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ABSTRACT

We measure whether expert patients – those trained as physicians and nurses – have fewer emergency department visits and the reasons for these differences. Relative to similar patients physicians and nurses had 19.8% and 5.1% fewer ED visits, principally due to fewer avoidable visits. The differences in avoidable visits between physicians and other patients were largest for diagnoses commonly requiring prescriptions, which physicians often self-prescribed. Our results suggest that improving access to prescriptions for acute symptoms, more than improving patient education, may reduce avoidable health care.

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1 Introduction

Estimates suggest that up to 25 to 35% of US health care spending may be inefficient, with half representing inefficient utilization and the other half representing inefficient pricing and administrative costs (Berwick and Hackbarth, 2012; Shrank, Rogstad and Parekh, 2019; Martin et al., 2021). Inefficient utilization occurs in two ways. First, patients may independently seek care that is avoidable, either because their needs are addressable in a lower intensity setting or are preventable through lower cost measures. Such behaviors may include seeking emergency department (ED) visits, specialist visits, and using direct-to-consumer products such as whole-body scans or over-the-counter medicines. Second, once a patient engages a provider, providers and patients may jointly choose an inefficient diagnostic or treatment. A large literature quantifies the mechanisms underlying this second channel, including the importance of providers' skills, beliefs, and incentives (Chandra, Cutler and Song, 2011; Johnson and Rehavi, 2016; Cutler et al., 2019; Chandra and Staiger, 2020; Chan, Gentzkow and Yu, 2022; Mullainathan and Obermeyer, 2022). Comparatively less is understood about the mechanisms explaining why patients independently seek avoidable care. These may include patients' lack of medical knowledge regarding the value of different types of care (Baicker, Mullainathan and Schwartzstein, 2015), lack of access to care in lower acuity settings and preventive care (Rust et al., 2008; Alexander, Currie and Schnell, 2019), and moral hazard (Taubman et al., 2014; Einav and Finkelstein, 2018).

We study why patients seek avoidable care in the ED setting. The ED provides an ideal setting to study avoidable care for multiple reasons. First, patients generally visit an ED without a provider referral; thus, the ED provides a setting to study patient care seeking, without confounding it with provider recommendations. Second, unlike other forms of potentially avoidable care, there exist validated and commonly used measures for whether an ED visit was avoidable (Billings, Parikh and Mijanovich, 2000; Taubman et al., 2014; Alexander, Currie and Schnell, 2019). Finally, avoidable ED visits are of interest in their own right. Estimates suggest that ED-initiated episodes of care account for over 12% of health care spending, and over 30% of ED visits, which cost more than \$60 B per year, may be avoidable (Galarraga and Pines, 2016). The indirect costs of

ED use may also be high due to hospital crowding (Kellermann, 2006) and cascades of follow-up care (Ganguli et al., 2020). Given the size of these costs, the impact of policies and programs on avoidable ED visits has been of interest including health insurance expansions (Kolstad and Kowalski, 2012; Taubman et al., 2014; Ayyagari, Shane and Wehby, 2017; Kowalski, 2023), rapid access to nurse hotlines (Lattimer et al., 1998), retail clinics (Alexander, Currie and Schnell, 2019), urgent care centers (Weinick, Burns and Mehrotra, 2010), and patient literacy programs (Raven et al., 2016; Van Den Heede and Van De Voorde, 2016).

We compare ED use between non-expert and expert patients who are themselves trained as physicians and nurses. We also evaluate the ED use of expert patients' spouses, who benefit from within-family expertise, to support our analysis. This comparison reveals the degree to which medical training may reduce avoidable care of oneself or of one's spouse. We then stratify results across diagnoses to shed light on whether differences in avoidable visits are likely driven by expert patients' medical knowledge or better access to other care options. We find limited evidence that patients' medical knowledge can reduce avoidable care and find far more evidence that better access, in particular to medicines for acute needs, reduces avoidable ED use.

We implement our approach in Medicare data using a novel linkage connecting Medicare claims data to beneficiaries' occupation and spouses. These data represent the largest sample of expert patients whose health care consumption has been studied to date. By examining the ED use of expert and non-experts in the same health plan, namely Medicare Fee-for-Service, we remove coverage generosity as a source of confounding. Avoidable ED visits are identified using two approaches. In our main specification, we use an algorithm developed in Billings, Parikh and Mijanovich (2000) and used widely in the medical and economics literature (Taubman et al., 2014; Alexander, Currie and Schnell, 2019). This algorithm assigns ED visits a probability of being avoidable by virtue of being non-urgent, treatable in a primary care setting, or emergent and directly avoidable with preventive care. We show that our results are robust to an alternative measure that stratifies ED visits by their empirical likelihood of resulting in hospitalization, under the premise that diagnoses with lower hospitalization probabilities (e.g., nose bleeds) are more likely avoidable than other diagnoses (e.g., heart attacks).

We compare the ED use of physicians, nurses and their spouses to others adjusting for observable differences in health, demographic, and socioeconomic factors. While this comparison is reasonable for nurses and their spouses, whose characteristics are similar to the general population, comparing physicians to other patients requires additional care for physicians may be unobservably socioeconomically advantaged in ways which may also impact their health care demand (Chetty et al., 2016). Therefore, we compare physicians to lawyers, who are socioeconomically more similar to physicians than the general public (Gottlieb et al., 2023). Although residual socioeconomic differences between physicians and lawyers may still persist, we show that greater socioeconomic advantage does not consistently predict fewer avoidable ED visits, using fewer observable health and socioeconomic controls does not change our results, and comparing the ED use of primary care physicians whose lifetime earnings are 10% lower than lawyers does not change our results (Gottlieb et al., 2023). Together, these tests reassure us about the relative size of socioeconomic confounders in comparing physicians to other patients.

We find that physicians and nurses have 19.8% and 5.1% fewer ED visits annually, after controlling for observable health, demographic, and socioeconomic factors. These differences are due primarily to lower use of avoidable ED visits, especially among physicians. Physicians and nurses used 24.8% and 6.8% fewer avoidable visits respectively, and results were similar among spouses.

The reduction in avoidable visits among expert patients could reflect several mechanisms: experts have more medical knowledge, but they also have more access to other medical providers through their networks, and physicians have greater ability to self-treat through self-prescribed medicines. We find that the ability to self-prescribe medicines is likely to be the primary mechanism for lower avoidable visits. Several lines of evidence support this conclusion. First, the reduction in avoidable visits among physicians and their spouses is substantially higher for diagnoses likely to require prescriptions; for diagnoses in the top quintile of the propensity to require a prescription, physicians had 40.0% fewer avoidable visits, but for diagnoses in the bottom quintile, physicians used only 5.6% fewer avoidable visits. Second, self-prescribing among physicians is common, with 44% of physicians self-prescribing and 33% of physician spouses receiving prescriptions from their spouse. Third, the medications filled most commonly after an ED visit were also the medications physicians were most likely to prescribe for themselves or their spouses. Fourth, nurses exhibited smaller reductions in avoidable visits and exhibited no gradient in effects based on the prescription propensity of diagnoses; this is consistent with a role for prescription access as nurses generally do not have independent prescribing authority, despite having significant medical knowledge. Finally, we did not find evidence for physicians' professional networks mediating effects; we did not find improved access to outpatient visits, stronger results on weekends, when professional networks may be weaker, or differential effects based on whether the diagnosis required other outpatient interventions, such as imaging.

Our results provide two insights. First, these findings suggest that improving access to outpatient prescriptions, particularly for urgent symptoms, may be a potentially powerful lever for reducing avoidable ED visits. Indeed, the 40% reduction in avoidable ED visits among physician patients for diagnoses most requiring prescriptions is substantially larger in magnitude than the 0-4% effects of payment reform efforts, such as Accountable Care Organizations and hospital global budgets, on emergency department use (McWilliams et al., 2018; Roberts et al., 2018). This insight may also justify considering other interventions that may improve prescription access for urgent needs such as retail-clinics, urgent care, expanded nurse and pharmacist prescribing authority, or easier access to over-the-counter medicines (Sachdev et al., 2020; Yang et al., 2021). At the same time, our results suggest important limits to our ability to reduce avoidable health care by informing patients. Nurse households only had 5-10% fewer avoidable visits. Similarly, physician households only had 5-10% fewer avoidable visits among diagnoses least likely to result in prescriptions. This implies 90-95% of avoidable visits would not be avoided when self-prescribing is not an option. In these cases, factors unrelated to medical training, such as risk aversion and moral hazard, are the likely drivers of avoidable care.

These findings contribute to three key strands of the economics literature. First, these findings contribute to the literature studying interventions to reduce avoidable health care. Prior work has focused on interventions such as insurance expansions (Kolstad and Kowalski, 2012; Ayyagari, Shane and Wehby, 2017; Taubman et al., 2014; Kowalski, 2023) and retail clinics (Alexander, Currie and Schnell, 2019). Our work reveals how rapid access to prescribers could reduce more costly avoidable care. Second, our work also relates to the literature on the effects of prescription drugs on medical utilization where prior work has revealed how cost-sharing on prescription drugs can increase downstream medical costs (Chandra, Gruber and McKnight, 2010; Borrescio-Higa, 2015; Ayyagari, Shane and Wehby, 2017). Our work reveals the potential for large medical cost offsets from rapid access to a prescriber. Finally, we contribute to the research on experts as health care consumers, where our work is the first to evaluate how expert patients seek health care services differently from others. Our finding that medical knowledge does not eliminate avoidable visits is consistent with the findings that physicians adhere to medical guidelines for diagnostics and treatments at rates that are similar to those for patients with less medical knowledge (Frakes, Gruber and Jena, 2021; Finkelstein et al., 2022). In other settings, expert patients were found to be less likely to have c-sections (Johnson and Rehavi, 2016), use branded over-the-counter medicines (Bronnenberg et al., 2015), and have improved health (Chen, Persson and Polyakova, 2022), which underscores that the role of expertise in explaining health care inefficiency is heterogeneous across contexts.

The remainder of the paper proceeds as follows. Section 2 describes our data and setting, Section 3 evaluates differences in overall ED visits, Section 4 evaluates differences in avoidable ED visits, Section 5 considers mechanisms, and Section 6 concludes.

2 Data and Estimation

Our principal dataset is a 100% sample of Medicare Fee-for-Service Claims (2006-2017) for patients originally eligible by age and thus age 65+, including inpatient and outpatient facility claims. In some analyses, we use prescription and professional services claims for a 20% random subsample for whom this data is available. These data are linked to patients' occupation and spousal relationships in a sequence of steps that we describe next.

2.1 Occupational Directories

First, we assembled occupational directories for physicians, nurses, and lawyers. For physicians, we used the Medicare Physician Identification and Eligibility Record, which includes all physicians who ever had a Unique Physician Identification Number (UPIN). The UPIN identifier was mandated for health care professionals receiving Medicare payments in 1985 and was used until 2007. The data contain physician records including name, specialty, gender, medical school graduation year, and billing zip code. For nurses, we obtained nursing directories from twenty-five State Nursing Boards.[1] These data vary by state but typically include name, gender, degree type, zip code, and either date of birth or year of degree receipt and include licensed practical nurses and registered nurses.[2] Finally, we obtained data on U.S. lawyers from *Martindale-Hubbell*, a private directory of lawyers, which includes name, year of birth, gender, and zip code and have been used in prior work (Bonica and Sen, 2017). We also performed validation checks documenting near comprehensive coverage of *Martindale-Hubbell* (Appendix Section A).

2.2 Linking Occupational Directories to Social Security Numbers

We linked the occupational directories to data on Social Security Numbers through data from *Infutor*, a private firm, and linked these data to Medicare data. *Infutor* provides a historical direc-

[1]Colorado, District of Columbia, Florida, Idaho, Illinois, Indiana, Iowa, Kansas, Kentucky, Louisiana, Massachusetts, Minnesota, Mississippi, Missouri, Montana, Nebraska, North Dakota, Oklahoma, Rhode Island, South Carolina, Tennessee, Texas, Virginia, Washington, and Wisconsin.

[2]In our final sample of nurses linked to Medicare data, 78% of the nurses are registered nurses. Less than 1% of the registered nurses were further certified as nurse practitioners.

tory of U.S. residents covering the last 30+ years and is created from varied sources including voter registration files, credit card records, phone books, property deeds, and the Social Security Administration's Death Master File. The data included aliases, gender, birth month and year, and prior addresses, and have been validated in prior work (Diamond, McQuade and Qian, 2019; Bernstein, Shai et al., 2022; Asquith, Mast and Reed, 2023). Our *Infutor* sample focused on 243M individuals with first and last names linked to Social Security Numbers. We linked the occupational directories to *Infutor*, using a multi-step process using the name, age, gender, and locational identifiers. Details on data cleaning and matching procedures are available in Appendix Section B and C, and details on validation checks are available in Appendix Section D.

To identify spouses in *Infutor*, we first identified each individual's potential family members with whom they shared a last name and previous addresses, excluding individuals linked to more than 5 potential family members as this usually reflected individuals erroneously matching to non-family members in large apartment buildings. We then identified spouses as family members of the opposite gender and less than 15 years apart in age. We ultimately linked 60% of individuals in Infutor to a likely spouse, and the median number of spouses found is 1.

2.3 Linking occupational and spousal data to Medicare data

We linked *Infutor* data to Medicare data using Social Security Numbers, which allowed us to identify Medicare beneficiaries who were physicians, nurses, lawyers, and their spouses. Of all Medicare beneficiaries between 2006-2017 originally eligible for Medicare by age, 83% were linked to *Infutor*, reflecting the completeness of *Infutor* for this cohort. There was also strong agreement between *Infutor* and Medicare on year of birth and gender, validating the linkage and accuracy of *Infutor* (see Appendix Section D).

We used the linked data to evaluate the representativeness of *Infutor* data, and found that *Infutor* is less likely to contain certain groups, including dual-eligibles and non-white and non-black race groups. This may reflect biases in the source data including voter, credit card, and property records that may be more likely to identify higher SES individuals and U.S. citizens (Appendix Section E).

2.4 Identifying Patient Cohorts

We limited our sample to observations in which patients matched to *Infutor* and were enrolled in Medicare Fee-for-Service Parts A and B continuously or until death in the index year and the prior year to facilitate estimation of a Charlson comorbidity index based on the prior years' claims (Charlson et al., 1987). We then identified seven patient cohorts: physicians, physician spouses, nurses, nurse spouses, lawyers, lawyer spouses, and all other beneficiaries.[3]

Our final sample includes 83,816 physicians, 87,041 physician spouses, 170,288 nurses, 174,177 nurse spouses, 131,406 lawyers, 102,773 lawyer spouses, and 37,149,709 other Medicare beneficiaries. Table 1 illustrates cohort characteristics in 2017. The tables show that physicians and their spouses are more comparable on socioeconomic and geographic factors to lawyers and their spouses than they are to the general public (e.g., mean household income in the patients' ZIP Code of residence, dual eligibility, urban/rural). Nurses and their spouses are more comparable to the general sample of beneficiaries.

2.5 Estimation

We model the annual number of ED visits per patient using a negative binomial model per equation 1, with standard errors clustered at the beneficiary level. We also report results using Poisson model[4], OLS and inverse propensity-score weighting (IPSW).

$$\begin{aligned} EDvisits_{it} = exp(&\beta_0 + \beta_1 X_{it} + \beta_2 Y_t + \beta_3 HighIncome_i\, x\, Physician_i \\ &+ \beta_4 HighIncomeSpouse_i\, x\, PhysicianSpouse_i + \beta_5 Nurse_i \\ &+ \beta_6 NurseSpouse_i + \beta_7 HighIncome_i + \beta_8 HighIncomeSpouse_i + \varepsilon_{it}) \end{aligned} \tag{1}$$

[3]For 3% of beneficiaries who could be attributed to multiple cohorts, we assigned a single cohort in the following order of priority, approximating decreasing levels of access to medical expertise: physicians, physician spouses, nurses, nurse spouses, lawyers, lawyer spouses. Thus, a lawyer who is also a physician's spouse is classified as a physician spouse; a physician who is also a nurse spouse is classified as a physician; a lawyer who is a nurse spouse is classified as a lawyer.

[4]We prefer a negative binomial for our primary analysis because of the over-dispersion of ED visits versus a Poisson distribution.

In equation 1, $EDvisits_{it}$ refers to the number of ED visits for patient i in year t, X_{it} is a set of controls for patient i in year t including age in 5-year intervals, race (black, white, other), sex, Part D enrollment, dual eligibility, urban residence, Charlson comorbidity index as estimated using the patients' inpatient claims from the prior year (and included as 11 indicators from 0 to 10+), indicators for ventiles of mean household income patients' ZIP code of residence (obtained from the American Community Survey 2018 5-year estimates), Y_t is a vector of indicators for the calendar year t, $Physician_i$ and $PhysicianSpouse_i$ are indicators for whether the patient i is a physician or physician spouse respectively, with variables for nurses and their spouses defined similarly. $HighIncome_i$ is an indicator for the patient having a high-income occupation (namely, physicians and lawyers) and $HighIncomeSpouse_i$ is an indicator for the patient being the spouse of an individual in a high-income occupation. With this specification, β_3 and β_4 are the log-difference in ED visits between physicians and lawyers, and physician spouses to lawyer spouses, holding other covariates constant. Similarly, β_5 and β_6, reflect the log-difference in ED visits between nurses and their spouses relative to all other Medicare beneficiaries who are not physicians or lawyers. Finally, β_7 measures the gap between lawyers relative to all other Medicare beneficiaries, and β_8 reports this gap for lawyer spouses. We transform each coefficient using $e^{\beta} - 1$ to report the precise percentage differences across groups using instead of the log-difference approximation; e^{β} is also referred to as the incidence rate ratio (IRR).

3 Results

We find that physicians and their spouses have 19.8% and 17.1% fewer ED visits annually relative to lawyers and and their spouses respectively (Table 2; Model 1). Nurses and their spouses have 5.1% and 7.0% fewer visits relative to the general public. The observation that ED use rates by physicians' and nurses' spouses are virtually identical to their partners is consistent with the view that experts are able to strongly influence their spouses' care. These results are insensitive to excluding ventiles of median household income in the patients' zip code of residence and the Charlson comorbidity score, suggesting that unobserved socioeconomic and health factor differences between physicians and lawyers and between nurses and the general public would need to be large to explain our results (Models 2-3; Oster (2019)). These results are also insensitive to the use of Poisson or OLS specifications (Models 4-5), showing that the key results in Model (1) are not the consequence of the negative binomial model. Finally, to address the concern that the relationship between covariates and the outcome may vary for physicians and lawyers relative to the general public, we show our results are robust to an IPSW approach in Models 6-9, where one cohort is reweighted to be like another by overweighting members who look like the other group (e.g. lawyers are reweighted to have the same distribution of covariates as physicians by putting more weight on the lawyers who resemble physicians).

Next, we sought to evaluate how the behavior of medical experts and their spouses varies for ED visits that are avoidable versus not. In our main specification, we rely on an algorithm defined by Billings, Parikh and Mijanovich (2000) to identify avoidable ED visits. This algorithm was developed via review of 5,800 medical records and has been widely used in economics and medical literature to identify avoidable ED visits (Taubman et al., 2014; Alexander, Currie and Schnell, 2019). It uses primary diagnoses associated with ED visits to assign visits a probability of falling into four categories: non-emergent (where immediate medical care was not required), emergent but primary care treatable (immediate care was required but could have been provided in an outpatient setting), emergent but preventable (required immediate ED care but was directly avoidable through better outpatient management), and emergent and non-preventable (required ED care and was not directly preventable). We considered non-emergent, primary care treatable, and preventable visits collectively as avoidable visits.

We examine differences in the ED use of medical experts and their spouses across these types of ED visits using Equation 1. The results, illustrated in Table 3, demonstrate that lower use of ED visits by medical experts and their spouses is primarily driven by fewer avoidable visits– physicians and their spouses use 24.8% and 21.7% fewer avoidable ED visits relative to lawyers and their spouses respectively. However, physicians and their spouses only use 7.5% and 11.8% fewer emergent/non-preventable ED visits relative to lawyers and their spouses respectively. This pattern is also apparent, but weaker, among nurses and their spouses who, relative to other Medicare beneficiaries, used 6.8% and 9.0% fewer avoidable ED visits, and 3.2% and 5.4% fewer emergent and non-preventable ED visits, respectively.

3.1 Robustness

First, we examine the robustness of our results to an alternative approach for classifying ED visits as avoidable. The *Billings* algorithm has limitations discussed in prior work (Johnston et al., 2017; Jeffery et al., 2016); it does not cover all diagnoses that patients may experience, nor is it specific for the Medicare population. It was also developed several years prior to our study period, so it does not reflect advances that change how diagnoses can be managed. A priori, it is difficult to know how large these issues are. Nonetheless, we show that our results are robust to an alternative approach, described further in Appendix Section F.1, that stratifies primary diagnoses in the ED by their empirical likelihood of resulting in hospitalization; ED visits for diagnoses with lower hospitalization risk likely reflect less serious cases that are more likely to be avoidable. This approach has the advantage of using all diagnoses and being estimated in Medicare and during our study period. We also validate this approach by estimating hospitalization risk for each diagnosis in a 90% random sample of ED visits, and demonstrating that estimated hospitalization risk is highly predictive of realized hospitalizations in a 10% hold-out sample. We view this approach as complementary but not strictly superior to Billings, Parikh and Mijanovich (2000), because hospitalization is an imperfect correlate for unavoidable visits.[5] Consistent with our primary findings, we find that physicians and their spouses had 30.2% and 23.4% fewer visits for diagnoses least likely to result in hospitalization respectively (Appendix Table A4).

We also address the concern that experts may differ from other patients in unobserved ways that explain differences in avoidable ED visits. This concern is shared by other work studying the behavior of physicians as patients (Johnson and Rehavi, 2016; Frakes, Gruber and Jena, 2021; Finkelstein et al., 2022) and motivated our comparison of physicians to lawyers, who are socioeco-

[5]For example, an ED visit for a broken leg is likely unavoidable but is treatable without hospitalization and thus would be coded as a low hospitalization risk visit.

nomically more similar to physicians than the general public (Gottlieb et al., 2023). Nonetheless, bias may persist if physicians and their spouses differ from lawyer or nurse households. Indeed, the observation that physicians and nurses have 7.5% and 3.2% fewer emergent/non-preventable ED visits suggests that differences in health between physicians, nurses, and their spouses and comparison groups persist, though these may also reflect the effect of medical training (Chen, Persson and Polyakova, 2022).

We performed several sensitivity analyses that suggest unobserved differences in socioeconomic status and health are unlikely to explain the decrease in avoidable ED visits seen between physicians and lawyers. We show that our results are robust to alternative specifications using fewer health and socioeconomic controls, such as removing controls for the typical income in the patients' zip code and the Charlson comorbidity index (Appendix Tables A5). This suggests that unobserved differences between lawyers and physicians would need to be larger than observed differences to explain results (Oster, 2019). Similarly, in Appendix Table A6, we show that our the results are robust to a specification limiting the physician sample to primary care physicians, who have incomes more comparable to lawyers than the general physician population (Gottlieb, Joshua et al., 2020). Finally, we show that socioeconomic advantage is not consistently related to reduced use of lower acuity ED visits conditional on observables. Indeed, relative to the general public, lawyers have 12.2% fewer avoidable ED visits (Table 3) but 3.8% *more* visits for diagnoses least likely to result in hospitalization (Appendix Table A4). Thus, even if physicians are unobservably socioeconomically advantaged relative to lawyers, this would not explain the observation that physicians have 30.2% fewer visits for diagnoses least likely to result in hospitalization.

4 Mechanisms

There are three theories that could explain the reduction in avoidable ED visits, particularly among physicians and their spouses. The first is that physicians have more *medical knowledge* and are better able to recognize and triage symptoms and avoid the ED when appropriate. The second is that experts, by virtue of their personal and professional *networks*, have greater access to other experts and treatment, which substitutes for ED visits. Finally, physicians may be authorized to *self-administer treatments* to alleviate minor ailments, which substitutes for ED visits. The most salient example of this is that physicians, but generally not nurses, are authorized to prescribe medicines for themselves and their family members, in emergencies and for non-controlled substances.

4.1 Self-treatment hypothesis

We then identify several pieces of evidence suggesting that the *"self-treatment"* hypothesis, and particularly the ability to self-prescribe medications, is likely the primary mechanism explaining fewer avoidable visits among physicians and their spouses. First, we evaluate whether the decrement in avoidable visits among physician households is larger for diagnoses that require a prescription. We assigned each primary diagnosis that appears on an ED visit an empirical likelihood of resulting in a prescription on the day of or day following discharge, and then stratified diagnoses into quintiles of prescription propensity.[6] We reestimated equation 1 separately for diagnoses in each quintile of prescription propensity.

We find that the decrement in physicians' use of avoidable ED visits is substantially stronger for diagnoses most likely to result in prescriptions (Table 4). In the highest quintile of prescription propensity, physicians and their spouses had 40.0% and 30.1% fewer avoidable ED visits relative to lawyers and their spouses. Meanwhile, in the lowest quintile, physicians and their spouses had only 5.6% and 11.1% fewer avoidable ED visits. These results are robust when, instead of evaluating avoidable ED visits as defined by Billings, Parikh and Mijanovich (2000), we define the outcome as ED visits for diagnoses least likely to result in hospitalizations (Appendix Table A7).

We then assessed whether it was plausible that these differences may be related to physician households' ability to self or spouse-prescribe, and find that self- and spouse-prescribing among

[6]Diagnoses in the highest quintile are followed by a prescription 43% of the time (e.g., urinary tract infection, back ache); diagnoses in the lowest quintile are followed by a prescription only 8% of the time (e.g., attention to dressings or sutures). This was done using a subset of ED visits for a 20% random sample of patients originally eligible by age, linkable to Infutor, and who were continuously enrolled in Medicare Parts A, B, and D.

physicians is very common.[7]. Specifically, 44% of physicians filled at least one self-prescribed prescription and 33% of physician spouses filled at least one prescription prescribed by their spouse in 2017. Moreover, for physicians and their spouses receiving at least one self or spouse-prescribed prescription, 48% of all prescription claims were self or spouse-prescribed in 2017.

We also evaluated whether the drugs that were most commonly self or spouse-prescribed by physicians were also the drugs most commonly used after avoidable ED visits. We identified the top-100 drug molecules by claim volume prescribed in Medicare Part D. We excluded ten drugs for controlled substances such as opioids, where state regulation often prohibits self or spouse-prescribing. For each drug, we calculated the share of claims that occurred on the day of or following discharge from an avoidable ED visit. We also calculated the share of physicians' and physician spouses' claims for each drug that were self or spouse-prescribed respectively. Across drugs, we estimated the correlation between the share of claims occurring after an avoidable visit and the share of prescriptions for physicians and their spouses that were self or spouse-prescribed.

We found that the drugs that were most commonly self or spouse-prescribed in physician households were indeed also the drugs most commonly used after avoidable ED visits (Figure 1). Indeed, there was a strong correlation between the share of a drug's claims prescribed after an avoidable ED visit and the share of a physician's own prescriptions that were self-prescribed (R = 0.35; $p < 0.001$) and the share of physician spouses' prescriptions that were spouse-prescribed (R = 0.61; $p<0.001$). This was driven largely by prescribing patterns for non-opioid pain and anti-inflammatory medicines and antibiotics, which were commonly self or spouse-prescribed in physician households and commonly used after avoidable ED visits.

4.2 Other hypotheses

We also performed several supplementary analyses suggesting that the networks hypothesis has limited explanatory power. If physicians' networks facilitate easier access to outpatient care,

[7]For this analysis we are limited to physicians and the spouses of physicians whose UPIN identifier we could link to National Provider Identifier, the prescriber identifier in claims, using a crosswalk described previously (Kakani et al., 2024)

then *ceteris paribus* physician households should have greater use of outpatient or primary care visits that may substitute for ED visits. However, physicians have 33.9% fewer outpatient and 53.4% fewer primary care visits annually, while their spouses have 14.6% fewer outpatient visits and 22.3% fewer primary care visits (Appendix Table A8). The network hypothesis would also predict more ED use by physicians on weekends, because their ability to access outpatient care via their networks is effectively smaller than on weekdays. But we find very similar results on weekends (Appendix Table A9). The networks hypothesis also predicts that physicians may have easier access to outpatient appointments for diagnostics, such as imaging, as an alternative for ED visits. Thus, the network hypothesis would imply that the lower rate of avoidable ED visits in physician households would be larger for diagnoses that often require imaging. To test this, we stratified the primary diagnoses appearing on ED visit claims by the likelihood of being adjacent to a claim for advanced imaging (such as CT, MRI, or a PET scan), and examined whether physician households were less likely to have ED visits for diagnoses that are likely to require advanced imaging. Contrary to the prediction, the estimated decrement in avoidable ED visits among physicians and their spouses was similar or weaker for diagnoses with the highest imaging propensity (Appendix Table A10).

5 Discussion

Reducing the degree to which patients initiate avoidable care, in settings such as the emergency room, specialist visits, or direct-to-consumer offerings, may be a valuable and overlooked way to improve health care efficiency. In the emergency room context, which is a consequential source of spending, we find physicians and nurses had 19.8% and 5.1% fewer ED visits compared to similar patients. This was driven primarily by fewer avoidable visits. Several pieces of evidence imply that physicians' ability to prescribe medications for themselves and their spouses is the primary mechanism for reduced avoidable ED visits. Most notably, the reduction in avoidable visits among physician households is substantially higher for primary diagnoses empirically most likely to require a prescription.

Our analysis has limitations. We focused on elderly clinicians covered by Medicare Fee-for-Service, whose behavior may differ from their younger counterparts. Second, while our analysis implies a primary role for self and spouse-prescribing, we cannot entirely eliminate other explanations. For example, if prescription propensity covaries with how recognizable symptoms are to experts, then the ability to triage symptoms through medical knowledge could be driving reduced avoidable ED visits rather than prescription access. If this were a first-order explanation, we should also see decreased use for nurses who have vastly more medical knowledge than non-physicians, but we do not see this. It is also possible that prescriptions are accessed through physicians' professional networks rather than through self and spouse-prescribing. However, self- and spouse-prescribing is highly prevalent, particularly for drugs commonly prescribed after an avoidable ED visit, suggesting this as a likely mechanism for accessing prescriptions for acute medical needs. Finally, these findings may differ for other types of avoidable care beyond the emergency room.

Our results help highlight the strategies that are likely to be successful in reducing avoidable care in the ED setting. Most notably, our findings underscore the opportunity to reduce avoidable ED use through interventions that improve prescription access for acute needs. These may include interventions such as retail clinics, nurse hotlines coupled with independent nurse prescribing, and expansions of nurse and pharmacist prescribing, which states are increasingly considering (Sachdev et al., 2020; Yang et al., 2021). Of course, such policies would need to balance improved prescription access with the possibility that incremental prescriptions may also be socially suboptimal due to cost, externalities (e.g., antibiotic resistance), or internalities (e.g., side effects). At the same time, our results suggest important limits to our ability to reduce avoidable health care use by patient education efforts. Nurses did not have substantial reductions in avoidable ED visits, despite immense medical knowledge. Similarly, even physicians were unable to substantially reduce avoidable ED visits for diagnoses not commonly requiring a prescription. These results may provide a partial explanation for why improving health care efficiency has been challenging.

Table 1: Characteristics of Patient Cohorts in 2017

	Physicians	Physicians' Spouses	Lawyers	Lawyers' Spouses	Nurses	Nurses' Spouses	All Medicare Beneficiaries
Age [SD]	75.2 (7.2)	75.1 (7.4)	73.3 (6.9)	74.2 (7.8)	74.0 (7.3)	73.8 (7.0)	75.1 (7.8)
Male	89.4%	14.6%	84.5%	12.9%	4.5%	89.9%	43.7%
White	80.9%	86.2%	91.1%	94.2%	92.1%	91.1%	87.7%
Black	1.4%	1.5%	1.1%	1.0%	4.1%	3.4%	6.3%
Other Race	17.7%	12.3%	7.7%	4.7%	3.8%	5.6%	6%
Zip Code Avg. Income (000s) [SD]	121.2 (57.1)	118.8 (55.7)	121.8 (58.4)	121.8 (58.1)	86.4 (32.6)	86.8 (32.8)	88.1 (38.2)
Part D Coverage	76.0%	78.3%	74.9%	77.0%	68.1%	62.3%	68.0%
Dual Eligibility	0.3%	1.5%	0.8%	1.2%	3.1%	2.4%	8.7%
Charlson Score [SD]	0.2 (0.9)	0.2 (0.8)	0.2 (0.9)	0.2 (0.8)	0.2 (0.9)	0.3 (1.0)	0.3 (1.1)
Urban	90.5%	90.8%	90.1%	90.6%	78.2%	77.7%	79.3%
Annual Mortality	3.1%	2.8%	2.8%	2.8%	3.0%	3.8%	4.4%
Total Spending (000s) [SD]	10.8 (23.8)	10.2 (21.7)	11.0 (24.3)	10.3 (21.0)	10.4 (20.5)	10.7 (22.6)	11.5 (23.8)
Observations	**60,752**	**62,684**	**94,536**	**70,967**	**116,147**	**108,456**	**21,116,806**

Note: Table reports characteristics of Medicare beneficiaries in the sample in 2017. The sample includes Medicare beneficiaries originally eligible by age enrolled in Medicare Fee-for-Service Part A and Part B on January 1, 2017, continuously or until death in 2017, and continuously in 2016. ZIP code avg. income refers to the mean household income in the patients' 5-digit zip code according to the American Community Survey 2018 5-year estimates. Part D coverage reflects whether the patient is ever enrolled in Part D prescription drug coverage during 2017. Charlson comorbidity scores are estimated using inpatient claims from previous calendar year. Patient ZIP codes are classified as urban using the National Center for Health Statistics Urban-Rural Classification Scheme. Total spending reflects total spending in Medicare Part A & B.

Table 2: Percentage Difference in Annual Emergency Department Visits Between Groups

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
High-income x physician	-0.198	-0.197	-0.204	-0.189	-0.176	-0.199			
95% CI	(-0.189, -0.208)	(-0.193, -0.214)	(-0.193, -0.214)	(-0.180, -0.199)	(-0.166, -0.187)	(-0.192, -0.212)			
High-income x physician spouse	-0.171	-0.170	-0.172	-0.171	-0.144		-0.154		
95% CI	(-0.161, -0.180)	(-0.160, -0.180)	(-0.161, -0.183)	(-0.161, -0.180)	(-0.134, -0.154)		(-0.141, -0.163)		
High-income	-0.067	-0.093	-0.118	-0.069	-0.039				
95% CI	(-0.06, -0.073)	(-0.088, -0.101)	(-0.112, -0.125)	(-0.063, -0.076)	(-0.033, -0.044)				
High-income spouses	-0.092	-0.118	-0.143	-0.086	-0.067				
95% CI	(-0.086, -0.100)	(-0.104, -0.122)	(-0.131, -0.148)	(-0.077, -0.086)	(-0.058, -0.058)				
Nurse	-0.051	-0.051	-0.054	-0.052	-0.040			-0.044	
95% CI	(-0.044, -0.056)	(-0.044, -0.056)	(-0.047, -0.060)	(-0.046, -0.058)	(-0.035, -0.046)			(-0.027, -0.064)	
Nurse Spouse	-0.070	-0.071	-0.076	-0.078	-0.058				-0.008
95% CI	(-0.065, -0.076)	(-0.066, -0.077)	(-0.069, -0.082)	(-0.072, -0.083)	(-0.039, -0.058)				(0.010, -0.025)
Approach		Negative Binomial		Poisson	OLS		Inverse propensity score weighting		
Controls included*									
Age, Race, Sex, Year, Part D, Dual, Urban	X	X	X		X	X	X	X	X
Comorbidities	X	X			X	X	X	X	X
Zip code income ventiles	X				X	X	X	X	X
Observations			**242,256,298**			**1,393,502**	**1,292,333**	**238,480,449**	**238,463,831**

Note: Table reports percent differences from estimating Equation (1). Reported estimates for high-income x physician and high-income x physician spouse are the percent increase in the outcome for physicians and their spouses relative to lawyers and their spouses respectively. Reported estimates for Nurses and Nurses' Spouses are percent differences relative to the general Medicare population. Models (1) to (3) reflect an estimation of the negative binomial model outlined in Equation 1 with varying sets of covariates. Models (4) to (5) uses poisson and ordinary least squares (OLS) specifications respectively. Models (6) - (9) reflect the implied percentage difference in annual ED visits using inverse propensity score weighting (IPSW) to estimate differences between physicians and lawyers (model 6), physicians' spouses and lawyers' spouses (model 7), nurses and the general public excluding medical experts and their spouses (model 8), and nurses' spouses and the general public excluding medical experts and their spouses (model 9). The coefficients from OLS and IPSW are transformed into an implied percentage change relative to the mean number of ED visits in the comparison group for each population to support comparability with Models (1) to (3). Standard errors are clustered at the patient level.

Table 3: Difference in Avoidable and Non-Avoidable Annual Emergency Department Visits Between Groups

	All avoidable visit categories	Emergent and non-preventable	Avoidable visits by type: Non-emergent	Avoidable visits by type: Emergent and primary care treatable	Avoidable visits by type: Emergent and preventable
	(1)	(2)	(3)	(4)	(5)
High-income x physician	-0.248	-0.075	-0.278	-0.218	-0.252
95% CI	(-0.235, -0.260)	(-0.060, -0.090)	(-0.262, -0.294)	(-0.204, -0.232)	(-0.231, -0.272)
High-income x physician spouse	-0.217	-0.118	-0.249	-0.197	-0.205
95% CI	(-0.204, -0.23)	(-0.102, -0.132)	(-0.234, -0.264)	(-0.183, -0.212)	(-0.185, -0.225)
High-income	-0.122	-0.083	-0.101	-0.110	-0.200
95% CI	(-0.114, -0.131)	(-0.074, -0.092)	(-0.089, -0.112)	(-0.101, -0.119)	(-0.187, -0.213)
High-income spouses	-0.137	-0.105	-0.118	-0.134	-0.174
95% CI	(-0.128, -0.146)	(-0.095, -0.115)	(-0.107, -0.13)	(-0.125, -0.144)	(-0.161, -0.188)
Nurse	-0.068	-0.032	-0.063	-0.065	-0.095
95% CI	(-0.059, -0.077)	(-0.025, -0.041)	(-0.051, -0.074)	(-0.056, -0.073)	(-0.083, -0.107)
Nurse Spouse	-0.090	-0.054	-0.095	-0.081	-0.124
95% CI	(-0.082, -0.098)	(-0.046, -0.061)	(-0.085, -0.105)	(-0.072, -0.089)	(-0.111, -0.135)
Observations	**242,256,298**	**242,256,298**	**242,256,298**	**242,256,298**	**242,256,298**

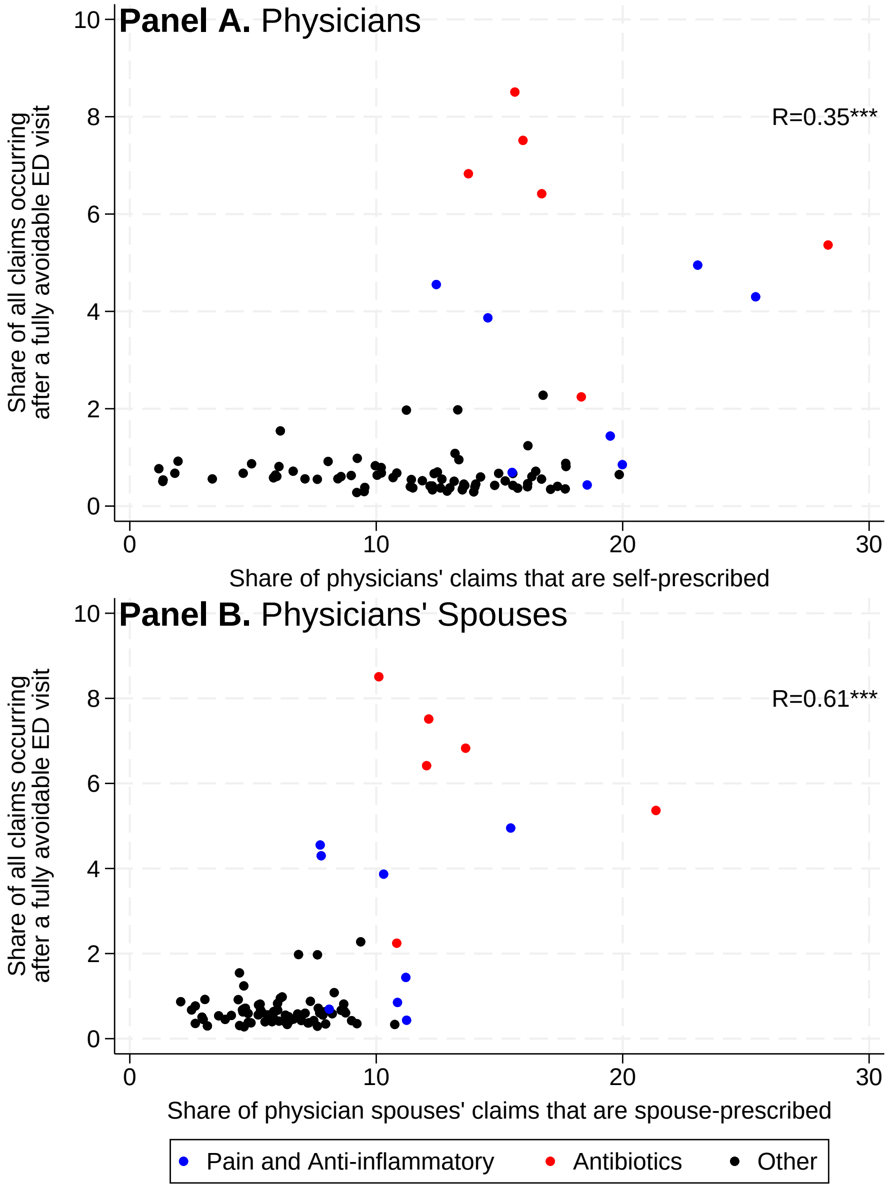
Note: Table reports percent differences from estimating Equation (1) using a negative-binomial model. Coefficients on High-income x physicians and High-income x physician spouse are the percent increase in the outcome associated with physicians and their spouses relative to lawyers and their spouses respectively. Coefficient on Nurses and Nurses' Spouses are percent differences relative to the general Medicare population. Models adjust for age, race, sex, year, Part D enrollment, dual eligibility, urban residence, Charlson comorbidity index, and zip code income ventiles. Standard errors are clustered at the patient level.

Table 4: Difference in Avoidable Emergency Department Visits Between Groups Stratifying Diagnoses by Quintiles of Prescription Propensity

	Quintile 1 (Lowest Prescription Propensity)	Quintile 2	Quintile 3	Quintile 4	Quintile 5 (Highest Prescription Propensity)
	(1)	(2)	(3)	(4)	(5)
High-income x physician	-0.056	-0.243	-0.281	-0.269	-0.400
95% CI	[-0.012, -0.100]	[-0.216, -0.269]	[-0.252, -0.309]	[-0.243, -0.295]	[-0.373, -0.426]
High-income x physician spouse	-0.111	-0.208	-0.229	-0.248	-0.301
95% CI	[-0.060, -0.162]	[-0.181, -0.234]	[-0.200, -0.258]	[-0.223, -0.272]	[-0.277, -0.326]
High-income	-0.168	-0.126	-0.187	-0.147	-0.096
95% CI	[-0.141, -0.196]	[-0.109, -0.142]	[-0.170, -0.205]	[-0.131, -0.162]	[-0.081, -0.112]
High-income spouses	-0.181	-0.131	-0.160	-0.158	-0.142
95% CI	[-0.148, -0.214]	[-0.114, -0.149]	[-0.142, -0.179]	[-0.143, -0.174]	[-0.126, -0.158]
Nurses	-0.080	-0.083	-0.088	-0.058	-0.080
95% CI	[-0.054, -0.105]	[-0.068, -0.099]	[-0.074, -0.103]	[-0.042, -0.075]	[-0.068, -0.091]
Nurses' Spouses	-0.074	-0.101	-0.113	-0.096	-0.086
95% CI	[-0.053, -0.096]	[-0.087, -0.114]	[-0.097, -0.128]	[-0.082, -0.110]	[-0.074, -0.099]
Observations	**242,256,298**	**242,256,298**	**242,256,298**	**242,256,298**	**242,256,298**

Note: Table reports percent differences in avoidable ED visits from estimating Equation (1) using a negative-binomial model. Models 1-5 limit to ED visits in five quintiles of prescription propensity. The outcome in model (1) is the number of avoidable ED visits among ED visits with primary diagnoses in the lowest quintile of prescription propensity, and the outcome in model (5) is the number of avoidable ED visits among ED visits with primary diagnoses in the highest quintile of prescription propensity. Coefficients on High-income x physicians and High-income x physician spouse are the percent increase in the outcome associated with physicians and their spouses relative to lawyers and their spouses respectively. Coefficient on Nurses and Nurses' Spouses are percent differences relative to the general Medicare population. Models adjust for age, race, sex, year, Part D enrollment, dual eligibility, urban residence, Charlson comorbidity index, and zip code income ventiles. Standard errors are clustered at the patient level.

Figure 1: Correlation Between Share of Prescriptions Written After an Avoidable Visit and Share of Physician Household Claims that are Self or Spouse Prescribed, for Top Prescribed Drug Molecules (2006-2017)



Note: Each year, sample includes a a 20% random patients linkable to Infutor, originally eligible by age, and enrolled in Medicare Fee-for-Service Parts A, B, and D continuously or until death. Analysis includes top-100 drug molecules by Medicare Part D claim volume between 2006-2017, excluding ten controlled substances (N = 90). The y-axes illustrate the share of claims for each index drug that occur on the day of or day after discharge from an ED visit with 100% probability of being avoidable according to Billings, Parikh and Mijanovich (2000). In Panel A, the x-axis illustrates the share of physician patients' prescriptions for the index molecule in Medicare Part D across all years that are self-prescribed. In Panel B, the x-axis illustrates the share of physician spouse patients' prescriptions for the index molecule in Medicare Part D across all years that are spouse-prescribed. Drugs are categorized into pain and anti-inflammatory, antibiotic, and other categories through manual review. R is the Pearson's correlation coefficient. ***P-value < .001.

References

Alexander, Diane, Janet Currie, and Molly Schnell. 2019. "Check up before you check out: Retail clinics and emergency room use." *Journal of Public Economics*, 178: 104050.

Asquith, Brian J., Evan Mast, and Davin Reed. 2023. "Local Effects of Large New Apartment Buildings in Low-Income Areas." *The Review of Economics and Statistics*, 105(2): 359–375.

Ayyagari, Padmaja, Dan M. Shane, and George L. Wehby. 2017. "The Impact of Medicare Part D on Emergency Department Visits." *Health Economics*, 26(4): 536–544. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/hec.3326.

Baicker, Katherine, Sendhil Mullainathan, and Joshua Schwartzstein. 2015. "Behavioral Hazard in Health Insurance*." *The Quarterly Journal of Economics*, 130(4): 1623–1667.

Bernstein, Shai, Diamond, Rebecca, Jiranaphawiboon, Abhisit, McQuade, Timothy, and Pousada, Beatriz. 2022. "The Contribution of High-Skilled Immigrants to Innovation in the United States." *National Bureau of Economic Research Working Paper Series*.

Berwick, Donald M., and Andrew D. Hackbarth. 2012. "Eliminating Waste in US Health Care." *JAMA*, 307(14): 1513–1516.

Billings, Parikh, and Mijanovich. 2000. "Emergency Department Use: The New York Story." *The Commonwealth Fund*.

Bonica, Adam, and Maya Sen. 2017. "A Common-Space Scaling of the American Judiciary and Legal Profession." *Political Analysis*, 25(1): 114–121.

Borrescio-Higa, Florencia. 2015. "Can Walmart make us healthier? Prescription drug prices and health care utilization." *Journal of Health Economics*, 44: 37–53.

Bronnenberg, Bart J., Jean-Pierre Dubé, Matthew Gentzkow, and Jesse M. Shapiro. 2015. "Do Pharmacists Buy Bayer? Informed Shoppers and the Brand Premium *." *The Quarterly Journal of Economics*, 130(4): 1669–1726.

Chan, David C, Matthew Gentzkow, and Chuan Yu. 2022. "Selection with Variation in Diagnostic Skill: Evidence from Radiologists*." *The Quarterly Journal of Economics*, 137(2): 729–783.

Chandra, Amitabh, and Douglas O Staiger. 2020. "Identifying Sources of Inefficiency in Healthcare*." *The Quarterly Journal of Economics*, 135(2): 785–843.

Chandra, Amitabh, David Cutler, and Zirui Song. 2011. "Chapter Six - Who Ordered That? The Economics of Treatment Choices in Medical Care." In *Handbook of Health Economics*. Vol. 2 of *Handbook of Health Economics*, , ed. Mark V. Pauly, Thomas G. Mcguire and Pedro P. Barros, 397–432. Elsevier.

Chandra, Amitabh, Jonathan Gruber, and Robin McKnight. 2010. "Patient Cost-Sharing and Hospitalization Offsets in the Elderly." *American Economic Review*, 100(1): 193–213.

Charlson, Mary E., Peter Pompei, Kathy L. Ales, and C.Ronald MacKenzie. 1987. "A new method of classifying prognostic comorbidity in longitudinal studies: Development and validation." *Journal of Chronic Diseases*, 40(5): 373–383.

Chen, Yiqun, Petra Persson, and Maria Polyakova. 2022. "The Roots of Health Inequality and the Value of Intrafamily Expertise." *American Economic Journal: Applied Economics*, 14(3): 185–223.

Chetty, Raj, Michael Stepner, Sarah Abraham, Shelby Lin, Benjamin Scuderi, Nicholas Turner, Augustin Bergeron, and David Cutler. 2016. "The Association Between Income and Life Expectancy in the United States, 2001-2014." *JAMA*, 315(16): 1750–1766.

Cutler, David, Jonathan S. Skinner, Ariel Dora Stern, and David Wennberg. 2019. "Physician Beliefs and Patient Preferences: A New Look at Regional Variation in Health Care Spending." *American Economic Journal: Economic Policy*, 11(1): 192–221.

Diamond, Rebecca, Tim McQuade, and Franklin Qian. 2019. "The Effects of Rent Control Expansion on Tenants, Landlords, and Inequality: Evidence from San Francisco." *American Economic Review*, 109(9): 3365–3394.

Einav, Liran, and Amy Finkelstein. 2018. "Moral Hazard in Health Insurance: What We Know and How We Know It." *Journal of the European Economic Association*, 16(4): 957–982.

Finkelstein, Amy, Petra Persson, Maria Polyakova, and Jesse M. Shapiro. 2022. "A taste of their own medicine: Guideline adherence and access to expertise." *American Economic Review:Insights*, 4(4): 507–526.

Frakes, Michael, Jonathan Gruber, and Anupam Jena. 2021. "Is great information good enough? Evidence from physicians as patients." *Journal of Health Economics*, 75: 102406.

Galarraga, Jessica E., and Jesse M. Pines. 2016. "Costs of ED episodes of care in the United States." *The American Journal of Emergency Medicine*, 34(3): 357–365.

Ganguli, Ishani, Arabella L. Simpkin, Carrie H. Colla, Arlene Weissman, Alexander J. Mainor, Meredith B. Rosenthal, and Thomas D. Sequist. 2020. "Why Do Physicians Pursue Cascades of Care After Incidental Findings? A National Survey." *Journal of General Internal Medicine*, 35(4): 1352–1354.

Gottlieb, Joshua D., Maria Polyakova, Kevin Rinz, Hugh Shiplett, and Victoria Udalova. 2023. "Who Values Human Capitalists' Human Capital? The Earnings and Labor Supply of U.S. Physicians."

Gottlieb, Joshua, Polyakova, Maria, Rinz, Kevin, Shiplett, Hugh, and Udalova, Victoria. 2020. "Who Values Human Capitalists' Human Capital? Healthcare Spending and Physician Earnings." United States Census Bureau.

Jeffery, Molly Moore, M. Fernanda Bellolio, Julian Wolfson, Jean M. Abraham, Bryan E. Dowd, and Robert L. Kane. 2016. "Validation of an algorithm to determine the primary care treatability of emergency department visits." *BMJ Open*, 6(8): e011739. Publisher: British Medical Journal Publishing Group Section: Health services research.

Johnson, Erin M., and M. Marit Rehavi. 2016. "Physicians Treating Physicians: Information and Incentives in Childbirth." *American Economic Journal: Economic Policy*, 8(1): 115–141.

Johnston, Kenton J., Lindsay Allen, Taylor A. Melanson, and Stephen R. Pitts. 2017. "A "Patch" to the NYU Emergency Department Visit Algorithm." *Health Services Research*, 52(4): 1264–1276. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/1475-6773.12638.

Kakani, Pragya, David M. Cutler, Meredith B. Rosenthal, and Nancy L. Keating. 2024. "Trends in Integration Between Physician Organizations and Pharmacies for Self-Administered Drugs." *JAMA Network Open*, 7(2): e2356592.

Kellermann, Arthur. 2006. "Crisis in the Emergency Department." *The New England journal of medicine*, 355: 1300–3.

Kolstad, Jonathan T., and Amanda E. Kowalski. 2012. "The impact of health care reform on hospital and preventive care: Evidence from Massachusetts." *Journal of Public Economics*, 96(11-12): 909–929.

Kowalski, Amanda E. 2023. "Reconciling Seemingly Contradictory Results from the Oregon Health Insurance Experiment and the Massachusetts Health Reform." *Review of Economics and Statistics*, 105(3): 646–664.

Lattimer, Val, Steve George, Felicity Thompson, Eileen Thomas, Mark Mullee, Joanne Turnbull, Helen Smith, Michael Moore, Hugh Bond, and Alan Glasper. 1998. "Safety and effectiveness of nurse telephone consultation in out of hours primary care: randomised controlled trial." *BMJ*, 317(7165): 1054–1059. Publisher: British Medical Journal Publishing Group Section: General Practice.

Martin, Anne B., Micah Hartman, David Lassman, and Aaron Catlin. 2021. "National Health Care Spending In 2019: Steady Growth For The Fourth Consecutive Year." *Health Affairs*, 40(1): 14–24. Publisher: Health Affairs.

McWilliams, J. Michael, Laura A. Hatfield, Bruce E. Landon, Pasha Hamed, and Michael E. Chernew. 2018. "Medicare Spending after 3 Years of the Medicare Shared Savings Program." *New England Journal of Medicine*, 379(12): 1139–1149.

Mullainathan, Sendhil, and Ziad Obermeyer. 2022. "Diagnosing Physician Error: A Machine Learning Approach to Low-Value Health Care." *The Quarterly Journal of Economics*, 137(2): 679–727.

Oster, Emily. 2019. "Unobservable Selection and Coefficient Stability: Theory and Evidence." *Journal of Business & Economic Statistics*, 37(2): 187–204. Publisher: Taylor & Francis _eprint: https://doi.org/10.1080/07350015.2016.1227711.

Raven, Maria C., Margot Kushel, Michelle J. Ko, Joanne Penko, and Andrew B. Bindman. 2016. "The Effectiveness of Emergency Department Visit Reduction Programs: A Systematic Review." *Annals of Emergency Medicine*, 68(4): 467–483.e15.

Roberts, Eric T., J. Michael McWilliams, Laura A. Hatfield, Sule Gerovich, Michael E. Chernew, Lauren G. Gilstrap, and Ateev Mehrotra. 2018. "Changes in Health Care Use Associated With the Introduction of Hospital Global Budgets in Maryland." *JAMA Internal Medicine*, 178(2): 260–268.

Rust, George, Jiali Ye, Peter Baltrus, Elvan Daniels, Bamidele Adesunloye, and George Edward Fryer. 2008. "Practical Barriers to Timely Primary Care Access: Impact on Adult Use of Emergency Department Services." *Archives of Internal Medicine*, 168(15): 1705–1710.

Sachdev, Gloria, Mary Ann Kliethermes, Veronica Vernon, Sandra Leal, and George Crabtree. 2020. "Current status of prescriptive authority by pharmacists in the United States." *JACCP: JOURNAL OF THE AMERICAN COLLEGE OF CLINICAL PHARMACY*, 3(4): 807–817. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/jac5.1245.

Shrank, William H., Teresa L. Rogstad, and Natasha Parekh. 2019. "Waste in the US Health Care System: Estimated Costs and Potential for Savings." *JAMA*, 322(15): 1501–1509.

Taubman, Sarah L., Heidi L. Allen, Bill J. Wright, Katherine Baicker, and Amy N. Finkelstein. 2014. "Medicaid Increases Emergency-Department Use: Evidence from Oregon's Health Insurance Experiment." *Science*, 343(6168): 263–268.

Van Den Heede, Koen, and Carine Van De Voorde. 2016. "Interventions to reduce emergency department utilisation: A review of reviews." *Health Policy*, 120(12): 1337–1349.

Weinick, Robin M., Rachel M. Burns, and Ateev Mehrotra. 2010. "Many Emergency Department Visits Could Be Managed At Urgent Care Centers And Retail Clinics." *Health Affairs*, 29(9): 1630–1636. Publisher: Health Affairs.

Yang, Bo Kyum, Mary E. Johantgen, Alison M. Trinkoff, Shannon R. Idzik, Jessica Wince, and Carissa Tomlinson. 2021. "State Nurse Practitioner Practice Regulations and U.S. Health Care Delivery Outcomes: A Systematic Review." *Medical Care Research and Review*, 78(3): 183–196. Publisher: SAGE Publications Inc.

Appendix To:

Expert Patients' Use of Avoidable Health Care

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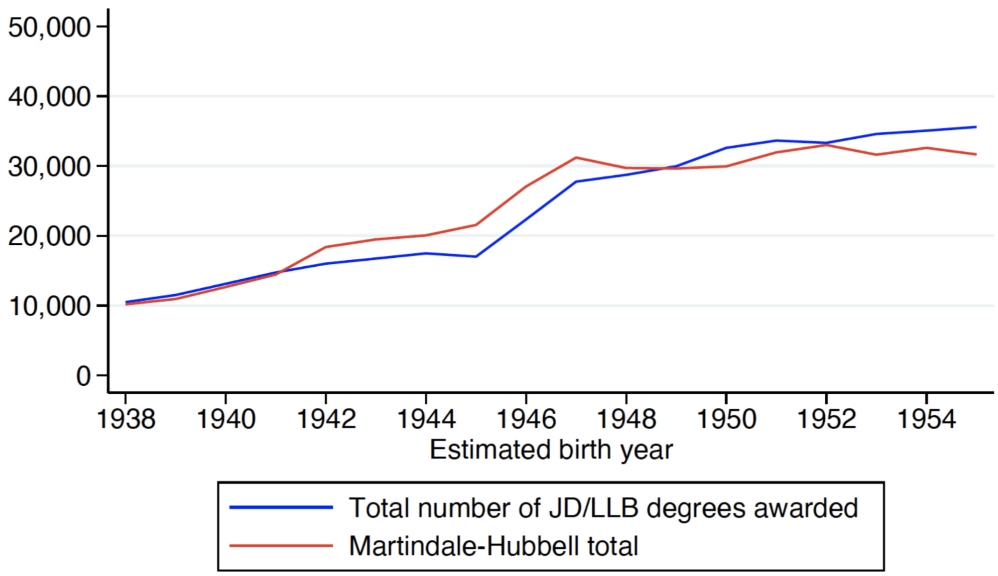
March 13, 2025

Appendix Table of Contents

A Validating Martindale-Hubbell data

To vet the comprehensiveness of Martindale-Hubbell data we performed two checks. First, we compared the total number of individuals in Martindale-Hubbell born in each year to the count of law school graduates reported 26 years later, the typical graduation age for lawyers, by the American Bar Association.[8] For birth cohorts from 1938 to 1955[9], Martindale-Hubbell included approximately the same number of lawyers as would be estimated using U.S. law graduate data from American Bar Association. The growth in lawyers identified in Martindale-Hubbell over time matches well with estimates derived from the American Bar Association suggesting high fidelity of the data for these birth cohorts. Small discrepancies may be due to lawyers immigrating into (or out of) the U.S., changes in time to law school graduation, or career changes.

Appendix Figure A1: Count of lawyers in Martindale-Hubbell data and lawyers awarded JD/LLBs by estimated birth years (1938-1955)



Note: Assumes lawyers graduate law school at age 26. Excludes lawyers with missing address information in Martindale-Hubbell, which likely reflect foreign practicing lawyers.

[8] American Bar Association. Enrollment and Degrees Awarded. Retrieved September 8, 2022, from https://www.americanbar.org/content/dam/aba/administrative/legal_education_and_admissions_to_the_bar/standards/2021-2022/21-22-standards-book-revisions-since-printed.pdf

[9] The American Bar Association reports data on the number of graduating lawyers beginning in 1964, corresponding to an expected birth cohort 1938.

As a second test, we compared Martindale-Hubbell data to historical data from the Ohio State Bar Association. Ohio is one of the few states to maintain and make publicly available relatively comprehensive historical data on lawyers who passed the Bar Exam in Ohio that includes year of birth information. Specifically, we attempted to find 33,384 lawyers in the Ohio Bar Association data born between 1910 - 1955 in the Martindale-Hubbell legal directory. We performed a match on last name, first name, and year of birth (+/- 1 year). We were able to find at least 1 match for 87% of Ohio Bar Association lawyers in the Martindale-Hubbell data. Of those matched, 73% were matched to an individual listed as being in Ohio in Martindale-Hubbell.[10] This is suggestive that the data are relatively accurate and complete.

B Infutor and occupational data cleaning and enhancements

Prior to matching the occupational data to Infutor, we take certain steps to clean and enhance the occupational datasets and Infutor. First, we cleaned the first and last name variables in both Infutor and the occupational datasets by removing periods and hyphens. We excluded any observations in Infutor and occupational data with missing entries for first or last name. We also excluded any observations in Infutor with no Social Security Number or an invalid Social Security Number format. We also linked the Infutor and occupational data to a county FIPS code based on ZIP code and linked individuals to Hospital Referral Regions (HRR) using a ZIP to HRR crosswalk provided by the Dartmouth Atlas.[11] We exclude any observations in Infutor or in occupational data that are unlinkable to HRRs. Our final Infutor sample included 243,209,696 individuals (identified by PIDs) in Infutor, 852,623 physicians in the UPIN directory[12], 4,720,147 nurses from the

[10] Matched lawyers in Martindale Hubbell listed as practicing in a state other than Ohio may reflect movers.

[11] Dartmouth Atlas. (2021, June 10). Supplemental data. Dartmouth Atlas DATA. Retrieved September 8, 2022, from https://data.dartmouthatlas.org/supplemental/. We use the 1995 - 2018 zip to HRR crosswalk files.

[12] In cases where a physician appeared multiple times in the UPIN data, we use the record with the physician's most recent information / geography.

Nursing State Board data[13], and 582,927 lawyers in the Martindale-Hubbell data.

We also use the linkage between Medicare data and SSNs appearing in Infutor data to enhance the Infutor data in several ways. The first enhancement uses characteristics in Medicare data to resolve SSN linkages in cases where there is not a 1:1 relationship between individuals in Infutor and SSN. Specifically, $< 1\%$ of individuals in Infutor have more than 1 SSN. This can occur in cases of conflicting documentation. More importantly, 22% of individuals share an SSN with another person. This can occur in cases of family members who may use family members' SSN in documentation.

To help eliminate any inaccurate PID-SSN linkages in Infutor, we use the characteristics associated with the Medicare beneficiary matched to the Infutor observation as described in Appendix Table A1. Specifically, we focus on resolving identities for the 52,697,271 PIDs in Infutor that are not associated with a unique, single SSN. For these PIDs, we invalidate PID-SSN linkages among individuals if gender in Infutor conflicts with gender in Medicare. For individuals that still lack a unique, single SSN, we invalidate linkages where the Infutor year of birth is non-missing and more than 2 years different compared with year of birth in Medicare. For individuals that still lack a unique, single SSN, we invalidate linkages where gender is missing. For individuals that still lack a unique, single SSN, we invalidate linkages where year of birth is missing in Infutor. For individuals that still lack a unique, single SSN, we invalidate PID-SSN linkages among individuals if year of birth in Medicare is available and disagrees with year of birth in Infutor. Finally, we invalidate any PID-SSN linkages that still lack a unique, single SSN. Our final sample includes 243,209,696 PIDs; 206,857,808 PIDs are linked to a unique SSN and 36,351,888 PIDs with missing SSNs. Of the PIDs linked to a unique, single SSN, 68,922,730 PIDs are linked to a Medicare beneficiary enrolled in Medicare between 2006-2017.

[13]For nurses that appear in the data more than once (across different states), we select the record / geography associated with the most recent date of licensure.

Appendix Table A1: Process for resolving identities in Infutor using Medicare data

	# of Unique SSNs	Corresponding # of individuals in Infutor	
# In Infutor sample	217,327,822	243,209,696	
# NOT associated with a unique, single	26,815,397	52,697,271	
Observations still not associated with a unique, single SSN (below exclusions only applied to individuals that do not have unique, single SSNs after each step)			**Resolved Identities**
Invalidate SSN linkages if gender is non-missing in Infutor and conflicts w/ Medicare	23,695,035	49,713,266	2,984,005
Invalidate SSN linkages if Infutor YOB is non-missing & more than 2 years different compared w/ Medicare	23,083,763	49,163,242	550,024
Invalidate SSN linkages if the gender in Infutor is missing	18,409,685	45,151,748	4,011,494
Invalidate SSN linkages if the YOB in Infutor is missing	7,317,666	36,532,983	8,618,765
Invalidate SSN linkages where Medicare YOB is available and disagrees with Infutor	7,069,759	36,351,888	181,095
Invalidate SSN linkages that still not unique,	**0**	**0**	**0**
Final Sample	**217,327,822**	**243,209,696**	
Unique, Single SSN	206,857,808	206,857,808	
Linked to a Medicare Beneficiary	68,922,730	68,922,730	
Missing SSN	10,470,014	36,351,888	

Note: For the 52,697,271 individuals in Infutor for whom there is not a unique, single SSN, the majority of cases correspond to cases where a single SSN is shared across multiple individuals; only 1,919,804 PIDs correspond to 2 or more SSNs. Resolved identities refers to cases where an individual in Infutor became newly associated with a unique, single SSN following the data cleaning step.

The second way we enhance the Infutor data is by imputing a gender and year of birth in cases where an observation in Infutor is missing gender or year of birth but the individual has a unique, single SSN that matches a Medicare beneficiary. In these cases we are able to enhance the Infutor data with the Medicare value for gender and year of birth. Specifically, Infutor was enhanced with Medicare data on gender in 2,872,990 cases and Infutor was enhanced with Medicare data on year of birth in 338,482 cases.

Lastly, we enhanced the occupational data by imputing gender in cases where gender was missing but first names were highly gendered. We did this by creating a list of "highly gendered" first names for males and for females using Infutor data and the observations that have gender. We then limited to the 299,509 first names associated with at least 5 people in Infutor. Of the 299,509 first names we considered, we classified 130,040 as highly gendered if $> 90\%$ of the individuals in Infutor associated with that name were of a single gender. This process identifies 82,720 female names and 47,320 male names.[14] We used this crosswalk to impute gender in the MPIER and Martindale-Hubbell data, which did not include gender, and for 9,133,340 nurses in the State Nursing Board directories for whom gender was missing.

[14] A random sample of 10 female names includes Nancy, Anna, Freddia, Hollirae, Hollibeth, Junee, Lessandra, Meshauna, Nilza, Stacy. A random sample of 10 male names includes Lessee, Lespaul, Lesmes, Meshawn, Nimer, Nimeshkumar, Plavin, Rexroy, Rexx, Soukar

C Infutor and occupational data cleaning and enhancements

We proceeded to match individuals in the occupational directories to Infutor based on name, geography, gender, and age. Specifically, we implement a three step process considering all prior addresses and aliases observable in Infutor:

- Step 1: We identify individuals in occupational data that match to exactly one person in Infutor on a set of "broad" variables. These broad variables include: (1) last name (2) first 3 letters of first name (3) Health Referral Region (4) gender (if included in both datasets) (5) middle initial (if included in both datasets) and (5) a "broad" range of ages that are considered match-worthy
- Step 2: We identify individuals in occupational data that match exactly one person in Infutor on a set of "narrow" variables. The narrow variables include: (1) full first name (2) county or adjacent county (3) a "narrow" range of ages that are considered match-worthy
- Step 3: Finalize matches between individuals in occupational data and Infutor only for individuals that meet criteria outlined in Step 1 and Step 2.

The key complication in implementing this match is the process used to match individuals on age. This is because the age identifier in Infutor was year of birth but in occupational data could be year of birth, graduation year, or missing. Martindale-Hubbell contained year of birth, MPIER contained medical school graduation year, and the nursing directories varied, with some states providing year of birth and/or graduation date and some states providing neither. Thus we defined "broad" and "narrow" approaches to matching based on age that varied depending on the data as outlined in Appendix Table A2. This approach allows for varying levels of error in either the occupational or Infutor data and various ages of graduation.

The specific graduation ranges, especially for observations where we only observe graduation date, are validated in two ways. First, for nurses we know, from states with both DOB and graduation date, that among nurses born between 1910-1955, 85% of nurses graduate between age 19 and

40. Second, we merged the MPIER directory with data from another physician practice directory (Medicare Data on Provider Practice and Specialty; MD-PPAS) that contains year of birth data, and we estimated the distribution of ages at graduation. The MD-PPAS is a directory of physicians maintained by the Centers for Medicare and Medicaid and includes physicians billing Medicare Part B from 2008 onwards and includes date of birth. Among physicians observable in both the MPIER and MD-PPAS directories, we can see that 82% of physicians born between 1910-1955 graduated between ages 23 and 30.

Appendix Table A2: Definition of allowable broad and narrow age match ranges

<table>
<tr><th colspan="2"></th><th>Broad age match
(based on year of birth in Infutor)</th><th>Narrow age match
(based on year of birth in Infutor)</th></tr>
<tr><td rowspan="3">**Nursing**</td><td>YOB available</td><td>YOB +/- 5 years</td><td>YOB +/- 1 year</td></tr>
<tr><td>Only graduation year available</td><td rowspan="2">All implied graduation ages permitted</td><td>Implied graduation age of 19-40</td></tr>
<tr><td>YOB and graduation year unavailable</td><td>All implied graduation ages permitted</td></tr>
<tr><td colspan="2">**Physicians**</td><td>Implied graduation age of 20-35</td><td>Implied graduation age of 23-30</td></tr>
<tr><td colspan="2">**Lawyers**</td><td>YOB +/- 5 years</td><td>YOB +/- 1 year</td></tr>
</table>

Note: Nursing data is heterogeneous in the data available, with some states providing YOB, some states providing graduation year, and some states providing neither. The approach to matching each of these types of data to observations on Infutor varies as illustrated in the table. Data on physicians from MPIER includes graduation year and data on lawyers from Martindale-Hubbell includes year of birth. YOB = year of birth.

Overall, our approach to matching occupational directories to Infutor data is stricter and is likely to generate less measurement error than approaches taken in prior work, which attempt to disambiguate cases where multiple matches are plausible by identifying the single most plausible match (Bernstein, Shai et al., 2022). Instead, to achieve a match, our algorithm requires that there is an individual in Infutor data that matches the individual very closely (i.e., exact last name, first name, county, gender, middle initial, strict date of birth range when included in both datasets). The algorithm also requires that there is no other individual in Infutor that could be a plausible alternative match (i.e., shared last name, first 3 letters of first name, health referral region, gender, middle initial, and lenient date of birth range). Thus, our approach had the advantage of having fewer false linkages, which was important for minimizing measurement error. However, there were likely many individuals in the occupational data who do appear in Infutor data, but who we fail to match. This can occur in cases where Infutor is missing certain addresses or aliases, in cases where the occupational data includes employment zip code but the individual lives far from where he or she works, in cases of misspellings or other data errors, or in cases where there are multiple people in Infutor who live in a Health Referral Region with similar names and ages.

The final match procedure and match rates are illustrated by cohort in Appendix Table A3. From our occupational directories, we are able to identify 17% of nurses, 68% of lawyers, and 39% of physicians with high confidence in Infutor. The match rate is lower for nurses than lawyers and physicians for multiple reasons. First, we observe that Infutor data has stronger coverage of older birth cohorts. However, the nursing data includes all recent graduates. Data on physicians also includes all physicians practicing between 1985 and 2007 and thus also include certain more recent graduates. Meanwhile, the lawyer data is limited to individuals born from 1910-1955. Second, we have less precision on nurses' and doctors' age for matching than lawyers, for whom we always have year of birth.

Appendix Table A3: Match results of occupational data to enhanced version of Infutor

	Nurses	Lawyers	Physicians
Starting sample	5,042,094	424,043	850,850
Match to 1 individual in Infutor using "Broad Variables"	1,563,724	327,780	437,048
Match to 1 individual in Infutor using "Narrow Variables"	905,070	292,290	327,935
Unique individuals in Infutor*	866,825	291,758	327,753
Matched sample + spouses	1,883,263	658,952	739,905
Matched sample + spouses in Medicare 2006-2017	762,497	397,444	292,844
Sample that have at least 1 year in final sample	**353,953**	**243,474**	**172,887**

Note: The starting sample is the sample of individuals in our occupational directories after all cleaning procedures have been applied. The starting sample is limited to those with a non-missing first and last name and a Hospital Reference Region (HRR). *The sample of unique individuals in Infutor is 2% smaller than the matched sample for each occupational group; this is because certain nurses, doctors, and lawyers matched to the same individual in Infutor. This is most common among nurses, because the original dataset of nurses across 25 states likely contains some duplicates for nurses moving across state lines.

D Validating Infutor data and match quality

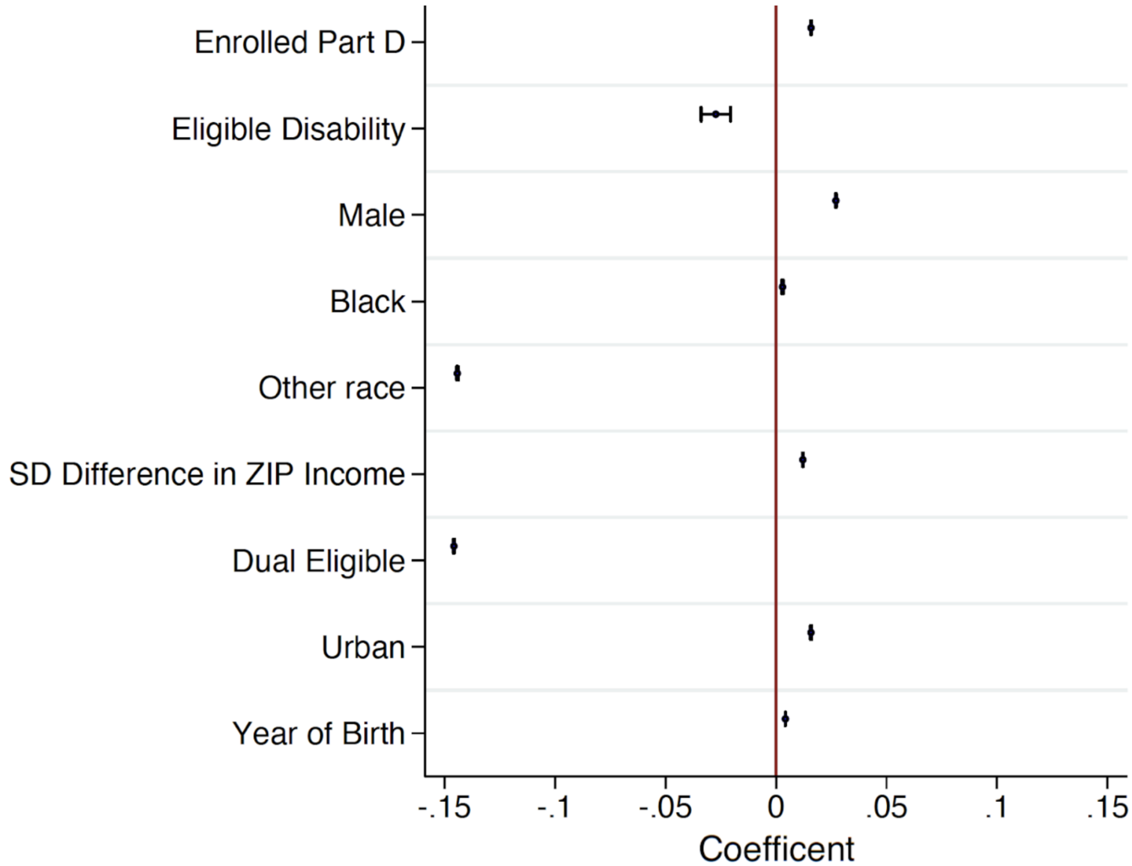
We performed two checks to validate the Infutor data fields, the match between Infutor and Medicare data, and the match between occupational directories and Infutor data. First, we compared the year of birth and gender fields between Infutor and Medicare data for individuals with a 1:1 relationship between individuals in Infutor and SSN prior to any enhancements and for whom gender and year of birth fields are available in both datasets. Among these individuals, the two sources agreed on year of birth in 87% of cases and for 93% of cases there was a difference of 2 years or less; the two sources agreed on gender 98% of the time. This supports the validity of Infutor characteristics and of the match between Infutor and Medicare data.

Second, to develop confidence in the quality of the match between the occupational directories and Infutor, we evaluate the correlation between Medicare beneficiaries identified as physicians and whether the ”prefix” variable, which is available in Infutor, appears as ”Dr.” While we do not expect all true physicians in Infutor to have their prefix listed as ”Dr.” and that some non-physicians may have a ”Dr.” prefix by virtue of having other doctorate degrees, we would expect the ”Dr.” prefix to be correlated with individuals we identify as physicians. We find that of all the Medicare beneficiaries from 2006-2017 who we identify as physicians, 67% of them have their prefix field in Infutor populated with ”Dr.” Meanwhile, $< 1\%$ of lawyers have a prefix field of ”Dr.” This finding is consistent with an algorithm that is indeed successfully differentiating between physicians and lawyers, though the exact accuracy cannot be confirmed.

E Representativeness of Infutor data

We further used the linkage between Medicare and Infutor data to evaluate the representativeness of Infutor data. We estimated a linear model of the likelihood that Medicare beneficiaries enrolled at any time between 2006-2017 and originally eligible by age matched to Infutor using characteristics in Medicare. The results, presented in Figure A2, suggest that Infutor data is not a random sampling of Medicare beneficiaries. Most notably, among Medicare beneficiaries, Infutor data are less likely to include non-white, non-black individuals and dual-eligible individuals among Medicare beneficiaries in our study period. Specifically, non-white, non-black individuals are 14.4 percentage points (95% CI: 14.4, 14.5) less likely to appear in Infutor, and dual-eligible beneficiaries are 14.6 percentage points (95% CI: 14.6, 14.6) less likely to appear in Infutor.

Appendix Figure A2: Likelihood of matching to Infutor among Medicare beneficiaries enrolled between 2006-2017



Note: Coefficients reflect the relative likelihood of matching to an individual in Infutor based on selected characteristics. Estimates are from a single linear regression predicting likelihood of matching, with indicators for part D enrollment, eligibility for disability, sex, race (black, other), dual eligibility, urban / rural status. We also control for average ZIP code income and year of birth. Patient characteristics taken from patients' final year in Medicare. ZIP code income is derived from the American Community Survey 2018 5-year estimates and the standard deviation (SD) is estimated using all Medicare beneficiaries in the regression sample; the standard deviation for ZIP code income is estimated to be $39,154. The linear model includes HRR fixed effects, and error bars reflect 95% confidence intervals.

F Sensitivity analyses for primary exhibits in main text

F.1 Stratifying ED Visits by the Empirical Risk of Hospitalization

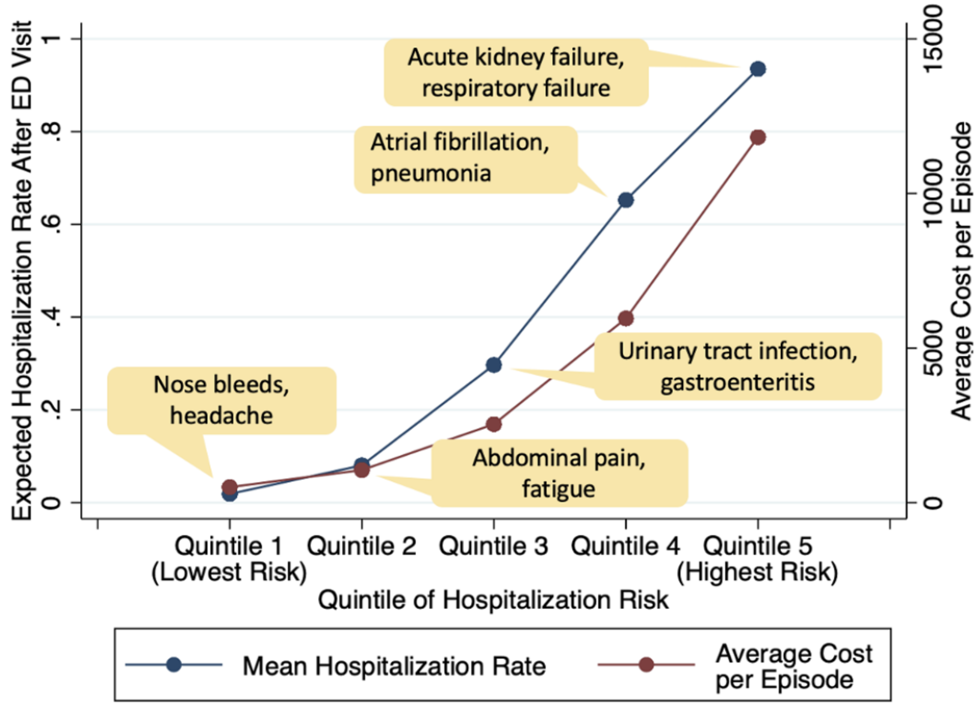
For all primary diagnosis codes for ED visits for Medicare patients in our sample, we defined a "hospitalization risk," which reflects the share of ED visits with that primary diagnosis code resulting in hospitalization.[15] We stratified diagnoses into five quintiles of this risk, with each quintile including an approximately equal number of admissions across the study period, subject to the constraint that each diagnosis code only appears in one quintile. We further validated that this approach generates a highly predictive measure of acuity by estimating "hospitalization risk" in a 90% random sample of ED visits. Then, in the 10% hold-out sample, we evaluated the share of variation in hospitalization explained by the hospitalization risk score and estimated the average hospitalization rate for diagnoses in each quintile; the hold-out sample avoids over-fitting. As illustrated in Appendix Figure A3, we find there is a monotonic relationship between estimated quintile of hospitalization risk and true hospitalization risk out-of-sample, with an out-of-sample R^2 of 0.53. Reassuringly, there is also a monotonic relationship between estimated quintile of hospitalization risk and other measures of acuity such as spending and 30-day mortality.

We report differences in the ED use of medical experts and their spouses across diagnoses stratified by quintile of hospitalization risk, using the same negative binomial model described in Equation 1. Consistent with the analysis in section 4, the results, illustrated in Appendix Table A4, demonstrate that lower use of ED visits by physicians and their spouses is driven primarily by fewer low acuity visits. Specifically,physicians and their spouses use 30.2% and 23.4% fewer visits for diagnoses in the lowest quintile of acuity relative to lawyers and their spouses respectively. However, physicians and their spouses only use 10.1% and 7.7% fewer ED visits for diagnoses

[15] ED visits resulting in hospitalization are defined as ED visits that appear in Inpatient MedPAR claims with a > \$0 ED charge, or those observed in Outpatient claims that are accompanied by an Inpatient claim on the same or subsequent day. This is in accordance with guidance from the Centers for Medicare and Medicaid's data partner ResDAC available here: https://resdac.org/articles/how-identify-hospital-claims-emergency-room-visits-medicare-claims-data

in the highest quintile of acuity relative to lawyers and their spouses respectively. The degree to which nurses and their spouses have fewer ED visits does not vary consistently with the acuity of their diagnosis.

Appendix Figure A3: Out-of-sample performance of hospitalization risk algorithm including overall fit, hospitalization risk by quintile, spending by quintile, mortality by quintile, and example diagnoses



Average 30-Day Mortality by Quintile (%)	1.3	3.1	3.1	7.0	14.7

Note: Hospitalization risk for each diagnosis is estimated on a 90% random sample of emergency department visits. Quintiles of hospitalization risk were defined to ensure each quintile has an approximately equal number of emergency department visits, subject to the constraint that each diagnosis code only appears in one quintile. Average hospitalization rates by quintile are reported on the 10% hold-out sample. Example diagnoses for each quintile are representative primary diagnoses for that quintile. Cost per episode reflects the sum of inpatient and outpatient claims costs associated with a given emergency department visit.

Appendix Table A4: Difference in Annual Emergency Department Visits by Quintile of Predicted Hospitalization Risk Between Groups

	Quintile 1 (Lowest Risk)	Quintile 2	Quintile 3	Quintile 4	Quintile 5 (Highest Risk)
	(1)	(2)	(3)	(4)	(5)
High-income x physician	-0.360	-0.265	-0.216	-0.102	-0.106
95% CI	[-0.342, -0.379]	[-0.245, -0.285]	[-0.198, -0.234]	[-0.083, -0.120]	[-0.088, -0.123]
High-income x physician spouse	-0.267	-0.238	-0.181	-0.132	-0.080
95% CI	[-0.249, -0.285]	[-0.219, -0.258]	[-0.163, -0.199]	[-0.114, -0.150]	[-0.062, -0.097]
High-income	0.037	-0.083	-0.039	-0.136	-0.154
95% CI	[0.048, 0.026]	[-0.072, -0.095]	[-0.029, -0.050]	[-0.125, -0.147]	[-0.143, -0.165]
High-income spouses	-0.001	-0.112	-0.108	-0.119	-0.152
95% CI	[0.010, -0.012]	[-0.100, -0.125]	[-0.097, -0.120]	[-0.108, -0.131]	[-0.141, -0.164]
Nurses	-0.046	-0.049	-0.052	-0.037	-0.085
95% CI	[-0.037, -0.056]	[-0.037, -0.061]	[-0.042, -0.062]	[-0.027, -0.046]	[-0.076, -0.095]
Nurses' Spouses	-0.073	-0.092	-0.068	-0.066	-0.081
95% CI	[-0.064, -0.082]	[-0.082, -0.102]	[-0.059, -0.078]	[-0.057, -0.076]	[-0.073, -0.090]
Observations	**242,256,298**	**242,256,298**	**242,256,298**	**242,256,298**	**242,256,298**

Note: Table reports percent differences from estimating Equation (1) using a negative-binomial model. Coefficients on High-income x physicians and High-income x physician spouse are the percent increase in the outcome associated with physicians and their spouses relative to lawyers and their spouses respectively. Coefficient on Nurses and Nurses' Spouses are percent differences relative to the Medicare population. Standard errors are clustered at the patient level.

Appendix Table A5: Implied percentage difference in avoidable emergency department visits between groups

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
High-income x physician	-0.248	-0.246	-0.253	-0.245	-0.233	-0.258			
95% CI	(-0.235, -0.26)	(-0.234, -0.258)	(-0.240, -0.266)	(-0.232, -0.257)	(-0.217, -0.250)	(-0.242, -0.275)			
High-income x physician spouse	-0.217	-0.215	-0.218	-0.217	-0.194		-0.201		
95% CI	(-0.204, -0.23)	(-0.202, -0.228)	(-0.205, -0.231)	(-0.205, -0.23)	(-0.180, -0.209)		(-0.180, -0.216)		
High-income	-0.122	-0.163	-0.186	-0.126	-0.058				
95% CI	(-0.114, -0.131)	(-0.156, -0.172)	(-0.178, -0.194)	(-0.118, -0.134)	(-0.053, -0.063)				
High-income spouses	-0.137	-0.175	-0.197	-0.135	-0.111				
95% CI	(-0.122, -0.139)	(-0.165, -0.181)	(-0.181, -0.205)	(-0.122, -0.139)	(-0.053, -0.105)				
Nurse	-0.068	-0.068	-0.069	-0.069	-0.063			-0.068	
95% CI	(-0.059, -0.077)	(-0.059, -0.076)	(-0.06, -0.078)	(-0.061, -0.078)	(-0.058, -0.074)			(-0.047, -0.089)	
Nurse Spouse	-0.090	-0.090	-0.093	-0.094	-0.063				-0.021
95% CI	(-0.082, -0.098)	(-0.082, -0.098)	(-0.085, -0.101)	(-0.087, -0.102)	(-0.053, -0.053)				(0.000, -0.042)
Approach		Negative Binomial		Poisson	OLS		Inverse propensity score weighting		
Controls included*									
Age, Race, Sex, Year, Part D, Dual, Urban	X	X	X		X	X	X	X	X
Comorbidities	X	X			X	X	X	X	X
Zip code income ventiles	X				X	X	X	X	X
Observations			**242,256,298**			**1,393,502**	**1,292,333**	**238,480,449**	**238,463,831**

Note: The outcome across amodels avoidable ED visits per Billings, Parikh and Mijanovich (2000). Models (1) to (3) reflect an estimation of the negative binomial model outlined in Equation 1 with varying sets of covariates included. The implied percent differences in the outcome reflects an estimate of $e^{\beta} - 1$. Model (4)-(5) reflects an the implied percentage difference in the outcome using a poisson and ordinary least squares (OLS) model respectively. Models (6) to (9) reflect the implied percentage difference in the outcome using inverse propensity score weighting (IPSW) approach to evaluating group differences between physicians and lawyers (model 6), physicians' spouses and lawyers' spouses (model 7), nurses and the general public excluding medical experts and their spouses (model 8), and nurses' spouses and the general public excluding medical experts and their spouses (model 9). The coefficients produced from OLS and the estimates for average treatment effects produced from IPSW are transformed into an implied percentage change relative to the mean value of the outcome in the comparison group for each population to support comparability with Models (1) to (3). The comparison group for physicians is lawyers, for physicians' spouses is lawyers' spouses, and for all other groups is the general public excluding all medical experts and their spouses. Standard errors are clustered at the patient level.

Appendix Table A6: Difference in Avoidable and Non-Avoidable Annual Emergency Department Visits Between Groups, Excluding Non-Primary Care Physicians and Their Spouses

			Avoidable visits by type		
	All avoidable visit categories	Emergent and non-preventable	Non-emergent	Emergent and primary care treatable	Emergent and preventable
	(1)	(2)	(3)	(4)	(5)
High-income x physician	-0.188	-0.033	-0.22	-0.16	-0.172
95% CI	(-0.169, -0.206)	(-0.011, -0.054)	(-0.196, -0.243)	(-0.138, -0.181)	(-0.142, -0.201)
High-income x physician spouse	-0.199	-0.093	-0.239	-0.176	-0.174
95% CI	(-0.182, -0.216)	(-0.073, -0.113)	(-0.218, -0.259)	(-0.157, -0.196)	(-0.146, -0.201)
High-income	-0.126	-0.086	-0.105	-0.115	-0.205
95% CI	(-0.118, -0.135)	(-0.077, -0.095)	(-0.093, -0.117)	(-0.105, -0.124)	(-0.192, -0.218)
High-income spouses	-0.139	-0.106	-0.12	-0.137	-0.176
95% CI	(-0.13, -0.149)	(-0.096, -0.117)	(-0.109, -0.132)	(-0.126, -0.146)	(-0.162, -0.189)
Nurse	-0.069	-0.034	-0.064	-0.067	-0.098
95% CI	(-0.061, -0.079)	(-0.026, -0.043)	(-0.053, -0.076)	(-0.058, -0.075)	(-0.086, -0.11)
Nurse Spouse	-0.091	-0.054	-0.095	-0.081	-0.125
95% CI	(-0.083, -0.099)	(-0.046, -0.062)	(-0.084, -0.105)	(-0.073, -0.091)	(-0.113, -0.136)
Observations	**241,548,224**	**241,548,224**	**241,548,224**	**241,548,224**	**241,548,224**

Note: Table reports percent differences from estimating Equation (1) using a negative-binomial model. Table reflects a variation of Table 3 in the main text excluding physicians who are non-primary care physicians and their spouses. Primary care physician specialties are defined as physicians with the following CMS specialty codes in the UPIN directory: 1 (general practice), 8 (family practice), 11 (internal medicine), 17 (hospice and palliative care), 23 (sports medicine), 26 (psychiatry), 37 (pediatric medicine), 38 (geriatric medicine), 72 (pain management), 79 (addiction medicine), 84 (preventive medicine), and C0 (sleep medicine), in order to replicate the approach used by Gottlieb et al. (2023) to identify primary care physicians and then compare primary care incomes with lawyer incomes. Standard errors are clustered at the patient level.

Appendix Table A7: Difference Between Groups in Emergency Department Visits in the Lowest Quintile of Hospitalization Risk, Stratifying Diagnoses by Quintiles of Prescription Propensity

	Quintile 1 (Lowest Prescription Propensity)	Quintile 2	Quintile 3	Quintile 4	Quintile 5 (Highest Prescription Propensity)
	(1)	(2)	(3)	(4)	(5)
High-income x physician	-0.027	-0.144	-0.367	-0.406	-0.469
95% CI	[0.162, -0.216]	[-0.104, -0.184]	[-0.34, -0.393]	[-0.377, -0.435]	[-0.435, -0.502]
High-income x physician spouse	-0.111	-0.206	-0.260	-0.247	-0.350
95% CI	[0.102, -0.324]	[-0.165, -0.247]	[-0.233, -0.287]	[-0.221, -0.273]	[-0.32, -0.381]
High-income	0.308	0.148	0.073	0.018	-0.064
95% CI	[0.418, 0.198]	[0.174, 0.123]	[0.088, 0.057]	[0.034, 0.002]	[-0.044, -0.083]
High-income spouses	0.342	0.088	0.079	-0.025	-0.092
95% CI	[0.484, 0.2]	[0.116, 0.06]	[0.096, 0.062]	[-0.009, -0.042]	[-0.073, -0.111]
Nurses	0.135	0.130	-0.028	-0.080	-0.089
95% CI	[0.244, 0.025]	[0.154, 0.107]	[-0.013, -0.043]	[-0.067, -0.093]	[-0.075, -0.103]
Nurses' Spouses	-0.071	-0.052	-0.068	-0.086	-0.070
95% CI	[0.067, -0.21]	[-0.028, -0.076]	[-0.053, -0.082]	[-0.072, -0.101]	[-0.055, -0.085]
Observations	**242,256,298**	**242,256,298**	**242,256,298**	**242,256,298**	**242,256,298**

Note: Table reports results of a negative binomial regression model analogous to Equation (1), except where the outcome is defined as the number of ED visits in the lowest quintile of hospitalization risk per section Appendix Section F1. Models 1-5 further limit to ED visits in five quintiles of prescription propensity. Coefficients are transformed such that coefficients can be interpreted as the percent differences in the share of ED visits. Coefficients on High-income x physician and High-income x physician spouse are the percent increase in the outcome associated with physicians and their spouses relative to lawyers and their spouses respectively. Coefficient on Nurses and Nurses' Spouses are percent differences relative to the general Medicare population. Models adjust for age, race, sex, year, Part D enrollment, dual eligibility, urban residence, Charlson comorbidity index, and zip code income ventiles. Standard errors are clustered at the patient level.

G Evidence on alternative mechanisms

Appendix Table A8: Difference in Annual Outpatient Visits and Primary Care Visits by Group

	Total number of outpatient visits	Total number of primary care visits
	(1)	(2)
High-income x physician	-0.339	-0.534
95% CI	[-0.322, -0.355]	[-0.512, -0.555]
High-income x physician spouse	-0.146	-0.223
95% CI	[-0.129, -0.162]	[-0.204, -0.242]
High-income	0.096	-0.059
95% CI	[0.105, 0.086]	[-0.047, -0.070]
High-income spouses	0.064	-0.060
95% CI	[0.074, 0.053]	[-0.048, -0.072]
Nurses	-0.017	-0.050
95% CI	[-0.008, -0.025]	[-0.041, -0.059]
Nurse spouses	-0.012	-0.019
95% CI	[-0.004, -0.020]	[-0.010, -0.029]
Observations	**48,468,972**	**48,468,972**

Note: Table reports results of a negative binomial regression model analogous to Equation (1), except where the outcome is defined as the number of outpatient visits (model 1) and the number of primary care visits (model 2). Outpatient visits are defined by the number of days in the year in which patients have an evaluation and management visit. Here, primary care visits are defined as days in the year in which patients have an evaluation and management with the following specialty codes: 1 (general practice), 8 (family practice), 11 (internal medicine), 37 (pediatric medicine), 38 (geriatric medicine), and 50 (nurse practitioner). Each year from 2006-2017, the sample is limited to a 20% random sample of Medicare patients eligible by age, identifiable in Infutor, and enrolled in Medicare FFS Parts A and B continuously or until death. This sample is used as data on outpatient visits is only available for this 20% subsample. Coefficients are transformed to reflect percent differences. Standard errors are clustered by patient.

Appendix Table A9: Difference in Avoidable and Non-Avoidable Annual Emergency Department Visits Between Groups, Main Specification and Limiting to ED Visits Occurring on Weekends

	Main specification		ED Visits on Weekends	
	All Avoidable Visit Categories	Emergent and Non-Preventable	All Avoidable Visit Categories	Emergent and Non-Preventable
	(1)	(2)	(3)	(4)
High-income x physician	-0.248	-0.075	-0.249	-0.031
95% CI	(-0.235, -0.26)	(-0.06, -0.09)	(-0.232, -0.266)	(-0.007, -0.054)
High-income x physician spouse	-0.217	-0.118	-0.234	-0.120
95% CI	(-0.204, -0.23)	(-0.102, -0.132)	(-0.217, -0.251)	(-0.097, -0.142)
High-income	-0.122	-0.083	-0.097	-0.075
95% CI	(-0.114, -0.131)	(-0.074, -0.092)	(-0.084, -0.11)	(-0.061, -0.089)
High-income spouses	-0.137	-0.105	-0.118	-0.101
95% CI	(-0.128, -0.146)	(-0.095, -0.115)	(-0.105, -0.13)	(-0.085, -0.116)
Nurses	-0.068	-0.032	-0.052	-0.026
95% CI	(-0.059, -0.077)	(-0.025, -0.041)	(-0.041, -0.062)	(-0.013, -0.038)
Nurse spouses	-0.09	-0.054	-0.067	-0.039
95% CI	(-0.082, -0.098)	(-0.046, -0.061)	(-0.056, -0.077)	(-0.027, -0.052)
Observations	**242,256,298**	**242,256,298**	**242,256,298**	**242,256,298**

Note: Models (1) and (2) reflect results presented in main text Table 3. Models (2) and (3) are variants of Models (1) and (2) respectively, where the outcome only includes ED visits occurring on weekends.

Appendix Table A10: Difference in Avoidable Emergency Department Visits Between Groups Stratifying Diagnoses by Quintiles of Imaging Propensity

	Quintile 1 (Lowest Imaging Propensity)	Quintile 2	Quintile 3	Quintile 4	Quintile 5 (Highest Imaging Propensity)
	(1)	(2)	(3)	(4)	(5)
High-income x physician	-0.414	-0.241	-0.267	-0.228	-0.263
95% CI	[-0.387, -0.442]	[-0.21, -0.272]	[-0.239, -0.295]	[-0.201, -0.256]	[-0.232, -0.295]
High-income x physician spouse	-0.274	-0.248	-0.248	-0.240	-0.222
95% CI	[-0.247, -0.301]	[-0.217, -0.279]	[-0.221, -0.275]	[-0.214, -0.265]	[-0.192, -0.251]
High-income	0.000	-0.314	-0.169	-0.141	-0.099
95% CI	[0.016, -0.016]	[-0.295, -0.333]	[-0.153, -0.186]	[-0.124, -0.157]	[-0.08, -0.117]
High-income spouses	-0.101	-0.243	-0.163	-0.125	-0.131
95% CI	[-0.084, -0.119]	[-0.223, -0.263]	[-0.145, -0.18]	[-0.109, -0.142]	[-0.112, -0.151]
Nurses	-0.066	-0.128	-0.032	-0.061	-0.095
95% CI	[-0.053, -0.079]	[-0.111, -0.144]	[-0.012, -0.051]	[-0.048, -0.074]	[-0.08, -0.11]
Nurses' Spouses	-0.060	-0.147	-0.105	-0.100	-0.075
95% CI	[-0.047, -0.074]	[-0.131, -0.163]	[-0.091, -0.119]	[-0.087, -0.113]	[-0.059, -0.09]
Observations	**242,256,298**	**242,256,298**	**242,256,298**	**242,256,298**	**242,256,298**

Note: Table reports results of a negative binomial regression analogous to those presented in main text Table 4. However, instead of stratifying diagnoses into quintiles by their likelihood of resulting in a prescription on the day of or following discharge, diagnoses are stratified into quintiles by their likelihood of requiring imaging between the day of admission and day after discharge. Imaging is defined to include CT scans, MRI scans, and PET Scans.