001

Notes: The dependent variable equals 1 if the patient had an observed emergency room (ER) visit in that month and zero otherwise. The IV analysis continues to use as an instrument the number of e-visits that a patient's provider conducts with all other patients in a given month. Our data includes 1,867 ER visits (but only those within the health system we study, which is a significant limitation) by 524 patients, 53 of which were adopters. The Wald F-statistic and test of underidentification are based on Kleibergen and Paap (2006). The Stock and Yogo (2005) critical value is 16.38 for the IV estimates to have no more than 10% of the bias of the OLS estimates. Standard errors in parentheses are robust and two-way clustered at the patient and the provider-month levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix B: Reviewer Supplement

Table B1 Relationship Between Provider Change and Patient Health

	(1) LDL	(2) HbA1c
Change in Provider	0.0028	-0.0003
	(0.005)	(0.006)
Patient FEs	✓	✓
Provider FEs	✓	✓
Month FEs	✓	✓
Year FEs	✓	✓
R-squared	0.013	0.015
Patient-Months	230,351	119,121

Notes: The independent variable equals 1 if the patient changed provider (using any type of primary care encounter) in that month and zero otherwise. Sample includes only patient-months in which LDL and HbA1c are binary variables that equal 1 if at least one measurement of the relevant outcome is unhealthy in a given month. Standard errors in parentheses are robust and two-way clustered at the patient and the provider-month levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B2 Difference-in-Differences Estimates on Visit Frequency, Controlling for the Instrument

	(1) Office	(2) Phone
Patient e-Visit Adoption	0.0087***	0.0169***
	(0.0022)	(0.0046)
Instrument	0.0001*	0.000007
	(0.00003)	(0.00006)
Patient FEs	✓	✓
Provider FEs	✓	✓
Month FEs	✓	✓
Year FEs	✓	✓
R-squared	0.002	0.001
Patient-Months	5,948,239	5,948,239

Notes: The mean and standard deviation of the instrument, defined as the number of e-visits a patient's provider conducts with all other patients in a given month, are respectively 10.97 and 27.50. Standard errors in parentheses are robust and two-way clustered at the patient and the provider-month levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

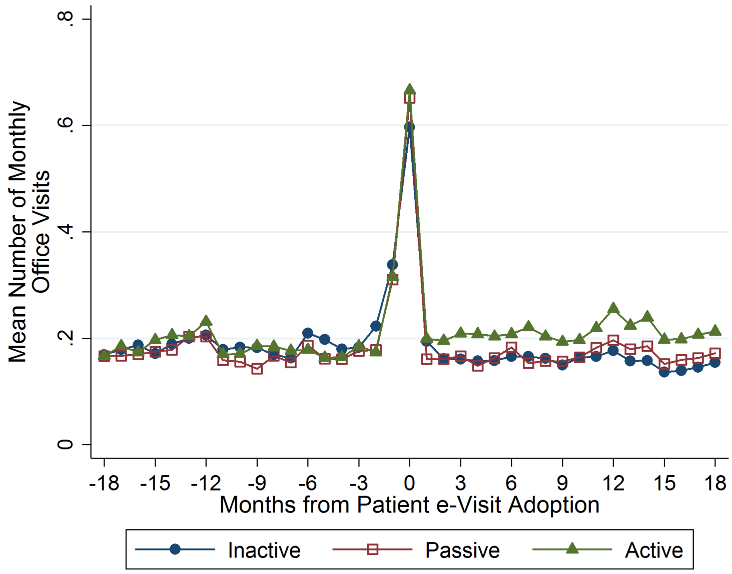

Figure B1 **Office Visit Frequency by Month of e-Visit Adoption, Stratified by e-Visit Usage Intensity**

Notes: The sample for these plots includes only patient e-visit adopters who are observed 18 months both before and after adoption. This includes 1,190 inactive, 1,829 passive, and 1,818 active adopters.

Table B3 **Summary Statistics by Patient e-Visit Adoption, Stratified by e-Visit Usage Intensity**

	(1) All		(2) Inactive		(3) Passive		(4) Active	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Demographics								
Age (in 2013)	56.68	14.57	55.22	15.47	57.29	14.04	57.38	14.15
Male	0.43	0.50	0.42	0.49	0.44	0.50	0.43	0.49
Black	0.18	0.38	0.20	0.40	0.17	0.37	0.17	0.37
White	0.72	0.45	0.68	0.47	0.75	0.44	0.74	0.44
Asian	0.04	0.19	0.04	0.21	0.04	0.18	0.03	0.18
Other Race	0.06	0.24	0.07	0.26	0.05	0.22	0.06	0.24
Outcomes								
Monthly Office Visits	0.18	0.12	0.17	0.12	0.17	0.12	0.20	0.13
Monthly Telephone Visits	0.32	0.33	0.27	0.31	0.31	0.31	0.38	0.36
Unhealthy Level of LDL	0.49	0.42	0.49	0.43	0.52	0.42	0.47	0.41
Unhealthy Level of HbA1c	0.10	0.25	0.11	0.26	0.09	0.23	0.11	0.26
Number of Patients	9,823		3,061		3,271		3,491	

Notes: Our sample includes patients who have at least six months of observations following e-visit adoption to enable a meaningful construction of e-visit usage intensity. For each patient-month, we calculate the number of e-visits conducted and categorize each patient as either inactive (one e-visit only), passive (below-median e-visits per month), and active (above-median e-visits per month.) The median is calculated on the subset of patients with more than one e-visit. Summary statistics for the intensity analysis. Included are patients who adopt e-visits are observed for at least 6 months after adoption. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B4 Difference-in-Differences Estimates of Patient e-Visit Adoption, Stratified by e-Visit Usage Intensity

	(1) Office	(2) Phone
Patient e-Visit Adoption	-0.036***	-0.044***
	(0.004)	(0.008)
Patient e-Visit Adoption × PASSIVE	0.017***	0.018*
	(0.004)	(0.009)
Patient e-Visit Adoption × ACTIVE	0.068***	0.129***
	(0.005)	(0.011)
Patient FEs	✓	✓
Provider FEs	✓	✓
Month FEs	✓	✓
Year FEs	✓	✓
Mean of Dep. Var.	0.18	0.32
R-squared	0.004	0.005
Patient-Months	579,626	579,626

Notes: Our sample includes patients who have at least six months of observations following e-visit adoption to enable a meaningful construction of e-visit usage intensity. For each patient-month, we calculate the number of e-visits conducted and categorize each patient as either inactive (one e-visit only), passive (below-median e-visits per month), and active (above-median e-visits per month.) The median is calculated on the subset of patients with more than one e-visit. Out of 9,823 patients in this sample, 3,061 were inactive, 3,271 were passive, and 3,491 were active. Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are robust and two-way clustered at the patient and the provider-month levels.

Table B5 Summary Statistics of Patients by Physician e-Visit Usage Intensity

	(1) All Physicians		(2) Below Median Intensity		(3) Above Median Intensity		(4) t-stat
	Mean	SD	Mean	SD	Mean	SD	
Demographics							
Age (in 2013)	57.90	18.54	56.45	20.12	59.36	16.92	-0.72
Male	0.36	0.19	0.37	0.18	0.34	0.20	0.63
Black	0.37	0.30	0.36	0.32	0.38	0.28	-0.22
White	0.54	0.29	0.53	0.30	0.56	0.28	-0.39
Asian	0.03	0.04	0.03	0.04	0.03	0.03	0.06
Other Race	0.06	0.07	0.08	0.08	0.04	0.04	2.75**
Outcomes							
Monthly Office Visits	154.02	102.88	192.38	110.85	115.67	78.26	3.66***
Monthly Phone Visits	239.53	171.39	265.55	198.98	213.52	135.98	1.40
Number of Physicians	84		42		42		

Notes: Providers only include physicians (e.g., not residents and nurse practitioners.) Physician e-Visit usage intensity equals the total number of e-visits following adoption over total number of total primary care encounters (office, phone, and e-visits) after adoption. Column (4) presents the t-statistic testing the difference of mean summary statistics between physicians with above and below median intensity of e-visit usage. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B6 Estimates of Patient e-Visit Adoption on Patient Health by Imputation Method

Imputation Method	Filling Forward		Filling with Average	
	(1) LDL	(2) HbA1c	(3) LDL	(4) HbA1c
Patient e-Visit Adoption	-0.017***	-0.007	-0.0017***	-0.0008**
	(0.004)	(0.005)	(0.0003)	(0.0004)
Missing Health Observation			-0.0001	0.0003
			(0.0006)	(0.0005)
Patient FEs	✓	✓	✓	✓
Provider FEs	✓	✓	✓	✓
Month FEs	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓
Mean of Dep. Var.	0.48	0.18	0.49	0.14
R-squared	0.005	0.007	0.001	0.001
Patient-Months	3,198,561	1,242,863	4,662,006	2,202,462

Notes: Sample begins with all patients with at least one LDL measurement for columns (1) and (3), and with at least one HbA1c for columns (2) and (4). LDL and HbA1c are binary variables that equal 1 if at least one measurement of the relevant outcome is unhealthy in a given month. Filling forward fills all missing observations for a patient's health outcome with the last observed measurement. Filling with Average fills a patient's all missing observations for a patient's health outcome with that patient's average health outcome and also includes a flag for the missing measurement. Standard errors in parentheses are robust and two-way clustered at the patient and the provider-month levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B7 Mean Value of Unhealthy LDL and HbA1c Observations by Physician

	Unhealthy Observation of LDL			Unhealthy Observation of HbA1c		
Provider	Mean	SD	# of Tests	Mean	SD	# of Tests
1	0.52	0.50	2,929	0.22	0.41	2,295
2	0.51	0.50	647	0.25	0.44	413
3	0.44	0.50	973	0.32	0.47	850
4	0.54	0.50	192	0.43	0.50	141
5	0.43	0.50	1,440	0.43	0.50	870
6	0.49	0.50	1,718	0.23	0.42	1,265
7	0.53	0.50	1,019	0.37	0.48	897
8	0.47	0.50	1,934	0.34	0.48	1,539
9	0.43	0.50	4,410	0.32	0.47	3,030
10	0.52	0.50	1,216	0.32	0.47	767
11	0.49	0.50	1,473	0.29	0.45	1,136
12	0.46	0.50	680	0.32	0.47	645
13	0.55	0.50	866	0.43	0.50	570
14	0.52	0.50	3,010	0.30	0.46	1,496
15	0.49	0.50	732	0.36	0.48	629
16	0.48	0.50	1,353	0.38	0.48	1,219
17	0.48	0.50	8,398	0.25	0.43	2,245
18	0.53	0.50	2,742	0.22	0.42	2,675
19	0.44	0.50	7,763	0.37	0.48	2,426
20	0.37	0.48	2,297	0.26	0.44	621
21	0.50	0.50	283	0.46	0.50	236
22	0.44	0.50	1,038	0.30	0.46	388
23	0.46	0.50	672	0.25	0.43	612
24	0.48	0.50	3,572	0.35	0.48	1,498
25	0.45	0.50	3,224	0.34	0.47	2,597
26	0.28	0.45	8,066	0.12	0.33	4,205
27	0.52	0.50	6,188	0.27	0.44	1,593
28	0.54	0.50	1,014	0.36	0.48	513
29	0.45	0.50	2,026	0.21	0.41	371
30	0.35	0.48	6,099	0.14	0.35	4,491
31	0.55	0.50	2,008	0.26	0.44	812
32	0.48	0.50	1,362	0.31	0.46	459
33	0.48	0.50	398	0.33	0.47	281
34	0.50	0.50	940	0.30	0.46	712
35	0.46	0.50	5,795	0.12	0.33	6,111
36	0.42	0.49	6,008	0.11	0.31	2,080
37	0.54	0.50	1,814	0.28	0.45	1,551
38	0.50	0.50	3,273	0.41	0.49	1,953
39	0.46	0.50	3,590	0.36	0.48	2,209
40	0.54	0.50	1,054	0.29	0.45	731
41	0.43	0.50	970	0.27	0.44	336
42	0.47	0.50	1,972	0.24	0.43	666
43	0.45	0.50	1,950	0.34	0.47	1,674
44	0.55	0.50	1,688	0.31	0.46	1,400
45	0.36	0.48	5,227	0.26	0.44	1,412
46	0.55	0.50	2,666	0.39	0.49	632
47	0.51	0.50	2,426	0.36	0.48	1,205
48	0.47	0.50	1,942	0.30	0.46	1,917
49	0.54	0.50	548	0.28	0.45	269
50	0.50	0.50	4,187	0.18	0.38	3,697
51	0.47	0.50	1,053	0.35	0.48	806
52	0.57	0.50	793	0.38	0.49	411
53	0.52	0.50	1,201	0.45	0.50	952
54	0.46	0.50	1,083	0.30	0.46	852
55	0.52	0.50	1,844	0.27	0.44	1,212
56	0.53	0.50	145	0.18	0.39	132
57	0.55	0.50	2,995	0.29	0.45	882
58	0.47	0.50	9,290	0.35	0.48	5,511
59	0.45	0.50	8,549	0.19	0.40	3,035
60	0.50	0.50	2,681	0.36	0.48	1,850
61	0.40	0.49	1,562	0.23	0.42	557
62	0.45	0.50	2,142	0.32	0.47	836
63	0.41	0.49	2,904	0.28	0.45	1,164
64	0.53	0.50	6,155	0.39	0.49	1,475
65	0.49	0.50	1,765	0.42	0.49	1,549
66	0.50	0.50	804	0.32	0.47	647
67	0.50	0.50	280	0.21	0.41	205
68	0.45	0.50	2,218	0.25	0.44	1,670
69	0.51	0.50	3,141	0.25	0.43	1,699
70	0.42	0.49	8,157	0.27	0.45	3,275
71	0.50	0.50	3,583	0.26	0.44	700
72	0.38	0.49	2,229	0.35	0.48	733
73	0.48	0.50	793	0.18	0.39	195
74	0.54	0.50	2,345	0.36	0.48	1,548
75	0.56	0.50	1,371	0.42	0.49	465
76	0.44	0.50	3,066	0.23	0.42	1,548
77	0.51	0.50	956	0.31	0.46	386
78	0.52	0.50	2,630	0.11	0.32	578
79	0.29	0.45	6,628	0.17	0.38	2,356
80	0.49	0.50	3,861	0.20	0.40	1,027
81	0.50	0.50	5,899	0.22	0.42	1,814
82	0.51	0.50	468	0.27	0.44	360
83	0.47	0.50	4,314	0.17	0.37	1,657
84	0.46	0.50	5,985	0.38	0.49	2,148
85	0.46	0.50	942	0.30	0.46	921
86	0.53	0.50	669	0.43	0.50	427
87	0.41	0.49	6,706	0.11	0.31	3,974
88	0.41	0.49	7,731	0.17	0.38	3,494
89	0.42	0.49	611	0.31	0.46	620
90	0.46	0.50	4,041	0.36	0.48	2,832
Total	**0.46**	**0.50**	**251382**	**0.27**	**0.44**	**128,843**

Notes: Table shows summary statistics on the health outcome tests (LDL and HbA1c) for all patients attributed to each physician.

Table B8 First Stage Results for Department and System Level Instruments

	Patient e-Visit Adoption					
	Department-level Instrument			System-level Intrument		
	(1)	(2)	(3)	(4)	(5)	(6)
Department-level Instrument	0.00015***	0.00017***	0.00011***			
	(0.000016)	(0.00001)	(0.00001)			
System-level Instrument				-0.000002	0.00001**	0.00001***
				(0.000002)	(0.000002)	(0.000002)
Patient FEs	✓	✓	✓	✓	✓	✓
Provider FEs	✓	✓	✓	✓	✓	✓
Month FEs	✓	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓	✓	✓
R-squared	0.083	0.097	0.091	0.070	0.085	0.085
Patient-Months	5,948,239	235,978	121,225	5,948,239	235,978	121,225
Sample	All	LDL	HbA1c	All	LDL	HbA1c
Weak id. (KP rk Wald F-stat.)	92.45	172.64	61.86	1.02	6.28	20.15
Underid. (KP rk LM p-value)	< 0.0001	< 0.0001	< 0.0001	0.306	0.014	< 0.0001
Mean of Instrument	92.64	97.28	122.61	739.18	750.44	853.35

Notes: The department-level instrument is defined as the monthly number of e-visits by the other physicians in a patients physicians department. The system-level instrument is defined as the monthly number of e-visits by the other physicians in other departments relative to the patients own physician. The Wald F-statistic and test of underidentification are based on Kleibergen and Paap (2006). The Stock and Yogo (2005) critical value is 16.38 for the IV estimates to have no more than 10% of the bias of the OLS estimates. Standard errors in parentheses are robust and two-way clustered at the patient and the provider-month levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.