Chasing the Missing Diagnoses: Exploring the Consequences of Removing Barriers to Information

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Abstract

We use three biomarker datasets to study the consequences of removing the barriers to acquiring information about asymptomatic conditions. We focus on screening for diabetes, hypertension, and high cholesterol, three common conditions that are often undiagnosed. We demonstrate that the impact of reducing the cost of screening on treatment can be undermined by patient composition effects: reducing the cost of screening increases the fraction of diagnosed patients with low uptake of ex-post medical treatment. These findings can be reconciled by a model in which patients with lower net benefits to medical treatment have lower demand for ex-ante information acquisition. We further show that this change in the composition of diagnosed patients can produce misleading conclusions during policy analysis, such as false reductions in measured health system performance after barriers to screening are removed.

Keywords: diabetes, chronic conditions, screening, self-selection, policy analysis, quality metrics. JEL Codes: I10, I12, I14.

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Highlights:

- Composition effects undermine apparent benefits of removing barriers to screening.
- Reduced-cost screening selectively diagnoses patients with low uptake of treatment.
- We replicate our findings using three biomarker datasets.
- We demonstrate possibilities for misleading conclusions in performance measurement.
- Our findings are consistent with rational models of patient behavior.

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1 Introduction

Many people, including some with health insurance, are not screened for conditions that can be asymptomatic and can be treated to prevent illness. For instance, diabetes, high cholesterol, and hypertension are top contributors to cardiovascular disease and end-stage renal disease in the United States and about one-fifth of cases are undiagnosed (Cowie et al., 2009; Global Burden of Disease Collaborators, 2013; McDonald et al., 2009; Olives et al., 2013; Patel et al., 2015; Zweifler et al., 2011). Due to the effectiveness of available treatments,[1] improving access to screening could have a substantial health impact if this change increases treatment of chronic conditions. Decreasing the cost of screening for these conditions, including both monetary costs and time costs, has been a focus of both public-sector and private-sector efforts in recent years. Medicare added a free "Welcome to Medicare" visit for new enrollees in which screening needs are discussed and addressed, and the Affordable Care Act required health insurance plans to offer free screening for diabetes, high cholesterol, and hypertension to people at high risk. In the private sector, pharmacy chains such as CVS, Walgreens, and stores such as Ralph's and Sam's Club now offer screening for diabetes, high cholesterol, and hypertension in convenient retail locations.

Although it may seem intuitive that reducing the cost of screening should increase treatment of chronic conditions, in fact the size of the effect is unclear because lower-cost screenings might diagnose patients with lower demand for medical treatment after diagnosis. Our logic is as follows. Patients who were not screened recently may have done so because they perceive lower benefits of medical treatment or higher barriers to medical treatment.[2] These barriers to care could include out-of-pocket costs, or non-pecuniary costs such as distance to a physician, language barriers, or psychological costs (Carpenter, 2010; Hyman et al., 1994; Kenkel, 1994; Manning et al., 1987; Musa et al., 2009). These same barriers could then translate to lower treatment rates for conditions detected after lowering screening costs. These gaps in treatment would shape the total costs and health benefits of policies and programs that subsidize screening, and affect physician practice after access to screening is expanded.

This paper provides an empirical assessment of these issues by examining the relationship between screening behavior and treatment of diagnosed conditions. We provide evidence that reducing the cost of screening increases the fraction of diagnosed patients with low uptake of

[1] See American Diabetes Association (2014); Collaborators (2005); Blood Pressure Lowering Treatment Trialists' Collaboration (2000); Bindman et al. (1995); Bressler et al. (2014); D'Agostino et al. (2008); Farley et al. (2010); James et al. (2014); Stone et al. (2014); Sytkowski et al. (1990) for evidence on the effectiveness of treatments.

[2] For evidence on screening, see Hyman et al. (1994); Lostao et al. (2001); Oster et al. (2013); Wilson (2011). For a discussion of self-selection into treatment and related econometric approaches, see, e.g., Carneiro et al. (2010); Eisenhauer et al. (2010); Heckman (2010).

ex-post medical treatment; these gaps in treatment are not driven by differences in need for treatment as measured by biomarker severity. Our findings have multiple implications for policy design and policy analysis. First, expanded screening could be less cost-effective than previously anticipated if uptake of treatment is low among the newly diagnosed patients. Second, our findings caution against using treatment of diagnosed conditions as an outcome metric in policy analysis, when analyzing policies that might expand access to screening. Such analyses might find misleading reductions in measured health system performance driven by changes to the composition of diagnosed patients. Third, the findings imply that in pay-for-performance systems where providers have financial incentives to maintain high treatment rates for diagnosed conditions, such as Accountable Care Organizations, expanding access to screening could carry a penalty by reducing other quality metrics. This would suggest reconsideration or reweighting of the metrics used in pay-for-performance systems to avoid penalizing health systems that expand screening in diverse patient populations.

We use three biomarker datasets to conduct cross-sectional and longitudinal analyses. Our cross-sectional analyses use data from a national biomarker study, the National Health and Nutrition Examination Survey (hereafter, NHANES) and a regional biomarker study, the Oregon Health Insurance Experiment (hereafter, OHIE) (Centers for Disease Control and Prevention, 2014; Finkelstein, 2013). Exploiting the fact that a person may have multiple chronic conditions, we show that people who have not had recent blood tests to screen for undiagnosed conditions are less likely to use recommended treatment for their other, diagnosed conditions. (For example, people who have not recently had a blood test to check for undiagnosed diabetes are less likely to use recommended treatment for their diagnosed high cholesterol.) Our longitudinal analysis explores the impacts of reducing barriers to screening using data from the REasons for Geographic and Racial Differences in Stroke study (hereafter, REGARDS). The REGARDS study randomly contacted older adults across the continental United States, conducted biomarker assessments in the participants' homes, compensated participants for their time, and informed participants of their biomarker results (Howard et al., 2005). Using merged individual-level Medicare claims, we show that after participants are made aware of their biomarkers, previously undiagnosed conditions remain less likely to receive annual doctor visits than previously diagnosed conditions. Both findings remain after controlling for demographic factors, health insurance status, and biomarker-based measures of condition severity.

These findings imply that changes in patient composition could mask the benefits of expanding access to screening, as captured by commonly used measures of health system performance. This problem arises because the true prevalence of conditions is not observed, whereas diagnosis status is observed. As a result, commonly used health system performance

metrics focus on treatment and control of conditions that are diagnosed (Center for Medicare and Medicaid Services, 2011, 2016a; National Committee on Quality Assurance, 2016; Song et al., 2011, 2014). However, use of these metrics can produce misleading conclusions - for example, that treatment of chronic conditions declines rather than improves as more patients become diagnosed. We demonstrate this possibility using the REGARDS data. We also show suggestive evidence using repeated cross-section data on the national level from NHANES: a rise in diagnosis of diabetes, hypertension and high cholesterol in recent years coincided with a fall in treatment of these conditions if diagnosed.

The paper proceeds as follows. Section 2 compares our study with previous literature. Section 3 presents our main empirical analyses. Section 4 presents our secondary analyses demonstrating the consequences of our findings for health system performance measurement. Section 5 presents a Grossman (1972) style model to show that no departure from a rational model of patient behavior would be necessary to produce our findings. Section 6 concludes.

2 Comparison with the literature

Anticipated costs and benefits of health care can differ across individuals, influencing individuals' willingness to pursue care (Egan and Philipson, 2014; Eisenhauer et al., 2010; Heckman, 2010). This premise underlies commonly used public health models such as the health belief model.[3] It follows that anticipated net benefits of particular health services can vary across individuals (Vanness and Mullahy, 2012). In certain cases, distributions of these individual-level net benefits can be estimated (Basu and Heckman, 2007; Carneiro et al., 2010; Eisenhauer et al., 2010). These distributions are useful because changes to out-of-pocket costs of health care will attract different patients to use the treatment based on their anticipated cost and benefit (Basu and Meltzer, 2007; Goldman and Philipson, 2007; Pauly and Blavin, 2008). A number of recent papers use new econometric methods to estimate distributions of net benefits of specific health services. These papers typically focus on how patients choose between treatments for their conditions (i.e., the intensive margin) (Basu and Heckman, 2007; Basu and Manning, 2009; Basu, 2011, 2013; Huang et al., 2006; Meltzer and Huang, 2007; Sculpher, 2008). In contrast, our theoretical model considers distributions of anticipated net benefits of screening, a determinant of which conditions are *not* treated (i.e., the extensive margin).

With respect to the model, our approach is based on the most commonly used economic

[3]See Glanz and Bishop (2010) for a review of commonly used health behavior models in the public health field. The health belief model includes perceived benefits and perceived barriers as a key construct, and these are the constructs that are most strongly predictive of behavior in empirical tests (Rosenstock et al., 1988; Carpenter, 2010).

framework for health investment, the Grossman (1972) health capital model. In this model, agents make decisions about how much time and money to invest in health to maximize their utility given practical constraints. In Grossman's original health capital model, there was no uncertainty: agents had perfect knowledge about their health and about the health production process. Previous research has incorporated uncertainty about how health investments translate to future health and productivity into the model using random shocks (Liljas, 1998; Grossman, 1982, 2000). Many of these papers, such as those of Chang (1996), Dardanoni and Wagstaff (1987) and Selden (1993), focus on health investment motivated by labor market returns. To allow our model to apply to agents not in the labor force, we follow Picone et al. (1998) and others by directly including health in the utility function. We allow agents' source of uncertainty about their health to be a lack of screening rather than exogenous shocks, as in Oster et al. (2013); Boozer and Philipson (2000) and others.

Finally, our study can be situated in the literature on health system performance measurement. As strategies to improve population health and promote health equity, the success of public reporting and pay-for-performance programs hinges on selection of appropriate metrics. Previous research has shown that some metrics used in existing public reporting schemes create incentivizes to select certain types of patients for care, because providers' scores decrease if they treat particularly vulnerable or sick patients (Dranove et al., 2003; Harris et al., 2016; Konetzka et al., 2013). These findings have raised concerns that public reporting could create a less inclusive health system depending on the metrics chosen (Casalino et al., 2007; Karve et al., 2008). Our study contributes this literature by generalizing previous findings for the case of screening. We find that expanding the set of diagnosed patients makes a health system more inclusive but carries a "quality penalty," in the form of decreased treatment rates for diagnosed conditions. We show that the effect remains after controlling for the observable factors that were at the center of previous studies, such as biomarker-measured clinical severity of detected cases, patient demographics, and patient health insurance status.

3 Empirical analysis

3.1 Statistical methods

Our analysis has two main goals. First, we wish to establish whether an association between treatment after diagnosis and willingness to pay for screening exists. If this association holds, then undiagnosed patients are not missing completely at random with respect to probability of treatment after diagnosis, with implications for policy design and policy analysis as de-

scribed above. Second, we wish to establish whether commonly measured variables related to the costs or benefit of accessing medical care, such as severity of the condition, demographic variables, or insurance status, fully account for this association. If the association can be eliminated by controlling for commonly measured variables, then the consequences discussed previously could be more readily avoided.

To clarify by using the example of diabetes, we would like to run models of the following form:

$$Pr(\text{Diabetes is Treated After Diagnosis}) = f(\text{Willingness to Pay for Diabetes Screening, Controls}) \tag{1}$$

In practice, an empirical roadblock prevents direct estimation of Model (1) using available data: the variable "Willingness to Pay for Diabetes Screening" is not directly measured. Typical data include measures of recent screening, not willingness to pay for screening. Furthermore, surveys do not ask about screening prior to diagnosis for patients who have been already diagnosed for a given condition. We side-step these issues empirically in two ways, using cross-sectional data and panel data. Additional details on these two strategies are provided below.

3.1.1 Cross-sectional data analysis

This analysis exploits the fact that a person may have multiple chronic conditions, and uses lack of screening for other conditions as an indicator of willingness to pay for screening on the patient-level. We use two cross-sectional datasets to run models of the following form:

$$\begin{aligned} Pr\,(\text{Condition is Treated After Diagnosis}) = & f(\text{Recent Blood Test to Screen} \\ & \text{for } \textit{Other} \text{ Undiagnosed Conditions,} \\ & \text{Controls}) \end{aligned} \tag{2}$$

While it may seem unusual to analyze multiple conditions in a single model, our conditions of interest (diabetes, high cholesterol, and hypertension) are frequently discussed together in the medical literature. They are often co-morbid and contribute to a cluster of risk factors called metabolic syndrome (Grundy, 2004; Sowers et al., 2001).

We focus on screening via blood tests rather than blood pressure measurements for two main reasons. First, none of our data sets include data on recent blood pressure tests conducted in a clinical setting. Second, blood pressure is considered a vital sign and is therefore measured at most clinic visits; in contrast, blood tests are conducted among undiagnosed patients for the express purpose of screening.

To ensure that no one condition is driving the results, we separately model treatment for diagnosed diabetes, high cholesterol, and hypertension. As such, models take the following form. (For brevity, controls are omitted below.)

$$\begin{aligned} Pr(\text{Diabetes Treated}) &= f(\text{Screened for Undiagnosed High Cholesterol}) \\ Pr(\text{High Cholesterol Treated}) &= f(\text{Screened for Undiagnosed Diabetes}) \\ Pr(\text{Hypertension Treated}) &= f(\text{Screened for Undiagnosed} \\ &\qquad \text{Diabetes or High Cholesterol}) \end{aligned} \tag{3}$$

For each model, each person is entered into the data only once. (Using the example of equation (3), each person can have at most one case of diagnosed diabetes.)

These models can be represented by the following general notation:

$$M_{ij} = \alpha + R_{i,-j}\gamma + X_i\beta + \epsilon_{ij} \tag{4}$$

M_{ij} indicates medical care received by person i for prevalent, diagnosed condition j. $R_{i,-j}$ takes the value 1 if person i recently had a blood test to screen for conditions $-j$ for which they were not already diagnosed, and 0 otherwise. Covariates X_i include race/ethnicity, age, education, income, English language preference, insurance status, condition severity, prevalence of diagnosed and undiagnosed comorbid conditions, and the year that participant i was surveyed. Because we estimate linear probability models and the M_{ij} outcomes are binary, we account for heteroskedasticity in ϵ_{ij} by using robust standard errors.

3.1.2 Panel data analysis

A limitation of the cross-sectional analysis is that the most screening-resistant people are dropped from the model entirely, since they will not have any diagnosed conditions. The panel data method side-steps this issue, and also provides a direct test of whether changes to the cost of screening result in changes in treatment for undiagnosed conditions.

The panel analysis exploits an exogenous change to the cost of biomarker assessment for participants in the REGARDS study. The REGARDS study provided participants with biomarker assessments and then informed participants about their previously undiagnosed conditions (Howard et al., 2005). The REGARDS baseline biomarker data have been merged with individual-level Medicare claims data, allowing us to track doctor visits to treat specific conditions before and after their biomarker assessment via REGARDS (Muntner et al., 2014). Howard et al. (2005) and Appendix A provide additional details on the REGARDS study.

We assume that lack of diagnosis prior to biomarker assessment via the REGARDS study

indicates, on average, a lower willingness to pay for screening. In this case, a model of the following form can serve as a proxy for our ideal model:

$$Pr\,(\text{Condition is Treated}) = f(\text{Condition was Undiagnosed Prior to Biomarker Assessment Via REGARDS, Controls})$$

More precisely, we use models of the following form to compare treatment of previously diagnosed vs. previously undiagnosed conditions data during the 1st and 2nd years after biomarker assessment via REGARDS:

$$M_{ijt} = \alpha_j + U_{ij,t-2}\gamma + X_{it}\beta + \epsilon_{ijt} \tag{5}$$

We do not parse out Hawthorne effects because we find no evidence of such effects for our outcomes of interest in a companion paper (Myerson et al., 2017).

Our predictor of interest is $U_{ij,t-2}$. This variable takes the value 1 if individual i's prevalent condition j was undiagnosed prior to biomarker assessment via REGARDS, and 0 if condition j was diagnosed prior to biomarker assessment via REGARDS. Time t denotes our periods of observation: this model includes data from the 1st year and 2nd year after each participant had his or her biomarkers assessed via the REGARDS study.

Because this model involves a comparison across individuals, we control for a large number of personal characteristics, including all demographic variables extracted from the OHIE and NHANES data for Model (4) as well as additional characteristics available from the REGARDS data.[4] Because participants were recruited to participate on a rolling basis over several years (2003-2007), calendar time of observation varies across participants; we include year and seasonal fixed effects as part of X_{it}. To account for repeated observations on the individual-level, we cluster standard errors by individual.

[4]These additional controls include Medicaid dual eligibility, past and current smoking status, marital status, the number of alcoholic drinks the participant reported having on a weekly basis, whether the participant was fasting at the time of biomarker assessment, and whether the participant had a usual source of care at the time of biomarker assessment. We also adjusted for additional tests and geographic variables available in the REGARDS data, namely, whether the participant lived in an county that had been characterized as a partial or complete health professional shortage area, whether the participant lived in a higher-poverty county (whether or not 25% or more of the participants live in poverty), the participants' cognitive status according to a short memory test (impaired or not), and reported physical health from the SF-12.

3.2 Data

We use data from three studies: the National Health and Nutrition Examination Survey (NHANES), the REasons for Geographic and Racial Differences in Stroke study (REGARDS), and the Oregon Health Insurance Experiment public use data files (OHIE). In all three studies, participants reported their diagnosed conditions in a survey, had their biomarkers taken, and were paid for their time. Table 1 summarizes the sample selection and characteristics of included participants from these three studies.

NHANES is a nationally representative biomarker survey run by the Center for Disease Control and Prevention. Comparable data have been collected on a rolling basis from 1999-2014, and these are the data most commonly used to track awareness of chronic conditions over time on the national level (Centers for Disease Control and Prevention, 2014). Data on recent screening for diabetes are only available starting in 2005; we therefore use data from 2005-2014. REGARDS is an epidemiological study of older adults that recruited participants across the continental United States over 2003-2007 using a commercial list of residential phone numbers (Howard et al., 2005). The REGARDS data have been linked with administrative records of doctor visits for participants enrolled in traditional Medicare (Muntner et al., 2014). We use the ICD-9 codes in the claims data to identify which of the patient's prevalent conditions were addressed in any given evaluation and management visit with a doctor; a single visit could address multiple conditions. (Myerson et al. (2017) provides additional discussion.)

Finally, we use publicly available data from the OHIE in-person biomarker data collection and 12-month mail-in survey, which were conducted during 2009-2010. Participants in these surveys had entered a lottery to apply for Medicaid in Oregon in 2008 (Allen et al., 2010; Baicker et al., 2013). In the OHIE data, both self-reported and validated measures of current medications are available, although the data are collected at slightly different times. To ensure that participants' treatment, screening, and diagnosis status are measured at the same time, we measure all of these variables using data from the 12 month follow-up survey in the main analysis; out of necessity, we measure the biomarkers using data from the in-person survey.[5] As a robustness check, we re-run our analyses using the medication measures collected during the in-person survey.

These three data sources have different advantages and disadvantages for our analysis.

[5] Although both surveys were implemented over 2009-2010, the median gap in time between the in-person survey and 12-month follow-up was just over 6 months; the in-person survey was completed later than the 12-month survey for most respondents. In the OHIE data, codebooks of the publicly available data indicate that questions about screening for high cholesterol were collected as part of the in-person survey but questions about screening for diabetes were not. In contrast, screening of both conditions was asked about in the 12-month follow-up survey.

Table 1: Characteristics of included participants from the three biomarker surveys

	NHANES	**OHIE**	**REGARDS**
Survey Inclusion Criteria	Nationally representative	Applicants to expanded Medicaid (in both the in-person survey and 12 month follow-up)	In traditional Medicare past 2 years; black or white; English speaking
Geography of Sample	National	Oregon	National
Year of Biomarker Collection	2005-2014	2009-2010	2003-2007
Age Range in Analysis	All	19+	67+
Participants with Any Condition(s) of Interest	18,735	3,482	5,721
Participants with Undiagnosed Condition(s) of Interest	6,281	1,546	1,077
Among Participants with Condition(s) of Interest:			
Average Age	55	45	74
Had Health Insurance	81%	48%	100%
African American	22%	9%	30%
Participants with Diabetes	4,282	705	1,309
Aware of Diabetes	3,482	666	1,192
Treating with Medication	2,991	500	1,161
Participants with Hypertension	11,576	1,917	4,502
Aware of Hypertension	10,193	1,657	4,170
Treating with Medication	7,680	1,056	3,846
Participants with High Cholesterol	13,716	2,663	4,268
Aware of High Cholesterol	9,030	1,301	3,542
Treating with Medication	4,860	672	2,457

We can only use NHANES and OHIE for estimating Model (4), because the NHANES and OHIE ask about recent screening whereas REGARDS does not. However, the merged REGARDS-Medicare data present the unique advantage of using administrative data to track participants' relevant doctor visits after their biomarkers were assessed.[6] We therefore estimate Model (5) using the REGARDS data, comparing doctor visits for newly diagnosed conditions vs. previously diagnosed conditions after the REGARDS study assessed patients' biomarkers.

The NHANES and OHIE data also have different advantages and disadvantages for estimating Model (4). The NHANES data include information on whether a doctor had ever recommended managing hypertension and high cholesterol using a prescription, whereas the OHIE (and REGARDS) data do not. This is important because national guidelines recommend treating less severe cases of these conditions with diet and exercise before prescribing medication (James et al., 2014; Stone et al., 2014). By tracking medication use only among participants who report that their doctor recommended medication, we can ensure that our results are not driven by medication non-use among patients whose doctors recommended controlling the condition through diet and exercise alone. As a nationally representative survey, the NHANES also samples the most diverse group of participants. In contrast, the OHIE data have a different advantage for the present analysis. Adding these data allows us to pursue a focused analysis of a group of importance given recent health policy changes: applicants to expanded Medicaid. In Medicaid expansion states, many patients who become diagnosed due to the Affordable Care Act could come from this group (Kaufman et al., 2015; Myerson and Laiteerapong, 2016; Simon et al., 2016; Wherry and Miller, 2016).

Tracking screening of undiagnosed conditions, for Model (4)

The questions about recent blood tests to screen for diabetes and high cholesterol in the OHIE and NHANES have slightly different look-back periods. The questions about screening for diabetes and high cholesterol in the OHIE data in the 12-month follow up survey focus on screening within the past 12 months (Finkelstein, 2013).[7] In contrast, the look-back period for diabetes screening in the NHANES data is 3 years. We combined data from multiple variables in the NHANES to construct measures of high cholesterol screening within the past

[6]The timing of biomarker assessment in OHIE precludes us from examining the impact of biomarker assessment on self-reported doctor visits or use of medications using the publicly available data.

[7]The relevant questions in 12-month follow-up survey are as follows: "Have you ever had your blood cholesterol checked?" and "Have you ever had a blood test for high blood sugar or diabetes?" The response options include "Yes, within the last year," "Yes, but it's been more than a year," and "Never" . In this case, we code both the second and third response options as a negative response and determine "recent" screening to be screening within the past year.

year and within the past two years.[8] We present results using the two-year look-back period in the main text, and include results using the one-year look-back period in Appendix B.

Tracking diagnosed and undiagnosed conditions, for Model (5)

We code participants as having a particular chronic condition (diabetes, hypertension, and/or high cholesterol) if they report prior diagnosis for the condition at the time of participation, with the appropriate exclusions for diagnosis during pregnancy, or if their biomarkers meet standard definitions for the condition after taking their fasting status into account (American Diabetes Association, 2014; Stone et al., 2014; James et al., 2014). Table B.1 in Appendix B includes details of each definition. Individuals are classified as undiagnosed for the condition if they meet the biomarker definitions for a condition, but report no prior diagnosis for that condition.

Using the merged REGARDS-Medicare data, we are able to correct for patients' under-reporting of diagnosis using Medicare claims. We accomplish this by also classifying participants as diagnosed if they meet biomarkers criteria of the condition and also meet Chronic Conditions Warehouse definitions for the condition based on their recent Medicare claims. This process increases the number of diagnosed cases of high cholesterol by 148 (4%), the number of diagnosed cases of diabetes by 26 (2%), and the number of diagnosed cases of hypertension by 119 (2%).

3.3 Results

3.3.1 Cross-sectional analysis: Treatment of previously diagnosed conditions

We first use NHANES data to show that use of recommended treatment for diagnosed conditions is lower among individuals not recently screened for other, undiagnosed conditions. Bivariate regressions indicate that participants with undiagnosed conditions are less likely to report taking their prescribed medications for diagnosed hypertension or high cholesterol, or having a foot exam or eye exam over the past year for their diagnosed diabetes.[9] See

[8] Timing of blood cholesterol screening is assessed using two questions: "Have you ever had your blood cholesterol checked?" and "About how long has it been since you last had your blood cholesterol checked? Has it been..." with the options "Less than a year ago," "1 year but less than 2 years ago," "2 years but less than 5 years ago," or "5 years or more." Timing of diabetes screening is assessed using the question: "Have you had a blood test for high blood sugar or diabetes within the past three years?" with responses either "Yes" or "No." (We code "Refused" or "Don't Know" as missing.)

[9] Doctors' recommendations to control hypertension and high cholesterol using medication are asked about in the NHANES, enabling us to track medication use only among diagnosed patients for whom medication was recommended. However, there is no comparable question for diabetes. However, annual foot exams and eye exams are recommended for all people with diabetes as standard care (American Diabetes Association, 2014).

column 1 of Table 2.

A key question is whether adjustment for commonly measured covariates can eliminate this association. If so, then bias in health system performance metrics could be readily addressed. To address this question, we adjust for the following commonly measured variables related to demographics and health insurance: self-reported age (in quartiles), gender, education, income, and English language preference; self-identification as African American; self-identification as Hispanic; and current self-reported health insurance status, Medicaid coverage, and Medicare coverage. We also adjust for the year of survey participation. To avoid conflating a drop in significance due to the addition of covariates with a drop in significance due to change in sample size after list-wise deletion of missing values, we include dummy variables capturing missing values for each of these variables. The results in column 2 of Table 2 indicate that the association between recent screening and treatment of other diagnosed conditions is diminished as these variables are added, but not eliminated.

One might argue that if people who are rarely screened have less severe conditions overall, lower treatment rates and screening rates in this group would represent an appropriate allocation of resources. The tractability of this argument is limited by the fact that people cannot know the severity of asymptomatic conditions without screening. Furthermore, we find in all three biomarker datasets that participants with undiagnosed conditions typically show more severe, not less severe, biomarkers for their diagnosed conditions. See Table B.2 in Appendix B. Regardless, we address this argument in the analysis by adding controls for patients' biomarkers including LDL and HDL cholesterol, HbA1c, and systolic and diastolic blood pressure to the model. Biomarker variables are divided into bins based on quartiles of the sample distribution. In the NHANES analysis we also adjust for self-reported retinopathy, a diabetes symptom that is consistently measured across different waves of the NHANES survey, to account for the possibility that onset of symptoms could spur demand for treatment and screening. As shown in columns 3 and 4 of Table 2, findings are similar when we adjust for comorbid conditions and/or condition severity.

Because questions about recommended treatment are only asked in the NHANES, we cannot restrict the sample to only patients whose doctors recommended treatment using medications (rather than dietary modification alone) when analyzing the OHIE data (Finkelstein, 2013). The OHIE data on use of medication for diabetes, hypertension, and high cholesterol are therefore presented with the caveat that our treatment metric is an imperfect measure of compliance with recommended treatment. Nonetheless, our findings using OHIE data on treatment, shown in Table 3, are qualitatively similar to those in Table 2. When we replicate this OHIE analysis using the NHANES data, we again find similar results.[10] See Table B.3

[10]In addition to the different sampling frame, the data are not perfectly comparable because the two

Table 2: Individuals not recently screened for undiagnosed conditions are less likely to use recommended care for their other, diagnosed conditions (NHANES data)

	(1)	(2)	(3)	(4)
Diagnosed diabetes				
(1) Had eye exam				
Not screened for undiagnosed	-0.256***	-0.174***	-0.186***	-0.173***
high cholesterol	(0.0306)	(0.0325)	(0.0325)	(0.0338)
Observations	1,373	1,373	1,373	1,373
Average outcome if screened	0.661	0.661	0.661	0.661
(2) Had foot exam				
Not screened for undiagnosed	-0.293***	-0.223***	-0.222***	-0.202***
high cholesterol	(0.0313)	(0.0326)	(0.0328)	(0.0340)
Observations	1,333	1,333	1,333	1,333
Average outcome if screened	0.739	0.739	0.739	0.739
Diagnosed hypertension				
(3) Take meds if recommended				
Not screened for undiagnosed	-0.102***	-0.0774***	-0.0822***	-0.0753***
diabetes or high cholesterol	(0.0113)	(0.0105)	(0.0106)	(0.0106)
Observations	6,960	6,960	6,960	6,960
Average outcome if screened	0.888	0.888	0.888	0.888
Diagnosed high cholesterol				
(4) Take meds if recommended				
Not screened for undiagnosed	-0.0799***	-0.0619***	-0.0529***	-0.0390***
diabetes	(0.0149)	(0.0142)	(0.0143)	(0.0134)
Observations	4,009	4,009	4,009	4,009
Average outcome if screened	0.803	0.803	0.803	0.803
Control for demographics	N	Y	Y	Y
Control for conditions	N	N	Y	Y
Control for biomarkers	N	N	N	Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table shows the relationship between recent screening for undiagnosed conditions and use of recommended treatment for other, diagnosed conditions. Look-back periods for screening for undiagnosed diabetes and high cholesterol are two and three years, respectively. The rows include coefficients and standard errors from linear probability models, adjusting for the listed control variables. The outcomes include (1) foot exams and (2) eye exams in the past year among participants reporting prior diagnosis of diabetes; (3) use of anti-hypertensive medication among participants reporting prior diagnosis of hypertension, and that a doctor recommended anti-hypertensive medication; and (4) use of cholesterol-lowering medication among participants reporting prior diagnosis of high cholesterol, and that a doctor recommended cholesterol-lowering medication.

Table 3: Individuals not recently screened for undiagnosed conditions are less likely to use medication for their other, diagnosed conditions (OHIE data)

	(1)	(2)	(3)	(4)
Diagnosed diabetes				
(1) Taking medication				
Not screened for undiagnosed	-0.322***	-0.341***	-0.306***	-0.285***
high cholesterol	(0.0577)	(0.0644)	(0.0613)	(0.0615)
Observations	254	254	254	254
Average outcome if screened	0.831	0.831	0.831	0.831
Diagnosed hypertension				
(2) Taking medication				
Not screened for undiagnosed	-0.369***	-0.291***	-0.279***	-0.260***
diabetes or high cholesterol	(0.0274)	(0.0291)	(0.0286)	(0.0291)
Observations	1,140	1,140	1,140	1,140
Average outcome if screened	0.774	0.774	0.774	0.774
Diagnosed high cholesterol				
(3) Taking medication				
Not screened for undiagnosed	-0.417***	-0.359***	-0.323***	-0.292***
diabetes	(0.0344)	(0.0366)	(0.0365)	(0.0375)
Observations	641	641	641	641
Average outcome if screened	0.591	0.591	0.591	0.591
Control for demographics	N	Y	Y	Y
Control for conditions	N	N	Y	Y
Control for biomarkers	N	N	N	Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table shows the relationship between screening for undiagnosed conditions within the past year and use of medication to treat other, diagnosed conditions. The rows include coefficients and standard errors obtained from linear probability models after adjusting for the listed control variables. The outcomes include (1) use of diabetes medication among participants reporting prior diagnosis of diabetes; (3) use of anti-hypertensive medication among participants reporting prior diagnosis of hypertension; and (4) use of cholesterol-lowering medication among participants reporting prior diagnosis of high cholesterol.

in Appendix B.

Additional robustness checks and comparisons across datasets The analysis thus far has the shortcoming that diagnosis and treatment of chronic conditions are only measured using self-reported data. We address this shortcoming in multiple ways. First, we replace the self-reported medication measure in the OHIE with the validated medication measure constructed using a medication review during an in-person survey. As shown in Table B.4 in Appendix B, the findings are unchanged. Second, we conduct additional checks using claims data available in the merged Medicare-REGARDS data. In this analysis, our main outcome of interest is doctor visits for evaluation and management of diagnosed conditions in the previous year, measured using Medicare claims assigned to conditions using ICD-9 codes based on Chronic Conditions Warehouse classifications. We find that participants with previously undiagnosed conditions had fewer doctor visits for their previously diagnosed conditions. See Table B.5 in Appendix B.

In addition, as noted in Section 3.2, we had multiple options for defining recent screening for high cholesterol in the NHANES data, due to the multiple look-back periods addressed in the survey questions. Tables B.6 and B.7 in Appendix B replicate Tables 2 and B.3, but using a one-year look-back period for high cholesterol screening rather than a two-year look-back period. The results are similar to those reported in the main text.

3.3.2 Panel data analysis: Doctor visits for previously undiagnosed conditions

All the analyses above have the disadvantage of relying on cross-sectional data. A key question is whether patients who are diagnosed after a drop in the price of screening, or outreach to encourage screening, would be less likely to treat conditions that become diagnosed as a result of this intervention.

To address this question, we use Medicare claims data from individuals whose biomarkers were assessed by the REGARDS study to estimate Model (5). This model estimates the gap in annual doctor visits for evaluation and management of previously diagnosed vs. previously undiagnosed conditions after all participants received biomarker assessment via REGARDS.

Results are shown in Table 4. Column 1 and column 2 of Table 4 present the results with vs. without adjustment for demographic controls. Column 3 presents results with additional adjustment for year fixed effects, season effects (winter vs. other), and region-by-year interactions, to account for the geographic diversity of REGARDS participants and the rolling recruitment into REGARDS over multiple years. Finally, column 4 presents results from the model with additional controls for presence of multiple co-morbid conditions, as well as

datasets have a different look-back period for screening. See section 3.2.

biomarkers including waist circumference, body mass index, plasma glucose, triglycerides, LDL cholesterol, HDL cholesterol, total cholesterol, the average of two blood pressure measures (both systolic and diastolic). These additional controls adjust for the possibility that less severe cases of hypertension or high cholesterol could be evaluated by a physician on less than an annual basis. (In the case of diabetes, foot exams, eye exams, and multiple hba1c measurements by a physician are recommended on an annual basis for all diabetes patients regardless of severity (American Diabetes Association, 2014).) All continuous variables were binned into four categories of equal size based on quartiles of the sample distribution to allow non-linearity in the relationship between these variables and doctor visits.

The results in all four columns of Table 4 are similar; in all analyses, previously undiagnosed conditions are significantly less likely than previously diagnosed conditions to receive an annual doctor visit. Our findings are qualitatively similar when we analyze number of visits per year, as shown in Table B.8 in the Appendix B. Results are also similar when we use coarsened exact matching to balance these two groups on race, sex, biomarkers (glucose, LDL cholesterol, and systolic blood pressure), and prevalence of diabetes, hypertension, and high cholesterol (prevalence of each condition alone, and prevalence of multiple co-morbid conditions) using the *cem* package in Stata (Blackwell et al., 2009). See Table B.9 in Appendix B.

Figure 1 shows a similar relationship in the raw data. The data show that doctor visits for previously undiagnosed conditions increased after biomarker assessment, but only to about half the level of previously diagnosed conditions. Finally, notification by mail for the diabetes and high cholesterol results is unlikely to account for the observed shortfall in doctor visits for newly diagnosed conditions. The gap in doctor visits exists for all three conditions, including high blood pressure.[11] This is shown in Table 4 in the text and in Tables B.8 and B.9 in Appendix B.

3.3.3 Summary

This section presented two key empirical findings. First, we find that people who have not recently had blood tests to screen for undiagnosed conditions are less likely to adhere to recommended treatment for their other, diagnosed conditions. Second, we find that conditions diagnosed as part of a biomarker study are less likely than previously diagnosed conditions to receive annual doctor visits. These findings are consistent with a hypothesis that reducing the cost of screening would increase the fraction of diagnosed patients with low probability of medical treatment.

[11] Participants received their blood pressure results immediately, in person.

Table 4: After all participants were notified about abnormal biomarkers and advised about the need to follow-up with a doctor, previously undiagnosed conditions were less likely than previously diagnosed conditions to receive an annual doctor visit (REGARDS data)

	(1)	(2)	(3)	(4)
Any Relevant Visits				
(1) All				
Previously undiagnosed	-0.450***	-0.445***	-0.445***	-0.420***
condition	(0.0126)	(0.0159)	(0.0159)	(0.0178)
(2) Diabetes				
Previously undiagnosed	-0.496***	-0.498***	-0.502***	-0.499***
condition	(0.0416)	(0.0475)	(0.0473)	(0.0478)
(3) Hypertension				
Previously undiagnosed	-0.517***	-0.513***	-0.513***	-0.500***
condition	(0.0229)	(0.0286)	(0.0286)	(0.0330)
(4) High Cholesterol				
Previously undiagnosed	-0.408***	-0.399***	-0.398***	-0.341***
condition	(0.0152)	(0.0197)	(0.0197)	(0.0233)
Control for demographics	N	Y	Y	Y
Control for time and region	N	N	Y	Y
Control for biomarkers	N	N	N	Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table compares annual doctor visits after biomarker assessment via REGARDS for evaluation and management of previously diagnosed vs. previously undiagnosed diabetes, hypertension, and high cholesterol. The rows include coefficients and standard errors obtained from linear probability models after adjusting for the listed control variables. All REGARDS participants were informed of their results and advised to see a doctor to follow-up about any abnormal results, as detailed in Appendix A. Doctor visits from the 24 months after biomarker assessment via REGARDS were measured using Medicare claims data, and categorized as relevant to each prevalent condition using ICD-9 codes.

We additionally find that these associations between screening and treatment are not fully explained by health insurance status, commonly measured demographic variables, prevalence of comorbid conditions, or biomarker-measured condition severity. This raises practical concerns for measurement of health system performance, as we explore in the next section.

4 Implications for analysis of health system performance

We have provided evidence that reducing the cost of screening should selectively increase diagnosis rates among patients who are less likely to use medical treatment after diagnosis. We now briefly describe the possible consequences of this change to the composition of diagnosed patients.

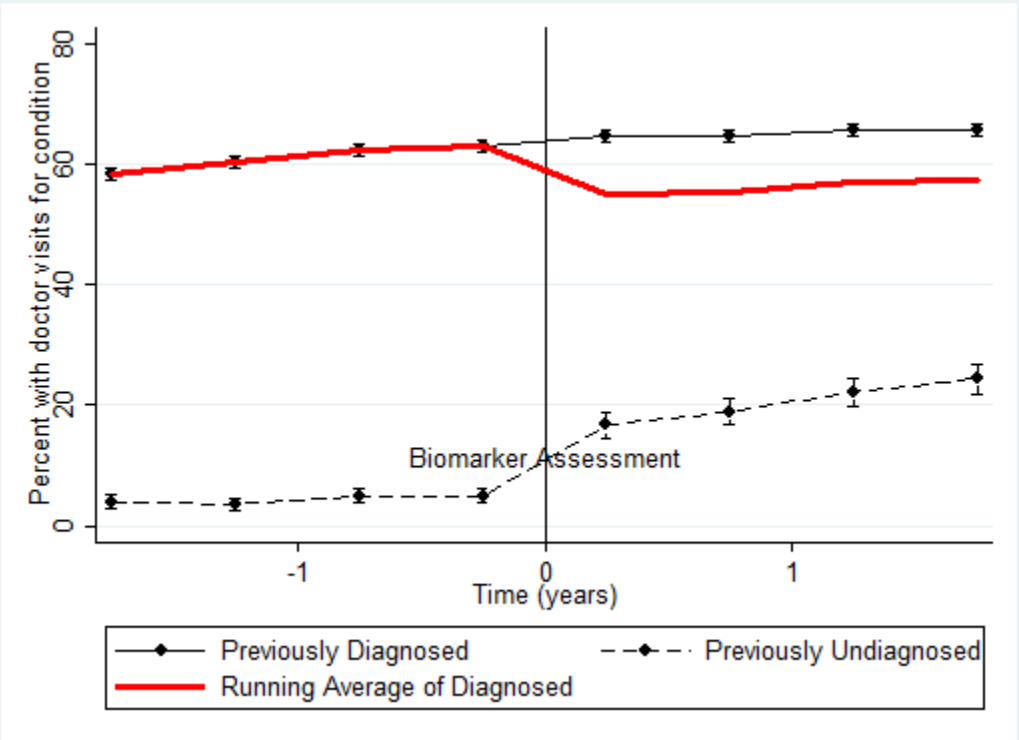
Changes in the composition of diagnosed patients could mask the benefits of expanding access to screening, as captured by commonly used measures of health system performance. This problem arises because true prevalence of conditions is not observed, whereas diagnosis status is observed. As a result, a number of health system performance metrics focus on treatment and control of diagnosed conditions (Center for Medicare and Medicaid Services, 2011, 2016b; National Committee on Quality Assurance, 2016). However, tracking the rate of treatment given diagnosis could lead to the incorrect conclusion that treatment of chronic conditions declines as more patients become diagnosed.

We are best able to demonstrate this point using the REGARDS data. Biomarker assessment via REGARDS increased doctor visits for undiagnosed conditions without changing doctor visits for diagnosed conditions: in total, the impact on doctor visits was positive (Myerson et al., 2017). When data from previously diagnosed and previously undiagnosed conditions are graphed separately (the solid and dashed lines in Figure 1), these data show an increase in doctor visits after biomarker assessment. In contrast, if the running average of doctor visits for currently diagnosed conditions is graphed (the red line in Figure 1), these data show a decrease in doctor visits after biomarker assessment.[12] This reversal of sign is driven by changes to the group of diagnosed conditions over time.

Adjusting for multiple control variables, including individual fixed effects, does not eliminate this reversal of sign. We demonstrate this point by implementing interrupted time

[12]The running average from before biomarker assessment via REGARDS only includes data on conditions that were diagnosed prior to recruitent into REGARDS. In contrast, the running average from after biomarker assessment via REGARDS includes these conditions, plus any previously undiagnosed conditions detected via REGARDS biomarker assessment.

Figure 1: Doctor visits for evaluation and management of previously diagnosed vs. previously undiagnosed conditions, before vs. after biomarker assessment via REGARDS



This figure compares doctor visits before and after biomarker assessment via REGARDS, for previously diagnosed vs. previously undiagnosed diabetes, high cholesterol, or hypertension. The x-axis indicates years since biomarker assessment via REGARDS; the 0-point indicates the month of biomarker assessment, which maps to a different calendar time for different participants due to rolling recruitment. The y-axis indicates the percent of conditions with any doctor visits on a semi-annual basis, as measured using Medicare claims data.

series models of the following form:

$$M_{ijt} = \mu t + After_{it} t\gamma + X_{ijt}\beta + \alpha_i + \epsilon_{ijt} \tag{6}$$

M_{ijt} denotes any annual doctor visits for individual i's diagnosed condition j at time t, and $After_{it}$ is a binary variable that takes the value 1 after biomarker assessment via REGARDS and 0 otherwise. Myerson et al. (2017) show that the γ coefficient is significant and positive when data from previously undiagnosed conditions are modeled separately. When data from all currently diagnosed conditions are pooled together, however, γ is significant and negative. See Table 5. Adjustment for individual-level fixed effects and the control variables used in Model (5), including county-level and time-varying controls, does not eliminate the statistical significance of the coefficient. In the graphical analysis described above, the regressions estimated in Myerson et al. (2017) use all data shown in the solid and dashed lines in Figure 1, whereas Table 5 uses data from the red line.

Similar trends in diagnosis and care for chronic conditions are found in the national data. Figure 2 depicts nationally representative estimates of the following three quantities of interest: (a) total prevalence on the population level, including undiagnosed conditions; (b) the fraction of people who truly have the condition who report being diagnosed, (c) and the fraction of people who are diagnosed for the condition who report taking medication to treat the condition. The national estimates are calculated using the NHANES repeated cross-section data, using the survey analysis commands to take into account the complex sampling scheme. These data demonstrate that an increase in diagnosis of diabetes, hypertension, and high cholesterol in recent years coincided with a fall in treatment of diagnosed conditions.

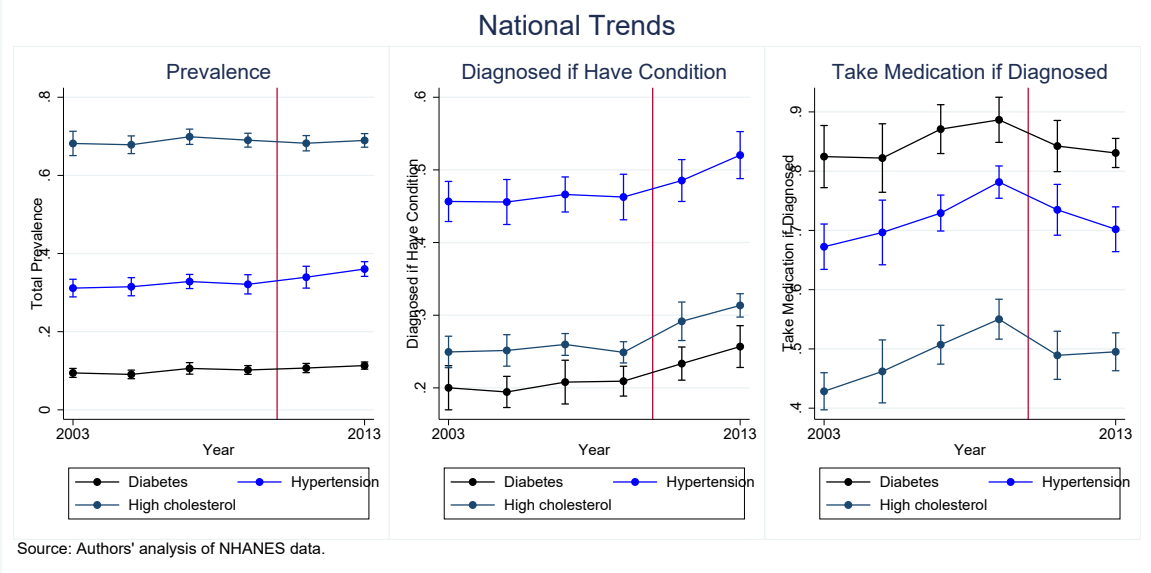
Table 5: Change in doctor visits after biomarker assessment via REGARDS, dropping previously undiagnosed conditions prior to their detection (REGARDS data)

	(1)	(2)	(3)	4
(1) Diabetes				
After assessment	-0.0763***	-0.0572***	-0.0753***	-0.0555***
	(0.00952)	(0.0180)	(0.00951)	(0.0183)
Observations	12,188	5,477	12,188	5,477
(2) High cholesterol				
After assessment	-0.140***	-0.133***	-0.135***	-0.128***
	(0.00903)	(0.0146)	(0.00903)	(0.0147)
Observations	30,570	16,839	30,570	16,839
(3) Hypertension				
After assessment	-0.120***	-0.0988***	-0.116***	-0.0937***
	(0.00778)	(0.0118)	(0.00778)	(0.0119)
Number of participants	4,518	2,501	4,518	2,501
Demographics	N	Y	N	Y
Time and region	N	Y	N	Y
Biomarkers	N	Y	N	Y
Person fixed effects	N	N	Y	Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table shows the change in annual doctor visits after biomarker assessment via REGARDS, omitting currently undiagnosed conditions. The rows include coefficients (γ in Model (6)) and standard errors obtained from linear probability models after adjusting for the listed control variables.

Figure 2: Increased diagnosis of chronic conditions is associated with decreased rates of medical care for diagnosed conditions (NHANES data)



This figure uses repeated cross-sectional data from the NHANES study to demonstrate that an increase in diagnosis of diabetes, hypertension, and high cholesterol on the national level in recent years coincided with a fall in treatment of diagnosed conditions. The left panel depicts total prevalence, including undiagnosed conditions; the middle panel depicts the fraction of prevalent conditions that are diagnosed; and the right panel depicts the fraction of diagnosed conditions that are treated with medications.

5 Theoretical model

In this section, we analyze a model of demand for screening and demand for medical treatment after diagnosis to show one reason why these two outcomes could be correlated on the patient-level. The purpose of this exercise is to demonstrate that although our empirical findings may be consistent with any number of theoretical models, no departure from a rational choice model of patients' health care consumption is required to account for our findings. We follow the Picone et al. (1998) simplification of the classic Grossman (1972) model.

5.1 Model

In the model, agents use medical treatment to ameliorate the negative effects of chronic health conditions. Agents who have been recently screened know whether they have a chronic condition, whereas agents who have not been recently screened hold beliefs about the probability they have a chronic condition. Agents differ only in their costs of medical treatment;

we separately model pecuniary and non-pecuniary costs. We analyze this model to derive predictions about which agents are willing to pay more for screening.

Agents maximize a continuously differentiable function of health (H) and consumption (C), net of disutility of medical treatment. Disutility of medical treatment due to non-pecuniary costs is linear in units of medical treatment M and the magnitude of disutility from non-pecuniary costs is captured by θ, which varies across agents.[13] The utility function is therefore:

$$u\left(C,\, H\left(M,\, D\right)\right) - \theta M$$

$u\left(\cdot\right)$ is concave in C and H, and agents have weakly higher marginal utility from consumption when they are healthier.

Health does not affect income, as in the pure consumption version of the Grossman model (see Grossman (2000)). To keep notation simple, we assume that agents have assets A and receive no further income. If an agent has a chronic condition, then $D = 1$; otherwise, $D = 0$. If $D = 1$ and the agent has been diagnosed, then he must decide how to divide his funds between medical treatment ($M \geq 0$ units, purchased at a price P per unit where P can vary across agents), and other consumption (C). This yields the budget constraint:

$$C + PM = A$$

If the agent does not have a diagnosed condition, he is not eligible to receive medical treatment. In this case, therefore, the entire budget is spent on other consumption: $C = A$.

Health H is a function of medical treatment M and chronic condition status D, as follows. When agents have a chronic condition, health becomes worse: $H\left(M,\, 0\right) > H\left(M,\, 1\right) \forall M$. However, medical treatment improves health for agents with chronic conditions: $\frac{\partial H(M,1)}{\partial M} > 0 \forall M$.

Because doctors only provide medical treatment to patients who are diagnosed for a condition, an agent's utility and decision variables vary based on whether he has been screened and the results of the screening. There are three possible cases:

1. The agent has not been recently screened and does not know whether he has a chronic condition, but has (correct) beliefs about π, the probability that he has a chronic condition. Because the agent is not diagnosed, he cannot receive medical treatment ($M = 0$) and therefore uses all funds for consumption. His expected utility is therefore:

$$\pi u\left(A,\, H\left(0,\, 1\right)\right) + \left(1 - \pi\right) u\left(A,\, H\left(0,\, 0\right)\right) \tag{7}$$

[13] Non-pecuniary costs could be related to factors such as language barriers, distance to a provider, depression symptoms or other psychological factors which provide barriers to accessing care.

2. The agent has been recently screened and knows he does not have a chronic condition ($D = 0$).[14] He is not eligible for medical treatment and therefore uses all funds for consumption. His utility is:

$$u\left(A,\, H\left(0,\, 0\right)\right) \tag{8}$$

3. The agent has been recently screened and knows he has a chronic condition ($D = 1$). Therefore, the agent can choose to use medical treatment. As such, the agent selects M and C to maximize his utility:

$$\max_{C,\, M} u\left(C,\, H\left(M,\, 1\right)\right) - \theta M \tag{9}$$

subject to $C + PM = A$.

Screening moves agents from case (1) to case (2) or (3) depending on the results of the test.

Equations (7), (8), and (9) can be combined to describe agents' willingness to pay for screening. In particular, agents are indifferent between being screened and not being screened at out-of-pocket price of screening κ if:

$$\begin{aligned}\pi\left(\max_{M} u\left(A - PM - \kappa,\, H\left(M,\, 1\right)\right) - \theta M\right) + \left(1 - \pi\right) u\left(A - \kappa,\, H\left(0,\, 0\right)\right) \\ - \left(\pi u\left(A,\, H\left(0,\, 1\right)\right) + \left(1 - \pi\right) u\left(A,\, H\left(0,\, 0\right)\right)\right) = 0\end{aligned} \tag{10}$$

We can then define κ^* as the price of screening that makes any given agent just indifferent between being screened and not being screened. As such, κ^* captures the agent's willingness to pay for screening.

5.2 Optimal decisions if screened and $D = 1$

In this case, the agent is eligible for medical treatment and can choose his consumption of medical treatment and other goods. The optimal solutions, denoted M^* and C^*, are defined by the first order condition:

$$\frac{\partial u\left(C,\, H\left(M^*,\, 1\right)\right)}{\partial H} \frac{\partial H\left(M^*,\, 1\right)}{\partial M} - \theta = P \frac{\partial u\left(C^*,\, H\left(M^*,\, 1\right)\right)}{\partial C} \tag{11}$$

[14] For simplicity, we present the case where the test is perfectly informative. This assumption can be relaxed without altering the main results.

The left-hand side of Equation (11) indicates the utility gains from consuming a unit of medical treatment. $\frac{\partial u(C,H(M^*,1))}{\partial H}\frac{\partial H(M^*,1)}{\partial M}$ is the utility benefit from improved health and $-\theta$ is the disutility of consuming a unit of medical treatment due to non-pecuniary costs. The right-hand side of Equation (11) indicates the utility gains from spending P additional dollars on consumption rather than on medical treatment. Therefore Equation (11) indicates that at the optimal point, the marginal benefits of purchasing a unit of medical treatment equal the marginal benefits of using the same funds for consumption.

5.3 Analysis of marginally screened individuals and empirical predictions

We now show that agents who become willing to be screened after a decrease in the out-of-pocket price of screening use less medical treatment after diagnosis than already screened individuals. This follows from two propositions.

Proposition 5.1 *Willingness to pay for screening is decreasing in agents' costs of medical treatment:* $\frac{\partial \kappa^*}{\partial \theta} < 0$ *and* $\frac{\partial \kappa^*}{\partial P} < 0$*, respectively.*

The proofs are based on the envelope theorem. See Appendix C.

Proposition 5.2 *Demand for medical treatment after diagnosis is also decreasing in agents' costs of medical treatment:* $\frac{\partial M^*}{\partial \theta} < 0$ *and* $\frac{\partial M^*}{\partial P} < 0$.

See Appendix D for the proofs.

Based on these propositions, higher costs of medical treatment decrease agents' demand for medical treatment after diagnosis, and also decrease agents' willingness to pay for screening. The implications for a policy that decreases the out-of-pocket price of screening when costs of medical treatment vary across agents are as follows. First, decreasing the out-of-pocket price of screening will attract agents with marginally lower willingness-to-pay for screening (κ^*) to become screened. Agents with marginally lower κ^* will also face marginally higher costs (θ and/or P) by Proposition 2.1. In turn, higher costs for medical treatment imply that these agents will use less medical treatment for their diagnosed conditions than previously screened agents by Proposition 2.2. This produces the empirical prediction that patients whose conditions become diagnosed because of a decline in the out-of-pocket price of screening use less medical treatment for their conditions after diagnosis.

6 Conclusion

Public and private sector efforts are improving access to screening for diabetes, high cholesterol, and hypertension. This paper explores possible consequences of the corresponding changes in the composition of diagnosed patients. Using cross-sectional and panel data from three biomarker datasets, we find that patients who are not regularly screened also seek less medical treatment for their conditions after diagnosis.

Our findings are important for policy analysis. In particular, our findings caution against using treatment of diagnosed conditions as an outcome metric when analyzing policies that affect access to screening. Such analyses might find misleading reductions in measured health system performance after improvements in access to screening, driven by changes to the composition of diagnosed patients. Patient composition effects would reduce the measured impact of policies that improve access to screening, such as the introduction of an essential health benefits package under the Affordable Care Act, and increase the measured impact of policies that limit access to screening.

We did not find that bias in health system performance metrics was eliminated by adjusting for biomarker-measured condition severity, or commonly measured covariates such as demographic variables and health insurance status. In the REGARDS Medicare data, the running average of doctor visits for currently diagnosed conditions shows a decrease in doctor visits after all participants were offered free, in-home biomarker assessment via REGARDS; this finding remains after adjusting for measured patient characteristics using survey data or using patient fixed effects. Using the OHIE and NHANES data, we find that within-patient associations between screening and treatment are not fully explained by biomarkers, health insurance status, commonly measured demographic variables, income, education, English language, or prevalence of comorbid conditions. We additionally find in all three biomarker datasets that participants with undiagnosed conditions typically show more severe, not less severe, biomarkers for their diagnosed conditions. This provides further evidence that condition severity is unlikely to account for our results.

Our findings can also help to inform the design of pay for performance schemes. Over 20 million Americans are served by Accountable Care Organizations, health provider organizations that are allocated financial rewards based in part on their performance on quality metrics, which include rates of screening and treatment of chronic conditions. Our results suggest that increasing performance on the screening metrics could reduce performance on the treatment metrics. Such concerns may be important in designing the new Merit-Based Incentive Payment System which, according to the Center for Medicare and Medicaid Services, will affect reimbursement for an estimated 600,000 Medicare Part B clinicians. Our

findings would suggest possible redesign or reweighting of metrics used in these pay-for-performance schemes, to eliminate the "quality penalty" produced by expanded access to screening.

Although no departure from a rational choice model of patients' health care consumption is required to account for our findings, the findings are consistent with a number of theoretical models. Better understanding of the causal pathways could facilitate the design of engagement strategies to eliminate gaps in uptake of recommended treatment across patients. Effective intervention design would require more detailed data on the key barriers faced by patients with newly diagnosed conditions. Factors not measured in our data, such as characteristics of the patients' health providers; patients' trust in health providers, health literacy, and discount factors; and each health plan's detailed cost-sharing information, should be assessed.

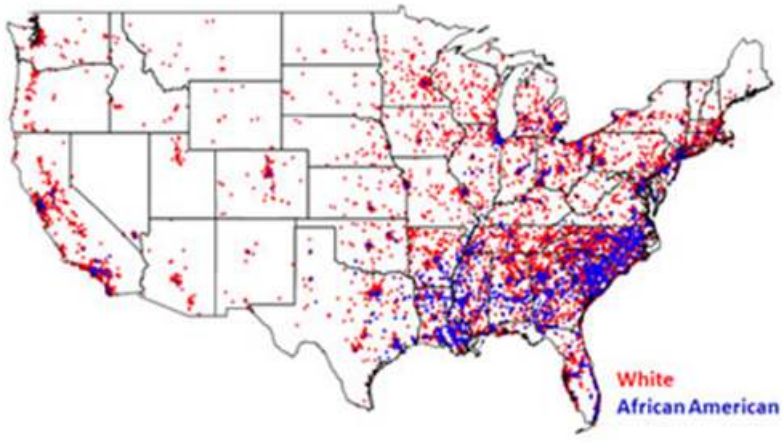
Finally, our findings suggest new directions for research on the economics of health care demand. In particular, classic health capital models should be revisited to see if conclusions drawn about the economics of health care demand change when agents can determine their own level of uncertainty about their health by choosing to be screened.

Appendix

A REGARDS data collection procedures

The REasons for Geographic and Racial Differences in Stroke (REGARDS) study recruited community-dwelling participants into an epidemiological longitudinal cohort study designed to answer questions about racial differences in stroke mortality. Recruitment was conducted from 2003-2007 and was accomplished through the use of commercially available lists of residential phone numbers and included the 48 contiguous United States (i.e., excluding Alaska and Hawaii). Sampling was stratified across African Americans and whites and three regions: the stroke belt (Alabama, Arkansas, Mississippi, and Tennessee), stroke buckle (North Carolina, South Carolina and Georgia) and all other states in the continental United States. Individuals who were under 45 years of age, did not identify as either African American or white, were non-English speaking, undergoing cancer treatment, or who resided in or were on a waiting list to enter a nursing home were excluded from the REGARDS study (Howard et al., 2005). Figure A.1 shows the geographic distribution of African American and white participants.

Figure A.1: Location of REGARDS participants (Source: Howard et al., 2011)



Participants were first interviewed, including questions about whether they had been diagnosed with high blood pressure, diabetes or high cholesterol by a doctor or nurse. For the in-home visit, participants were instructed to fast for 8-10 hours,[15] and had their blood

[15]About 80% of participants met the fasting requirement at the time that their labs were taken. We use

glucose, blood pressure and lipid panel plus other biomarkers assessed in their home on a morning of their choosing. Blood pressure was measured as an average of two measurements taken by a trained technician using a regularly tested aneroid sphygmomanometer, after the participant was seated with both feet on the floor for 5 minutes. Glucose and the lipid panel were measured using colorimetric reflectance spectrophotometry with the Ortho Vitros 950 IRC Clinical Analyzer (Johnson and Johnson Clinical Diagnostics) after being shipped on ice packs overnight to a central laboratory. Participants were compensated $30 for their time, and were notified of their results and advised to seek medical care for abnormal results using three levels of notification: (1) by telephone if any value is in the critical range, with instructions to immediately seek care; (2) by mail when a value is in the alert range with instructions to promptly seek care, and (3) general mail notification otherwise. The text of the mail notification for notification of high cholesterol or blood glucose and cards used for notification of high blood pressure are shown in Appendix Figure A.2 below.

fasting- or non-fasting specific cutoffs where applicable when judging participants' disease status based on their biomarkers.

Figure A.2: Text from the card and letter given to REGARDS participants informing them about their blood pressure and the results of their lab tests

Your Blood Pressure:_____/_____mmHg

	Systolic	Diastolic	Recommended Action
☐	<140	<90	Normal blood pressure: no action required
☐	140-159	90-99	Moderately high blood pressure: should be managed by a doctor within 2 months
☐	160-179	100-109	High blood pressure: should be seen by a doctor within 1 month
☐	>180	>110	Very high blood pressure: should be seen by a doctor within 1 week

Your Lipid panel (levels of blood fats):

Your Values	Desirable Values
Total: _____ mg/dL	less than 200 mg/dL
LDL: _____ mg/dL	less than 130 mg/dL
HDL: ____ mg/dL	greater than 40 mg/dL
Triglycerides _____ mg/dL	less than 200 mg/dL

If your values are not within the desirable range, you should discuss this with your doctor at your next visit.

Glucose (level of sugar in your blood):

Your Value	Desirable Value
_____ mg/dL	less than 126 mg/dL

If your level for glucose is over 200 mg/dL and you DO NOT have diabetes, you should have this rechecked with your doctor as soon as possible. If your level is above 126 mg/dL, you should have this rechecked with your doctor soon.

B Supplemental tables and figures

Table B.1: Definitions used for diabetes, hypertension, and high cholesterol

Condition	Status	Definition
Diabetes	No condition	No self-reported diagnosis of diabetes and FPG<126 mg/dl or NFPG<200mg/dl
	Undiagnosed	No self-reported diagnosis of diabetes, but FPG>126 mg/dl or NFPG>200mg/dl
	Diagnosed	Self-reported diagnosis of diabetes (when non-pregnant for women)
Hypertension	No condition	No self-reported diagnosis, SBP<140mmHg, and DBP<90mmHg
	Undiagnosed	No self-reported diagnosis of hypertension, but SBP>140mmHg or DBP>90mmHg
	Diagnosed	Self-reported diagnosis of hypertension (when non-pregnant for women)
High cholesterol	No condition	No self-reported diagnosis, total cholesterol <200 mg/dl, LDL cholesterol<160 mg/dl, and HDL cholesterol>40 mg/dl
	Undiagnosed	No self-reported diagnosis, but total cholesterol >200 mg/dl, LDL cholesterol>160 mg/dl, or HDL cholesterol<40 mg/dl
	Diagnosed	Self-reported diagnosis

Note: FPG=fasting plasma glucose; NFPG=non-fasting plasma glucose; SBP=systolic blood pressure; DBP=diastolic blood pressure; HDL=high-density lipoprotein, LDL= low-density lipoprotein. In the REGARDS data, we calculated LDL cholesterol using the Friedewald equation (Friedewald et al., 1972). Because neither LDL cholesterol nor triglycerides were available in the OHIE data, we could not calculate LDL cholesterol and therefore defined high cholesterol using HDL and total cholesterol only.

Table B.2: Participants with undiagnosed conditions show more severe biomarkers for their other, diagnosed conditions than do patients who are aware of all their conditions

	(1) HbA1c or FPG	(2) SBP	(3) DBP	(4) LDL	(5) TChol
Unadjusted data					
NHANES data					
Undiagnosed condition(s)	0.326***	0.490	1.545***	2.438	6.861***
	(0.0902)	(0.600)	(0.446)	(2.354)	(1.965)
Observations	3,157	8,209	8,209	3,903	8,285
OHIE data					
Undiagnosed condition(s)	-0.0188	0.346	1.836**		9.045*
	(0.129)	(1.255)	(0.849)		(5.454)
Observations	663	1,649	1,649		1,297
REGARDS data					
Undiagnosed condition(s)	15.75***	3.986***	2.438***	7.476***	9.838***
	(4.350)	(0.787)	(0.443)	(2.782)	(3.049)
Observations	1,132	4,169	4,169	3,016	3,542
Adjusted data					
NHANES data					
Undiagnosed condition(s)	0.254***	2.061***	1.133***	15.65***	17.12***
	(0.0919)	(0.612)	(0.432)	(2.310)	(1.908)
Observations	3,157	8,209	8,209	3,903	8,285
OHIE data					
Undiagnosed condition(s)	-0.102	2.043	2.366**		11.83**
	(0.137)	(1.367)	(0.945)		(5.355)
Observations	663	1,649	1,649		1,297
REGARDS data					
Undiagnosed condition(s)	16.60***	3.354***	2.842***	14.12***	16.76***
	(4.458)	(0.829)	(0.466)	(2.711)	(2.879)
Observations	1,083	3,636	3,636	2,872	3,373

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table shows that participants with some undiagnosed conditions show more severe biomarkers for their other, previously diagnosed conditions. The rows show coefficients of linear probability models with vs. without adjusting for sex, race, age, education, income, year, and co-morbid conditions. Glycated hemoglobin (HbA1c) or fasting plasma glucose (FPG) are only included for participants with diagnosed diabetes; systolic blood pressure (SBP) and diastolic blood pressure (DBP) are included only for participants with diagnosed hypertension; and low-density lipoprotein cholesterol (LDL) and total cholesterol (TChol) are included only for participants with diagnosed high cholesterol. LDL cholesterol is not measured in the OHIE data and cannot be calculated using the Friedewald equation because data on triglycerides are also not available. We use FPG rather than HbA1c in the REGARDS data because HbA1c is not measured in these data.

Table B.3: Individuals not recently screened for undiagnosed conditions are less likely to use medication for their other, diagnosed conditions (NHANES data)

	(1)	(2)	(3)	(4)
Diagnosed diabetes				
(1) Taking medication				
Not screened for undiagnosed	-0.150***	-0.110***	-0.111***	-0.0850***
high cholesterol	(0.0268)	(0.0280)	(0.0282)	(0.0287)
Observations	1,391	1,391	1,391	1,391
Average outcome if screened	0.859	0.859	0.859	0.859
Diagnosed hypertension				
(2) Taking medication				
Not screened for undiagnosed	-0.205***	-0.134***	-0.139***	-0.129***
diabetes or high cholesterol	(0.0120)	(0.0106)	(0.0105)	(0.0105)
Observations	8,286	8,286	8,286	8,286
Average outcome if screened	0.779	0.779	0.779	0.779
Diagnosed high cholesterol				
(3) Taking medication				
Not screened for undiagnosed	-0.141***	-0.0959***	-0.0824***	-0.0591***
diabetes	(0.0125)	(0.0115)	(0.0114)	(0.0108)
Observations	6,695	6,695	6,695	6,695
Average outcome if screened	0.516	0.516	0.516	0.516
Control for demographics	N	Y	Y	Y
Control for conditions	N	N	Y	Y
Control for biomarkers	N	N	N	Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table shows the relationship between recent screening for undiagnosed conditions and use of medication to treat other, diagnosed conditions. Look-back periods for screening for undiagnosed diabetes and high cholesterol are two and three years, respectively. The rows include coefficients and standard errors obtained from linear probability models after adjusting for the listed control variables. The outcomes include (1) use of diabetes medication among participants who report prior diagnosis of diabetes; (2) use of anti-hypertensive medication among participants who report prior diagnosis of hypertension; and (3) use of cholesterol-lowering medication among participants who report prior diagnosis of high cholesterol.

Table B.4: Individuals not recently screened for undiagnosed conditions are less likely to use medication for their diagnosed conditions (OHIE data, using medication information from in-person medication review)

	(1)	(2)	(3)	(4)
Diagnosed diabetes				
(1) Taking medication				
Not screened for undiagnosed	-0.291***	-0.200***	-0.176**	-0.160**
high cholesterol	(0.0590)	(0.0685)	(0.0681)	(0.0651)
Observations	271	271	271	271
Average outcome if screened	0.647	0.647	0.647	0.647
Diagnosed hypertension				
(2) Taking medication				
Not screened for undiagnosed	-0.314***	-0.235***	-0.227***	-0.212***
diabetes or high cholesterol	(0.0265)	(0.0284)	(0.0283)	(0.0289)
Observations	1,237	1,237	1,237	1,237
Average outcome if screened	0.570	0.570	0.570	0.570
Diagnosed high cholesterol				
(3) Taking medication				
Not screened for undiagnosed	-0.339***	-0.285***	-0.269***	-0.247***
diabetes	(0.0298)	(0.0314)	(0.0321)	(0.0330)
Observations	717	717	717	717
Average outcome if screened	0.434	0.434	0.434	0.434
Control for demographics	N	Y	Y	Y
Control for conditions	N	N	Y	Y
Control for biomarkers	N	N	N	Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table shows the relationship between screening for undiagnosed conditions within the past year and use of medication for other, diagnosed conditions. This is similar to the Table 3 except for the use of medication use data that are verified through a medication review, rather than self-reported data. (The self-reported data had the advantage of being collected in the same survey as the self-reported screening, whereas these data were typically collected months later.) The rows include coefficients and standard errors obtained from linear probability models after adjusting for the listed control variables. The outcome in row 1 is self-reported use of medication for among participants who reported prior diagnosis of diabetes. Similarly, the outcomes in rows 2 and 3 are self-reported use of anti-hypertensive medication or cholesterol lowering medication among participants who self-reported prior diagnosis of hypertension or high cholesterol, respectively.

Table B.5: Individuals with undiagnosed conditions have fewer doctor visits for their diagnosed conditions per year (REGARDS data)

	(1)	(2)	(3)	(4)
Any Relevant Visits				
(1a) Diabetes				
Undiagnosed condition(s)	-0.0520***	-0.0452***	-0.0495***	-0.0502***
	(0.0158)	(0.0157)	(0.0160)	(0.0172)
(2a) Hypertension				
Undiagnosed condition(s)	-0.0743***	-0.0575***	-0.0717***	-0.0644***
	(0.0105)	(0.0103)	(0.0105)	(0.0111)
(3a) High Cholesterol				
Undiagnosed condition(s)	-0.0864***	-0.0848***	-0.105***	-0.0681***
	(0.0183)	(0.0182)	(0.0184)	(0.0189)
Number of Relevant Visits				
(1b) Diabetes				
Undiagnosed condition(s)	-1.196***	-1.367***	-1.266***	-1.129***
	(0.184)	(0.188)	(0.192)	(0.212)
(2b) Hypertension				
Undiagnosed condition(s)	-0.618***	-0.598***	-0.744***	-0.717***
	(0.0803)	(0.0796)	(0.0837)	(0.0899)
(3b) High Cholesterol				
Undiagnosed condition(s)	-0.447***	-0.426***	-0.543***	-0.390***
	(0.0659)	(0.0664)	(0.0680)	(0.0726)
Control for demographics	N	Y	Y	Y
Control for conditions	N	N	Y	Y
Control for biomarkers	N	N	N	Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table summarizes the relationships prevalence of undiagnosed conditions and doctor visits for other, previously diagnosed conditions during the 24 months prior to biomarker assessment via REGARDS. Due to the use of Medicare claims data, we only include individuals who had fee-for-service Medicare insurance during this time. The rows include coefficients and standard errors obtained from linear probability models after adjusting for the listed control variables. Outcome 1a denotes any evaluation and management visits from the prior year coded as relevant to diabetes, among participants with prior diagnosis of diabetes. Outcome 1b denotes the number of evaluation and management visits from the prior year coded as relevant to diabetes among participants with prior diagnosis of diabetes. Outcomes 2 and 3 are coded similarly, for participants with prior diagnosis of hypertension or high cholesterol, respectively.

Table B.6: Individuals not recently screened are less likely to use recommended care for their diagnosed conditions (NHANES data, using shorter look-back period for high cholesterol)

	(1)	(2)	(3)	(4)
Diagnosed diabetes				
(1) Had eye exam				
Not screened for undiagnosed	-0.220***	-0.137***	-0.141***	-0.120***
high cholesterol	(0.0278)	(0.0289)	(0.0289)	(0.0299)
Observations	1,373	1,373	1,373	1,373
Average outcome if screened	0.674	0.674	0.674	0.674
(2) Had foot exam				
Not screened for undiagnosed	-0.293***	-0.223***	-0.222***	-0.202***
high cholesterol	(0.0313)	(0.0326)	(0.0328)	(0.0340)
Observations	1,333	1,333	1,333	1,333
Average outcome if screened	0.760	0.760	0.760	0.760
Diagnosed hypertension				
(3) Take meds if recommended				
Not screened for undiagnosed	-0.0992***	-0.0743***	-0.0781***	-0.0702***
diabetes or high cholesterol	(0.0106)	(0.00987)	(0.00988)	(0.00990)
Observations	6,942	6,942	6,942	6,942
Average outcome if screened	0.890	0.890	0.890	0.890
Diagnosed high cholesterol				
(4) Take meds if recommended				
Not screened for undiagnosed	-0.0799***	-0.0619***	-0.0529***	-0.0390***
diabetes	(0.0149)	(0.0142)	(0.0143)	(0.0134)
Observations	4,009	4,009	4,009	4,009
Average outcome if screened	0.803	0.803	0.803	0.803
Control for demographics	N	Y	Y	Y
Control for conditions	N	N	Y	Y
Control for biomarkers	N	N	N	Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table shows the relationship between recent screening for undiagnosed conditions and use of recommended treatment for other, diagnosed conditions. Look-back periods for screening for undiagnosed diabetes and high cholesterol are one and three years, respectively. This analysis is identical to Table 2 except that a one-year look-back period is used for high cholesterol, rather than a two-year look-back period. The outcomes include (1) foot exams and (2) eye exams in the past year among participants who report prior diagnosis of diabetes; (3) use of anti-hypertensive medication among participants who report prior diagnosis of hypertension, and report that a doctor recommended anti-hypertensive medication; and (4) use of cholesterol-lowering medication among participants who report prior diagnosis of high cholesterol, and report that a doctor recommended cholesterol-lowering medication.

Table B.7: Individuals not recently screened are less likely to use medication for their diagnosed conditions (NHANES data, using shorter look-back period for high cholesterol)

	(1)	(2)	(3)	(4)
Diagnosed diabetes				
(1) Taking medication				
Not screened for undiagnosed	-0.147***	-0.115***	-0.116***	-0.0953***
high cholesterol	(0.0232)	(0.0237)	(0.0240)	(0.0241)
Observations	1,391	1,391	1,391	1,391
Average outcome if screened	0.873	0.873	0.873	0.873
Diagnosed hypertension				
(2) Taking medication				
Not screened for undiagnosed	-0.200***	-0.132***	-0.136***	-0.124***
diabetes or high cholesterol	(0.0115)	(0.0101)	(0.0101)	(0.0100)
Observations	8,264	8,264	8,264	8,264
Average outcome if screened	0.784	0.784	0.784	0.784
Diagnosed high cholesterol				
(3) Taking medication				
Not screened for undiagnosed	-0.141***	-0.0959***	-0.0824***	-0.0591***
diabetes	(0.0125)	(0.0115)	(0.0114)	(0.0108)
Observations	6,695	6,695	6,695	6,695
Average outcome if screened	0.516	0.516	0.516	0.516
Control for demographics	N	Y	Y	Y
Control for conditions	N	N	Y	Y
Control for biomarkers	N	N	N	Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table shows the relationship between recent screening for undiagnosed conditions and use of medication for other, diagnosed conditions. Look-back periods for screening for undiagnosed diabetes and high cholesterol are one and three years, respectively. This analysis is identical to Table B.3 except that a one-year look-back period is used for high cholesterol, rather than a two-year look-back period. The rows include coefficients and standard errors obtained from linear probability models after adjusting for the listed control variables. The outcomes include (1) use of diabetes medication among participants who report prior diagnosis of diabetes; (2) use of anti-hypertensive medication among participants who report prior diagnosis of hypertension; and (3) use of cholesterol-lowering medication among participants who report prior diagnosis of high cholesterol.

Table B.8: Newly diagnosed conditions receive fewer relevant doctor visits per year (REGARDS data)

	(1)	(2)	(3)	(4)
Number of Relevant Visits				
(1) All				
Previously undiagnosed	-2.046***	-1.975***	-1.972***	-1.887***
	(0.0602)	(0.0778)	(0.0778)	(0.0932)
(2) Diabetes				
Previously undiagnosed	-4.251***	-4.005***	-4.030***	-4.199***
	(0.254)	(0.326)	(0.329)	(0.390)
(3) Hypertension				
Previously undiagnosed	-2.854***	-2.442***	-2.441***	-2.377***
	(0.107)	(0.144)	(0.144)	(0.194)
(4) High Cholesterol				
Previously undiagnosed	-1.243***	-1.245***	-1.238***	-1.067***
	(0.0494)	(0.0623)	(0.0621)	(0.0761)
Control for demographics	N	Y	Y	Y
Control for time and region	N	N	Y	Y
Control for biomarkers	N	N	N	Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table compares annual doctor visits after biomarker assessment via REGARDS for evaluation and management of previously diagnosed vs. previously undiagnosed diabetes, hypertension, and high cholesterol. All REGARDS participants were informed of their results and advised to see a clinician for any abnormal results, as detailed in Section A. Doctor visits from the 24 months after biomarker assessment via REGARDS were measured using Medicare claims data, and categorized as relevant to each prevalent condition using ICD-9 codes. The rows include coefficients and standard errors obtained from linear probability models after adjusting for the listed control variables.

Table B.9: Newly diagnosed conditions receive fewer relevant doctor visits per year; replicated using coarsened exact matching (REGARDS data)

	(1)	(2)	(3)	(4)
Any Relevant Visits				
(1a) All				
Previously undiagnosed	-0.434***	-0.433***	-0.433***	-0.421***
	(0.0138)	(0.0172)	(0.0172)	(0.0188)
(2a) Diabetes				
Previously undiagnosed	-0.485***	-0.503***	-0.505***	-0.499***
	(0.0451)	(0.0501)	(0.0498)	(0.0493)
(3a) Hypertension				
Previously undiagnosed	-0.508***	-0.513***	-0.512***	-0.494***
	(0.0240)	(0.0300)	(0.0301)	(0.0346)
(4a) High Cholesterol				
Previously undiagnosed	-0.385***	-0.378***	-0.377***	-0.358***
	(0.0169)	(0.0216)	(0.0216)	(0.0247)
Number of Relevant Visits				
(1b) All				
Previously undiagnosed	-1.992***	-1.877***	-1.881***	-1.832***
	(0.0696)	(0.0857)	(0.0858)	(0.0967)
(2b) Diabetes				
Previously undiagnosed	-4.160***	-3.898***	-3.969***	-4.016***
	(0.293)	(0.370)	(0.382)	(0.422)
(3b) Hypertension				
Previously undiagnosed	-2.806***	-2.386***	-2.392***	-2.237***
	(0.124)	(0.162)	(0.163)	(0.215)
(4b) High Cholesterol				
Previously undiagnosed	-1.169***	-1.154***	-1.148***	-1.074***
	(0.0583)	(0.0719)	(0.0714)	(0.0823)
Control for demographics	N	Y	Y	Y
Control for time and region	N	N	Y	Y
Control for biomarkers	N	N	N	Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table replicates Tables 4 and Appendix Table B.8 but restricting the sample using coarsened exact matching to balance the samples on prevalence of conditions, binned biomarkers (glucose, LDL cholesterol, and systolic blood pressure), prevalence of multiple conditions, race, and sex. This table compares annual doctor visits after biomarker assessment via REGARDS for evaluation and management of previously diagnosed vs. previously undiagnosed conditions. Doctor visits were measured using Medicare claims data from the 24 months after biomarker assessment via REGARDS, and categorized as relevant to each prevalent condition using ICD-9 codes. The rows include coefficients and standard errors obtained from linear probability models after adjusting for the listed control variables.

C Proofs: Demand for screening is (weakly) decreasing in θ and P

C.1 Demand for screening is weakly decreasing in θ

When the price of screening equals willingness to pay for screening κ^*, agents are just indifferent between being screened and not being screened as follows:

$$\pi\left(\max_M u\left(A-PM-\kappa^*,\, H\left(M,\,1\right)\right)-\theta M\right)+\left(1-\pi\right)u\left(A-\kappa^*,\, H\left(0,\,0\right)\right) \\ -\left(\pi u\left(A,\, H\left(0,\,1\right)\right)+\left(1-\pi\right)u\left(A,\, H\left(0,\,0\right)\right)\right)=0 \tag{12}$$

Differentiating (12) with respect to θ yields the following expression (by the envelope theorem, we can ignore the fact that the optimal M varies with θ):

$$\pi\left(-\frac{\partial u\left(A-PM^*-\kappa^*,\, H\left(M^*,\,1\right)\right)}{\partial C}\frac{\partial \kappa^*}{\partial \theta}-M^*\right)-\left(1-\pi\right)\frac{\partial u\left(A-\kappa^*,\, H\left(0,\,0\right)\right)}{\partial C}\frac{\partial \kappa^*}{\partial \theta}=0 \tag{13}$$

Then rearranging to solve for $\frac{\partial \kappa^*}{\partial \theta}$ yields:

$$-\left(\pi\frac{\partial u\left(A-PM^*-\kappa^*,\, H\left(M^*,\,1\right)\right)}{\partial C}\frac{\partial \kappa^*}{\partial \theta}\right)-\left(1-\pi\right)\frac{\partial u\left(A-\kappa^*,\, H\left(0,\,0\right)\right)}{\partial C}\frac{\partial \kappa^*}{\partial \theta}=\pi M^*$$

$$\frac{\partial \kappa^*}{\partial \theta}\left(-\pi\frac{\partial u\left(A-PM^*-\kappa^*,\, H\left(M^*,\,1\right)\right)}{\partial C}-\left(1-\pi\right)\frac{\partial u\left(A-\kappa^*,\, H\left(0,\,0\right)\right)}{\partial C}\right)=\pi M^*$$

$$\implies \frac{\partial \kappa^*}{\partial \theta}=-\frac{\pi M^*}{\pi\frac{\partial u(A-PM^*-\kappa^*,\, H(M^*,\,1))}{\partial C}+\left(1-\pi\right)\frac{\partial u(A-\kappa^*,\, H(0,\,0))}{\partial C}}\leq 0$$

We conclude $\frac{\partial \kappa^*}{\partial \theta}\leq 0$ because $\frac{\partial u}{\partial C}>0$, $\pi>0$ and $M^*\geq 0$.

C.2 Demand for screening is decreasing in P

When the price of screening equals willingness to pay for screening κ^*, agents are just indifferent between being screened and not being screened as follows:

$$\pi\left(\max_M u\left(A-PM-\kappa^*,\, H\left(M,\,1\right)\right)-\theta M\right)+\left(1-\pi\right)u\left(A-\kappa^*,\, H\left(0,\,0\right)\right) \\ -\left(\pi u\left(A,\, H\left(0,\,1\right)\right)+\left(1-\pi\right)u\left(A,\, H\left(0,\,0\right)\right)\right)=0 \tag{14}$$

Differentiating (14) with respect to P yields the following expression (by the envelope theorem, we can ignore the fact that the optimal M varies with P):

$$\pi\left(-\frac{\partial u\left(A-PM^{*}-\kappa^{*},\, H\left(M^{*},\, 1\right)\right)}{\partial C}\frac{\partial \kappa^{*}}{\partial P}+\frac{\partial u\left(A-PM^{*}-\kappa^{*},\, H\left(M^{*},\, 1\right)\right)}{\partial C}\right) - (1-\pi)\frac{\partial u\left(A-\kappa^{*},\, H\left(0,\, 0\right)\right)}{\partial C}\frac{\partial \kappa^{*}}{\partial P}=0 \quad (15)$$

Then rearranging to solve for $\frac{\partial \kappa^{*}}{\partial P}$ yields:

$$-\left(\pi\frac{\partial u\left(A-PM^{*}-\kappa^{*},\, H\left(M^{*},\, 1\right)\right)}{\partial C}\frac{\partial \kappa^{*}}{\partial P}\right)-(1-\pi)\frac{\partial u\left(A-\kappa^{*},\, H\left(0,\, 0\right)\right)}{\partial C}\frac{\partial \kappa^{*}}{\partial P} = \pi\frac{\partial u\left(A-PM^{*}-\kappa^{*},\, H\left(M^{*},\, 1\right)\right)}{\partial C}$$

$$\frac{\partial \kappa^{*}}{\partial P}\left(-\pi\frac{\partial u\left(A-PM^{*}-\kappa^{*},\, H\left(M^{*},\, 1\right)\right)}{\partial C}-(1-\pi)\frac{\partial u\left(A-\kappa^{*},\, H\left(0,\, 0\right)\right)}{\partial C}\right) = \pi\frac{\partial u\left(A-PM^{*}-\kappa^{*},\, H\left(M^{*},\, 1\right)\right)}{\partial C}$$

$$\implies \frac{\partial \kappa^{*}}{\partial P}=-\frac{\pi\frac{\partial u(A-PM^{*}-\kappa^{*},\, H(M^{*},1))}{\partial C}}{\pi\frac{\partial u(A-PM^{*}-\kappa^{*},\, H(M^{*},1))}{\partial C}+(1-\pi)\frac{\partial u(A-\kappa^{*},\, H(0,0))}{\partial C}}<0$$

We conclude $\frac{\partial \kappa^{*}}{\partial P}<0$ because $\frac{\partial u}{\partial C}>0$ and $\pi>0$.

D Proofs: Demand for medical treatment is decreasing in θ and P

D.1 Demand for medical treatment is decreasing in θ

We show that agents must demand less medical treatment when they have higher non-pecuniary costs of treatment (captured by θ), because to do otherwise would violate the first-order conditions.

Consider the optimal decisions when agents know that $D=1$. (This is the only case where purchase of medical treatment is an option, because medical treatment is not available without a prescription.) Now consider that θ decreases from $\overline{\theta}$ to $\underline{\theta}$. Let $M_{\overline{\theta}}$ and $C_{\overline{\theta}}$ denote the optimal decisions before the change and $M_{\underline{\theta}}$ and $C_{\underline{\theta}}$ denote the optimal decisions after the change.

$M_{\overline{\theta}}$ and $C_{\overline{\theta}}$ must fulfill the first-order conditions summarized in equation (11), as follows:

$$\frac{\partial u\left(C_{\overline{\theta}},\, H\left(M_{\overline{\theta}},\, 1\right)\right)}{\partial H}\frac{\partial H\left(M_{\overline{\theta}},\, 1\right)}{\partial M} - \overline{\theta} = P\frac{\partial u\left(C_{\overline{\theta}},\, H\left(M_{\overline{\theta}},\, 1\right)\right)}{\partial C} \tag{16}$$

After non-pecuniary cost decreases from $\overline{\theta}$ to $\underline{\theta}$, previously optimal decisions $M_{\overline{\theta}}$ and $C_{\overline{\theta}}$ would violate equation (11) as follows:

$$\frac{\partial u\left(C_{\overline{\theta}},\, H\left(M_{\overline{\theta}},\, 1\right)\right)}{\partial H}\frac{\partial H\left(M_{\overline{\theta}},\, 1\right)}{\partial M} - \underline{\theta} > P\frac{\partial u\left(C_{\overline{\theta}},\, H\left(M_{\overline{\theta}},\, 1\right)\right)}{\partial C} \tag{17}$$

To make inequality (17) an equality, M and C must change so that the left-hand side decreases and/or the right-hand side increases. By concavity of the utility function in H and C, the weakly positive cross-partial $\frac{\partial^2 u(C,H)}{\partial C \partial H}$, and weakly decreasing marginal returns to medical care, increasing M and decreasing C achieves both. Therefore $M_{\overline{\theta}} < M_{\underline{\theta}}$ and $C_{\overline{\theta}} > C_{\underline{\theta}}$ resolves the contradiction in the first-order conditions. We conclude that $\frac{\partial M^*}{\partial \theta} < 0$.

D.2 Demand for medical treatment is decreasing in P

We show that agents must demand less treatment when they have higher cost of medical treatment P, because to do otherwise would violate the first-order conditions.

Consider the optimal decisions when agents know that $D = 1$. (This is the only case where purchase of medical treatment is an option, because medical treatment is not available without a prescription.) Now consider that P decreases from $\overline{P}$ to $\underline{P}$. Let $M_{\overline{P}}$ and $C_{\overline{P}}$ denote the optimal decisions before the change and $M_{\underline{P}}$ and $C_{\underline{P}}$ denote the optimal decisions after the change.

$M_{\overline{P}}$ and $C_{\overline{P}}$ must fulfill the first-order conditions summarized in equation (11), as follows:

$$\frac{\partial u\left(C_{\overline{P}},\, H\left(M_{\overline{P}},\, 1\right)\right)}{\partial H}\frac{\partial H\left(M_{\overline{P}},\, 1\right)}{\partial M} - \theta = \overline{P}\frac{\partial u\left(C_{\overline{P}},\, H\left(M_{\overline{P}},\, 1\right)\right)}{\partial C} \tag{18}$$

After cost of care P decreases from $\overline{P}$ to $\underline{P}$, previously optimal decisions $M_{\overline{P}}$ and $C_{\overline{P}}$ would violate equation (11) as follows:

$$\frac{\partial u\left(C_{\overline{P}},\, H\left(M_{\overline{P}},\, 1\right)\right)}{\partial H}\frac{\partial H\left(M_{\overline{P}},\, 1\right)}{\partial M} - \theta > \underline{P}\frac{\partial u\left(C_{\overline{P}},\, H\left(M_{\overline{P}},\, 1\right)\right)}{\partial C} \tag{19}$$

To make inequality (19) an equality, M and C must change so that the left-hand side decreases and/or the right-hand side increases. As before, increasing M and decreasing C achieves both. Therefore $M_{\overline{P}} < M_{\underline{P}}$ and $C_{\overline{P}} > C_{\underline{P}}$ resolves the contradiction in the first-order conditions. We conclude that $\frac{\partial M^*}{\partial P} < 0$.

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